Université de Montréal

An Enforced Cooperation: Understanding Scientific Assessments in Adversarial Polities through Quebec Shale Gas Policymaking, 2010-2014

Par Alexandre Harvey

Département de Science politique, Faculté des Arts et des Sciences

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Résumé

Les biotechnologies, le réchauffement climatique, les ressources naturelles et la gestion des écosystèmes sont tous représentatifs de la “nouvelle politique de la nature” (Hajer 2003), un terme englobant les enjeux marqués par une grande incertitude scientifique et un encadrement réglementaire inadapté aux nouvelles réalités, suscitant de fait un conflit politique hors du commun. Dans l'espoir de diminuer ces tensions et de générer un savoir consensuel, de nombreux gouvernements se tournent vers des institutions scientifiques *ad hoc* pour documenter l'élaboration des politiques et répondre aux préoccupations des partie-prenantes. Mais ces évaluations scientifiques permettent-elles réellement de créer une compréhension commune partagée par ces acteurs politiques polarisés? Alors que l'on pourrait croire que celles-ci génèrent un climat d'apprentissage collectif rassembleur, un environnement politique conflictuel rend l'apprentissage entre opposant extrêmement improbable. Ainsi, cette recherche documente le potentiel conciliateur des évaluation scientifique en utilisant le cas des gaz de schiste québécois (2010-2014). Ce faisant, elle mobilise la littérature sur les dimensions politiques du savoir et de la science afin de conceptualiser le rôle des évaluations scientifiques au sein d'une théorie de la médiation scientifique (*scientific brokerage*). Une analyse de réseau (SNA) des 5751 références contenues dans les documents déposés par 268 organisations participant aux consultations publiques de 2010 et 2014 constitue le corps de la démonstration empirique. Précisément, il y est démontré comment un médiateur scientifique peut rediriger le flux d'information afin de contrer l'incompatibilité entre apprentissage collectif et conflit politique. L'argument mobilise les mécanismes cognitifs traditionnellement présents dans la théorie des médiateurs de politique (*policy broker*), mais introduit aussi les jeux de pouvoir fondamentaux à la circulation de la connaissance entre acteurs politiques.

Mots clés : médiation, évaluation scientifique, apprentissage collectif, élaboration des politiques publiques, conflit politique, analyse de réseau, sous-système, Exponential Random Graph Model

Summary

Biotechnology, climate change, natural resources, and ecosystem management are all representative of the “new politics of nature” (Hajer 2003), a term encompassing policy issues with high scientific uncertainties, unadapted regulatory regimes, and acute political conflict. In the hope of diminishing these tensions and generating a consensual understanding, several governments mandated *ad hoc* scientific institutions to document policymaking and answer stakeholder’s concerns. But do those scientific assessments really help to generate a shared understanding between otherwise polarized policy actors? While it would be possible that these create inclusive collective learning dynamics, policy learning has been shown as being extremely unlikely among competing policy actors. Accordingly, this research documents the conciliatory power of scientific assessments using the Quebec shale gas policymaking case (2010–2014). In doing so, it mobilizes the literature stressing the political nature of science to conceptualize scientific assessment in light of a scientific brokerage theory. Empirically, the research uses Social Network Analysis to unravel the collective learning dynamics found in two information networks built from the 5751 references found in the advocacy and technical documents published by 268 organizations during two public consultations. Precisely, findings demonstrate that scientific brokerage can redirect information flows to counteract the divide between collective learning and political conflict. The argument mobilizes cognitive mechanisms traditionally found in policy brokerage theory, but also introduces often forgotten power interplays prominent in policy-related knowledge diffusion.

Keywords: brokerage, scientific assessment, collective learning, policymaking, policy, political conflict, social network analysis, subsystem, Exponential Random Graph Model

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List of Abbreviations

ACF .... Advocacy Coalition Framework

BAPE .... Bureau d'audience publique sur l'environnment

EES .... Évaluation environnementale stratégique

ERGM .... Exponential Random Graph Model

IPCC .... Intergovernmental Panel on Climate Change

SNA .... Social Network Analysis

Introduction

Climate change mitigation, biotechnology, and ecosystem management are all representative of the "new politics of nature" (Hajer 2003). Characterized by an increasing complexity, they regularly exhibit an important degree of technicality, ambiguity, and uncertainty. Their scope goes well beyond the human one and possesses a multidimensional nature. Such peculiarities often lead to a broad range of individuals to involve in the policymaking process, each of them having their own—and most of the time incompatible—set of political preferences, worldviews, and interests. Those actors respective expertise are diverse and range from a user-gathered local knowledge to an impressive amount of scientific sophistication in a delimited field of inquiry. As a consequence, post-materialist issues such as those noted above are frequently entangled with acute political contention resulting from competing interests.

From a governmental point of view, the new politics of nature poses important challenges to good management. The significant amount of complexity induces legitimacy and analytical capacity concerns, which in turn push governments toward a broader articulation of governance to achieve efficient problem solving. Such articulation of governance, however, falls outside traditional policymaking institutions. Indeed, issues of the new politics of nature transcend existing structures of governance and occur through what Hajer called the "institutional void":

> *"established institutional arrangements often lack the powers to deliver the required or requested policy results on their own [and, accordingly, policymaking takes] part in transnational, polycentric networks of governance in which power is dispersed" (2003, 175).*

In the absence of agreed rules, the polity becomes mostly informal and emerges as a consequence of deliberative policymaking instead of constraining it. Understood simultaneously, the interaction between (1) the need for a decentralized form of governance (2) high potential for political conflict, and (3) deliberative and poorly institutionalized political arenas poses crucial political challenges to contemporary societies.

To grasp those challenges, numerous societies rely on broad, open, and deliberative scientific assessments to document the issue at hand and give political actors a common understanding of a given phenomenon. However, insights from the new politics of nature suggest the probabilities of success are rather thin. As explained with greater details in the theoretical part of this research, political conflict, deliberation, and genuine collective learning make poor associates. Strong policy-related beliefs induce political confrontations, which in turn activate cognitive defence mechanisms further limiting the potential for constructive dialogue. Hence, understanding the processes by which societal debates become polarized and means of mitigating such outcome rises as a pressing and necessary research agenda. Assessing how information is created, how it circulates across policy actors, and why a particular argument is rejected or welcomed into an individual's cognitive system constitutes a significant contribution to the new politics of nature. Specifically, this research contributes to this research agenda by investigating the capacity of scientific assessments to diminish political conflict:

Can scientific assessments create a shared understanding between political actors operating in adversarial policymaking?

I - An Important Inquiry

While one should acknowledge that the authority of science and expertise in policymaking has been severely criticized in the literature to the point where some practitioners developed their own skepticism about their validity (Jasanoff and Wynne 1998), reasons are strong to believe that scientific knowledge remains central to policymaking and still holds a firm intellectual leverage and legitimacy-building potential. From an empirical perspective, science is frequently invoked on pragmatic grounds as the predominant technique to reduce uncertainty. Shale gas, which constitutes the empirical foundation of this research, remarkably illustrates such phenomenon. Heavily concerned by the environmental, social, and health-related problems emanating from hydraulic fracturing, environmental and local groups around the globe mobilized against the industry, fuelling controversy over the soundness of extracting the resource. In the hope of increasing knowledge about hydraulic fracturing and managing the rising animosity, many jurisdictions sponsored scientific assessments to guide their policymaking process (e.g. Advanced Resources International 2013; British Columbia Ministry of Health 2014; Bureau d'audiences publiques sur l'environnement 2014; U.K. Geological Survey 2015; U.S. EPA 2015; U.S. Geological Survey 2015). To be sure, whether or nor these operations succeeded in generating collective learning and rallying political actors around a common policy stance is a matter of empirical investigations. Yet, from a new politics of nature perspective, success appears unlikely, and the absence of formal institutions to structure the policymaking process presumably increases the prominence of knowledge, arguments, and persuasion as political tools. Accordingly, "to better understand policy processes is thus to understand how scientific and technical explanations are integrated into (or deflected from) belief systems, used in political debates and negotiations, and integrated with other forms of knowledge, especially local knowledge" (Jenkins-Smith et al. 2014, 187).

This research understands scientific assessments as the processes by which an open, transparent institution reviews the state knowledge, orders further scientific studies, and draws conclusions from an amalgam of scientific disciplines. From the outset, those institutions are constructed for the explicit purpose of policy-oriented learning and possess high salience among policy actors. These peculiarities make them a particularly interesting object to study collective learning in adversarial policymaking, yet assessments remain under-investigated. As Nilsson argues:

> *"there are relatively few empirical studies on how assessments are used in national policymaking. There is a need for longitudinal research on how assessments' recommendations, arguments, and underlying premises link to the evolution of public policies and their underlying arguments, as well as key actors' policy positions and underlying belief systems."* (2005, 228).

In line with this reasoning, Sabatier (1987) suggested that such professional forums could facilitate collective learning and diminish the chances of policy stalemate. However, empirical investigations of this hypothesis remain scarce (Jenkins-Smith et al. 2014), and understanding exactly how assessments could create a shared understanding in context of extreme political conflict continues to be an unresolved question.

II - The Study in Theoretical Perspectives

Unfortunately, the under-investigation of the phenomenon is all the more problematic given that conciliation of ideas is a normatively appealing ideal. As Ansell & Gash wrote:

> *"The term" collaborative governance" promises a sweet reward. It seems to promise that if we govern collaboratively, we may avoid the high costs of adversarial policy making, expand democratic participation, and even restore rationality to public management. A number of the studies reviewed here have pointed toward the value of collaborative strategies: bitter adversaries have sometimes learned to engage in productive discussions; public managers have developed more fruitful relationships with stakeholders; and sophisticated forms of collective learning and problem solving have been developed."*(2008, 561)

Indeed, apart from collective learning, collaborative governance has been linked to better management of complex and ambiguous ecological systems, reducing uncertainty, building a stronger knowledge base, aggregating diverse perspectives, taking into account social, political and ethical values, enhancing democratic legitimacy, transparency, efficiency, and social acceptability, adapting policy to the local context, and empowering marginalized groups (Griffiths 2000; Jacobs, Luoma, and Taylor 2003; Reed et al. 2006; Rogers 2006; Steyaert and Jiggins 2007). In their meta-analysis of 137 case studies, Ansell and Gash (2008) identified nine independent variables contributing to these outcomes: the forum is formal, consensus-driven, involves in-person dialogues, is initiated by a public agency, participants include non-state actors, participants engage directly in policymaking and are not merely consulted, organic leaders create brokerage and shuttle diplomacy and, lastly, achieving small intermediate gains to build commitment and satisfaction is possible.

In spite of its efforts to explain how collaborative policymaking emerges, this literature faces severe criticisms, to the point where it appears unadapted to investigate with great details the present inquiry, especially when it comes to explaining the failure of collaborative institutions or the nature of political interplays. Among the recognized problems, dealing with ubiquitous power relationships is the most obvious one. Indeed, research on knowledge in policymaking convincingly demonstrated how increased technical and analytical knowledge does not necessarily lead to compromises and new understandings. In fact, articulation between science and politics is highly contextual and variable, but even in participative institutions, power remains a fundamental part of social relations (Adams 2004; Griffiths 2000; Jasanoff and Wynne 1998; van Kerkhoff and Lebel 2006; Pielke 2007; Pielke Jr. 2004; Weiss 1979). Moreover, the approach "has been challenged for failing to produce the objective empirical and normative standards implied by its scientific aspirations" (DeLeon and Varda 2009, 59). Finally, one can note the imperfect adequacy between collaborative institutions as conceptualized by the literature and the assessments as defined above. Indeed, assessments do not correspond to cooperative arenas of policymaking *per se;* they do not involve face-to-face dialogues, are expert-based processes, have most of the time a mere consultative function, and their scope is often too large to implement efficiently deliberative democracy's prescriptions (Parkinson 2003).

Consequently, this research leaves deliberative democracy aside, and instead tries to minimize the limitations mentioned above by concentrating on the more power-oriented policy network literature (e.g. Heikkila and Gerlak 2013; Ingold 2011; Ingold and Varone 2011; Jenkins-Smith et al. 2014; Weible 2008). In doing so, it rejects the view upon which information floats in a disembodied, freely available "knowledge reservoir". Not only is knowledge indistinguishable from its political vehicle, but it is also more-or-less complex, redundant, coherent, fragmented, and more. As a results, this research argues that the general state of knowledge can be outlined and differentiated across subsystems, but also that the natural flow of information in adversarial networks can be mapped, both theoretically and methodologically. The advantage of doing so is that scientific assessments can be conceptualized as an element within the broader information network: a *scientific brokers*, i.e. an actor dedicated to the integration of competing viewpoints and multiple scientific disciplines in the hope of producing compromising policymaking (Ingold and Varone 2011). Seeing assessments as such yielded fruitful understandings: the exact mechanisms by which they can distort antagonistic flows of information to foster greater collective learning are exposed in Chapter 1, along with the network-wide benefits resulting from such activity.

III - Methodological Strategy

The study takes a quantitative, case-based approach to test the hypothesis on scientific brokerage. Namely, Social Network Analysis (SNA) is used to measure information flows. The data come from the Quebec shale gas subsystem, which constitutes an ideal case to materialize the new politics of nature. Indeed, a 5-year, highly adversarial debate occurred between 2010 and 2015. The object of contention was whether or not shale gas should be exploited in the province, a subject encompassing an important level of technical uncertainty, possessing multiple dimensions, being the concern of several scientific disciplines, and involving a plurality of political groups advocating for incompatible outcomes. But aside from being a good representation of the new politics of nature, what makes it a remarkable case to study the problem is that the societal debate took place in an open and deliberation-oriented institution—the *Bureau d'audience publique sur l'environnment* (BAPE)—and occurred twice, once before and once after a scientific assessment—the *Évaluation environnementale stratégique* (EES). As the consultations were separated by a broad, highly salient scientific assessment, the design makes it possible to grasp the effect of scientific brokerage by comparing the state of collective learning before and after it occurred.

Reasons are strong to believe the case represents a robust test for scientific brokerage. As Ingold and Varone argue, "it would be very beneficial to expand the empirical basis by also considering negative cases. […] explaining both change and stability (despite intense policy brokerage) within an integrated theoretical framework is still a major challenge" (2011, 22). As stated earlier, it is assumed that whether scientific brokerage succeeded or failed to sustain a shared understanding is a matter of empirical investigations. What is interesting about the Quebec case is that it directly answers Ingold and Varone's argument. If brokerage can, indeed, induce collective learning despite a high level of contention, then it should be observable in the selected settings. Alternatively, if failure is observed, then the comparative mapping of information flows should make it easier to assess why brokerage was inefficient.

Admittedly, operationalizing such vague concepts as information flows and collective learning appears like a sizeable challenge (Bennett and Howlett 1992). While numerous studies investigated the phenomenon using qualitative approaches (e.g. Béland 2006; Frantz and Sato 2005; Frey 2010; Harrison 2001, 2002; Nilsson 2005; Vifell and Sjögren 2011), the methodological strategy used in this research takes an innovative stance and assumes that the references contained in policy documents—in-text references, citations, footnotes, and bibliography—are reliable demonstrations of external influence on an actor's rationale (McNutt 2012; Shwed and Bearman 2010). Accordingly, the 5751 references found in technical and advocacy documents published by 268 policy actors during the two public consultations were transformed into relational matrices exploitable by Social Network Analysis (SNA).

SNA is a statistical technique aimed at studying the links (relations) between nodes (actors). In political science terms, this means that SNA "offers a means of addressing one of the holy grails of the social sciences: effectively analyzing the interdependence and flows of influence among individuals, groups, and institutions" (Ward, Stovel, and Sacks 2011, 145). Amidst the advantages of the approach, one can note the possibility to study, visually and quantitatively, important aspects of social organizations that are not captured by study of actors' attributes. Moreover, the model has a capacity to extract relational data from the systemic level, for instance the density of interactions, the existence of communities, the equivalent position of two or more actors, the structural divisions between subgroups, etc. In addition, SNA can provide fruitful information at the individual level, for example by documenting the proximity between two actors, central or peripheral positions in the network, the dependencies upon others to reach a particular individual, etc. (Knoke and Yang 2008;

Scott 2013; Ward, Stovel, and Sacks 2011). For the purpose of this study, SNA allowed to measure collective learning and scientific brokerage, but also to assess whether or not these observations were statistically reliable from an inferential point of view.

IV - Structure of the Thesis

The first chapter provides the theoretical foundations of the analysis and develops a hypothesis regarding the capacity of scientific assessment to sustain collective learning. Case, method, and data justifications are provided in the first part of Chapter 2, followed by an explanation of the analytical strategy. The third chapter presents the empirical results along with a discussion engaging brokerage theory. An appraisal of this study's limits and suggestions about further investigations anchor the concluding section.

Chapter 1: Theoretical Framework

This chapter lays the foundations needed to understand how scientific assessments can create a shared understanding between policy actors. Three main objectives drive its structure: (1) describe the role of knowledge in the policymaking process (2) understand how knowledge is constructed, gathered, transformed and assimilated by actors, and (3) predict how scientific brokerage may alter such information flows.

I - Understanding Policy-oriented Knowledge

Giving an exact definition of knowledge is a daunting task, but the first step toward its completion is to acknowledge the existence of a "plurality of expertise, with ideas coming from a wide variety of sources, including think tanks (Abelson 2007; Lindquist 1993), consultants (Spears 2007), academics (Borins 2003; Cohn 2007), and advocacy groups (Stritch 2007)" (McNutt 2012, 17). It is usual to see science being promoted as one of the purest representations of knowledge, mostly because of its collective responsibility for progress (Oreskes 2004) and objectives of generalization, causality demonstration, and empirical validation (Rogers 2006). Nevertheless, it should be acknowledged that science, at least with regard to policymaking, shares many attributes of the common. Its authority emerges from a socially accepted claim of rationality, but like all forms of knowledge, a palatable truth ultimately relies on an intellectual consensus among similar actors based on a shared methodology and a communal set of social, historical, economic, political, and epistemological attributes (Oreskes 2004).

Policy-oriented knowledge is frequently widespread, heterogeneous, and divided between several policy actors, each of them having their own perspective regarding (1) the seriousness of various dimensions of the problem (2) the importance of its causes, and (3) the potential benefits of the solution they advocate for. Taken as a whole, these three objects represent the core of policy-oriented knowledge. This knowledge may be more or less intellectually demanding, ranging between what is known [e.g. gravity], what is complicated but knowable [e.g. car engineering], what is unknowable but partly predictable [e.g. meteorology], and what is completely chaotic [e.g. the behaviour of a double pendulum] (Steyaert and Jiggins 2007). The difference between the known and the chaotic lies within the ability of experts to make better predictions than non-experts. In most modern policy issues, the level of complexity is such that even the most erudite are no more useful than a basic statistical model to predict outcomes (Hird 2005). In light of these limitations, many scholars argued for a withdrawal from expert-based policymaking in favour of a deliberative turn and an empowerment of marginalized groups (e.g. Albæk 1995; Gibbons et al. 1994; Rogers 2006). Such a transition, however, has been criticized for its negligence of a ubiquitous element of knowledge relationships: its political nature (Griffiths 2000).

Political Knowledge

The concept of political knowledge encompasses many different ideas. For instance, Stehr (2005) talks about knowledge as an object of regulation, about "attempts to channel the social role of knowledge, to generate rules and enforce sanctions […], to affix certain attributes […], and—likely the most controversial strategy—to restrict the application of new knowledge and technical artifacts." More relevant for this study is the idea that information constitutes a powerful political resource to promote policy preferences (Bennett and Howlett 1992). An improvement of knowledge about ecosystems, for example, might increase the awareness among policy actors of their interdependencies and transform their relationship (Steyaert and Jiggins 2007). Similarly, a government delegating decision-making to an apolitical and knowledge-oriented institution may in fact abdicate a portion of its policy capacity, as even apparently meaningless technical decisions often have significant political implications (Vifell and Sjögren 2011).

The value of information as a political resource is increased when policymaking occurs through what Hajer (2003) named the "institutional void". In the absence of established structures, the elaboration takes a discursive turn; exchanges between actors involve viewpoints, persuasions, arguments, but also a negotiation about the rule of the game and who ought to govern the policymaking process. Such a deliberative process exacerbates the already extensive role of argumentation in shaping power relations:

> *"[because] decision-making processes are rooted in language and based on argumentation and discussion, they can never be entirely arbitrary and can never be fully explained by saying that a single actor or coalition of actors determines the form and content of the decision-making process. Arguments are always subject to certain rules and procedures; and the content of the arguments must refer to, and be integrated with, a wider set of concept formations, which in a concrete historical situation cannot be freely selected by the actors themselves"* (Albæk 1995, 90).

While strongly institutionalized structures have the necessary "rules and procedures" to determine insiders and frame their interactions, the institutional void creates a porous policymaking environment open to a plurality of expertise competing with each other to establish norms of governance (Frey 2010; Grundmann 2007). Sources may fight over which type of knowledge should be considered relevant (science, practitioners' experience, user-based information, etc.), its object (effectiveness, political acceptability, or costs of recommendations), interpretation of shared information, or the political settings surrounding the debate (closed vs open subsystems, pluralism vs corporatism, collaborative vs expert-based institutions, etc.). This battle is not superficial or purely motivated by a willingness to dominate the process, but rather results from deep intellectual divides. As knowledge is seldom a pure accumulation of neutral facts, but more frequently produced to answer ambiguous criteria and issues, prior professional, emotional, intellectual, and psychological assets inevitably alter the meaning attributed to knowledge and the related behaviours it sustains (Vifell and Sjögren 2011). The point here is that the institutional void opens policymaking to a wide variety of more or less compatible expertizes competing to establish their influence, a phenomenon which in turn increases the likelihood of knowledge politicization.

A prominent step toward a better comprehension of knowledge politicization is to delineate what it is not. Practitioners frequently describe the connection between science and policymaking as being "linear" (Pielke Jr. 2004). At the core of this conception is the idea that:

> *"technological development is the prime driver of progress and enlightenment; that non-scientific belief systems are based on popular ignorance and superstition; that advances in scientific knowledge inevitably reduce uncertainty; and that increased absorption of science leads to convergence in social understanding and public policy" (Jasanoff and Wynne 1998, 4)*

Scholars have shown that the mere existence of such function is utterly dubious, for the alignment of necessary conditions is highly unlikely (Weiss 1979), and the conceptual coherence of the model appears questionable (Albæk 1995). Most importantly, the model has been criticized for disregarding the possibility that knowledge acts as a political instrument (Hoppe 1999).

By opposition, models acknowledging knowledge politicization (e.g. Weible 2008) point toward two major components. Firstly, knowledge can become an arm of persuasion, an instrument to convince and gather political capital. Second, actors embedded within conflicting relations tend to increase their skepticism about novel information and diminish their willingness to listen to competing ideas. Taken as a whole, the phenomenon produces political settings in which information is more instrumental than enlightening. In such a context, the predicted advantages of deliberative democracy, notably fostering learning to improve policy outputs, seem thoroughly implausible. But what exactly are the factors stimulating collective learning?

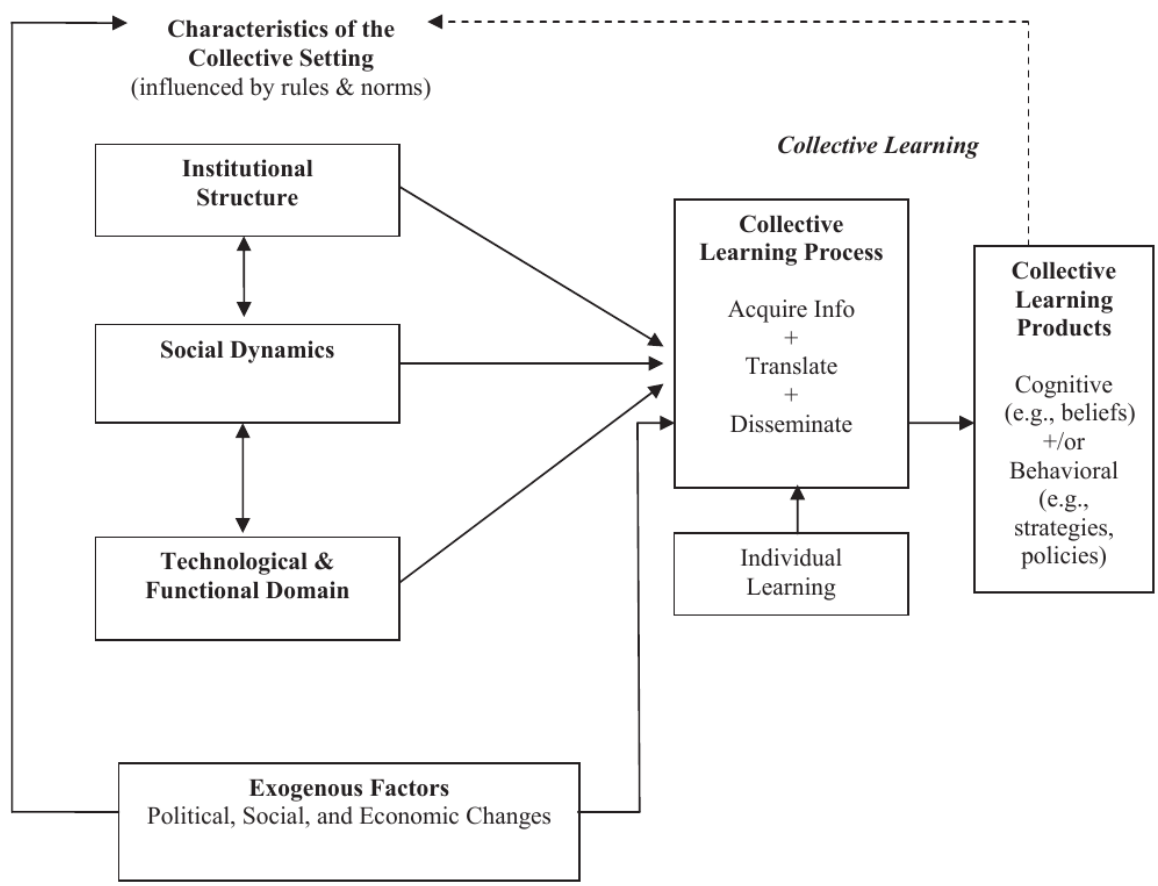
A Review of Collective Learning

For Bennett and Howlett (1992), policy learning is a complex, multi-faceted phenomenon by which perceptions about the what, who, how, and why dimensions of a policy are transformed (see also Hall 1993; Sabatier 1987). More precisely, learning may be understood as an "enduring alterations of […] behavioural intentions that result from experience and which are concerned with the attainment or revision of the precepts of the belief system of individuals […]" (Jenkins-Smith et al. 2014, 42–56). Even if the concept of learning has been extended to programs, instruments, organizations, and collectivities, learning remains purely limited to individuals; only the interplays between these actors can give the concept its social resonance and lead to political consequences (Gerlak and Heikkila 2011; P. A. Sabatier and Zafonte 2001).

The exact means by which learning becomes collective are complex, but the literature converges toward a three-stage phenomenon, as summarized in Figure 1.1 (Gerlak and Heikkila 2011; Heikkila and Gerlak 2013; Nilsson 2005; Wolman and Page 2002). Firstly, an individual must acquire novel information from others, for example by assimilating experiences, new ideas, or concepts. The stage implies a receiver, a producer and a sender of information who exchange information through an at least semi-structured sustainable network. In other words, it entails a supply, a demand, and an activity linking both (Craft and Howlett 2012). Information acquisition is, however, insufficient to sustain learning, which can only be achieved through a second stage: translation. Translation represents the consolidation of novel knowledge into an individual's beliefs. It is a latent process strongly affected by cognitive assets, frames, problem definition, perception of validity and accurateness, as well as institutional, historical, cultural, and political settings (Wolman and Page 2002). When successfully implemented, gaining new understandings of cause-effect relations of policy problems and how to resolve them can foster behavioural changes pertaining to goals, strategies, or activities.

Translating this alteration of thoughts into a social phenomenon is only possible if the third phase of collective learning—dissemination—is fulfilled, which may bolster convergence of subsystems' actors. When policy actors share similar ideas about an issue, the increased agreement makes it easier to move beyond the *status quo* and revise procedures or policies. This is not to say that dissemination of ideas always leads to convergence of opinions. Indeed, diffusion of knowledge does not guarantee persuasion, and the encounter of prior beliefs with novel information may lead to four types of responses at the individual level: (1) opinion shifting [complete change of opinion] (2) opinion softening [relaxation of policy preferences] (3) position-taking [from neutral to partial], or (4) opinion hardening [reinforcement of policy preferences] (Montpetit and Lachapelle 2015; unpublished paper). Of those, only the first three are compatible with the ideals of deliberative democracy.

Figure 1.1: A Comprehensive Framework of Collective Learning[1]



Collectively, policy actors may not share a common response to a given information, for knowledge may be prevented from circulating freely or may have a differentiated influence on actors' rationale. For instance, a subgroup may temper its preferences while the other strengthens them, in which case one cannot talk about beneficial collective learning. The

1 Taken in Heikkila and Gerlak (2013)

picture is even worst if both sides strengthen their position. Thus, whether diffusion of ideas occurs at the subsystem level, is limited to subgroups, or leads to a polarization of actors has serious consequences for policymaking. As shown in Figure 1.1, empirical investigations of the phenomenon identified four broad categories of variables affecting the occurrence of each of these outcomes: (1) exogenous events (2) the technological and functional domain (3) structural factors, and (4) social relationships (Gerlak and Heikkila 2011; Heikkila and Gerlak 2013).

1. Exogenous Events

The first category pertains to external events, of which macroeconomic crises and political turnovers are conceivably the most prominent examples (Gerlak and Heikkila 2011). Obviously, listing exhaustively the possibilities and explaining how each of them impacts policy networks lies well beyond the scope of this research. Rather, the important point is to bear in mind that policy network can be relatively stable units over time (Larsen, Vrangbæk, and Traulsen 2006; Meijerink 2005; Paul A. Sabatier and Jenkins-Smith 1993, 1999; Zafonte and Sabatier 2004). Hence, exogenous factors may sometimes be necessary to challenge established dynamics:

> *“More broadly, these constraints on learning may be because rapid social, economic, or physical changes in the environment can threaten the stability of an institutional arrangement (Ostrom, 2005, p. 272) and in so doing may weaken some of the structural features or social dynamics that might support learning. However, such changes also could positively alter structural features, social dynamics, or technological and functional domains in ways that allow them to be more conducive to learning”* (Heikkila and Gerlak 2013, 500).

From a theoretical perspective, exogenous impacts have, therefore, the power to dispute the *status quo*. Nevertheless, events erupt on a contingent basis and are hardly predictable, casting some doubts on their usefulness to model typical patterns of collective learning.

2. Technological and Functional Domain

The second set of variables possesses stability similar to exogenous events, although with greater predictability. The technological and functional domain relates to the attributes of the policy and polity at hand. By delineating the levels of ambiguity, uncertainty, availability, transparency, and reliability of information:

> "the technological and functional domain can determine the type of information that a collective group will be interested in learning, seek out, or have access to, as well as how frequently and easily information can be shared, therefore shaping the acquisition, translation, and dissemination phases of the learning process" (Heikkila and Gerlak 2013, 497).

