INTRODUCTION

Public policymaking and regulation are getting increasingly complex (Lubell 2013). Different policy subsystems, and especially environmental policy, are characterized by scientific uncertainty about the effects of environmental problems or about the anthropogenic uses of natural resources (Metz and Ingold 2014). Under the condition of uncertainty, human action as well as political regulation is often guided by the precautionary principle: even in the absence of a scientific consensus about the impact of a (physical, chemical, natural or human-made) phenomenon on the public or the environment, policy actions are taken to reduce potential risks (Prieur 2012) or to enhance economic or social welfare. What is more, scientific uncertainty challenges political decision-making processes by increasing the difficulties in anticipating the behavior of actors and selecting appropriate policy instruments to tackle the uncertain problem (Aoki 2007).
Scientific uncertainty about a problem to solve is expected to affect the policy-making process in a particular way. Actors involved in public policy production might be particularly keen in reducing uncertainties when relaying on information provided by ideological peers, well-known others, or by scientists.

In this article, we are interested in major drivers of information exchange in a policy domain characterized by its complexity and uncertainty about the problem to tackle. We define information exchange as one relevant pre-condition impacting policy outputs and as a major indicator of how political actors organize in complex policy subsystems.

To investigate one specific policy subsystem strongly impacted by scientific uncertainties and regulatory complexity, we focus our study here on unconventional gas development and its political regulation. Unconventional gas is extracted using new and controversial technologies of hydraulic fracturing (later: fracking). Fracking allows extracting sizable resources of natural gas from basins that were considered to be difficult or costly to exploit before (IEA 2012). Potentially, the extraction of unconventional gas can have important implications not only for the global energy market and geopolitical world map, but there are also many environmental risks related to fracking such as the contamination of surface waters and aquifers, the causation of seismic activity, or the generation of fugitive methane emissions (Stevens 2010). As of today, there is not enough scientific evidence estimating the exact environmental impacts caused by fracking (Stevens 2010). This, again, poses considerable challenges to its promotion or regulation and consists thus an ideal case to study information exchange in a policy subsystem characterized by scientific uncertainty.

For the development of our research design, we rely on previous studies about information networks and adopt the differentiation between technical and political information relations (such
as Leifeld and Schneider 2012). The first consists of scientific knowledge about the given problem and is often provided by researchers; while the second is inherent to policy making and concerns information about actors’ strategies and behavior. Also recent research about the role of experts and knowledge in public communication about unconventional gas highlights the lack of factual scientific legitimization, and thus technical information exchange (Wagner 2014). One major aim here is to further contribute to the research about unconventional gas development and knowledge transfer, by asking if different drivers can be identified that explain the creation of technical versus political information relations.

Similar than others, we adopt a network approach and also argue that authority over a decision-making process can be exchanged for resources such as information, public support or technical expertise (Leifeld and Schneider 2012; Henning 2009; Pappi and Henning 1999; Knoke 1996; Coleman 1986). Information exchange is thus conceived as one particular relational type that shapes structures of political decision-making. The literature suggests that preference similarity (Sabatier 1988), social trust (Carpenter, Esterling et al. 2004), perceived power and functional interdependence (Leifeld and Schneider 2012; Pfeffer 2003) are particularly important drivers of information exchange relations between actors. Through exponential random graph models (ERGM) we explore causal mechanisms between those drivers and tie creation within the technical and the political information exchange network.

Data was gathered in summer 2014 about the case of unconventional gas development in the UK between 2007 and 2014. In the UK, both the energy industry and government identified the high economic potential of unconventional gas development; but environmental risks persist and environmental organizations and the local population oppose fracking sites. Still, the UK is likely to develop shale gas in spite of strong public opposition and mobilization (Stevens 2013).
This paper is structured as follows: after discussing the importance of information exchange for political decision-making and in the particular case of political subsystems driven by scientific uncertainty about the problem at stake, we deduce our hypotheses from policy process and resource dependence theories. In section three, we shortly present the case, the data and the method. In sections four and five, we present and discuss the results received via the exponential graph models. Section six concludes and highlights shortcomings and major findings of this research.

