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How Knowledge Brokers Shape the Evidence-Based Policy Landscape

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Abstract

Knowledge brokers, usually conceptualized as passive intermediaries between scientists and policymakers in evidence-based policymaking, are understudied in the philosophy of science. Here, we challenge that usual conceptualization. As agents in their own right, knowledge brokers have their own goals and incentives, which complicate the effects of their presence at the science–policy interface. We illustrate this in an agent-based model and suggest several avenues for further exploration of the role of knowledge brokers in evidence-based policy.

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1. Introduction

Billions of dollars of economic activity are dedicated to the notion that the connection between scientific knowledge and society needs maintenance. The maintenance crews are impossible to miss: governmental expert groups, international scientific committees, lobbyist think tanks, research institutes, and so on. Whether local, regional, national, international, or global, they go by the label *knowledge brokers* (KBs). The KB label derives from a nominal purpose: to broker knowledge between those at its source (typically, scientific research) and societal users (often policymakers).

Despite the strategic position of KBs at the interface between scientific research and society, philosophers of science have generally neglected how KBs get involved in brokering the knowledge that shapes what we know.[1] Not so in adjacent fields: In the science and technology studies, political science, and knowledge management literature that researches *knowledge brokering*, there is a long history of discussion about the *linear model* of the science–policy interface, which posits that science feeds into policymaking activities through KBs acting as intermediaries (although for historical context, see Edgerton 2004). That KBs perform in the role of intermediaries according to the linear model allegedly gives historical context for the naming convention that emphasizes a brokering arrangement between science and society. But in this literature, it is generally recognized that the linear model suppresses crucial complexities: At the science–policy interface, all relevant parties, KBs among them, *co-produce* policy. Hence, one commonly finds endorsements of a rival *co-production model* (Jasanoff 2004; Bandola-Gill

[1] Some philosophers of science have, however, considered the epistemic consequences of particular knowledge-brokering arrangements, for example, the Intergovernmental Panel on Climate Change (IPCC; an example of a KB), as in Katzav (2014) and references therein. Others have focused on epistemic consequences of science's embedding in a larger social context, for example, work on science communication (Dethier 2025), misinformation (O'Connor and Weatherall 2018; Friedman and Šešelja 2023), or science funding (Sanders and Robison 1992; Pinto 2021; Shaw 2022).

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et al. 2023). Examining the roles of KBs within the context of either the linear or the co-production model is an active area of ongoing research.

To catch up with the adjacent literature and to properly study the growth of scientific knowledge in society, philosophers of science require an epistemology of KBs. In this article, we get started by asking: What are the general effects of KBs on how policymakers might learn and decide how to act, given ongoing scientific research? We argue that we must go beyond a passive characterization of KBs given in terms of their ideal roles (*relays* in the linear model, *facilitators* in the co-production model). Instead, KBs are strategic agents, with distinctive incentives surrounding their participation in an overall knowledge ecosystem (sec. 2). On this basis, and given our interest in studying the effects of KBs, we develop a model of information flow through that knowledge ecosystem, which lets us track the effects of the decisions motivated by the diversity of incentives at play (sec. 3). We show that KBs have effects on the overall epistemic health of the society in which they operate that are not captured by the existing literature (sec. 4). Finally, we discuss the future research that is needed to more fully study the impacts of KBs (sec. 5).

2. Incentives surrounding knowledge brokering

There are three types of agents operating at the science–policy interface: scientists (knowledge producers), policymakers (knowledge users), and KBs. In a particular situation, each of these three types is instantiated by some number of agents—individuals or organizations. These agents each have their own goals and implicit or explicit beliefs about how best to achieve these goals. They are therefore *incentivized* to act in some ways as opposed to others.

The epistemic consequences of the goals and incentives of scientists are quite well studied (Strevens 2003; Heesen 2017; Zollman 2018; O'Connor and Bruner 2019; Rubin and Schneider 2021). For instance, it can matter in questions of pursuit that an important goal for most scientists is to build a reputation for significant discoveries, as this is key

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to a successful academic career (Merton 1973). Policymakers have their own goals and incentives, which are quite different (Choi et al. 2005; Uneke et al. 2011; Beesley et al. 2022). It is worth noting here that the term *policymaker* is used in different ways. Here, we primarily have in mind those who organize relevant knowledge and write and implement detailed policy proposals (e.g., civil servants or bureaucrats) rather than politicians who set broad policy directions.