This hypothesis has been empirically corroborated by numerous scholars. For instance, a given ecological system with high level of uncertainty, bad quality of data and low availability of information is expected to limit agreement between competing coalitions (Jenkins-Smith et al. 2014). Silva and Jenkins-Smith (2007) found an association between variations in scientists' recommendation of the precautionary principle and the ambiguity of the problem. In Hird's study (2005) of U.S. state legislators, the political environment had positive and significant effects on legislators' perception of their source, even controlling for their cognitive assets. In further support of those results, Harrison (2002) demonstrated how the political structures caused an alteration in the use of scientific information about the pulp and paper industry pollution in the U.S., Canada, and Sweden. Frantz and Sato (2005) documented how domestic contexts affected the perception and usage of knowledge about leprosy in Japan and the U.S. Along the same lines, Grundmann (2007) showed how the national media impaired the transmission of IPCC's conclusions in Germany and the U.S.

The influence of functional and technological domain is, then, thoroughly documented. But just like exogenous events, the technological and functional domains of a policy are not expected to fluctuate intensely over a short period. As a consequence, trying to explain short- to mid-term collective learning with technological innovations, scientific enlightenment, or major alterations of political structures is unlikely to yield interesting theoretical predictions.

3. Structural Factors

The third category of variables corresponds to what Heikkila and Gerlak (2013, 494) defined "in terms of how the functions, tasks, or responsibilities in a group are organized and coordinated". Unlike social relationships, structural factors do not encompass dynamic relational dimensions, for instance cognitive heuristics affecting the perception of trustworthiness, but rather express the organization of a network resulting from the aggregation of its members. Counter-intuitively, structure is not solely the attribute of organizations or institutions, but also applies to knowledge. Information, far from floating randomly in a disembodied, indefinite reservoir, is rather organized in a structure reflecting its complexity, redundancy, compatibility, fragmentation, and more. Accordingly, for each policy network, a corresponding information network delimits the state, range, and potential uses of available knowledge.

The most basic structural attribute of information networks relates to the type of knowledge available, i.e. the supply side. Contemporary "advisory capacity" is on the edge of being chaotic: it is dispersed, fluid, pluralist, and polycentric. Policy-relevant knowledge combines technical expertise and political preferences, can be reactive or anticipatory, and comes from multiple sources addressing a broad range of decision-makers (Craft and Howlett 2012). Such a striking diversity has been empirically observed by Hird (2005) in his previously mentioned study of state legislators, who listed their information sources in descending order of relevance: constituents, nonpartisan legislative staff, fellow legislators, community organizations, legislative leaders, special committees, lobbyists, university-based research, executive agencies, national organizations, think tanks, partisan legislative staff, governors, media, political parties, and the Internet. Similarly, Wolman and Page (2002) observed that, for local officials, perception of relevance varied considerably between information channels (in descending order): informal conversation with fellow officials, governmental publications, good-practice guides, practitioner journals, conferences, study tours, newsletters, electronic information, conversation with researchers, academic journals, and conversation with councillors.

From a cognitive perspective, the duplication of information sources and channels poses prominent challenges to collective learning. Indeed, it has been shown that information availability and consistency, as well as its perceived validity, quality, and usefulness were all positively correlated with the translation of external knowledge into internal beliefs (Frey 2010). When sources and media are overabundant, the multiplication of messages brings considerable noise into the information network and increases the chances of contradictory signals. Workman, Jones, and Jochim (2009) clarified the phenomenon by differentiating overlapping from cumulative information. Whereas socially independent actors may increase the overall supply of information by providing non-repetitive and complementary knowledge, a multiplication of interconnections between sources—as when a common political cause pushes them to join the same policy network—is likely to expand redundancy to a point where the system becomes maladapted and "relevant information [is] drowned out by the echo" (2009, 85). Thus, the more salient the issue, the more numerous the sources will be, enhancing probabilities to observe a confused and oversupplied information network. In such a case, distinguishing the relevant knowledge from irrelevant pollution becomes a cumbersome task, especially considering the bounded rationality of organizations (Korfmacher and Koontz 2003; Nilsson 2005; Workman, Jones, and Jochim 2009) and individuals (Béland 2006; Gowda 1999; Weyland 2009).

In addition to the quantity and diversity of information present in a network, the structure of information flows may affect probabilities of generating collective learning. Basically, information networks must constantly handle the tension between the range of available information and the efficiency of its management. Indeed, a centralized structure facilitates information acquisition and diffusion to the cost of inclusion, inasmuch as a decentralized structure yields better inclusiveness but harder management. To use the words of Heikkila and Gerlak (2013, 495–6):

> *"With a more integrated or centralized structure, learning could potentially be compromised if it insulates actors and leads to fewer opportunities to acquire diverse and*

new sources of information. However, with a more integrated structure, actors may have more opportunities to acquire information within a group and in the disseminate phase of learning to distribute information quickly and adopt new learning products. This is because the decision-making costs in a centralized context may be lower, or the structure may be designed such that a relatively smaller proportion of the actors in a group are needed for learning to be disseminated“.

4. Social Relationships

Akin to structural characteristics, social relationships bestow important explanatory power. What is understood by social relationships is mostly the influence of cognitive attributes in building a perception of trustworthiness, relevance, and leadership among policy actors. Such perceptions, in turn, enhance social connections, willingness to cooperate, and propensity to listen to. With regards to scientific assessments, some contemporary political actors developed what could be defined as an active cognitive suspicion against scientific information and claims of rationality. Hoppe (1999) called the phenomenon the “epistemological transformation of society”:

> “That social scientists shape the world they study by the way they define the problem has come to be accepted not only by social scientists but by sophisticated political actors as well. They are aware that researchers’ assumptions, theories, and choice of variables can have large effects on the answer they find. This new understanding throws into doubt the accommodation [with political and administrative practice] that earlier generations of social scientists had negotiated” (Weiss 1991; cited in Hoppe 1999).

A complementary literature suggests, however, that most individuals have a more limited awareness and remain mostly affected by passive cognitive attributes such as thinking styles, interpretative frames, belief systems, ideologies, professional paradigms, worldviews, scientific perspectives, and so on. Among the numerous examples of such processes, Béland (2006) identifies the heuristic of availability. Affected by existing ideological commitments and institutional legacies, the heuristic of availability is a cognitive shortcut giving higher saliency to easily attainable concepts. Weyland (2009) adds to the list the heuristic of representativeness—which leads to an overstatement of the benefits associated with a policy—and the heuristic of anchorage—which translates strong preferences for minimal adaptation of initial policy. More importantly, he demonstrates in his study of pension and health reforms in Latin America how these cognitive mechanisms affect even the most sophisticated of policy actors.

Moreover, prior attitudes have an important role to play in the assimilation of novel information. Recognition of a policy problem has been demonstrated as being dependent upon the reception of (1) a persuasive information—which implies credible messenger, high saliency, and efficient framing—that is different from the existing mental representation of the social or physical environment, and (2) a negative valence, i.e. a negative emotional reaction associated with this information (Munro and Ditto 1997; Oxley, Vedlitz, and Wood 2014). The combination of cognitive heuristics with prior attitudes "explain[s] how one and the same dynamic—whether affect, availability, biased assimilation, source credibility, or others—can, nevertheless, produce diametrically opposed risk perceptions in different people and indeed intense forms of polarization across groups of persons." (Kahan, Jenkins-Smith, and Braman 2011, 149). Illustrative of such processes, studies showed that the interaction between worldviews (Wildavsky 1987) and framing of risks affects the perception of scientific consensus (Kahan, Jenkins-Smith, and Braman 2011) as well as the perceived credibility of the source (Lachapelle, Montpetit, and Gauvin 2014). In addition, some results further add that social and cultural similarity as well as the level of involvement in the policy-process significantly affect the transfer of tacit and formal information (Lee and Meene 2012).

More subtle influences are also at play, as even professional affiliation and scientific fields of inquiry have been shown to influence risk perception. As Barke and Jenkins-Smith (1993, 432) wrote:

> *"Even where the scientific evidence is relatively rich, beliefs and judgments like those listed above can play a substantial role in giving context to these risks. Perhaps even more importantly, where uncertainty remains a large factor these beliefs and judgments may serve to plug the gaps in the data, filling in the unknowns with prior beliefs. For these reasons, the broader belief systems of scientists are likely to be of considerable importance".*

To be sure, heuristics, prior attitudes, and worldviews can have huge consequences for scientific assessments. Indeed, Nilsson (2005) found that scientific assessments were subject to strong manipulation of analytical scope by governments in an effort to bolster their preferences. He also found that assessments were strongly affected by framing effects from their own analysts' professional paradigms, biases, and beliefs. As a corollary, one should expect advocacy organizations to adopt a similar, strategic behaviour when interacting with the assessment.

An Integrated Picture of Collective Learning

Collective learning has been shown to involve two dimensions, the first one being the translation of novel information into one's beliefs, and the second one pertaining to the diffusion of those updated beliefs across the network. Moreover, knowledge diffusion is constrained by (1) relatively fixed exogenous events and functional characteristics and (2) more fluid structures of information networks and cognitive attributes of their members. In order to apply those results to the problem, one should recall that the new politics of nature involves a multidimensional character, high levels of uncertainty and ambiguity, as well as low-information accessibility. Equally important, the institutional void gives further strength to cognitive processes and information networks. Under the assumption of interest dissension, the active involvement of multiple stakeholders will increase exponentially sources and mediums of information, each of which communicates its own preferences. A plausible outcome for information networks is the appearance of an oversupply of knowledge leading to redundancies and drowning effects. Making things worst, information is expected to circulate with great difficulties within the network, as active and passive cognitive processes enhance mistrust and skepticism regarding unfamiliar frames, expertise, worldviews, and—more broadly—unshared physical or cultural attributes. Ultimately, adversarial networks appear constrained within a vicious cycle of intellectual isolation and social mistrust.

A priori, the presence of a scientific broker dedicated to conciliation may diminish most of the negative effects associated with oversupply, bounded rationality, cognitive heuristics, and inefficient structures of information flows (Heikkila and Gerlak 2013), provided that he can bridge between isolated actors, clean redundant information, facilitate the acquisition and diffusion phases of collective learning by centralizing knowledge repositories, and stimulate trust-building by bringing adversaries together. From a theoretical point of view, scientific brokerage has a fundamental role to play in adversarial networks by promoting collective learning in the short- to mid-term. However, and as will be shown in the final section, brokerage remains a blurred concept despite the existence of numerous theoretical and empirical insights, and would benefit from theoretical refinements. But before delving further into scientific brokerage, the next section mobilizes the policy network literature to give an empirical and network-grounded resonance to the collective learning framework explained above.

II – A Network-based Approach to Collective Learning

Networks represent an interesting way of making relational concepts such as collective learning easier to investigate empirically. From a mathematical point of view, a network is a mere representation of nodes linked together by ties of various intensities (Ward, Stovel, and Sacks 2011). When it comes to information network, nodes represent policy actors, and ties between them flows of information (Workman, Jones, and Jochim 2009). But before addressing information networks with greater details, one should first consider its foundations: policy network.

A useful conceptualization of policy networks can be found in the Advocacy Coalition Framework (ACF) (Jenkins-Smith et al. 2014; Sabatier and Jenkins-Smith 1993, 1999), a model which translates interpersonal interactions into a structural unit called the subsystem. The subsystem is composed of a set of actors involved over a common issue delimited in time and space for at least a fairly long period. Actors are aggregated into more or less adversarial coalitions, each of which possesses its own set of policy preferences and political resources—legal authority, public opinion, information, mobilizable troops, financial resources, skillful leadership, and more (Weible 2007). In addition, similarity of policy preferences, called the belief system, is assumed to incite actors to maintain non-trivial degree of coordination and to have an important role to play in inter-coalition interactions as well as policy change (Fischer 2014; Sabatier 1987). This emphasis on belief systems makes the framework well-adapted to study the research's question, just like the fact that 57% of empirical applications reported between 1987 and 2013 regarded environmental issues (Jenkins-Smith et al. 2014), including shale gas (Cook 2014).

In order to grasp the political environment in which scientific brokerage operates, the next section lists the range of policy actors expected in a subsystem, followed by an overview of the dynamics expected in adversarial policymaking.

Coalitions and belief systems

The ACF understands coalitions as being the prime units of analysis within a network. Those encompass a broad range of actors, from university scientists to environmentally engaged citizens, all of which possesses preferences more or less similar to the average of the group. Of course, the macro-political context is acknowledged to have an influence upon coalition's behaviour (Kriesi, Adam, and Jochum 2006), yet a greater emphasis is laid upon an endogenous element: the belief system.

A belief system is composed of three hierarchical orders of thoughts. The first of them pertains to deep core beliefs, which can be conceptualized in light of the four worldviews developed by cultural theory (Jenkins-Smith et al. 2014; Ripberger et al. 2014; Wildavsky 1987). Worldviews are assumed to be the most basic and stable component of a personality and to have considerable leverage on subsequent and more specific thoughts. The second order, named policy core beliefs, relates to perceptions about the severity, causes, attributes, solutions, as well as preferred distribution of power and authority within the policymaking process (Weible 2007). The third and most superficial order concerns secondary beliefs. That is, preferences about the calibration of instruments used to resolve the problem. In addition to being intuitive, this framework is very similar to the three orders of policy-oriented cognition suggested by Hall (1993), and is supported by studies of environmental psychology (Henry and Dietz 2012). Moreover, the decreasing resistance to change is coherent with bounded rationality, stability of prior attitudes, and cognitive heuristics of availability, anchorage, and representativeness developed in the first section of this chapter.

Belief systems are useful to delineate the cognitive aspects of social relations. Indeed, the similarity of beliefs between individuals is considered the most important catalyst of grouping behaviours (Sabatier 1987). This hypothesis has been confirmed by a number of studies (Weible 2005), which further added that (1) belief similarity had a stronger correlation with identification of allies and coordination with them than with transmission of information (Weible and Sabatier 2005) (2) perceived influence had a positive impact on an actor's willingness to coordinate with another one, but only when belief systems were similar (Henry 2011) (3) policy core and instrumental beliefs were more influential than deep beliefs with regard to coalition formation (Ingold 2011), and (4) beliefs kept their influence even when controlling for strategic, political considerations (Carpenter, Esterling, and Lazer 2004).

Additionally, belief systems' decreasing resistance to change has fundamental consequences for collective learning. While communication between individuals may alter their beliefs and policy preferences, such an outcome is more plausible for secondary than for policy core beliefs, and more likely for policy core than for deep core beliefs. To the extent that coalitions are constructed around more important and more stable attitudes, cross-coalition learning is unlikely when the cognitive distance between their respective belief systems is too prominent (Weible 2008).

Other Actors

Throughout theoretical improvements, some scholars argued that the ACF could gain leverage by acknowledging the presence of actors with an exceptional role inside a subsystem (e.g. Christopoulos and Ingold 2014; Ellison and Newmark 2010; Meijerink 2005). Generally speaking, coalitions may not always be the most relevant unit of analysis. Because asymmetric distributions of power are unavoidable even inside horizontal structures such as policy networks, some individuals may use their political resources to exert more influence than others. For instance, Ellison and Newmark (2010) explicitly recognized that the ACF failed to show how public agencies frequently operate at the core of coalitions and dominate subsystem interactions by virtue of their expertise, professionalism, constituency support, esprit-de-corps, and else. Besides, some actors may possess different incentives to involve in the process rather than promoting their preferences. Ingold and Varone (2011, 5) give a most useful illustration of this situation:

> *Administrative agencies when they do not have a specific mission or mandate in a subsystem, which would make them belong to a coalition—typically defend more neutral positions (according to the Weberian ideal-type of rational-legal bureaucracy) and do not have strong belief systems. Located between conflicting coalitions in the policy subsystem, they therefore have the opportunity to assume a mediating role which may increase their own political power and policy influence (through additional budget assignments, new implementation competencies, etc.).*

The literature points toward three types of exceptional actors, all having particular beliefs and incentives: epistemic communities, policy entrepreneurs, and policy brokers.

1. Epistemic Communities

Members of epistemic communities may have various degree of affiliation with existing coalitions or even form a coalition of their own, yet four main features differentiate them from classic actors:

> *"(1) Shared set of normative and principled beliefs, which provide a value-based rationale for the social action of community members; (2) shared causal beliefs, which are derived from their analysis of practices leading or contributing to a central set of problems in their domain and which then serve as the basis for elucidating the multiple linkages between internally possible policy actions and desired outcomes; (3) shared notions of validity—that is, intersubjective, internally defined criteria for weighing and validating knowledge in the domain of their expertise; and (4) a common policy enterprise—that is, a set of common practices associated with a set of problems to which their professional competence is directed, presumably out of the conviction that human welfare will be enhanced as a consequence"* (Haas 1992, 3).

Figuratively, an epistemic community could be a group of scientists or experts operating within a similar field of inquiry who developed a common policy position regarding an issue, but who at the same time gives at least as much importance to the scientific method as to the obtained results. Such scientists would change their policy core beliefs more easily than traditional actors if a demonstration they consider valid shows they are misguided. Hence, epistemic communities theoretically have a higher degree of sophistication and a reduced—but not absent—dependency upon prior attitudes than coalitions. When extrapolated to the structural level, the preceding implies that a subsystem dominated by an epistemic community should engage in collective learning processes more easily than if it was controlled by traditional coalitions.

2. Entrepreneurs and Brokers

But how do epistemic communities dominate policymaking? For Zito (2001, 598–9), "the epistemic community concept may not encompass the entire entrepreneurial effort at work […]; [yet] *the ACF explanation of actors outside the immediate coalition may offer greater clarification* [emphasis added]." On this point, the policy entrepreneur and the broker are theoretically interesting to explain how resources of all sorts—including epistemic communities—have influence upon the policymaking process. While further distinctions will be made in the final section of this chapter, one should note at this point that both operate with distinct logic and interests: whereas entrepreneurs try to exploit resources to achieve their policy preferences, brokerage activities are dedicated to seeking stability and avoiding hurting stalemate (Christopoulos and Ingold 2014).

Expected Dynamics of Adversarial Subsystems

When it comes to political conflict, subsystems can be outlined as being (1) unitary, where a single coalition dominates the process and disagreement remains low (2) collaborative, where two coalitions compete but nevertheless talk to each other, or (3) adversarial, which describes a state of complete antagonism induced by a strong incompatibility of belief systems. In theory, one should expect cross-coalition learning to be highest in collaborative subsystem, mostly because the existence of a permanent threat gives the necessary incentives to seek out for novel information and the gap between belief systems is not so large as to generate mistrust (Weible 2008). By opposition, acute political conflict diminishes trust between actors, which in turn are more likely to converge into distinct coalitions, reject arguments incompatible with their beliefs, and restrict their interactions to alter egos sharing similar expertise, professional affiliation, or policy preferences (Weible and Sabatier 2005).

Investigations of the phenomenon suggest that empirical knowledge is seldom the object of collective learning, even in collaborative settings, and that "scientific certainty and collaborative management are not surefire strategies for limiting the influence of normative beliefs in steering the direction of a policy subsystem" (Weible and Sabatier 2009, 207-8). In accordance with this argument, it has been observed that scientists were significantly less likely to be identified as opponents or allies in collaborative subsystem than in adversarial ones. This suggests that political conflict increases experts' embeddedness within coalitions, losing by the same token a part of their legitimacy associated with their ability to work toward the common good (Parkinson, 2003; Weible, Pattison, and Sabatier 2010). Interestingly, studies showed how a minimal number of experts can nevertheless operate outside coalitions (Ingold and Gschwend 2014). Those actors generally display increased advocacy and advising activities (Frank et al. 2012) and possess a higher potential to positively influence collective learning (Larsen, Vrangbæk, and Traulsen 2006), possibly by acting as entrepreneurs or brokers.

Another important dynamic pertains to the multiplication of political perspectives. Adversarial debates are often correlated with important media saliency. As a result, the saliency pushes more actors to involve in the policymaking process, which in turn brings confusion in the information network by increasing the number of different fields of expertise represented (Culpepper 2011). Sarewitz (2004, 386) summarizes the phenomenon in the following terms:

> "*nature itself—the reality out there—is sufficiently rich and complex to support a science enterprise of enormous methodological, disciplinary, and institutional diversity. […] science, in doing its job well, presents this richness, through a proliferation of facts*

> *assembled via a variety of disciplinary lenses, in ways that can legitimately support, and are causally indistinguishable from, a range of competing, value-based political positions. […] from this perspective, scientific uncertainty, which so often occupies a central place in environmental controversies, can be understood not as a lack of scientific understanding but as the lack of coherence among competing scientific understandings".*

The argument is coherent with Barke and Jenkins-Smith's findings (1993, 437), which showed that professional affiliations, fields of inquiry, belief systems, and aversion to risks caused substantial variations in risk perception among experts. Similar results were achieved by Silva and Jenkins-Smith (2007) with respect to policy recommendations. As Barke and Jenkins-Smith concluded: "implicit differences are likely to exacerbate conflict over potentially risky policies as patterns of beliefs and value judgments become conflated with 'scientific' findings". In this respect, Montpetit (2011, 520–1) showed how scientists in context of adversarial debate are not only as likely to have internal disagreement as other groups, but even have necessary incentives to emphasize scientific uncertainty and, therefore, promote dissension. As he concluded:

> *"if the exclusionary processes associated with the production of knowledge sometimes provide the illusion of a scientific consensus upon which policymakers can rely, reliance on this knowledge by policymakers increases error cost to a level that encourages scientific contestation. Scientific disagreement and eventually political divisions are the most likely outcomes of such a dynamic."*

Thus, the ACF points toward three hypotheses with regard to adversarial environment: (1) actors interpret critically novel knowledge and are unlikely to accept information incompatible with their beliefs; (2) scientists may be active in subsystems, but they are likely to drop out or be instrumentalized; (3) issues of the new politics of nature bring ambiguities, scientific uncertainty, and an institutional void limiting collective learning (Jenkins-Smith et al. 2014; Sabatier 1987; Sabatier and Zafonte 2001). At first sight, the combination of biases in production and interpretation of knowledge with ubiquitous uncertainty, legitimacy downfalls, instrumentalization of science, and clustering of individuals around competing belief systems casts serious doubts on the plausibility of collective learning in adversarial environment. Nevertheless, scientific brokerage might constitute an important way of avoiding such a dead-end.

III – Brokering a Crisis Recovery

This section constitutes the core of the theoretical framework. As such, it assesses studies on knowledge diffusion and policy brokerage to develop a hypothesis regarding the collective learning potential of scientific brokerage. Briefly explained, the argument is that a scientific broker possesses sufficient capital and abilities to bridge between divisions in the information network and activate the three processes of collective learning, even if his influence is limited to a subset of individuals. The following lines answer three important questions underlying this line of reasoning: (1) *Who is the broker?* (2) *What are the expected effects of brokerage on information networks?* (3) *How can he reach the position of influence required to have those effects?*

Delineating the Broker: A Definition

When it comes to brokerage, the most basic question relates to the exact definition of brokerage: who is the broker? The idea that forums of discussion represent a form of brokerage has been an early proposition of the ACF (Sabatier 1987). While the idea has been, to some extent, empirically supported (Elliott and Schlaepfer 2001), explanations of the mechanisms behind the process remain unsatisfactory. In the case studied by Eliott and Schlaepfer, the inquiry did not go much further than to conclude: “The forum in this case was the FSC working group which met both criteria in the hypothesis and clearly played a vital role in policy learning. The chairman of the working group appears to have played a key role as a ‘policy broker’ (2001, 658).” Larsen, Vrangbæk, and Traulsen (2006) further added that some scientists may be central to conflict mitigation by framing an issue in a technical manner. Meijerink (2005), for its part, found that epistemic communities can play a substantial role in learning, especially when they operate in close relations with a coalition and are able to diffuse what they learned. These studies give an interesting preliminary view of brokerage, but the picture continues to be partial. As a matter of facts, those studies assume that scientists are the most common actors doing brokerage, but this assumption goes against what has been observed in adversarial subsystems. Moreover, they rely on an *a priori* identification of brokers based on their professional affiliations instead of using a functional definition. Lastly, they confirm the ACF's hypotheses without clearly identifying the mechanisms linking brokerage and conflict reduction. Hence, numerous questions remain: Who is the broker? What is his role in the subsystem? And how does he foster conflict reduction and collective learning?

Within ACF's hypotheses, the broker is defined as an individual whose "principal concern is to keep the level of conflict within acceptable limits and to help the parties reach some 'reasonable' solution (Ingold 2011, 439)." The first logical step toward a definition of brokerage is then to recognize that a policy broker is not an entrepreneur. Unfortunately, this basic distinction has not always been done. Zito (2001) illustrated this confusion by providing a list of the expected entrepreneurial behaviours which encompassed setting the policy agenda, popularizing the issue and solutions, building support and legitimacy for particular positions, cajoling other actors to support their causes, fostering legitimacy to the cause, defecting external opposition, and forming resistance against the status quo supporters—which are all expected from policy entrepreneurs—, but further added to the list inventing solutions that overcome political hurdles, brokering deals, building exchange relationships with other participants, and building a win-win collective goods process, all of which should be expected from conflict reduction activities and not from preference promotion. One should then clarify the distinction: whereas entrepreneurs seek to reduce the scope of choices available to policy-makers, the brokers seek to expand them by finding new compromises linking divergent positions; whereas the entrepreneurs advocate strategically for their preferences, the brokers take a more facilitative approach and are less interested in lobbying than in communicating more complex aspects of policies (Koski 2010).

If objectives at the core of entrepreneurship and brokerage diverge, the same cannot be said for the means used to achieve them: both have an interest in building their social capital, i.e. enhancing their influence by expanding the number and quality of their social relations.

Social capital has been identified as a key political asset leading to increased control of information flows, which can in turn facilitate transmission—or blockage—of knowledge between political actors unaware of each other and allow the identification of advocacy or advisory opportunities (Frank et al. 2012). Entrepreneurs and brokers, however, do not use their social capital in the same way. Entrepreneurs seek influence and resources; they exploit the political resource in an active, if not aggressive way. They instrumentalize their network to (1) favour their preferences (2) enhance their knowledge of the policymaking process (3) identify quickly new opportunities, and (4) understand the ideas, motives, and concerns of others to respond strategically (Mintrom and Norman 2009). Brokers, on the contrary, seek to create stability within the subsystem by (1) linking competing coalitions together (2) generating exchanges of information (3) promoting conciliatory policy solutions (4) using social capital to infuse trust in the process and position themselves as mediators, and (5) communicating interests, difficulties, and best practices from one group to the other (Burt 2004; Christopoulos and Ingold 2014). As strategic agents, entrepreneurs are a self-interested individuals who may achieve personal gain by hiding knowledge to their adversaries, focusing their efforts on the most influential policymakers, and exploiting dependencies of weak actors. To the other end of the spectrum, policy brokers need to be open toward every actors, even the weakest and most dependent of them, to generate the trust needed to sustain legitimacy and truly enhance knowledge diffusion. Two entrepreneurs may compete with each other and create a zero-sum game, whereas two brokers should promote more efficiently the conciliation of actors.

Building social capital is costly, implying that it requires a minimal number of incentives. For policy entrepreneurs, strong belief systems motivate them to engage in capital-building activities. The case of brokerage is not as straightforward, as brokers are agents with a moderate to non-existent belief system (Ingold and Varone 2011). This being so, Burt's study (2004) showed that having a strong social capital within an organization led to more creative ideas, better salaries, better job evaluations, and faster career progression. Those results suggest that building social capital could be in itself rewarding, at least from a professional perspective. Regarding organizations, they might find the necessary incentives within their organizational mission, as when governmental authorities have a conflict-reduction mandate, or when members of a group, for instance political parties, are internally divided over their belief systems and conflict avoidance becomes an integral part of self-preservation (Ingold and Varone 2011). Additionally, the brokers may be normatively appealed by ideals of deliberation and engage in conflict mitigation activities for the sake of democracy.

How Brokerage Improves Policy Networks: The Functions

From a structural perspective, the fundamental role of policy brokers is to bridge between divisions in the subsystem, namely competing coalitions in adversarial environment. Because coalitions theoretically favour outcomes closest to their belief system, accepting moderate positions advocated by the broker should be expected solely in context of a policy stalemate, i.e. when both coalitions have access to about equivalent veto points to block each other and *status quo* becomes the only possible outcome (Ingold 2011; Ingold and Varone 2011).

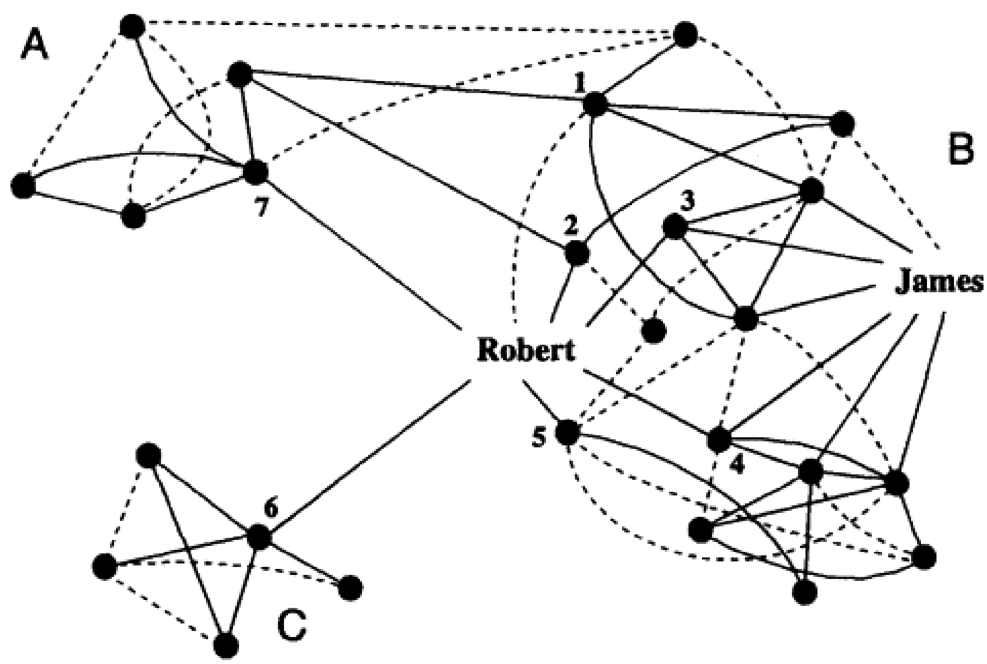
However, institutional veto points might be very scarce, if not completely absent, from issues operating within an institutional void. As Ingold and Varone (2011, 21) noted: "It is still an open question as to how policy brokers are likely to act in a political system which does not offer several institutionalized veto points. We might assume that policy brokers would have little influence on the policy output in such case". Nevertheless, the lack of institutions does not directly imply the absence of structures; informal power relations may induce structural divisions in a network, named structural holes, which create positions of influence akin to veto points. Interestingly, identifying structural holes is only possible by being aware of the whole network, a common asset of policy brokers and entrepreneurs. Hence, entrepreneurs may take advantage of these structural holes to block competing coalitions, but the broker may also use them to reach an advantageous policymaking seat by means of reputation. In theory, doing so would allow him to influence positively the whole network and produce an outcome similar to what would have occurred under stalemate conditions.