THEORY

In political decision-making, information exchange seems crucial. The flow of information is defined as one important pre-condition of how political actors form decisions and organize to impact political outputs (Leifeld and Schneider 2012; Grosser and Schram 2006) It is further defined as being at the core of why the immediate social environment affects individuals’ political decisions (Kenny 1992). To access decision-making and to compensate for limited individual resources, political actors provide information and expertise and coordinate actions (Heaney 2014; Henning 2009). Deduced from that, we define information exchange as a major indicator of how political actors organize in complex policy subsystems.

Before discussing the main drivers of information exchange as developed in literature; we first outline our main interest in information exchange within complex and uncertain policy domains and differentiate in this regard between two types, technical versus political information exchange.
**Information exchange under uncertainty**

Complex policy issues or decision situations are going hand in hand with a certain degree of uncertainty about the societal problem to resolve, all current and future institutions, the interconnectedness of others’ and other decisions (see Lubell 2013). This uncertainty may enhance political actors’ willingness or need to strive for, provide or exchange information. Three types of uncertainty in policy analysis and design can be highlighted from the literature: uncertainty with respect to the political problem (scientific uncertainty) (O'Riordan and Cameron 2013; Gollier and Treich 2003); uncertainty with respect to the preferences and attitude of other actors (behavioral uncertainty) (Lubell 2013; Fink and Harms 2012; Krishnan, Martin et al. 2006); and uncertainty with respect to how policy instruments work (Howlett 2005). All three types of uncertainty affect actors to different degrees. Even if some actors have more information than others, no actor is expected to be aware of the complete picture (Lubell 2013; Aoki 2007).

**Behavioral uncertainty** and thus the difficulties for actors to anticipate and understand the behavior of other actors (Krishnan, Martin et al. 2006); as well as the **uncertainty regarding policy design**, instrument selection and their effects (Landry and Varone 2005) are characteristics of all modern policy domains. This is because of their complexity, of rapid and constant changes in politics and economy, and because of limited information.

In the presence of **scientific uncertainty** it is difficult to estimate the effects of a policy problem. This phenomenon is most prominently discussed in the environmental policy literature (see Metz and Ingold 2014; Ingold, Balsiger et al. 2010). Under scientific uncertainty, political action is often justified and based on the precautionary principle (O'Riordan and Cameron 2013; Gollier and Treich 2003). Scientific uncertainty further disables actors to define the seriousness of the
problem, to set clear subsystem boundaries, and to “know the links or probabilities between actions and consequences” (Weible 2008).

As mentioned above, this study is particularly interested in scientific uncertainty about the problem at stake\(^1\) in contrast to behavioral or instrument uncertainties. Still, we acknowledge that scientific uncertainty might impact uncertainty about other actors’ preferences and strategies as well as uncertainties with respect to the policy design, i.e. scientific uncertainty can increase both other types of uncertainty (see Metz and Ingold 2014).

**Two types of information exchange**

Recent studies on information exchange among political actors argue that depending on their purposes, actors might exchange different types of information. In their study about information exchange in political decision-making, Leifeld and Schneider (2012) demonstrate the relevance of differentiating between two types of relations: On the one hand, technical or scientific information (later: technical information) that is used to enhance knowledge about the problem as such; and on the other hand, political or strategic information (later: political information) that concerns the strategic exchange about similar beliefs, venue shopping, and resources. Both types of information can be used to influence the political decision-making process and thereby the policy output, but in different ways. Technical information consist of knowledge about the given problem, often generated by the scientists in the first place (Leifeld and Schneider 2012). Still, several policy process theories define technical knowledge as a resource not only generated by

---

\(^1\) We are aware that the discussion of scientific uncertainty is going close to the discussion of ambiguity, meaning the potential to frame the issues in very different ways depending on the interests of a given actor. However, the aim of this study is understanding the specifics of information exchange under scientific uncertainty, and it is beyond the scope of this study to examine the ways the actors use the obtained information later in the political decision-making or implementation process.
scientists, but also consultancies, policy analysts and government specialists (Weible 2008). This type of information can be used by actors directly in order to influence the decision-making process through knowledge provision such as the preparation of reports for decision-makers. More often however, technical information is used indirectly through influencing the public perception of the problem and the public opinion on it (Leifeld and Schneider 2012).

