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Elite Networks, Political Belief Formation and Government Performance:

An agent-based approach to a general political
economy equilibrium

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This paper investigates the impact of the embeddedness of politicians in a local elite network on government performance in decentralized and centralized political systems. Formal political decision-making among a set of legislators is modeled via a *mean voter decision rule* derived from a *modified non-cooperative legislative bargaining game of a Baron-Ferejohn type*. Legislators' policy preferences are derived endogenously from political support maximization based on legislators' beliefs how a rural development policy translates into the welfare of the agrarian and non-agrarian population. Legislators are generally uncertain regarding the political technology, i.e. the welfare changes induced by a policy. Accordingly, legislators communicate with the local elite to learn more about the true political technology and hence to undertake better informed political decisions. However, local elites might be biased in favor of a specific population group, i.e. communication might also bias political beliefs. A trade-off between more efficient policy learning and an increased policy bias induced by an increased embeddedness in local elite networks is identified. Policy bias is attenuated in centralized when compared to decentralized systems, while vice versa the speed of policy learning through local elite networks is c.p. higher in decentralized when compared to centralized systems. Moreover, within a constitutional system elite network structures such as local size, clustering or centralization have an impact on overall efficiency of political decision-making.

1 Introduction

Although economic theory of politics or new political economy has underlined the interconnection between politics and the economy for a long time (Weber, 1921; Commons, 1931; Schneider et al., 1981; Miller, 1997), classical applied political economy models assigned politics only a minor role and focused mainly on modeling the economic sector.

In contrast more recent approaches focus on modeling the political decision-making process as an interaction between a set of individually rational political actors. Within these new political economy approaches, biased policies result as specific incentive problems, where political institutions are considered as key factors influencing individual incentives of political actors. Thus, in light of these new approaches, beyond economic factors determining deadweight costs and demographic factors determining cost of interest organization, formal political institutions are the main factors in explaining observed variances of economic policies across countries (Persson and Tabellini, 2002).

For example, Persson and Tabellini or Milesi-Ferretti et al. nicely demonstrate how the electorate system and the organization of legislature determine general macroeconomic policies (Persson and Tabellini, 2002; Milesi-Ferretti et al., 2002). Although these new approaches nicely explain the role of political institutions in determining policy choice, they focus on modeling formal political institutions, while informal network relations among governmental and non-governmental organizations have not been taken into account, yet.

In contrast, the early 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 nicely to the political influence of individual actors, these studies do neither provide a rational model of political influence nor do they relate policy network structures to political performance at the macro level. In this context this paper suggests a theoretical model that provides a rationality for the social influence of non-governmental actors on the political position of governmental agents and allows the relation of policy network structures with the efficiency of political decision-making at the macro level. In particular, 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 on 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 although they are uncertain regarding the evaluation of different alternatives. But in a world of uncertainty it turns out that maximization of individual utility can only be achieved by some supplement strategies. For example, to be able 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. Accordingly, we analyze in an agent-based model framework how political communication network structures among a local elite influences information aggregation via communication and hence overall efficiency of local government.

This research relates to the burgeoning literature focusing on the influence of social network structures on economic and political behaviors including the formation of opinions, decisions of which products to buy, investment in education, just to name a few (see also Currarini et al. (2009)).

Moreover, the idea of social influence models to explain agent's opinion formation has been taken up by economists, e.g. models of herding behavior (Krause, 2004), where Battiston et al. (2004) explicitly analyzed the role of social networks in agents' opinion formation and decision. Moreover, Bala and Goyal (1998) analyze belief formation in a social network. However, they do not analyze how specific network structures influence agents' belief formation. Later Gale and Kariv (2003) as well as Choi et al. (2004) or Celen et al. (2004) explore the interaction between network structures and beliefs, but they focus their analysis on small networks (3 nodes) and have not considered large and more complex networks. More recently Currarini et al. (2009) analyzes in a very interesting theoretical paper the impact of communication network structures among a set of actors on their opinion formation. However, although Currarini et al. (2009) nicely analyzed how communication network structures influence the overall efficiency of collective decision-making in the limit of infinitely large societies, they have not yet analyzed how network structures affect efficiency of political decision-making in real small societies. Moreover, Currarini et al. (2009) analyze the impact of network structures on learning and efficiency of decision-making applying a rather abstract model, while they do not provide a realistic model of how and why elite networks influence political decision-making.

In this regard this paper aims to contribute to closing this gap. In detail, it is demonstrated 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. Given a policy bias of local elite the overall impact of communication on the efficiency of local government decision-making depends on the network structures, i.e. random networks are c.p. more efficient when compared to clustered or centralized communication network. Therefore, communication networks correspond to information aggregation mechanisms and hence can be interpreted as social capital in the sense of Coleman or Burt, where concrete individual and collective values of a communication network depend on its specific structure and the interplay between informal network structures and formal political institutions. For example, our simple simulation analyses imply a trade-off between more efficient policy learning and an increased policy bias induced by an increased embeddedness in local elite networks. Interestingly, this policy bias is attenuated in centralized when compared to decentralized systems, while vice-versa the speed of policy learning through local elite networks is c.p. higher in decentralized when compared to centralized systems. Moreover, within a constitutional system elite network structures such as centralization have a significant impact on overall efficiency of political decision-making, while for local size and clustering only a minor impact results.

Finally, the paper is related to the literature on information and political decision-making, e.g. the very interesting work of Ball (1995), Krehbiel (1991) and Lohmann (1994) as well as the classical jury theorem formulated by Condorcet.

The rest of the paper is structured as follows. In section 2 a description of the theoretical model is provided. In section 3 the simulation set-up is described, while key results of the simulation analyzes are discussed in section 4.2. Section ?? includes a critical discussion of the potential contribution of the suggested approach and a brief outlook on future research.

2 The theoretical model

2.1 Background and motivation

The basic structure of the political economy equilibrium model corresponds to an economic and a political decision-making model. Political agents are interested in maximizing their level of political support. In doing so, the political support, S , depends on the

state of the economic system, z : $S = S(z)$. In turn, the state of the economic system depends on the policy, (α) : $T(z, \alpha) = 0$. Policy preferences of the political representatives $U(\alpha)$ are the result of the maximization of political support $S(z)$ restricted by the political technology $T(z, \alpha)$ (Rausser and Freebairn, 1974; Zusman, 1976).

Accordingly, political economy equilibrium models simultaneously include an economic equilibrium model $T(z, \alpha)$, relating exogenous policy instruments (α) with relevant state variables of the economic system, z , as well as a legislative decision-making model deriving policy choice, α , endogenously from legislator's policy preferences, $u(\alpha)$ and given formal constitutional rules, e.g. $\alpha^* = \Gamma[u(\alpha)]$.

While $T(z, \alpha)$ corresponds to the true political technology $\Gamma[u(\alpha)]$ corresponds to a formal legislative decision-making model. Although political economy equilibrium has been fully characterized at theoretical level, applied political economy models existing in the literature have not yet even come close to being able to model both levels simultaneously.

In contrast, classical economic analysis of policy intervention focuses on modeling the impact of exogenous policy on the state of the economy using a specific functional form of $T(z, \alpha)$ (Tinbergen, 1956), while in political science formal models of legislative decision-making focus on the analysis of policy choice under various constitutional rules based on a specific form of $\Gamma[u(\alpha)]$.

An integration of these two approaches to a general political economy equilibrium model results when legislators' policy preferences, $u(\alpha)$, entering into the legislative decision-making model are endogenously derived from political support maximization:

$$u(\alpha) = \text{Max} \{S(z) | T(z, \alpha) \equiv 0\}$$

Empirically the political technology is often modelled applying an economic partial or general equilibrium model. However, for almost all policies neither economists nor politicians know the true political technology and there hardly exists consensus regarding the true political technology. Accordingly, politicians form prior beliefs regarding the political technology. Given prior beliefs observed policy outcomes are informative regarding the true political technology, thus comparing observed and expected policy outcome politicians can learn about the true political technology and up-date their beliefs accordingly. However, individually observed policy outcomes are often noisy, which restricts an effective observational learning of individual agents.

Taking the complexity of belief up-dating via communication in networks into account, a fully rational learning becomes infeasible (Golub and Jackson, 2009). However, as

Golub and Jackson (2009) pointed out it is nonethelss possible that agents using fairly simple updating rules will arrive at outcomes like those achived through fully rational learning.

