The co-evolution of policy networks and political knowledge: An econometric approach to the emergence of local elite networks and government performance

Christian Aßmann
University of Bamberg, Germany

Christian Henning*
University of Kiel, Germany

Johannes Hedtrich
University of Kiel, Germany

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Abstract

This paper analyzes the determinants and causes of communication in local elite networks. Based on a Non-Bayesian model of political belief formation, we show that observational and communicational learning in an elite network induces a wisdom of the crowd effect and a policy bias. Both effects are influenced by the structure of communication networks. The paper focuses on an empirical analysis of the elite communication generating process based on policy network data collected in four rural communities in Slovakia. At the methodological level we suggest for estimation of dyadic network relations a probit framework, which is extended to deal with measurement errors in the dependent variable as well as missing values in explanatory factors. Estimation is performed via Bayesian methodology incorporating a sequential regression algorithm for handling of missing values. Empirical results suggest that political communication among local elites is mainly determined by political knowledge, while we found less empirical evidence for political homophily. Beyond, political knowledge, the structure of the meeting process, i.e. a common membership in local organizations and political party membership, also shapes political communication. Moreover, counterfactual experiments indicate that characteristic properties of elite networks are jointly determined by specific interaction effects between elite composition and the network generating process.

Keywords: policy elite networks, MCMC estimation, network generating process, observational and communicational learning, missing values.

*Corresponding author. Tel.: +49-431-8804453. *E-mail address:* chenning@ae.uni-kiel.de

1 Introduction

Early political sociology studies of policy networks focused on social network structures among governmental and non-governmental organizations to explain political decision-making (Parsons, 1963) and (Coleman, 1963). In particular, Laumann and Knoke (1987) and Knoke et al. (1996) have developed social influence models to explain opinion formation within a political communication process, where governmental actors partly adopt their policy positions to the positions communicated by other non-governmental organizations. However, while early policy network studies relate network structures to the political influence of individual actors, these studies do not yet relate policy network structures to political performance at the macro level. In contrast to classical policy network studies focusing on biased political incentives through political influence of interest groups Laumann and Knoke (1987); Pappi et al. (1995); Knoke et al. (1996); Carpenter et al. (2004) or biased voter behavior Huckfeldt and Sprague (1995); Fowler (2005), recent studies highlight the role of social network structures as an aggregation mechanism of dispersed knowledge (Jackson, 2008; Golub and Jackson, 2009; DeMarzo et al., 2003; Acemoglu and Ozdaglar, 2010). This latter effect is also denoted as the *wisdom of the crowd effect* (Jackson, 2008). One of the first scholars who analyzed the issue of whether a group of agents who hold dispersed information can aggregate the information and reach a correct consensus was Marquis de Condorcet. His seminal work is now referred to as the *Condorcet's Jury Theorem.* Later Francis Galton in a famous Nature article espoused the view that a group of relatively uniformed individuals would collectively have much more knowledge than any single one of them. In contrast, experimental and theoretical studies demonstrate that social influence might destroy *wisdom of the crowd effects* (Lorenz et al., 2011). For example, the idea of social influence models has been taken up in economic contexts to explain agents opinion formation, e.g. models of herding behavior (Krause, 2004).

Generally, communication learning can be modeled as perfect Bayesian up-dating processes (see Jackson (2008)). However, Golub and Jackson (2009) point out that Bayesian learning implies that actors have extremely high mental capabilities and complete information, which is hardly realistic for real political elite members. Therefore, they suggest much simpler Non-Bayesian naive learning models which assume that agents up-date their beliefs and apply simple rules of thumb. The DeGroot model is a classic model of Non-Bayesian opinion formation, which has been applied by Golub and Jackson (2009) to analyze the impact of communication network structures on opinion formation among a set of actors. Golub and Jackson (2009) focus their analyses on network properties that imply a consensus, while they have not yet analyzed how communication structures influence the overall efficiency of collective decision making.

As we will see, however, consensus as implied by the DeGroot model is not a very realistic feature for political opinion formation among political elite members who normally have heterogenous interests. Therefore, we suggest an alternative model of how political agents form their political opinion via communication. This model corresponds to a theoretical model suggested by Friedkin and Johnsen (1990, 1997). Independently, a very similar model has been used by Pappi et al. (1995) to empirically analyze political decision-making in national labor policy of USA, Germany and Japan. Neither of the authors, however, relate their model explicitly to the problem of correct belief formation and the efficiency of information aggregation. Moreover, neither of the studies provides a rational model of social influence.

Within our suggested theoretical framework, the rationality of political influence follows from the fact, that from the viewpoint of political agents political decision making is characterized by a fundamental uncertainty regarding the impact of policies on the state of the world. Thus, while most politicians have a clear preference regarding the desirable state of the world, they have only limited and incomplete information about the political technology, i.e. how different policy instruments actually translate into a specific state of the world. Accordingly, agents have to choose among policy alternatives even though they are uncertain regarding the evaluation of different alternatives. However, in a world of uncertainty it transpires that the maximization of individual utility can only be achieved by applying some supplemental strategies. For example, in order to make a rational choice in these situations agents form beliefs regarding the uncertain impact of various policy alternatives on the state of the world and thus on their utility.

In this context this paper analyzes how political communication network structures among local elite members influences information aggregation via communication and hence the overall efficiency of local government decision-making at the macro level. In particular, we demonstrate that political communication among governmental and non-governmental actors implies both a more efficient learning of the true political technology and a policy bias towards particular interest of local community, respectively. Therefore, communication networks correspond to information aggregation mechanisms and hence can be interpreted as social capital in the sense of Coleman, i.e. at the macro level, as well as at the micro level in the sense of Burt.

Interestingly, within our theoretical framework, no ideal typical network structure can be identified that generally guarantees high governmental performance, but rather, political decision-making becomes increasingly efficient the more elite network structures reflect the specific distribution of political knowledge and political interest across elite members. Thus, in contrast to most existing literature which explains the impact of networks on collective decision-making, our theory focuses much more on the network generating process, where efficient processes guarantee that elite networks match specific elite compositions, i.e. distribution of political knowledge and interest across elite members.

Accordingly, in a second step we focus our analysis on the network generating process. In this regard Moody (2001) point out that the formation of network structures is basically determined by two different processes: actors' preferences and the structure of the meeting process among the set of relevant actors. On the one hand actors choose their network contacts according to their preferences; while on the other hand, the meeting process determines the probability that two actors actually have the opportunity to form a network tie.

Hence we suggest an empirical model for analyzing and estimation of the elite network generating process based on policy network data collected in four rural communities in Slovakia. A transformation based approach based on distance measures is adapted to achieve the aggregation of individual explaining factors to the dyadic level. The core of the empirical model is thereby given by a probit framework. A Bayesian estimation approach is adopted, whereby the estimation is based on an MCMC methodology, namely Gibbs sampling. This estimation techniques is well suited to dealing with missing values in explaining factors via incorporation of a sequential regression algorithm, as well as with measurement errors in the dependent variable. The proposed modeling thereby allows for determining the extent of measurement error present in the data, and account for the uncertainty associated when performing network analysis, as discussed in Butts (2003). A straightforward extension is also at hand allowing for extension of potential mechanisms producing the measurement error. Forecast criteria are provided to allow comparison of model fitness for non nested model specifications.

Based on our theory we include three sets of variables as potential determinants of political communication ties: political interests, indicator variables describing individual political knowledge and variables describing the structure of the meeting process. Estimation results suggest that political communication among local elites in four Slovakian rural communities are mainly determined by political knowledge, where elite members with low political knowledge preferably communicate with high knowledge members. Beyond, political knowledge the structure of the meeting process also shapes political communication significantly, i.e. the number of common non-governmental organizational memberships is among the most important determinants of communication in local elite networks. Moreover, especially in low performing communities political party membership is identified being a significant factor in determining political communication among elite members. Further dissimilarity in political interests reduces political communication thereby indicating political homophily. This effect is, however, only significant for one of the four communities. Hence, our estimation results hardly support political homophily as being a determinant of political communication. Beyond general similarities network generating processes also differ significantly across communities. For example, when comparing the quantitative effects of political preference and structural meeting variables across communities a clear picture for high and low performing communities emerges. While political communication is strongly determined by joint organizational membership in high performing communities, political communication in low performing communities seems to be mainly driven by party membership. Further, although personal reputation in regard to political expertise is the main determinant of political communication in all communities, in quantitative terms, this effect is much higher for high opposed to low performing communities, i.e. communication seems to be more strongly driven by political expertise in the former.

Finally, to better understand the relative importance of the network generating process in determining local government performance when compared to the elite composition, we undertake a mechanism design experiment, where we simulate the elite network structures in low performing communities applying the network generating process estimated for high performing communities. Simulated elite network structures are transformed into political performance using an estimated structure performance function. Based on the observed shift of political performance implied by simulated elite network structures in low performing communities we are able to conclude to what extend high political performance is based on a specific network generation process, or on elite composition, respectively. If the former is more important than the latter future research should focus on strategic models of network formation, while otherwise future research should focus on gaining a deeper understanding of elite recruitment processes.

The paper proceeds as follows. In section 2 we derive a theoretical framework for analyzing the impact of elite network structure on political performance. Section 3 presents the econometric models and data, with subsection 3.1 reviewing the two different model frameworks, the Bayesian estimation methodology and the data generating process. The database is described in subsection 3.2. The empirical results are discussed in Section 4. Section 5 presents the results of the mechanism design experiment, while section 6 concludes.

2 Policy networks and government performance: A theoretical framework

2.1 General set-up

To illustrate how naive Non-Bayesian policy learning in political communication networks functions, let E denote a set of community elite members. The community elite is comprised of political agents, who by constitution collectively determine the community policy. Beyond political agents, however, the community elite include a subset of non-governmental actors, e.g. representatives of stakeholder organizations, which by constitution are not involved in legislative decision-making. We denote $i \in E$ a generic element of the political elite, while $G \subset E$ denotes the subset of political agents, $g \in G$.