In contrast, political information concerns strategic motivation of political actors and deals with questions of how actors organize in order to impact policy outputs. According to the Advocacy Coalition Framework, for instance, political actors exchange information within their coalition, and thus with members sharing the same policy beliefs, in order to coordinate their actions (Weible 2008; Sabatier and Weible 2007). In this regard, political information is used to communicate with peers, and to exchange information about strategic actions to influence decision-making, such as venue shopping and the coordination of joint lobbying activities (Leifeld and Schneider 2012).
The main drivers of information exchange

Hereafter, we outline prominent drivers of information exchange derived from policy process and resource dependence theories as well as network approaches to trust building and information exchange (Leifeld and Schneider 2012; Berardo and Scholz 2010; Carpenter, Esterling et al. 2004; Sabatier 1988).

Preference similarity

Previous studies indicate that shared values and beliefs are the basis for coalition formation and coordination among actors involved in the same political subsystem (Sabatier 1988). More concretely, preferences similarities are identified as major drivers for coordinated action among actors and therefore also for information exchange within coalitions (Weible 2006; Sabatier and Weible 2005). Actors prefer to receive information from like-minded others, and additionally gain support for their arguments through scientifically proved knowledge.

The fact that joint beliefs are important for coalition formation leads us to assume that this factor is a stronger predictor for political information exchange than for exchange of technical information. In the technical information exchange network preferences similarities are less vital: actors contact others to gain new information about the complex issue in order to reduce their uncertainty, rather than in order to find alliances and to impact policy outputs in accordance to their belief systems (Leifeld and Schneider 2012; Carpenter, Esterling et al. 2004).

Hypothesis 1a: Actors with similar preferences tend to exchange political and technical information.
Hypothesis 1b: The influence of similar preference on the exchange of political information is stronger than on the exchange of technical information.

Power perception and resource dependence

According to the resource dependence theory, actors seek contacts to powerful others in order to impact policy decisions more successfully (Pfeffer 2003). Power is a more relevant characteristic of actors mainly active in the political decision-making arena, as compared to the academic arena where most technical knowledge is provided. We therefore deduce that in the political information exchange network actors are likely to establish relations towards powerful allies, thus actors being perceived as particularly influential, or organizations holding an impressive amount of resources (such as personnel, knowledge or money; see Fischer and Sciarini 2013; Leifeld and Schneider 2012).

Hypothesis 2a. Powerful actors tend to have more incoming political information ties than other actors.

Still, in the struggle against uncertainty, actors also seek technical information. Political actors need knowledge about the problem to tackle in the first place, in order to consequently be able to form strategies and justify their preferences and decisions. As mentioned above, mainly scientific actors and think tanks are expected to be providers for such objective technical information (Leifeld and Schneider 2012). Recent studies suggest that the lack of scientific certainty creates a need for knowledge acquisition (Leach, Weible et al. 2013). Or said differently, scientific actors are important knowledge providers and thus substantively create technical information ties towards others.
Hypothesis 2b. In the technical information exchange network, scientific actors tend to have more outgoing ties than other actors.

Social trust and third parties

Actors tend to contact those actors they trust most. Social trust is expected to be an even more vital driver of information exchange in settings of uncertainty (Berardo and Scholz 2010). On the one hand, having common acquaintances helps actors to reduce the uncertainty about the quality of the alter and to know which other actors to trust (Leifeld and Schneider 2012). On the other hand, actors can also rely on those actors with whom they had contacts before, or with whom they have other social similarities (Carpenter, Esterling et al. 2004). Given the strategic nature of political information, this tendency is expected to be even stronger with respect to the exchange of political information as compared to technical information. Technical information is supposed to be a priori objective and reliable.

Hypothesis 3a. If two actors have shared contacts or have collaborated in the past, they are likely to exchange information in political and technical information exchange networks.

Hypothesis 3b. The influence of shared contacts and past collaboration on the exchange of political information is stronger than on the exchange of technical information.
CASE, DATA AND METHODS

Case selection and context

This paper deals with the case of fracking in the United Kingdom (UK). The current situation in the energy domain is challenging in the UK as well as in many other countries, which could well explain the interest for new sources of energy (Goldthau 2013) and why unconventional gas exploitation appeared on the political agenda. Several rather than one single event can be regarded as triggers for creating attention for the issue in the UK. On the one hand, methods of drilling were improved and now include horizontal drilling or seismic techniques, which made shale gas extraction economically profitable. On the other hand, the success of the United States in shale gas production opened up the discussion around developing fracking also in the UK.

