**The Global Diffusion of Tobacco Control**

**3. RESEARCH STRATEGY**

**A. SIGNIFICANCE**

This proposal is in response to Program Announcement PAR**-**10-145, Social Network Analysis and Health (R01) and addresses fundamental questions about social interactions and processes in social networks. The significance of this proposal has two dimensions: 1) the importance of understanding how public health law and policy can contribute to population health; and 2) understand how social networks influence the adoption and spread of health-related behaviors.

Public health advocates have used many tools to reduce tobacco use including media campaigns, restricting advertising, restricting sales to minors, increased taxation, and so on [[1](#_ENREF_1)]. The global impact of tobacco use on mortality and morbidity, however, is still substantial. There are an estimated 1.3 billion smokers globally, and tobacco use is still the leading cause of preventable death worldwide. To combat the ongoing problem of tobacco use, the World Health Organization (WHO) Member States negotiated and unanimously adopted the WHO Framework Convention on Tobacco Control (FCTC) which is an international treaty aimed at reducing tobacco use. The Intergovernmental Negotiating Body (INB) negotiated the text of the treaty over six formal negotiating sessions in Geneva, Switzerland, between 2000 and 2003. Over 170 countries sent at least one delegate to at least one of the INB sessions. Scientific experts and representatives of advocacy networks also attended the negotiations where they held seminars on technical aspects of the FCTC and distributed information to delegates.

The World Health Assembly formally adopted the final FCTC text in May 2003 [[2](#_ENREF_2)]. The key provisions of the FCTC include a comprehensive ban on tobacco advertising, promotion, and sponsorship; a ban on misleading descriptors intended to convince smokers that certain products are safer than standard cigarettes (for example, the term “lights” in Marlboro Lights); and a mandate to place rotating warnings that cover at least 30% of tobacco packaging. The FCTC also encourages countries to implement smoke-free workplace laws, address tobacco smuggling, and increase tobacco taxes. The FCTC entered into force on February 27, 2005, 90 days after the 40th Member State had ratified the treaty. Further ratifications continued over the next 5 years. As of April 2011, the mean date of ratification was March 2006, whereas the median was November 2005. Approximately 87% of the 193 WHO Member States have ratified the FCTC (or its legal equivalent). Figure 1 graphs the diffusion of the FCTC along with two other treaties.

Comparison Treaties. We searched the United Nations Treaty Database for multi-party (all non-bilateral) treaties received between January 1, 2001, and December 31, 2003; and treaties that went into force between January 1, 2004, and December 31, 2009. Twenty treaties fit these criteria. Four of these 20 treaties concerned the protocol and amendments for one treaty on weapons ([Convention on Prohibitions or Restrictions on the Use of Certain Conventional Weapons which may be deemed to be Excessively Injurious or to have Indiscriminate Effects](javascript:void%20window.open('showDetails.aspx?objid=080000028003ac2c','_blank','location=yes,scrollbars=yes,status=no,width=600px,resizable=yes'))), which has not been widely adopted. Nine were regional treaties (e.g., Inter-governmental Agreement on the Asian Highway Network) that are restricted to a few countries and so not comparable to the FCTC. Of the seven remaining treaties, three have been ratified by a significant portion of countries: 1) FCTC; 2) Convention against Corruption (Corrupt); and 3) Convention on Persistent Organic Pollutant (Pollute). The data for the diffusion of these treaties are graphed in Figure 1. To make the graphs comparable, we adjusted the starting dates to be similar, although the actual starting dates range from May 4, 2001, to September 12, 2003. These three treaties have spread internationally over similar time periods and at approximately the same rate.

Figure 1: Diffusion of FCTC along with two other treaties.

The FCTC represented the first time that the WHO Member States enacted the Organization’s power under Article 19 of its constitution to negotiate and sign a binding treaty aimed at protecting and promoting public health. It also represented the first time that countries cooperated worldwide in a collective response to prevent a chronic disease. Considerable time and effort have been invested in the negotiation, ratification, and implementation of the FCTC. **Understanding when, how, and why individual countries ratified and subsequently adopted policies implementing the treaty obligations is critical to understanding how future international health treaties may diffuse through the international community and how global health governance should be developed in the future.**

The second significant component of this research is the theoretical contribution to be made from estimating dynamic social influence models containing data on multiple behaviors and multiple networks. Our prior research indicated that GLOBALink (GL), an electronic forum for communication and information exchange about tobacco control, was instrumental in driving ratification of the FCTC. The data used for that study, however, were incomplete and raised several important research questions that can be explored by creating a more extensive dataset on tobacco control communications and international networks, and testing more theoretically driven hypotheses. We propose to estimate the influence of GL social networks on the ratification and strength of implementation of the FCTC among the 193 member countries over a 9-year period. Although network exposure may be associated with ratification and enforcement of the FCTC, many country attributes may be associated with these outcomes and network connectivity. To test this explanation, we propose to develop an extensive database of country attributes to supplement the network data. **We will test if social network effects persist after controlling for country-level characteristics such as population, population distribution, size (area), income, tobacco production, governmental form, region, tobacco control NGOs, and so on.** In addition to controlling for these characteristics, we will determine whether these country characteristics are associated with FCTC ratification, enforcement, infectivity, and/or susceptibility.