Structural Holes: The Informal Fractures Inherent to Social Networks

It has been mentioned above that veto points and institutions were not the sole producers of political structure; informal relations also induce divisions between subsets of individuals. In network terminology, those social fractures have been named structural holes. As Figure 1.2 illustrates, they describe the absence of relations between two groups of actors. Because "actors are situated in communication flows, which constitute an informal social structure that differs from the formal institutions which shape official conduct", structural holes can alter the stream of information, stop the diffusion of shared frames, diminish innovation, and sustain intellectual isolation leading to self-reinforcement of ideas, political views, and policy beliefs (Considine and Lewis 2007, 593). For Burt (2004), this does not imply that groups are unaware of each other, but rather that "behaviour, opinion, and information, broadly conceived, are more homogeneous within than between groups […] people focus on activities inside their own group, which creates holes in the information flow between groups, or more simply, structural holes." (Burt 2004, 353). For policymaking activities, the consequences of structural holes may be a misconception of the nature of the problem, poor policy design, and inefficient implementation.

Structural holes should be especially present within institutional voids or nascent subsystems, mostly because confusion and instability is expected to be higher (Jones and Jenkins-Smith 2009). Sporadic participations of actors from diverse policy sectors can bring considerable confusion the first time an issue rises to the public agenda, but the formation of a set of dedicated and stable actors should occur as time goes by (Zafonte and Sabatier 2004). Because political involvement occurs mostly among individuals whose social network share a single mindset (Mutz 2002), coalition formation, beliefs, and political involvement all emerge in a process of mutual-reinforcement. Over time, actors with a strong belief system will seek a single-minded social network, which further encourages political involvement and facilitates information-seeking. On the contrary, actors with moderate beliefs will diminish their participation in light of the contradictory signals they receive from their divided partners. Over time, moderate actors will drop out, those with strong preferences will build coalitions to enhance coordination and information-sharing, and each communities will converge toward its own language, preferences, and methodological norms. At the end of the process, one should expect the subsystem to look like Figure 1.2: structured in few subgroups of strongly connected actors, one for each coalition, with structural holes separating them.

Figure 1.2: Structural Holes of Policy Network[2]



The Political Resource Behind Structural Holes

The notion of structural hole has been developed above and applied to the subsystem, yet

2 Taken from Burt (2004). If Robert was absent from this example, structural holes would insulate cluster A from B, B from C, and C from A. While Robert and James have about an equivalent number of social relations, Robert possesses more social capital than James: Robert is able to bridge across structural holes, but James is embedded within a subset of very similar and already linked individuals.

the question of why structural holes matter for the broker remains open. The complex answer can be summarized as follows: an individual occupying a structural hole may manage the whole network by influencing its isolated subgroups. Occupying a structural hole gives access to a greater diversity of information, increases the control over information flows, helps generate innovative ideas by bridging separate worlds and exploiting never-seen-before opportunities, and makes possible the diffusion of preferences in the whole network (Burt 2004). From a network-level perspective, the critical advantages emanating from the presence of a broker spanning multiple structural holes are three-fold: governance improvements, trust-building, and, more importantly, knowledge transmission.

1. Governance Consolidation

For Provan and Kenis (2008), networks are a mode of governance in the same way as markets or governmental regulation, yet with greater dependencies upon interpersonal relations. Network-based governance is especially adapted to multi-stakeholder contexts, multidimensional issues, highly conflicting political objects, as well as challenging policy designs and implementations. For goal-directed networks such as those dedicated to policymaking, a minimal presence of authority and coordination is fundamental to ensure mutually supporting actions, proceed to conflict resolution, and secure efficient uses of scarce resources. In other words, governance of broad and complex networks is sometime dependent upon the presence of an actor with network-level knowledge and capacities.

Figuratively, a decentralized network with a high density of social interactions helps mitigate dissension among members, but makes coordination almost impossible. To the other extreme of the spectrum, a network composed of subgroups and structural holes may make coordination easier within these groups, yet conflicting relations and counterproductive activities may surface. Brokerage lies, to varying degrees, between both ends; subgroups of actors can still coordinate among themselves, but structural holes no longer obstruct network management. As the broker gains influence by spanning between multiple structural holes, he strengthens his policy capacity. He may then use his peculiar position to improve the policymaking process: detect information, affect behaviours, shape network outcomes, reduce transaction costs, manipulate political resources, and build collaboration-oriented institutions (Heikkila and Gerlak 2005; McNutt 2012).

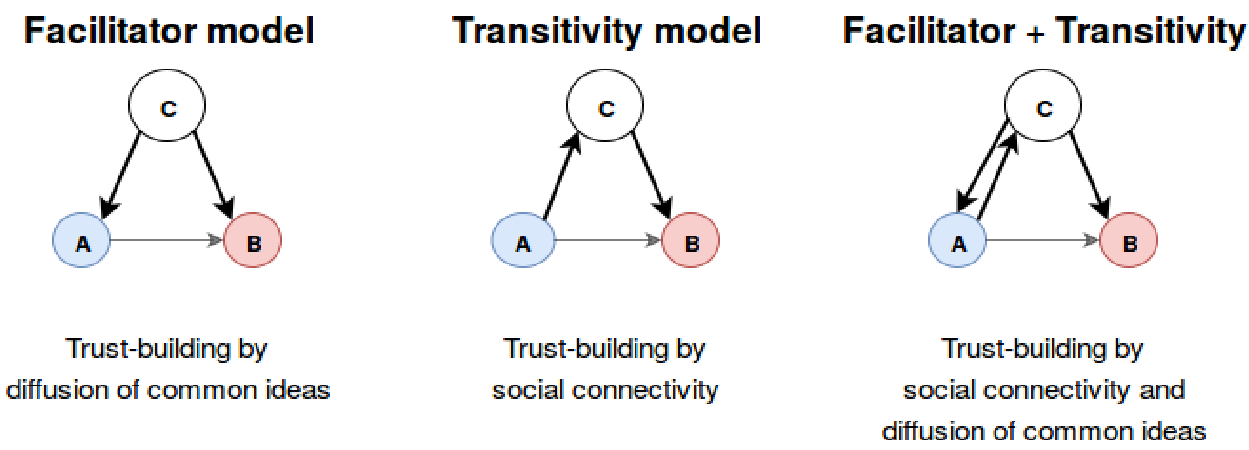
2. Trust-building

By doing shuttle diplomacy between adversaries, the broker may ease tensions and initiate trust-building dynamics (Ansell and Gash 2008). For instance, providing linkages between otherwise separated actors enhances the social capital prominent in the collaborative governance literature:

> *"Discursive democracy is often operationalized as a form of social capital, defined structurally as "the aggregate of the actual or potential resources which are linked to the possession of a durable network of more or less institutionalized relationships of mutual acquaintance and recognition" (Bourdieu, 1997, p. 46) and is referred to here as "bridging social capital"* (DeLeon and Varda 2009, 62).

Conceptually, brokerage can be divided between two complementary forms (Carpenter, Esterling, and Lazer 2004). As Figure 1.3 shows, the facilitator effect describes a phenomenon by which the broker provides a common frame of reference to competing coalitions to initiate discussions. The second effect, called the transitivity model, relies on explicit trust-building to operate. That is, because coalition A trusts the broker who himself trusts coalition B, A is likely to increase its trust for B. What is interesting about these models is that both have been shown to have significant influence on information diffusion among actors, but more importantly that cumulating transitivity and facilitation effects had by far the most meaningful contribution, even when preferences and organizational affiliations were controlled for (Carpenter, Esterling, and Lazer 2004).

Figure 1.3: Models of Trust-building[3]



3. Knowledge improvements

The last benefit emanating from structural holes reduction pertains to knowledge creation. As Albæk (1995, 92) explains it:

> *"Much research—and at least the most original research—does not produce new knowledge in the empirically verified sense, but deals rather with the reorganization and reformulation of the structures of knowledge. This, rather than empirical testing, is what Nobel Laureates are best known for."*

By bridging between formerly separated clusters of knowledge, the broker provides the necessary foundation for knowledge generation. He may use his structural advantage to create a cohesive narrative, a "culturally clumsy policy solution" linking different worldviews and having greater conflict-avoidance potential than former propositions (Jenkins-Smith et al. 2014). Knowledge-based advantages, however, are not limited to production. Koski (2010), in his study of LEED certification diffusion across U.S. cities, demonstrated how a broker (1) linked a policy to a broader set of societal values (2) developed a common policy vocabulary facilitating exchanges between actors (3) produced a reference policy to begin discussions (4)

3 Adapted from Carpenter, Esterling, and Lazer (2004)

acted as a diffusion hub, and (5) built the necessary infrastructure for autonomous information transmission.

Figure 1.4: Structural Advantages of Brokers for Information Circulation

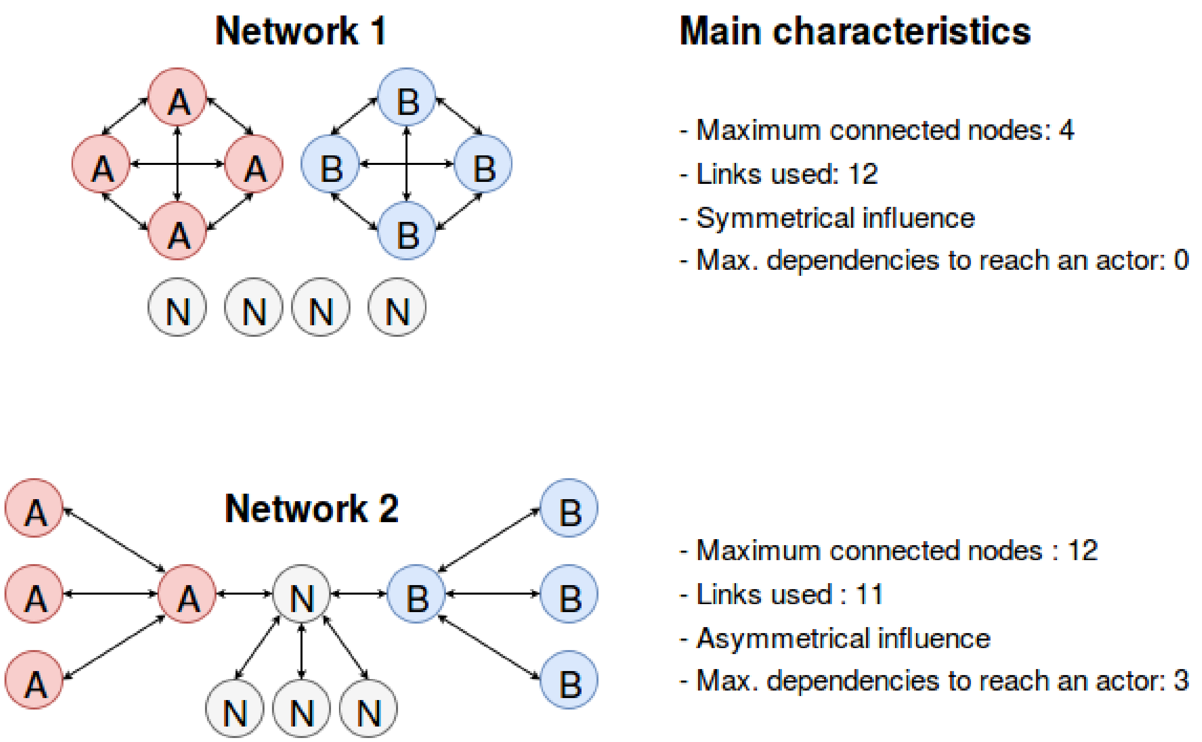


Figure 1.4 gives a schematic view of how brokerage enhances information transmission. In network 1, individuals are strongly connected with one another and information acquisition is faster and easier: each actor has access to three information sources. Nevertheless, members of coalition A cannot obtain coalition B's knowledge and information redundancy is frequent, assuming that the three sources possess similar information. In short, knowledge circulation is inefficient. By contrast, network 2 uses about the same number of links, but they are strategically distributed around the broker. As a result, the four actors that were previously excluded are now available as information sources. Moreover, the structure minimizes information redundancy and allows coalitions to learn from the whole set of actors. The management of information at the network-level is made easier: the broker may act as a "one-

stop shop" for information seekers, identify holes in the knowledge repository, and launch further investigations to fill them.

How Brokers Reach Structural Holes: Acquiring Influence

Unfortunately, advantages associated with brokered information networks come at a cost; peripheral actors become highly dependent upon the good faith of central ones to promote their interests and cannot double-check what they are told, as shown in Figure 1.4. As a consequence, achieving efficient knowledge diffusion requires at least one of two conditions: (1) coercive influence from the broker or (2) an amount of trust that may not be obtained overnight (Scholz, Berardo, and Kile 2008). While the correlation between trust and reaching structural holes is easily understood, the case of "coercive influence" requires more subtle explanations. Shortly expressed, the idea is that brokers can take advantage of coalitions' weaknesses to occupy a structural hole, which should allow him to lead the policymaking process toward greater collaboration. The following sections describe the role of trust before giving more information about the weaknesses argument.

Trust

At this point of the analysis, all the necessary foundations have been laid to understand how trust affects cognition, which in turn affects whether an individual will learn from a fellow's arguments or strategically instrumentalize them. Without trust, accepting a brokered proposition instead of searching for first-hand information is highly implausible (Carpenter, Esterling, and Lazer 2004). Predicting which types of actors are more likely to trust a broker is rather hard, but studies about collaborative governance suggest that prior collaborations and experiences with multistakeholder institutions ease trust-building processes, just like cultural similarities and perceived capacities to perform well (Ansell and Gash 2008; Gerlak and Heikkila 2011; Heikkila and Gerlak 2005; Lee and van de Meene 2012; Steyaert and Jiggins 2007). Hence, the more alike, familiar, and favourable an individual is with regard to a broker, the more he is likely to incorporate the brokered picture.

Dependencies

The interplay between trust and cognitive obstructions to learning pushed many studies to express serious doubts about the probabilities of observing a shared understanding of policy-relevant information in adversarial subsystems (Heikkila and Gerlak 2013; Ingold 2011; Ingold and Gschwend 2014; Parkinson 2003; Sarewitz 2004; Weible 2008; Weible and Sabatier 2009). Interestingly, the possibility that conciliation be forced upon a subsystem is not explicitly recognized by the literature, yet numerous analyses support such counter-intuitive dynamic. Shortly depicted, three types of dependencies may constrain actors —or even coalitions—to rely on policy brokerage: bounded policy capacity, constraining social image, and collective action issues. This suggests by the same token that brokers may achieve considerable collaborative improvements despite widespread skepticism.

1. Bounded Policy Capacity

The first set of constraints has been introduced by Weible and Sabatier (2005) to explain cross-coalition interactions and pertains to the capacity of coalitions to promote their preferences efficiently. Because individuals are likely to distrust people with a different belief system, they should not collaborate with adversaries unless facing important levels of dependencies. In other words, an organization with limited capacities must rely on another one to achieve its goals, whether because the latter holds an important structural position [functional dependency], or because it possesses valuable political resources [resource dependency]. Hypothetically, the more the actor is constrained by dependencies, the more cross-coalition relationships he is likely to set up. In their account of California marine protected areas, Weible and Sabatier distinguished between ally networks (mere identification of allies), coordination networks (cohesion of actions), as well as information networks (gathering information). They convincingly showed that dependencies for identifying allies are almost non-existent, yet more constraining regarding coordination behaviours. More importantly, knowledge gathering activities are the most constrained of activities, mostly because information seeking is long, costly, may require considerable scientific sophistication, and is often affected by an asymmetric distribution of knowledge. Hence, actors with tiny resources to devote to information seeking, low incentives to do so, or a limited knowledge processing capacity should be dependent upon the broker to gain relevant information easily. Structurally, the presence of numerous structural holes—common in novel subsystems of the new politics of nature—exacerbates the phenomenon.

2. Constraining Social Image

Interestingly, belief systems themselves induce some form of dependencies. Montpetit (2012, 624-5) distinguished between purposive and material beliefs, the former involving "a proposition calling for immediate sacrifices, notably from the belief holders, in view of producing long-term diffused benefits", and the latter requiring "immediate concentrated benefits for the sake of longer-term diffused benefits". Purposive belief holders may be criticized for their lack of consistency if they moderate their arguments and acknowledge some claims of competing interests as being legitimate. On the contrary, material belief holders may be judged for their selfishness and foster suspicion if they refuse to incorporate elements of social well-being in their proposals. Of course, actors with material beliefs would be better off by maximizing concentrated interests, just like some purposive individuals possibly think reaching objectives would be easier by working with authorities considered illegitimate by their counterparts. But in both cases, their social image compels them to avoid such behaviour in order to keep a minimal amount of legitimacy. This dynamic has important implications for brokerage. For material coalitions, listening to a broker promoting a moderate and comprehensive policy stance represents the most efficient way of gaining the coveted legitimacy. On the other hand, purposive coalitions have no interest in being moderate, and accepting the broker's arguments is by no means necessary.

3. Collective Action Issues

Compatible with the dependencies thesis is the idea promoted by Berardo and Scholz (2010) whereby a broker will have more influence when policy actors face coordination rather than defection problems. On the one hand, the main challenges facing a coalition dealing with high collective benefits and low individual advantages to defect are to ensure shared understandings and planned efforts. On the other hand, some issues might yield interesting collective gains but even higher returns for betraying individuals, in which case ensuring compliance and mutual monitoring become the main concerns. For contentions such as those operating within an institutional void, the most pressing concern of coalitions is expected to be bridging between structural holes to construct a strong argumentative defense rather than preventing actors from shifting coalitions—an unlikely behaviour considering the relative stability of belief systems.

A critical reader might argue, however, that coalitions should prefer to rely on a partial policy entrepreneur instead of a neutral broker bounding competing coalitions, and he would be right to some extent. However, the influencse of brokerage on coalitions with coordination issues remains plausible when time is taken into account. For Scholz, Berardo, and Kile (2008), "the importance of degree and centrality [i.e. network-level brokerage] is most likely in dynamic, relatively unstructured policymaking arenas, and becomes increasingly less applicable in arenas with more stable interorganizational relationships". Carpenter, Esterling, and Lazer's study (2004) supports such interpretation by showing how brokerage does not necessarily structure information flows in a hierarchical manner, but also increases the probabilities of communication across network members. Considering that (1) building and maintaining linkages between individuals is a costly activity that is unlikely to be undertaken without valid reasons (Scholz, Berardo, and Kile 2008), and that (2) coalitions operating in nascent subsystems may be considerably restricted by structural holes (Jones and Jenkins-Smith 2009), reliance on a centralized broker offers an easy way of identifying, sharing, gathering, and structuring information for coalitions, at least until they fully understand the attributes of the subsystem and structure themselves around policy entrepreneurs.

Understanding How Trust and Dependencies Affect Subsystems

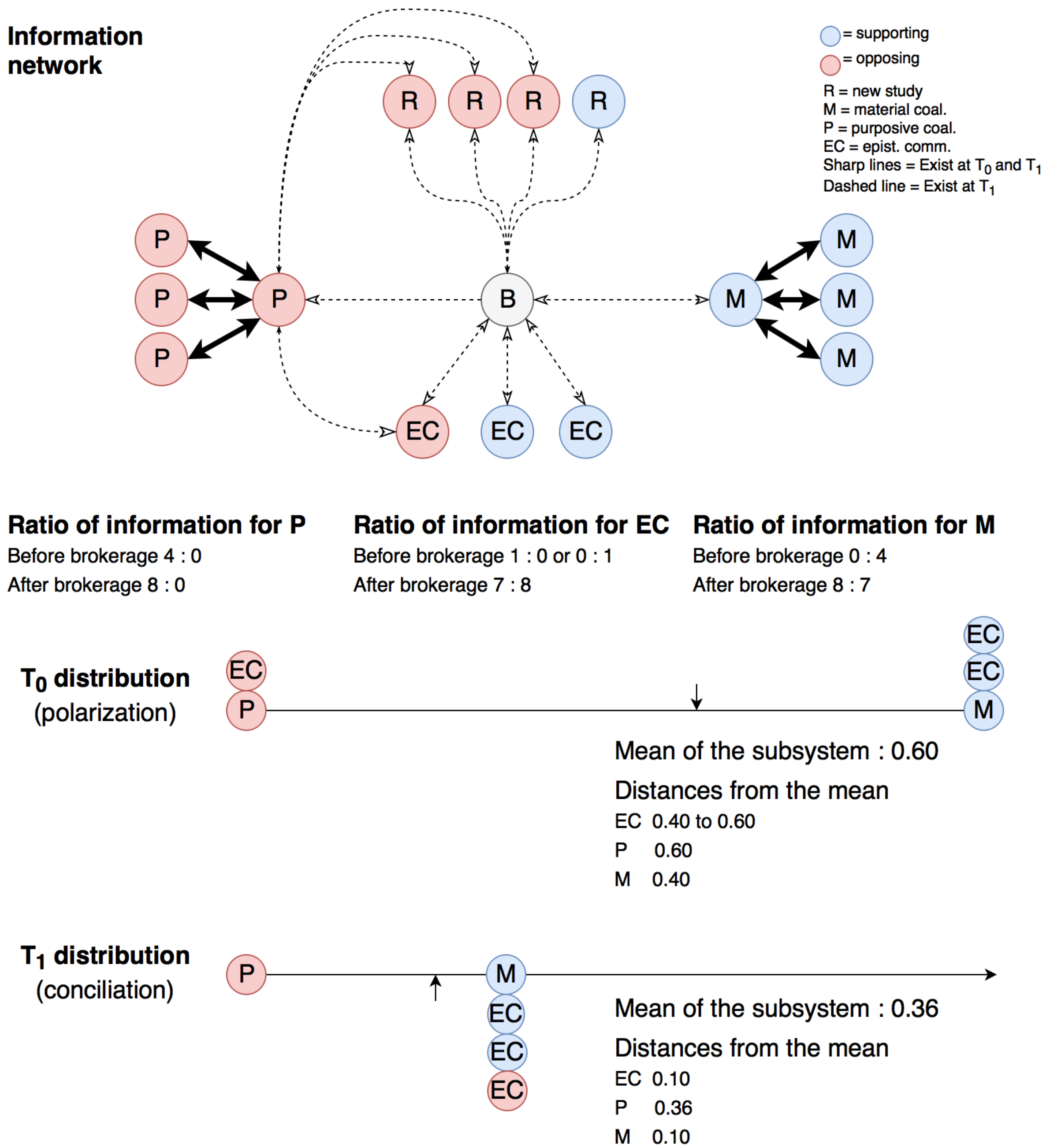
In summary, trust, policy capacity, belief systems, and collective action problems all affect the influence a broker is likely to exert on a given policy actors. But how does this influence on people translate into influence on networks?

Figure 1.5 illustrates the process in a hypothetical subsystem presumed to be new, bipartisan, and adversarial. Each circle corresponds to an actor, with the central *B* corresponding to the broker. Actors on the left-hand side of the broker correspond to the purposive coalition and initially strongly opposed the policy as shown by their red colour. On the right-hand side, blue circles represent the material coalition which initially strongly supported the policy. Blue and red circles underneath the broker illustrate diverse scientists, named epistemic communities, who timidly joined the debate. Lines represent a directed or reciprocated exchange of information between two actors. Sharp lines within material and purposive coalitions existed before the appearance of an influential broker and remained intact during the whole example. Dashed lines result from brokerage activities. Ratios of information are coarse and idealized measure of policy preferences; they give the ratio of opposing to supportive information sources influencing a coalition's rationale.

As the Figure shows, coalitions are isolated from each other at T_0; they are aware of each other, but their cognitive heuristics and lack of trust prompt suspicion to the point where collective learning becomes impossible. The T_0 distribution line depicts the resulting pattern of polarization: as three actors are on the right-end of the spectrum (1.00) and two others on the left-end (0.00), the average policy position of the subsystem is 0.60 and the ideological distance between the mean and actors' position ranges between 0.40 and 0.60.

Hereafter, imagine a government-mandated scientific broker enters the scene. He collects the whole set of information and even launches further investigations to fill knowledge gaps, as illustrated by the four circles above him. The broker ensures an accessible and complete summary of network-wide knowledge for individuals willing to listen to him. But how do coalitions perceive him? On the one hand, the purposive coalition remains highly doubtful and decides to reject the brokered picture. Indeed, their peculiar beliefs make the acknowledgement of competing views unnecessary to sustain legitimacy; they are familiar with a very specific picture of the problem—their "purpose"—and feel gathering information

Figure 1.5: The Framework Applied to Information Networks and Scientific Brokerage



outside their field of expertise is unnecessary. Purposive coalitions have the necessary incentives to critically assess broker-sponsored investigations, relying on their cognitive heuristics to cherry-pick favourable studies. Moreover, as purposive coalitions do not need to engage with their adversaries to build legitimacy, they have limited imperatives regarding coordination with external actors, i.e. collective action problems. Depending on the exact maturity of organizations, they may already rely on internal structures of coordination and knowledge diffusion, which further limits the dependency upon brokerage. After collecting information sources compatible with their belief system, inertia leaves them on the left end of the preferences spectrum.

On the contrary, material coalitions must build a dialogue with external actors to sustain public legitimacy, fostering collective action problems related to knowledge gathering and information diffusion among previously unrelated organizations. To engage this broader debate, the coalition may, moreover, have to deal with never-seen-before expertise and unfamiliar field of inquiry, enhancing the attractiveness of the broker as a single-access point of relevant knowledge. As is the case with petroleum, agribusiness, and financial industries, the material coalition potentially has among its members individuals who have had previous relations with governmental authorities, in which case their acquaintance of official institutions and the perceived trustworthiness of state-mandated brokers further increase. The resulting portrait is a coalition which, on the one hand, has incentives to incorporate the brokered knowledge repository and, on the other, does not *a priori* completely reject the broker's legitimacy. As a consequence, it does not abandon its former sources of information, but nevertheless embraces the whole set of information made available through the broker, producing an information ratio of 8:7 at T_1.

Lastly, the behaviour of epistemic communities is harder to predict. On the one hand, they do not possess special needs for acknowledging competing views, but they should neither have an aversion to it. Their scientific training gives them considerable sophistication within their field of inquiry, but also a capacity to manage complementary knowledge. As truth-seeking entities, scientific brokerage should constitute an easy way for them to have a general and useful overview of relevant knowledge, providing that the approach used to gather and assess information is considered compatible with their methodological norms. For the purpose of the present example, it is assumed that they espouse brokerage and adopt a policy stance reflecting the whole network, i.e. a ratio of 8:7.

At T_1, the average of the subsystem is now 0.36 and the distance from the mean is 0.10 for epistemic communities and the material coalition. Importantly, the distance from the average for the purposive coalition diminished by 0.24 despite its immobility and is now 0.36. The general portrait is that all actors, even those strongly opposed to brokerage activities, are closer to each other at T_1 than at T_0; information is therefore better shared than before.

A Hypothesis

To be sure, this idealized example roughly portraits the intricacies of a real-world scenario. Real-world brokerage may have limited influence on both coalitions; information communities may be more numerous; the broker may exhibit important biases in his general account of information; he may forget important information sources; actors may drop-out of the subsystem; coalition membership may change; and even more unpredictable events may occur. While the exact probabilities of brokering a rallying policy are impossible to predict considering the plethora of independent variables identified in the first part of this chapter, what this exercise clearly illustrates is that, in context of adversarial policymaking, even the slightest influence of a broker on one coalition can improve the probabilities of observing an understanding shared by the whole set of actors. Formally, this proposition can be summarized by the following hypothesis:

> *Hypothesis: The presence of a broker in an adversarial structure of governance increases the probabilities of observing a shared understanding of policy-relevant information between policy actors.*

IV - Summary

To shortly outline the argument developed in this chapter, one should recall that knowledge is political by nature. Power relations underlying information flows are best understood using ACF's assessment of policy networks: competing coalitions structure themselves according to their belief similarities, are more easily influenced by favourable knowledge, and critically reject hostile information. When the difference between the two belief systems is too important, political contention makes cross-coalition learning implausible and intellectual confinement becomes the dominant dynamic. However, it has been shown that brokerage possessed an important, yet asymmetric, potential to sustain collective learning and create a shared understanding within adversarial subsystems. An empirical investigation of the hypothesis is designed in the following chapter and tested in Chapter 3.

Chapter 2: Case and Methodology

As chapter 1 showed, understanding the role of scientific brokerage in adversarial policymaking constitutes a complex theoretical enterprise. The empirical challenge is at least as prominent, and a careful methodological design should reflect the intricacies of the problem. As such, this research takes advantage of events occurring in the Province of Quebec between 2010 and 2014. To summarize briefly the case, the province discovered in 2007 that shale gas rested underneath its bedrock formations. As hydraulic fracturing, the process by which natural gas can be extracted from bedrock formations, is loaded with considerable scientific, environmental, social, and health-related controversies, an extensive political quarrel over the exploitation of the resource followed. To respond to the rising opposition, the government mandated an independent institution—the *Bureau d'audience publique sur l'environnement* (BAPE)—to conduct province-wide consultations between 2010 and 2011. Following the recommendations of the consultation agency, the government launched in 2012 an *Évaluation environnementale stratégique* (EES), a science-based institution which had the mandate to assess existing peer-reviewed papers and document missing information by financing novel scientific investigations. Following the scientific assessment, a second public consultation occurred in 2014. From a methodological point of view, the EES appeared like a faithful representation of the policy broker described in the preceding chapter. Moreover, two consultations make it possible to appraise the state of the subsystem before and after scientific brokerage activities.

The following chapter begins by describing the scientific controversies behind shale gas and how these translated into Quebec policymaking. It then explains how documents and memoirs presented to the consultation agency were converted into quantitative data representing the status of the information network in 2011 and 2014. Furthermore, the two statistical tools used to investigate the phenomenon—Social Network Analysis (SNA) and the Exponential Random Graph Model (ERGM)—are introduced along with the analytical strategy and the operationalization of the dependent variable: collaborative dynamics in information networks.

I - The politics of shale gas

For many columnists of the energy sector, the emergence of shale gas exploitation is an utter economic and technological revolution. Originally developed as a commercially viable enterprise by a small petroleum producer of Texas in 1993, horizontal fracturing of shale formations rapidly spread across the globe. The U.S. Energy Information Administration (2015) evaluated that 46 countries share 8,576.6 trillion cubic feets of shale gas. In the U.S. alone, the 567 trillion cubic feets technically recoverable represent 22 years of energy supply (Helmholtz Center Potsdam 2016). As Figure 2.1 shows, shale gas extraction requires hydraulic fracturing, a process using pressured water mixed with sand and various chemicals to fissure bedrock formations and allow the natural gas to escape (BAPE 2011: 29–35).