In the period between 2007 and 2014, the UK government took the initiative to attract investors, to increase public acceptance and to provide the necessary regulation. The British Geological Survey started to review the potential for unconventional gas extraction in the UK in 2008 and identified a relevant production potential (Selley 2005). Subsequently, also the House of Commons and the House of Lords held consultations and mandated reports to increase knowledge about the impacts of shale gas on energy markets, energy security, water supply or the economy in general. Finally, and to attract investors the UK government proposed a new tax regime for companies active in the domain of shale gas extraction that is finally included in the Finance Bill 2014.

Until now, the most important outcomes of this policy process about the regulation of unconventional gas development in the UK are: The establishment of a new administrative office, the Office of Unconventional Gas and Oil (OUGO); the inclusion of unconventional gas sources into the Gas Generation Strategy; and the publication of supporting details (“Developing shale

---

gas and oil in the UK”) to the government policy “Providing regulation and licensing of energy industries and infrastructure”.

Data
Data on all relevant dependent and independent variables was gathered through a structured online survey conducted in summer 2014. In order to identify survey partners, and thus the organizations that are either directly or indirectly involved in the policy process related to the development and regulation of fracking in the UK, we consider collective actors such as political parties, interest groups, NGOs, administrative agencies or scientific institutions; and rely on the classical combination of decisional, positional and reputational approaches (Knoke 1993). First, and following the decisional approach, we identify actors participating in different arenas of the here studies political process (Magill and Clark 1975). Therefore, we analyze secondary sources such as protocols and participants’ lists of official meetings, information from official administrative websites of the administration, or reports of think tanks, energy companies and other involved actors. We finally identified 17 relevant arenas and phases between 2007 and 2014. Second, and according to the positional approach, we completed the list with actors holding an overall strategic position or have important formal competences in the UK political system. At this stage, we had a list comprising 40 organizations to whom we sent the survey. Following the reputational approach, all survey participants were asked to indicate the most important actors and to add further actors if they thought actors were missing. Via this approach, we could reduce our list to 34 relevant actors involved in decision-making about unconventional gas regulation and includes 10 scientific actors, 5 environmental non-governmental organizations (NGOs), 9 industry representatives and 10 political actors in the narrow sense (i.e. political parties or government administration). The response rate corresponds to 50%.
The dependent variable consists of two distinct network relations: technical and political information exchange. In order to gather data on the technical information exchange network between actors, we provided the following definition to survey partners: *Information on the technical aspects of unconventional gas development, as well as scientific information on potential implications for the environment and neighboring population.*

We further asked them the following questions: From the following list of actors that are active in the domain of shale gas extraction in the UK between 2007 and 2014,

- from which organizations does your organization regularly obtain technical information related to fracking?
- which organizations does your organization regularly provide with technical information related to fracking?

Political information exchange was defined in the survey as: *Information related to political affairs, i.e. information that allows your organization to organize.*

The following questions were included: From the following list of actors that are active in the domain of shale gas extraction in the UK between 2007 and 2014,

- from which organizations does your organization regularly obtain political information related to fracking?
- which organizations does your organization regularly provide with political information related to fracking?

Also several independent variables were operationalized via network relations gathered through the online survey. First, and as a proxy for shared policy beliefs (Ingold 2011), we asked actors to indicate with whom they agree, and with whom they disagree upon policy measures to be taken to regulate unconventional gas development. The so created ally and enemy network helps testing the first two hypotheses about belief similarity and its positive impact on information
exchange creation: Two actors sharing positive ally relation would enhance, sharing a negative enemy relation reduce the probability of them to create an information relation.

Second, and to assess the power of actors, we rely on reputational power. We asked actors to indicate which other actors they consider as very important in decision-making around unconventional gas development in the UK. Based on these answers, we calculated the reputational power score of each actor, which corresponds to the mean of the total judgments from all other actors. Third, and as a proxy for trust relations among actors, we asked survey partners to indicate with whom they strongly collaborated within other policymaking processes and during the last ten years. Finally, we coded each actor following the organizational type such as political and administrative entity, industry and private interest groups, green NGOs, and research institutes. The last actor type (science) is said to provide other actors with considerable technical information (hypothesis 2b).