These initial models are limited by the idiosyncratic nature of examining one treaty (the FCTC) and network data derived from on source (GL). Replication of the results will enhance the robustness of the findings and strengthen the theoretical claims in the study. To do so, we propose testing the network influence models on the diffusion of the two “comparison treaties” (a legal one “Corrupt” and an environmental one “Pollute” from Figure 1). Thus, we propose to compare, contrast, and cross-test models using data on the diffusion of the two other treaties as a function of two general international networks (communication and trade). The analytic strategy to be employed will use diffusion network modeling appropriate for longitudinal data of this nature [[3-6](#_ENREF_3)]. There are concerns, however, that diffusion network effects may be mis-specified for at least two reasons: 1) exposure modeling does not capture the dependencies developed in P\* models [[7](#_ENREF_7), [8](#_ENREF_8)]; and 2) dynamic network processes such as selection are not incorporated into the diffusion network approach. To address these issues, we are building a platform that combines the stochastic actor oriented models with diffusion network approaches to test dynamic social influence hypotheses. Thus, all models will be tested using a combined diffusion network actor-oriented stochastic model of adoption using MCMC and event history approaches. **The theoretical significance of this study lies in the acquisition of a unique longitudinal dataset containing passive measures of multiple behaviors and multiple networks whose association will be estimated using a combined diffusion network stochastic actor oriented approach.**

Finally we intend to use content analyses of postings and messages to explore whether there is qualitative evidence of GL network effects on the adoption of the FCTC

**B. INNOVATION**

There are several facets of this study that are innovative: 1) we specify dynamic hypotheses that consider the influence of network context and position on behavior change; 2) the outcomes we study are conceptualized and operationalized as multiple stages in the behavior change process; and 3) we estimate models that compare and contrast different networks with different behaviors.

**B.1. Dynamic Hypotheses**. The proposed research study draws on diffusion of innovations theory which attempts to explain how new ideas and practices spread within and between communities [[9](#_ENREF_9), [10](#_ENREF_10)]. The theory has its roots in anthropology, economics, geography, sociology, marketing, mathematics, among other disciplines [[9](#_ENREF_9)], and has in some ways been adapted from epidemiology [[11](#_ENREF_11), [12](#_ENREF_12)]. The premise, confirmed by empirical research, is that new ideas and practices spread through interpersonal contacts largely consisting of interpersonal communication [[3](#_ENREF_3)]. Diffusion research peaked in the 1950s with several studies of diffusion networks being conducted at that time. The most notable diffusion network study was the one conducted by Coleman, Katz, and Menzel (1966) on the diffusion of tetracycline among physicians [[4](#_ENREF_4), [13-16](#_ENREF_13)]. Adoption data were recorded by examining pharmacy records, making a reasonably accurate estimate of individual physician adoption available. Tetracycline diffused to almost all of the 125 physicians in the 4 communities over an 18-month period. Two other subsequent studies (Korean Family Planning and Brazilian Farmers) also provided data on time of adoption and social networks [[17](#_ENREF_17)]. These two studies were much larger, but relied on recall to record time of adoption. Three other studies diffusion network studies were conducted in the 1960s, but the data are no longer available. These diffusion network studies provided empirical data useful for estimating network influences on diffusion. Few other studies have been conducted that provide data on adoption/diffusion and social network contacts. The paucity of diffusion data has severely restricted theoretical development of social network effects and a more profound understanding of contagion mechanisms.

There have been studies specifically on the diffusion of policies [[18](#_ENREF_18)]. Walker’s1966 [[19](#_ENREF_19)] seminal paper outlined the importance of diffusion approaches for studying policy adoption. In an analysis of a dozen policies adopted by US states, Gray showed how a model of state-to-state diffusion predicted the patterns of state adoptions [[20](#_ENREF_20)]. Although the pattern of state adoption suggested interaction as a primary influence on adoption, Gray also showed that the earliest adopting states often did so for economic or political reasons. Most diffusion studies, however, have inferred person-to-person interaction as an explanation for diffusion without having data appropriate to test it. There is hope and expectation that computerized communications will provide a rich trove of data useful for modeling dynamic network diffusion processes [[21](#_ENREF_21)]. Such data have been elusive for at least two reasons: 1) often the innovative behavior being studied is part of the computerized network within which the data are collected; and 2) many behavioral studies involve the adoption of consumer goods for which the data are proprietary, though there are notable exceptions [[22](#_ENREF_22)]. A recent replication of the Coleman and others (1966) study has advanced specification of diffusion effects and suggested additional avenues of research such as specifying how individual characteristics are associated with resistance to change[[5](#_ENREF_5)].

Given studies of diffusion in other contexts [[17](#_ENREF_17), [23-25](#_ENREF_23)], we hypothesize that the global diffusion of the FCTC has been driven in part by interpersonal communication and networking developed throughout the negotiation of the FCTC and facilitated through existing global tobacco control networks. In other words, the extent of a country’s participation in the FCTC negotiations and its citizens’ involvement in international tobacco control networks should be associated with early or late FCTC ratification, as well as the number and strength of policies aimed at implementing the treaties obligations. We also expect, however, the predictably of these social network variables to be impacted to some extent by the structural and demographic aspects of states (eg, location, population, income-level, degree of political freedom, tobacco prevalence, and tobacco production). For example, a country with high smoking prevalence may perceive tobacco control as more important and ratify sooner than a country with low smoking prevalence, and implement relevant and stronger policy changes quicker. Conversely, a tobacco producing and exporting country may view tobacco control as a threat to its financial success and resist ratification, or resist policy changes required by the FCTC following its ratification. In this study we wish to compare the structural, demographic, and social network variables that led individual countries to ratify the FCTC and how these variables impacted the extent to which the countries adopted policies implementing their treaty commitments. Together, the study represents a first attempt at specifying the driving forces behind global tobacco control diffusion. Its significance lies with the importance of global health legislation and the scientific study of network effects and diffusion processes.