Accordingly, we propose an agent-based model of the belief formation in communication networks, which in contrast to standard economic approaches and in line with sociological approaches only assumes bounded rationality of agents applying partly rules of thumb to cope with the complexity of their decision problem. In particular, our model corresponds to rational agents as it derives agents' decision from expected utility maximization. However, to cope with fundamental uncertainty agents form beliefs applying more simple heuristics or rules of thumb to cope with complexity.

Further, as will be shown in detail below belief up-dating via communication in elite networks involves a trade-off between a higher efficiency of political learning and a policy bias resulting from biased policy preferences of non-governmental elite members. Thus, when compared to political decison-making without political communication the overall impact on political performance, i.e. efficiency of political decision-making, depends on both elite network structures, policy bias of governmental and non-governmental elite members and formal constitutional rules.

Our complete political economy model includes three stages: 1) agents' belief formation via political communication in networks, 2) derivation of agents' policy preferences based on political beliefs, and 3) final political decision-making as the result of legislative bargaining determined by agents' policy preferences and given constitutional rules.

2.2 The model

2.2.1 Legislative bargaining

Following Baron and Ferejohn (1989), we consider a legislature comprising of a set N of n legislators, where $l = 1, \dots, n$ denotes the index of legislator l , and a constitutionally fixed majority voting rule φ . Legislature has to choose collectively a policy α out of a compact and convex subset R^m of the m -dimensional cube $(0, 1)^m$. Each legislator $l \in N$ has a complete, transitive binary preference relation defined for all $\alpha, \alpha' \in R^m$, that is represented by a concave utility function $U_l(\alpha)$. Formally, the rule φ corresponds to a binary choice procedure, which determines legislature choice among two alternatives α and α' , and a random recognition rule that determines which legislator can make a proposal.

In general, the random recognition rule can be represented by a vector of individual probabilities $q = q_1, \dots, q_{n_L}$, where q_l denotes the probability that legislator l is chosen to make a proposal. For simplicity we assume in the following that $q_l = 1/n$ for all $l \in N$.

The choice procedure can be represented by a set of winning coalitions, G . A winning coalition $g \in G$ is defined as an element of the superset 2^N , for which the following holds: if all members of g vote for an alternative α in comparison to an alternative α' , then legislature chooses the alternative α .

If s denotes the status-quo policy, a necessary condition for a change of the status-quo policy is the existence of a winning coalition g whose members uniquely prefer an alternative to the status quo SQ . Let $W(SQ) \subseteq R^m$ denote the subset of alternatives α , for which a winning coalition exists that prefers α to SQ . A general characteristic of legislative decision-making is that $W(s)$ is generally a large subset of R^m and there exists a large number of different winning coalitions preferring different alternatives to the status quo. Moreover, constitutional rules neither determine which winning coalition has to form nor which element of $W(SQ)$ has to be proposed.

In this context Baron and Ferejohn (1989) model legislature's choice of a policy $\alpha \in R^m$ as an infinite horizon non-cooperative bargaining game among legislators determined by the following rules. At a first stage an individual legislator, $l \in N_L$, is selected according to the randomized recognition rule to propose a policy, and at a second stage all legislators vote on the made proposal. If the proposed policy received sufficient votes, i.e., a winning coalition forms for the proposal, this proposal is the new policy. Otherwise a new legislator is selected and the procedure starts from the beginning. Assuming individual preferences are common knowledge, Baron and Ferejohn (1989); Banks and Duggan (1998) have shown that the non-cooperative bargaining game has a stationary subgame perfect Nash equilibrium even for multidimensional policies and multiple legislators, i.e., $m, n > 1$.

Given the limited mental capacities of human beings, it is quite obvious that legislators could not perfectly know spatial preferences of all other legislators in a multi-dimensional policy space. In contrast, to deal with imperfect information, legislators simplify real world phenomena, i.e., apply low-dimensional ideological spaces to approximate legislators true preferences. Based on the ideological approximation of the true policy space, legislators are able to anticipate other legislators' response to policy proposals. Of course, since information is imperfect, this anticipation is also imperfect; i.e., legislators can only estimate the probability that other legislators will agree with their proposal.

To include imperfect knowledge of other legislators' preferences, we suggest a modified legislative bargaining game via relaxing the assumption of noise free perfect rational behavior of legislators (Henning, 2005; Henning et al., 2008).

In particular, we assume that voting on a policy proposal at the second stage of the game is probabilistic rather than deterministic; i.e., legislators do not always "best respond" according to their expected utilities since there is some noise in their choices. This noise can be due to errors in terms of perception biases, distractions, or miscalculations that lead to non-optimal decisions, or it can be due to unobserved utility shocks that make rational behavior look noisy to an outside observer. Regardless of the source of the noise, choice becomes stochastic, and the distribution of the random variables determine the form of the choice probabilities. Following the interesting work of McKelvey and Palfrey (1998, 1995), a quantal response equilibrium can be defined as a vector of individual response probabilities that is a stochastic best response to itself (Goeree and Holt, 2005).

To simplify derivation of our model, we assume for the moment that legislators' proposals are exogenously determined; that is, whenever a legislator k is selected according to the random recognition rule, he will suggest his proposal x_k .

To formalize the probabilistic behavior, we follow Goeree and Holt (2005). Thus, assuming probabilistic voting, the total utility of legislator l received from a vote in favor or not in favor of the proposal x_k , is received by adding a stochastic utility term $\xi\omega_i$ to the spatial utility, where $\xi > 0$ is an error parameter and ω_i represent identically and independently distributed realizations of a random variable for the decision to vote for the party platform, $i = 1$, or against it, $i = 2$. Total utility to vote for the proposal is greater than total utility from voting against it if it holds:

$$U(x_k) + \xi\omega_1 > \delta W_l + \xi\omega_2.$$

ξ is a parameter determining the level of agents' rationality; the larger ξ the more agents' voting behavior becomes stochastic and independent of agents' policy preferences. Assuming a double exponential distribution for ω results in the following choice probability (Goeree and Holt, 2005):

$$\pi_{lk} = \frac{e^{\xi U(x_k)}}{e^{\xi U(x_k)} + e^{\xi \delta W_l}} \quad (1)$$

Of course, legislators always vote for their own proposal, i.e.:

$$\pi_{kk} = 1 \quad \forall k$$

Further, let W_l denote the continuation value of a legislator l playing the modified infinite horizon non-cooperative legislative bargaining game, and let Π_{gk} denote the probability that the winning coalition g is formed to support the proposal x^k while Π_k denotes the probability that the proposal x^k is accepted, then it follows:

$$\begin{aligned}\Pi_{gk} &= \prod_{l \in g} \pi_{lk} \prod_{l' \notin g} (1 - \pi_{l'k}) \\ \Pi_k &= \sum_{g \in G} \Pi_{gk}\end{aligned}\tag{2}$$

Given the definition above and let δ denote the common discount factor of legislators, the continuation value of the infinite legislative bargaining game is defined as follows:

$$\begin{aligned}W_l &= \sum_p q_p \Pi_p U_l(x^p) + \delta W_l \sum_p q_p (1 - \Pi_p) \\ \Leftrightarrow \\ W_l &= \frac{\sum_{k'} q_{k'} \Pi_{k'}}{1 - \delta + \delta \sum_{k'} q_{k'} \Pi_{k'}} \sum_k \frac{q_k \Pi_k}{\sum_{k'} q_{k'} \Pi_{k'}} U_l(x_k)\end{aligned}\tag{3}$$

Finally, if we denote the vector of probabilities that legislators vote for a party proposal k by $\pi_k = \{\pi_{1k}, \dots, \pi_{nk}\}$ and define the vector $\pi = \{\pi_1, \dots, \pi_k, \dots, \pi_n\}$, then, given the exposition above, it follows that π is defined as a function of itself: $\pi = h(\pi)$.

Accordingly, we define π^* as a fix point of h . Then π^* can be considered as a (stationary) quantal response equilibrium (QRE) of the game as it is the best stochastic response to itself in every bargaining period.

So far we have assumed that legislators' proposals are exogenously given. However, in real legislative bargaining, this is obviously not the case. A contrario when formulating a proposal, legislators try to formulate a policy that guarantees the support of a winning coalition while maximizing legislators' own policy preferences.

