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Diffusion of innovations theory applied to global tobacco control treaty ratification

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ABSTRACT

This study applies diffusion of innovations theory to understand network influences on country ratification of an international health treaty, the Framework Convention for Tobacco Control (FCTC). From 2003 to 2014 approximately 90% of United Nations member countries ratified the FCTC. We hypothesized that communication between tobacco control advocates on GLOBALink, a 7000-member online communication forum in existence from 1992 to 2012, would be associated with the timing of treaty ratification. We further hypothesized dynamic network influences such that external influence decreased over time, internal influence increased over time, and the role of opinion leader countries varied over time. In addition we develop two concepts: Susceptibility and influence that uncover the micro-level dynamics of network influence. Statistical analyses lend support to the influence of co-subscriptions on GLOBALink providing a conduit for inter-country influences on treaty ratification and some support for the dynamic hypotheses. Analyses of susceptibility and infection indicated particularly influential countries. These results have implications for the study of policy diffusion as well as dynamic models of behavior change.

The Framework Convention on Tobacco Control (FCTC) is the first international public health treaty. The World Health Assembly formally adopted the final FCTC text in May 2003 (WHO, 2003, 2009) whose key provisions 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 requires countries to implement smoke-free workplace laws, and encourages them to address tobacco smuggling, and increase tobacco taxes. As of December 31, 2011, 89% (170) of the World Health Organization's (WHO) 191 countries had ratified the FCTC with six more ratifying in 2012, 2013 and 2014 (92%).

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.

This paper applies diffusion of innovations theory to understand factors associated with ratification of the FCTC and develops new tools that articulate micro-level diffusion processes. Diffusion of innovations theory explains how new ideas and practices spread within and between communities (Rogers, 2003; Valente, 1995, 2005). The premise, confirmed by considerable empirical research, is that new ideas and practices often spread through interpersonal contacts largely through interpersonal communication (Rogers, 2003). Diffusion research peaked in the 1950s with several studies specifically on diffusion networks being conducted at that time (Valente and Rogers, 1995). The most notable diffusion network study was conducted by Coleman et al. (1966) on the diffusion of tetracycline among physicians in four Illinois communities (also see Van den Bulte and Lillien, 2001). Early diffusion network studies provided empirical data useful for estimating network influences on diffusion, yet were based on static networks

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and/or incomplete data. The paucity of diffusion data has severely restricted theoretical development of diffusion network effects and a more profound understanding of contagion mechanisms.

There have been studies specifically on the diffusion of policies (Savage, 1985; Berry and Berry, 1990; Meseguer, 2005). Walker's (1966) seminal paper outlined the importance of diffusion approaches for studying policy adoption. In an analysis of a dozen policies adopted by US states, Gray (1973) showed that state-to-state diffusion predicted the patterns of state adoptions. 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 the appropriate data 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 (Lazer et al., 2009). 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 (Aral et al., 2009).

Several other studies have used network methods to test whether exposure to prior adopters is associated with adoption (Burt, 1987; Hedström, 1994; Hedström et al., 2000; Iyengar et al., 2011, 2015; Valente, 1995; Yamagata et al., 2013). These studies have shown that being exposed to prior adopters via network connectivity often leads to adoption. These network exposure models (Burt, 1987; Marsden and Podolny, 1990; Valente, 1995, 1996, 2005) have been quite useful for showing that behaviors can spread through networks like a disease, a so called contagion model. Yet Van den Bulte and Lillien (2001) showed that omitting variables can lead to mis-specification of effects, in their example the omission of marketing effort.

This study addresses the limitations of prior diffusion network studies by analyzing the diffusion of the FCTC treaty with data specifically on time of adoption indicating exactly when each country ratified the FCTC. In addition, we have network data from several sources that are likely to be associated with the timing of FCTC adoption. We take a diffusion network approach by constructing network exposure terms from these networks and extend the model further by examining predictors of susceptibility and infectiousness; and by analyzing how contagion effects vary over time.

Fig. 1 shows the diffusion curve for the ratification of the FCTC which represents adoption behavior of the countries. Time of adoption is aggregated annually because the network and attribute data are recorded annually. For comparison purposes we graph a logistic function representing a hypothetical diffusion process over the same 10-year period (Monin et al., 1976; Mahajan and Peterson, 1985). We also graph the hazard rate which is the instantaneous probability of adopting at each time period (Allison, 1984). It is clear from visual inspection that FCTC ratification occurred rapidly during the early stages of diffusion and then tapered off over time.

We hypothesize that diffusion of the FCTC was driven in part by interpersonal communication and networking developed throughout the negotiation of the FCTC and participation in global tobacco control networks. We use data from GLOBALink, an electronic forum for communication and information exchange about tobacco control sponsored and hosted by the Union for International Cancer Control based in Geneva (GLOBALink, 2010). GLOBALink (GL) was established in 1992 and operated by the Union for International Cancer Control (UICC) until May 2012. Over the 20-year period GLOBALink grew to over 7000 members from 112 countries. GLOBALink has several features that provided network data. First, referrals, any person wishing to join GLOBALink was required to provide the names of two tobacco control advocates that could attest to the person's integrity with regard to tobacco control. In the beginning most of the verifications were done by UICC staff in Geneva but gradually the verifications diversified to other GLOBALink members in other countries. Second, posts, individuals posted comments and questions that others replied to. Third, subscriptions, individuals could subscribe to any of 48 interests groups which provided subscription services on various topics (Table S1).