The linear model portrays KBs as (merely) transmitting information from scientists to policymakers, perhaps reducing uncertainty or improving clarity while doing so. But KBs, agents in their own right, have goals and incentives. These will shape what information they are willing and able to receive, as well as what information they are interested in passing on. Even before knowing any specifics about their goals and incentives (which we get into later), we should expect the presence of KBs to affect the science–policy interface in more complicated and interesting ways than if they passively transmitted information. This point appears to be underappreciated in the literature on KBs (for an overview, see, e.g., MacKillop et al. 2020).

Our aim, then, is to study the effects of KBs with different sorts of incentives on the science–policy interface, specifically in terms of what science gets done and what policies get implemented. A recent empirical paper distinguishes a wide range of different types of KBs, the goals or incentives for people to get involved with these KBs, and the goals or incentives of the KBs themselves (Bortolus et al. 2025). Types of KBs include professional societies and academies, expert groups with a governmental mandate (standing committees, task forces), research and advocacy groups (Indigenous organizations, nongovernmental organizations [NGOs], think tanks, lobbyists and consultants), and more.

As discussed by Bortolus et al. (2025), all of these KB types have incentives for why they want to interact with policymakers, and policymakers have different incentives for wanting to interact with KBs. For instance, policymakers may be looking for clarity on their questions or translation of research into language they understand. Equally,

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consider the incentives that different types of KBs have to interact with policymakers: In some cases, financial incentives matter; in others, influence.

Moreover, consider the incentives for different types of KBs to interact with researchers, and for researchers to interact with KBs. KBs may get free labor or new knowledge from researchers, or they may derive prestige from having esteemed scientists as members. Conversely, researchers may look forward to the prestige to be gained, for example, by being associated with a highly regarded academy or a government-mandated expert group that receives a lot of media attention. Alternatively, interacting with KBs may yield resources for researchers (KBs may pay members or provide access to research equipment or conference space) or offer paths to greater influence and impact for their research.

The previous two paragraphs hint at the complexity that is ultimately of concern in developing an epistemology of KBs. In this article, we construct a first model to furnish insight into the epistemic consequences of KBs. For this purpose, we simplify the broad diversity of KB types and incentives while aiming to retain some of the major distinctions just outlined. Specifically, although the KB motivations we discuss are not mutually exclusive or exhaustive, we will distinguish three broad types of KBs, each characterized by a dominant motivation. The first type is primarily motivated by good science, whatever the KBs take that to be: They want the "best" scientists as members. We will refer to these as *productivity-driven* KBs. The second type is primarily motivated by having policy impact. The extreme cases are standing committees, which really only have a reason to exist if the policymaker is listening to what they have to say. Such KBs, we assume, care about being listened to by policymakers more than the actual policy directions chosen. We call these *impact-driven* KBs. The third type, in contrast, is primarily motivated by the KB's policy agenda or mission, such as an industrial lobbying organization whose goal is to achieve looser regulations. These will be referred to as *agenda-driven* KBs.

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We assume, moreover, that individual researchers also vary in their motivations, in a way that matches the KB types. Thus, productivity-driven researchers care primarily about producing the most high-quality science. Impact-driven researchers care primarily about influencing policy, regardless of direction, perhaps because they want the prestige associated with policy impact. And agenda-driven researchers care primarily about steering policy outcomes in a particular direction, for example, a researcher who chooses their career path because they are motivated to preserve ecosystems.

3. Model

The basic setup of the model is a community of scientists performing research, which KBs then process and communicate to the policymaker. The incentives of scientists and KBs affect which scientists associate with which KBs and the communication channels through which the policymaker receives evidence relevant to policy decisions.

Two things to note about this setup: First, KBs communicate what they consider important, which we refer to as a *signal*. This is a necessary simplification of what the research says; if they did not simplify in any way, they would not be doing their job. Second, policymakers do not always listen to every KB. They might see some as making claims that are totally implausible or outside their ability or willingness to act. We assume that policymakers have some prior expectations about the kind of evidence they will receive and that they ignore signals that are outside those expectations. By taking evidence within those expectations on board, policymakers show a minimal commitment to practices ordinarily associated with *evidence-based policy*. And recall: Policymakers are mostly government bureaucrats, not politicians.