The society is comprised of two groups, where ω_s is the share of group $s = 1, 2$ in the total society. The elite has to make a policy choice, $\alpha \in (-1, 1)$, that is consequential for the state of the world in their community. Let z denote the state of the world in the community. Community members derive a utility from the state of the world, where $U_s(z)$ denotes the utility of a individual member of group s. Technically, the relation between the policy α and policy outcomes z is captured by the political technology $T(z, \alpha)$. Moreover, each elite member has a specific political support function, $S_i(u(z))$, that relate group welfare into her individual political support received from community members. For simplicity, we assume the following simple linear political technology and log-linear support functions:

$$Z_s = U_s = U_s^0 + a_s\alpha, \qquad S_i = \prod_s {Z_s}^{\theta_{is}}, \quad \text{and} \quad \sum_s \theta_{is} = 1, \tag{1}$$

where U_s^0 denotes the welfare of a group member s without the policy, i.e. $\alpha = 0$ and θ_{is} denotes the interest of an elite member i in the welfare of group s. Groups have conflicting preferences regarding the state of the world, i.e. $a_1 * a_2 < 0$. For notational convenience we assume $a_1 > 0$. Moreover, elite members might have heterogeneous interests in the welfare of community groups, which might reflect different social or political relations between elite members to community groups. For example, assumed log-linear political support functions could be derived from electoral competition, where different elite members are elected in different electoral districts characterized by different group shares in the district population (Persson and Tabellini, 2000).

Each elite member maximizes her political support within the community, e.g. assuming for the moment that elite members have perfect knowledge of the political technology, the preferred policy position, P_i, of an individual elite members results from political support maximization:

$$P_i = \sum_s (1 - \theta_{is}) \frac{U_s^0}{a_s}. \tag{2}$$

Thus, depending on their relative interest in welfare of community groups members prefer different policies.

Final policy choices result from legislative bargaining among political agents. The work-horse-model in this regard is the non-cooperative legislative bargaining model of Baron and Ferejohn (1989). For simplicity we assume, however, that the outcome of legislative bargaining corresponds with a mean voter decision rule[1]:

$$\alpha = \sum_g C_g^a P_g. \tag{3}$$

C_g^a denote the vector of legislator's weights determined by constitutional rules.

2.2 Political belief formation and political influence

Sofar we have assumed that elite members have perfect knowledge of the political technology. In reality, however, policy choices are characterized by fundamental uncertainty. Thus, elite members do not know the true political technology and hence have to form beliefs to make a rational policy decisions. Let $\tilde{a}_{is}^0$ denote the initial political beliefs held by an elite member $i \in E$. We assume that initial individual beliefs are independently drawn from a symmetric distribution around the true political technology parameter, i.e. it holds:

$$\tilde{a}_{is}^0 = a_s + \mu_{is},$$

where μ_{is} denotes an idiosyncratic error term, with $E(\mu_{is}) = 0$. Accordingly, individual policy positions of elite members depend on both their policy interests, θ_i and their policy beliefs, $\tilde{a}_{is}^0$, respectively. Convergence or divergence in the policy space, α, no longer corresponds perfectly to convergence or divergence, respectively, in the policy interests space, θ, since policy beliefs additionally impact on this

[1] Henning (2000) derives the mean voter decision rule in the framework of a modified Baron-Ferejohn-model. According to the mean voter decision rule, legislature directly formulate a common proposal, which corresponds to the weighted mean of legislators' policy proposals. Under specific assumptions, the weights of individual proposals ($C\hat{a}_g$) equal the ex ante probabilities that legislators' proposals will be the final outcome of the formal non-cooperative decision making procedure. Under specific assumptions individual weights are solely determined by constitutional rules, and hence can be straightforwardly calculated empirically. Applying the mean voter decision rule is a "legislative norm" that becomes self-enforcing as long as legislators do not discount future gains from cooperation too much (Henning, 2000).

correspondence. Interestingly, heterogeneous beliefs might imply both a convergence in the α-space, even though two elite members have divergent policy interests and vice versa a divergence in the policy space, even though two elite members have the same policy interests, but hold different policy beliefs.

Next we introduce policy learning. Individual elite members can learn via two mechanism. First observational learning, that is elite member can up-date their political beliefs based on observed policy outcomes induced by their policy choices. Second, communication learning; that is elite members up-date their political positions based on preferred policy positions communicated by other elite members. To illustrate how naive policy learning via political communication works assume individual elite members observe policy outcomes implied by a policy α, $z_i^b(\alpha) = (Z_{i1}^b, Z_{i2}^b)$. Obviously, these observations are informative regarding the true political technology. However, individual observations are noisy, e.g.:

$$Z_{is}^b = U_s^0 + a_s\alpha + \varepsilon_{is},$$

where ε_{is} denotes an idiosyncratic error term, with $E(\varepsilon_{is}) = 0$. Accordingly, elite members can up-date their political beliefs based on the comparison of observed (z^b) and expected (z^e) policy outcomes. Assuming a Nerlovian belief formation of individual actors, it follows:

$$\tilde{a}_{is} = \tilde{a}_{is} + \xi\Delta a_{is} \tag{4}$$

with:

$$\Delta a_{is} = \left[\frac{\Delta Z_{is}}{\alpha}\right], \quad \text{where} \quad \Delta Z_{is} = Z_{is}^b - Z_{is}^e \quad \text{and} \quad Z_{is}^e = U_s^0 + \tilde{a}_{is}\alpha.$$

The parameter $0 \leq \xi \leq 1$ denotes the adaptive-expectation coefficient.

Given the fact that individual observations are noisy, agents are only imperfectly informed about the true political technology a. In contrast, in the aggregate the total set of agents is generally well-informed, since it observes a number of independent draws of the signal z_s^b. Therefore, agents are interested in a collective communication process, where agents communicate their received signals. An optimal communication process would correspond to a super-agent who aggregates the privately received signals of all agents and communicates the aggregated signals back to all individual agents. But, in reality agents' ability to communicate their experience may very well be limited. Actors might not communicate the true signals they have observed, but rather their opinion regarding the optimal policy, P_i. Since agents' communicated opinions are based on agents' private experience, they still are informative to other agents. Obviously, as long as the set of agents is sufficiently large the application of a naive belief-updating procedure, where agents simply form their final policy position as the average of all policy positions communicated by other agents, leads to an aggregation of dispersed information, which under specific assumptions can imply a more efficient learning when compared to individual up-dating without communication.

However, communication is normally more structured and restricted, e.g. agents only communicate directly with a small subset of the total population. In this context Golub and Jackson (2009) have shown how specific communication structures relate to overall efficiency of belief up-dating in a limit society applying the DeGroot model. In particular, Golub and Jackson (2009) established that under fairly weak assumptions, i.e. communication networks is strongly connected component, a perfect consensus of opinions is reached in the limit. Given that opinion formation occurs in the policy space, α, perfect consensus is not a realistic feature, as long as elite members fundamentally differ regarding their political interests, θ. Therefore, we suggest the following model of opinion formation.

To analyze communication structures we define a network Y^1, where $Y_{ij}^1 > 0$ indicates that agent i and agent j have an established communication tie. Accordingly, we define the subset $E_i = \left\{i \in E, Y_{ij}^1 > 1\right\}$

as the neighborhood of agent i, where it holds:

$$\sum_{j \in E_i} y_{ij} = 1 \quad y_{ij} = \frac{Y^1_{ij}}{\sum\limits_{j' \in E_i} Y^1_{ij'}}.$$

Accordingly, $Y = [y_{ij}]$ denotes the communication network, where $y_{ij} > 0$ indicates that actor i pays attention to actor j. Y is a stochastic matrix, i.e. for each actor the sum of total weights equals one. Within one period a political communication process occurs, where elite members repeatedly update their political opinion via taking weighted averages of their neighbors' opinions with y_{ij} being the weight or trust that actor i places on the current belief of agent j in forming his or her belief for the next period (see also Jackson (2008). Let $r = 1, .., R$ denote the communication round then it follows:

$$P_i^{r+1} = y_{ii} P_i^0 + \sum_{j \neq i} y_{ij} P_j^r \tag{5}$$

Moreover, the initial opinion P_j^0 just follows from political support maximization given an actor's initial beliefs regarding the political technology:

$$Y_j^o = \sum_s (1 - \theta_s) \frac{U_s^0}{\tilde{a}_{js}} \tag{6}$$

Rewriting equation 6 results in:

$$P_{it}^{r+1} = y_{ii} P_{it}^0 + (1 - y_{ii}) \cdot \sum_j \hat{y}_{ij} P_{jt}^r \quad \text{with} \quad \hat{y}_{ij} = \frac{y_{ij}}{(1 - y_{ii})}, \tag{7}$$

where P_i^r is the opinion of agent i resulting after r communication rounds, and P_i^0 denotes agent i's initial opinion before communication. The parameter $\gamma_i = y_{ii}$ represents the weight for their own opinion. As Y is row normalized to one, $(1 - y_{ii})$ is the aggregated weight for all neighbors, i.e. the influence or communication field of other agents. Let γ denote the diagonal matrix with the diagonal elements y_{ii}, than writing eq. (7) in matrix notation results after further rearrangements:

$$p_t = \left[I - (1 - \gamma) \hat{Y}\right]^{-1} \cdot \gamma \cdot p_t^0, \tag{8}$$

with $M = \left(\left[I - (1 - \gamma) \hat{Y}\right]^{-1} \gamma\right)$ being the network multiplier which is similar to the Hubbell index (Hubbell, 1965). Please note that our model perfectly corresponds with the DeGroot model for $\gamma = 0$, while it corresponds with the Friedkin-model for $\gamma_i = \gamma_j = \bar{\gamma} > 0$.

Accordingly, assuming $\gamma = 0$ our opinion formation process would result in a perfect consensus as long as we assume that the communication network Y is a connected component (Golub and Jackson, 2009). The consensus corresponds to a weighted average of the elite members initial position, Y^∞ is the matrix including individual weights of elite members as columns. Although consensus regarding community policy might be desirable, it is, however, not a very realistic implication for empirical political opinion formation, since political actors normally have divergent policy interests. Consensus regarding political beliefs would be conceivable even for heterogenous elite members, as here no interest conflicts occur among elite members. In political practice, however, political communication normally corresponds to an exchange of opinions regarding policy instruments and not of policy beliefs regarding the technical relations between policies and outcomes.

Assuming that $\gamma > 0$ implies that communication still converge to an equilibrium, but agents hold heterogeneous policy positions in equilibrium. In particular, note that for any row stochastic matrix $\hat{Y}$

belief formation converge to a well-defined limit y^∞ corresponding to the vector of actors' equilibrium opinion reached after communication. Accordingly, the limit opinion of each agent after communication results as a weighted average of the initial opinion of all agents before communication (p^0), where the weight of agent j's initial opinion (P_j^o) for agent i's opinion after communication (P_i) just equals the element m_{ij} of the multiplier matrix M. Thus, the multiplier defines the field strength of agent j's initial opinion operating on agent i's final opinion. Note that the multiplier includes all communication loops among actors, i.e. all direct and indirect effects of j's initial opinion on the opinion of agent i resulting from communication.