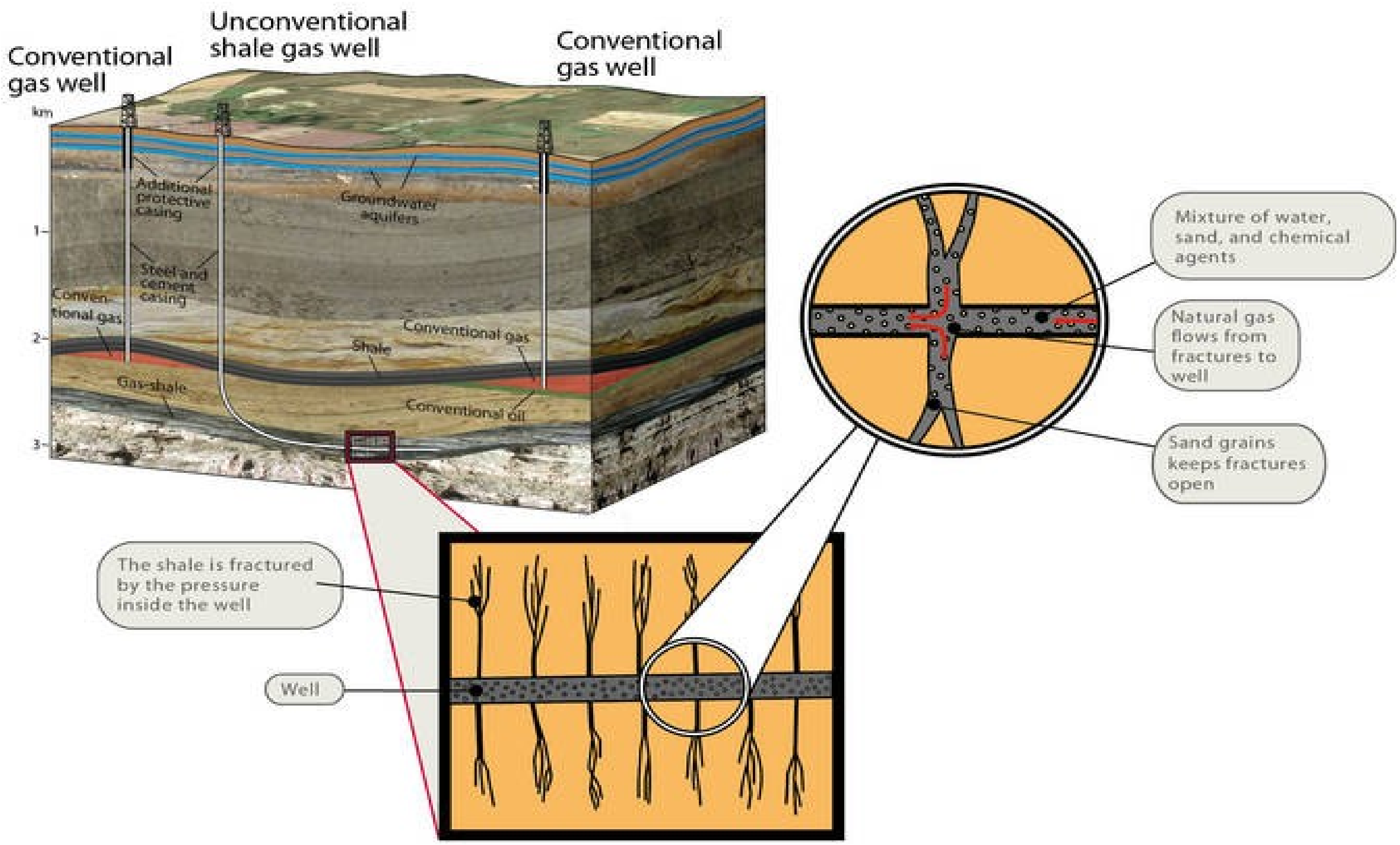
Scientific Controversies

While being an important phenomenon, the process is not free from scientific controversies. Foremost, financial benefits of the industry advanced by some economists (Considine, Watson, and Blumsack 2010; IHS Global Insight 2009) have been questioned by others. They argued that their methodology lacks theoretical justification, has unrealistic assumptions, and neglects environmental and social costs (Barth 2013; Kinnaman 2011). Moreover, some researchers described the relation between shale gas and the economy as a form of "resource curse": negative impacts of the energy burst are more important than the positive effects of the boom, inducing long-term systemic poverty in communities with former resource-intensive industries (Barth 2013). Others pointed to the numerous uncertainties in the global-value-chain of shale gas that might threaten long-term investments (Stevens 2010). Overall, commercial viability of some sites appears ambiguous and likely depends on the technical ability to target the "sweet spot" of shale formations, i.e. the exact location maximizing resource removal (Weijermars 2013). Lastly, the existence of an employment cap in the energy sector might limit economic benefits when the economy will have recovered from the 2008 crisis (Kinnaman 2011).

Economics left aside, another important controversy concerns the impact of shale gas extraction on greenhouse gases. On the whole, natural gas emits fewer carbon dioxide (CO_2) than coal and petroleum, hence constituting an interesting bridge toward low-carbon future (Wang, Ryan, and Anthony 2011). However, alternative interpretations argued that shale gas development might undercut markets for sustainable energies and contribute to the lock-in of carbon-intensive infrastructures (Council of Canadian Academies 2014). The investigations of Howarth, Santoro, and Ingraffea (2011), Caulton et al. (2014), and Osborn et al. (2011) showed a strong correlation between hydraulic fracturing and methane emissions (CH_4). They further added that methane leakages of few wells might raise the GHG emissions of shale gas up to 20% above coal level on a 20 years scale, and could be twice as damaging over 100 years. Those studies have been criticized by Davies (2011) and Cathles et al. (2012) on various points: small non-random samples of geologically different areas, absence of pre-fracturing data, unproven causality, overestimation of fugitive emissions, under-evaluation of green technologies, comparison of coal and shale gas on heat rather than electricity generation, and time scales that do not capture the contrast between long persistence of CO_2 and the short one of CH_4. Building on those criticisms, other studies affirmed that system-wide leakages were unlikely to be large enough to negate climate benefits of coal-to-natural-gas substitution, and a 1% discharge rate—about 1/2 to 2/3 below current level—would ensure the benefits (Bradbury et al. 2013; Brandt et al. 2014). Whether this level is achievable remains a matter of controversies.

Because fracturing fluids are mostly composed of water mixed with chemicals, the questions of water consumption and waste management quickly rose to the scientific agenda. Multiple sources of contamination have been identified, such as transportation spills, well casing leaks, leaks through fractured rocks, drilling site discharges, construction of pipelines and roads, reduced stream flows, and wastewater disposal (Entrekin et al. 2011; Rozell and Reaven 2012), but causal demonstration remains contentious. Water pollution pathways

Figure 2.1: Horizontal Fracturing and Shale Gas Extraction[4]



4 Taken in Helmholtz Center Potsdam (2016)

fluctuate between contaminants, are compelled by local geology, and can hardly be generalized (Council of Canadian Academies 2014). Assessments of risks is highly dependent upon various natural parameters (e.g. Rutqvist 2015). Even when the pollutants and the site were similar, different methodologies yielded different results. For instance, Jiang et al. (2013) documented an effective treatment of water flowbacks, but alternative analyses of flowbacks themselves showed cross-contamination of seawater, fresh water, saline shallow groundwater, and infected fluids (Haluszczak, Rose, and Kump 2013; Vengosh et al. 2013). By opposition, Warner et al. (2013) did not find evidence of contamination, as the spatial distribution of saline groundwater was not correlated with the location of shale gas wells. Applying similar spatial correlation techniques to drinking water, other examinations pointed toward strong correlation between well proximity and methane, ethane, and propane pollution (Jackson et al. 2013; U.S. EPA 2011). While some studies concluded that surface water contamination was unlikely to cause harm if proper precautionary management practices were followed (Council of Canadian Academies 2014; U.S. EPA 2015; Vidic et al. 2013), others identified stray gas contamination of surface water in areas of intensive shale gas development, along with accumulation of radium isotopes in disposal sites (Vengosh et al. 2014). It should be noted, however, that studies documenting limited risks also expressed concerns about deficient scientific fundings, exponential expansion of commercial activities, possible long-term bioaccumulation, lack of data before, during, and after the phenomenon, industry opacity regarding chemicals used, and difficulty to monitor and assess in-depth aquifers (Council of Canadian Academies 2014; U.S. EPA 2015; Vidic et al. 2013).

In addition to environmental impacts, numerous studies documented health-related problems associated with shale gas exploitation. Neurological degradation and increased cancer hazards, greater presence of physical stressors with negative psychological influence on communities, and expanded occupational risks such as industrial accidents, truck traffic, air impurity, noise pollution, and exposure to toxic chemicals are all among the identified dangers (Adgate, Goldstein, and McKenzie 2014; Council of Canadian Academies 2014; McKenzie et al. 2012). Yet, lack of data and measurement problems again hampered causal demonstrations and induced scientific disputes (Adgate, Goldstein, and McKenzie 2014; Bamberger and Oswald 2012; Steinzor, Subra, and Sumi 2013). Similarly, studies on wildlife impact found threshold effects when assessing the influence of well proximity on cardiac and neural defects of birds, but also noted a negative correlation between well proximity, preterm births, and underweight nativity (McKenzie et al. 2014).

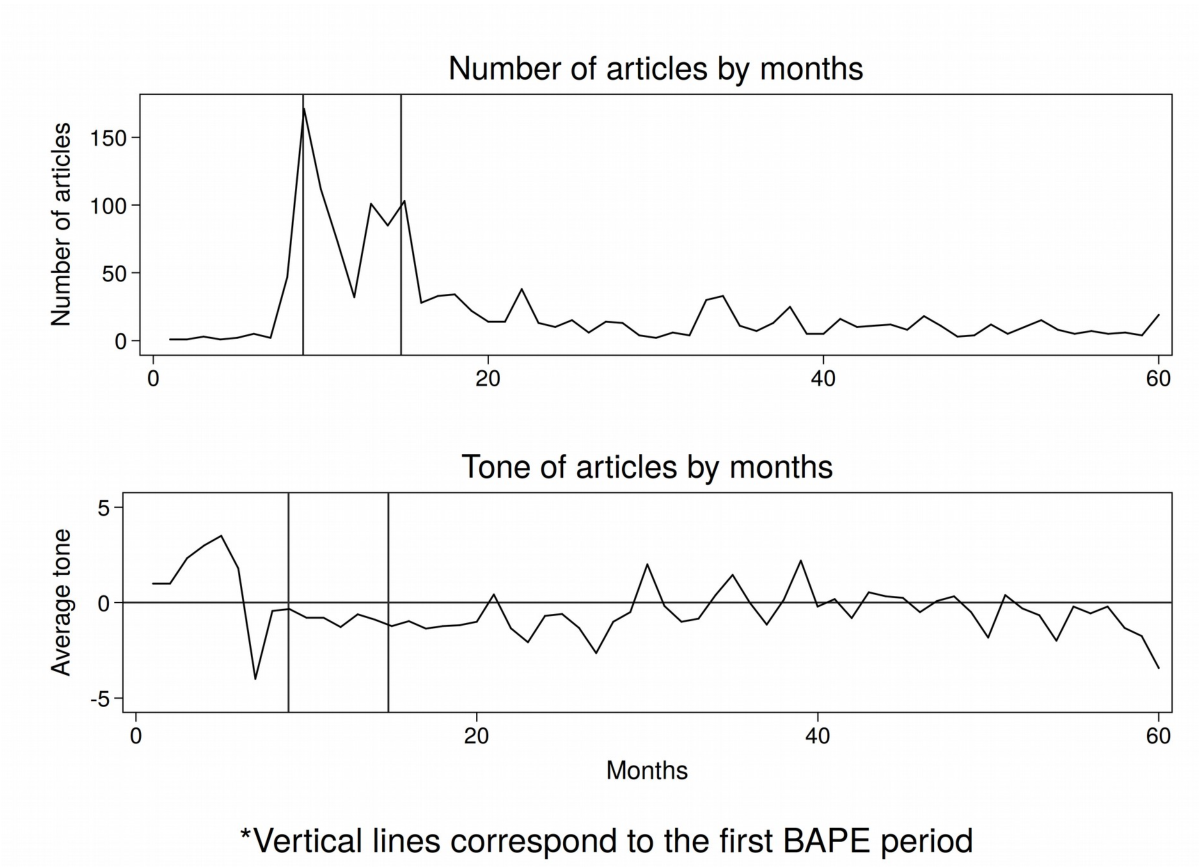
On the whole, it makes no doubt that shale gas represents a strong case of scientific controversy. Divergent methodological approaches, different units of analysis, incompatible assumptions, incomparable time scopes, lack of reliable data, persistent uncertainties, complexity of ecological systems, threshold effects, statistical moderation and mediation, challenging causal demonstrations, and low generalization potential invigorate incoherent interpretations of the state of science and stimulate misunderstandings that expand well beyond the frontiers of academia.

From Science to Quebec Politics

Without surprises, policymaking in diverse countries have strongly echoed the experts' disagreement developed in the last section. In light of the controversies and the increasingly important public suspicion, numerous Canadian and American jurisdictions adopted temporary moratoriums or permanent bans on the extraction of the resource. According to a review of various newspapers and advocacy websites (e.g. Baddour 2015; Keep Tap Water Safe 2012; Petro Global News 2013; Protect Limestone Coast 2015; The Economist 2013; The Huffington Post 2016), those jurisdictions include California, New Brunswick, Nova Scotia, New York, Maryland, Vermont, and major cities in California, Pennsylvania, Ohio, Hawaii, New Mexico and Texas. At the international level, Scotland, Wales, Germany, France, Bulgaria, Czech Republic, Netherlands, Luxembourg, Catalonia, Cantabria, Navarra, and La Rioja (Spain), Fribourg and Vaud (Switzerland), and Victoria (Australia) all adopted moratorium on hydraulic fracturing of shale gas. Surveys of public opinion documented non-trivial polarization of policy preferences. Boudet et al. (2014) found for instance that about 20% of Americans strongly opposed to the exploitation, 22% strongly supported it, and 58%

did not know. The University of Michigan (2013) aggregated 38 national American polls and concluded that the public opinion was divided about equally on the matter, with low political awareness, republican affiliation, male gender, and limited education increasing support for the industry.

Figure 2.2: Montly Coverage of Shale Gas in the Province of Quebec, 2010-14[5]



5*Month 0 correspond to January 2010. The tone equals the sum of positive arguments minus the sum of negative arguments in an article. Arguments could either be positive, negative, both, or absent for each of the following categories: national economy, investment, local economy, tax revenue, energy costs, energy security, environment, greenhouse gases, water, soil, air, earthquakes, sustainable energy, wastewater, landscape, health, drinking water, local communities, mortgages, rent, security of extraction, occupational hazards, regulatory capacity of government, legislation, experts' reliability, uncertainty, industrial secret, and other jurisdictions' experiences. In addition, residual categories were added to include other arguments about economy, environment, governance, human interests, and health.

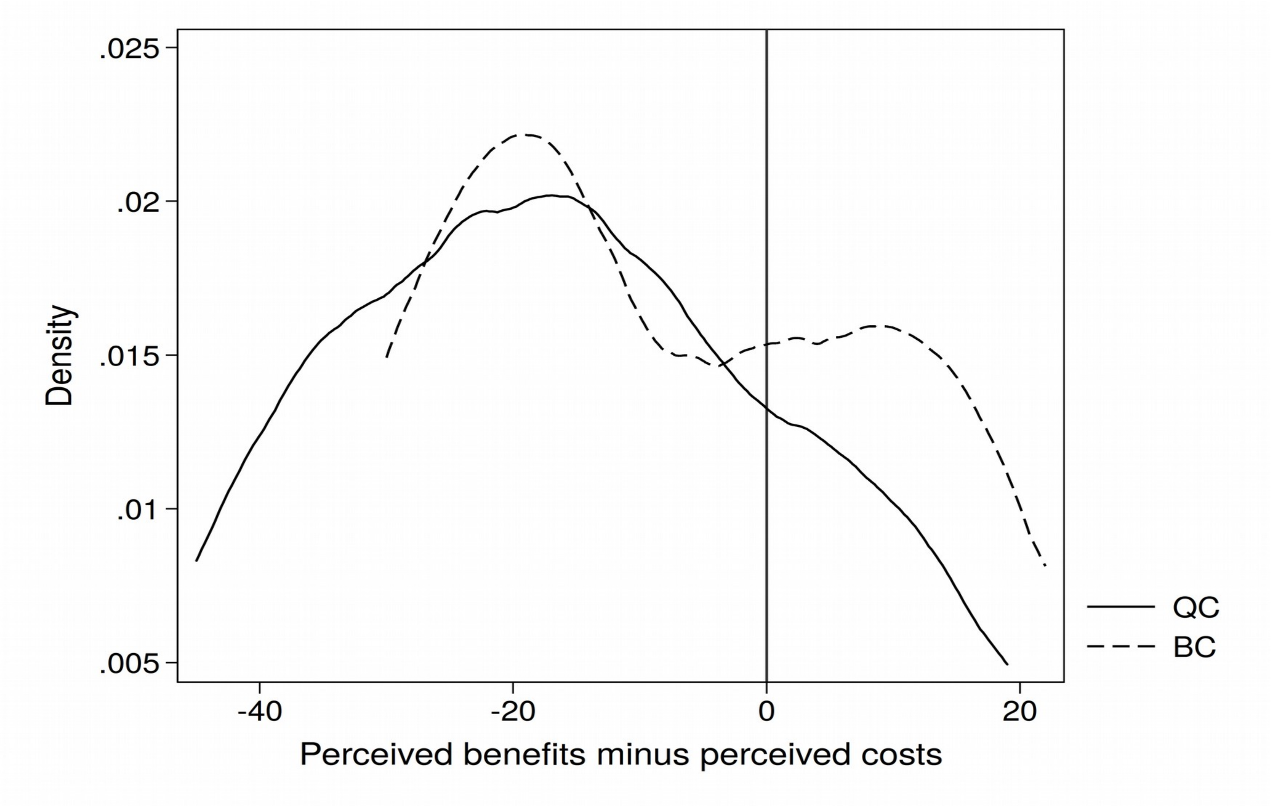
The Province of Quebec does not differ much from the general portrait depicted above. Shale gas reached the province in 2007. Three years and 31 wells later, the initially non-existent concerns turned into a massive and province-wide public contention, mobilizing an impressive number of citizens, experts, scientists, state officials, MLAs, environmentalists, industrialists, and media to discuss whether exploitation was economically, environmentally, and socially worth it. While this research is not a qualitative case study *per* se, it nevertheless acknowledges the importance to contextualize. Accordingly, the following subsection summarizes those events, from the appearance on the public agenda in 2010 to the definitive adoption of the moratorium in late 2014. Information comes from various media as well as a review of the province's legal gazette (Gouvernement du Québec 2016). The description of events is supplemented by an online survey of 84 organizations or experts who participated in the provincial public consultations and a content analysis of 1327 newspaper articles published on the matter between 2010 and 2014 (Montpetit and Lachapelle, unpublished; Montpetit, Lachapelle, and Harvey 2016)[6].

Between 2007 and early 2010, the issue of hydraulic fracturing gathered very limited attention in the province. The government regulated the industry to some extent in January 2010, but the statutes were not different from conventional resources and were latterly considered by many as strongly permissive: to respect the "state of the art" with regard to security, to comply with a minimal distance of 200 metres from groundwater catchment stations, to lease exploitation zones to the government, and to provide a 10% deposit in case of abandonment of activities (Gouvernement du Québec 2010). As Figure 2.2 shows, the issue remained technical at this point, and mostly positive articles were published on the matter between January and July 2010. However, local and environmental groups strongly mobilized

6. The survey and the content analysis are not the primary sources of data used in this research and were gathered for complementary projects. 141 organizations or individual experts were contacted for the survey and 84 questionnaires were completed (response rate of 60%). Media articles come form four newspapers (La Presse, Le Devoir, Le Soleil, The Gazette) and were coded by two coders (mean inter-coder reliability alpha = 0.8). Articles published between 2010 and 2014 were selected using "fracking", "hydraulic fracturing" and "shale gas" as keywords. The search resulted in 1680 articles, of which 1327 were considered to have shale gas as their main topic by the coders.

against the industry in light of social, health, and environmental risks (Dufour, Bherer, and Rothmayr 2012). They started asking for a moratorium in July 2010, followed by opposition parties, local governments, and a storm-like critical media coverage (Côté 2010; Shields 2010).

Figure 2.3: Distribution of Policy Preferences[7]



7*Figure 2.3 represents the kernel density of shale gas perceptions, as reported by 98 organizations who participated in the BAPE consultation process and the 39 respondents from British-Columbia who participated in similar processes. The gap between the number of respondents reflects the saliency of the issue in both provinces. The measure equals the sum of perceived positive impacts minus the sum of negative perceived impacts. Respondents were asked to qualify each of the potential problems and whether they agreed that the suggested benefit was real. Both measures were on a 5-point scale ranging from 0 (not a problem / strongly disagree) to 4 (Severe problem / strongly agree). Problems included disposing of waste water, violation of indigenous rights, earthquakes, traffic, noise, and light nuisance, conflict between landowners and their neighbours, air pollution, public opposition, drinking water contamination, insufficient regulatory capacity, inadequate public consultations, mortgage instability, and loss of agricultural lands. Potential benefits included mitigation of climate change, benefits to local landowners, energy independence, decrease of energy costs, increase of provincial revenues, job creations, and bridge toward renewable energy sources.

In response to the rising opposition, the government announced the end of the free-mining regime, a first-come, first-served structure of claims allocation, and replaced it by a permit based-system. At the same moment, it mandated the independent *Bureau des audiences publiques sur l'environnement* (BAPE) to conduct province-wide consultations and document the exploitation in light of sustainable development principles (BAPE 2011). Far from being apolitical, the debate became increasingly adversarial. Signs of social polarization included the emergence of a pro-gas lobby to defend the industry, publicly held criticisms of existing regulation by the *Commissaire au développement durable*, and a 200,000 signatures petition against the industry deposed to the National Assembly of Quebec (La Presse Canadienne 2011b; Radio-Canada 2010; Shields 2010b). Public opinion polls conducted by Montpetit and Lachapelle (2013) revealed that about 70% of Quebecers rebutted the exploitation in 2012. As Figure 2.3 shows, the proportion was similar among stakeholders. Interestingly, there are considerably more strongly opposing individuals than strongly supporting ones, yet the distribution of policy preferences appears normally shaped and centred on a moderately negative position when compared with the polarized picture given by British-Columbia. Thus, the consensus against shale gas exploitation appeared stronger in Quebec than in BC, where the opinion was divided about equally on the issue. The contention was not, however, softened as a consequence of this consensus-like distribution. On the one hand, the supporters of extraction, mostly government officials and the industry, were less numerous, but more influential. On the other, some policy actors held policy preferences that were considerably more extreme than what was found in BC, as shown by the proportion of actors falling below -30 on the axis.

In February 2011, the BAPE published its first report. After noticing that sparse scientific knowledge impinged definitive conclusions, it recommended (1) the creation of a permanent local consultation mechanism acknowledging subsidiarity principles (2) the adoption of the precautionary principle, sustainable development standards, and a single window approach centralized around the Environmental department, and (3) the composition of a scientific assessment gathering existing knowledge and investigating missing information

(BAPE 2011). The government responded to the report by launching the *Évaluation environnementale stratégique* (EES) to assess scientific evidences along with a temporary moratorium on commercial fracturing (Comité d'évaluation environnementale stratégique sur le gaz de schiste 2014).

After the provincial ballot of 2012, the first opposition party, the *Parti Québécois*, formed a minority government. Consistent with its prior opposition to the industry, the newly elected government increased royalties, widened the mandate of the EES to include social and environmental issues, and answered legitimacy concerns by assigning the management of the EES to the independent BAPE instead of the Natural Resources Department (Chailleux 2015; La Presse Canadienne 2011a; Shields 2013). The EES took two years to complete its assessment and mainly concluded that (1) the adoption of the precautionary principle was warranted (2) aquifers could support the industry's needs (3) air pollution mitigation was possible, but in all cases GHG were likely to increase (4) risks resulting from chemicals in fracturing brines were manageable, but risks of long-term bioaccumulation existed, and (5) scientific investigation should be continued to answer remaining knowledge gaps (Comité d'évaluation environnementale stratégique sur le gaz de schiste 2014).

In response to the assessment, the PQ government mandated the BAPE in February 2014 to conduct a second province-wide public consultation. Their second report was published in November 2014, and concluded that, in light of the geographic proximity between repositories and the population, the shale gas industry might generate important depreciative impacts on local communities, including air pollution, noise, traffic, mortgage instability, landscape degradation, health-related problems, environmental pollution, aquifer contamination, GHG, forest erosion, negative economic side-effects, and increased occupational risks. While it acknowledged that mitigation methods existed and were used by the industry, it also stressed the impossibility to completely eliminate those risks. Overall, the BAPE argued that costs exceeded benefits (BAPE 2014). Meanwhile, the *Parti québécois* lost power and the *Parti libéral* formed a new majority government, but despite the political turnover, the government extended indefinitely the moratorium, at least until economic profitability and social licence were acquired (Fortier 2014).

From Events to Research Design

From a methodological point of view, the Quebec case provides an interesting opportunity to assess the impact of scientific brokerage on adversarial information networks. On the one hand, the two independent consultations make it possible to compare the state of the information network in 2011 and 2014. On the other, the EES represents of the most faithful real-world illustrations of a scientific broker.

Readers unfamiliar with those institutions should note that the BAPE is an independent advisory agency created in 1978 with two missions: (1) document environmental and social implications of major industrial projects and (2) gather and answer stakeholders' concerns through public hearings. In doing so, the BAPE facilitates access to policy-relevant information, allows the expression of conflicting views, and produces recommendations to the government that, most of the time, are taken into account (Gauthier and Simard 2007). Consultations are strongly institutionalized. They are open to the entire population and include multiple dimensions of the project under investigation, but mostly focus on environmental impacts. Ministries, public agencies, and individual experts provide initial information about the project and answer participants’ questions during the whole process, avoiding pronouncing their preferences until the end of the consultations. Gauthier and Simard (2007) observed that those consultations led to direct and indirect learning for many attendees, even if some strategic agreements between promoters and the public sometimes occurred before, during, or after consultations to avoid, prepare, or repair the debate. For the purpose of the present inquiry, the BAPE should be understood as an institution governed by strong deliberative principles: clarity, accessibility, and brevity of information, credibility, impartiality and independence of the consultative process, procedural equity, fairness, and flexibility, all-encompassing conception of ecological concerns, and in-depth analysis (BAPE 2009, 2015; Gauthier and Simard 2011).

Regarding the *Évaluation environnementale stratégique* (ÉES), this *ad hoc* independent process compiled existing peer-review articles and contracted out 69 scientific studies to individual experts from universities, public agencies, ministries, or consulting firms. Its knowledge gathering activities correspond to the theoretical expectations depicted in Chapter 1. Authors cited by the EES include 44 administrations, 31 peer-reviewed articles, 35 general scientific institutions, 2 professional associations, 5 industry representatives, 69 contracted studies, and 36 laws. In terms of expertise, those sources are divided as follows: 2 local development, 3 management, 2 public health, 5 physics, 1 energy, 5 hydrology, 4 sociology, 7 geochemistry, 7 political science, 9 law, 12 risk management, 18 hydrogeology, 14 economy, 11 engineering, 30 geosciences, and 10 administration studies (Chailleux 2015). Results from the EES were publicly available and formed the basis of 2014 hearings.

II – Data

The state of the information network and collaborative dynamics are measured using Social Network Analysis. Formally, SNA is the mathematical study of links between nodes. In political science terms, SNA "offers a means of addressing one the holy grails of the social sciences: effectively analyzing the interdependence and flows of influence between individuals, groups, and institutions" (Ward, Stovel, and Sacks 2011, 245). Among the advantages of the approach, one may note the possibility to review, visually and quantitatively, important aspects of social organizations that are not captured by study of personal attributes or characteristics. By taking into account social configurations and systemic properties, SNA extracts features from the network level—density of interactions, clustering, structural holes, centralization, etc.—as well as from the individual level—proximity between individuals, peripheral positions, dependencies upon others, etc.

Given these capacities, SNA appears well-suited to political science, and has been applied accordingly. For instance, Ingold and Varone (2011) used it to identify brokerage activities in a subsystem; Ingold (2011) qualified advocacy coalitions in light of coordination relations between organizations; Scholz, Berardo, and Kile (2008) evaluated the correlation between network properties and collective action problems; Considine and Lewis (2007) identified sources of innovation among local governments; Ingold and Gschwend (2014) documented the position of scientists within adversarial, collaborative, and dominated subsystems; Frank et al. (2012) showed the relations between occupying a structural hole and increased advocacy and advisory behaviours; Weible and Sabatier (2005) measured the asymmetric influence of policy beliefs on information, ally, and coordination networks; Fischer (2014) associated patterns of coalition structures with policy change; Kriesi, Adam, and Jochum (2006) developed a typology of policy networks in Western Europe using SNA; finally, Lee and van de Meene (2012) explained learning dynamics of local governments with regard to green-building policy networks. On the whole, it makes little doubts that SNA can be a valuable tool to study inquiries dealing with relational phenomena.

Relational Data: From References to Collaborative Dynamics

Those numerous examples show that, on the whole, the main challenge of SNA does not concern its scope of implementation, but rather is the compilation of the relational data needed to measure systemic properties. This is especially true for subtle phenomena such as collective learning and scientific policy brokerage. To circumvent such problems, the data used in this research come from a content analysis of 5751 references included in documents—memoirs, working papers, and scientific studies—published by 268 advocacy or governmental organizations during the two public consultations of 2011 and 2014. The ensuing database is two matrices of relations, with senders and receivers of links.

Only organizations were included in the content analysis, with the exception of individual experts. That is, individual citizens were excluded. This methodological choice resulted from empirical observations: political sophistication of lone residents appeared objectively low when compared with organized groups. Most of them expressed their views without engaging the policy debate. On average, rational justifications of opinion were seldom articulated, references to intellectual authorities uncommon, and the length of the argumentation short. Accordingly, to include individual citizens in information networks would have created more methodological noise than insights. In 2011, documents from 168 organizations were coded: 24 autonomous experts, 27 industry representatives, 42 environmental groups, 10 local groups, 8 governmental departments, 23 local governments, 3 public agencies, 22 business and labour associations, and 7 others. The participation was slightly more homogeneous in 2014 and included 100 organizations: 3 independent experts, 19 experts from the scientific assessment (EES), 10 industry representatives, 17 environmental groups, 18 local groups, 8 governmental departments, 14 local governments, 3 public agencies, 7 business and labour associations, and 1 other.

References contained in policy documents are among the most reliable and consistent relational data available to delve into system-wide intellectual interactions. Structural approaches to references have been a common in science mapping. For instance, Shwed and Bearman (2010) relied on citation networks to identify scientific sub-communities and concluded that structural approaches enabled the identification of scientific consensus without requiring qualitative investigations; network structure in itself reflects substantive attributes. Just like Shwed and Bearman (2010) and Hanney et al. (2005), this study assumes that the act of citing and referring is not a trivial behaviour. By doing so, an individual implicitly acknowledges the reliability of the source and tacitly concedes the presence of external influence on its own rationale. Mcnutt and Pal (2011 : 450), in spite of using hyperlinks instead of references, convincingly relate the process involved:

> *[…] a substantial body of research has found that when a source page links to a target Web page, the source of the hyperlink is conferring trust in the receiving Web page's content (Cugelman, Thelwall, and Dawes 2008; Gefen 2000). This does not suggest hyperlink creators necessarily agree with or endorse the meaning of the content but rather than the creators endorse the reliability and credibility of the source of the content and the information provided.*

Readers should bear special attention to the meaning of those references, as they do not necessarily reflect policy preferences directly, but rather illustrate the flows of information. As a consequence, two organizations might share a common policy position and participate in the same coalition, but nevertheless rely on completely different information sources. Similarly, two competing actors might argue over the soundness of exploitation, but nevertheless share common information sources. This might appear surprising to some readers, yet measuring the flow of information is of considerable relevance with regard to policy learning. Because sharing common understandings can be achieved via conjoint knowledge, two actors possessing a common information source might at least talk the same language when debating about an issue, a first step toward policy learning. Pushing the process a little further, those two actors might even reach total understanding if they abandon their respective, unshared sources of information to the benefit of their common knowledge-provider. On the whole, then, references, and the information flows they represent, seem worthy of interest and might even provide better causal demonstrations than relying solely on policy preferences.