Figure 2: Graphical Description of Behavioral Hypotheses.

The analytic strategy we propose estimates dynamic network effects using a combined diffusion actor-oriented stochastic model of adoption using MCMC and event history approaches. Prior research using the stochastic actor oriented model (SIENA) [[26](#_ENREF_26)] have been based on two, three, or at most four waves of data[[27](#_ENREF_27)]. In contrast, diffusion studies take a macro perspective and often have 10 or 20 time points. The opportunity to dynamically analyze networks and behavior provides multiple opportunities for theory building and hypotheses testing. Here we outline four behavioral hypotheses we will test that combine the diffusion network stochastic actor-oriented model (DN/SAOM) perspectives: 1) influence and selection; 2) leaders or network position; 3) external influence; and 4) thresholds. Figure 2 depicts these hypotheses graphically.

Behavioral Hypothesis: Influence and Selection. Network influence has been associated with behaviors across many domains. For example, in the field of adolescent health, students who have friends who smoke are more likely to smoke themselves[[28](#_ENREF_28)]. Recent advances in stochastic actor oriented models SAOM have permitted researchers to test influence versus selection mechanisms as explanations for this behavioral homophily. Typically, these tests have been conducted with longitudinal panel data collected over two waves of observations (a baseline and 1-year follow up). Yet diffusion theory predicts evolution in the influence and selection processes such that they are expected to vary over time. Specifically, early in the diffusion process, there are few adopters able to provide influence, and usually these innovative and early adopters are generally not good role models given that their behavior deviates significantly from community norms [[29](#_ENREF_29)]. This is particularly true if these innovators are marginal in the social system [[30](#_ENREF_30)]. Thus, we expect the influence coefficient to be low or near zero early in the diffusion of the FCTC. Conversely, as individuals seek new information about the new idea or behavior, they select individuals who have adopted the innovation to learn from, thus the selection coefficient should be significantly greater than zero early in the diffusion process. As the FCTC diffuses and it becomes more accepted, individuals (within countries) may be more susceptible to peer influence. Consequently, the influence coefficient should increase over time proportionate to the number of adopters. Conversely, as the population fills with adopters, individuals do not need to seek out those who have adopted, and can readily find experienced users in their existing network. Thus, the selection coefficient, as a mechanism driving homophily, should decrease over time. Past studies have found evidence for selection and influence operating simultaneously between two time points. By analyzing data over many time periods, we can hypothesize differences in the evolution of influence and selection effects over time.

Behavioral Hypothesis: Leaders. The second behavioral hypothesis we wish to test is the association between network leaders and behavior. Several studies have shown that network position is associated with behavior. For example, two studies have shown a correlation between adolescent smoking and popularity[[28](#_ENREF_28), [31](#_ENREF_31)]. In the DN/SAOM framework, we expect this association to vary over time. Leaders are generally not innovative as they have a built-in desire to support the status quo [[29](#_ENREF_29), [32](#_ENREF_32)]. Innovating too early demonstrates deviation from community norms, and thus we expect marginal and bridging individuals to be the earliest adopters whereas central actors will innovative during the early and late majority periods. Leaders need to embrace attitudes that are consistence with community norms and yet their privileged position provides early access to information enabling them to adopt before the majority of their reference group. Marginals are most likely to adopt at the earliest and latest stages of diffusion, but for different reasons. The earliest marginal adopters are innovative and demonstrate their independence from group norms[[33](#_ENREF_33)]. The latest marginal adopters do so because their position in the network prevents them from learning about the innovation until a majority have adopted[[17](#_ENREF_17)].

Behavioral Hypothesis: External Influence. The function of external influence in the adoption process is the third hypothesis to be tested. Consistent with diffusion theory and the two-step flow hypothesis, it is expected that external influence is associated with adoption early in the diffusion process, before there are too many adopters in the community. The coefficient for external influence should be significantly greater than zero early in diffusion and decrease to zero as diffusion approaches saturation. External influence can be created as a node attribute and the significance of this attribute tested dynamically. In the case of the FCTC, external influence will be defined as the number of tobacco NGOs in each country. Tobacco NGOs represent an influence that is external to the internal networking that exists between countries.