In this regard Friedkin and Johnsen (1997) assume that all actors attribute the same weight to their own initial position, i.e. they assume the same own-control for each actor. Accordingly, biased political opinions only occur in equilibrium due to a biased communication structure. In our more general model actors might also differ regarding their individual up-date strategy, i.e. the relative weight they put on their own opinion and that of other actors, respectively, might significantly differ across actors. For example, different own-control might reflect an actor's individual motives or information level, e.g. highly uncertain actors might but more weight on the communicated positions of other actors, while actors, e.g. lobbyist, who mainly engage in political communication to manipulate other agents would strategically assign a very low weight on other actors' positions, i.e. an own-control close to one would result.

Thus, overall our suggested model is more flexible in capturing a large variety of different communication patterns and opinion formation strategies which might be empirically observed in community elite networks. In particular, our model includes the deGroot and the Friedkin model as a special case.

Moreover, it is interesting to analyze the impact of communication network structures on the process of opinion formation. We are especially interested in analyzing this impact at the micro and macro level, i.e. from the perspective of an individual elite member and the total community, respectively. To this end consider the community elite are involved in a sequence of political decision-making, where $t = 1, .., T_m$ denotes the period of time decisions are made. Nerlove belief up-dating then implies that the difference between the belief held by an individual elite members in time period t=T and the true technology parameter results in the following:

$$\tilde{a}_{is} - a_s = \Delta\tilde{a}_{isT} = (1-\xi)^T \mu_{is} + \sum_{t=1}^{T} \frac{\xi}{\alpha_t} \varepsilon_{ist} (1-\xi)^{T-t}. \tag{9}$$

Political support maximization implies that agent's preferred policy position is a function of an agent's policy interest, θ and policy beliefs, $\tilde{a}$. Approximating this function by a first order Taylor series at the point $(\bar{\theta},\ \Delta\tilde{a} = 0)$, results in:

$$P_{iT}^0 = P^0(\bar{\theta}, a) + \sum_s \frac{\partial P_i}{\partial \tilde{a}_s} \Delta\tilde{a}_{isT} + \frac{\partial P_i}{\partial \theta}(\theta_i - \bar{\theta}), \tag{10}$$

where $P^0(\bar{\theta}, a)$ denotes the optimal policy position of an agent with policy interest, $\bar{\theta}$, assuming she knows the true political technology. Up-dating via communication implies that the elite members final opinion results from the weighted average of the initial opinions of all elite members:

$$P_{iT} = \sum_i m_{ij} P_{jT} = P^0(\bar{\theta}, a) + \sum_j \sum_s \frac{\partial P_i}{\partial \tilde{a}_s} m_{ij} \Delta\tilde{a}_{jsT} + \sum_j \frac{\partial P_i}{\partial \theta} m_{ij}(\theta_j - \bar{\theta}), \tag{11}$$

while the final policy decision results from legislative bargaining which we approximate with the mean voter decision-rule. Thus, the final policy, α_t, in each period is derived from the weighted mean of the legislators' final ideal position. Further, the ideal position of each legislator g in period t, P_{gt}, results from observational and communication learning as the weighted sum of communicated initial ideal positions.

Hence, overall, under this assumption, final policy decision in a period t is derived from the average mean of the preferred policy positions of all elite members:

$$\alpha_t = \sum_{i \in E} C_i P^0_{it}, \quad \sum_{i \in E} C_i = 1, \tag{12}$$

where the political weight or influence , C_i, of an individual elite member just equals:

$$C_i = \sum_{g \in G} C^a_g m_{gi}. \tag{13}$$

A next interesting question is how observational and communication policy learning processes can be evaluated from society's perspective. A benchmark for this evaluation is an ideal political process that aggregates the divergent interest of community members. Following standard theory (Mueller, 1989) an optimal community policy (α^{opt} results from the maximization of a Nash welfare function, where the weight of community groups just equal their population share, hence it follows that:

$$\alpha^{opt} = \sum_s (1 - w_s) \frac{U^0_s}{a_s}. \tag{14}$$

Accordingly, policy outcomes can be evaluated by applying the following political loss function:

$$L_t(\alpha_t) = (\alpha_t - \alpha^{opt})^2. \tag{15}$$

Moreover, different policy learning processes can be evaluated by the aggregated loss over a specific time period[2] T:

$$L(T) = \sum_{t=1}^{T} L_t. \tag{16}$$

Interestingly, from the viewpoint of the society belief updating in elite networks implies a trade-off between a more efficient policy learning through the aggregation of dispersed information signals within the elite and a potential policy bias resulting from the biased influence of special interests due to biased political communication networks. To see this assume that individual ideal points of elite members are approximated by a first order Taylor series at the point $\bar{\theta} = \omega, \Delta\tilde{a} = 0$. Substituting eq.10 (for $\bar{\theta} = \omega$) into the mean voter decision rule implies that final policy choice results as:

$$\begin{aligned}
\alpha_t &= \sum_i C_i P^0_{it} = \alpha^{opt}(\omega, a) + \sum_s \frac{\partial P}{\partial \tilde{a}_s} \sum_j C_j \Delta\tilde{a}_{jst} + \frac{\partial P}{\partial \theta} \sum_j C_j(\theta_j - \omega) && (17)\\
\Leftrightarrow \alpha_t - \alpha^{opt} &= \frac{\partial P}{\partial \theta} F + W_t && (18)\\
F &= \sum_j C_j(\theta_j - \omega), \quad W_t = \sum_s \frac{\partial P}{\partial \tilde{a}_s} W_{st} \quad \text{and} \quad W_{st} = \sum_j C_j \Delta\tilde{a}_{jst}. && (19)
\end{aligned}$$

Hence, the policy loss can be expressed as:

$$L_t(T) = \phi_2 F^2 + \phi_1 F W_t + W_t^2 \quad \text{with} \quad \phi_2 = \left[\frac{\partial P}{\partial \theta}\right]^2, \quad \phi_1 = 2\frac{\partial P}{\partial \theta}. \tag{20}$$

Thus, from Equation (17) it direct follows that from a societal perspective observational and communi-

[2] One might also introduce a discount factor into the overall political loss function to include the possibility that a society might assign a lower weight on future welfare. Furthermore, discounting would also imply that the speed of learning is important for governmental performance.

cation learning implies both a *wisdom of the crowd effect* (W_s), as long as $\sum_j C_j \Delta\tilde{a}_{jsT}$ approximates zero for large elites and a *special interest bias effect* to the extent that the policy interest of the elite is biased in favor of a specific population group, i.e. $\sum_j C_j(\theta_j - \omega) \neq 0$.

Obviously,the elite network structure has an impact on both effects, since the individual weights are determined by the elite network structure. An appropriate indicator which measures both the field strengths and the bias of political interests operating on the local government corresponds to a generalization of Battiston et al.'s concept of force (Battiston et al., 2004). Battiston et al. (2004) define the force as the average field strength which opinion leaders exert on individual agents. The force as defined by Battiston et al. (2004) only takes the direct effects of elite bias into account, while indirect effects are neglected. Accordingly, in the framework of our simple opinion formation model the *special interest bias effect*, F, corresponds to a straightforward generalization of the force concept suggested by Battiston et al. (2004).

Note that the generalized force varies between -1 and 1, where a force of -1 and 1 indicates that the government's final policy choice is totally biased towards non-agrarian and agrarian interests, respectively. To understand how or which network structure impact on *the wisdom on the crowd effect* we insert eq.(9) into eq.(17), which results after rearrangements in:

$$W_T = \sum_s \frac{\partial P}{\partial \tilde{a}_s} W_{sT} \quad \text{with} \quad W_{sT} = \sum_j C_j \Delta\tilde{a}_{jsT} = (1-\xi)^T \sum_j C_j \mu_{js} + \xi \left[\sum_{t=1}^{T} \frac{(1-\xi)^{T-t}}{\alpha_t} \sum_j C_j \varepsilon_{jt} \right]. \tag{21}$$

Thus, assuming that all error terms are independently distributed the variance of the wisdom of the crowd effect is derived from a linear combination of the squared individual political influence coefficients:

$$\sigma^2_{W_T} = \sum_i \Lambda_{iT} C_i^2 \quad \text{with} \quad \Lambda_{iT} = \sum_s \left[\frac{\partial P}{\partial \tilde{a}_s}\right]^2 \sigma^2_{W_{sT}} \quad \text{and} \tag{22}$$

$$\sigma^2_{W_{sT}} = \sum_j C_j^2 \sigma^2_{\Delta\tilde{a}_{jsT}} = \left[(1-\xi)^T\right]^2 \sum_j C_j^2 \sigma^2_{\mu_{js}} + \xi^2 \left[\sum_{t=1}^{T} \left\{ \frac{(1-\xi)^{T-t}}{\alpha_t} \right\}^2 \sum_j C_j^2 \sigma^2_{\varepsilon_{js}} \right]. \tag{23}$$

Accordingly, maximizing the *wisdom of the crowd effect* for a finite elite implies:

$$\frac{C_i}{C_j} = \frac{\Lambda_{jT}}{\Lambda_{iT}}. \tag{24}$$

Please note that Λ_{iT} just equal a linear combination of the variances of idiosyncratic error terms. Hence, the lower the relationship between Λ_{iT} and Λ_{jT} the higher is the informational value of an elite member i in comparison to the elite member j. Thus, actors' optimal political influence reflects their relative informational value. In this regard Golub and Jackson (2009) assumed that all idiosyncratic errors are independent and are drawn from a common distribution with a zero mean. Under this specific assumption the optimal political influence would be $\frac{1}{n}$ for all elite members as they would all have the same informational value. In general Golub and Jackson (2009) show under this specific assumption that the *wisdom of the crowd effect* results for large society as long as the communication matrix has the property that C_i approximates zero for every elite member when society grows to infinity. Thus, a random network would correspond to an almost ideal communication network assuming a own control of $\gamma_i = \frac{1}{n}$ for all elite members. Assuming, however, that elite members are heterogenous with regards to their political knowledge, would imply that elite members observe different variances in their idiosyncratic error terms and the results of Golub and Jackson (2009) do no more hold true.