Accordingly, define $\pi^*(x)$ as the QRE implied by the proposal vector x , then the formulation of a policy proposal corresponds to the following expected utility maximization:

$$x_k^* = \underset{x_k}{Max} C(x_k, x_{-k}) U_k(x_k)$$

,where x_{-k} denotes the vector of legislators' proposals without the proposal of legislator k .

Thus, assuming a simple Nash equilibrium for legislators' endogenous proposal formulation, an overall equilibrium for the modified non-cooperative legislative bargaining game can be stated as in *Proposition 1*:

Proposition 1: A vector of policy proposals, x^ , and a vector of legislators' choice probabilities, π^* , correspond to an equilibrium of the modified infinite legislative session game with endogenous proposal formulation if the following condition hold: (a) π^* is a QRE for the given proposal vector x^* , i.e it holds: $\pi^* = h(\pi^*, x^*)$, and b) it holds for all x_k^* :*

$$x_k^* = \underset{x_k}{\text{Max}} C(x_k, x_{-k}^*) U_k(x_k)$$

Moreover, in equilibrium the expected policy outcome corresponds to a weighted mean of legislator's ideal points, $E(z) = \sum_k C_k^ x_k^*$, where the weight of a legislator k corresponds to the ex ante probability that its platform will be the final policy outcome. In particular, it holds:*

$$C_k^* = \frac{q_k \Pi_k(\pi^*, x^*)}{\sum_p q_p \Pi_p(\pi^*, x^*)} \quad (4)$$

The proof of proposition 1 follows directly from Goeree and Holt (2005) and, therefore, is omitted here.

2.2.1.1 Cooperative legislative bargaining

Note that given the noise of legislators' choices at the voting stages as well as due to the random recognition rule, policy outcome is uncertain ex ante. Therefore, as long as it is assumed that legislators are risk averse, policy outcome is inefficient; i.e., certain policy outcomes, which are commonly preferred by all legislators, always exist. Thus, legislators have incentives to agree on informal decision making procedures if these informal procedures lead *ex ante* to more efficient outcome. Weingast (1979) was one of the first scholars who emphasized the role of self-enforcing informal procedures in legislative decision-making. Based on Weingast, Henning (2000) suggests a mean voter decision rule as a self-enforcing informal procedure of legislative decision-making derived in the shadow of the uncertain outcome of non-cooperative legislative bargaining. According to the mean voter decision rule, legislature directly formulate a common proposal, which corresponds to the weighted mean of legislator's policy proposals, where the weights of individual proposals equal legislators' ex ante probabilities that their proposals will

be the final outcome of the formal non-cooperative decision making procedure. Thus, formally the mean voter decision rule is defined as:

$$\alpha^m = \sum_k C_k x^k \quad (5)$$

Given the concavity of legislators' utility functions, it follows directly that the mean voter decision rule implies for every legislator a higher *ex ante* expected utility when compared to the non-cooperative outcome of the modified Baron-Ferejohn legislative bargaining game.¹ Hence, the mean voter decision rule is self-enforcing.²

Note, that although applying the mean voter decision rule leads to policy outcomes that are *ex ante* Pareto dominant vis-a-vis the non-cooperative legislative bargaining, a winning coalition of legislators might have an incentive to deviate from this procedure. That is applying the mean voter decision rule is a "legislative norm" that only becomes self-enforcing if legislators do not discount future gains from cooperation too much. Finally, please note that another advantage of our cooperative legislative bargaining model when compared to the Baron-Ferejohn model is that it can be directly applied empirically to real political systems including multiple heterogeneous actors and multi-dimensional policy decisions.

Finally, assuming perfect uncertainty regarding the preferences of other legislators implies that for any proposal x_k the expected probability that other legislators will vote in favor of this proposal equals 0.5. Under this assumption the mean voter decision rule simplifies as follows (Henning (2008)):

$$\alpha^m = \sum_g C_g Y^g \quad (6)$$

with:

$$C_g = \frac{n_g}{\sum_k n_k} \quad (7)$$

,where n_g is the number of winning coalitions of which agent g is a member and Y^g denotes the preferred policy position of agent g .

¹Note that even in the original BF-model assuming perfect knowledge of legislators' preferences policy outcome is *ex ante* inefficient from legislators' point of view due to legislators' uncertainty to be a member of the winning coalition.

²In a more general version, it can also be considered that the process of legislative decision making includes always finite sessions *ex post*; i.e., it is possible that no proposal will be accepted and thus, the status quo remains as the final policy outcome (Henning, 2004).

Furthermore, it holds for Y^g :

$$Y^g = \operatorname{argmax} U_g(\alpha) \quad (8)$$

2.3 Political belief formation

As explained above individual politicians do not know the true political technology and hence have to form beliefs to make a rational policy decisions.

To illustrate how naive policy learning in political communication networks works let E denote the set of elite members, where the set N of political agents is a subset of the E . Beyond political agents a subset of non-governmental actors, e.g. representatives of stakeholders which by constitution are not involved in legislative decision-making. We denote $i, j \in E$ a generic element of the political elite.

Further, we assume for simplicity in the following that the true political technology is linear, i.e. the matrix A denotes the true political technology, i.e. $z = A\alpha$.

Let $\tilde{A}_i$ denote a simple linear political technology believed by a elite member, then her policy preferences $u(\alpha)$ result from the following support maximization:

$$u_i(\alpha) = \operatorname{Max} \left\{ S_i(z) \mid z = \tilde{A}_i \alpha \right\}$$

Assume further actors observe policy outcomes implied by a policy α , $z(\alpha)$. Obviously, these observations are informative regarding the true political technology. However, individual observations are noisy, e.g.:

$$z_i^b = A\alpha + \varepsilon_i$$

,where ε_i denotes an ideosyncratic error term, with $E(\varepsilon_i) = 0$.

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 Nerlove belief formation of individual actors, it follows:

$$\tilde{A}_{t+1} = \tilde{A}_t + \beta \left[\frac{dz}{d\alpha_t} \right] \quad (9)$$

with:

$$dz = z^b - z^e = \left[\frac{dz}{d\alpha_t} \right] \alpha$$

The parameter $0 \leq \beta \leq 1$ denotes the adaptive-expectation coefficient. The matrix $\left[\frac{dz}{d\alpha_t}\right]$ needs to be further specified. For a concrete example please see below.

Given the fact that individual observations are noisy, agents are only imperfectly informed about the true political technology A .

In contrast, even if individual signals are noisy, in the aggregate the total set of agents is generally well-informed, since it observes a number of independent draws of the signal $z^b = A\alpha + \varepsilon_i$.

To see this note that Nerlove belief up-date results for each actor an error, δ regarding his estimation of the true political technology:

$$\tilde{a}_i = a + \delta_i \quad (10)$$

Please note that 'a' and ' $\tilde{a}$ ' are vector representations of the matrices A and $\tilde{A}$, where all row vectors are simply connected to a long row vector. Accordingly, δ_g is a vector of errors for each component of A . Obviously, δ is a stochastic variable, where each individual error δ_i is a realization of this stochastic variable. To facilitate our expositions on naive learning we assume in the following that the expectation value of δ is zero.

Under this assumption a naive updating rule taking simply the average of all individual beliefs, $a = \sum_i a_i$ results in the limit in the true political technology and for a finite number of actors it results c.p. in a lower error when compared to an individual belief update.

However, no single agent observes all signals. 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 privately received signals of all agents and communicates aggregated signals back to all individual agents. But, in reality agents' ability to communicate their experience may very well be limited.

In particular, actors might not communicate the true signals they have observed, but rather their opinion regarding the optimal policy. Let Y_i denote policy preferred by an actor i , then it holds:

$$Y_i = \underset{\alpha}{argmax} S_i(z) \quad s.t. \quad z = \tilde{A}_i \alpha \quad (11)$$

However, as long as the communicated opinion is based on agents' private experience, it might still be informative to other agents.

To see this we further assume for the moment that all agents have the same initial beliefs and the same adaptive-expectation coefficient. Thus, under this assumption it fol-

lows quite plainly that agents' preferred policy positions (y_i) are symmetrically distributed around the optimal policy α^* ³

Obviously, as long as the set of agents is sufficiently large applying 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 decentral information and hence to a more efficient learning when compared to individual updating without communication.