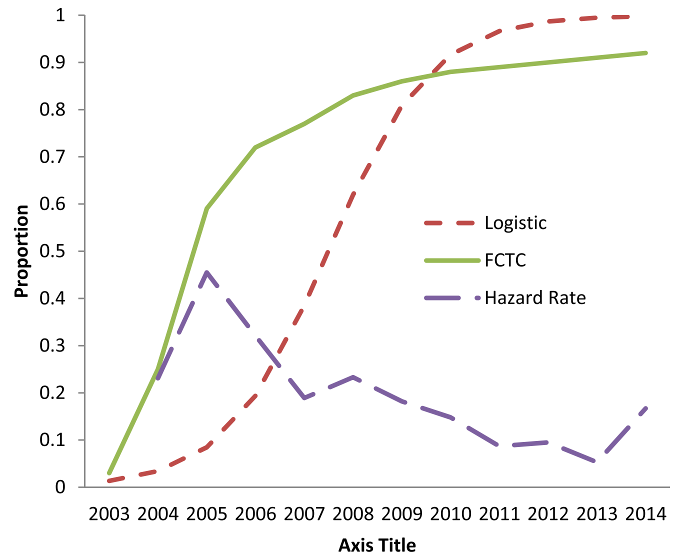

Fig. 1. Prevalence of countries that ratified the FCTC over time compared to a logistic growth function, along with the hazard rate (the instantaneous probability of ratification). The y-axis for the FCTC and Logistic diffusion curves represent cumulative proportion of adopters whereas for the hazard rate it is the probability of adoption.

We also expect, however, that the timing of FCTC ratification may be associated with structural and demographic aspects of states (e.g., population, degree of political freedom, smoking prevalence, and tobacco production). For example, a country with high smoking prevalence may perceive tobacco control as important and ratify sooner than a country with low smoking prevalence. Conversely, a tobacco producing and exporting country may view tobacco control as a threat to its finances and resist ratification.

We hypothesize that network exposure to prior adopters in these networks will be associated with the timing of FCTC ratification. In addition, we make three predictions illustrated in Fig. 2 about how the influence processes varies over time. First, we expect that the effect of external influence on adoption decreases over time. This hypothesis is consistent with the general diffusion model which states that early adopters are influenced by sources external to the community (Menzel et al., 1959; Menzel, 1960). Because there are no or few adopters within the community, early adopters rely on sources of information and influence external to the community. As diffusion progresses these external sources lose their value.

Second, interpersonal, or contagion influences increase over time. As more countries ratify the treaty, non-ratifiers can be influenced by them. Individuals have a preference for information within their networks and so will increasingly rely on these networks for information in order to make adoption decisions. Third, we propose that the influence of opinion leaders, those countries active on GLOBALink diminish over time. The rationale for this hypothesis is that opinion leaders are important early in the

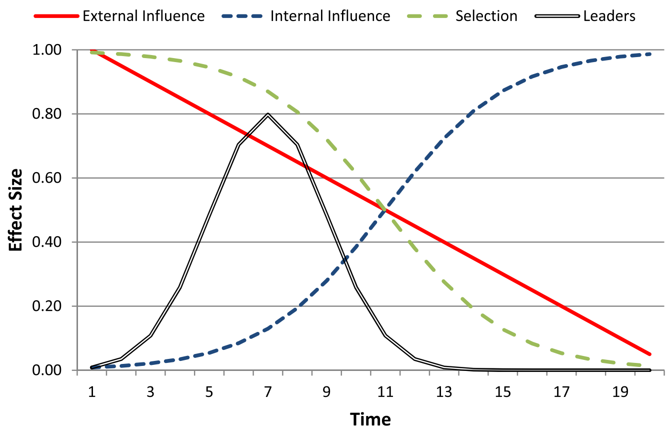

Fig. 2. Hypothesized dynamic diffusion effects. External influence decreases as the community fills with adopters. Selection decreases as individuals do not need to make network changes to find adopters in their network. Internal influence increases as individuals have opportunities to be persuaded by their network peers. Leaders may be important influences early in diffusion, but not the earliest, when the outcome of diffusion is uncertain, but their influence decreases over time.