Thus, although Golub and Jackson (2009) have nicely derive sufficient and necessary properties of communication networks that guarantee perfect learning in infinitely large societies, their results are based on very specific assumptions that hardly apply to real political systems, which are characterized by finite elites and individual elite members with heterogeneous political knowledge. In this regard an interesting conflict between micro motives and macro outcomes might result inasmuch as from the individual perspective of elite members it might be favorable beyond agents informational value to update on policy positions communicated by other elites members with similar political interests. Political homophily, however, increases ceteris paribus the *special interest bias*, i.e. has a negative impact on overall governmental performance at the macro level. To see that political homophily is favorable for individual agents, consider again the weighted average of communicated position in eq. (10) evolved from the individual viewpoint of an elite member i with political interest, i.e. $\bar{\theta} = \theta_i$. From the viewpoint of an individual agent updating on communicated positions of elite members with divergent political interests induces a bias away from agent's optimal policy position. Therefore, to avoid this bias agents prefer to communicate with other agents who have similar political interests, i.e. communication networks should be characterized by homophily regarding political interests. Moreover, communication is costly, i.e. it is also determined by the frequency of meeting opportunities. Thus, overall it is interesting to analyze empirically to what extend political communication among elite members is determined by political homophily, political expertise and structural meeting opportunities, respectively, and to what extend network generating processes differ in the relative importance of these various determinants across high and low communities. Please note that within our theoretical framework it follows quite plainly that high governmental performance is not guarantee by a specific ideal typical communication network structure, but much more that the fact that elite communication network structures corresponds with political expertise of elite members. Hence, since elite members composition easily changes over time, it is especially important that the underlying network generating process guarantees that communication network structures correspond with the political expertise of elite members.

To analyze these questions empirically we estimate the network generating process based on elite network survey data for four Slovakian rural communities. Econometric estimations are undertaken using agents' policy preferences, structural variables which determine meeting opportunities as well as indicator variables of agents' individual political knowledge as predictors of dyadic communication network ties applying a Bayesian estimation procedure. Further, to be able to compare the impact of estimated elite network structures on governmental performance we simulate policy outcomes implied by the different communication networks based on an agent-based model version of our simple theoretical framework described above and calibrated using empirical elite survey data collected in four rural communities in Slovakia. Based on simulated data we could estimate a structure performance function transforming network structures into governmental performance. Finally, to better understand the relative importance of the network generating process in determining local government performance when compared to the elite composition, we undertook a mechanism design experiment. In this experiment we simulated elite network structures in low performing communities by applying the network generating process estimated for high performing communities, whilst we also estimated elite networks in high performing communities using the network generating process estimated for low performing regions. Simulated elite network structures are transformed into political performance using the estimated structure performance function. Based on the observed shift of political performance implied by simulated elite network structures in high and low performing communities we are able to conclude to what extent high political performance is based on a specific network generation process or on elite composition. If the former is more important than the latter future research should focus on strategic models of network formation, while otherwise future research should focus on understanding elite recruitment processes.

3 Econometric models and data

3.1 Model Framework and Estimation

We setup a model to capture key elements for analyzing the process which establishes communication ties $\delta_{ij} = \delta_{ji}$ between local elite members $i = 1, \ldots, n$ and $j = i + 1, \ldots, n$. Determinants of communication relationships are analyzed within a probit framework:

$$\delta_{ij} = \begin{cases} 1, & \delta^*_{ij} > 0 \\ 0, & \delta^*_{ij} \leq 0, \end{cases}$$

where $y^*_{ij} = X_{ij}\beta + e_{ij}$, where $X_{ij}\beta = X^{(1)}_{ij}\beta_1 + h_{ij}$ and $e_{ij} \sim \mathcal{N}(0, 1)$. h_{ij} is thereby parameterized in such a way as to allow the aggregation of individual specific characteristics to the dyadic level, i.e.

$$h_{ij} = \sum_{k=1}^{K} \beta^{(k)}_2 |q^{(k)}_i - q^{(k)}_j| + \sum_{k=1}^{K} \beta^{(k)}_3 q^{(k)}_i q^{(k)}_j.$$

Using a probit link allows to establishment of a Bayesian estimation routine facilitated by MCMC sampling from closed form full conditional distributions. An additional model feature which is necessary to meet the observed network data is the incorporation of a measurement error to cope with asymmetrically reported communication relationships $y_{ij} \neq y_{ji}$. The measurement is modeled by assuming that each person misreports his true relationship with some probability, say π, yielding:

$$p(\delta_{ij}|y_{ij}y_{ji}) = \pi^{y_{ji}}\pi^{y_{ji}}(1-\pi)^{1-y_{ji}}(1-\pi)^{1-y_{ij}}.$$

Assuming conjugate priors for parameters $\theta = \{\beta = \{\beta_1, \beta_2, \beta_3\}, \pi\}$, the overall likelihood is then given as

$$\begin{aligned} \mathcal{L}(\theta; \text{data}) \quad = \quad & \prod_{i=1}^{n} \prod_{j=i+1}^{n} \left[\pi^2\Phi(X_{ij}\beta) + (1-\pi)^2\Phi(-X_{ij}\beta)\right]^{(1-y_{ij})(1-y_{ji})} \\ & \times \left[\pi(1-\pi)\Phi(X_{ij}\beta) + (1-\pi)\pi\Phi(-X_{ij}\beta)\right]^{y_{ij}(1-y_{ji})} \\ & \times \left[\pi(1-\pi)\Phi(X_{ij}\beta) + (1-\pi)\pi\Phi(-X_{ij}\beta)\right]^{(1-y_{ij})y_{ji}} \\ & \times \left[(1-\pi)^2\Phi(X_{ij}\beta) + \pi^2\Phi(-X_{ij}\beta)\right]^{y_{ij}y_{ji}}, \end{aligned}$$

where $\Phi(\cdot)$ denotes the cumulative standard normal distribution function. Bayesian estimation via Gibbs sampling is then based on the following set of full conditional distributions:

1. Sample for each i and $j > i$ from a binary distribution with probability

$$\Pr(\delta_{ij} = 1|y_{ij}, y_{ji}, \theta, X_{ij}) \propto \pi^{1-y_{ij}}\pi^{1-y_{ji}}(1-\pi)^{y_{ij}}(1-\pi)^{y_{ji}}\Phi(X_{ij}\beta).$$

2. Sample for each i and $j > i$ from δ^*_{ij} a truncated normal distribution with:

$$\mu_{\delta^*_{ij}} = X_{ij}\beta, \quad \sigma_{\delta^*_{ij}} = 1, \tag{25}$$

   where the truncation sphere is $(-\infty, 0)$ if $y_{it} = 0$ and $(0, \infty)$ if $y_{it} = 1$.

3. Sample parameters β from a multivariate normal distribution obtained from linear regression setup

given by $\delta^* = X\beta + E$, given as:

$$f(\beta; \mu_\beta, \Sigma_\beta) \propto |\Sigma_{\beta_k}|^{-\frac{1}{2}} \exp\{-\frac{1}{2}(\beta - \mu_\beta)\Sigma_\beta^{-1}(\beta - \mu_\beta)\}.$$

with moments

$$\Sigma_\beta = (\tilde{X}'\tilde{X} + \Omega_\beta^{-1})^{-1}, \qquad \mu_\beta = \Sigma_\beta^{-1}(\tilde{X}'Y^* + \Omega_\beta^{-1}\psi_\beta), \tag{26}$$

whereby ψ_β and Ω_β denote the moments of the multivariate normal conjugate prior distribution.

4. Sample π from Beta distribution

$$f(\pi|\lambda_1, \lambda_2) \propto \pi^{\lambda_1}(1 - \pi)^{\lambda_2}$$

with moments

$$\lambda_1 = \sum_{i<j}(|\delta_{ij} - y_{ij}| + |\delta_{ij} - y_{ji}|) + \xi_{01} \quad \lambda_2 = n^* - \sum_{i<j}(|\delta_{ij} - y_{ij}| + |\delta_{ij} - y_{ji}|) + \xi_{02},$$

with n^* denoting the total number of possible links and ξ_{01}, ξ_{02} denoting the corresponding hyperparameter of a conjugate prior Beta distribution.

As has been noted in the literature, (see Butts (2003)), the incorporation of a measurement error is well suited to dealing with missing data in the dependent network relationship. However, as data is gained via a survey, the explaining variables often also show missing data. The proposed MCMC estimation approach can easily be extended to deal with any resulting uncertainty of the parameter and process estimation.

While the natural approach to dealing with missing data in the explanatory variables is to build up a joint modeling of all considered variables, this would often result in prohibitive large models and parameter sets in terms of both data requirements and computational costs, at least for realistic and rich models. Hence, considering the often quite low number of missing values, we propose an alternative approach to incorporating the resulting uncertainty of missing explanatory values for parameter estimation. The treatment of missing values is hence based on data augmentation as suggested by Tanner and Wong (1987). The parameter vector is thereby augmented to also include the missing variables. Draws for the missing values within each iteration of the Gibbs sampler are then obtained from simple parametric of non parametric approximation of the full conditional distributions. Given the non continuous scale of the explanatory variables, we follow the approach of Burgette and Reiter (2010) and use classification and regression tree (CART) models to provide an accurate approximation of the underlying full conditional distributions. The Gibbs sampler is then augmented to include the following further steps.

5. Based on an initialization of missing values within the initialization of the Gibbs sampler, for which draws of missing values are sampled from the corresponding unconditional distribution of observed values, for each variable showing missing variables, two additional steps are calculated.

   (a) We constructed a reference group via CART modeling which serves as a non parametric approximation of the underlying full conditional distribution. The construction of reference groups via a CART model thereby relies on a set of specifications, e.g. the minimum number of observations per reference group, (see Breiman et al. (1984) for complete listing of the involved specification parameters). We adopt the specification parameters suggested by Burgette and Reiter (2010) in the context of multiple imputations. Note that the case of network data the following case occurs. When data is missing within the variables which capture individual specific variables, which are aggregated towards the dyadic level, the total number of available observations may not allow for grouping in order to provide a reasonable approximation of the underlying full conditional distribution. Hence, in this case the approximation delivered by CART modeling often coincides with the unconditional distribution of observed variables.

(b) Obtain a simple random draw from the reference group as a draw from the underlying full conditional distribution.

Given the outlined Gibbs sampler parameter estimates can be readily obtained as means and standard deviations of sampled sweeps. The numerical adequacy of the presented estimation approach is checked via MCMC diagnostics. Convergence is assessed via simple autocorrelation plots and the diagnostic test statistic proposed by Geweke (1992). The test statistic tests for the equality of the sample mean at the beginning and end of the sample sequence with:

$$CD = \frac{\bar{X}_A - \bar{X}_B}{\sqrt{\frac{S_A^2}{n_A} + \frac{S_B^2}{n_B}}} \overset{\text{asy}}{\sim} \mathcal{N}(0,1),$$

where A refers to the first 10% and B to the last 50% of the Gibbs sequence with total number of observations given as n_A and n_B. The corresponding variances S_A and S_B are estimated according to a Newey-West robust estimator Newey and West (1987) as the numerical equivalent of 2π times the spectral density estimator at frequency zero used in Geweke (1992). Estimation is based on 10000 iterations of the Gibbs sampler, where discarding the first 2000 has been found to be sufficient to remove the dependence on initial conditions.