Network approach and Exponential Random Graph Models (ERGM)

For decades, scholars have recognized that public organizations with an enduring interest in a particular substantive policy area are embedded in informal webs of relationships (Rethemeyer and Hatmaker 2007). Such policy networks provide a platform to political actors to exchange resources and information to impact policy decisions (Baumgartner, Berry et al. 2009; Baumgartner and Leech 2001). Similarly, we adopt a perspective that focuses on information exchange networks among political actors when it comes to frame our dependent variable (Leifeld and Schneider 2012; Bouwen 2004; Pappi and Henning 1999). But similar to others, we also recognize that one type of relations among actors (and actors relational profile of one type), might be impacted by another type of relations (for an example, see Ingold and Fischer 2014).
We test the impact of the different factors laid out in the theoretical section on the networks of political and technical information exchange by estimating Exponential Random Graph Models (ERGM, Robins, Pattison et al. 2007). ERGMs allow for statistical inference on network data, which by definition are non-independent (for applications in political science, see, e.g., Gerber, Henry et al. 2013; Leifeld and Schneider 2012; Cranmer and Desmarais 2011). Non-independency among observations in network data means that the probability of a tie of information exchange between two actors might depend upon the structural properties of the network in which the two actors are embedded. Standard regression models are unable to take this dependency into account and would erroneously attribute explanatory power to exogenous variables (Cranmer and Desmarais 2011). Given the dependency among observations, error terms would be correlated across observations, standard errors would be too small, and p-values for exogenous variables too optimistic (Leifeld and Schneider 2012).

In order to avoid the assumption of relational independence, the dependent variable of an ERGM is a single observation on the whole network (Cranmer and Desmarais 2011). The structure of the whole network is then modeled depending on actor-level variables (node covariates), dyadic variables (edge covariates), and endogenous network structures. The latter refer to effects of network structures on the network itself, such as actors' tendency to reciprocate ties or close triangles (i.e. to collaborate with an actor to which one is already indirectly connected). The relation between the probability of a network $m$ and the network statistics in $\Gamma$ can be expressed by the following formula, where $\Theta$ is the vector of $k$ parameters that describe the dependence of $P(Y_m)$ on the network statistics in $\Gamma$ (Cranmer and Desmarais 2011; Hunter, Handcock et al. 2008):

$$
P(Y_m) = \frac{\exp(-\sum_{j=1}^{k} \Gamma_{m,j} \theta_j)}{\sum_{m=1}^{k} \exp(-\sum_{j=1}^{k} \Gamma_{m,j} \theta_j)}$$
As represented in this formula, ERGMs calculate the probability of observing the given network over all other networks that could potentially have been observed. Given the formula above, ERGMs integrate an exponential family form log-likelihood function. Due to the very high number of possible network configurations, computing the exact maximum likelihood is however too computationally demanding (Cranmer and Desmarais 2011). Therefore, we estimate ERGMs using Markov Chain Monte Carlo Maximum Likelihood (MCMC-MLE), which approximates the exact likelihood by relying on a sample from the range of possible networks to estimate the parameters (Cranmer and Desmarais 2011). In a given step, MCMC-MLE proceeds by approximating the sum in the denominator of the likelihood function based on a series of networks sampled from the distribution parameterized with those parameters that maximized the likelihood using the previous sample of networks. This iterative optimization proceeds until the value of the approximate likelihood function does no longer change, i.e. when the differences between the coefficients in the observed network and the average coefficients in the sample of simulated networks are no longer significant (p greater than 0.05) (Cranmer and Desmarais 2011).

ANALYSIS

In the following analysis part, we present the results of the same models run on both types of dependent variables, i.e. technical and political information exchange. Both networks include 34 nodes (collective actors involved in UK fracking politics). While both networks are rather sparse, the network of technical information exchange is clearly more dense (0.16, meaning that 16% of all possible ties in the network do exist in reality) than the network of political information exchange (0.08). This tends to confirm our basic assumption that we are dealing with an important amount of uncertainty in this policy domain. Under uncertainty – and in an early stage
of political decision-making – actors mainly need to gather information on the issue itself, and deal less with forming coalitions or discussing influence strategies.