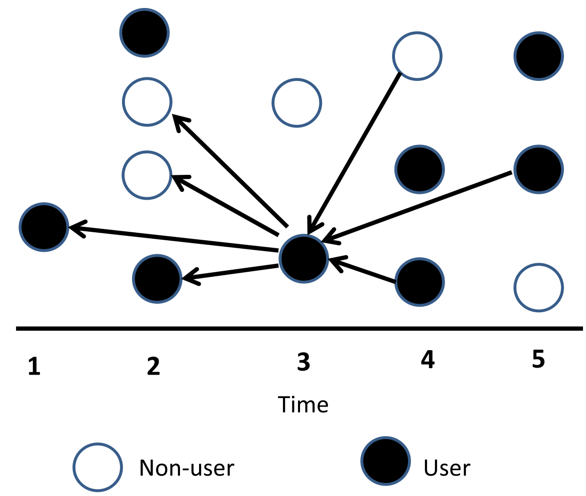

Fig. 3. Illustration of susceptibility and infection calculations: Susceptibility for Ego who adopted at time period 3 is 0.50 (of the 4 outgoing ties, 2 were prior adopters and 1 immediately before he/she did). Normalized susceptibility is 0.25 which is 0.50 divided by 2, the total number of adopters at the prior time period. Infection is 0.50 (of the 3 incoming ties, 2 were later adopters and 1 adopted immediately after he/she did). Normalized infection is 0.25 (which is 0.50 divided by 2, the total number of adopters at that next time period).

diffusion process when uncertainty over the innovation is high (Valente and Davis, 1999). As that uncertainty decreases with more countries adopting, the influence of important nodes diminishes and countries can be influenced by peers that are not necessarily prominent. As shown in Fig. 2, however, the influence of opinion leaders is negligible at the earliest stage of diffusion because leaders are not the first to embrace new ideas but instead must wait until some acceptability is established (Menzel, 1960; Valente, 1995). Finally, we propose that selection, changing networks to be compatible with one's behavior (Steglich et al., 2010), will decrease over time. Early in diffusion there are few adopters so new adopters must change their network in order to have others in their network who are users. As diffusion progresses individuals no longer need to make such changes to have users in their network and so selection decreases.

In addition to this standard network diffusion approach, we build on the work of others (Strange and Tuma, 1993; Myers, 2000; Grennan, 2015), to develop two contagion measures that enable the examination of the micro-level diffusion process over time. These measures are susceptibility and infection: Susceptibility is the rate at which a person adopts a behavior immediately after his/her ties have adopted it and infection is the rate a person's ties adopt a behavior immediately after he/she adopts it. Fig. 3 provides an illustration. The R code for calculating these network diffusion measures is available publicly at Github. The mathematical formulas for susceptibility and infection are provided in the online supplement (see Fig. 4).

These susceptibility and infection measures are similar to ones published in the marketing literature. In particular, Iyengar et al. (2011) introduced a term called "use contagion" which enables influence to occur across dyads when an individual has used the innovation at the time period prior to ego's adoption (also see Hu and Van den Bulte, 2014; and Iyengar et al., 2015). Aral and Walker (2012) measured influence and susceptibility as time to adoption after receiving influence messages over social media. The main difference in our new measures and these earlier ones is that we divide influence and susceptibility by the cumulative number of adopters just before and after ego's time of adoption.

Note that susceptibility is conceived as a function of outgoing ties, whom one nominates; and infection as a function of incoming ties, who nominates ego. These formulations can be modified by varying whether calculated on outgoing or incoming ties or the time window considered for influence beyond the immediate pre- and post-time periods (and even including contemporaneous time periods). For most purposes, and for our purposes here, these formulations seem the most appropriate: Individuals are susceptible to the behavior of the ones they nominate and infect people who nominate them immediately before and after their own adoptions, respectively.

A concept related to susceptibility used in diffusion network models is a node's adoption threshold, the proportion of prior adopters in each node's network (Valente, 1996). Thresholds indicate the level of resistance to change with low threshold countries willing to ratify when few of their network members have done so, and high threshold countries waiting until a majority of their network has. Thresholds are susceptibility calculated from exposure to all prior adopters, not just immediate prior adopters.

We do not have hypotheses regarding factors associated with thresholds, infection, and susceptibility as these concepts have not been applied to policy adoption. The purpose of this study is to illustrate these micro-level diffusion network processes. Moreover, we show that participation in an online communication network forum accelerated the ratification process while controlling for country attributes. The unique aspect of diffusion research is the element of time, and in this study we examine how influence processes change over time.

1. Methods

There are three sets of variables used for the models. First, country attributes such as democracy status, population, tobacco production, and so on (online supplement Table S2). These are country characteristics which may affect the timing of policy adoption. For example, there is regional variation in participation of FCTC-related meetings (Plotnikova et al., 2014). Generally, these country characteristics are fixed, but some vary during the course of diffusion. Second, we include a count of the number of representatives each country sent to the intergovernmental negotiating body (INB) meetings that crafted the language of the FCTC. There were six such meetings between October 2000 and February 2003. We also include a count of the number of people from each country