Beside estimation and inference on model parameters θ, insights can be gained from marginal effects. Conceptually, the marginal effect evaluated for a particular value of the covariates x^*, which may represent the mean of the sample covariates in the case of metric variables or the mode in the case of binary variables, with θ summarizing all parameters, is given as

$$\frac{\partial}{\partial x}\Pr(\delta = 1|x = x^*, \theta), \tag{27}$$

for continuous variables. For discrete binary variables, it is given as

$$(-1)^{1-x^*}\left(\Pr(\delta = 1|x = x^*, \theta) - \Pr(\delta = 1|x = 1 - x^*, \theta)\right). \tag{28}$$

For the considered model specification, the marginal effect is well known to be

$$ME = \phi(x^*\beta)\beta, \tag{29}$$

where $\phi(\cdot)$ denotes the density of the standard normal distribution. A point estimate thereof, as well as variation measures, can be extracted directly from the Gibbs output and is hence given as:

$$\widetilde{ME} = \frac{1}{R}\sum_{r=1}^{R}\phi(\overline{x}\beta^{(r)})\beta^{(r)}. \tag{30}$$

Given the established estimation routine, an important point is to check adequacy of the model . A common approach is to use the predictive ability of a model to assess mode fit (see Geisser and Eddy (1979)). A recent application to binary models can be found in Jara et al. (2007) and Aßmann and Boysen-Hogrefe (2011). However these papers deal with a situation, in which the dependent binary variable is assumed to be observed without error. In order to assess the appropriateness of the suggested econometric model framework, we conduct a model comparison in two directions. The first direction is to check the model specification for the latent regression model given the presence of the measurement error. This model checking is implicitly undertaken when gauging the posterior distribution of parameters. However, the predictive ability of the models can also serve as a measure of fitness. Using the predictive power of a model is a common approach to assess model fitness in the context of binary dependent variables. However, in the presence of measurement error, the natural yardstick to measure model fitness is not present, since the *true* relational status remains unobserved. In order to provide a comparison of the model specification including the measurement error, two (misspecified) baseline scenarios are constructed, both based on the idea of ad hoc symmetrization. The first baseline scenario is established as follows: All relational observation showing a mismatch ($y_{ij} \neq y_{ji}$) are set to zero. The second baseline specification is constructed by setting all mismatching relations to one. These two specifications serve as a benchmark and allow to gauge the extent to which the consideration of a measurement error improves the ability to match the observed pseudo true relationship. The pseudo true relationship either obtained via crude symmetrization within the two benchmark scenarios or inferred as the mode of the posterior of δ_{ij}'s is then utilized to state the rate of true positive and false negative classified relationships. The predictive probabilities of the different model specifications are then formally derived as:

$$p(g(\delta|\mathcal{M})) = \int g(\delta|\mathcal{M})p(\theta|\delta, X, \mathcal{M})d\theta, \tag{31}$$

which is estimated as:

$$p(\widetilde{g(\delta|\mathcal{M})}) = \frac{1}{R}\sum_{r=1}^{R} g(\delta|\mathcal{M})p(\theta^{(r)}|\delta, X, \mathcal{M}). \tag{32}$$

Here $g(\delta|\mathcal{M})$ denotes a forecasting measure for the observations δ based on the model specification $\mathcal{M}$. Superscript f denotes the set of all observations classified within the prediction sample. Typically, to forecast a binary variable in a probit model, the cdf of the latent model is calculated and checked whether it exceeds 0.5. The fraction of correctly classified observations is then used as a model selection criterion, i.e.,

$$\frac{\sum_{i=1}^{n}\sum_{j=i+1}^{n}(I\left[\Pr(\delta^*_{ij} \geq 0|\delta_{ij} = 1, \mathcal{M}) > 0.5\right] + I\left[\Pr(\delta^*_{ij} \leq 0|\delta_{ij} = 0, \mathcal{M}) > 0.5\right])}{\sum_{i=1}^{n}(n-i)}. \tag{33}$$

Egan (1975) provides an extension by proposing the Receiver Operator Characteristics (ROC) curve. Based on the predictive performance of the model under consideration, it comprises the set $\{a(w_g), b(w_g)\}_{g=1}^{G}$, with the set of thresholds $\{w_g : g = 1, \ldots, G \text{ and } 0 \leq w_1 \leq w_2 \leq \ldots w_G \leq 1\}$, where

$$a(w_g) = 1 - \frac{1}{\sum_{i=1}^{n}[n-i]}\sum_{i=1}^{N}\sum_{j=i+1}^{N} I\left[\Pr(\delta^*_{ij} \geq 0|\delta_{ij} = 1, \mathcal{M}) > w_g\right], \tag{34}$$

$$b(w_g) = \frac{1}{\sum_{i=1}^{n}[n-i]}\sum_{i=1}^{N}\sum_{j=i+1}^{N} I\left[\Pr(\delta^*_{ij} \geq 0|\delta_{ij} = 0, \mathcal{M}) > w_g\right]. \tag{35}$$

Note that $a(w_g)$ and $b(w_g)$ relate to the fraction of true positive and false negative predictions respectively.

The ROC graph therefore assesses the predictive performance for alternative values of the prediction threshold ranging from 0 to 1, and not just 0.5. In the empirical analysis, the above-mentioned probabilities are replaced by the relative frequencies obtained via computation of the predictive probabilities for each single observation. By calculating the area under the ROC curve, the AUC, the information about the rates of false positive and true negative prediction contained within the ROC graph is comprised into a single number, which allows a simple specification comparison. Its minimum is 0.5, which reflects random forecasts, and its maximum is 1, which implies perfect forecasts. Mylne (2002) and Richardson (2001) show that the AUC is closely related to the economic value of a forecast system. Formally, the AUC measure is calculated as:

$$\mathrm{AUC} = \sum_{g=1}^{G-1} \frac{1}{2}(b(w_{g+1}) + b(w_g))(a(w_{g+1}) - a(w_g)). \tag{36}$$

The use of pseudo-out-of-sample criteria allows the comparison of non-nested model specifications and is hence well suited to perform alternative model approaches to assess the features of social network data.[3]

3.2 Data description

To estimate the described econometric models, we used local elite survey data collected in four rural communities in Slovakia, where elite surveys were undertaken within the European research project ADVANCED-EVAL [4] funded by the European Commission under the sixth framework from 2006-2009. Communities where selected according to their general economic development level measured by a estimated quality of life index (Michalek and Zarnekow, 2011) and their geographical distance to a larger city. Accordingly, community selection followed a two-by-two design combining high and low performing communities with a location close to and far from a large city, where community I and III are low and II and IV are high performing communities. Moreover, communities I and II are located close to a large city, while communities III and IV are located far from a large city.

Elite surveys were undertaken via personal interviews with identified political elite members in each community. Relevant elite members were identified in a two step procedure. In the first step a list of potentially relevant individual community members was compiled based on expert interviews. Normally, a highly ranked community administrative was selected as an expert. Based on this list, personal interviews were conducted beginning with the members of the community council, including the mayor. During the interview, a reputation question was asked, and interviewees had to mark all influential elite members on the identified list. Based on the reputation question, new elite members who had received more than 3 nominations were interviewed. Overall, we identified 45, 53, 51 and 49 potentially important elite members in communities I, II, III and IV, respectively, of which we interviewed 29, 34, 23 and 27, respectively.

The elite questionnaires included three parts: a) Policy network data, in which personal and organizational network data was collected; b) Policy preferences, which collected information on interest and position of policy issues and c) Data on socio-economic characteristics of identified elite members including organizational affiliation and organizational memberships. Based on collected elite survey data the following endogenous and exogenous variables have been calculated (see also Table 1. First, we collected data on five personal networks including a reputation, a political communication, as well as business and private contact network and a family relation. The fraction of missing values within the explaining factors is also given in Table1. Is is below 2% for all considered communities. All personal network questions were asked in a from which we have found especially helpful in earlier network studies (Henning, 2009; Pappi and Henning, 1998, 1999). The respondents were asked to go over the prepared list of potentially important elite members and to name all those with whom they had a specific relation. Additionally, respondents could always add persons that were not on the list. Thus, we created a complete network of relations among important elite members. Moreover, since we interviewed all important elite members,

[3]Note that the above described approach could be easily extended towards a cross validation experiment in order to prevent possible overfitting due to a larger number of parameter in the model incorporating the measure error. This is done as follows. As discussed by Stone (1974), the sample is split along its time dimension into an estimation and a prediction part to prevent overfitting. We run a modified Gibbs sampler where the distributions of the parameters solely depend on the observations in the estimation part.

[4]For further details see http://www.advanced-eval.eu/.

for each tie between a member i and j, we collected two data points, one from the perspective of i and one from the perspective of j. We used the network of personal political communication among identified elite members as the endogenous variable, Y, in our estimation.

Second, we include three classes of exogenous variables, X, in our estimations: variables describing policy preferences, indicator variables of individual political knowledge, and variables describing the structural meeting process. Generally policy preferences included actors' political interests and positions in various policy issues nested in three levels. In this study we only use top level preferences regarding policy concerns[5] (Z), where policy preferences are summarized within a political distance index providing dyad specific information on the probability to observe communication between local elite members. The index is calculated as follows:

$$CI_{ij} = \sqrt{\sum_{k=1}^{K} |p_{ik} - p_{jk}| d_{ik} d_{jk}},$$

where d_{ik} denotes the interest of individual i in policy concern k and p_{ik} the position of individual i in policy concern k.

Interest was ascertained by distributing 100 points across policy concerns, while positions were ascertained by using a 7-point rating scale, where the end points were defined and the midpoint corresponded to the status quo. Moreover, based on political interest data we were able to compute the interest bias of individual elite members, where interest bias was calculated in terms of political interests in the welfare of agrarian versus non-agrarian populations. Accordingly, we calculate the interest bias of an individual agents as being the difference between the normalized stated interest in the policy concern "welfare of agrarian population" (Z_1) and the sum of the normalized stated interest in the policy concern "welfare of the non-agrarian population" (Z_2 to Z_4). Normalization was undertaken via mean-scaling. Hence, a positive bias expressed an interest bias in favor of agrarian interest, while a negative bias corresponded to a bias in favor of non-agrarian interests. Alternatively, we undertook a factor analysis of stated policy interests within each community elite and took calculated the individual factor values of the first principal component as a measure of agents' special political interest bias.

As we could not observe political expertise we use age, education and job prestige as indicators which approximate the political knowledge of individual elite members[6]. Moreover, we used political reputation as an additional indicator of political expertise, where we took actor's indegrees of the collected political reputation network as a measure of personal reputation. In order to aggregate individual specific characteristics to the dyadic level all political knowledge indicator variables were transformed as described by the function h_{ij} above, e.g. for each variable X, we estimated the impact of two corresponding dyadic variables, (i) the difference between each pair of elite members i and j, $X_i^k - X_j^k$, and (ii) the product, $X_i^k X_j^k$.