However, communication is normally more structured and restricted, e.g. agents communicate directly only with a small subset of the total population. In this context ? have proven in a very interesting paper how specific communication structures relate to overall efficiency of belief up-dating in a limit society applying the DeGroot model. In contrast to ? we analyze how communication network structures within a finite political elite influence efficiency of political decision-making given different central and decentral legislative constitutions. Moreover, also we apply a similar naive learning process our model differs from the DeGroot model.

To consider communication structures we define a binary network T^1 , where $T_{ij}^1 = 1$ indicates that agent i and agent j have an established communication tie. Accordingly, we define the subset $E_i = \{i \in E, T_{ij}^1 = 1\}$ as the neighborhood of agent i , where it holds:

$$\sum_{j \in E_i} t_{ij} = 1 \quad t_{ij} = \frac{T_{ij}^1}{\sum_{j' \in E_i} T_{ij'}^1}$$

Accordingly, $T = [t_{ij}]$ denotes the communication network, where $t_{ij} > 0$ indicates that actor i pays attention to actor j . T is a stochastic matrix, i.e. for each actor the sum of total weights equals 1.

Within one period a political communication process occurs, where elite members repeatedly update their political opinion via taking weighted averages of their neighbors' beliefs with t_{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 ?). Let $r = 1, \dots, R$ denote the communication round than it follows:

$$Y_i^{r+1} = t_{ii}Y_i^0 + \sum_{j \neq i} t_{ij}Y_j^r \quad (12)$$

³From eq.11 follows that y_i is a function of the true political technology, a , and the error δ . Thus, applying a first order Taylor approximation at the point $\delta = 0$ results that the expectation value of y_i equals α^* .

Moreover, the initial belief Y_j^0 just follows from actor's belief regarding the political technology:

$$Y_j^o = \underset{\alpha}{argmax} S_j(z) \quad s.t. \quad z = \tilde{A}_j \alpha \quad (13)$$

Rewriting equation 13 results:

$$\begin{aligned} Y_i^{r+1} &= t_{ii} Y_i^0 + (1 - t_{ii}) \cdot \sum_j \hat{t}_{ij} Y_j^r \\ \text{with : } \hat{t}_{ij} &= \frac{t_{ij}}{(1 - t_{ii})} \end{aligned} \quad (14)$$

where Y_i^r is the opinion of agent i resulting after r communication rounds, and Y_i^0 denotes agent i 's initial opinion before communication.

Actors form their intital opinion via Nerlove up-dating after they have received the private signals. The parameter t_{ii} represents the weight for their own opinion. As T is row normalized to one, $(1 - t_{ii})$ is the aggregated weight for all neighbors, i.e. the influence or communication field of other agents.

Writing eq. (14) in matrix notation results after further rearrangements:

$$y = [I - (1 - t_{diag}) \hat{T}]^{-1} \cdot t_{diag} \cdot y^0 \quad (15)$$

with $M = [I - (1 - w_{diag}) \hat{C}]^{-1} t_{diag}$ being the network multiplier which is similar to the Hubbell index (Hubbell, 1965).

Please note that the belief up-dating in eq. 15 is similiar, but still differs from the DeGroot model analyzed by ?. In particular, note that for any row stochastic matrix $\hat{T}$ belief formation converge to a well-defined limit y corresponding to the belief vector of actors 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 (y^0), where the weight of agent j 's initial opinion (Y_j^o) for agent i 's opinion after communication (Y_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 all indirect effects of j 's initial opinion on the opinion of agent i resulting from communication.

Assuming for the moment an equal field strength for all agents, i.e. $M_{ij} = \frac{1}{n}$ for all $i, j \in E$, implies that the opinion of all agents after communication just equals the average initial opinion held before communication.

Assuming further that elite members are homogenous regarding their political support functions, the naive belief-updating procedure via communication leads to an aggregation of decentral information and hence to a more efficient learning when compared to individual up-dating without communication.

But in general agents are heterogenous which further biases communication among agents. Thus, beyond observed signals agents' political opinions might be determined by other private characteristics, e.g. heterogeneous individual support functions or prior beliefs.

It is a well-known empirical fact that political elites are often dominated by special interest groups which prefer biased policies in favor of particular economic interests at the expense of the general public (Persson et al., 2003).

Hence, from the viewpoint of the society belief updating in elite networks implies a trade-off between a more efficient policy learning and a policy bias towards special interests.

Thus, the question is how this trade-off is affected by elite network structures and the interplay between formal constitutional rules and informal elite network structures. To analyze these questions we apply a rather simple agent-based model including both political belief formation via political communication in elite networks and political decision-making resulting from legislative bargaining. To facilitate analysis we assume for the latter that cooperative legislative bargaining can be modeled applying the mean voter decision rules as derived in eq.6 above.

3 Simulation Setup

3.1 Economy and population

We consider two communities $c = 1, 2$. Each community has a population comprising two groups, an agrarian and a non-agrarian population, where μ_c denotes the share of the agrarian population in community c . In particular, we assume one community corresponds to a rural, while the other corresponds to an urban community, i.e. $\mu_1 > 0.5$ and $\mu_2 < 0.5$.

Furthermore, let Z_1^c and Z_2^c denote the per capita welfare of the agrarian and non-agrarian population, respectively.

3.2 Political System

3.2.1 Legislative System

The political system comprises of a set N of $n = 20$ legislators, where legislators can be subdivided into the two communities $c = 1, 2$. For notational convenience legislators $l = 1, \dots, 10$ belong to the rural community $c = 1$, while legislators $l = 11, \dots, 20$ belong to urban community $c = 2$. For each community legislature has to choose an unidimensional policy $\alpha \in R = (0, 1)$.

The policy α is considered as a redistribution of welfare among agrarian and non-agrarian population, where the political technology A corresponds to the following simple linear mapping:

$$Z_w^c = a_{0w}^c + a_{1w}^c \alpha \quad (16)$$

, where a_{0w}^c denotes the welfare of group w in community c without any policy.

In detail 2 different constitutional scenarios are analyzed. (1) A decentral system: i.e. for each community a community council comprising the subset of legislators of each community chooses separately the community policy according to a simple majority role. (2) A central system: i.e. a joint council comprising the total set of legislators chooses one policy that is applied for both communities according to a simple majority role.

Accordingly, political control of legislators, C_{cl} over community policy, α_c results as follows:

For scenario $s=1$:

$$C_{cl}^s = \begin{cases} 0.1 & l \in N_c \\ 0 & otherwise \end{cases}$$

For scenario 2:

$$C_{cl}^s = 0.05 \quad l \in N, \quad c = 1, 2$$

The final political decision resulting from legislative bargaining corresponds to the mean voter decision rule:

$$\alpha_c^{s*} = \sum_{l \in N} C_{cl}^s Y_{cl} \quad (17)$$

, where Y_{cl} denotes the ideal point of legislator l regarding the community policy α_c .

3.3 Derivation of legislators' political preferences

Legislators care about community policy because they are reelected in communities. In particular, we assume that rural legislators are reelected in the rural community, while urban legislators are reelected in the urban community.

In principle reelection chances of individual legislators depend on realized welfare of agrarian and non-agrarian population in their community. However, we assume that individual legislators differ regarding their specific affiliation to the agrarian group in their community. Thus, overall political support of individual legislators results from the following Cobb-Douglas support function:

$$S_l = \prod_{w,l \in C} Z_{1c}^{X_l} Z_{2c}^{(1-X_l)} \quad (18)$$

A legislator is biased in favor of the agrarian population if the weight of the welfare of the agrarian population, X_l , is higher in his or her political support function than the corresponding population share, mu_c , in his community.

Hence, since legislators form only beliefs regarding the political technology relevant for their community, single-peaked policy preferences result from political support maximization given legislators' beliefs of the true political technology, $\tilde{a} = [\tilde{a}_{w1}^c]$, with $l \in c$:

$$U_l(\alpha_c) = (\tilde{a}_{01}^l + \tilde{a}_{11}^l)^{X_l} (\tilde{a}_{02}^l + \tilde{a}_{12}^l)^{(1-X_l)} \quad (19)$$

In particular, legislators ideal position results as:

$$Y_l = X_l \frac{\tilde{a}_{02}^l}{\tilde{a}_{12}^l} + (1 - X_l) \frac{\tilde{a}_{01}^l}{\tilde{a}_{11}^l} \quad (20)$$

, where legislators' ideal position is the same for both communities, i.e. it holds: $Y_{cl} = Y_l$.