Behavioral Hypothesis: Thresholds. The fourth behavioral hypothesis (not graphed in Figure 2) is the existence of social network thresholds (SNTs) defined as the proportion of network alters needed to have adopted for a focal node to adopt an innovation [[34](#_ENREF_34), [35](#_ENREF_35)]. Low threshold adopters embrace an innovation earlier than their colleagues whereas high threshold ones wait until most (or all) of their network alters adopt the behavior before they are willing to. Prior analyses of network thresholds were limited by the static nature of existing diffusion network data. If out-degree changed during the course of the study, the threshold measure would be quite biased. For example, changing the denominator from one to three creates a dramatically different threshold calculation. Thus, obtaining accurate and dynamic network data creates the opportunity to calculate accurate thresholds. Thresholds provide one explanation for varying adoption times and their construct validity has been demonstrated. By estimating country thresholds to FCTC ratification and related policy adoptions, we can determine which countries led the diffusion process and which followed. We anticipate that low threshold countries will have particularly strong anti-tobacco lobbying groups; and high threshold countries will be high tobacco-producing countries. Further, a parameter to test for threshold effects can be incorporated into the DN/SAOM toolkit. We will calculate thresholds for treaty adoption and test factors associated with low versus high thresholds. Countries with low thresholds are willing to sign, ratify, and enforce the FCTC before their peers do so.

These four hypotheses represent fundamental tenets of diffusion theory and social influence that can be tested with the current dataset using the dynamic DN/SAOM platform and perspective. Across all of these hypotheses it is further stipulated that the hypotheses need to be tested while simultaneously controlling for and testing for the presence of endogenous network structural characteristics. Specifically, degree (expansiveness), homophily on nodal attributes, and the tendency for triads to be transitive need to be included in the modeling. Inclusion of these structural effects will permit theoretical testing of diffusion theory-derived behavior change mechanisms. This proposal seeks to build the platform upon which these hypotheses can be tested using the FCTC and other treaty diffusion data and making the programs available to use on other longitudinal datasets with behavior and network data over multiple waves. **The innovative significance of this proposed research is derived from addressing an important global health topic, retrieving data of unprecedented richness and granularity, and employing a dynamic modeling approach that enables the specification of a new class of dynamic network effects.**

**B.2. Behavior Stages.** Most behavioral research focuses on one behavior such as the initiation of smoking, prescribing a drug, or the adoption of a policy. In this study we have data on when each individual country signed the treaty. These data indicate a country’s awareness of the treaty and signals their interest in adopting it. Ratification of the treaty represents adoption and acceptance of its provisions. For the FCTC, the average time between signing and ratifying was approximately 2 years (for the other two treaties it was just over 3 years). We also have data on the actions taken within each country to enforce the treaty provisions. These three stages of policy adoption are not unlike stages of adoption put forward in many theoretical models [[36](#_ENREF_36), [37](#_ENREF_37)]. We expect network effects to be more pronounced for later stages of the adoption process than earlier ones because the later stages require more political effort and more subject specific knowledge. Thus, we expect the network effect estimates in section B.1. to be stronger for policy enforcement than for policy ratification, which should be stronger than those for treaty signature.

We also expect different networks to be associated with different stages of the policy adoption process. In the case of the FCTC, we expect that those countries who were involved in the negotiation of the initial treaty would have signed the treaty earlier but they might not have been able to carry forward this effort in the enforcement. In addition to participation in the negotiations, however, we expect position (centrality) in the negotiation networks to be positively associated with early signing, less strongly associated with early ratification, and less strongly with enforcement. Conversely, those countries that occupy central positions in the GL communication networks will have earlier and stronger enforcement than those less central in the GL communication networks.

**B.3. Different Behaviors (Treaties) and Different Networks.** Perhaps the most innovative aspect of this study is the simultaneous analysis of multiple behaviors (treaties) and multiple networks. Three treaties diffused to almost 90% of all countries from May 2001 to December 2011: 1) FCTC, a public health treaty; 2) Pollution, an environmental treaty; and 3) Corruption, a legal treaty. Although the different starting dates (the date the secretary general receives the treaty) are significantly different from one another (May 5, 2001; April 5, 2001; and December 9, 2003, respectively), relatively similar geo-political forces would operate on the decisions to sign, ratify, and enforce these treaties during the years 2001 to 2010. Analyses for each treaty will be date-specific so the network data align with the treaty data.

Networks. Unlike most studies of social influence, this study proposes to analyze multiple networks monitored in different ways and consisting of both one- and two-mode data. The networks to be measured in this study include networks based on 1) INB participation; 2) GL co-membership; 3) GL interest group co-participation; 4) GL sponsorship; 5) GL nominations; 6) GL communications; 7) tobacco trade; 8) phone communications; 9) general trade; and 10) geographic proximity. The networks in this study are dynamic: some change daily (networks 2 to 6) and some change annually (networks 7 to 9). Some networks are derived from two-mode affiliations (networks1 to 3) whereas others are one-mode (networks 4 to 9). The network geographic data may be both valued and dichotomous depending on how the links are operationalized [[38](#_ENREF_38)]. Importantly, networks 1 to 7 are specific to the FCTC or tobacco use whereas networks 8 to 10 are general. **In sum, the networks in this study are dynamic; derived from nominations and co-membership; are both valued and dichotomous; and consist of relations specific to tobacco control and those that are general.**

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| --- | --- | --- |
| Table 1. Cross testing of network effects. | | |
|  | FCTC | Other Treaties |
| Global Link Networks | Effects | No Assoc. |
| Communication & Trade Networks | No Assoc. | Effects |