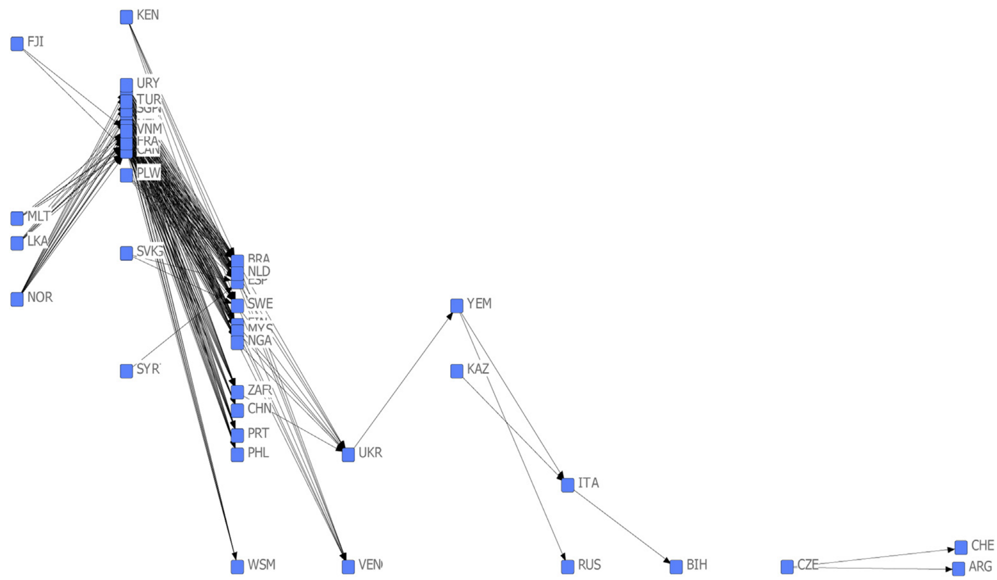

Fig. 4. Graph of infection for GLOBALink joint subscription network effects. The x-axis is the year of adoption and the y-axis the proportion of countries influenced by each country. Fiji and Kenya influenced many countries early in the diffusion process. Graph made with Netdraw (Borgatti, 2002).

Table 1
Means (standard deviations) or percent for FCTC diffusion variables.

Median year of ratification	2005
Attributes	
Americas	18.3%
Africa	24.1%
Southeast Asia	5.8%
Europe	27.8%
Eastern Mediterranean	11.0%
Western Pacific	13.1%
Population	29M
Democracy	6.33 (3.2)
Tobacco production (in tons)	54,433 (267,885)
Smoking prevalence Male	31.90%
Smoking prevalence Female	10.40%
Percent female in labor force	41.10%
Female involvement in politics	0.76 (0.43)
GDP per capita	7763 (15,037)
Number of NGOs in the FCA	1.89 (3.97)
Participation	
Square root of number of people sent to INB	7.75 (8.18)
Square root total members on GLOBALink	2.39 (4.85)
In-degree	
Geographic distance	97.1 (37.3)
General trade	46.5 (28.6)
Tobacco trade	11 (11.8)
GLOBALink referrals	1.79 (3.55)
GLOBALink posts	16.8 (27.9)
GLOBALink interest group co-membership	13.1 (24.4)
Network Exposures	
Geographic distance	28%
General trade	22.30%
Tobacco trade	15.30%
GLOBALink referrals – dichotomized	5.80%
GLOBALink posts – dichotomized	10%
GLOBALink subscription list co-membership	18%
Time Interactions	
External Influence – NGOs	7.98 (23.6)
Influence – exposure to GLOBALink Subscription	1.07 (2.01)
Opinion leader – in-degree	97.4 (205)

that were members of GLOBALink each year. Because these two count variables are highly skewed, we use their square roots.

Third, we include network exposure terms (see online supplement for its mathematical formula) derived from one static (distance) and five dynamic networks included in the analyses: (1) geographic distance dichotomized on being closer than the median distance between all countries, (2) general trade (dichotomized on the median), (3) tobacco trade (dichotomized on the median), (4) GLOBALink referrals, (5) GLOBALink posts, and (6) GLOBALink subscription interest group co-membership. We also include in-degree scores for each network to control for being connected in the network as a source of influence in contrast to being connected to prior adopters. Detailed information for each network is provided in the online supplement Table S2.

This study was considered exempt from IRB review because the data were aggregated to the country level and no individual data were available.

Analyses plan. We first estimate influences on likelihood of ratification/adoption of the treaty using a discrete event history dataset constructed by country-years and a logit link function (Allison, 1984; Jenkins, 1997). This enables the estimation of time-constant and time-varying variables on the likelihood of ratification. Each country contributes a case to the data for each year it has not ratified and one case for the year it did. The sample size is 777 which is the sum of the number of countries who ratified each year multiplied by that year. Because the GLOBALink network data terminate as of 2011 but adoptions continued, the six countries adopting after 2011 (2012, 2; 2013, 1; and 2014, 3) are treated as right-censored and hence non-adopting during the interval of study. All computations were performed in R (2013) an open-source platform for mathematical and statistical programming using the STATNET library (Butts, 2008); and all statistical analyses were conducted using STATA 12 (StataCorp, 2011).