References also possess the methodological advantage of being directional measures, allowing to distinguish between mutual and asymmetric relations. As shown in the next section, this important attribute considerably improves SNA's analytical power, especially with regard to brokerage activities and influence. Another asset of these data is that theoretical assumptions regarding information sources can be left aside, expertise being defined in an empirically grounded fashion. Lastly, the measure can be systematized across individuals, networks, and time periods.

The portrait is not entirely bright, though. One of the most serious limits pertains to inconsistency between uses of references. Professional norms and academic formations may influence how, and how often, actors mention external sources. For instance, independent experts may have higher likelihood of listing their references rigorously in bibliography. By opposition, local groups may employ vague phrasing such as "a study by Professor Howarth" or "the U.S. EPA showed". To limit such bias, the coding procedure was applied to in-text, footnotes, and bibliographic references. Unfortunately, such ambiguous references also made the identification of documents unreliable. Accordingly, authors are used as units of analysis instead of documents themselves. Similar considerations constrained the adjacency matrix to binary relations rather than weighted influence, i.e. actors either refer to someone [1] or they don't [0].

The second limit of the approach is that some references may contain severe criticisms, to the point where assumptions about the meaning of references no longer hold. To avoid those kind of invalid data, negative references and instrumentalized citations were excluded from the database. Precisely, the reference was coded if the answer to the following question was affirmative: *Does the actor cite, refer to, or name another actor to lead the BAPE toward an additional source of information, or to build on the other actor's knowledge?* In the few cases where participants mentioned a study through a newspaper, the research was coded instead of the media article.

Some skeptical readers might append a third limit: memoirs and working documents do not mirror academic papers, people may not be transparent about their sources of information. Such criticism is relevant, yet empirical results showed that the argument is not entirely warranted. In 2011, the 168 actors used on average 10.15 references, totalling 1706 links. In 2014, the 4045 references represented an average of 40.45 by actors. While it is impossible to dismiss completely the risks associated with undervaluation of relations, it seems reasonable to assume that political actors' willingness to improve their credibility in a technically framed process gave them the necessary incentives to outline their references.

III - Analytical Strategy: A Dual Investigation

In order to fully grasp the analytical power of SNA, the appraisal presented in Chapter 3 answers the two sub-questions underlying the hypothesis: (1) *Did collective learning dynamics improve between 2011 and 2014, and if so, how?* (2) *Is scientific brokerage responsible for this outcome, and if so, how?*

A Macro-Order Analysis

The first sub-question is answered using a macro-order scope of analysis. Using network statistics and the R package Igraph (Csardi and Nepusz 2006), the information networks of 2011 and 2014 are compared with regard to collective learning. Admittedly, collective learning is an abstract concept with numerous subjacent dimensions, and it seems unlikely that any empirically measurable metric faithfully represents the whole phenomenon.

Nevertheless, DeLeon and Varda (2009) argued that collaborative and adversarial network members do not, by nature, behave in a similar fashion. Accordingly, they hypothesized that some of those behaviours were empirically observable, and that describing these patterns cumulatively should make valid inferences regarding the amount of collaboration found in a network possible. Hence, the first part of the analytical strategy draws heavily on their work and adapts it to information networks. On the whole, seven statistics measured four dimensions of collective learning. Because only the members of the subsystem and not the entire set of sources were of interest, nodal statistics were only calculated for actors who participated in the hearings. Mathematical details are given in Appendix A.

1. Reciprocity

First of all, networks with higher collective learning should exhibit frequent reciprocated ties. That is, people tend to perceive each other as reliable sources, and information flows in a bilateral manner instead of being unidirectional. Reciprocity is measured as the ratio of mutual links to total links.

2. Structural Holes and Authority-hub Scores

The second dimension pertains to hierarchical relationships. In settings with strong collective learning, horizontal and decentralized interactions should constitute the norm rather than the exception. As a corollary, the number of structural holes and individuals in disproportionate positions of influence should be limited. With regard to information networks, this does not imply that actors cannot be notorious. After all, the theoretical framework developed in Chapter 1 explicitly recognized that an influential broker may improve collective learning. Rather, authority should be distributed more equally among individuals, with peripheral actors receiving similar attention as central ones.

The first measure of hierarchy relies on Burt’s constraint (Burt 2004). The statistic range from 0 to 1 for each network members. The closer to 1 the score is, the more the individual is constrained by structural holes: his relations are either sparse, strongly redundant, or both.

The second measure of hierarchy uses Kleinberg's (1999) hubs-authorities algorithm. The hub and authority scores were initially designed to study links between Web pages, with the idea that some of them issued complex authoritative content, for instance scientists publishing papers about various illnesses, while others acted as information hubs and bridged between numerous authoritative sources to provide a more accessible and wider understanding of the topic at hand, for example a medical association publishing summaries of these scientific reports. Hence, a good authority is pointed by many good hubs, and a good hub points toward many good authorities. Using this definition, Kleinberg developed an iterative algorithm. At each step of the process, the score of an individual is updated in light of the authority and hub scores of its connected neighbours. The sequence is repeated until the algorithm stabilizes. See Figure 2.2 on page 61 for an illustration of good hubs and authorities. Authority and hub scores have been normalized such that 1.00 corresponds to the greatest and 0.00 the least; a score of 0.50 stands for 50% of the largest authority.

3. Communities and Modularity Score

Diversity of ties, by opposition to homogeneity of relations, constitutes the third dimension. Because accumulating connections outside one's immediate intellectual network yields valuable opportunities for learning (Granovetter 1973), intellectual isolationism in the form of homophily[8] should remain an unusual phenomenon in collective learning settings. In other words, tie formation should "be based on the policy topic at hand with a tendency to draw together a diverse group of stakeholders" (DeLeon and Varda 2009, 67).

Measuring homophily in information networks, however, is not as straightforward as with social networks. That is, because two actors may share identical information sources without sending links to each other, using traditional community detection methods to localize dense intellectual subgroups is ill-suited. To circumvent the problem, the 2011 and 2014 information networks were transformed using structural equivalence. Structural equivalence

8 Homophily describes the tendency of people to relate with individuals sharing similar attributes, for instance expertise or organizational type.

occurs when two actors hold the same position inside a network. For instance, if A refers to C, and B also refers to C, then A and B are considered structurally equivalent. In the transformed networks, the strength of the relation between two actors is given by the Jaccard coefficient: the number of neighbours they share divided by the total number of neighbours they have (Csardi and Nepusz 2006). In other words, it measures the ratio of common references to total references. Prior to transformation, loops were added to each nodes, i.e. actors are considered sending a link to themselves. Without such addition, a link from an actor to another would count in the total number of links instead of the number of shared links, which makes no sense if the objective is to measure intellectual congruence. The outputs are two weighted networks, where the weights of relations between two actors correspond to their Jaccard similarity coefficient.

Once similarity networks were calculated, the Louvain community detection algorithm was applied to uncover underlying communities (Blondel et al. 2008). This iterative algorithm works by finding the two most similar actors and merging them into a single node, hence creating a new network with a higher modularity. The process goes on until modularity can no longer improve. Modularity varies between -1 and 1, and corresponds to the density of links inside communities as opposed to links between communities. The higher the score, the more divisible a network is into “modules”. Therefore, the first measure of the third dimension—diversity of relationships—is the number and size of communities determined by the Louvain algorithm in the similarity network. Those communities do not necessarily mirror advocacy coalitions sharing similar preferences, but rather illustrate subgroups of actors sharing similar knowledge; competing organizations may occupy a common community if they debate over the same sources.

The modularity score constitutes the second one. Precisely, computing modularity requires both a network on which divisibility is to be measured and predetermined categories to guide the internal/external density ratio. In the present case, information community membership is applied to the raw information networks, as coded from advocacy documents.

4. Closeness and Local Transitivity

The last dynamic corresponds to the amount of integration found in the network. As Deleon and Varda (2009, 68) argued: "The theory of embeddedness suggests that people will make choices based on past interactions and will be particularly inclined to initiate network connections with those whom they can trust. Collaborative policy networks may work well when stakeholders are familiar with one another along a continuum of relationship dimensions."

The first measure of the phenomenon is the closeness statistic, which corresponds to the inverse of the average distance between an actor and all other members of the network (Freeman 1979). Hence, a high closeness score indicates that an actor is strongly integrated within the network as a whole. The distance equals 1 for immediate neighbours and increases by 1 for every intermediary between two actors. If two nodes are not connected, then the distance is assumed to equal the total number of nodes in the network. To avoid biases associated with different network sizes, closeness scores have been normalized by multiplying them by N-1, where N relates to the quantity of nodes.

The second measure is called local transitivity, also known as clustering coefficient (Watts and Strogatz 1998). Local transitivity corresponds to the number of relations between an actor's neighbours divided by the number of possible relations between them. If all the neighbours of a nodes are interconnected, the node is strongly embedded and the score takes a value of 1; if there is no attachment between them, then embeddedness is at its lowest and local transitivity takes the value of 0.

Table I summarizes the statistics. Combining the four dimensions has the advantage of allowing a very precise analysis of improvements in collective learning. Moreover, the two instruments of the second, third, and fourth dimensions can be seen as robustness checks strengthening inferences. That being said, demonstrating improvements along the collaborative continuum does not explain why those happened; a situation addressed by the second part of the analysis.

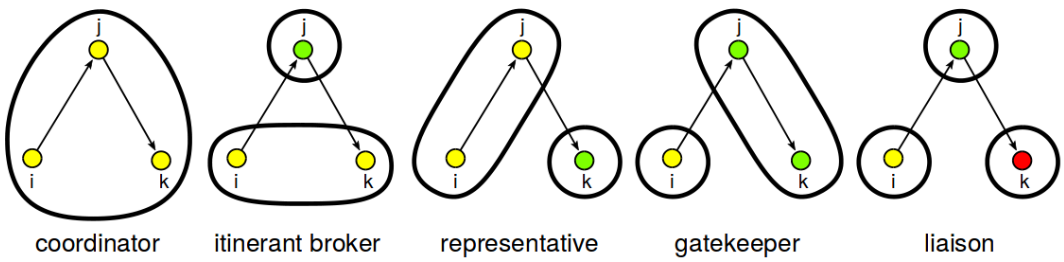
Table I: Summary of the Macro-order Instruments

Macro analysis: ***Did collective learning dynamics improve between 2011 and 2014?***		
Dynamics	**Measures**	**Descriptions**
I - Reciprocity	Reciprocity	Ratio of reciprocated links to total links
II - Hierarchy	1. Burt's constraint	Ranges between 0 and 1. The more an actor is constrained by a structural hole (few ties, redundant ties, or both), the closer to 1 the score is.
	2. Distribution of authority	Good authorities are pointed at by good hubs. Good hubs point toward good authorities. (See Figure 2.5 for an illustration)
III - Diversity of relations	1. Number and size of communities	Communities are detected by merging iteratively most-similar actors together until modularity is maximized. Similarity is based on the number of common references.
	2. Modularity score	Ranges between -1 and 1. Measures the density of links inside communities as opposed to density between communities.
IV - Integration	1. Closeness	The inverse of the average distance between an actor and every other actors in the network. Distance equals 1 for immediate neighbours and increases by 1 for every intermediary.
	2. Local transitivity	Number of links between an actor's neighbours divided by the maximum potential connections between them. Ranges between 0 and 1.

A Micro Order of Analysis

Is scientific brokerage responsible for this outcome, and if so, how? Answering this requires, on the one hand, the identification of influential actors and, on the other, the validation of their impacts. To be sure, this complex demonstration would, in a best-case scenario, rely on objective and conscientious self-reports about the influence of the scientific broker. To overcome the lack of such data, the micro order part of the analysis combines two descriptive statistics to assess individual influence, and confirms observations through inferential network modelling.

Figure 2.4: Brokerage Types[9]



1. Descriptive Statistics

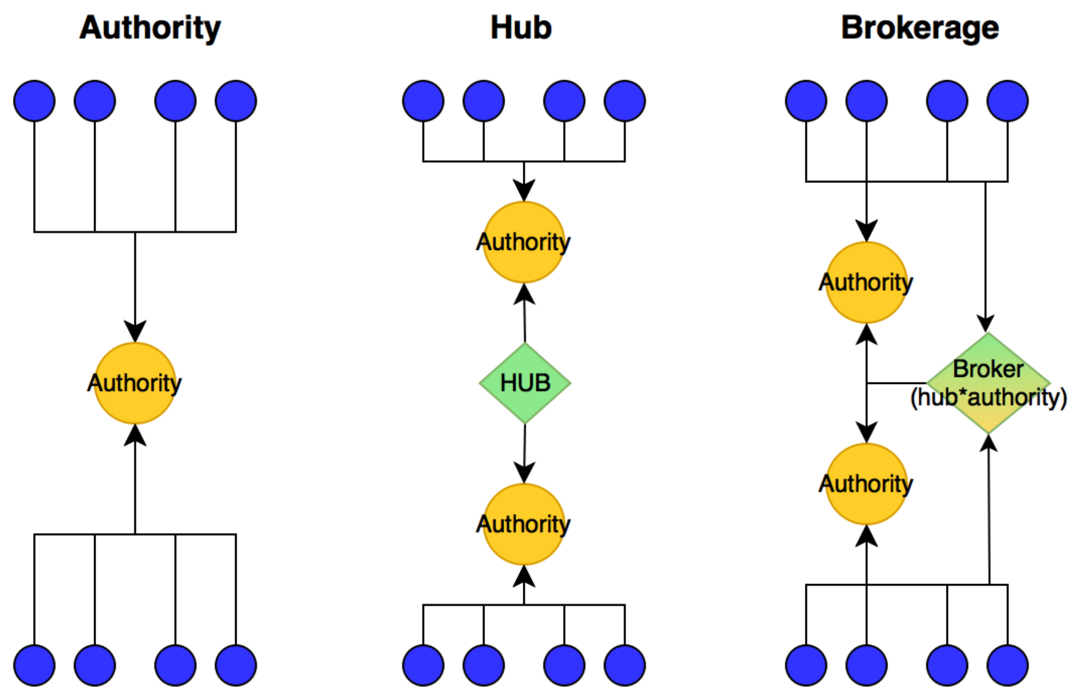
First, a measure counts the number of times an actor act as a broker between two actors that may, or may not, adhere to the same information community. As Figure 2.4 shows, brokerage activities can be divided into five distinct roles: (1) coordinating a community [coordinator] (2) coordinating a community without belonging to it [itinerant broker] (3) representing a community before another one [representative] (4) representing another community before its own one [gatekeeper], and (5) linking between two communities to which one does not belong [liaison] (Gould and Fernandez 1989). Brokerage activities are quantified using the software Pajek (Batagelj and Mrvar 1999). The communities dividing actors are those computed by the Louvain algorithm.

To fortify the results, a second measure of influence is added: authority and hub scores, as described above. While the macro order analysis focused on the distribution of authority, what is under scrutiny here are the scores of the scientific broker. Indeed, an effective broker is expected to have an elevated amount of authority within its network; that is, most subsystem members refer to him. In addition to being popular, a broker must act as an information hub and point toward other influential sources to "close" the knowledge gap. Accordingly, a broker is expected to possess a substantial combination of authority and hub

9*Brokerage types have been defined by Gould and Fernandez (1989). The Figure comes from Batagelj and Mrvar (2011, 34).

scores. Hence, the instrument used to identify brokerage behaviour is a factor of hub and authority scores. Figure 2.6 illustrates the idea behind the metric.

Figure 2.6: The Relation Between Authority Score, Hub score, and Brokerage



2. Inferential Modelling

Descriptive statistics, however, may lead to spurious inferences. One of the main issue is that there are no means of knowing whether brokerage activities are higher or lower than what would be expected by pure chance. Similarly, qualifying the amount of collective learning dynamics found in a network as opposed to a random behaviour is impossible. Fortunately, tools for inferential network analysis have been developed over the past few years. Unlike traditional inferential models, those do not assume the autonomy of observations, but rather embrace the interdependencies between them. As Cranmer and Desmarais (2011, 69) expressed: “The failure of a model to recognize dependence among outcomes is as threatening to the validity of results as omitting an important covariate.” The reason is simple: interacting individuals likely change their behaviour according to their environment. For example, the odds of interaction between two actors with the same expertise are higher in closely-knit communities than in sparse networks. The same goes for brokerage activities. A given number of brokerage activities might be considered low in a collaborative network, but high in an adversarial one. Accordingly, an observation about brokerage may be spurious if the environment in which it occurs is not controlled for.

This research relies on the Exponential Random Graph Model to include environmental variables in the inferential model (Cranmer and Desmarais 2011; Hunter et al. 2008; Ward, Stovel, and Sacks 2011). In an ERGM, the dependent variable is binary; it reflects the existence—or absence—of a tie (relation) between two nodes (actors). The independent variables may be individual, structural, or both. Individual variables include, for instance, the impact of wealth on the probabilities of receiving a tie, or the increased probabilities of friendship resulting from age or gender homophily. Structural variables encompass popularity effects, clustering effects, density of interactions, number of isolated individuals, etc. An ERGM without structural variables equals a logistic regression (Cranmer and Desmarais 2011). When structural variables are added to the model, ERGM simulates a number of similar, randomly distributed networks—usually 1000—and then estimates the likelihood of observing a given statistic by pure chance. Because computational limits make the estimation of the exact likelihood impossible, the ERGM uses the Markov Chain Monte Carlo to approximate it. The model outputs a logistic coefficient expressing the increased probabilities of detecting a tie between two actors resulting from an increase of one unit in the independent variable, controlling for the remaining variables. Interpretation can either be systemic, i.e. inferences about the state of the network, or localized, i.e. relational dynamics between subsections of the network (Desmarais and Cranmer 2012). Again, further details about ERGM can be found in Appendix A.

It is important to note that ERGM possesses serious limits, the most constraining of them being degeneracy problems associated with poor comparability between the observed network and simulated ones, in which case the coefficients are simply impossible to evaluate or strongly biased (Ward, Stovel, and Sacks 2011). Fortunately, robustness checks exist and the model described in Chapter 3 does not appear degenerate (Appendix B). Table II summarizes the micro-order instruments.

Table II: Summary of the Micro-order Instruments

Micro analysis: ***Is scientific brokerage responsible for this outcome, and if so, how?***		
Dynamics	**Measures**	**Descriptions**
I – Influence	Authority * hub score	Good authorities are pointed by many good hubs. Good hubs point toward many good authorities. Effective brokerage is expected to cumulate both behaviours.
II – Brokerage activities	Brokerage types	Five types of brokerage are calculated based on the link they create between communities of information. Communities used are those calculated by the Louvain community detection algorithm.
III – Inferential validation	ERGM	Randomly creates 1000 networks comparable in structural attributes. Using the normal distribution of statistics created, ERGM calculates the impact of individual and structural variables on tie formation, along with the likelihood of observing such impact by pure chance.

IV - Conclusion

As a whole, the research design presented above took advantage of the scientific uncertainties of shale gas and its related political disputes. It selected a case where the impacts of scientific brokerage activities on an adversarial network can be measured. If the hypothesis advanced in Chapter 1—*The presence of a broker in an adversarial structure of governance increases the probabilities of observing a shared understanding of policy-relevant information between policy actors*—has empirical resonance, then the selected events represent a best-case scenario to document it. If, on the other hand, brokerage activities do not influence policymaking in adversarial settings, then the case constitutes a robust demonstration of the failure. The measurement of successes or failures is made possible by scrutinizing multi-scale dynamics with numerous indicators from Social Network Analysis. In addition, observations are validated using ERGM, which further increases reliability of the interpretations. Next chapter presents the results along with a theoretical discussion.

Chapter 3: Results and Discussion

Following the analytical strategy presented in Chapter 2, the next chapter empirically documents the role played by scientific brokerage in adversarial policymaking before engaging a theoretical debate. Results are divided in two sections reflecting the analytical subquestions.

I - Improved Collective Learning

As stated in chapter 2, the measure of collective learning relies on 4 dynamics estimated by 7 metrics: (1) reciprocity of relations (2) amount of hierarchy regulating information exchanges (3) heterogeneity of sources, and (4) proximity to the network as a whole. Readers unfamiliar with Social Network Analysis should refer to Chapter 2 and Appendix A to grasp the details of each statistics.

Table III summarizes the findings: collective learning improved on all four dynamics between 2011 and 2014[10]. Namely, the proportion of mutual links increased by more than three times (from 0.009 to 0.032), implying that transmission of knowledge is less one-sided in 2014 than it was in 2011. Moreover, information diffusion appeared considerably less hierarchical in 2014. Burt's constraint diminished by 2.6 times (from 0.39 to 0.15; $p < 0.001$). Such a transformation points toward fewer dependencies and more homogeneous opportunities to learn from others. In addition, not only did the average authority among policy actors increase by more than five times (from 0.034 to 0.175; $p < 0.001$), but authority also tended to be apportioned more evenly between members. As Figure 3.1 shows, the

10 Burt's constraint, distribution of authority, local transitivity and closeness report the *average score of active policy actors only, i.e.* "internal information sources.*" A contrario,* the averages exclude all information sources that are not consultation participants, i.e. "external information sources". The research purpose makes such disqualification mandatory; failing to remove external information sources would have strongly biased the interpretations. For instance, the closeness statistic represents the inverse of the average distance between a node and all other nodes in the network. In the case of external information sources, they do not perform any link-sending activities. Hence, their closeness is considerably lower than active subsystem participants, and including them would push the average toward zero. Similar consideration applies to the three additional statistics.

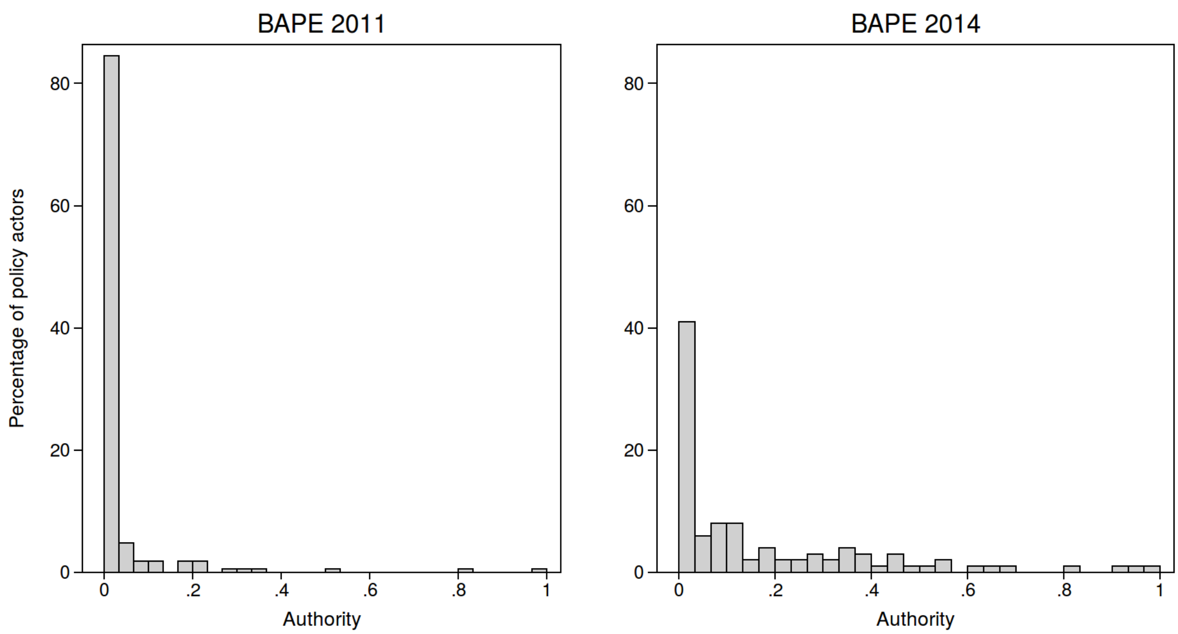
distribution was considerably more localized in 2011 than in 2014. Specifically, the high and positive kurtosis of 2011 (83.82) indicates few individuals possessed a large amount of the total authority, whereas a smaller kurtosis (17.18) shows concentration of influence was a phenomenon of smaller significance in 2014.

Table III: Summary of Collective Learning Dynamics

Measure	2011	2014	T-test
Reciprocity	0.009	0.032	N.A.
Burt's constraint	0.39	0.15	P <0.001
Distribution of authority	0.034 Kurtosis = 83.82	0.175 Kurtosis = 17.18	P <0.001
Communities	49 communities 7 meaningful	21 communities 9 meaningful	N.A.
Modularity score	0.44	0.31	N.A.
Closeness	0.0012	0.0046	P <0.001
Local transitivity	0.059	0.148	P <0.001

Regarding diversity of relationships, the number of information communities identified by the Louvain algorithm decreased from 49 to 21. That being said, 42 individuals were the sole active member of their groups in 2011, indicating that the accurate number of meaningful communities—i.e. between 2 and 31 people—was 7 in 2011. By contrast, there were only three isolates in 2014, and the number of real communities was 9, comprising between 2 and 21 policy actors. Whereas the absolute quantity of groups increased by 2 in three years, the biggest community encompassed a total of 1802 information sources in 2014 (71% of the entire set), by opposition to 336 (34%) in 2011. Importantly, the 2014 network appeared less divisible with regard to intellectual similarity than its 2011 counterpart, as shown by the modularity scores [from 0.44 to 0.31]. On the whole, the picture suggests intellectual partitioning declined: the number of isolated actors melted, the size of the principal information community doubled in relative terms, and the density of inter-community relations amplified by about 30%.

Figure 3.1: Distribution of Normalized Authority in 2011 and 2014



Looking at embeddedness comforts the aforementioned analysis. As Table III shows, the average closeness between an actor and the entire set of information sources grew by about 4 times (from 0.0012 to 0.0046; p <0.001). Conceptually, those results indicate that the network collapsed into a denser, more intertwined entity that shortened the intellectual gap between active subsystem members. A three-times increase of local transitivity further reinforces these observations (from 0.059 to 0.148; p <0.001). Since transitivity can be understood as the number of triangles a given political actor is participating to[11], those results either demonstrate that actors had more inclination to adopt the same references as their informants, or that they had a greater propensity to refer to political actors sharing the same sources. In any case, the outcome of such process was that the frame of understanding converged. As a matter of fact, the number of links sent to internal actors confirms this interpretation: in 2011, subsystem members received on average 1.89 ties, whereas the average reached 5.21 in 2014 (p <0.001).

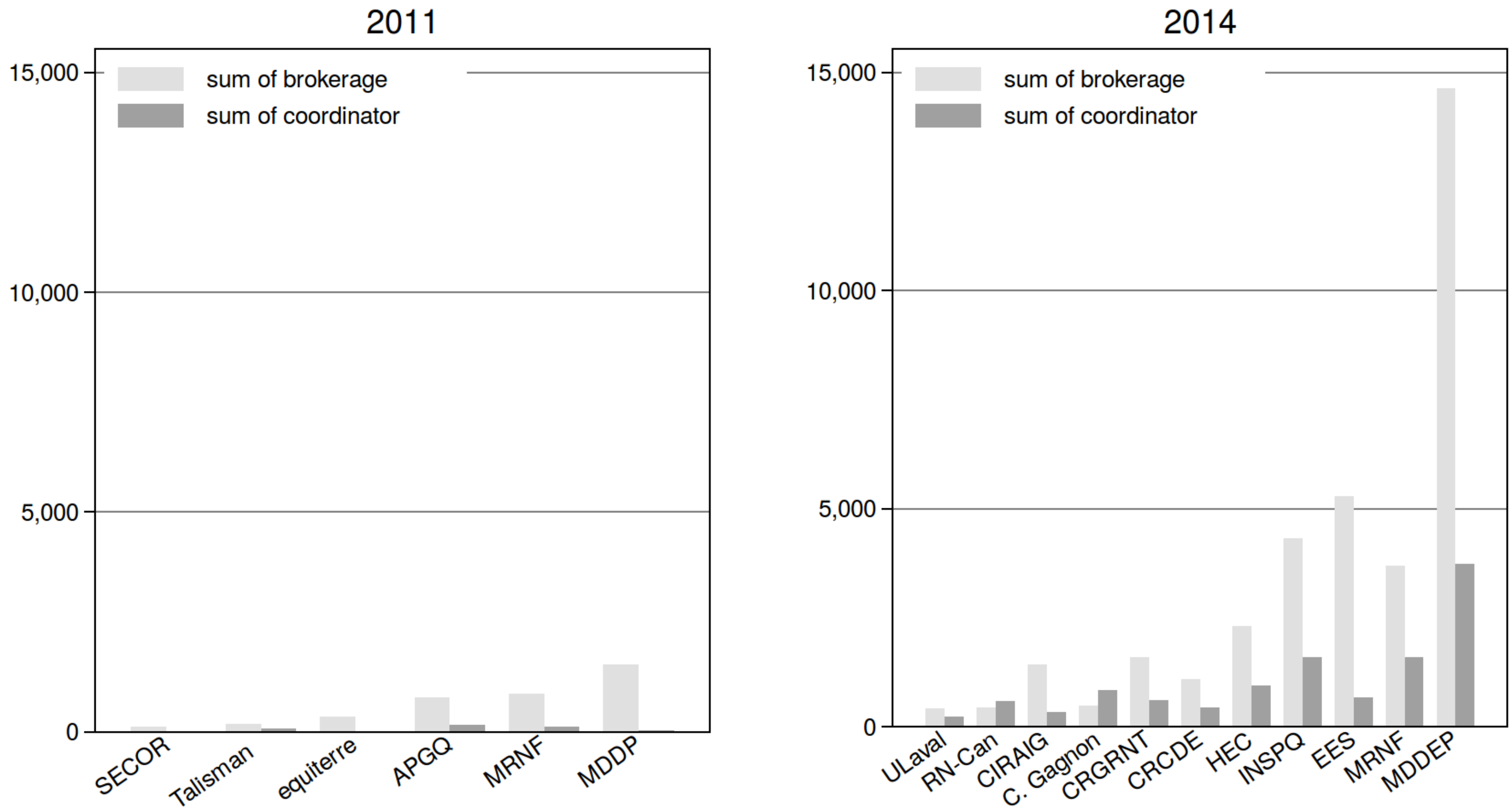
11 For example: a→ b; b→ c; a→ c, where a and b are internal information sources

All things considered, did collective learning dynamics increase between 2011 and 2014? Reinforcement of the four dimensions combined with consistency across statistics point toward a robust affirmative answer to this subquestion. This being so, an important caveat appears necessary. Collective learning did improve, but the outcome is far from peaceful policymaking and global collaboration. Even in 2014, real-world ramifications of the outputs indicate that collective learning remained a scarce phenomenon. Approximately 3% of links were mutual. Structural holes persisted to constrain access to information sources. Hierarchical authority endured. 9 communities partitioning 100 people combined with a modularity of 0.31 show that divisibility persisted. Closeness appears objectively low considering its theoretical maximum of 1.00: assuming infinity corresponds to 2537, the average distance between a node and all others was approximately 546,448 liaisons. Similarly, about only 15% of possible relations between the information sources of the average policy actor existed in 2014. It is not to say, however, that those changes are insignificant. After all, theory suggests a strong resistance to collective learning in conflicting environment, and improving collective learning by about three time over three years is a non-trivial achievement.