Another series of hypotheses we wish to test is whether different content networks are associated with different treaty outcomes. For example, we expect FCTC/tobacco networks (GL participation) to be associated with FCTC outcomes whereas the general communication and trade networks would not be. Conversely, the general communication and trade networks might be expected to be associated with the other treaty outcomes (Pollution and Corruption), but not the FCTC outcomes. Indeed we expect the general networks to be associated with FCTC outcomes, provided the GL networks are not included in the model (Table 1). This cross-testing of hypotheses provides a comparison and contrast not typically available in international studies. Thus, we propose developing a contrast between FCTC diffusion via tobacco control communications and other policy diffusion via other networks. We should find that the tobacco control networks are not important for the adoption of the other treaties and that the other networks are not important for the adoption of the FCTC. We are agnostic, however, on whether we can expect differential network effects across behavioral outcomes. In other words, we pose as a research question the possibility that general communication and trade networks might be associated with treaty signing (awareness) but not treaty ratification and enforcement.

**C. APPROACH**

**C. 1. Data.** At least three sources of data are used in this study. Data on country ratification/adoption of the FCTC are available from the WHO Tobacco Free Initiative website ([www.who.int/tobacco](http://www.who.int/tobacco)). These data indicate the day the FCTC was ratified in each country. For analysis purposes, these data are recoded to the month of adoption, providing a time line of 9 years (June 2003 to June 2012) or 108 months. If we modeled the adoption as the specific day of adoption, the timeline would expand beyond a reasonable number and would inflate associations between static measurements. Moreover, outcome dates may vary slightly due to the vagaries of the calendar and legislative scheduling. We will also conduct sensitivity analysis by recoding the data to be overlapping months. For example, rather than adoption being each month of ratification (January, February, March, etc.), the interval of the 15th to the 14th of the subsequent month will be used for the month of adoption.

We also intend to get data from this same source on the adoption of tobacco control policies within individual countries during the 9-year period of FCTC negotiation and ratification. These data measure the strength of country implementation of the treaty. For example, if the US were to ratify the treaty, it would also need to pass legislation increasing the size of warning labels in order to effectively implement its treaty obligations. The failure to change the policy would indicate only partial adoption of the FCTC. Thus, the outcome variables for this study represent a time of ratification and a scaled variable that is a composite of policy adoptions.

Several structural characteristics or attributes of the countries will be obtained from the WHO’s annual Global Tobacco Control Report database [[39](#_ENREF_39)] and other open source resources (World Bank, Freedom House, etc). These attributes function in part as control variables but also as characteristics to be investigated for their influence on the time of country adoption. These characteristics include population, population distribution (e.g., the percent under 25), gross national income, degree of political freedom, tobacco production (in tons) [[40](#_ENREF_40)], and current male and female smoking prevalence [[41](#_ENREF_41)]. Other country attributes will be explored to determine their association with treaty ratification. We have compiled a list of potential variables from the CIA World Factbook(<https://www.cia.gov/library/> ) which includes: [Infant mortality rate](https://www.cia.gov/library/publications/the-world-factbook/docs/notesanddefs.html?countryName=France&countryCode=fr&regionCode=eu#2091); [Life](https://www.cia.gov/library/publications/the-world-factbook/docs/notesanddefs.html?countryName=France&countryCode=fr&regionCode=eu#2102) expectancy at birth; fertility rates, literacy, and schooling expenditures. We will also test economic indicators such as gross domestic production (GDP), the distribution of family income (Gini Index); spending on power (electricity, oil, and gas); and spending on communications and transportation. All CIA factbook data are available yearly from 2000 to 2010. Data are also available on the number of tobacco Non-Governmental Organizations (NGOs) in each country which is a measure of the strength of anti-tobacco advocacy. (Recall this variable will also be used to test for external influence effects.) We also have data on participation in the International Negotiating Bodies (INBs) convened to draft the FCTC. Country participation in the negotiations will be measured by the number of delegates sent to each INB session published in the official list of participants. These data are publicly available on the WHO Governing Bodies website (www.who.int/gb/fctc/). This provides a measure of pre-ratification involvement in composing the treaty. An important characteristic that is both an attribute and network variable is geographic location. Our preliminary analyses indicated that geography was relevant: Ratifications were later in Africa than East Asia/Western Pacific for example. So geography will be included both as an attribute and in diffusion modeling (see below).

Networks. Network data are derived from GL, an online forum for anti-tobacco control advocates to exchange information and resources ([www.globalink.com](http://www.globalink.com)). (Dr. Julie Torode, deputy CEO of the UICC has pledged her support, Appendix A.) Several types of interaction data are available. We have access to three affiliation datasets constituting two-mode or bipartite networks [[42-44](#_ENREF_42)]. The first is participation in the INB sessions at which the treaty was negotiated. Each element in the adjacency matrix represents the number of people from any two countries that jointly attended an INB session. This network measures the degree of potential interaction between countries involved in negotiating the treaty. The second affiliation network is data on monthly membership in GL from 1993 through 2012. These data are used to construct a two-mode network based on joint participation in GL. The average number of new GL members per country has varied over its 17-year history. Membership has generally increased, though not monotonically. Cumulatively, by April 2011, membership in GL by country ranged from 0 to 1,602, with a mean of 31.8.These data are treated as two-mode and co-membership matrices and derived by transposing and post-multiplying the transposed matrix with the original affiliation matrix to generate dynamic adjacency matrices [[42-45](#_ENREF_42)]. The INB participation network is static over the diffusion period but the GL membership network is dynamic and updated monthly. The third network is derived from system data indicating which interest groups each person belongs to. There are several interest groups on GL and members can join different communities. Co-membership in communities or interest groups will be used as another form of two-mode data that evolves during the study period.