Moreover, we collected organizational data. First, we asked each respondent to name all community organizations of which he or she was a member. Again, we prepared a list of potentially relevant community organizations based on expert interviews undertaken within a pre-study, which we presented respondents during the interview. Based on the local elite members' organizational membership a further dyad specific information variable was calculated, i.e. it how often two local elite members were members of the same organizations, e.g. social, political, or religious ones, was counted [7]. Moreover, a dummy

[5] Overall, we included seven policy concerns: Z_1 = Welfare of farmers, Z_2= Welfare of non-farm households, Z_3= Welfare of the elderly people, Z_4= Welfare of non-agrarian business companies, Z_5= Rural development Z_6 = Environmental protection, Z_7 = Tourism.

[6] The following ordinal scheme is used: (1) Unfinished primary school, (2)Completed primary school, (3)Vocational training, (4) Unfinished high school, (5) Completed high school without matura, (6) Completed high school with matura, (7) General gymnasium certificate, (8) Completed professional training, (9) Bachelor diploma at university, (10) Completed university study, Magister. The social prestige index is constructed based on the asked job occupations of local elite network members, see van der Gaag (2005) for details on the construction approach.

[7] All organizations are classified according to their main purpose as follows: (1) Policy and administration, (2) Agriculture,

variable, which indicated political party membership was used to calculate an indicator of the structural meeting process. In particular, based on the party dummy variable we calculated the indicator variable party membership as being the sum of actors' party dummy, e.g. the resulting party membership variable ranges between 0 (both actors are not a party member) and 2 (both actors are a party member. Summary statistics for all exogenous variables under consideration as well as network parameters of the political communication network are provided in Table (1).

4 Empirical Results

The estimation results of our network generating process are presented in Table (2) for all four communities. As can be seen from table (2), in all four communities, the formation of political communication network ties is significantly and positively determined by organizational membership and personal reputation. With regards to content, the positive impact of joint organizational membership underlines the empirical importance of structural meeting opportunities for political communication. Although for the second indicator variable of structural meeting opportunities, party membership, the estimation reveals a significant and positive impact on political communication at least for the low performing communities, I and III. In contrast, the impact of party membership on political communication is negative and insignificant for the high performing communities, II and IV. Party membership, however, is constructed as a dyadic variable ranging from 0 no elite members are party members to 2 both elite members are party members. Thus, a value of 2 does not indicate joint membership in the same party. With regards to content, a high positive impact of this variable in the low performing communities, I and III, implies that political communication is mainly organized via parties in these communities. This specific organization of political communication via political parties can be interpreted as a specific political culture inherited from the former socialistic regime. Traditionally the WSA as the predecessor of the former socialistic party received a high vote share in eastern Slovakia, where both low performing communities are located.

The positive impact of the difference of personal reputation on the probability to form a communication tie implies that communication is hierarchical. Two alternative interpretations are conceivable. First, personal reputation corresponds with other agents' perception of political expertise. Accordingly, members with a high reputation are contacted by agents with a low reputation to up-date their political knowledge.

A second interpretation of this result is that communication is mainly strategic, where low reputation elite members, who mainly correspond to non-governmental actors, try to lobby high reputation elite members, who mainly correspond to council members and especially the mayor. In the first case own control of high reputation members should be relatively high when compared to low reputation members, while in the second case own control of low reputation members should be relatively high when compared to high reputation members. Interestingly, own control is highly and positively correlated with reputation for high performing communities (II and IV), while it is only moderately correlated for low performing communities. Thus, for high performing communities the first explanation seems to be supported, while for low performing communities, the estimation results also provide some evidence for strategic communication, i.e. non-governmental actors try to influence council members and the mayor.

Moreover, all other socio-economic indicator variables for political knowledge, i.e. education, age or job prestige, have no significant impact on the formation of political communication ties in any community. Analogously, in contrast to the difference the product of personal reputation as the second component of the dyadic aggregation function h_{ij} has no significant impact on communication, i.e. in contrast to the

(3) Industry, (4) Handcraft, (5) Trade, (6) Consumer goods, (7) Cultural/educational/media, (8) Associations and clubs, (9) Religious/church, (10) Other organization purposes.

β_2-parameter the β_3-parameter is not significant for personal reputation.

Therefore, it seems that at least for the analyzed Slovakian community elites the perception of political expertise is mainly determined by reputation. However, this perception via reputation might be biased due to herding behavior. Of course, the more the evaluation of political knowledge is characterized by herding behavior and the less the evaluation depends on observable indicator variables such as education or political seniority or qualifications due to acquired job skills, the less the evaluation corresponds to agents' true political knowledge. Since we do not have an objective measure of agents' political knowledge we cannot further clarify this important question. Nevertheless, the indegrees of the reputation networks are asymmetrically distributed which suggests a power law distribution. The fact that none of the other socio-economic indicator variables for political expertise are significant supports the hypothesis that the evaluation of political knowledge is at least partly driven by herding behavior.

Further, for all communities, a negative sign for the political conflict index can be observed indicating political homophily, i.e. as expected, political communication seems to be driven by homogenous political interests. This effect is, however, only significant for community II. Thus, surprisingly, our estimation results hardly support political homophily as being a determinant of political communication.

In order to quantitatively compare network generating processes across communities, we calculated the marginal effects of different variables in Table (3). Interestingly, when comparing the effects of political preference and structural meeting variables across communities, a clear picture for high and low performing communities emerges. While political communication is strongly determined by joint organizational membership in high performing communities, political communication in low performing communities seems to be also driven by party membership. As can be seen from Table (3), one additional overlapping organizational membership increases the probability to form a communication tie by 0,54% to 0.67% in high, but only by 0.1% to 0.04% in low performing communities. On the contrary, joint party membership increases the probability of communicating only marginally, except for community III, where joint party membership significantly increases the probability of communicating by 0.28% when compared to joint non-membership.

For all communities, however, personal reputation is the main determinant of political communication, where the increase in the probability of communicating induced by an additional difference in the reputation measure by 1 indegree ranges from 3.5% in community I to 6.6% in community III. Since the marginal effects reported in table 3 were calculated using county specific mean values, they reflect the county specific elite composition. Thus, to disentangle the effects exerted by the identified specific network generating processes and specific elite compositions of communities, on communication network structures, respectively, we perform a mechanism design experiment in the next section.

5 A mechanism design experiment

We simulate the elite network structures in each community by applying the network generating process estimated for the other communities. Technically, elite communication networks were simulated via posterior forecasting described in equations (31-32). Based on random draws from the posterior distribution of β-parameters, network data are generated by calculating the latent model $\delta_{ij}^{*(s)} = X_{ij}\beta^{(s)} + e_{ij}$ where a link is established, when $\delta_{ij}^{*(s)} > 0$. This approach, thereby, incorporates the uncertainty of the estimated network forming process and provides direct access to the posterior distribution of important network characteristics via the repeated simulation of networks which reflect the observed characteristics and the estimated network process.

For each combination of a network generating process and elite survey data, 100 networks are generated, thus providing 100 random networks for each of the 16 simulated elite network types. To see how elite network structures vary across specific elite compositions and network generating processes, respectively, we first computed the average characteristic network parameters for each combination type, i.e. the average number of degrees (AD), clustering coefficient (CC), and degree centrality defined as the variance of degrees (CENTRAL)). Moreover, for each generated network, we calculated the political influence of individual elite members according to eq. (13). Political power, C_g^a was calculated using the Banzhaf Index following Henning et al. (2006), where in each community, legislature is comprised of a community council including 9 elected council members and the mayor. The community council accepts or rejects the mayor's proposals on the basis of simple majority rule, i.e. we assume that the mayor has the power to set the agenda vis-a-vis the council [8]. Moreover, the matrix of network multipliers was calculated for each simulated communication network based on empirically derived individual elite members' own-control parameters, γ. Individual elite members' own-control was calculated as follows. Within the elite survey all respondents were asked to evaluate the relative importance of their own political information when compared to information received from other elite members by distributing 100 points. Based on this individual assessment of own control (γ_i), we calculated the relative weight elite member i ascribes to information communicated to him by another elite member j as:

$$\hat{y}_{ik} = (1-\gamma_i)\frac{Y_{ik}\sum\limits_j Y_{jk}}{\sum\limits_{k\in E_i}\sum\limits_j Yjk}.$$

To see how the distribution of political influence varies across network types we calculated the Herfindahl index (HI) and also the maximal influence exerted by an individual elite member (MAX-INF) [9] and report the average values of these two influence concentration measures in Table 5.

As can be seen from Table 5, network characteristics vary significantly across both community elites, as well as estimated network generating processes. Further, we can observe some interesting interaction effects between the specific elite composition and the network generating process of communities. For example, while the network generating processes estimated for low performing communities imply a comparatively low centralization (16.1 and 19,5 compared to 25,3 and 24,0 for the high performing communities II and IV, see Table 5), elite composition implies a comparatively high centralization especially for the low performing community I (30.3 compared to an overall mean of 21, see Table 5). In contrast, for both the high performing communities II and IV elite composition and the network generating process jointly induce a comparatively high centralization, while for the low performing community III, elite composition and the network generating process jointly induce a comparatively low centralization. Accordingly, overall centralization is high for the high performing communities, II and IV, when compared to the low performing communities, I and III. But this empirical observation follows from an interaction effect between the elite composition and the network generating process. When comparing the isolated effects of the network generating process with the elite composition, the former effect implies a low centralization for community I , while the specific elite composition of community I clearly implies the highest centralization when compared to the elite compositions of the other communities.

Analogously, also for clustering the opposing effects of the elite composition and the network generating process can be observed. For example, the elite composition of high performing communities when compared to low performing communities implies, ceteris paribus, a relatively low clustering of communication ((48.0 and 60.7 for the high performing communities II and IV compared to 63.7 and 76.8 for the low performing communities I and III , see Table 5). In contrast, the corresponding network generating processes of high, compared to low performing communities, imply high clustering (see Table

[8]Banzhaf indices of regular council members resulted in 0.08, while for the mayor a Banzhaf index of 0.28 was calculated for all communities

[9]Generally the mayor has the maximal influence in all simulated, as well as empirically observed, elite networks followed by the group of council members with medium influence ranging from 4-7 %. The less influential elite members are normally non-governmental actors with an individual influence of less than 3 %.

5).