Susceptibility, infection, and thresholds are all calculated at one time point, the time of the individual country's adoption, and so the sample size reverts to the number of countries. Note however, countries who ratify in the first year have zero susceptibility (no one can influence them) and countries who ratify in the last year have zero infection (they cannot influence anyone) and these are removed from the analysis. Susceptibility, infection, and thresholds are proportions on the zero to one interval. We used a generalized linear model (Nelder and Wedderburn, 1972) with a logit link and a binomial distribution. We also used robust standard errors to address potential model mis-specification.

2. Results

Table 1 reports the univariate characteristics of the variables included in the analyses. Table 2 reports estimates of the associations with four dependent variables: likelihood of adoption, threshold, susceptibility, and infection. For adoption, the time dummy variables indicate that the likelihood of adoption is high for years 2004, 2005, and 2006; and then attenuates to non-significance consistent with the diffusion data shown in Fig. 1. The results also show that the likelihood of adoption increases if the country is in the Pacific or Southeast Asian regions, it is a democratic country, has lower male smoking prevalence, and a lower rate of female participation in the labor force. Sending many people to the INB sessions and having many members on GLOBALink were not associated with ratification.

In-degree for the trade network was negatively associated with adoption: Countries that traded with a lot of other countries were less likely to ratify. Only one network exposure term was significant: joint interest group subscribership on GLOBALink. The likelihood of ratification increased when countries who subscribed to the same interest groups had already ratified (AOR $= 3.73$, $p < 0.001$). These results indicate that there is an association between ratification of FCTC and ratification by countries that belonged to the same GLOBALink subscription groups.

In three separate models we tested time interaction variables consistent with the theoretical model in Fig. 2: external influence measured as the number of tobacco NGOs in each country that are members to the Framework Convention Alliance for Tobacco Control, contagion influence as the effects of exposure over time, and opinion leader influence as the effect of in-degree centrality weighted exposure over time. Each model was calculated separately due to the collinearity of these three terms.

External influence decreased over time with an adjusted odds ratio (AOR) of 0.94 ($p = 0.062$). Countries with many NGOs were more likely to ratify the FCTC early and less likely as time passed. The coefficient for the interaction between contagion (exposure)

Table 2
Predictors of FCTC adoption, threshold, susceptibility, and infection.

	Adoption (N = 777) adjusted odds ratios	Threshold (N = 170) coefficients	Susceptibility from GLOBALink co-subscriptions (N = 165) coefficients	Infection from GLOBALink co-subscriptions (N = 170) coefficients
Constant	0.013**	−18.2**	−7.07**	−6.44**
Year (2003 if the reference)				
2004	13.9**	12.4**		−1.91**
2005	50.7**	13.9**	−3.72**	−3.29**
2006	44.4*	14.0**	−6.86**	−4.73**
2007	27.7	14.2**	−9.14**	−0.90
2008	40.9	14.4**	−9.68**	−6.25**
2009	29.7	14.1**	−7.84**	−16.19**
2010	25.5	14.4**	−18.11**	−16.20**
2011	13.2	2.8*	−11.78**	−12.61**
Attributes				
Regions (Americas is the reference)				
Africa	1.63	0.62**	0.66	−1.42
Southeast Asia	10.67**	0.38	0.70	−1.22**
Europe	2.07	0.72**	0.95	0.42
Eastern Mediterranean	1.0	0.50*	0.82	0.78
Western Pacific	13.2**	1.15**	1.14*	0.18
Population	1	0	0	0
Democracy	1.21**	−0.015	−0.04	0.15*
Tobacco production (in tons)	1	0	0	0
Smoking prevalence Male	0.99	0	0.01	0.03*
Smoking prevalence Female	0.99	0	0.02	−0.04**
Percent female in labor force	0.96*	0.001	0.006	0.01
Female involvement in politics	0.65	−0.18	0.15	−0.39
GDP per capita	1	0	0	0
Number of NGOs in the FCA	1.08	0	−0.05	0.02
Participation				
Number of people sent to INB (sq rt)	1.0	0.003	0.03	−0.04
Number of members on GLOBALink (sq rt)	1.10	0.02	−0.09**	−0.06
In-degree				
Geographic distance	1.0	−0.003	0	−0.005
General trade	1.01	0.01**	0.009	0.02*
Tobacco trade	0.98	−0.02**	−0.01	0
GLOBALink (GL) referrals	0.81*	0.09**	0.20*	0.13
GLOBALink posts	1.01	0.004*	0.03**	0.007
GLOBALink interest group co-membership	0.99	0	0.02*	0.01
Network Exposures				
Geographic distance	0.77	−2.45*	−0.39	−2.37
General trade	1.23	0.41*	0.94	2.29*
Tobacco trade	0.37	0.14	−0.51	0.78
GLOBALink referrals	0.43	−0.43**	−0.30	1.68*
GLOBALink posts	0.52	−0.42*	−3.71**	0.99
GLOBALink subscription list co-membership	4.10**	8.03**	8.55**	0.29
Time Interactions – each a separate model				
External Influence – NGOs	0.94 (p = 0.062)			
Influence – exposure to GLOBALink Subscription	0.55** (p = 0.009)			
Opinion leaders by years 2005 & 2006	1.01 (p = 0.085)			

*$p < 0.05$; **$p < 0.01$.

and time was negative (AOR = 0.55, $p < 0.01$) indicating that the amount of exposure needed for adoption decreased over time. Thus, we find support for inter-country influence because countries require fewer prior adopters in the network to adopt.