Here is how the model works, also summarized in the schematic in figure 1.[2] We start with a question scientists are trying to answer, such as how much of an invasion threat

[2] For reasons of space, we describe the model in broad terms. A description of the model with enough detail to facilitate replication is available at https://philsci-archive.pitt.edu/29827/. Full detail can also be

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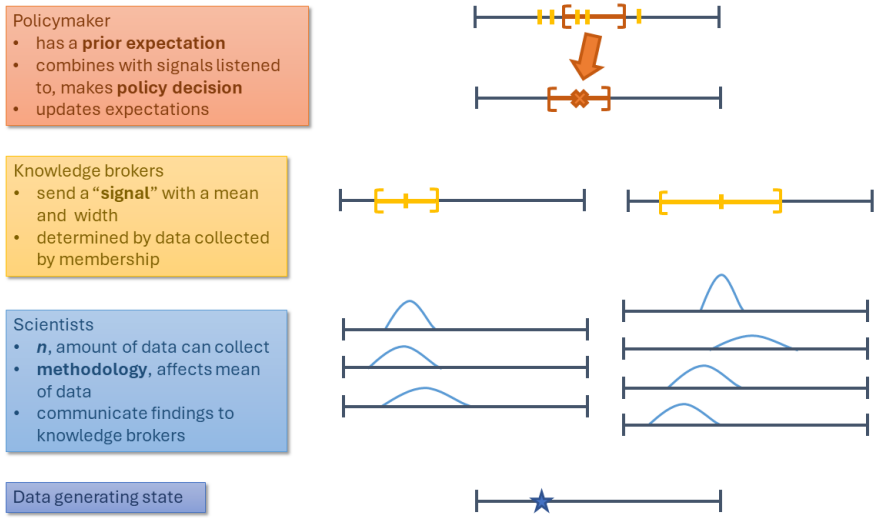


Figure 1: A schematic overview of the model. The process is depicted from the bottom up, starting with the data-generating state (indigo star) and ending in policymaker action. Scientists gather data (blue distributions), which KBs consolidate into signals (yellow intervals and vertical lines) to send to the policymaker. The policymaker incorporates those KB signals inside their expectations (orange interval) and makes a policy decision (orange X) based on those signals. The policymaker then updates their expectations (orange arrow) for the next round.

some species is, and there is some fact of the matter that research aims to uncover, for example, the chances the population will rise to a certain level and the scale of negative effects should the species rise to that level. This fact of the matter is represented by a *data-generating state* in the model, a number between 0 and 1 (ranging, e.g., from no invasion threat to the worst invasion threat readily imaginable).

Each scientist has a different *productivity*, n, the amount of data they collect. They also employ different *methodologies*, captured by slightly adjusting the mean of their data away from the data-generating state.[3] They draw n data points from a normal distribution with mean equal to their methodology. Variation in methodology need not

obtained by viewing the MATLAB code at https://osf.io/5cbnf/?view_only=46aa69f06d204af0adc318bc22aaf5e4 .

[3] Agenda-driven agents further have their methodology moved by 0.5 to capture a tendency to adopt methodologies that support their agenda.

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represent any kind of illegitimate science going on; it is just a feature of diverse methods at work to tackle complex problems.[4] Some methods might be better suited to investigating short-term effects on fish populations, others on long-term tree growth, and others on economic impact, for example.

The signal a KB sends to the policymaker consists of the mean and the 95% confidence interval of the data gathered by its members. The mean indicates what the KB's evidence on average recommends, and the width of the confidence interval indicates how uncertain the KB thinks that evidence is. The policymaker will listen to those signals whose means fall within their expectations.[5] We varied the *policy width*, or the range of signals the policymaker is willing to listen to, to capture varying expectations for different types of questions.

The policymaker's belief is the average of the mean of each signal they listened to, which they subsequently act upon. For instance, they respond with the appropriate level of intensity to a given invasion threat, for example, by restricting trade in a particular area or tightening water purity regulations. Finally, they update their policy expectations for the next round by centering expectations on this round's decision (plus a small random shift).

Incentives come into play in determining which scientists are members of which KBs. Each scientist and KB is assigned one of the three drivers, and agenda-driven scientists additionally have an agenda, 0 or 1, representing, for example, a position on environmental regulation or deregulation. The membership of each scientist is determined by a weighted draw among KBs and an additional "no KB" option (some scientists with interests in evidence-based policymaking fail to get involved). Researchers are more likely to be assigned to KBs if their type matches (and for agenda-driven

[4] See also Holman and Bruner (2017).

[5] Note that although the KBs send information about uncertainty, this information is ignored. We think this is not an unreasonable assumption. Potential effects of reporting uncertainty are reserved for future investigation.

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agents, if they share an agenda). The weight is also increased if the scientist produces research with features the KB finds desirable. Productivity-driven KBs are more likely to have members with high productivity. Agenda-driven KBs are more likely to have members whose methodology is closer to their agenda. Impact-driven KBs are more likely to have members whose methodology is in line with what they think the policymaker will listen to, that is, relatively close to the policymaker's expectations.