II – Influential Brokerage

Is scientific brokerage responsible for the observed outcome? According to the results described in the following lines, it is. This being said, what occurred does not exactly correspond to theoretical expectations. On the one hand, the—rather coarse—count of bridges suggests that brokerage increased, but also that the scientific assessment (EES) was not the sole broker participating to the phenomenon. Figure 3.2 gives the number of times an organization bridged between two individuals [a→ b; b→ c] from different information communities [brokerage], along with the number of times it bridged between two actors in the same community [coordination]. Only the most important brokers are presented.

Figure 3.2: Brokerage Count in 2011 and 2014



In 2011, both brokerage and coordination activities were uncommon. At most, the Environmental Department bridged 1531 times, followed by the Natural Resources Department (877) and the Industry association (784). Regarding coordination, the number is appreciably lower, with industry representing a large part of it (Junex = 198; ALL consulting = 177; Industry association = 159; Natural Resources Department = 126; Talisman Energy = 81). While one might interpret these absolute numbers as being significant, their relative weight is trivial when compared with the 2014 count. Indeed, the Environmental Department spanned between different communities 14,637 times in 2014, followed by the scientific broker (5285), the INSPQ—a public health agency (4318)—, and the Natural Resources Department (4318). Coordination also increased substantially (e.g. Environmental Department = 3740), but nevertheless remained a phenomenon of tinier significance.

By opposition to what was theoretically expected, the EES is neither the sole nor the most important broker. Rather, the Environmental Department acted as a broker almost three times as much as the EES did. Even if the EES ranked second, his followers scored objectively close. Overall, the Environmental Department, the EES, the INSPQ, the Natural Resources Department, HEC, and the CRCDE all did more brokerage than 2011 best broker. As a consequence, it is possible to conclude that brokerage was considerably more present in 2014 than in 2011, but also that brokerage was not exclusive to any political actors.

Unfortunately, the count of brokerage and coordination activities only gives a partial diagnostic. First, whether increased brokerage had influence on collective learning stays an unanswered question. Second, the count of brokerage does not account for the relative size of networks, which is an important insufficiency considering that opportunities to bridge between actors rise exponentially when the network size inflates. As a consequence, part of the rise results from an increased quantity of information sources. Third, the measure is highly dependent upon the number of references possessed by a broker. For instance, most of the 383 references of the Environmental Department have been classified in the Environmental Department’s community. This means that the count of brokerage activities rises by almost 383 each time an individual from another community refers to the Environmental Department.

By contrast, the same department only had 33 references in 2011. This does not mean, however, that the observations are completely spurious. After all, bridging with 383 sources corresponds to an objectively better brokerage than bridging with 33 references. Nevertheless, an additional measure of brokerage appears warranted to dissipate this uncertainty.

This second measure looks at unscaled authority and hub scores. Under the assumption that an effective broker is both influential and aware of its intellectual environment, the multiplication of authority and hub scores should allow for the identification of brokers. As the upper part of Figure 3.3 shows, the Environmental Department again scored the highest in 2011 and 2014. Precisely, it almost doubled its brokerage score in three years, i.e. from 0.05 to 0.09. The rest of the picture, however, is not conclusive regarding brokerage improvements. The second most likely broker, the Natural Resources Department, scored almost equivalently in 2011 and 2014 [from 0.049 to 0.046]. Most importantly, the EES and all remaining brokers obtained less than 2011 leaders, except for the Environmental Department.

Why is that so? A part of the answer lies within the lower part of Figure 3.3. As can be seen by comparing the graphs, the absolute authority scores declined between 2011 and 2014. That is, even if authority was better distributed among policy actors, they individually possessed less influence in 2014 than in 2011. For instance, the most authoritative broker of 2014—the scientific broker—enjoyed an authority of 0.15, whereas the Natural Resources Department scored an absolute 0:43 in 2011. On the contrary, hub scores are strikingly different. They increased from an average of 0.14 to 0.23. Again, the Environmental Department, the Natural Resources Department, and the EES scored among the highest of 2014, with a respective 0.68, 0.36, and 0.22.

Substantively, Figure 3.3 reveals that a dual process is at play: while network-aware organizations are both more numerous and more enlightened, they have a smaller influence on the rest of the network. Hence, the abundance of bridges is not purely the consequence of influential brokerage, but rather the outcome of more comprehensive knowledge-gathering activities. This is puzzling: if collective learning, community-bridging, and knowledge gathering did proliferate, how did authority decline, and why?

Figure 3.3: Authority and Hub Scores

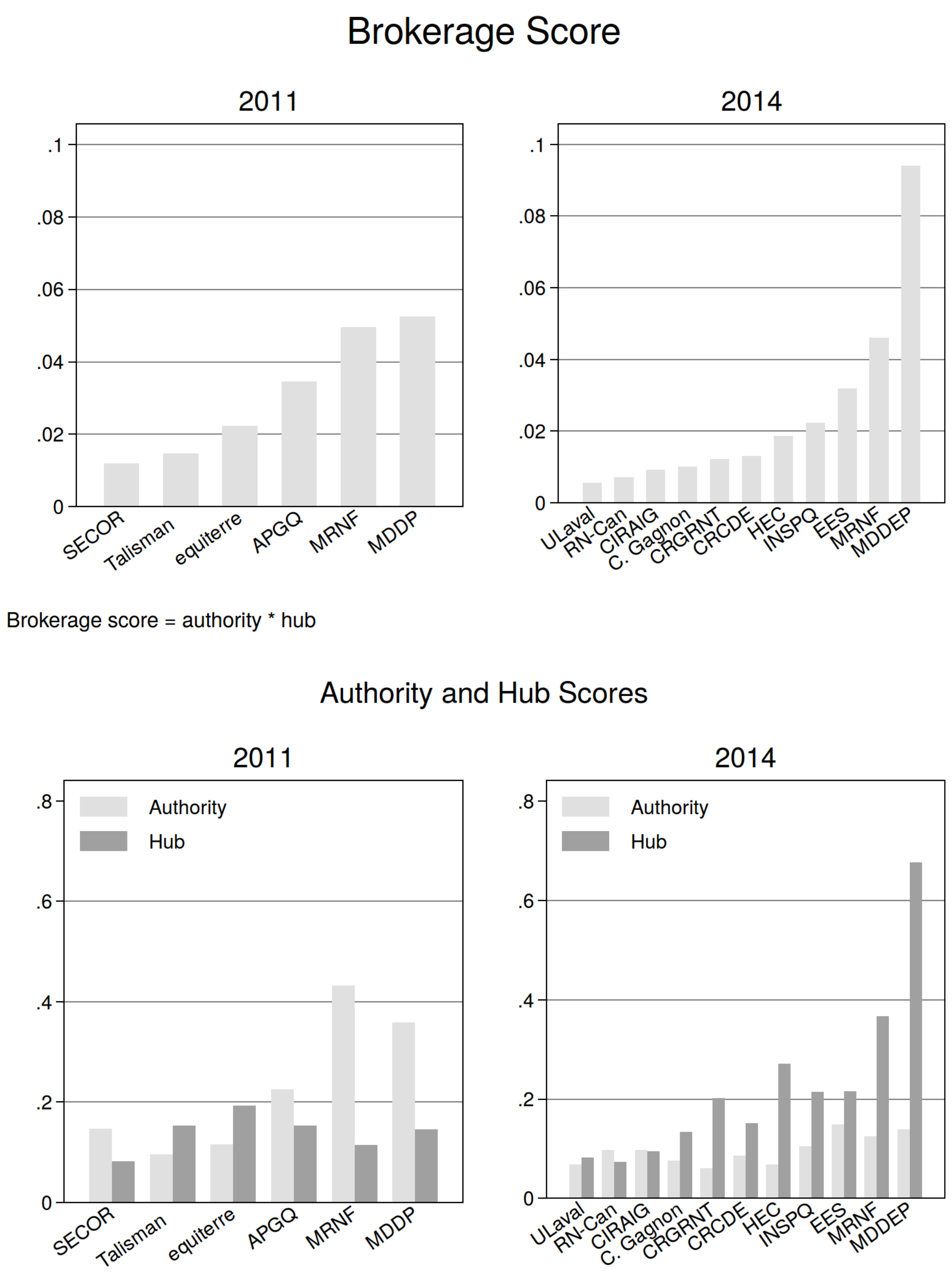
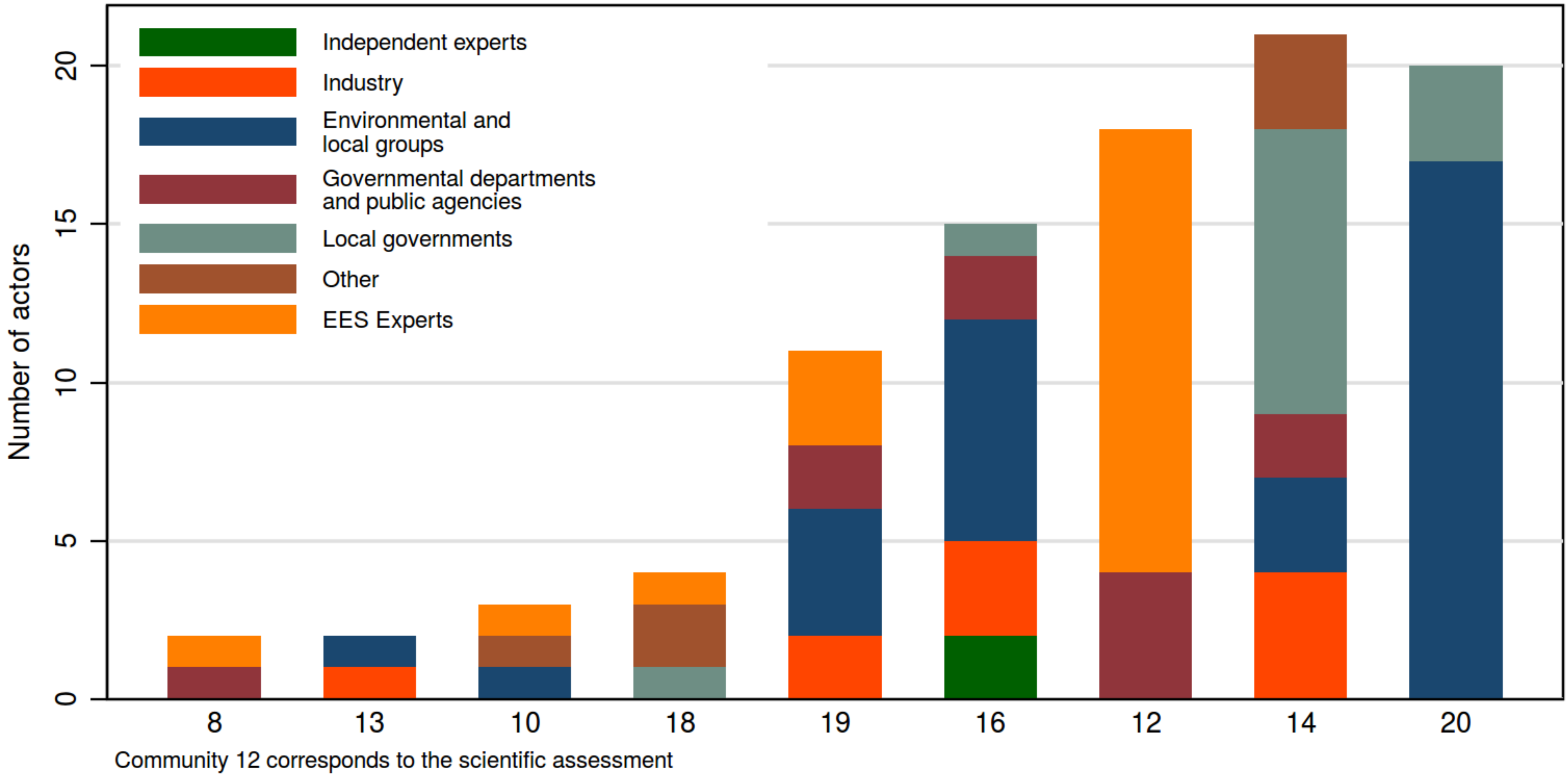


Figure 3.4: Distribution of Organizational Affiliations by Information Communities



An Explanation: The Collaborative Core Thesis

As the horizontal axis of Figure 3.3 illustrates, virtually all brokering organizations of 2014 were experts mandated by the scientific assessment, including the two governmental departments. Figure 3.4 exposes the distribution of organizational affiliations within information communities of at least 2 people. As can be seen, the community detection algorithm grouped 14 out of 19 EES experts with 4 governmental departments—Environment, Transport, as well as federal and provincial Natural Resources. Importantly, no other policy actors have been classified with those 18 organizations, which casts further doubts on the unifying power of the scientific assessment. If, indeed, the EES had successfully positioned itself as a dominant access-point for information, then some actors would have been categorized in its community. To be sure, these results do not mean that no links existed between subsystem members and the scientific assessment. In fact, EES and affiliated experts were among the top internal information sources (i.e. 53 references to the EES, 50 to the Environmental Department). Rather, those results imply that the relations between the scientific assessment and policy actors referring to him were considered trivial by the algorithm in light of the vast number of competing references they kept. By opposition, the EES, his experts, and governmental departments sustained sufficient acquaintance with each other's references and shared a common understanding of the issue.

To dig further into the assessment/advocacy divide, the 2014 information network was divided in two subnetworks; the first of which encompassed solely the scientific assessment, his experts, and governmental departments [assessment network], while the second constrained membership to advocacy organizations [advocacy network][12]. Table IV summarizes three of the four collective learning dynamics within those networks[13]. Simply looking at the density of interactions outlines the amount of collective learning found inside the assessment network: 30 organizations nourished 189 relations, of which 32% were

12 References to external sources were removed to delve into the quality of internal relations.

13 Community and modularity were excluded from this analysis because measuring structural equivalence is irrelevant without external information sources.

reciprocated. The assessment's experts and departments were moderately constrained by structural holes (Burt = 0.29); average authority appeared relatively high (0.15) and well distributed (kurtosis = -0.39); closeness reached impressive heights (0.50); local transitivity indicated 47% of possible triangles were closed.

Table IV: Collective Learning Dynamics in Assessment and Advocacy Subnetworks

Measures	Assessment	Advocacy	Both
Number of Nodes	30	70	100
Number of Ties	189	41	527
Reciprocity	0.32	0.03	0.14
Burt's constraint	0.29	0.83	0.33
Distribution of authority	0.15 Kurtosis = -0.39	0.04 Kurtosis = 9.77	0.05 Kurtosis = 7.26
Closeness	0.50	0:01	0.03
Local transitivity	0.47	0.03	0.40

By opposition, collective learning was largely absent from advocacy actors, as shown by their small number of relations (41). Among this second subnetwork of 70 organizations, reciprocity fell to only 3% of ties, structural constraints were almost total (Burt = 0.83), relative authority was low (0.03) and concentrated around few individuals (kurtosis = 9.77), closeness only equalled 2% of its assessment counterpart, and about 3% of potential triangles were closed. Unsurprisingly, all dynamics ranged somewhere between both extremes when the subnetwork encompasses every policy actors, as shown by the right-hand column of Table IV. Nevertheless, the total number of relations (527) suggests considerable advocacy-to-assessment awareness, or vice-versa.

On the whole, it makes little doubts that the observations made about improved collective learning were entirely imputable to the appearance of the assessment community: the phenomenon arose as the exclusive domain of EES experts and governmental authorities. While the community was densely knit, it was far from being closed on itself. Assessment experts acknowledged advocacy actors and their information sources in an effort to integrate policy-relevant information. These efforts, by contrast, were insufficient to influence advocacy rationales. As a matter of fact, advocacy actors examined the brokered picture as well as experts' research, yet they largely kept their own, distinct information sources. On a micro-order of analysis, then, brokerage in adversarial policymaking failed.

This being said, the picture is completely different when one moves away from individual-level effects and instead embraces a systemic view based on communities. Because adversarial communities refuse to acknowledge the relevance of competing claims, they subdue each other's power over policymaking. In this environment, a community gaining partial recognition from the whole set of subsystem members, whether by means of reputation or coercive influence, rapidly emerges as the most central, well-known group. While every other communities possess virtually no external influence, the central community enjoys the best systemic position to steer policymaking. This phenomenon is hereafter referred to as the *structural predominance* of a community. To some extent, structural predominance is a factor of political division and external recognition.

$$\textit{structural predominance} = \textit{political division} * \textit{external recognition}$$

Both are necessary conditions. Without political division, possessing external recognition can seldom be beneficial: all communities are considered legitimate and influence is more or less equally divided. Without external recognition, a community cannot take advantage of political division: efforts to influence are either blocked or ineffective. In the present case, the data at hand suggest that structural predominance gave the collaborative, brokering community considerable significance in the information network, and thus in policymaking. The assessment community became the collaborative core of an adversarial network.

Figure 3.5: Cumulative Authority of Information Sources by Community

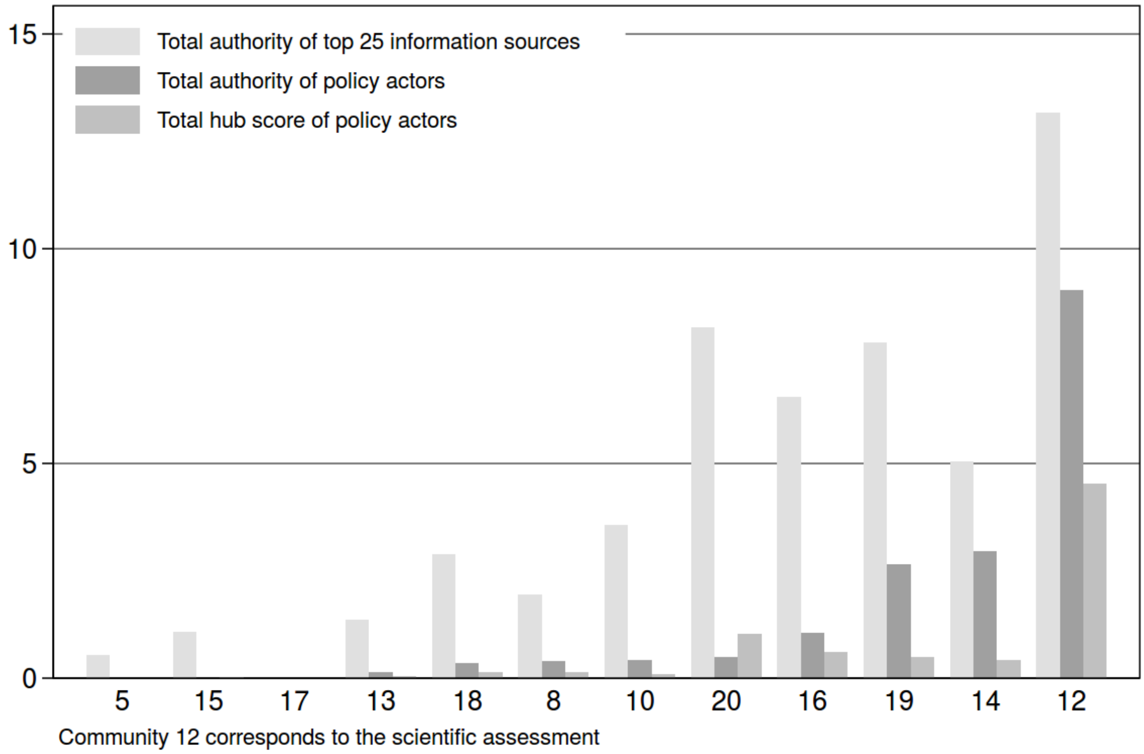


Figure 3.5 sustains this interpretation by showing that information provided by the assessment community [id = 12] was considerably more authoritative than the rest of the network. Both the cumulative authority of policy actors and the cumulative authority of top 25 information sources demonstrate that the assessment community dominated the information network[14]. In addition, the cumulative hub score shows that it was also the community doing the most knowledge-gathering activities. In short, the network-conscious, collaborative community enjoyed structural predominance in addition to proximity with shale gas's most relevant governmental departments: environment, natural resources and transport.

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14 Using top 25 authorities instead of total information sources is important to avoid a bias associated with asymmetric community sizes. For instance, a community of 1800 information sources having an authority score of 0.01 would equal the same total authority as 18 highly influential sources having an authority of 1.00. However, influence of the latter is logically higher than the former.

Inferential Modelling

So far, the collaborative core thesis has been supported by descriptive statistics only. While numerous measures were used and consistency across them appeared convincing, an effective demonstration should reduce the likelihood of spurious observations. This section addresses this situation using the Exponential Random Graph Model. Readers unfamiliar with ERGM should pay careful attention to the explanations provided in Chapter 2 and Appendix A. Robustest probes and degeneracy diagnostics are available in Appendix B. R codes are displayed in Appendix C.

In the present case, the dependent variable is the probability of observing a relation between two actors, and the independent variables include community homophily, subnetwork membership, reciprocated relations, transitivity[15], and popularity[16]. Subnetwork membership terms (assessment-to-assessment, advocacy-to-advocacy, assessment-to-advocacy, and advocacy-to-assessment) gives the probabilities of observing a relation going from the former to the latter. For example, the assessment-to-advocacy coefficient gives the increase in probabilities associated with a link going from an assessment member to an advocacy organization. Regression results are presented in Table V. Models A, B, C, D, and E are performed on the same network[17], the only differences being the set of independent variables. Advocacy-to-advocacy subnetwork membership represents the base term.

From a network perspective, coefficients of model E are all large and significant at the 0.001 threshold; the observed network is strongly different from randomly generated ones with regard to selected characteristics. At first sight, all type of relations, regardless of network membership, are less likely than what would be expected by chance, i.e. tie density is extremely low. This being said, all types of subnetwork interactions are more likely than

15 Transitivity can be summarized as “a reference of my reference is also my reference”. The coefficient associated with transitivity illustrates the increased likelihood of observing a tie that closes one triangle.

16 Popularity can be summarized as “I refer to you because everybody refers to you”. It is the ERGM counterpart of the hub-authority algorithm.

17 Akin to what was done with the comparison of subnetworks, ties to external information sources were excluded from the analysis to grasp internal dynamics.

advocacy-to-advocacy exchanges of information. Community homophily, reciprocity of ties, transitivity and popularity are all more present than what can be found in similar, randomly created networks, which is coherent with the view upon which information flows reflect identifiable social interplays.

Table V: ERGM Results

Variable	Model A	Model B	Model C	Model D	Model E
Advocacy-to-advocacy	-4.76* (0.16) 0.009	-4.97* (0.16) 0.007	-4.95* (0.16) 0.007	-5.55* (0.17) 0.004	-5.33* (0.16) 0.005
Assessment-to-advocacy	1.59* (0.19) 4.90	1.75* (0.19) 5.75	1.52* (0.20) 4.57	0.98* (0.21) 2.66	1.37* (0.20) 3.94
Advocacy-to-assessment	2.57* (0.17) 13.07	2.73* (0.18) 15.33	2.64* (0.18) 14.01	1.80* (0.19) 6.05	1.56* (0.17) 4.76
Assessment-to-assessment	3.47* (0.18) 32.14	3.35* (0.18) 28.50	3.02* (0.18) 20.49	1.51* (0.19) 4.53	1.91* (0.17) 6.75
Community homophily		0.77* (0.12) 2.16	0.65* (0.11) 1.92	0.64* (0.11) 1.90	0.72* (0.12) 2.05
Reciprocity			1.27* (0.18) 3.56	0.83* (0.19) 2.29	0.71* (0.21) 2.03
Transitivity				1.46* (0.12) 4.31	0.74* (0.11) 2.10
Popularity					0:04* (0.003) 1.04
AIC	3475	3440	3398	3205	3053
BIC	3503	3476	3441	3255	3110

*** p <0.001; Standard errors in parentheses**
Odds ratios are presented underneath logistic coefficients.

Lowering the scope of analysis gives interesting insights about the plausibility of the collaborative core thesis. Firstly, odds ratios of Model A show that the raw likelihood of inter-subnetwork relations is extremely higher for assessment-to-assessment ties than for advocacy-to-advocacy (32.14 and 0.009, respectively; p <0.001). Moreover, odds ratios are greater than one for assessment-to-advocacy and advocacy-to-assessment references, the latter outstanding the former by about three times (13.07 and 4.90; $p < 0.001$).

Tracing the evolution of those coefficients as structural factors are added to the model yields additional understandings of the dynamics at play. As can be seen with model B, taking into account community homophily slightly reduces the likelihood of within-subnetwork ties, but also moderately increases the probabilities of observing cross-subnetwork relations. Substantively, this confirms the view upon which information communities do not span the assessment-advocacy divide. Regarding reciprocity, adding the variable to model C reduces the coefficients of all but advocacy-to-advocacy relations, with assessment-to-assessment linkages exhibiting the most important drop in probabilities. Corollaries are twofold: (1) only a small part of cross-subnetwork interactions occurred following the “a refer to you because you referred to me” principle and (2) mutual exchanges of information is a phenomenon predominantly circumscribed within the assessment community boundaries.

Model D is conclusive regarding transitivity: it is by far the strongest structural explanation at hand. While the plunge of coefficients is objectively large for all categories of ties, the effect is striking in the assessment subnetwork: a sharp decline in the odds ratio, from 20.49 to 4.53 [$p < 0.001$]. Again, this substantiates the idea that the EES core is by far the most collaborative. The last addition is made by Model E, which incorporates a popularity effect. As can be seen by comparing the two right-hand columns of Table V, within-subnetwork probabilities increase—marginally so for advocacy actors—and cross-subnetwork equivalents diminish. The nuance is noteworthy, because it demonstrates that interactions among EES experts or governmental departments are not based on the popularity of the source in the whole network, but rather correspond to the dense web of relations expected in a collaborative core. By opposition, cross-subnetwork dynamics are partly mediated by the popularity term: advocacy actors tend to refer to important assessment members such as the Environmental department or the EES, and collaborative core affiliates lean toward well-known purposive or material organizations, for instance the industry representatives, the union of agricultural producers, a collective of advocacy scientists, etc.

Table VI: Typical Cases Facilitating ERGM Interpretation

Case	Coefficients included	Tie probabilities
Advocacy to advocacy	Popularity = 1.8	1.4%
Advocacy to influential advocacy (Industry association)	Homophily = 1 Popularity = 12	4.3%
Assessment to assessment	Advocacy-to-advocacy = 1 Homophily = 1 Popularity = 12 Mutuality = 1 Transitivity = 1	55.7%
Assessment to assessment broker (MDDEP & EES)	Assessment-to-assessment = 1 Homophily = 1 Popularity = 52 Mutuality = 1 Transitivity = 1	86.1%
Advocacy to assessment	Advocacy-to-assessment = 1 Popularity = 12	9.5%
Assessment to advocacy	Assessment-to-assessment = 1 Popularity = 1.8	5.3%
Advocacy to assessment broker (EES & MDDEP)	Advocacy-to-assessment = 1 Popularity = 52 Mutuality = 1	11.1%

Overall, ERGM results corroborate the collaborative core thesis. But what are the exact probabilities of observing a relation, and what do those results imply for collective learning? To push the analysis of logistic coefficients further and answer these questions, realistic illustrative cases inspired by subnetwork statistics are created. For instance, Table IV showed that reciprocity of ties was highly unlikely in the advocacy subnetwork, just like the number of closed triangles. Accordingly, reciprocity and transitivity coefficients should be excluded from advocacy-to-advocacy probability computation. By opposition, those characteristics were very important in the assessment subnetwork, and should be included in the assessment-to-assessment equivalent. Popularity effects are based on the number of references received by typical actors. Table VI dresses the list of illustrative cases[18].

According to Table V, the likelihood of observing a tie between two advocacy actors is merely 1.4%. Even if one hypothesizes that both actors are in the same information community and one of them coordinates the community—as would be the case for the Industry association—, the probabilities only rise to 4.3%. On the opposite, members of the collaborative core have 55.7% chances of being in relation, assuming mutuality and a common reference. For the potential brokers such as the Environmental Department and the EES, the probabilities increase to 86.1%. Importantly, advocacy-to-assessment and assessment-to-advocacy relations are both more likely than advocacy-to-advocacy relations, but nevertheless remain marginal (9.5% and 5.3%, respectively). Even for scientific brokers, the probabilities of receiving a tie from advocacy actors are only of 11.1%. Overall, the collaborative core sent links to outsiders and received some from advocacy actors, but these activities were relatively trivial when compared with what occurred within the assessment subnetwork ($p < 0.001$).

III - Discussion: Strengthening Brokerage Theory

A theory on policy brokerage began emerging over the last few years (Ansell, Reckhow, and Kelly 2009; Carpenter, Esterling, and Lazer 2004; Christopoulos and Ingold 2014; Ingold 2011; Ingold and Varone 2011; Pielke 2007), and this research constitutes an interesting opportunity to test and refine existing conceptions. Chiefly, the findings support the hypothesis developed in chapter 1: *the presence of a broker in an adversarial structure of governance does increase the probabilities of observing a shared understanding of policy-relevant information between policy actors.* This being said, multiple important caveats must be added to this assertion. Precisely, there are several differences between micro and macro phenomena at play. The following lines propose 6 considerations to nuance or enrich this

18 Tie probabilities were calculated by transforming odds ratios into probabilities: probabilities = odds/ (1+odds) where odds = 0.005 + (assessment-to-assessment*3.94 OR advocacy-to-assessment*4.76 OR assessment-to-assessment*6.75) + homophily*2.05 + reciprocity*2.03 + transitivity*2.10 + popularity*1.04

conclusion.

Explaining the Collaborative Core

Foremost, the fact the scientific brokerage created a collaborative core in a persistently adversarial subsystem is an utterly surprising result. Why did the EES only improved collective learning among close collaborators, and what are the consequences for brokerage theory? Answering these questions offers an opportunity to address the debate about necessary and sufficient conditions, but also to suggest a novel consideration pertaining to the scope of effects. Regarding micro-level interactions, the existing literature implicitly supports the idea that brokerage is only possible if three necessary conditions are reunited: the broker (1) displays moderate beliefs (2) is familiar to and (3) deemed trustworthy by policy actors (Ansell and Gash 2008; Gerlak and Heikkila 2011; Heikkila and Gerlak 2005; Lee and Meene 2012; Steyaert and Jiggins 2007; Weible, Pattison, and Sabatier 2010). To some extents, the results described in the first part of this chapter are coherent with these conditions, although a fourth condition must be added to the list: moderate beliefs by brokered individuals. Indeed, all members of the collaborative core were experts or governmental departments, that is people and institutions well-known for their moderation (e.g. Ingold and Gschwend 2014; Jenkins-Smith et al. 2014; Meijerink 2005; Weible 2008). Moreover, it seems acceptable to assume that experts and governmental departments considered themselves familiar with the procedure and expressed considerably greater deference toward the EES than advocacy organizations. The logical corollary goes as follows:

> *Contribution 1: Results sustain the idea whereby trust, familiarity, and moderate policy beliefs are necessary conditions for individuals to relate to policy brokers. In adversarial polity, the strongest advocates should not accept brokerage without a serious stalemate.*

However, the findings also point toward a novel consideration: on a macro scale, a majority of trustworthy, familiar, and moderate policy actors is by no means necessary to shift the subsystem from adversarial to collaborative. An accessible way of dealing with inter-coalition dynamics is to assume that the quantity of adversarial or collaborative relations echoes the state of the subsystem. Yet scholars should be careful going down that path, as all actors are not born politically equal with regard to influence over policymaking. By considering the dominant trend as a mirror of the whole process, studies will likely miss out significant information covered up by power asymmetries: governmental departments have greater control of the output, experts reputed as such by those departments have higher probabilities of impacting the course of actions than unknown counterparts, and closely-knit communities in fragmented environment plausibly have greater structural predominance. This is an important consideration because it implies that a broker does not have to transform the whole subsystem to help generate policies akin to what would have occurred under perfect collaboration. As long as main policymakers adopt a compromising attitude and consider the entire set of available arguments, whether secondary actors engage in similar behaviour and change their beliefs accordingly is irrelevant for the policy at hand. Hence, the idea suggested in Chapter 1 that brokers may build on dependencies—bounded policy capacity, constraining social image, and collective action problems—to compel collaboration in an adversarial subsystem takes on its full significance when one moves away from individual cognition and considers the macro-dimension of political interactions. Theoretically, dependencies may be the explanatory factor behind external recognition, one of the two conditions for structural predominance to exist. Formally, the contribution goes as follows:

> *Contribution 2: While trust, familiarity, and moderate policy beliefs are necessary conditions for brokerage to have an effect on individuals, they are by no means necessary for brokerage to have an effect on subsystems. Precisely, a subgroup affected by brokerage activities can build on structural dependencies of the remaining actors to achieve structural predominance and impose collaborative-like policymaking. Structural dependencies include, but are not limited to, collective action problems, bounded policy capacity, and constraining social image.*

$$\textit{structural predominance} = \textit{political division} * \textit{external recognition}$$

Where *political division = conflict * balanced power*

and *external recognition = favourable structural dependencies*

A Better Definition of Policy Brokers

Second, the impressive empirical complexity of brokerage contrasts seriously from textbook conceptions of a single broker bridging competing, otherwise-unconnected subgroups. In fact, the results described above even cast some doubts about the existence of brokers as a *category* of actors. By asking themselves who was the broker, many scholars, including the author of the present investigation, designed their analytical strategy to identify exceptional structural positions, for instance by looking at betweenness centrality (e.g. Ansell and Gash 2008; Ingold and Varone 2011). Such procedure would be well-suited if brokers were solely definable by their relative network location. The picture, however, is considerably more complex, and empirical observations suggest policy science has much to gain from conceptualizing brokerage as a behaviour. In other words, asking whether brokerage occurred seems of greater interest than searching for the broker, and identifying the latter doesn't prove the former exist.