Finally, we tested whether degree centrality weighted exposure was significant and whether it varied over time to test for the effects of opinion leadership. The main effect of degree centrality weighted exposure was significantly associated with adoption (similar to its non-weighted counterpart, results not shown). The interaction term was negative (AOR = 0.997) and statistically significance ($p < 0.05$) indicating that opinion leader influence decreased over time. The hypothesis, however, stated that we expect leaders to be influential during the early (but not the earliest) stage of diffusion. To test this we created an interaction of centrality-weighted (in-degree) exposure and years 2005 and 2006 (after 25% (48) countries had ratified). This term was positively associated with ratification (AOR = 1.01, $p = 0.081$) although it did not attain statistical significance. These three results provide partial support to the hypotheses depicted in Fig. 2.

For thresholds, the time variables indicate a consistent increase in the threshold value needed for adoption. African countries had lower and Western Pacific ones had higher thresholds relative to the Americas. Few other variables were associated with thresholds: Being prominent in the general trade network and having few tobacco trade partners increased the threshold. Countries with members providing many referrals and those with members responding to many posts had higher thresholds (think USA and Switzerland). Having geographic neighbors who ratified the FCTC lowered thresholds. Interestingly, having high exposures to adopters via GLOBALink referrals and posts also lowered a country's threshold. Higher exposure via GLOBALink subscribership co-membership increased thresholds as expected because the threshold is computed from this network.

For susceptibility the time dummies indicate a constant decreasing level of susceptibility indicating that countries ratified when fewer of their network partners ratified the year before. This highlights the difference between thresholds and susceptibility: Susceptibility controls for the number of prior adopters so it is possible for it to decrease whereas thresholds will usually increase because exposure increases. The increasingly negative time dummies also indicate that countries became more sensitive to the adoption behavior of their network partners. Over time countries lowered their resistance and allowed the contagion/persuasion process to occur more easily.

Only two attributes were associated with susceptibility: being in the Western Pacific region increased susceptibility and having more members on GLOBALink decreased it. Countries in the Western Pacific region were not inclined to ratify after members of their network did. In contrast, countries with more members on GLOBALink were more likely to ratify immediately after their network partners did so. General trade increased susceptibility while tobacco trade decreased it. In other words, countries with many trading partners were not susceptible to their peers' ratification whereas those with many tobacco trading partners were. Interestingly, being exposed to adopters via GLOBALink posts decreased susceptibility indicating that those countries with active members posting to GLOBALink were sensitive to the ratification behavior of their co-subscribers. Being exposed to adopters via GLOBALink subscription co-membership was positively associated with susceptibility (again this is expected as susceptibility is calculated on this network).

For infection the time dummies indicated that infectivity decreased over time. At each time interval country adoptions are less likely to lead to adoptions by their contacts. This result is consistent with the adoption model as well as the graphic displays in Fig. 1 which indicate a trend toward decreasing network influence over time. Infectivity was low among Southeast Asian countries. Infectiousness was positively associated with democracy. Male smoking prevalence increased infection whereas female smoking prevalence decreased it. Having many trading partners was positively associated with being infective. Being exposed to ratification by trading partners increased infectivity as did being exposed to referral country ratifications. The online supplemental Table S3 reports the infection and normalized infection scores for the top 10 countries.

Selection cannot be tested in a regression model with adoption as an outcome because a country needs to adopt to calculate selection. There were 10 countries who adopted and then made network changes by adding a link to other adopters. The average year they did this was 3.1 years (roughly January 2005) compared to the overall average adoption times of 3.72 among adopters. Although consistent with the hypothesized effect, this difference was not statistically significant.

We also calculated Moran's I (1950) as implemented in APE (Paradis, 2012; Gittleman and Kot, 1990) on these data to determine if there was evidence of contagion using this metric. Moran's I calculates a coefficient that determines whether elements that are near one another have the same value on an attribute. In this case Moran's I tests whether countries near one another in any of the networks have similar adoption values at each time point. The results support the regression analyses in that there was evidence of contagion in the geographic network in years 2004 through 2007; in the general trade and GLOBALink referrals networks in years 2004 and 2005; and in the GLOBALink posts and subscription co-membership networks in the years 2004 through 2010. Thus according to Moran's I calculations, there is evidence of contagion in these data.