We present two models. As basic controls, all ERGMs include an “edges” and a “reciprocity” parameter. The first controls for the number of ties in a network. Its negative values, as observed in all of our models, indicate that actors have a negative tendency to send random ties. The reciprocity parameter controls for a very basic network mechanism. It is positive in all our models, indicating that actors tend to reciprocate ties of information exchange. If actor $a$ sends information to actor $b$, then actor $b$ tends to send information to actor $a$ too. Further, an important endogenous network effect is given by the tendency of actors to form triangular structures when exchanging information. More specifically, we use this network statistic to test whether actors tend to exchange information with other actors they share collaboration partners with, i.e. via indirect ties of information exchange through a third actors. This is operationalized by two statistics, i.e. the GWESP (geometrically weighted edgewise shared partner) and GWDSP (geometrically weighted dyadwise shared partner), which should be interpreted together (Hunter 2007). The GWDSP captures the tendency of a dyad (i.e. of a pair of actors that are related or not) to have one or more shared partners. It is a baseline effect that controls whether any two actors in the network tend to have shared partners. Once dyadwise shared partners have been controlled for, the GWESP measures whether two actors that exchange information are more likely than pure chance to have shared partners (Leifeld and Schneider 2012).

Besides these endogenous network effects, model 1 is the basic, parsimonious model and includes parameters for assessing the receiving and sending patterns of powerful actors (node covariates), and a parameter for estimating whether actors’ belief similarity (edge covariate) influences their activities of information exchange. With respect to actors’ power, a high share of 18 out of 34 actors has been mentioned as being powerful by at least 50% of the other actors.
With respect to belief similarity, there is slightly more agreement (1) on beliefs than disagreement (-1) in the network, as the average value of all ties is positive (0.02). In model 2, we add parameters for assessing the receiving and sending patterns of scientific actors (node covariates), as well as a variable measuring whether two actors already collaborated on similar issues in the past (edge covariate). 10 out of the 34 actors in our networks were classified as scientific actors. The density of the network of past collaboration amounts to 0.13. Results from model 1 and 2 both appear in table 1. Bold values indicate a significant effect at the conventional level of \( p \leq 0.05 \).

First, both models of technical information exchange show the values that indicate triadic closure, i.e. the fact that actors with shared partners tend to collaborate. A negative GWDSP parameter means that any two actors have a negative tendency to have shared partners. However, the positive GWESP parameter indicates that whenever two actors are related by a tie of information exchange, they tend to have shared partners. The GWDSP is positive in both models of political information exchange, but the GWESP is insignificant in both. Second, turning to exogenous effects, there is a significantly positive effect for powerful actors to send and receive technical information. Powerful actors tend to send and receive technical information more than powerless actors. However, note that the effect that powerful actors receive technical information disappears in model 2. Powerful actors also have a strong tendency to send political information. The tendency of powerful actors to send political information is clearly stronger than their tendency to send technical information. While the coefficients for technical information are 0.81 and 1.11, respectively, the coefficients in the political information models are 2.87 and 2.20, respectively. The size of effects, i.e. the odds ratio of observing a collaborative tie if the independent variable increases by one unit, can be obtained by calculating the exponential function of effects. Thus, being considered as powerful by other actors increases the odds of
sending out political information by 803% (8.03, i.e. $e^{2.20} − 1$) or more. Yet, it increases the odds of sending technical information by only 125% (1.25, i.e. $e^{0.81} − 1$). Further, by contrast to their strong tendency to send political information, powerful actors do receive political information much less than other actors.