3.4 Political performance indicator

Based on legislators policy preferences legislative bargaining occurs in eqch time period $t = 1$ and given the constitutional rules the final policy decisions results from the mean voter decision rule:

$$\alpha_c^{s*} = \sum_{l \in N} C_{cl}^s Y_{cl}^o \quad (21)$$

To measure political performance we apply a political loss function $L(\alpha)$ defined as the euclidian difference between the actual policy decision α_c^{s*} and the optimal policy decision α_c^{opt} . The latter is defined as the policy that maximized a community welfare function: $W_c = \prod_{w \in C} Z_{1c}^{\mu_c} Z_{2c}^{(1-\mu_c)}$:

$$L(\alpha) = \|\alpha_c^{s*} - \alpha_c^{opt}\| \quad (22)$$

Of course, the loss function can be evaluated for each time period or alternatively the aggregate loss over all time periods can be calculated. We will use both performance indicators to evaluate the impact of elite network structure on political performance in the following simulation analyses.

3.5 Belief formation

Generally, legislators do not know the true political technology $A^c = [a_{w1}^c]$ for each community, but we assume for simplicity that legislators know for their community the welfare of groups without policy intervention, i.e. rural legislators $l = 1, \dots, 10$ know a_{w0}^1 and urban legislators $l = 11, \dots, 20$ know a_{w0}^2 .

Moreover, legislators form beliefs only regarding the true political technology parameters a_{w1}^l in their community.

In particular, we assume that legislators' initial beliefs regarding each single political technology parameter, $\tilde{a}_{w1t=0}^l$ result as random draws from independent normal distributions with the corresponding true political technology parameters, a_{w1}^c as expectation values:

$$\tilde{a}_{12t=0}^l = a_{12}^c + \omega_{l12}$$

,where ω_{l12} is a realization of a stochastic error term that is normally distributed with an expectation value equal to zero.

Based on their initial beliefs legislators form their policy preferences and legislative bargaining occurs in time period $t=1$. Given the constitutional rules the final policy decisions results from the mean voter decision rule:

$$\alpha_c^{s*} = \sum_{l \in N} C_{cl}^s Y_{cl}^o \quad (23)$$

Community policies are implemented and changes of per capita welfare of groups are realized as implied policy outcomes $dz(\alpha_{c(i)t}^{s*})$. The index $c(i)$ denotes a mapping of an actor i into his or her corresponding community.

The latter are observed by individual elite members, but individual observations are noisy, e.g.:

$$dz_i^b = A d\alpha_{c(i)t}^{s*} + \varepsilon_i$$

,where ε_i denotes an idiosyncratic error term, with $E(\varepsilon_i) = 0$ and $d\alpha_{c(i)t}^{s*}$ is the policy change in period t when compared to the previous policy in period $t-1$.

Accordingly, elite members can up-date their political beliefs based on the comparison of observed (dz^b) and expected (dz^e) policy outcomes, with:

$$dz_i^e = \tilde{A} d\alpha_{c(i)t}^{s*}$$

Assuming a Nerlove belief formation of individual actors, it follows:

$$\tilde{a}_{1wt+1}^i = \tilde{a}_{1wt}^i + \beta \left[\frac{dz_{wt}}{d\alpha_{c(i)t}} \right] \quad (24)$$

Based on the new policy beliefs, the process starts again in the next time period $t+1$.

3.5.1 Belief formation in elite networks

So far we have only considered individual belief up-dating of agents based on the observation of policy outcomes. Beyond observational learning based on private information we additionally consider belief updating via political communication in elite networks. To this end, individual actors derive their ideal position in each time period t from political support maximization based on their actual policy beliefs:

$$Y_{lt}^o = X_l \frac{\tilde{a}_{02}^l}{\tilde{a}_{12t}^l} + (1 - X_l) \frac{\tilde{a}_{01}^l}{\tilde{a}_{11t}^l} \quad (25)$$

Next the vector of final policy positions y_t held after communication is calculated applying the network multiplier matrix M derived from the political communication network T using eq. 15 above:

$$y_t = M y_{lt}^o \quad (26)$$

The final policy decision is then derived applying the mean voter decision rule using the final policy positions y_t .

$$\alpha_{ct}^{s*} = \sum_{l \in N} C_{cl}^s Y_{lt} \quad (27)$$

3.5.2 Generation of elite networks

To be able to analyze the impact of network structures on political belief formation and performance we have systematically simulated information accumulation in various random as well as small-world respectively hybrid networks. Networks have been generated using the modified α -model of Watts (1999)⁴. A central parameter of this network generation algorithm is α which determines global network characteristics, i.e. clustering and characteristic path length. In particular, we investigated two basic networks types, random and small-world networks which we also call "branched" since the preference to form a tie is driven by the same branch respectively the same ideology. The small-world networks have been constructed by the modified α -model. In order to test the influence of network structures, about 200 different network settings have been tested. For each setting 20 networks were generated so that the variance could be covered. The details will be explained in the technical description.

At first the parameter settings will be explained inasmuch as this is driving the structure of the networks. The structure of the networks will always be linked to the economic performance where the indicator is the so called α -loss described above. The following list displays the setting elements which are varied for changing the network structure:

1. Increasing the number of agents from $n_1 = 40$ to $n_2 = 150$ for both network types where average number of ties $k = 6$
2. Varying the average number of ties: $k = 1, \dots, 15$ where the self-control $\mu = 1$. Each performed for the four network types: $n = 40$ random, $n = 40$ branched, $n = 150$ random, $n = 150$ branched
3. Varying the clustering by varying α (only for small-world networks). Each performed for the four following combinations: k [$\mu = 1$, $(k = 6, n = 40)$, $(k = 10, n = 40)$, $(k = 6, n = 150)$, $(k = 10, n = 150)$]
4. Varying centralization by varying the number of ties for a central political agent from $central k = 10, \dots, 130$ with $\mu = 1$. Each performed for the following four

⁴The detailed algorithm is described in Henning and Saggau (2009)

combinations: $(n = 40, \alpha = 1)$, $(n = 40, \alpha = 10)$, $(n = 150, \alpha = 1)$, $(n = 150, \alpha = 10)$

5. Varying the self-control $\mu = 0.5, \dots, 5$ with $(n = 40, \alpha = 1)$, $(n = 40, \alpha = 10)$, $(n = 150, \alpha = 1)$, $(n = 150, \alpha = 10)$

The multiplier matrices have been calculated in Java. These multiplier matrices display the influence of the actors on each other (Hubbell, 1965) and are derived by the network structures. To measure the network structure and the performance of the network indicators have been calculated and logged per setting and per iteration.

3.6 Simulated elite network scenarios

The simulation scenarios consist of the already mentioned parameter settings regarding the network structure, i.e. the common model parameters, and also of bias scenarios. The last term, the bias scenarios, is referred to the politically interesting combinations of biased influence measured by the force of the complete elite network as well as for the two separated governmental and non-governmental networks (for the definition of the force see below). In particular, both political agents and interest groups can be biased in favor of a specific population group, agrarian and non-agrarian, respectively. We tested all bias combinations, that is all variations of the separate forces.

- bias political agents +,-
- bias lobbying groups +,-
- bias both +,- and opposing

Thus the resulting scenario names are

```
set scenarios /  
  bias_no_no  
  bias_pa_pos  
  bias_pa_neg  
  bias_lb_pos  
  bias_lb_neg  
  bias_pos_pos  
  bias_neg_neg  
  bias_pos_neg
```

```

    bias_neg_pos
/;

```

This general political economic equilibrium was constructed with GAMS. Due to the random nature of our model we repeated each simulation run for each network parameter constellation 20 times, which means that all reported variable values generally correspond to the mean over 20 simulation runs: 1 run equals 9 scenarios * 20 network-iterations * 20 model-iterations (different rng)

$\Rightarrow \sum networks * run = \sum \approx 720,000$ times solved the model

$\Rightarrow$ indicators for comparison / "sorting"

$\Rightarrow$ rerun k .times each "scenario"

$\Rightarrow$ result indicators: $\text{avg } \mu = \frac{\sum Y}{k} / \text{var } \sigma^2 = \frac{(\mu - Y)^2}{k} / SE = \frac{\sigma}{\sqrt{k}}$ for observed variable Y

The simulation scenarios contain in a log file the calculated averages, variances, standard deviations, standard errors, min, and max for all indicators and all iterations. The log files were then used to produce T_EX-Plots from the simulation results, i.e. the results from GAMS were read by Java which wrote plots into a T_EX-file.