GL networks 4 to 6 are one-mode network datasets. The fourth network is the sponsorship data collected when each person joined GL. At enrollment, applicant’s needed to provide the names of two other members that could vouch for the new member. These data provide a sparse network of strong ties limited to two other members. The fifth network is derived from reports in the membership form in which new members were asked to provide the names of other members with whom they seek advice or exchange information. These data are analogous to survey data provided by each member when they joined GL. The sixth and final network is derived from GL data on who responds to whose posts and the email traffic between members.

Non-GL networks. GL membership and exchanges are unlikely to be the only influences driving national governments to adopt health policy legislation in the form of an international treaty. The most significant non-GL network likely to influence FCTC outcomes is tobacco trade. The tobacco trade data (<http://www.fas.usda.gov/gats>) are available for the entire study period (2001 – 2012) on a monthly basis. Two other non-GL networks will be used to test the contrast modeling in which non-tobacco networks are associated with non-tobacco treaties. Countries maintain complex relationships with other nations in the form of communications, bilateral treaties, alliances, and trade and cultural exchanges. These represent multiple bonds and layers of information that are perhaps more influential than messages sent between tobacco control advocates. We will acquire two international longitudinal network databases to test the association between international networks and treaty signing, ratification, and enforcement. These two databases are 1) phone communication available annually from 2001 to 2011 [[46](#_ENREF_46)]; 2) monthly global trade (<http://www.gtis.com/>). The phone data provide a measure of general communication and interaction between countries; whereas the trade data provide a measure of economic interdependence. The phone data act as a proxy for cultural similarity which may be driving the adoption behavior of the countries. To help understand and process the international communication and trade data we have solicited the input from Dr. George Barnett, see letter in Appendix B. The monthly global trade data also provide a measure of interaction that captures the economic dependencies between countries.

Finally, we will also construct a geographic proximity matrix to measure contagion via geographic contiguity. We will construct the geographic network two ways: 1) based on distance between capitals; and 2) based shared borders. These 10 network datasets provide information on the social networks of tobacco control advocates that will be analyzed separately and jointly in the diffusion network stochastic actor oriented model (DN/SAOM) platform. The rationale for collecting multiple networks is that we expect different networks to have different influences as mentioned above [[47](#_ENREF_47)]. To assist with understanding how these multiple networks may be expected to interact and differentially influence outcomes, we have enlisted the support of Dr. Mark Handcock, see letter Appendix C.

**C.2. Model Estimation.** We take a diffusion network perspective which estimates the likelihood of adoption of the innovation at each point in time for which an individual country is at risk to adoption as a function of individual characteristics and network exposures [[4](#_ENREF_4), [17](#_ENREF_17), [48-50](#_ENREF_48)]. The time of adoption (TOA) data are converted into an NxT adoption matrix with N being the number of countries (193) and T the maximum time of adoption (Tmax=108). In the adoption matrix, each country-time is coded as a zero until the time the country adopts the treaty [[51](#_ENREF_51), [52](#_ENREF_52)]. At each time period (month), the matrix of network connections is multiplied by the vector for that time in the adoption matrix to calculate network exposures, the proportion of linked countries that have adopted the FCTC by that time period. Both contemporaneous and lagged models will be estimated.

Time-constant and time-varying country characteristics are included in the event history dataset. Time-constant variables include country characteristics such as geographic region or population (which does not vary much over the study time period). Time-varying variables are those that change during the course of the study. For example, a time-varying variable could be smoking prevalence which might be decreasing in some countries and increasing in others. Governmental form might also be a time-varying covariate if the government changed during the study. Once the exposure terms are calculated and the co-variates merged into the dataset, the following model can be tested for country (*i*) and time (*t*):

(1)

where y*it* is the binary indicator of FCTC ratification for country *i* (*i* =1, .., *N*) at time *t*, *α* the intercept, *βk* parameter estimates for vectors of *k* time-constant and time-varying characteristics (X*ki*) of country i, *ρl* parameter estimates for the time-varying network exposure variables [*ωil*]y*t*. The *ωil* network weight matrices are the *ωi* network matrices described above. To assist with model specification and interpretation we have enlisted the support of Dr. Christophe Van den Bulte, see letter Appendix E.

Note that *ωil*, the weight matrices derived from different networks, vary over time as the network data evolve. For example, in GL there are multiple persons per country who have joined GL and over the years each person who joins makes sponsorship requests which span country borders. These sponsorship requests are new links between countries that vary over time. For example, a new member from Canada who makes sponsorship requests to an Australian colleague is establishing a link between Canada and Australia at the time of membership. These links can be stored as counts or proportions (see [[53](#_ENREF_53)] supplemental method appendix).