This model simplifies in many ways. To name a few: We ignore how data are produced. Thus, our model is consistent with both the linear view of KBs, where KBs merely collect data and process the data, and the co-production view, where KBs facilitate what data scientists collect. The model only considers quantitative scientific evidence. We also only include one policymaker. Finally, we assume that there is no intentional misrepresentation of evidence by any party involved. Therefore, we are describing the influence KB incentives have on policymaking while restricting their actions to accurately announcing an aggregation of their members' data; presumably, this is a lower bound on the amount of "distortion" KBs create on the information flow from scientists to policymakers.

4. Results

Because of KBs, the total body of scientific knowledge learned by the policymaker is structured by features of the professional social structure of scientific research, in addition to the world itself.

Here, we present results from six different variations of the model. First, we present results from *Random*, a base case with no incentives in play, where matching of scientists and KBs is random. This allows us to evaluate how KBs affect policymaking just by the fact that they process and simplify data in their communication of scientific evidence. We then present results from *Matched*, a variation where there is matching based on incentives, as described earlier. The differences in outcomes between this variation and

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Random show how KB incentives further distort the policymaking process (even though they continue to faithfully represent the evidence at hand).

We then present four variations where some KBs are more influential than others, which we capture by allowing their signals (if listened to) to be given more weight when the policymaker averages signals[6] to form a belief: *Dominant Agenda*, where all KBs of one agenda have extra influence; *External Organizations*, where all agenda-driven KBs have extra influence; *Good Science*, where productivity-driven KBs have extra influence; and *Government Investment*, where impact-driven KBs have extra influence.[7] These variations let us explore the effects on policymaking if some KB incentives are allowed to dominate in the process.

In this model, we are interested in how KBs affect policy decisions. The main measure we use to evaluate the effects of KBs is the distance from the "truth." For our purposes, we equate truth with the mean of all the data actually gathered by the research community. That is, this notion of truth is the truth from the perspective of what society could, in some abstract, idealized sense, be getting from science. We then think of distance from the truth as how far off the policy decision is from what it would be if the policymaker knew the truth. We look at how far off the policymakers are (on average, over many rounds of simulating this communication process) from what they would be doing if they knew what the science actually says.

[6] Each broker is given the same base influence (10 for the results presented here), which is then multiplied by some value if their type is being given extra influence in the condition.

[7] We also ran simulations for an alternative version of the model where influence instead affects the likelihood that KBs are listened to by the policymaker. In this version, KBs must first be listened to (given a foot in the door of the policymaker) and then be heard (have their signal be within the policymakers' expectations) in order to affect policy. Results for this version of the model were similar.

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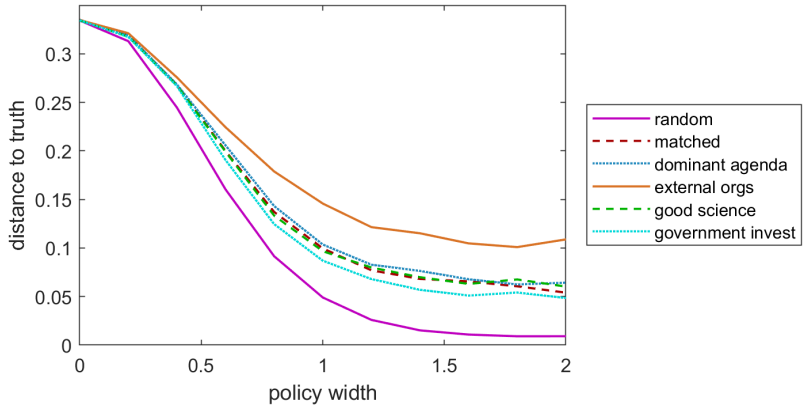


Figure 2: Distance from truth, over various policy widths, for each of the six variations of the model.

Results are presented for simulations with 10 KBs, 100 scientists, and 1,000 rounds. For easy visualization, we set the extra influence multiplier to 5 and the extra matching chance m to 2,000. We choose these large values so that we can easily see the differences between variations as we vary policy width (because policy width has such a large impact on outcomes). Importantly, similar qualitative results occur for less extreme choices of these variables. Policy width was varied from 0 to 2, where 0 represents a case where the policymaker never listens to any evidence, and 2 represents a case where the policymaker is essentially guaranteed to listen to every signal. Each parameter combination was run 1,000 times in order to get an estimate of the expected distance from the truth.