3.7 Network types

In the emerging literature on "networks and economics" different types of networks characterized by specific network indicators have become very popular (Jackson, 2005), i.e., random networks (Erdős and Renyi, 1959; Bollobás, 2001), small-world networks (see Watts and Strogatz (1998) and Watts (1999)), and scale-free networks (Watts, 1999). Moreover, hybrid models to generate networks have been developed since purely random graph models do not exhibit the clustering or degree distribution that match many observed networks, while generated small-world networks do not exhibit observed degree distribution and power law or scale free networks do not exhibit observed clustering (Pennock et al., 2002; Kleinberg et al., 1999; Levene et al., 2002; Kumar et al., 2000; Cooper and A., 2003).

To construct elite networks of different types a modified α -model of Watts (1999) is applied, which can generate hybrid networks combining properties of scale-free, small-world, and random networks. The model is described in detail in Henning and Saggau (2009).

A specific property of a social network is clustering, this means the fact that the likelihood of a connection among two firms is correlated with the existing connections among firms. In detail, the higher the number of overlapping connections between a

pair of firms, the higher the probability that these two will form a connection as well. How exactly clustering occurs is a very interesting topic in itself. In the Watt's α -model clustering is basically determined by a single parameter, α , which can vary between 0 and infinity. The lower the values for α the more a network is clustered.

However, within our modified α -algorithm clustering also occurs via homophily, e.g. agents with similar characteristics like the same political ideology or a similar spatial location have a higher probability to form a tie.

Moreover, the modified α -algorithm allows the existence of stars keeping the idea of clustering. In detail, we assume that only one star exists, and we vary the number of ties this star forms (for detailed network generation mechanism see Henning and Saggau (2009)).

3.8 Network indicators

3.8.1 Local and global network indicators

Given the fact that we are mainly interested in the impact of social network structures on efficiency of political decision-making, the following global and local indicators are of general interest:

Local network size

If we denote the number of ties an individual actor i forms by z_i , then local network size, $\bar{z}$, is defined as the average number of ties of actors:

$$\bar{z} = \frac{\sum_{i \in E} z_i}{n} \quad (28)$$

Global centralization

Global centralization of a network measures the difference in individual network ties (degrees). Accordingly, the larger the variance of individual degrees of actors, the larger is c.p. the centralization. Let σ^2 denote the variance of degrees in a network, then it holds:

$$\sigma^2 = \frac{1}{n} \sum_{i \in E} (z_i - \bar{z})^2 \quad (29)$$

Thus, by definition, centralization is measured by the variance or standard deviation of network degrees, σ^2 or σ , respectively.

Clustering/transitivity

Network clustering or transitivity is defined as the average density of the actor's neighborhood network. A neighborhood network E_i of an actor $i \in E$ is defined as the subset of actors $j \in E$ which have a tie to i :

$$E_i = \{j \in E \mid z_{ij} = 1\} \quad (30)$$

Now, given z_i neighbors of an actor i , the density of the neighborhood network E_i is defined as:

$$\gamma_i = \frac{\sum_{k \in E_i} \sum_{j \in E_i} z_{kj}}{z_i(z_i - 1)} \quad (31)$$

Finally, the global clustering is defined as the average density of all neighborhood networks:

$$\gamma = \frac{1}{n} \sum_{i \in E} \gamma_i \quad (32)$$

3.8.2 Force F

If we denote N as the subset of political agents, Battiston et al. (2004) define the force as the field strength operating on individual political agents, i.e.:

$$F = \frac{1}{n} \sum_{i \in N} \sum_{j \in E} t_{ij} D_j \quad (33)$$

, where $D_j = X_j - \mu_c(j)$ denotes the bias of an actor towards or against the agrarian population. $D_j > 0$ denotes a bias in favor of the agrarian population, while $D_j < 0$ denotes a bias in favor of the non-agrarian population. But, the force as defined by Battiston et al. (2004) only takes direct influence of communication into account, while indirect effects are neglected. Accordingly, in the framework of our simple linear opinion formation model a straightforward generalization of the force concept would be:

$$F = \frac{1}{n} \sum_{i \in N} \sum_{j \in E} M_{ij} D_j \quad (34)$$

Note that the generalized force varies between -1 and 1 , where a force of 1 indicates that political agents' political opinions are totally biased in favor of the agrarian population. Vice versa a force of -1 indicates that agents' opinion is totally biased in favor of the non-agrarian population.

Moreover, we can separate the force F_N operating in the subset of political agents N and the force operating in the subset of non-governmental actors, F_{E-N} :

$$F_N = \frac{1}{n} \sum_{i \in N} \sum_{j \in N} M_{ij} D_j \quad (35)$$

$$F_{E-N} = \frac{1}{n_2} \sum_{i \in E-N} \sum_{j \in E-N} M_{ij} D_j \quad (36)$$

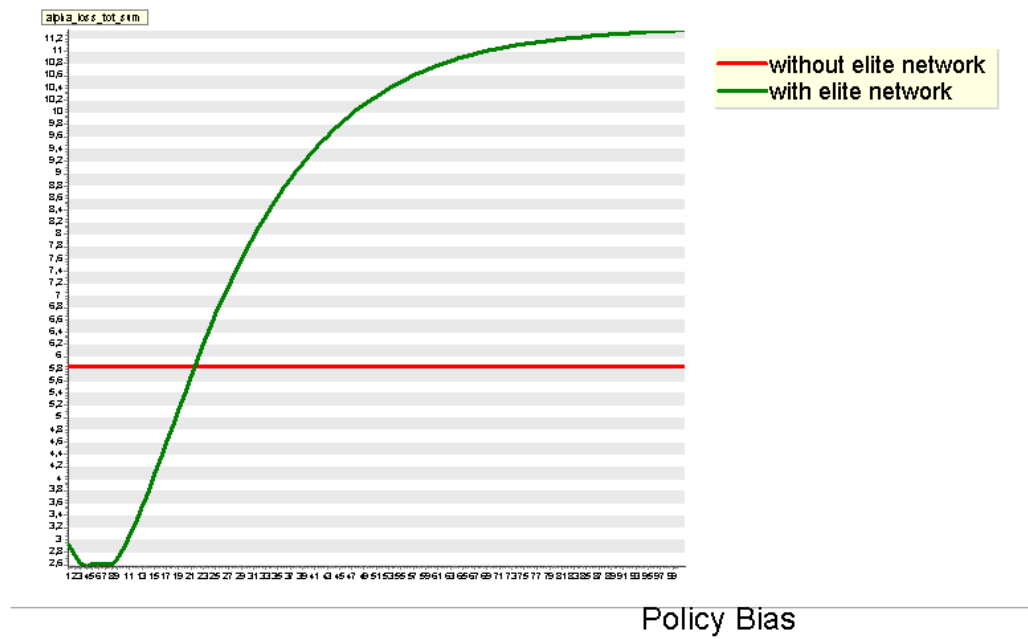
Separating the force for the political agents and the non-governmental elite members implies four different policy bias scenarios, i.e. both subsets are biased towards the same population group (agrarian or non-agrarian) or the subsets are biased towards different subgroups.

4 Results

4.1 Trade-off between policy learning and government capture

As can be seen from figure 1 collective up-dating via political communication within in a local elite has a significant impact on political performance. However, there is a trade-off between a positive affect resulting from information aggregation via political communication and a negative affect resulting from a policy bias. The stonger the elite is biased in favor of a specific population group the more the positive effect on policy learning in networks is compensated. If the bias within the elite network is above a specific treshold the overall effect of political communication becomes increasingly negative as induced community policies are increasingly biased towards special interests.