Reasons are twofold. First, understanding brokers as a special type of actor induces risks of developing non-mutually exclusive categories. To be sure, coalitions are not the sole units of interest inside subsystems, and the idea of "exceptional actors" proposed by Christopoulos and Ingold (2014) seems worthy of further investigations. But to take the present inquiry as an example, it is unclear whether the assessment was indeed exceptional, or merely an influential epistemic community well aware of its intellectual environment. But what about the large body of literature demonstrating brokers' distinctive good faith, moderate belief system, and attachment for conflict-avoidance, communication, and unifying frames (Burt 2004; Christopoulos and Ingold 2014; Ingold 2011; Ingold and Varone 2011; Koski 2010; Mintrom and Norman 2009; Zito 2001)? To be clear, the argument does not, by any means, disregard the literature identifying these singular attributes. After all, people engaged in such activities logically have different incentives than traditional rent-seekers. Rather, the claim is simply that conceptualizing brokerage as a behaviour that can be undertaken by any political actors avoids unnecessary confusion.

The second problem pertains to documenting the existence of real brokerage activities. Taking again this research as an illustration, if one had relied on *a priori* expectations, betweenness centrality, or mere number of references received to consider the EES as a broker, then it would have missed two crucial points: (1) the EES was neither the sole nor the most prominent broker and (2) virtually every advocacy actors, despite referring to the EES experts, kept strong external relations suppressing the relative significance of brokerage. Moreover, assuming that theoretical insights about the trust-building, bridge-building, structural-hole-reduction and knowledge-diffusion effects have an empirical resonance, a method relying purely on structural positions could generate misleading conclusions. Indeed, people seldom limit their interactions to a single individual—i.e. the broker—when they accept, consciously or not, to engage in collaborative behaviour. If, as a result of brokerage operations, competing organizations relate to each other, then searching for betweenness centrality in a web of ties no longer makes sense. Of course, a single actor might initiate the phenomenon, but once it is activated and diffused, looking for localized, microscopic traces of it is unlikely to yield reliable insights. As an alternative, approaches encompassing several cumulative indicators (e.g. Ingold and Gschwend 2014), longitudinal data, behavioural networks such as ally recognition, coordination, and information gathering (e.g. Weible and Sabatier 2005), and patterns of collaboration surrounding potential brokers could foster worthier findings. For instance, digging further into the authority-hub algorithm could be an interesting path toward differentiating fact mapping from knowledge diffusion.

Contribution 3: Conceptualizing brokerage as a dynamic process based on trust-building, bridge-building, structural hole reduction, and knowledge-diffusion *would likely yield better empirical leverage than seeing it as a peculiar structural position*.

The State of Information in Adversarial Policymaking

In addition to brokerage, the findings offer an interesting opportunity to address questions pertaining to the state of knowledge in adversarial policymaking. At first sight, the extreme dispersion of sources is striking, as shown by the impressive number of information communities found in subsystems of 168 and 100 organizations: 49 and 21, respectively. These communities transcended groupings typically scrutinized by political science (environmental and local organizations, industry, scientists, governments, etc.); organizational affiliations, advocacy coalitions, and information networks do not echo each other. The contrast between both is sharp: in the 2011 case, 168 organizations referred to 986 different sources. The picture is even more evident in 2014: 100 actors mobilized 2538 knowledge providers. This tends to confirm, with novel methodological tools and data, the widely held views regarding the political nature of policy intelligence, the multiplication of incompatible interpretations, and the unshared understandings about societal issues (Barke and Jenkins-Smith 1993; Hoppe 1999; Kahan, Jenkins-Smith, and Braman 2011; Lachapelle, Montpetit, and Gauvin 2014; Nilsson 2005; Vifell and Sjögren 2011). Even under the assumption that all references are fact-based knowledge, with is rather unrealistic, their vast and persisting diversity shows that much more than the advocacy/empirical divide is at work: expertise familiarity, perception of being trustworthy, experiences with the authors, reputation within social circles, and popularity among friends all remain credible explanations of source selection.

Contribution 4: Results tend to confirm the political nature of knowledge in adversarial policymaking: contested, disparate, unshared, and often exclusive.

Findings have much more to say about the cognitive processes of enlightenment, however. Precisely, many studies alleged that preferences were relatively stable across time, and that the likelihood of transforming belief systems with collective learning was extremely low when views were polarized (Jenkins-Smith et al. 2014; Paul A. Sabatier 1987; P. A. Sabatier and Zafonte 2001; Weible, Pattison, and Sabatier 2010; Weible and Sabatier 2009). Unfortunately for proponents of deliberative democracy, the statistics presented earlier reinforce such thesis. Of course, collective learning dynamics did improve in the short run, yet the progress is marginal and intellectual alienation persisted. The demonstration may not close the debate, but it surely adds another layer of evidence supporting conflict stability and the importance of exceptional events to shift predominant attitudes.

> *Contribution 5: Results confirm the minimal probabilities of changing belief systems through collective learning in adversarial settings in the short-term. By the same token, findings pinpoint that partial acceleration of the process through brokerage is possible, yet total transformation unlikely.*

The last contribution discusses a specific claim made by Jones and Jenkins-Smith (2009), who contented that nascent subsystems had to deal with considerable confusion with respect to policy-relevant information. They further added that as time goes by, familiarity should increase and the knowledge may become more accessible to policymakers and advocacy organizations. Their argument was mainly theoretical and falls outside the scope of this research, but few words on the matter should nevertheless be expressed considering the supportive findings. In 2011, the relatively new shale gas subsystem exhibited considerable fragmentation with regard to information, yet between 2011 and 2014, the average size of communities increased, modularity diminished, and several structural holes were suppressed. It is, of course, impossible to claim that the same process would have occurred without policy brokerage, but the following statement seems noteworthy:

> *Contribution 6: Results are compatible with Jones and Jenkins-Smith's thesis (2009), which argues that the initial fragmentation of knowledge typical of nascent subsystems should diminish as time and institutionalization go by.*

IV - Conclusion

Hopefully, readers considered the evidences conclusive about the collective-learning potential of brokerage in adversarial subsystems. Of course, the outcome is far from perfect: conflict requires much more than a two-year inclusive assessment to disappear. Nevertheless, it has been shown that some actors were more sensitive to scientific mediation than others, and as long as those are the most influential of the subsystem, collaborative-like policymaking can flourish in conflicting polity.

The conclusive chapter describes this research’s main limits, along with methodological recommendations intended to researchers interested in continuing the research agenda on policy brokerage.

Concluding Remarks

Can scientific assessments foster a shared understanding between political actors operating in adversarial policymaking? Answering this question constituted the main goal of this research, and the verdict is somehow mixed. Specifically, the inquiry drew upon three innovations to foster novel insights on the matter. From a purely conceptual perspective, mobilizing brokerage theory was a suited, original, and fruitful way of understanding how scientific assessments may positively affect their policymaking environment to stimulate collective learning. In the present case, picturing such environment in light of network theory refocused the scope of analysis on macro-order dimensions of the phenomenon: presence of structural holes, distribution of intellectual authority, advantageous network positioning, governance improvements, number of bridges, facilitation of knowledge transmission, interactions between sub-communities, etc. On the whole, the conceptual framework developed in Chapter 1 sustained a positive response: scientific assessments likely behave as policy brokers in information networks, easing optimization of collective learning dynamics.

A method was designed to confirm—or overturn—theoretical perceptions. The challenge was to appraise the state of collective learning in the whole subsystem before and after a scientific assessment mobilized its brokerage functions. Drawing on the Quebec Shale Gas case, this research innovated by extracting quantitative data from policy and advocacy documents published in two province-wide consultations separated by a sophisticated, inclusive scientific assessment. Precisely, the second innovation was to apply methods commonly implemented in science mapping to subsystems: using references as a measure of influence on actors' rationale. Inspired by the work of DeLeon and Varda (2009), this research developed four dimensions and seven instruments which cumulatively grasped the state of collective learning in the two information networks emerging from citation matrices. By employing the number of bridges between information communities (Gould and Fernandez 1989) and the authority-hub algorithm (Kleinberg 1999), brokers were identified along with their respective influence on collective learning improvements. The descriptive results were validated using ERGM, an inferential network analysis tool generating normal distributions of various statistics from randomly created, similar networks (Cranmer and Desmarais 2011; Desmarais and Cranmer 2012; Handcock et al. 2008; Hunter et al. 2008; Morris, Handcock, and Hunter 2008; Ward, Stovel, and Sacks 2011).

While the scientific assessment and surrounding governmental departments were identified as the most likely brokers, they only had marginal influence on advocacy actors. Unfortunately for defenders of scientific enlightenment, empirical insights were, thus, highly coherent with the body of literature pointing toward the instrumentation of science and limited propensities to understand adversaries when conflict is excessive. A detailed investigation of subnetworks showed that launching a scientific assessment did not challenge efficiently one-sided belief systems, but nevertheless created a closely knit, highly cooperative core encompassing governmental departments and shale gas experts. Because the group surrounding the broker enjoyed structural predominance, this research's third innovation, and gathered knowledge from the whole information network, the policy emerging from the process at hand was plausibly very similar to what would have occurred under perfect synergy. That is, subsystem-wide cooperation appears unnecessary to conduct cooperation-like policymaking.

I - Addressing Limits and Their Consequences

Reflexivity on the reliability of a research design is an integral part of any good scientific study. Accordingly, this subsection dresses the—hopefully exhaustive—list of limitations, assesses their impact on the results, and defends them from alternatives.

Capturing Collective Learning

From the outset, readers should bear in mind the methodology's imperfect character. Foremost, it would be important to consider the value of collective learning proxies, which contrast sharply with how social science traditionally deal with cognitive processes. Of course, learning is a subtle phenomenon hardly comprehended by a single indicator or outright questionnaires, a picture that even worsen when researchers consider the underlying social components of interdependent intellects. Some readers might argue that well-fashioned surveys would have shed brighter light upon the matter, but financial and time constraints left aside, Social Network Analysis and surveys make bad associates. Precisely, because participation rate seldom—if ever—reach 100 percent, important network ties may be missed out with serious consequences on the inferences—imagine, for instance, that the EES had not accepted to collaborate (Ward, Stovel, and Sacks 2011).

Other researchers might assert that traditional content analyses could have been a valuable alternative to construct a collective learning scale relying on longitudinal changes in, say, policy preferences, the tone adopted, the level of scientific sophistication, the perception of adversaries, the aversion to risk, the types of benefits and/or problems identified, etc. Yet again, this approach possesses three major challenges, the first of them being time and financial constraints associated with dissecting 268 policy documents encompassing several hundreds of pages. Second, reliability and transparency of a single-coder procedure would have emerged as a striking problem. Third, it is unclear how isolated content analyses can be conclusive about the relational dimension of collective learning. By contrast, the structural approach exposed novel interplays: density of ties, reciprocity of relations, intellectual similarities, bridges, information hubs, authorities, clustering behaviours, structural holes, and closeness to the whole set of information sources. Moreover, analyzing those factors cumulatively strengthened confidence about the reliability of inferences.

However suited, the structural proxies were partly incomplete when compared with what DeLeon and Varda (2009) suggested. First, it would have been useful to understand modularity more thoroughly, for instance by taking into account expertise and organizational homophilies. Unfortunately, this would have required considerable research on more than 3500 organizations, an unrealistic goal given the scope of this study. Similarly, DeLeon and Varda conceptualized embeddedness as the diversification of relations between actors. In theory, this could have been measured by specifying the purposive nature of references, e.g.

showing an example of good practices, acquiring an argument, suggesting an authority on the matter, etc. Nevertheless, coding more than 5900 ties was unfeasible. Circumventing the lack of data with the closeness score was partially useful, but this approach is not perfectly suited to segmented networks because of unrealistic assumptions about the infinite distance between unconnected nodes (Opsahl, Agneessens, and Skvoretz 2010). Lastly, measures of trust, formality, and transparency throughout the network were dropped out due to operationalization issues. Surely, then, the set of proxies could have been more complete, but this by no means implies the unreliability of the dependent variable. Besides, it is among the most suited operationalizations of collective learning available. The problems noted above should not pose major threats to internal validity.

Before considering limits associated with citations and information networks, one last criticism deserves attention. Precisely, some readers might think that the seven statistics display strong collinearity. For instance, the closeness score logically increases when transitivity, number of common references, and mutuality expand, and the effect is similar when modularity and structural holes erode. At first sight, the argument appears partially founded. After all, social structures are inherently intertwined. That being said, the reasoning is fallacious, as each statistic does quantify very different dynamics. Taking again closeness as an example, the score could have lowered as a consequence of stronger ties, more shared references, and higher transitivity if those phenomena consolidated existing network divisions, for instance by generating completely isolated clusters of individuals. The same goes for remaining characteristics: mutuality does not imply common references, transitivity does not lead to mutuality, multiplying useless social relations may increase structural holes, etc. In other words, those several interplays may evolve together, yet they are not bounded to do so.

Network Construction

Using a well-fitted operationalization of collective learning is worthless if the underlying network on which it is applied is ill-convinced. On such matter, assuming that information networks are a good structural representation of social cognition is legitimately debatable. The instrument is fairly imperfect: references do not bear the same connotation in every contexts, qualitative nuances are of substantial significance, the propensity to cite differs across policy actors, and searching for in-text references may have induced some mistakes. Nevertheless, those caveats should not push policy researchers to abandon citation networks, for reliability threats appear objectively thin.

Advocacy actors and experts may not share a common commitment for intellectual transparency, yet the scientific nature of the procedure and a willingness to convince policymakers logically gave the necessary incentives to strengthen arguments via references. The remaining effect of heterogeneous propensities to cite was tempered by looking carefully at in-text references. To be sure, missing links potentially results from this approach, but the coding experience showed that the most significant information sources of individuals were referred to several times in a document. Hence, a major misidentification seems unlikely. Furthermore, overlooked secondary relations presumably distribute at random between policy actors, thus failing to induce serious bias.

ERGM Degeneracy

While the degeneracy problems of ERGM have been mentioned before, their consequences on the research have not. The most serious consequence has been the impossibility to include structural equivalence as an independent variable, i.e. shared references. Whenever the model took into account this statistic, it either failed to converge or was so unstable that serious reliability threats arose. This is especially unfortunate considering that structural equivalence embodies a dynamic of utter interest for collective learning. Nevertheless, the exclusion doesn’t compromise the accuracy of remaining coefficients, it simply implies that the effect stays intertwined with subnetwork terms. Furthermore, information communities were based on structural equivalence, and including community homophily among independent variables provided a partial workaround. In any case, structural equivalence becomes of secondary worry when the analysis excludes external sources from scrutiny: the vast majority of shared references vanished from the network.

This last point brings another concern in the debate: why was the ERGM model only applied to internal information sources, and not to the whole network? Part of the justification is theoretical, i.e. collective learning is only possible for policy actors. Just like external sources were excluded from the computation of descriptive statistics, omitting to do so for ERGM would have seriously biased the coefficients toward zero. Still, some might reasonably think it would have been interesting to compare with the whole information network. Unfortunately, ERGM degeneracy surfaces when one tries to do so. The problem is that the density of ties is so unusual—bear in mind that 2438 nodes did not send any references in 2014—that the algorithm fails to generate networks of comparable densities. Holding the number of links constant is a partial workaround, but doing so causes coefficient estimation issues with other variables.

External Validity

Under the largely quantitative character of this research lies a case study. Thus, legitimate concerns about its representativeness may arise: is the Quebec Shale Gas subsystem valid for scientific inferences? At first sight, there are no reasons to believe it is not. Just like it did in many jurisdictions around the globe, shale gas stimulated major debates in the province. Moreover, the events allowed building a robust test for brokerage theory. This being so, commitments to scientific transparency justify two caveats. Firstly, Quebec as been described for its distinctive character among the Canadian federation. Long story short, Quebec inhabitants exhibit stronger attachment to egalitarian values than their Rest-of-Canada and American counterparts (Montpetit and Lachapelle 2013). Second, everything was not held constant during the period of analysis; two non-negligible political turnovers changed the governing party between 2011 and 2014. It is unclear how this might exactly affect external validity, but one possibility could be that the strong popular opposition to shale gas and the brief interlude where the *Parti Quebecois* took power influenced membership and decision-making inside governmental departments, which helped the assessment community to reach a common understanding.

II - Few Words on a Brokerage Research Agenda

This study innovated on various points, as mentioned above, and yielded noteworthy contributions upon which future research might draw upon, both theoretically and methodologically. Methodologically, the thesis illustrated how worthy policy documents were from a quantitative perspective. For good reasons associated with richness and accessibility, qualitative researchers have long dealt with policy documents, yet the trend is younger for purely quantitative studies, i.e. not relying on substantive content analysis. In the present case, transforming in-text references, footnotes, and bibliographies into relational matrices yielded enough understandings to reach transparent and reproducible analyses of subtle phenomena. Hopefully, researchers will share an interest for those metadata, which surely are well-suited for a wide array of complementary investigations.

Second, this research contributed to the new body of literature using SNA or, more specifically, inferential modelling such as ERGM in political science (Considine and Lewis 2007; Cranmer and Desmarais 2011; Desmarais and Cranmer 2012; Fischer 2014; Frank et al. 2012; Ingold 2011; Ingold and Gschwend 2014; Ingold and Varone 2011; Kriesi, Adam, and Jochum 2006; Lee and Meene 2012; Scholz, Berardo, and Kile 2008; Ward, Stovel, and Sacks 2011; Weible and Sabatier 2005). It confirmed that by transforming structural factors into independent variables explaining the likelihood of interactions between two individuals, the ERGM provides a useful heuristic to dissect widespread social relations, but also local phenomena. In fact, the ERGM may even have been more fruitful to understand collective learning than purely descriptive SNA, and further applications of the method are thoroughly encouraged.

Lastly, and most importantly, the dual order of analysis confirmed a traditional micro understanding of brokerage—prominence of trust, familiarity, and moderate policy beliefs—, but also stressed the importance of power dynamics at play at the subsystem level. The former specifies why brokers influence individuals; the latter explains how broker-friendly communities formed by those people affect the policymaking process and compete with advocacy organizations. Both should be integral parts of a theory, and it might be useful to reposition brokerage in light of political confrontations, structural predominance, and dependencies. Of course, the community-building potential of policy brokers deserves special attention, but searching restlessly for optimistic humanism won't favour its materialization. After all, isn't ubiquitous power relations the realm of political science?

Appendix A: SNA Statistics Details

Reciprocity

Reciprocity measures probability that the inverted counterpart of a directed edge is also included in the graph. Or simply put:

$$a/b$$

where: a = number mutual links

b = number of total links

Burt's constraint

Burt's constraint (Burt 2004) measures how constrained in structural holes an actor is, or more specifically, how dependent he is upon an individual to reach others, as measured by the proportion of efforts he puts in that individual in addition to how redundant his contacts are. Mathematically:

$$\sum c_{ij} = \left(p_{ij} + \sum_q p_{iq} p_{qj}\right)^2$$

where:

i = the actor on which burt's constraint is being measured

j = a contact of i

$\sum c_{ij}$ = Burt's constraint, i.e. the sum of squared constraints for every contact of i

$p_{ij} = \frac{z_{ij}}{\sum_q z_{iq}}$ where z_{ij} = the strength of the relation with j on a 0-1 scale and

$\sum_q z_{iq}$ = total strength of all relations of i

p_{qj} = the proportion of i's relations that are linked with j, i.e. redundancies of contact

Hubs and Authorities Algorithm

The hubs and authorities algorithm was designed by Kleinberg (1999). It works by iteratively updating the authority and hub scores of nodes. The more the hub scores of a tie-sending neighbour is high, the higher the authority scores of a node will be. Similarly, the higher the authority score of a node is, the higher the hub score of a node connecting to it will be. It begins by the following assumptions:

$$auth(p) = 1$$

$$hub(p) = 1$$

Where p is a node. Then, update rules are iteratively applied:

authority update rule: $$auth(p) = \sum_{i=1}^{n} hub(i)$$

where:

n = total number of nodes connected to p

i = a node connected to p

hub update rule: $$hub(p) = \sum_{i=1}^{n} auth(i)$$

where:

n = total number of nodes p connects to

i = a node which p connects to

Similarity Matrices

The similarity matrices are transformations of the raw citation matrices as coded from the advocacy and working documents. Instead of assuming the strength of the relation from a node to another one equals 1 if the former cites the latter and zero otherwise, the strength of the relation becomes the number of common neighbors divided by the sum of total neighbors. Furthermore, a loop was added to every nodes in the network, i.e. the measure assumes that people refer to themselves. Without this addition, a reference from a nodes to another one would have counted in the sum of total neighbors instead of in the sum of common neighbors.

Louvain algorithm

The Louvain community detection algorithm (Blondel et al. 2008) works by repeating iteratively two phases. In the initial phase, there are as many communities as there are nodes in the network. For each relations between *i* and *j*, the algorithm evaluates the gain of modularity resulting from placing *i* in the community of *j*. Only the move that maximizes the modularity of the whole network is done. This principle is repeated for all nodes until modularity can no longer improve, in which case the first phase is completed. In the second phase, a new network is created, where the communities in the first network correspond to the nodes of the second one. The weights of links between those new communities correspond to the sum of the weights linking members of those communities in phase 1. Similarly, a self-loop is added for each new nodes, which corresponds to the strength of relations between the nodes that formed that community in phase 1. Once this new network is created, phase 1 is applied again, and so on until modularity can no longer improve.

Modularity is a scalar value ranging between -1 and 1 that measures the density of links inside a communities as compared to links between communities. Mathematically, modularity can be expressed as follow:

$$Q=\frac{1}{2m}\sum_{ij}[A_{ij}-\frac{k_i k_j}{2m}]\delta(c_i,c_j)$$

where:

A_{ij} = the weight of the edge between *i* and *j*

$k_i=\sum_j A_{ij}$ i.e. the sum of the weights of the edges attached to *i*

c_i = the community to which *i* is assigned

$\delta(c_i,c_j)$ = 1 if $c_i=c_j$ and 0 otherwise and $m = \frac{1}{2} \sum_{ij} A_{ij}$

Closeness

Closeness gives the inverse of the sum of the distance between a node and all other nodes in the network. If there is not a directed path between both, then the distance is assumed to be the total number of nodes in the network (Freeman 1979). The formula goes as follows:

$$closeness = \frac{1}{\sum_{ij} (d_{ij})}$$

where: $d = \text{distance}; ij = \text{a pair of nodes}; \text{and } i \neq j$

Local transitivity

Transitivity measures the probability that the adjacent nodes of a node are connected together. Transitivity makes no difference between the direction of relations, as long as a triangle is formed (Watts and Strogatz 1998).

Exponential Random Graph Model

As Cranmer and Desmarais (2011) explains it, ERGM begins by assuming that each of the network statistics calculated on a network *m* are the expected values of those statistics across all possible networks: $E[\Gamma_i] = \Gamma_i$ where Γ_i is any network statistics

The second assumption is that only the statistics included in Γ influence the probability that network *m* is observed. As a result, the relationship between the probability of a network *m* and the network statistics in Γ is:

$$P(Y_m) = \frac{\exp(-\sum_{j-1}^{k} \Gamma_{mj} \theta_j)}{\sum_{m-1}^{M} \exp(-\sum_{j-1}^{k} \Gamma_{mj} \theta_j)}$$ where θ is the vector of *k* parameters describing the dependence of $P(Y_m)$ on the network statistics in Γ

Appendix B: Degeneracy and Goodness of-Fit

ERGM is a statistical tool relying on random network generation to draw normal distributions of independent variables included in the model. As a consequence, coefficients' reliability depends on whether or not the networks are comparable with the observed one. Another concern regards the generation of those networks. That is, because each network statistics are structurally dependent upon others, it can be extremely demanding for a computer to generate comparable networks. To counteract the problem, an algorithm facilitating the iterative computation is necessary: the Markov Chain Monte-Carlo algorithm. Unfortunately, this algorithm can often behave unpredictably, for instance by generating networks with a complete density of links, i.e. all possible relations are filled, instead of oscillating randomly around the mean of the observed network. This is called "model degeneracy" (Hunter et al. 2008). Multiple causes are possible, but one of them is that the model specifications are too sparse to effectively describe the real network: the algorithm doesn't know how to constrain network generation. The consequences are either that the coefficients are impossible to estimate—the maximum likelihood estimator does not exist—or that the coefficients are unreliable—the maximum likelihood estimator does not fit the data (Handcock et al. 2008).

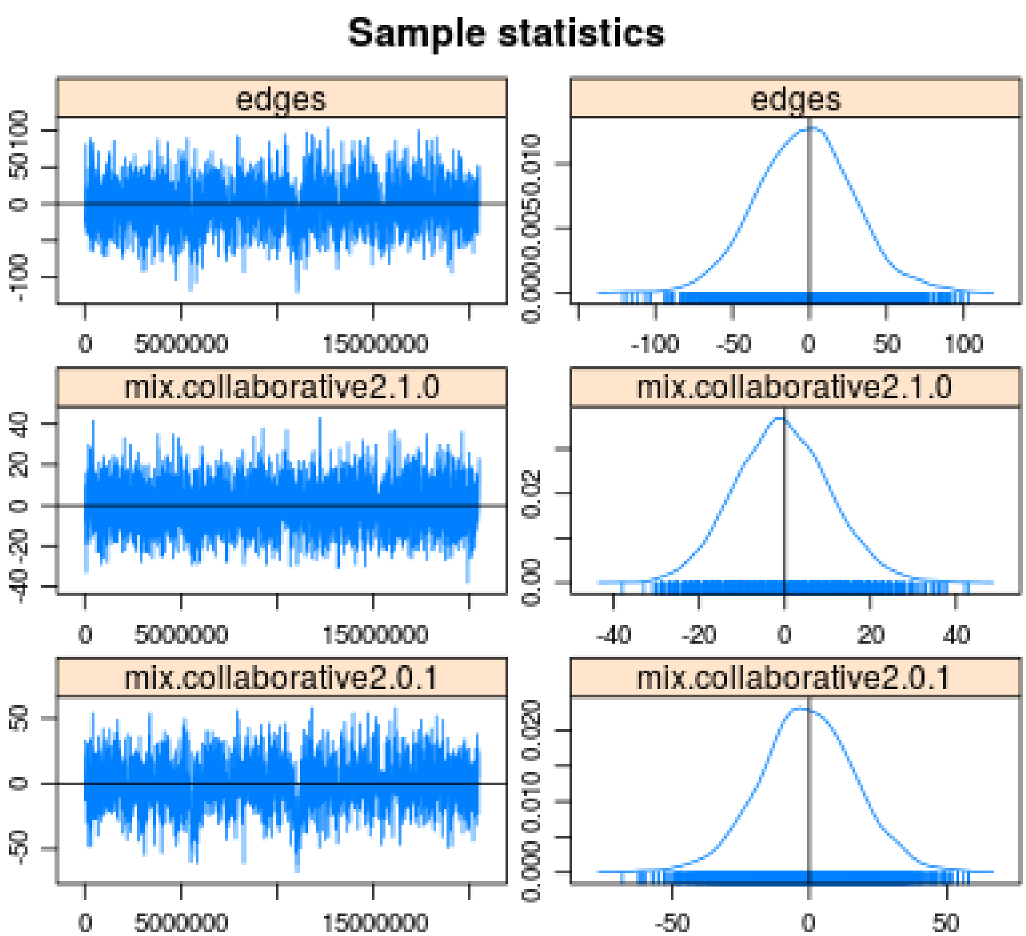
Fortunately, it was possible to avoid those problems for the ERGM presented in Chapter 3. For simplicity reasons, only the degeneracy analyzes of Model E are presented, but the MCMC algorithm exhibited a similarly sane behaviour with regard to the other models.

MCMC Behaviour

Ideally, the MCMC algorithm would oscillate randomly around the mean. In addition, each statistic should not be strongly correlated with another one, and the correlation between networks with regards to one statistic—e.g. triangles in the 1000 randomly generated networks—should gradually decrease as the number of estimated networks increases.