*Table 1. ERGM results*

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th></th>
<th>Model 2</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Technical information</td>
<td>Political information</td>
<td>Technical information</td>
<td>Political information</td>
</tr>
<tr>
<td>Edges</td>
<td>-3.50</td>
<td>-4.92</td>
<td>-3.80</td>
<td>-4.85</td>
</tr>
<tr>
<td></td>
<td>-0.33</td>
<td>-0.33</td>
<td>-0.36</td>
<td>-0.39</td>
</tr>
<tr>
<td>Reciprocity</td>
<td>1.84</td>
<td>5.18</td>
<td>2.07</td>
<td>5.53</td>
</tr>
<tr>
<td>GWESP</td>
<td>1.12</td>
<td>0.11</td>
<td>1.08</td>
<td>0.06</td>
</tr>
<tr>
<td>GWDSP</td>
<td>-0.22</td>
<td>-0.14</td>
<td>-0.22</td>
<td>-0.14</td>
</tr>
<tr>
<td>Powerful actors - receiving</td>
<td>0.48</td>
<td>-2.42</td>
<td>0.33</td>
<td>-2.06</td>
</tr>
<tr>
<td></td>
<td>-0.24</td>
<td>-0.57</td>
<td>-0.27</td>
<td>-0.60</td>
</tr>
<tr>
<td>Powerful actors - sending</td>
<td>0.81</td>
<td>2.87</td>
<td>1.11</td>
<td>2.20</td>
</tr>
<tr>
<td></td>
<td>-0.25</td>
<td>-0.56</td>
<td>-0.28</td>
<td>-0.57</td>
</tr>
<tr>
<td>Science - receiving</td>
<td></td>
<td></td>
<td>-0.49</td>
<td>0.84</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>-0.20</td>
<td>-0.39</td>
</tr>
<tr>
<td>Science - sending</td>
<td></td>
<td></td>
<td>0.51</td>
<td>-1.79</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>-0.20</td>
<td>-0.49</td>
</tr>
<tr>
<td>Belief similarity</td>
<td>0.57</td>
<td>1.28</td>
<td>0.53</td>
<td>1.29</td>
</tr>
<tr>
<td></td>
<td>-0.17</td>
<td>-0.26</td>
<td>-0.17</td>
<td>-0.25</td>
</tr>
<tr>
<td>Past collaboration</td>
<td>0.63</td>
<td>0.70</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>-0.20</td>
<td>-0.24</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AIC</td>
<td>757.89</td>
<td>437.32</td>
<td>743.18</td>
<td>420.24</td>
</tr>
<tr>
<td>BIC</td>
<td>793.05</td>
<td>472.48</td>
<td>793.41</td>
<td>470.47</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-371.95</td>
<td>-211.66</td>
<td>-361.59</td>
<td>-200.12</td>
</tr>
</tbody>
</table>
The last effect in models 1 is given by belief similarity, which has a positive influence on actors’ sending technical as well as political information. Still, the size of these effects is different. Coefficients are 0.53 and 0.57, respectively, in the technical information exchange models and 1.28 and 1.29, respectively, in the political exchange models. Again, we can calculate the size of effects. While the probability that two actors exchange technical information increases by 69% (0.69, i.e. $e^{0.53} - 1$) if they have similar beliefs, the odds that they exchange political information increases by 260% (2.60, i.e. $e^{1.28} - 1$).

All these effects are robust if we add additional variables in model 2, unless the effect of powerful actors receiving technical information. Additionally, model 2 shows that scientific actors have a negative tendency to receive technical information, but tend to receive more political information than other actors. On the contrary, while scientific actors send out more technical information than other actors, they do so much less than other actors for political information. Finally, the effect of two actors having collaborated in the past is significant and positive in both networks.³

**DISCUSSION**

We hypothesized that belief similarity, power, scientific competences and trust have a positive impact on the creation of ties among actors in the information network. In accordance with hypothesis 1a, we can confirm that actors who perceive each other as allies and that substantially agree on policy design to regulate unconventional gas development, have the positive tendency to exchange information among each other. In the same vein, also hypothesis 1b can be confirmed:

³ Additional control variables (node covariate for political actors’ sending and receiving ties, node covariate for industry actors’ sending and receiving ties, edge covariate for political information exchange in the technical information exchange network, and vice versa), do not substantially affect our results. The only effects that disappear are the sending and receiving effects for scientific actors in the political information exchange network.
similar preferences are more relevant in the political than the technical information exchange network. This result tells us two things: first, and as already argued by Leifeld and Schneider (2012), it seems crucial to differentiate between information that concerns the technical nature of the policy problem to solve; and information concerning properties and institutional specificities such as venue shopping strategies and agenda setting of a political setting. The latter thus also seems to come closer to what can be defined as coordination patterns among like-minded peers or coalition members (Weible 2006; Sabatier 1988).