Even more interesting, these interaction effects can also be observed regarding the distribution of political influence among elite members. Here, generally the elite composition of low, when compared to high performing communities implies a lower concentration of political influence (this holds for both concentration measures reported in Table 5). Estimated network generating processes, however, counterbalance the elite composition effects. The estimated process of community III, in particular, seems to imply a high concentration of political influence when compared to the processes estimated for the other communities, i.e. average maximum influence for process III amounts to 21.5% compared to a maximum influence ranging from 17.3% to 17.9% for the other communities. Analogous results can be observed for the average Herfindahl index of political influence distribution reported in Table 5.

5.1 Assessing governmental performance

Of course, the final interesting question is how network structure relate to local government performance. Within our community elite studies in Slovakia we did not empirically observe local government performance. Given our theoretical framework it follows, however, that the relationship between the communication network structure and induced governmental performance crucially depends on the distribution of political interests and true political knowledge across elite members.

We did collect data on individual political interests, and we did not directly observe the political knowledge of individual elite members. Therefore, to access the relationship between elite network structure and governmental performance we focused on the implication of network structure on political bias. As we developed in the theoretical framework, the force, F, is a relevant indicator of the overall political bias in elite networks.

To investigate the impact of the communication network structure on local government performance we proceeded as follows. First, for each of the 1600 simulated networks from our mechanism design experiment, we calculated the force according to Equation 17 using the political bias calculated based on our elite survey data as described above.

Further, to relate the force to governmental performance, we simulated local government performance within an agent-based model of our simple theoretical framework assuming different elite network structures. In order to obtain empirically relevant simulation results, central parameters of the ABM model were calibrated based on collected elite survey data. In particular, we considered a community elite E is comprised of n=40 actors. 10 of the elite members were politicians, where legislative decisions are made by a community council comprised of 9 regular council members and one mayor. The mayor has agenda-setting power vis-a-vis the council. The 30 non-governmental elite members are representatives of different community organizations. To systematically simulate communication network structures among elite members we applied a modified α-algorithm of Watts (1999) (for a detailed description see Henning and Saggau (2010)). A central parameter of this algorithm is the alpha-parameter which determines clustering and the characteristic path length of generated networks. We simulated networks varying the value of alpha from 1 to 10. Moreover, for each alpha-parameter we varied the average local network size from 2-10. Finally, to simulate network centrality we selected 0, 2,3 and 5 stars, where in the case of the 2-star scenario the degree of each star is randomly selected between 20 and 30, whilst for the 5-star scenario, the degree of each star was randomly selected between 10 and 20. For each network parameter constellation we generated 20 networks. Thus, overall we generated 7200 communication networks corresponding to 360 different network constellations. For each of the 7200 communication networks, we simulated policy outcomes by applying our simple agent based model of community decision-making. To this end, we randomly drew political interest parameters for each individual community member by applying the following procedure. Given the simple structure of our model, political interest corresponds to a single parameter that indicates an agent's relative interest in the welfare of the agrarian population. For each individual elite member, this parameter was independently drawn from a normal distribution. To introduce bias in political interests, we assumed different distributions for governmental and non-governmental elite members. Further, to guarantee that means differ from the corresponding agrarian population share they were independently drawn from a uniform distribution over the interval [0.1,0.9], while the agrarian population share was constantly set to 0.5. Individual interest parameters were then drawn from a normal distribution with the randomly drawn means. The individual bias results from the difference between agent's actual political interest in the welfare of the agrarian population and the agrarian population share, i.e. $Bias_i = (X_i/0.5 - 1)$. Thus, the bias varies between -1 and 1, where -1 indicates a total bias towards non-agrarian and 1 a total bias towards agrarian interests. For all simulated networks, relevant network parameters were calculated. In particular, we calculated the force for each simulated network. As explained in the theoretical framework to simulate the impact of communication networks on the wisdom of the crowd effect, the important determinant is the error structure which drives belief formation, i.e. the individual distribution of the errors, ε_{is} and μ_{is}. Since we had no empirical information, we simulated the underlying error structures by assuming that all errors are independently and identically distributed. Based on assumed error structures, we were able to simulate individual belief formation within our ABM model and hence to calculate individual ideal points and final policy decisions, α_t for each of the simulated 50 time periods. Thus, within our ABM model, we were able to simulate governmental performance L. Of course, this is a rather strict assumption and hence we certainly do not consider our simulation results to be empirically founded. In particular, the simulated *wisdom of the crowd effects* are not empirically founded as these are conditional on assumed error structures. Hence, in the following, we focus our analysis on how elite network structure influences on local government performance on the force. Technically, we estimated a structure performance function as defined in Equation (20), where we regressed the calculated loss on relevant network and policy preference parameters using simulated data sets:

$$L_r = \phi_0 + \phi_1 F_r + \phi_2 F_r^2 + \epsilon_r, \qquad r = 1, \ldots, 7200.$$

Corresponding OLS estimation implies a high goodness of fit (R^2 =86,32%) and highly significant parameters estimated as $\hat{\phi_0} = 7.006$, $\hat{\phi_1} = -57.28$ and $\hat{\phi_2} = 279.05$.[10] Based on the estimated quadratic structure-performance functions we transformed the force to assess governmental performance for simulated 16 counter-factorial elite network types of our mechanism design experiment. Average force parameters (F) and corresponding average governmental performance values (L) are reported in table 6. Comparing the overall impact of elite composition versus the network generating process on the policy bias it can be seen from the corresponding total row and column effects in table 6 that the policy bias is mainly determined by elite composition in the communities. However, the network generating processes also have a significant impact on the force. For example, combining the network generating processes of the high performing communities II and IV with the elite composition of community III implies a significant reduction of the force from -23.05 to -16.20 and -15.91, respectively (see Table 6). Interestingly, the effects of the network generating process on the policy bias are inconsistent across communities, e.g. combining the elite composition of community II with the network generating process of community III results in the lowest policy bias with an average force value of only -1.1. Overall, combining the elite composition of a community with the corresponding network generating process that was estimated for the community implies that policy bias is c.p. higher for low performing communities compared to high performing communities with force values on the diagonal of Table 6 ranging from -25.44 to -9.59 for low and -7.41 to +15.58 for high performing communities. Accordingly, simulated government performance is also higher for high compared to low performing communities, where calculated average policy loss

[10]A similar result is obtained when using non parametric Kernel regression, see Figure (6).

ranges from 16.77 to 40.05 for low performing and from 5.02 to 12.99 for high performing communities (see Table 6). Interestingly, although the policy bias is significantly higher for community IV when compared to community II, government performance calculated on the basis of the estimated structure performance function is significantly higher for community IV. Technically, this surprising result follows from an interaction effect between the policy bias and the wisdom of the crowd effect implicitly inherent in the estimated structure performance function. But, we interpret our results with caution as they are based on assumed error structures which have not been empirically observed .

6 Conclusion

We provide a Non-Bayesian model of political beliefs formation via observational and communication learning in a community elite. At the micro level individual agents have an incentive to focus their political communication on agents who have high political knowledge and similar political interests. At the macro level the former induced a wisdom of the crowd effect, i.e. a more efficient aggregation of dispersed information via communication learning, while the latter induced a policy bias due to the asymmetric political influence of special interests that counterbalanced the wisdom of the crowd effect. Both effects are influenced by the structure of communication networks. In contrast to most existing literature which explains the impact of networks on collective decision-making within our theoretical framework no ideal typical network structure that generally guarantees a high governmental performance could be identified, but rather political decision-making becomes more efficient the more elite network structures reflect the specific distribution of political knowledge and political interests across elite members.

The paper then focuses on an empirical analysis of the elite network generating process based on policy network data collected in four rural communities in Slovakia. At the methodological level, we suggest an econometric approach to estimate dyadic network relations based on a probit framework. A Bayesian estimation approach was pursued, where estimation was based on an MCMC methodology, namely Gibbs sampling. This estimation technique is well suited to dealing with missing values in explanatory factors via incorporation of a sequential regression algorithm, as well as with measurement errors in the dependent variable. The proposed modeling thereby allows us to for determine the extent of measurement error present in the data, and account for the uncertainty associated with performing network analysis. Estimation results suggest that political communication among local elites in four Slovakian rural communities is mainly determined by political knowledge, where elite members with low political knowledge prefer to communicate with high knowledge members. Beyond, political knowledge, the structure of the meeting process also shapes political communication significantly, i.e. the number of common non-governmental organizational memberships is among the most important determinants of communication in local elite networks. Furthermore, especially in low performing communities, political party membership is identified as being a significant factor in determining political communication among elite members.

Moreover, undertaken counterfactual experiments indicate that network characteristics and induced political performance levels are more strongly determined by elite composition when compared to the network generation process. Simulation results, however, also underline the fact that the characteristic properties of elite networks are jointly determined by specific interaction effects between the elite composition and the network generating process. Therefore, even if it is assumed that the most favorable network structures for a specific community are known designing these can be a rather complex task. Hence, we consider the comprehensive theoretical and empirical analysis of policy network generating processes to be a fascinating topic for future research. Nevertheless, our simulation results also underline, that a comprehensive understanding of the role of policy networks as a determinant of government performance still requires an understanding of classical mechanisms of elite recruitment, e.g. political participation via voting and contributing to interest groups that have been studied by political scientist for decades.

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Table 1: Network and Variable Summary Statistics

	I	*II*	*III*	*IV*
Network statistics				
Force	0.155	-0.021	-0.257	0.075
Network Size	29	34	23	27
Centralization	25.9	35.4	27.5	19.6
Clustering	0.524	0.504	0.746	0.534
Local Size	6.7	6.1	7.8	4
Maximal influence	0.167	0.286	0.226	0.423
Herfindahl Index	8.7	12.2	10.7	22.5
variable statistics (mean/std)				
# joint organizations	0.475 / 0.7782	0.0736 / 0.2725	0.3571 / 0.5869	0.4229 / 0.6836
Political distance index	1.489 / 0.8271	1.5362 / 0.9128	1.7376 / 1.0546	1.5459 / 1.0912
Age (in years)	54.9 / 11.8082	45.53571 / 11.10383	55.5926 / 9.5041	50.72727 / 10.20822
Educational level	7.43 / 2.4859	4.142857 / 1.693436	4.1481 / 1.7030	8.318182 / 1.783158
Political party membership	0.286 / 0.4600	.1428571 / .3563483	0.2593 / 0.4466	.2727273 / .4558423
Personal reputation	0.274 / 0.1955	.4942085 / .2547981	0.4115 / 0.2228	.3557312 / .2195079
Social prestige index	56.1 / 16.4758	50.28571 / 13.52599	49.7407 / 11.8924	60.95455 / 12.72222
Political bias	-0.572 / 1.842	-0.029 / 0.8066	0.017 / 0.821	0.261 / 0.824
Own control	0.471 / 0.158	0.378 / 0.792	0.477 / 0.129	0.452 / 0.174
fraction of missing values in explaining factors				
	<1%	<2%	<1%	<1%