3. Discussion

This study applied diffusion of innovations theory to the ratification of the Framework Convention on Tobacco Control (FCTC) in order to elucidate factors associated with the timing of treaty adoption. The results show that the adoption rate was high early in the FCTC diffusion and then tapered off. Few attributes were associated with early ratification. Being in the WHO-defined Western Pacific or Southeast Asia region was a strong one, however. In addition, more democratic countries and those with fewer women in the workforce were associated with adoption. The few state characteristics associated with ratification may indicate that tobacco control has become a global norm not defined by income group, religion or political affiliation. The same cannot be said for other health issues (abortion, environmental protection, access to care) in which state characteristics may be more strongly associated with adoption.

Being exposed to adopters via joint membership in the same GLOBALink subscription service was also strongly associated with FCTC ratification indicating that GLOBALink may have contributed to the FCTC's rapid diffusion. Being exposed to other countries via referrals or postings was not associated with ratification. This indicates that GLOBALink influence was diffuse in nature, providing general information rather than specific pieces of advice. More specifically, the role of the different networks (posting versus subscribing) may be viewed as active versus passive information transfer. Posting messages entails spending time on message boards and reading others' messages whereas subscribing entails merely reading an e-mail feed. It is possible that people who post are different or reside in countries that are different than those who just received information. The influence of co-subscribing may also indicate that influence was in part regional and linguistic since some of the subscriptions would be regional or based on common language. This is consistent with how the FCTC was developed as regional negotiation was a large part of the treaty development process.

We tested several hypotheses regarding changing influences over time. Specifically, we hypothesized that external influence would decrease, internal influence increase, and the role of opinion leaders would peak early in diffusion but not at the earliest time period. Data supported all three hypotheses but only one attained statistical significance though the other two were suggestive (p values less than 0.10). Diffusion theory stipulates that as new ideas spread the role of interpersonal influence should increase, which paradoxically means that it takes fewer peers to persuade someone to adopt. These data support this proposition as exposure effects decreased over time, thresholds were constant over time, and susceptibility and infection decreased over time.

The nearly identical coefficients for thresholds over time indicate a consistent rate in the percent of adopters needed to prompt ratification. Thresholds at year 1 were zero as there are no other adopters. Subsequent years will generally have higher thresholds as exposures increase over time. Yet the time coefficients for thresholds, unlike those for susceptibility, are nearly identical throughout diffusion indicating that they did not increase dramatically during diffusion. Indeed, the threshold values from years 2005 to 2010 were: 0.36, 0.44, 0.51, 0.48, 0.27, and 0.35 which were not statistically significantly different from one another.

Further evidence for GLOBALink network effects were evident in the susceptibility and infection models. The time variables show that over time countries became more susceptible and exerted more influence on each other. The increasing negative time dummy coefficients indicate that at each time period countries ratified when fewer of their partners ratified in the time period immediately before they did, thus becoming more susceptible to peer influence. The increasing negative time dummy coefficients for infection indicate that, over time, countries have much lower rates of infectivity. Both processes occur simultaneously so that diffusion continued at a declining rate.

The *sine qua non* of diffusion theory is time and yet to date most research has ignored how contagion and other social influences vary over time. Here we have provided a model that uses diffusion theory to explicitly specify how selection, external influence, contagion, and opinion leadership vary over time; and have presented dynamic empirical data that somewhat supports it. The next step is to see how the model applies to other diffusion network data.

In a prior paper we showed that being exposed to other ratifying countries who joined GLOBALink at the same time was associated with ratification (Wipfli et al., 2010). This study takes that finding one step further to show that subscribing to the same interest groups was associated with ratification influence. We reported susceptibility and infection influences only for the GLOBALink joint subscription network data. These terms were calculated on the other networks reported in this study as well but since the co-subscription network was the one in which the exposure terms were significantly associated with adoption, it is these susceptibility and infections results we report here. It is quite possible that susceptibility and infection via other networks also occurred in these data. Indeed, countries exposed to online posts by prior ratifiers had lower susceptibility rates.

The likelihood of ratification was high early in the diffusion process and decreased over time. This pattern was evident for adoption, susceptibility and infection; indicating that influence occurred early in the diffusion of the ratification of the FCTC then tapered off. This pattern is different from other diffusion studies which more closely resemble a logistic growth curve. Unlike a new product, the FCTC had been in development for nearly a decade before being released to countries for ratification. Thus, there was likely pent-up demand for treaty ratifications and many countries ready to be influenced to adopt it early (Wipfli and Huang, 2011; Oberdorster, 2008).

Perhaps one of the most significant contributions of this study is the provision of tools enabling others to conduct the type of micro-level dynamic analyses reported in this paper. We have provided a suite of programs to replicate this research and apply these tools to other datasets and settings. Measuring whether exposure via networks is associated with adoption is an important analytic tool. In this study we confined ourselves to measuring exposure via direct contacts and estimated models with degree-weighted exposures. Many extensions are possible including exposures via structural equivalence, indirect ties, and other centrality measures. Future theorizing and modeling will shed light on which types of exposure influences are important for which types of behaviors.