Network exposure is usually conceived of as the influence of one country on another via direct connection through the networks. In the spatial case this represents being exposed to FCTC ratification when a neighbor country ratifies it. Social influence models, however, allow for more complex social influence modeling to occur. The most notable extension of social influence has been the development of social influence via structural equivalence. Structural equivalence (SE) is the degree two nodes occupy the same position in a network [[54](#_ENREF_54), [55](#_ENREF_55)]. Two people are SE when they have connections (and perhaps non-connections) to the same others. Influence via SE occurs when a focal individual is influenced to adopt an innovation when his/her structurally equivalent alters adopt [[4](#_ENREF_4)]. This can occur, for example, when structurally equivalent actors feel competition with one another and adoption by one increases the likelihood of adoption by the other to remain competitive. In this project, we propose to construct SE weight matrices and calculate exposure based on SE and test its association with adoption. Although our expectation is that cohesion will be a stronger influence on adoption, given that adoption decisions are being made at the country level, it is conceivable that country legislatures will be motivated to ratify the FCTC when similarly positioned countries adopt and will be more motivated to adopt or implement policies after similarly positioned countries have done so.

A second extension of the exposure framework we wish to test is estimating the effects of infection and susceptibility [[6](#_ENREF_6), [56](#_ENREF_56)]. In diffusion network terms, infection occurs when an individual’s adoption accelerates the adoption of those they are connected to. For example, if Bob is linked directionally to Sue and Alice, and Bob’s adoption is followed by Sue and Alices’ adoption, then Bob is infectious. Diffusion network modeling can be used to estimate the degree of infectivity of FCTC-related adoptions across the networks. A similar calculation is made for susceptibility. A person is susceptible when they are influenced directly by others they are connected to. In this study, we will estimate infection and susceptibility and determine whether particular countries or particular country characteristics are associated with elevated levels of infection or susceptibility. For example, it may be that high tobacco producing countries are more infective than low producing countries because other countries are influenced by countries that produce tobacco (i.e., “if they can do it, so can we”).

SIENA. The diffusion network approach is limited by its inability to control for and estimate the influence of endogenous structural dependencies in the networks. Several research teams have developed statistical models that account for network dependencies which test network influence effects while simultaneous incorporating network structural effects and the estimation of network evolution parameters [[7](#_ENREF_7), [27](#_ENREF_27), [57-60](#_ENREF_57)]. SIENA accounts for the joint evolution of behaviors and networks by constructing an objective function such as [[61](#_ENREF_61)]:

(2)

where specifies the functions for individual behaviors and the networks. The terms represent the strengths of these functions. We will reconcile the diffusion network approach with recent advances in longitudinal network effects using MCMC approaches as specified in Aim 4[[61](#_ENREF_61), [62](#_ENREF_62)]. The diffusion network stochastic actor oriented model (DN/SAOM) will be implemented in RSIENA and enable estimation of network influences in a dynamic framework allowing for co-evolution of networks and behavior. We will initially specify a model that tests for network influence, and then include the selection effect to test co-evolution of network and outcomes[[3](#_ENREF_3), [8](#_ENREF_8)]. The diffusion network model does not test for selection and so the DN/SAOM analysis can now include a test for selection and specify how it affects influence estimates. Structural parameters will include density, reciprocity, transitivity, and balance effects[[63](#_ENREF_63)]. The homophily variable is the time of adoption. We will include the region attribute as a covariate to control for variations in regional adoption rates, and test for influences of other country attributes. Dr. Tom Snijders will act as a consultant on this study to help build the DN/SAOM platform, see appendix E.

The fundamental research question to investigate is whether influence effects estimated in the diffusion network modeling disappear or attenuate when the more advanced structural controls available in SIENA are included as well as the control for selection effects. Alternatively, the DN/SAOM analyses might capture influence or selection effects not previously captured in diffusion network analyses once these controls are included. In other words, diffusion analyses may have previously underestimated influence effects. This alternative is quite likely given recent studies showing negative bias in network influence models[[64](#_ENREF_64), [65](#_ENREF_65)], particularly in the case of dense networks as in this study. The expectation is that network exposure effects are over-estimated since the potential increased effects of reciprocated and triadic structural effects are not corrected for using simple exposure terms. Although the actor-oriented co-evolution modeling framework is a few years old, developing models within this framework is just beginning and there have been no applications using diffusion data. The science of network effects will grow when SAOM can be applied in theoretically rich and informed ways.

The DN/SAOM platform will then be used to estimate the four hypotheses specified in section B.2 (exposure, position, thresholds, and external influence); estimate differential network effects for different stages of adoption (section B.3); and conduct the contrast specified in section B.4. **In sum, we will build a diffusion network stochastic actor oriented model (DN/SAOM) to test multiple dynamic social influence hypotheses that capture the varied nature of how different networks can influence different outcomes and differentially influence outcomes along the stages of change**. The study represents an unprecedented opportunity to use passively collected data to test important hypotheses regarding network effects on an important public health problem.

**C.3. Additional Considerations**. QAP. Another methodology useful for testing network effects is the quadratic assignment procedure (QAP) [[66-68](#_ENREF_66)]. QAP regression is used to correlate two or more networks to determine their association with one another. These networks can be connections but can also be networks of shared characteristics such as gender or co-residence. QAP regression permutes the rows and columns of the dependent variable to generate a distribution of correlations between a randomized dependent variable and the independent variable. The simulated correlations indicate a test of the null hypothesis and the empirical regression coefficient can be compared to the simulated distribution. In this study, similarity of time of adoption will be converted into a matrix and then correlated with the matrices described above at multiple time points. An MRQAP [[69](#_ENREF_69)] will also be conducted to determine which of the networks are associated with similarity of adoption times.