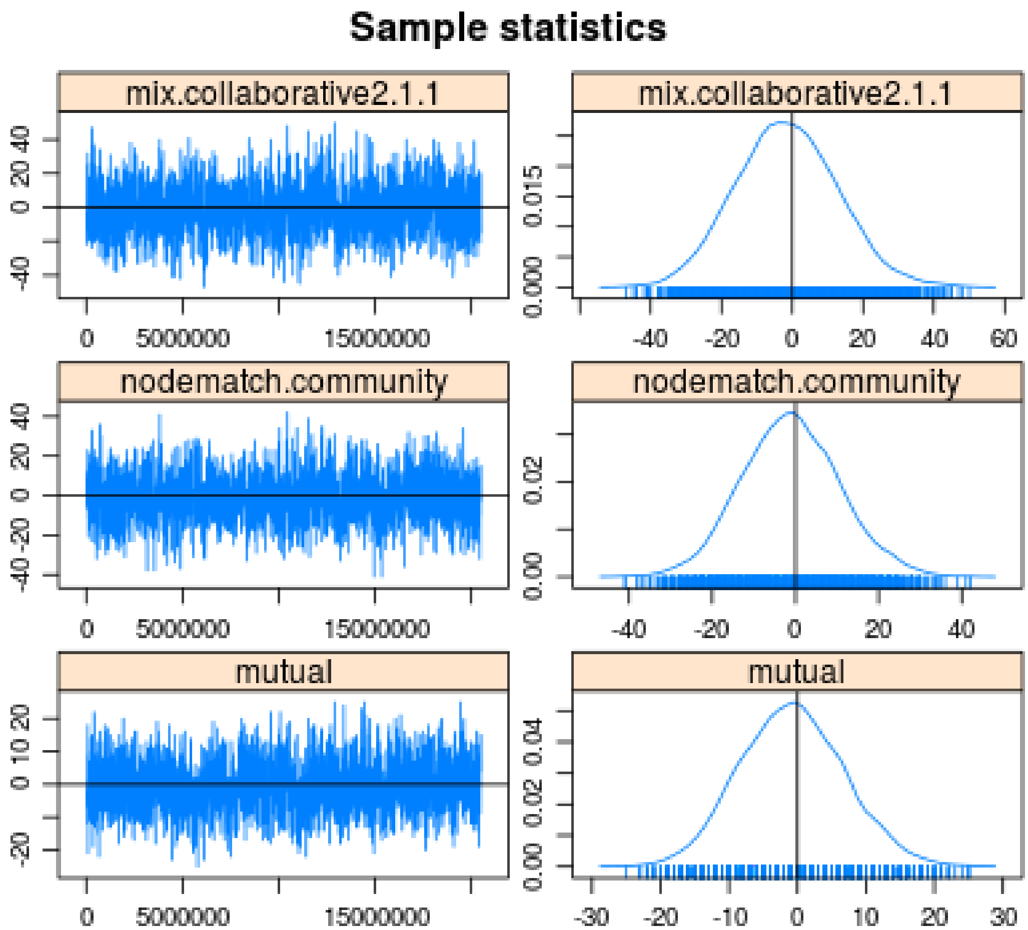
Figures 4.1 to 4.3 show that the first condition is met, and the degeneracy analyses outputs given by the MCMC. diagnostics Statnet R software presented afterwards demonstrate that the second and third are also fulfilled.

Figure 4.1: MCMC Estimation Behaviour [1/3]



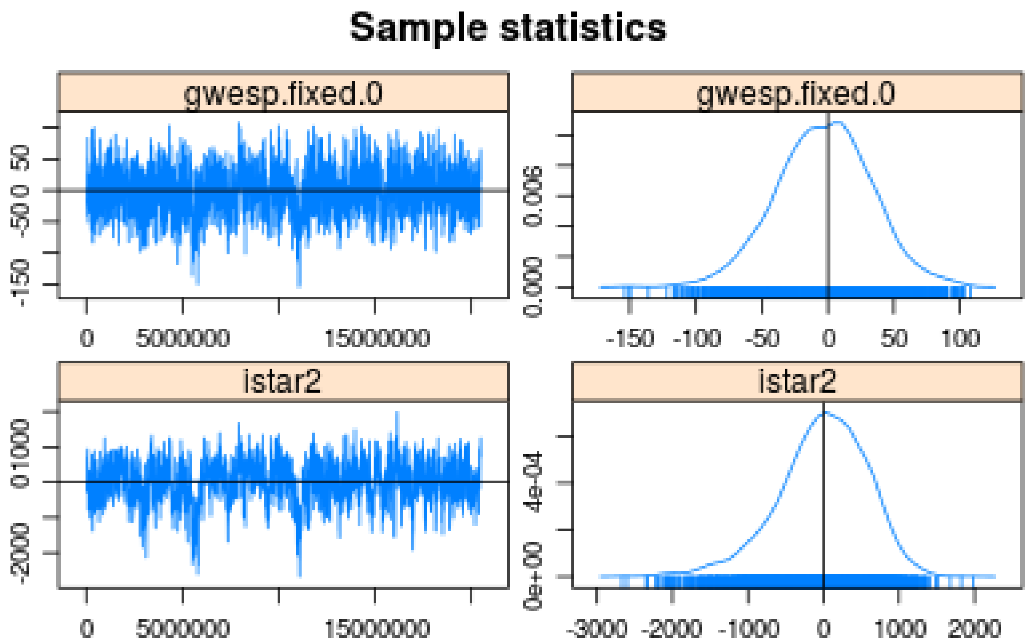
Edges term corresponds to advocacy-to-advocacy relations; mix. collaborative2.1.0 corresponds to assessment-to-advocacy; mix. collaborative2.0.1 corresponds to advocacy-to-assessment.

Figure 4.2: MCMC Estimation Behaviour [2/3]



Mix.collaborative2.1.1 corresponds to assessment-to-assessment; nodematch. community is the information community homophily term; mutual is the mutuality term.

Figure 4.3: MCMC Estimation Behaviour [3/3]



Gwesp.fixed.0 is a term encompassing the number of edges involved in at least one triangle in the network and corresponds to the transitivity term (e.g. Goodreau et al. 2008). Istar2 counts the number of 2-star received by a node, i.e. the number of pairs of links received by an actor, and represents the popularity term. This statistic is, by far, the one which posed the biggest estimation problems. It was, indeed, frequent to have degeneracy problems with this term. The problem was partially resolved by increasing the number of estimated network "burned" before adding the first network to the random set, as well as before adding each additional network to the set. Doing so reduced the correlation between each network and allowed the algorithm to get back on the right track after the three "falls" observable in Figure 4.3. That being said, the coefficient was relatively stable across estimations, regardless of fine tuning.

The following tables summarize the MCMC diagnostic outputs given by the Statnet R software. Table VII gives indication about the number of burned networks, sample size, and number of iterations needed to estimate the maximum-likelihood.

Table VII: General Estimation Information

Characteristic	Information	Comments
Number of iterations	4 out of a maximum of 50	
Burned network	10,000	Number of networks burned before starting the random sampling.
Interval burning	5000	Number of network burned between each network of the sample.
Sample size	4096	Number of random networks in the sample.

Table VIII: Descriptive Statistics for Each Variable

Variable	Mean	Standard Deviation	Quantiles
Advocacy-to-Advocacy	-2.54	31.17	2.5% = -63.00 97.5% = 61.62
Assessment-to-Advocacy	-0.45	11.00	2.5% = -21.62 97.5% = 22.00
Advocacy-to-Assessment	-0.60	17.44	2.5% = -35.00 97.5% = 34.00
Assessment-to-Assessment	-1.48	14.28	2.5% = -29.00 97.5% = 27.00
Community homophily	-1.13	11.68	2.5% = -23.00 97.5% = 23.00
Mutuality	-0.75	7.53	2.5% = -15.00 97.5% = 14.00
Transitivity	-2.86	36.05	2.5% = -75.00 97.5% = 68.00
Popularity	-9.75	591.41	2.5% = -1372.38 97.5% = 994.00

Table VIII gives the descriptive statistics of the variables in the model. As can be seen, the mean is approximately zero for every variable, with popularity being the farthest at -9.75. Tables IX and X display the cross-correlation and auto-correlation of network statistics, respectively. As can be seen in Table X, every variables decrease rapidly from 1.00 toward zero, with the exception, again, of popularity. Overall, the picture is that there are no major degeneracy problems with the MCMC algorithm, although readers should bear in mind that the popularity term is on the edge of being unstable. The Geweke test, which is equivalent to a t-test comparing the first 10% of networks generated by the MCMC algorithm with the subsequent 50%, indicates that taken individually, the assessment-to-assessment and popularity term may be problematic. They do not reach the 0.05 threshold, but are closer to it than one. However, the joint p-value of all variables (0.42) attests that the model, on the whole, does not have auto-correlation problems. Also, it was impossible to completely reduce auto-correlation through fine tuning, as modifying the model induced problems with other variables. Hence, the MCMC behaviour might not be perfect, but it does not pose major reliability threats.

Table IX: Cross-correlation

Variable	Advocacy-to-Advocacy	Assessment-to-Advocacy	Advocacy-to-Assessment	Assessment-to-Asssessment	Community homophily	Mutuality	Transitivity	Popularity
Advocacy-to-Advocacy		0.55	0.76	0.67	0.61	0.68	0.92	0.67
Assessment-to-Advocacy	0.55		0.16	0.14	0.23	0.49	0.47	0.76
Advocacy-to-Assessment	0.76	0.16		0.29	0.30	0.44	0.78	0.77
Assessment-to-Asssessment	0.67	0.13	0.29		0.68	0.50	0.60	0.30
Community homophily	0.61	0.22	0.30	0.68		0.46	0.51	0.26
Mutuality	0.68	0.49	0.44	0.50	0.46		0.74	0.51
Transitivity	0.92	0.46	0.78	0.60	0.51	0.74		0.80
Popularity	0.67	0.21	0.76	0.30	0.26	0.52	0.80	

Table X: Auto-correlation

Variable	Advocacy-to-Advocacy	Assessment-to-Advocacy	Advocacy-to-Assessment	Assessment-to-Asssessment	Community homophily	Mutuality	Transitivity	Popularity
Lag 0	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Lag 5000	0.45	0.16	0.42	0.49	0.47	0.42	0.55	0.79
Lag 10 000	0.27	0.06	0.30	0.29	0.28	0.25	0.38	0.67
Lag 15 000	0.17	0.02	0.24	0.18	0.17	0.16	0.29	0.59
Lag 20 000	0.13	0.04	0.19	0.12	0.12	0.13	0.24	0.52
Lag 25 000	0.11	0.01	0.17	0.09	0.09	0.11	0.21	0.48
Geweke individual P-values	0.75	0.39	0.14	0.07	0.30	0.70	0.39	0.14
Joint P-value = 0.42								

Goodness-of-fit

The second concerns regarding ERGM reliability is whether or not the randomly generated networks are comparable with the observed one. Figures 5.1 to 5.4 compare the distribution of random networks [whisker plots] with the observed one [solid line]. Four dimensions are compared: the number of links received [in-degree], the number of links sent [out-degree], the number of shared partners, and the geodesic distance distribution between the nodes. Although the fit is not perfect—the solid lines often fall outside the whisker plots —, the general pattern appears comparable.

Figure 5.1: In-degree Goodness-of-fit

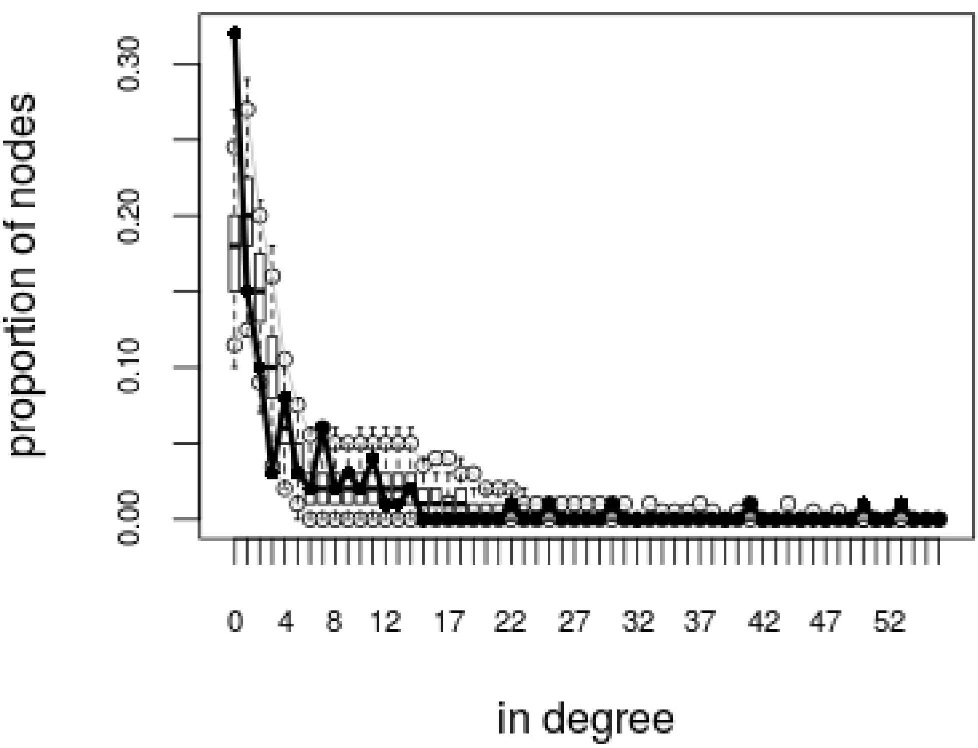


Figure 5.2: Out-degree Goodness-of-fit

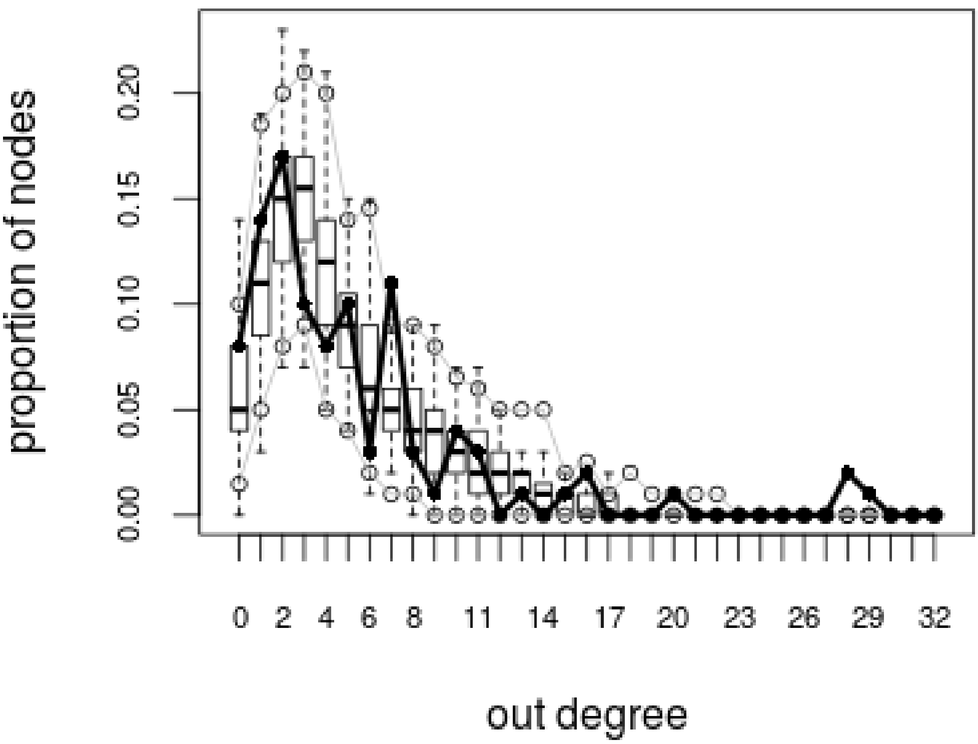


Figure 5.3: Shared-partners Goodness-of-fit

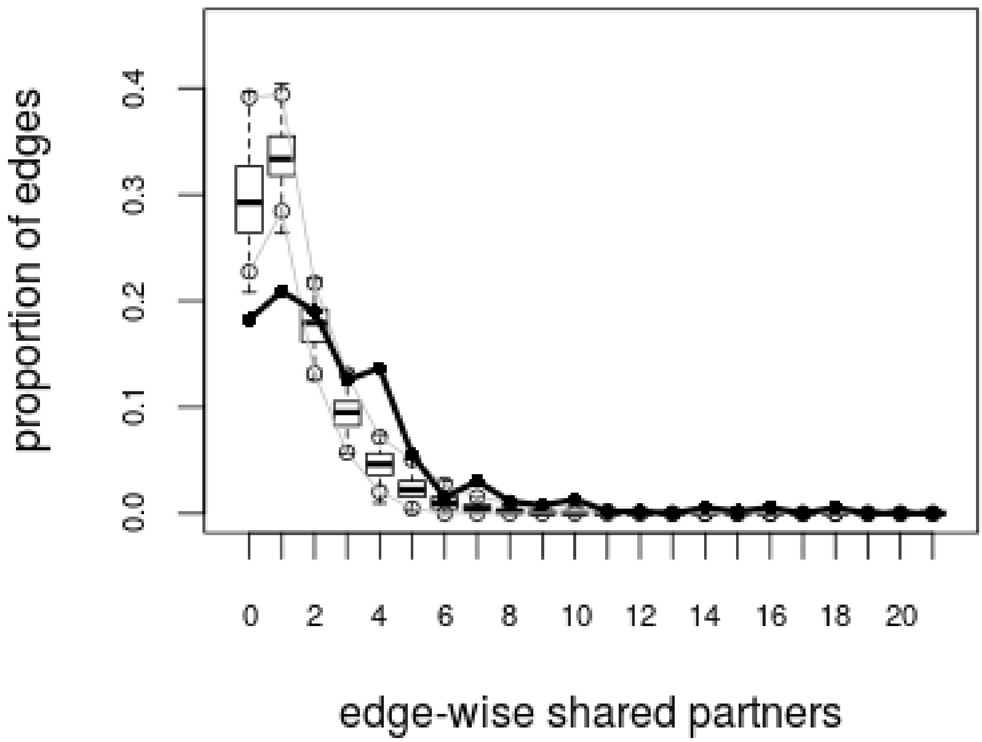
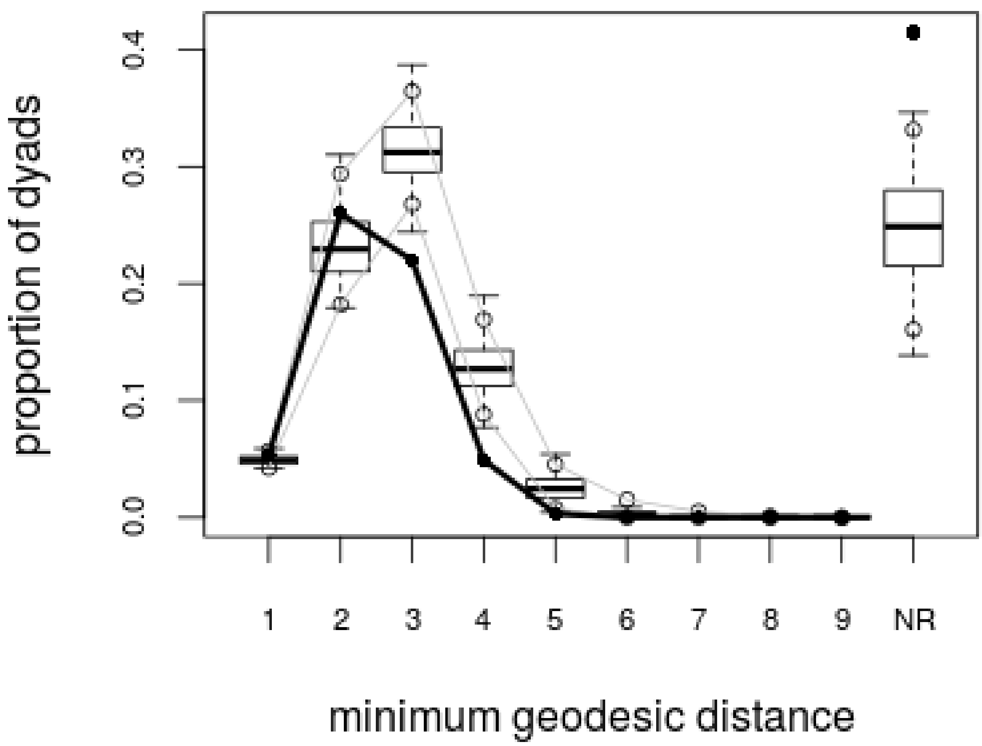


Figure 5.4: Minimum Geodesic Distance Goodness-of-Fit



Appendix C: R codes

For simplicity reasons, only the codes necessary to compute the statistics are provided, i.e. readers willing to replicate the results should add the codes to load the database.

–--

```
#Load R packages

library(igraph)
library(intergraph)
library(e1071)
library(statnet)
library(ergm)
library(sna)
library(coda)
library(latticeExtra)

#Transforming the data into R objects
b2011=graph.data.frame(BAPE_2011_Edges_clean, directed = TRUE, vertices = BAPE_2011_Nodes)
b2014=graph.data.frame(BAPE_2014_Edges_ID, directed = TRUE, vertices = BAPE_2014_Nodes)
b2014_NE=graph.data.frame(BAPE_2014_Edges_NoEES, directed = TRUE, vertices = BAPE_2014_Nodes)

#Building the subnetworks
ees = induced_subgraph(b2014, vids = which(V(b2014)$collaborative2=="1"))
actors = induced_subgraph(b2014, vids = which(V(b2014)$actors2=="1"))
stake = induced_subgraph(b2014, vids = which(V(b2014)$stakeholder=="1"))

#Building the similarity matrices
similarity2011 = similarity(b2011, vids = V(b2011), mode = c("out"), loops = TRUE, method = c("jaccard"))
similarity2014 = similarity(b2014, vids = V(b2014), mode = c("out"), loops = TRUE, method = c("jaccard"))
similarity2014_NE = similarity(b2014_NE, vids = V(b2014_NE), mode = c("out"), loops = TRUE, method = c("jaccard"))
```

```
similarity2014_ees = similarity(b2014, vids = which(V(b2014)$collaborative2=="1"), mode = c("out"), loops = TRUE, method = c("jaccard"))

similarity2014_actors = similarity(b2014, vids = which(V(b2014)$actors2=="1"), mode = c("out"), loops = TRUE, method = c("jaccard"))

similarity2014_stake = similarity(b2014, vids = which(V(b2014)$stakeholder=="1"), mode = c("out"), loops = TRUE, method = c("jaccard"))


ms2011 = graph.adjacency(similarity2011, mode = c("lower"), weighted = TRUE, diag=FALSE)

V(ms2011)$id = BAPE_2011_Nodes[,1]

ms2014 = graph.adjacency(similarity2014, mode = c("lower"), weighted = TRUE, diag=FALSE)

V(ms2014)$id = BAPE_2014_Nodes[,1]

ms2014_NE = graph.adjacency(similarity2014_NE, mode = c("lower"), weighted = TRUE, diag=FALSE)

V(ms2014_NE)$id = BAPE_2014_Nodes[,1]


ms2014_ees = graph.adjacency(similarity2014_ees,  mode = c("lower"), weighted = TRUE, diag=FALSE)

ms2014_actors = graph.adjacency(similarity2014_actors, mode = c("lower"), weighted = TRUE, diag=FALSE)

ms2014_stake = graph.adjacency(similarity2014_stake, mode = c("lower"), weighted = TRUE, diag=FALSE)

V(ms2014_stake)$collaborative = nodes_stake[, 37]

V(ms2014_stake)$id = nodes_stake[, 1]


#Reciprocity

reciprocity2011 = reciprocity(b2011)

reciprocity2014 = reciprocity(b2014)

reciprocity2014_NE = reciprocity(b2014_NE)


reciprocity(ees, mode = c("ratio"))

reciprocity(actors, mode = c("ratio"))

reciprocity(stake, mode = c("ratio"))


#Transitivity

local_transityvity2011 = transitivity(b2011, type = c("local"), vids = NULL, weights = NULL, isolates = c("zero"))

local_transityvity2014 = transitivity(b2014, type = c("local"), vids = NULL, weights = NULL, isolates = c("zero"))
```

```
local_transitivity2014_NE = transitivity(b2014_NE, type = c("local"), vids = NULL, weights = NULL, isolates = c("zero"))

local_transityvity2014_ees = transitivity(ees, type = c("local"), vids = NULL, weights = NULL, isolates = c("zero"))
local_transityvity2014_actors = transitivity(actors, type = c("local"), vids = NULL, weights = NULL, isolates = c("zero"))
local_transityvity2014_stake = transitivity(stake, type = c("local"), vids = NULL, weights = NULL, isolates = c("zero"))
```

#In-degree and out-degree

```
indegree2011 = graph.strength(b2011, vids = V(b2011), mode = c("in"), loops = FALSE, weights = NULL)
indegree2014 = graph.strength(b2014, vids = V(b2014), mode = c("in"), loops = FALSE, weights = NULL)
indegree2014_NE = graph.strength(b2014_NE, vids = V(b2014_NE), mode = c("in"), loops = FALSE, weights = NULL)
indegree2014_ees = graph.strength(ees, vids = V(ees), mode = c("in"), loops = FALSE, weights = NULL)
indegree2014_actors = graph.strength(actors, vids = V(actors), mode = c("in"), loops = FALSE, weights = NULL)
indegree2014_stake = graph.strength(stake, vids = V(stake), mode = c("in"), loops = FALSE, weights = NULL)

outdegree2011 = graph.strength(b2011, vids = V(b2011), mode = c("out"), loops = FALSE, weights = NULL)
outdegree2014 = graph.strength(b2014, vids = V(b2014), mode = c("out"), loops = FALSE, weights = NULL)
outdegree2014_NE = graph.strength(b2014_NE, vids = V(b2014_NE), mode = c("out"), loops = FALSE, weights = NULL)
outdegree2014_ees = graph.strength(ees, vids = V(ees), mode = c("out"), loops = FALSE, weights = NULL)
outdegree2014_actors = graph.strength(actors, vids = V(actors), mode = c("out"), loops = FALSE, weights = NULL)
outdegree2014_stake = graph.strength(stake, vids = V(stake), mode = c("out"), loops = FALSE, weights = NULL)
```

#Hubs and Autority scaled

```
hub2011 = hub.score (b2011, scale = NULL, weights=NULL, options = igraph.arpack.default)$vector
hub2014 = hub.score (b2014, scale = TRUE, weights=NULL, options = igraph.arpack.default)$vector
hub2014_NE = hub.score (b2014_NE, scale = TRUE, weights=NULL, options = igraph.arpack.default)$vector
hub2014_ees = hub.score (ees, scale = TRUE, weights=NULL, options = igraph.arpack.default)$vector
hub2014_actors = hub.score (actors, scale = TRUE, weights=NULL, options = igraph.arpack.default)$vector
hub2014_stake = hub.score (stake, scale = TRUE, weights=NULL, options = igraph.arpack.default)$vector

authority2011 = authority.score (b2011, scale = TRUE, weights=NULL, options = igraph.arpack.default)$vector
authority2014 = authority.score (b2014, scale = TRUE, weights=NULL, options = igraph.arpack.default)$vector
```

authority2014_NE = authority.score (b2014_NE, scale = TRUE, weights=NULL, options = igraph.arpack.default)$vector

authority2014_ees = authority.score (ees, scale = FALSE, weights=NULL, options = igraph.arpack.default)$vector

authority2014_actors = authority.score (actors, scale = FALSE, weights=NULL, options = igraph.arpack.default)$vector

authority2014_stake = authority.score (stake, scale = FALSE, weights=NULL, options = igraph.arpack.default)$vector

#Authority unscaled

authority2011_ns = authority.score (b2011, scale = FALSE, weights=NULL, options = igraph.arpack.default)$vector

hub2011_ns = hub.score (b2011, scale = FALSE, weights=NULL, options = igraph.arpack.default)$vector

authority2014_ns = authority.score (b2014, scale = FALSE, weights=NULL, options = igraph.arpack.default)$vector

hub2014_ns = hub.score (b2014, scale = FALSE, weights=NULL, options = igraph.arpack.default)$vector

#Closeness centrality normalized

closeness2011 = closeness(b2011, weights = NULL, normalized = TRUE)

closeness2014 = closeness(b2014, weights = NULL, normalized = TRUE)

closeness2014_NE = closeness(b2014_NE, weights = NULL, normalized = TRUE)

closeness2014_ees = closeness(ees, weights = NULL, normalized = TRUE)

closeness2014_actors = closeness(actors, weights = NULL, normalized = TRUE)

closeness2014_stake = closeness(stake, weights = NULL, normalized = TRUE)

#Raw closeness centrality

closeness_NN_2011 = closeness(b2011, weights = NULL, normalized = FALSE)

closeness_NN_2014 = closeness(b2014, weights = NULL, normalized = FALSE)

closeness_NN_2014_NE = closeness(b2014_NE, weights = NULL, normalized = FALSE)

#Structural holes

constraint2011= constraint(b2011, nodes=V(b2011))

constraint2014= constraint(b2014, nodes=V(b2014))

constraint2014_NE= constraint(b2014_NE, nodes=V(b2014_NE))

constraint2014_ees= constraint(ees, nodes=V(ees))

constraint2014_actors= constraint(actors, nodes=V(actors))

constraint2014_stake= constraint(stake, nodes=V(stake))

#Community analysis - louvain community detection

louvain2011 = cluster_louvain(ms2011, weights = E(ms2011)$weight)

louvain2014 = cluster_louvain(ms2014, weights = E(ms2014)$weight)

louvain2014_NE = cluster_louvain(ms2014_NE, weights = E(ms2014_NE)$weight)

l_ees= cluster_louvain(ms2014_ees, weights = E(ms2014_ees)$weight)

l_actors= cluster_louvain(ms2014_actors, weights = E(ms2014_actors)$weight)

l_stake = cluster_louvain(ms2014_stake, weights = E(ms2014_stake)$weight)

sizes(louvain2011)

sizes(louvain2014)

sizes(louvain2014_NE)

sizes(l_ees)

sizes(l_actors)

sizes(l_stake)

V(b2011)$community = membership(louvain2011)

V(b2014)$community = membership(louvain2014)

V(b2014_NE)$community = membership(louvain2014_NE)

#Modularity of original network according to information communities

modularity(b2011, membership(louvain2011))

modularity(b2014, membership(louvain2014))

modularity(b2014_NE, membership(louvain2014))

modularity(ees, membership(l_ees))

modularity(actors, membership(l_actors))

modularity(stake, membership(l_stake))

#ERGM

b2014 = asNetwork(b2014_igraph)

#Model A

b2model.A = ergm(b2014~edges+nodemix('collaborative2', base=1), control = control.ergm(MCMLE.maxit ='50', drop = TRUE, MCMC.prop.weights="TNT", MCMC.burnin =10000, MCMC.interval = 5000, seed = 800), verbose = FALSE)

summary(b2model.A)

#Model B

b2model.B = ergm(b2014~edges+nodemix('collaborative2', base=1)+nodematch('community'), control = control.ergm(MCMLE.maxit ='50', drop = TRUE, MCMC.prop.weights="TNT", MCMC.burnin =10000, MCMC.interval = 5000, seed = 800), verbose = FALSE)

summary(b2model.B)

#Model C

b2model.C = ergm(b2014~edges+nodemix('collaborative2', base=1)+nodematch('community')+mutual, control = control.ergm(MCMLE.maxit ='50', drop = TRUE, MCMC.prop.weights="TNT", MCMC.burnin =10000, MCMC.interval = 5000, seed = 800), verbose = FALSE)

summary(b2model.C)

#Model D

b2model.D = ergm(b2014~edges+nodemix('collaborative2', base=1)+nodematch('community')+mutual+gwesp(0, fixed=TRUE), control = control.ergm(MCMLE.maxit ='50', drop = TRUE, MCMC.prop.weights="TNT", MCMC.burnin =10000, MCMC.interval = 5000, seed = 800), verbose = FALSE)

summary(b2model.best)

#Model E

b2model.E = ergm(b2014~edges+nodemix('collaborative2', base=1)+nodematch('community')+mutual+gwesp(0, fixed=TRUE)+istar(2), control = control.ergm(MCMLE.maxit ='50', drop = TRUE, MCMC.prop.weights="TNT", MCMC.burnin =10000, MCMC.interval = 5000, seed = 800), verbose = FALSE)

summary(b2model.best)

#Model E diagnostic

mcmc.diagnostics(b2model.best)

#Model E GOF

```
gof.b2model.best = gof.ergm(b2model.best)

plot(gof.b2model.best)

summary(gof.b2model.best)
```

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