Table 2: Parameter estimates

	I		*II*		*III*		*IV*	
Parameter estimates	mean	sd	mean	sd	mean	sd	mean	sd
				β_a-parameter				
constant	-0.2366	0.3967	-0.7389	0.3745	-1.6476	0.8031	-1.3060	0.5063
# of joint organizations	0.2755	0.0849	1.3667	0.1737	0.2037	0.1094	1.6721	0.2450
political conflict index	-0.0437	0.0792	-0.0825	0.0441	-0.0814	0.0848	-0.0490	0.0430
political party membership	0.0006	0.0002	-0.0673	0.0967	0.3945	0.1592	-0.0866	0.1442
				β_2-parameter				
social prestige index	-0.0021	0.0040	-0.0063	0.0058	0.0156	0.0080	-0.0023	0.0068
educational level	-0.0313	0.0394	-0.0356	0.0445	-0.0688	0.0596	-0.0359	0.0525
age	-0.0102	0.0068	-0.0096	0.0053	0.0084	0.0100	0.0116	0.0083
personal reputation	8.9215	1.4946	13.6725	2.1662	11.7139	2.4232	16.7222	1.6172
				β_3-parameter				
social prestige index	-0.0001	0.0001	-0.0004	0.0001	0.0004	0.0001	-0.0003	0.0002
educational level	0.0038	0.0037	0.0083	0.0037	-0.0090	0.0049	-0.0020	0.0044
age	-0.0000	0.0001	0.0000	0.0001	0.0002	0.0002	0.0003	0.0001
personal reputation	11.1489	9.9737	13.5532	9.3192	12.9835	9.9790	16.5492	9.9463
π	0.0747	0.0303	0.0537	0.0226	0.1213	0.0505	0.1173	0.0426
model fitness								
measurement error	0	1	0	1	0	1	0	1
0	235	30	357	23	92	14	252	7
1	72	69	103	82	72	76	44	48
benchmark - 0	0	1	0	1	0	1	0	1
0	388	17	536	23	195	10	345	4
1	0	1	0	2	28	20	0	2
benchmark - 1	0	1	0	1	0	1	0	1
0	231	31	352	24	90	15	242	7
1	75	69	103	82	72	76	54	48
AUC - measurement error	0.8047		0.8729		0.7870		0.9349	
AUC - benchmark - 0	0.8429		0.9231		0.9058		0.9932	
AUC - benchmark - 1	0.8015		0.8685		0.7830		0.9222	

Notes: Estimation is based on 10000 MCMC draws, where initial 2000 were discarded for burn-in.

Table 3: Marginal effects

	I		*II*		*III*		*IV*	
Marginal effects	mean	sd	mean	sd	mean	sd	mean	sd
- county specific elites	β_1-parameter							
# of joint organizations	0.1096	0.0338	0.5393	0.0693	0.0770	0.0414	0.6652	0.0975
political conflict index	-0.0174	0.0315	-0.0326	0.0174	-0.0308	0.0321	-0.0195	0.0171
political party membership	0.0002	0.0001	-0.0265	0.0381	0.1493	0.0602	-0.0345	0.0574
	β_2-parameter							
social prestige index	-0.0008	0.0016	-0.0025	0.0023	0.0059	0.0030	-0.0009	0.0027
educational level	-0.0125	0.0157	-0.0140	0.0176	-0.0261	0.0226	-0.0143	0.0209
age	-0.0041	0.0027	-0.0038	0.0021	0.0032	0.0038	0.0046	0.0033
personal reputation	3.5509	0.5953	5.3962	0.8649	4.4332	0.9174	6.6524	0.6424
	β_3-parameter							
social prestige index	-0.0000	0.0000	-0.0002	0.0000	0.0001	0.0000	-0.0001	0.0001
educational level	0.0015	0.0015	0.0033	0.0015	-0.0034	0.0018	-0.0008	0.0018
age	-0.0000	0.0000	0.0000	0.0000	0.0001	0.0001	0.0001	0.0000
personal reputation	4.4381	3.9711	5.3480	3.6771	4.9186	3.7861	6.5830	3.9565

Notes: Estimation is based on 10000 MCMC draws, where initial 2000 were discarded for burn-in.

Table 4: Convergence diagnostic

CD - test statistic	I	II	III	IV
constant	1.0463	0.8085	-1.0602	0.4173
β_1	-0.3436	0.0025	1.3953	0.7004
	1.2354	-0.7076	0.9341	-0.4689
	0.6036	-0.3547	-1.7602	-1.3226
β_2	-0.9784	0.3333	0.6504	0.8673
	0.8332	-0.7693	1.4971	-0.4962
	0.3378	-0.6974	0.2446	0.6306
	-0.9627	-0.6995	-0.1966	0.4843
β_3	0.7017	0.9592	0.7304	-1.0191
	0.0558	-0.1547	1.8306	0.3127
	-2.9157	-0.9473	-0.8118	-0.6437
	0.4905	-0.4577	-0.0369	0.5609
λ	-0.6005	-0.0184	0.1278	1.7758

Notes: Test statistic as suggested by Geweke (1992), see Equation (27).

Table 5: Network characteristics of simulated elite network types

		Process				
	Elite	I	II	III	IV	Total
Centralization	I	21,3	36,8	27,6	35,1	30,2
(CENTRAL)	II	16,9	31,1	13,4	30,4	23,0
	III	8,2	6,1	13,6	4,5	8,6
	IV	17,9	27,5	23,5	26,3	23,8
	Total	16,1	25,3	19,5	24,0	21,2
Clustering	I	58,2%	68,7%	58,2%	69,6%	63,7%
(CC)	II	53,4%	56,8%	28,0%	53,6%	48,0%
	III	66,8%	84,4%	67,9%	88,2%	76,8%
	IV	61,4%	64,0%	55,6%	61,7%	60,7%
	Total	60,0%	68,5%	52,4%	68,3%	62,3%
Local Size	I	6,71	6,19	6,18	6,93	6,50
(AD)	II	8,10	7,22	3,33	6,25	6,22
	III	7,00	9,06	6,60	9,53	8,05
	IV	6,82	5,87	4,00	5,57	5,57
	Total	7,16	7,08	5,02	7,07	6,58
Maximal influence	I	14,1%	13,9%	13,5%	13,0%	13,6%
(MAX-INF)	II	14,4%	16,4%	20,2%	18,1%	17,3%
	III	18,2%	15,1%	17,9%	14,4%	16,4%
	IV	22,5%	24,9%	34,3%	26,0%	26,9%
	Total	17,3%	17,6%	21,5%	17,9%	18,5%
Herfindahl Index	I	6,31	6,89	6,34	6,38	6,48
(HI)	II	5,12	6,31	7,52	6,95	6,47
	III	6,96	5,92	7,70	5,77	6,59
	IV	8,69	10,41	15,55	11,00	11,41
	Total	6,77	7,38	9,28	7,52	7,74

Notes: Simulation is based on 100 random draws from estimated a posteriori parameters distributions.

Table 6: Policy Bias and Governmental Performance in simulated elite networks (Standard deviation in parantesses)

		Process				
	Elite	I	II	III	IV	Total
Force	I	-9,59	-19,99	-14,01	-21,51	-16,27
		(7,85)	(9,66)	(10,44)	(7,73)	(10,15)
	II	-6,22	-7,41	-1,10	-4,77	-4,87
		(2,72)	(2,69)	(4,85)	(2,81)	(4,13)
	III	-23,05	-16,29	-25,44	-15,91	-20,17
		(3,51)	(2,03)	(3,74)	(1,81)	(5,07)
	IV	16,67	15,52	15,61	15,58	15,85
		(2,68)	(2,33)	(4,42)	(2,35)	(3,09)
	Total	-5,55	-7,04	-6,23	-6,65	-6,37
		(15,05)	(14,78)	(16,58)	(14,85)	(15,33)
Government	I	16,77	32,21	23,53	33,91	26,61
Performance		(9,37)	(14,47)	(14,70)	(13,54)	(14,86)
	II	11,86	12,99	8,32	10,59	10,94
		(2,58)	(2,65)	(3,20)	(2,3)	(3,2)
	III	35,40	23,87	40,05	23,28	30,65
		(6,55)	(3,08)	(7,48)	(2,73)	(9,04)
	IV	5,43	5,00	5,42	5,02	5,22
		(1,01)	(0,76)	(1,68)	(0,79)	(1,14)
	Total	17,37	18,52	19,33	18,20	18,35
		(12,62)	(12,80)	(16,18)	(13,24)	(13,79)

Notes: Simulation is based on 100 random draws from estimated aposteriori parameters distributions.

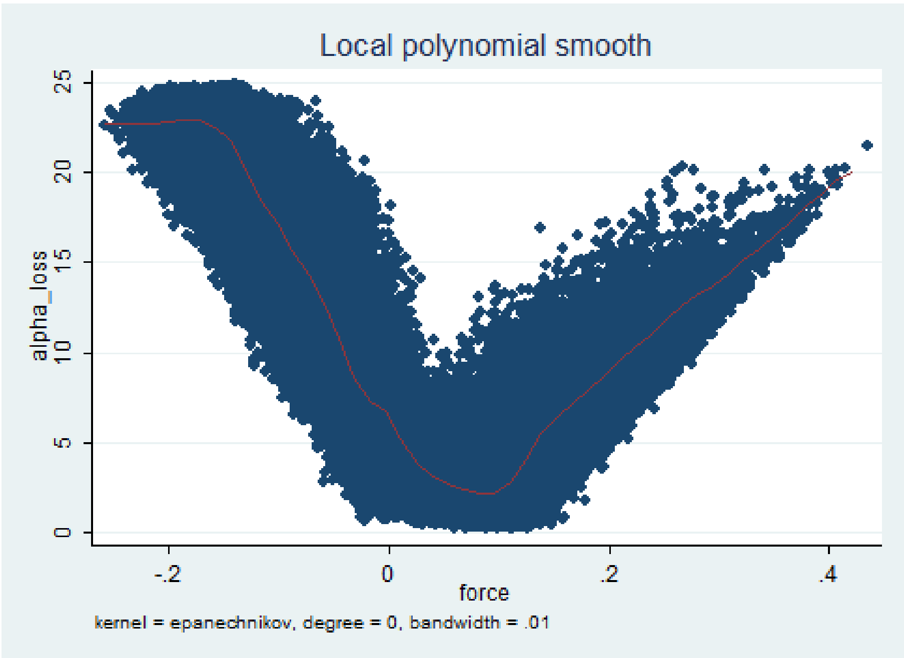

Figure 1: Force and government performance