Regional divisions. In our preliminary analysis [[70](#_ENREF_70)], it was evident that geographic region was associated with FCTC ratification date. Countries in Southeast Asia and Western Pacific ratified the FCTC earlier than countries in other regions and those in Africa and the Americas later. Consequently, we will conduct additional analyses separately by region treating each region as a separate network as a test of the robustness of the global findings. A second confounder we will explore is the US. The US has the largest economy and the greatest number of anti-tobacco activists, yet has not ratified the FCTC. In all models, we will repeat the analysis removing the US from the data.

Valued data. One analytic challenge we face in this study is how to use the valued networks developed for this study. In all prior diffusion network analysis, and almost all behavior change studies, linkages among adopting actors have been binary. Advice seeking, friendships, and discussion partners are either present or not, and no attempt is made to value the association between dyads by adding frequency of communication or some other value. Evidence exists, however, that strength is not important[[71](#_ENREF_71)], contrary to intuition and popular conceptions. All of the network relations in this study will be valued because there are multiple actors per country. In other words, the GL data are aggregated for all individuals from each country into country-level connections, thus making all the network ties valued. These values will need to be divided by the number of advocates per country, yet simply reducing links to a proportion seems inadequate for capturing the theoretical influence processes under investigation. The communication and trade data are also valued, so we will investigate ways to estimate network effects using valued network data.

We will also have indicators that measure the strength FCTC implementation, rather than just whether each country ratified the treaty or not. Strength of implementation is derived from three measures: 1) health warning labeling; 2) advertising policies; and 3) secondhand smoke legislation. Each measure is scored on a 1 to 3 scale based on the extent of policy endorsement. For example, a country with health warning labels and only one non-specific warning is scored a 1, multiple disease warnings on front or back a 2, and warnings covering 30% or more of the front or back of the pack as a 3. Therefore, a country with the maximum policy implementation would score a 9. Most network exposure modeling has been conducted with binary indicators (e.g., whether each person adopted). In this study, we will compare regression results estimating the strength of implementation. Our working hypothesis is that strength of implementation will be associated with influence such that we expect countries with stronger FCTC implementation to be more influential on spreading adoptions to other countries (i.e., be more infective).

Content analyses. A final advantage of the proposed study is that GL is a communication system with data on exactly what messages have been sent by whom. This detailed information can provide rich contextual information that can support analyses and conclusions derived from the quantitative analysis. In this proposal, we do not propose to do a full content analyses of all the messages posted to GL, this could be laborious and beyond the scope of this team’s expertise. We do intend to use the e-mail data in a confirmatory and exploratory manner. That is, we expect the quantitative analyses to identify time intervals over which specific countries may be debating ratification of the FCTC and for whom message traffic should be particularly salient. We intend to search the email traffic database during these time windows to determine if there are specific information requests associated with ratification of the FCTC. We also intend to determine what types of messages are exchanged between adopting and non-adopting countries that lead to adoption.

New data. GL will be renovated in the latter half of 2011. GL administrative staff and UICC administration have pledged support for this proposal and expressed an interest in collecting more extensive network and attribute data among current members when they are requested to re-register with the updated GL. Although not formally part of this proposal, the intention of this team is to move forward with this data collection to supplement the existing datasets. We also intend to ask questions retrospectively regarding the role of GL in the FCTC adoption process.

**C.4. Limitations**

One limitation of the present study is that we do not have multiple settings across which to compare findings. Other behavioral network studies have compared multiple cities, towns, schools, or communities. We do not have access to other worlds. We have attempted to address this limitation by comparing findings across treaties and using multiple networks. The second limitation is the less than perfect match of the time the treaties were introduced, although the differences are not substantial.

**C.5. Timeline and Milestones**.

The timeline for specific activities of the proposed project diagrammed below illustrates the specific activities and milestones for the current research proposal.

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Year 1 | | | | Year 2 | | | | Year 3 | | | | Year 4 | | | | Year 5 | | | |
| Quarter | 1 | 2 | 3 | 4 | 1 | 2 | 3 | 4 | 1 | 2 | 3 | 4 | 1 | 2 | 3 | 4 | 1 | 2 | 3 | 4 |
| Develop & test DN/SAOM |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Analyze classic diffusion data |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| (Potential New Survey) |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Update treaty data |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Acquire & clean GL datasets |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Two-mode data |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| One mode data |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Conduct multi-network analyses |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Compile strength indicators |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Compare valued and binary networks |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Build stage of change data |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Run DN/SAOM on FCTC data |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Build country attribute data |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Test dynamic hypotheses |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Conduct sensitivity analyses |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Convene model meeting |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Compare valued and binary networks |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Compile other treaty outcomes |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Acquire comm. & trade data |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Run DN/SAOM on treaty data |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Re-test FCTC models |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Build Struct. Eq. models |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Test for infection & susceptibility |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Run QAP models |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Conduct sub-region analysis |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Alternate geographic specifications |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Run cross-test analysis |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Documentation for DN/SAOM |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Content analyses |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Make data publicly available |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Disseminate Results |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |

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