It seems likely that both susceptibility and infection in their raw and normalized forms can be applied to many studies to understand which nodes (individuals, countries, or organizations) are most important in the influence process. One application of susceptibility and infection is as a manipulation check: Many studies are designed to stimulate interpersonal interaction and communication to promote behavior change. If the intervention is successful, it should increase rates of infection, and in some cases may be used to determine if infection increases for specific nodes (e.g., opinion leaders).

Creating an international health treaty is only the first step in a long process to improve global public health. The second step is the time interval for diffusion to occur and the variability in when countries ratify and implement treaty provisions. There are country attributes that affect this timing which influences when county populations will experience the benefits of public health treaties. There are also interactive characteristics. In a world increasingly characterized by social and online media communications, the timing of adoptions is influenced by country advocates' use of social media. How individual advocates use information and communication has implications for the health benefits their fellow citizens might experience. Most other global health interest areas lack a communication tool like GLOBALink and this may hamper their development. When contemplating the development of future international health treaties, investment in the creation and population of online networks could be essential to eventual treaty adoption and policy diffusion.

Although many countries adopted the FCTC early, nearly a quarter of countries had not ratified five years after the treaty opened for ratification and this after five years of negotiations. Provisions need to be made to accelerate the diffusion of health policies even before they are created. The FCTC represents a very successful initiative, yet there is still considerable variability in the timing of adoption and in which countries were influential and susceptible to communication messages.

These findings and methods should also be viewed in light of recent revelations that the US Chamber of Commerce has been actively opposing anti-tobacco policies (Hakim, 2015). Typically the Chamber acts through other countries, for example, by encouraging Ukraine to file a lawsuit against Australia using bilateral investment treaties when it proposed to enact anti-tobacco legislation. Hakim (2015) documented quite a few cases in which the US Chamber or one of its affiliates attempted to persuade policymakers within countries or have those policymakers take actions between countries (Lencucha and Drope, 2013). The question for researchers then becomes: Are these actions raising thresholds and/or susceptibility by creating negative influences on tobacco control policies?

There is growing interest in applying agent based modeling and other systems science approaches to inform policy at local, regional, national, and international levels (IOM, 2015). Our research here points to important components to incorporate into such models as there is a dire need to understand what makes people/agencies/countries susceptible and/or influential in the spread of tobacco-related behaviors and tobacco control efforts. Models are informed by theory and we believe that these extensions to diffusion theory provide robust and policy relevant additions needed for better models and better model results.

Finally, support for the dynamic hypotheses proposed here indicates that factors affecting health policy adoption change over time. The types of activities and interventions needed to accelerate policy diffusion early are different than those needed later. External influences on policy adoption are relevant when there is no network or possibility of network influences. Over time, as the policy diffuses, external influences become less relevant as adopting countries can rely on other countries for information and support. As countries rely on the experiences of other countries during the diffusion process, internal influences increase. The dynamic influence most likely to vary depending on policy type and network is the influence of opinion leaders. In some cases they may be influential early, when the advantages and risks to adoption are favorable (as in this study), but in other cases they will be influential late, particularly when risk and uncertainty over the policy are high.

4. Limitations

There are several limitations to this study that might affect both its internal and external validity. First, we aggregated treaty ratifications to the year rather than the specific day and month of ratification. Although we know the exact date of ratification, because the time-varying network and attribute data are compiled annually, we treated the ratification data similarly. Second, all networks were dichotomized on the median. Models for valued networks are not sufficiently developed for valued data and many network measures are defined only for binary networks. While that provides a rationale for dichotomizing, certainly some nuance in effects is lost when dichotomizing. Third, the choice of statistical model for estimating network effects is subject to debate (Lyons, 2011; VanderWeele et al., 2012). In this study, we used the most commonly agreed upon methods: Event history analysis with discrete time variables, controlling for intra-class correlation at the community level, including time dummies (Fujimoto et al., 2011). Although we could have used a network autocorrelation model (Doreian, 1989; Dow, 1984) to address potential correlation of an endogenous network effect variable with the error term, it is uncertain that this is a valid approach for this complex longitudinal data.

Fourth, these data use person-level behaviors aggregated to the country to analyze country ratification behavior. Fifth, we included a broad set of country attribute variables compiled from a larger list of over 100. Although we believe we included the most pertinent attributes in this study, there may be variables not included that might influence the models reported here. A final concern is that the calculations for susceptibility and infection allow for nodes to infect and be susceptible to the influence of many others. In other words, a person can simultaneously infect many others. While this seems realistic, a possible extension to this formulation is to penalize individuals who have many ties.

These limitations aside, these results have important implications for understanding the policy diffusion process as well as methods for estimating dynamic network effects on behaviors. Future studies are planned in which we compare diffusion effects across more treaties and across more networks. We also intend to estimate stochastic actor-oriented network dynamic models (Ripley et al., 2015), most relevantly, a model for diffusion of innovations in dynamic networks (Greenan, 2015) to replicate and extend the findings reported here. These analyses however, provide a clear portrait of how the FCTC diffused through the international community and the mechanisms by which adoption behaviors spread in the network.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.socscimed.2015.10.001.

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