Policy loss

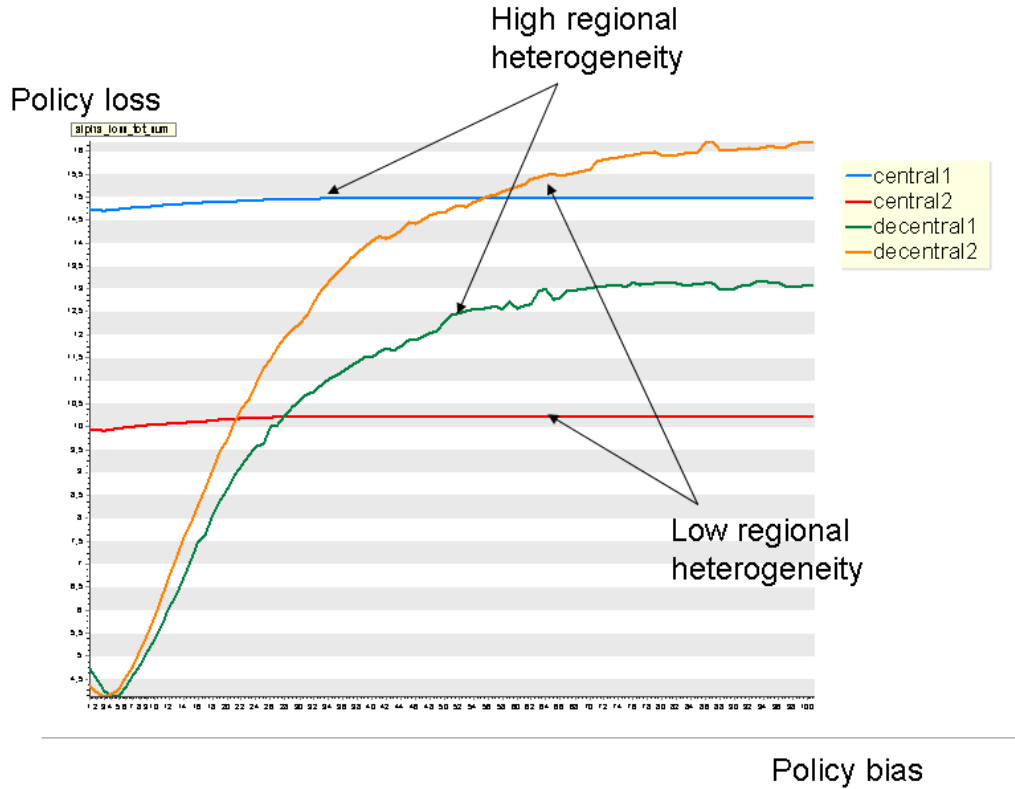


Source: Own calculations

Figure 1: Trade-off between policy learning and government capture

Interestingly, comparing the impact of political communication within elite networks in central and decentral systems policy learning is c.p. more efficient in a central when compared to a decentral system assuming communities are not too heterogeneous (see figure 2). The main reason for this observation follows from the fact that the overall bias of the elites is c.p. lower in central when compared to decentral systems, because local elite biases in rural and urban communities compensate each other. However, if communities become too heterogeneous common policy formulated in a central political system as a compromise between different local community elites differs extremely from each corresponding optimal community policies. Hence, if communities are sufficiently heterogeneous decentral systems imply a higher political performance, while central sys-

tems are c.p. more efficient, when communities are relative homogenous and local elites are biased towards different population groups.



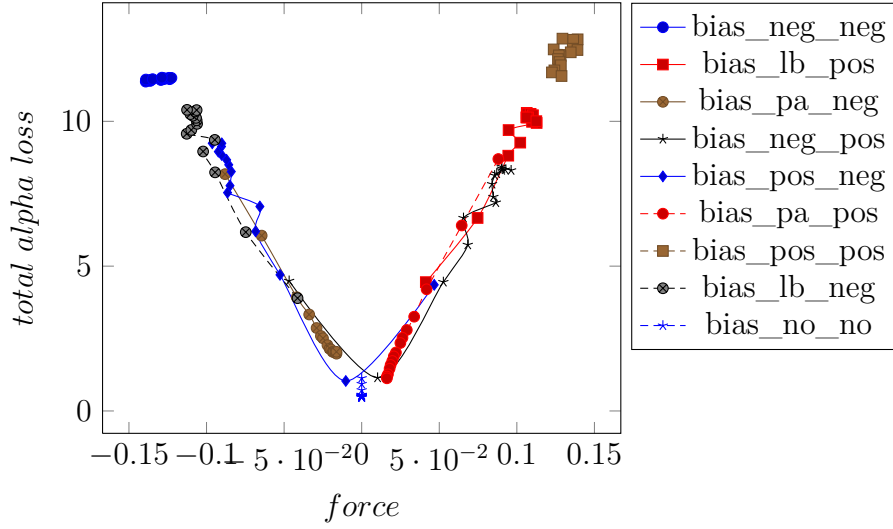
Source: Own calculations

Figure 2: Trade-off between policy learning and government capture in central and decentral systems

4.1.1 Force and political performance

In general the impact of elite networks on political performance significantly varies with the overall preference bias observed for an elite. This can be clearly seen from figure below, where the policy loss is tabulated against the calculated force for different elite networks.

Figure 3: varying_k - n=150 Random - force - total alpha loss

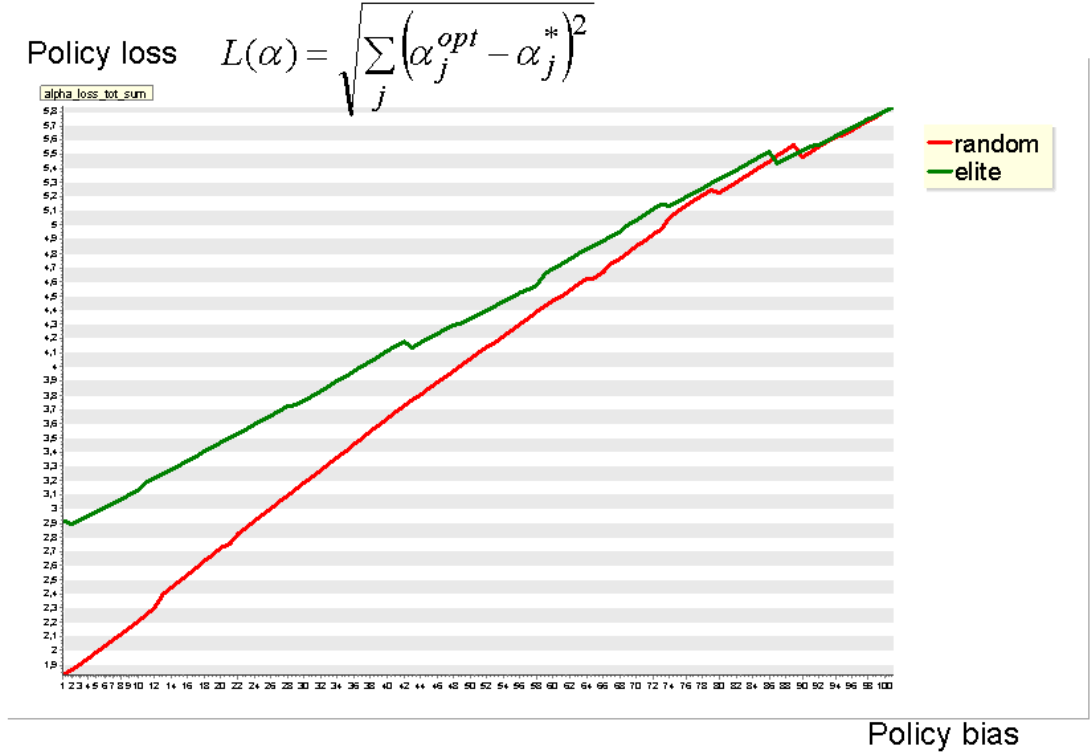


4.2 Network structure and performance

The influence of networks and the structure of networks on the economic performance in terms of "choosing the right policy" is shown in this section. The indicator α_{loss} is derived above and displays the relationship between the optimal policy α_{opt} and the realized policy α_t . The higher the value of α_{loss} the less is the political performance due to the fact, at least in the model, that politicians or interest groups are biased. In the following subsections, several network indicators which are structure-determining parameters will be analysed concerning their influence on the political performance of the network.

4.2.1 Network structure and performance: random vs. small-world networks (clustering)

In figure 4 none of both groups is biased hence we can investigate the impact of the network types on the political performance. The higher the number of agents in the network the less is the total loss this clearly supports the information aggregation function of networks. In the case of 150 agents there is also only little difference between the network types whereas in the case of only 40 agents the difference increases with increasing numbers of ties k .