Results with respect to actors’ power in the network are less clear and do, basically, not support our hypothesis. On the one hand, powerful actors do considerably exchange (send and receive) technical information, but we did not formulate any theoretical expectations with respect to this type of information exchange. On the other hand, powerful actors do send political information more than others, but different than hypothesized, they have a negative tendency to receive political information from others. One explanation for this counter-intuitive finding could be that other actors have the impression that those actors are powerful exactly because they already hold an important amount of information about the political activities of others. Complementarily, powerful actors are already in a politically favorable position and might therefore not feel the need to further enhance their position through the gathering of additional information. Both elements would probably mean that in the long run, powerful actors would not be able to keep this position.

We can corroborate the hypothesized role of science in policymaking under uncertainty: Scientific actors considerably provide other actors with technical information. They do not receive technical information and are rather passive in the political information exchange network. All this is not surprising, as scientific actors definitely need technical information for their research and activities, but do typically not search them in the political decision-making
process. Furthermore, the mere role of scientific actors is knowledge provision rather than lobbying or accessing formal decision-making. This is suggested by their negative tendency to send political information relations.

Finally, we can partly confirm our third hypothesis. On the one hand, there is strong evidence for our hypothesis 3a, which suggested that if two actors have shared contacts or have collaborated in the past, they are likely to exchange information in political and technical information exchange networks. If two actors have collaborated in the past, they have indeed a higher probability to exchange both technical and political information. If two actors have shared contacts (assessed via transitive triads as measured by the GWESP parameter), this leads them to exchange technical information, but not political information. In hypothesis 3b we expected the trust effects to be stronger for the exchange of political information than for the exchange of technical information. However, this seems not to be the case. First, there is no difference between the strength of the influence of past collaboration on political and technical information exchange. Second, the pattern with respect to shared partners is exactly the opposite of what we expected, as shared partners matter in the technical information exchange network, but not in the political exchange network. As an ad-hoc explanation, we can again point towards the early stage of decision-making and the high uncertainty influencing this policy domain. Given strong scientific uncertainty, actors need to rely on trust contacts to gather technical information. By contrast, under behavioral uncertainty, it might even be difficult for actors to realize they have shared partners, and, as a consequence, to rely on this information to assess who to contact for political information exchange.
CONCLUSIONS

We defined information exchange as an important pre-condition for political decision-making and therefore as having an important impact on policy outputs. More specifically, we argue that this holds particularly for subsystems dealing with yet scientifically uncertain phenomena or problems. Under scientific uncertainty, political actors are keen to exchange information with others to increase their ability to form and justify (voting) decisions (Kenny 1992). We further outline that actors particularly rely on information from ideological peers, from organizations they perceive as powerful and that they trust, and from scientists.

To test these assumptions, we analyzed regulation and decision-making about unconventional gas development in the UK between 2007 and 2012. Unconventional gas exploitation and the method of fracking still come with several uncertainties related to their impact on the environment (Stevens 2013; IEA 2012; Stevens 2010). Based on survey data on a set of actors participating in the UK fracking politics subsystem, we run exponential random graph models. Results from these models allow us to answer the question of what drivers lead actors to exchange technical and political relations in the context of uncertainty.

We can conclude that belief similarities on how to regulate unconventional gas development matters more for information exchange than power. In a political subsystem that is characterized through certain scientific uncertainties, actors thus seem to rely on information from like-minded others rather than from organizations they perceive as powerful. The same holds true for organizations who already know each other from previous processes and over one decade: actors who share past contacts and collaboration relations tend to considerably exchange information in an uncertain policy domain. Further, trust as assessed through shared partner configurations plays a role for the exchange of technical information. Finally, we could confirm that scientific actors
play the mere role of technical knowledge providers and are less active in political information exchange.

Furthermore, this study also confirmed that the type of relations matter. Information exchange can take various and very different forms. We therefore differentiated between technical information and political information relations (see Leifeld and Schneider 2012). The first is typically provided by scientists, as our results confirm; whereas the latter seems rather relevant to other political actors in the policy network.

Besides those insights, there is one limitation that future research may try to overcome: we strongly argue in this paper that information exchange and several causal mechanisms are particularly relevant in policy domains dealing with a social or environmental problem that still is very complex and uncertain. To test this assumption, comparative research is needed including cases with different degrees of scientific uncertainty.
References