Source: Own calculations

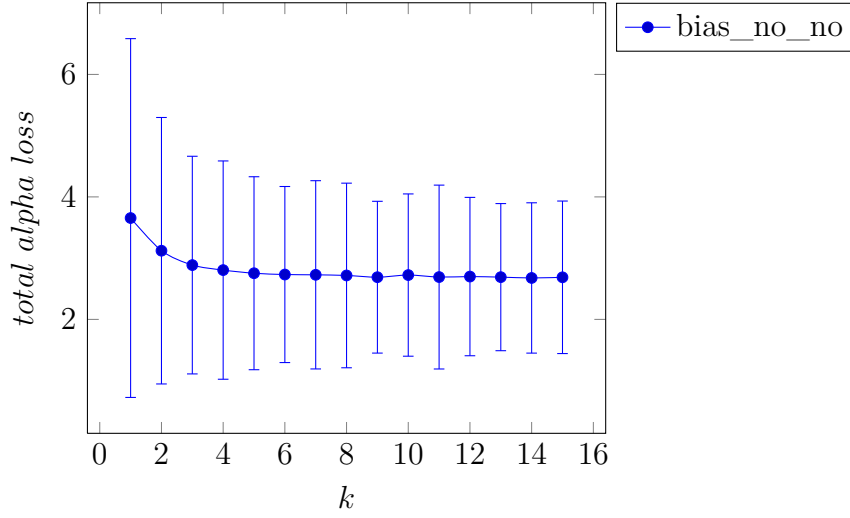
Figure 4: Impact of network type on political performance

The random network reaches a higher political performance compared to the small-world network.

4.2.2 The influence of local network size k

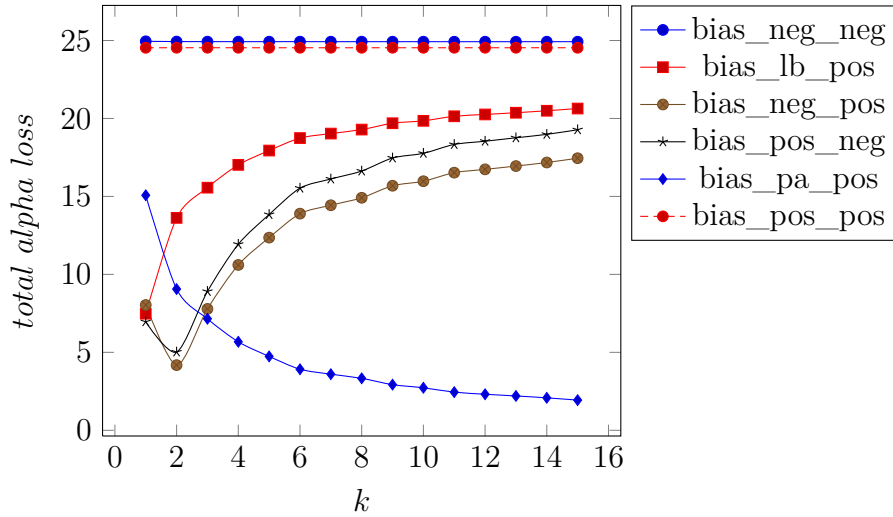
The local network size k of the network is varied from 1 to 15, this means that the average number of network ties will subsequently be increased from 1 to 15. The impact on α_{loss} , i.e. the economic performance, is displayed in figure 5.

Figure 5: varying_k - n=150 Branched - k - total alpha loss



The first result is that, if both groups are positively biased, there is no network effect and the α_{loss} relatively high. The second result is that, if one group is biased or contrarily biased, the network type matters, that is the local network size k has an impact on the economic performance.

Figure 6: varying_k - n=150 Branched - k - total alpha loss



4.2.3 Centralization

The centralization has a significant impact on the political performance although it depends on who is biased and who is not. If the interest groups are biased the political

performance increases with increasing centralization due to the fact that the information aggregation effect of the network and the power of the central political agent overcompensates the lobby bias. Whereas if the political agent is biased the political performance increases with increasing centralization. The influence of the unbiased lobby decreases. In the case of counter bias with respect to the two groups the political performance first increases, i.e. α_{loss} decreases and afterwards decreases with increasing centralization. There is a phase when the information aggregation of the network leads to increasing political performance but there are two phases in which the bias decreases political performance.

Figure 7: varying_centralization - n=150 alpha=10 - centralK - total alpha loss

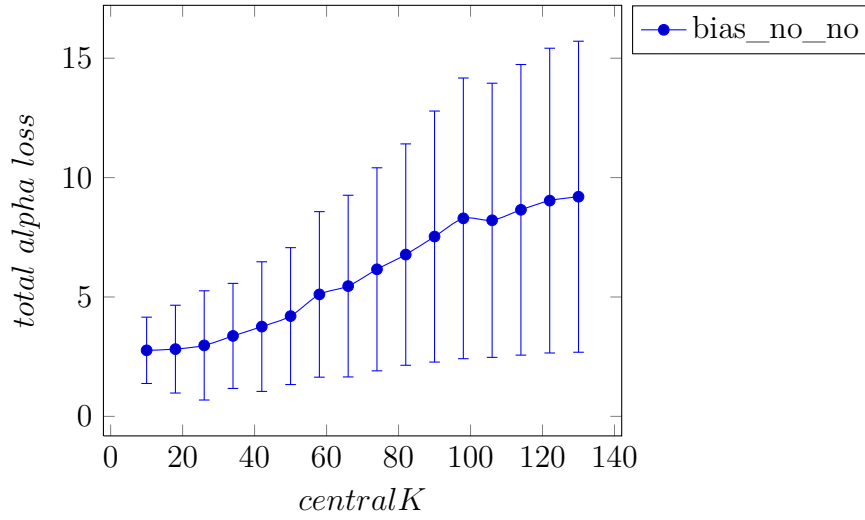
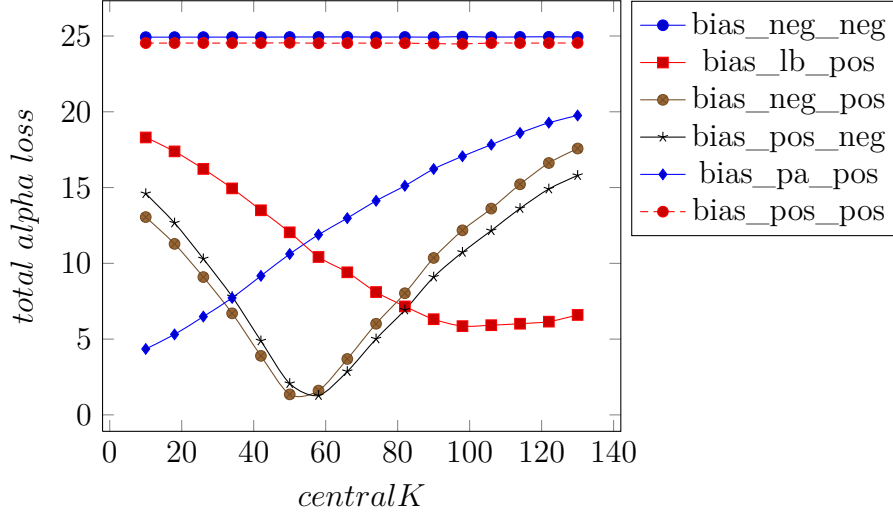


Figure 8: varying_centralization - n=150 alpha=10 - centralK - total alpha loss



5 Conclusion

This paper investigates the impact of the embeddedness of politicians in a local elite network on government performance in decentralized and centralized political systems. Formal political decision-making among a set of legislators is modeled via a *mean voter decision rule* derived from a *modified non-cooperative legislative bargaining game of a Baron-Ferejohn type*. Legislators' policy preferences are derived endogenously from political support maximization based on legislators' beliefs how a rural development policy translates into the welfare of the agrarian and non-agrarian population. Legislators are generally uncertain regarding the political technology, i.e. the welfare changes induced by a policy. Accordingly, legislators communicate with the local elite to learn more about the true political technology and hence to undertake better informed political decisions. However, local elites might be biased in favor of a specific population group, i.e. communication might also bias political beliefs. The model allows a simultaneous analysis of formal political institutions and the structure of informal elite networks determining policy outcome. A trade-off between more efficient policy learning and an increased policy bias induced by an increased embeddedness in local elite networks is identified. Policy bias is attenuated in centralized when compared to decentralized systems, while vice versa the speed of policy learning through local elite networks is c.p. higher in decentralized when compared to centralized systems. Moreover, beyond the policy bias within an elite towards special interests elite network structures such as network type, local size

and centralization have an impact on overall efficiency of political decision-making. In particular, random networks imply c.p. a higher political performance

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