As figure 2 shows, the distance from the truth is affected by the width of the policymakers' expectations for all variations. When their expectations are narrow, they generally make decisions that are pretty far from what they would do with complete understanding of the scientific evidence. Larger policy widths lead to better decision making in this model.

Looking at *Random* (in pink), where there are no incentives or differences in influence, we can see that the policy width has a large impact on the distance from the truth. As the policy width increases, the policymaker gets very close, but not all the way, to

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perfect decision making. By definition, taking the average of all data gathered by the scientists would yield a distance of 0. The deviation from that we observe here is the result of KBs grouping the data (the policymaker averages KB signals, which themselves average different quantities of data) and of the data lost because some scientists do not join a KB.

What happens when we add in incentives, where KBs tend to choose members who align with their aims? In *Matched* (in red), the distance from the truth now increases. Although the distance is similar when policymaker expectations are narrow, the impact increases further from the truth once the policymaker is listening to most signals.

So: KBs distort the evidence just by being part of the process and filtering the data. The *Random* variation shows that introducing this kind of filtration leads to some small distance from the truth. The *Matched* variation shows that once that filtration is not completely random, this leads to an even greater distance from the truth. So, the incentives of these agents matter. We think of *Matched* as a sort of minimal or baseline description of the impact of incentives.

Results for when certain types of KBs are more influential, in that their signals are given more weight by the policymaker, are also shown in figure 2. Two interesting results: First, although it is unsurprising that the two variations where agenda-driven KBs are influential tend to be the furthest from the truth, it is somewhat surprising that *External Organizations* (in orange) is worse than *Dominant Agenda* (in blue). That is, having influential people pushing both sides of the issue turns out to be worse than one side having all the influence. This is because, in our model, with only one side of the issue having extra influence, the policymaker can only be pushed into really bad decision making in one direction (e.g., they're generally looser on regulations than they should be, but only occasionally drastically underprepared to deal with an invasion threat), whereas with both sides of the issue having extra influence, the policymaker can be

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pushed very far from the truth in both directions. Occasionally, they drastically overreact, and occasionally, they drastically underreact and overall spend more time doing wildly the wrong thing.[8]

Second, *Government Investment* (in cyan) is better than *Good Science* (in green). This is a somewhat surprising result—why should an eye toward telling the policymaker what they want to hear do better than picking based on the most productive scientists? One might think that the policymaker is closer to the truth because they are listening to more signals when impact-driven KBs are influential, but once the policy width is sufficiently wide, the policymaker is guaranteed to listen to everything, and government investment is still better. Instead, thinking about the signals sent by each KB type can help us get a sense of why this might be the case. Although there is substantial overlap in the kinds of signals sent by productivity- and impact-driven brokers, there is more variance in what the productivity-driven KBs send.[9] Because they pick members without regard to methodology, as long as they are productive, there is greater variance in what their membership's research says about the situation at hand. As a result, the signals sent by productivity-driven KBs are consistently (although only slightly) further from the truth.

So, we might say something like the following: We have to conditionalize our expectations on the brokering landscape, not just go with what we a priori think should be best. If there's a sufficient industry presence to skew the overall availability of methods in the rest of the population, government investment is the best. In that case, we might want more publicly funded research, with an eye toward impact.

[8] See the longer version of the article at https://philsci-archive.pitt.edu/29827/ for visualizations of example runs.

[9] Again, visualizations of these results are provided in the longer version of the article at https://philsci-archive.pitt.edu/29827/.

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5. Conclusion

KBs are major players in society's overall knowledge ecosystem. How we conceptualize them matters in the study of the growth of scientific knowledge in society. Yet little is known about the epistemology of KBs: how these players' incentives affect knowledge flow from its origin in scientific research to its end point in use by society, especially in the decisions of policymakers. To develop an adequate epistemology of KBs, it is necessary to depart from simplistic narratives about KBs motivated by the linear and co-production models of the science–policy interface. Agent-based modeling is well suited to the task.

Of course, the model we have presented is still highly simplified. In reality, there may be multiple policymakers, with different incentives or agendas, and KBs may employ different strategies to try to be heard by some or all of them. Scientists may also have more than one KB membership, and how many memberships they have may depend on their productivity, methodology, or something else. There might also be multiple, competing incentives for a given KB or for a given scientist, which means they have to make trade-offs when they think about their membership. There might also be multiple questions to gather evidence about and co-production of knowledge in which KBs facilitate what research is produced by scientists. In this article, we have assumed that all the science is in fact relevant to the policy, but this is generally not the case. KBs having influence over what science gets done could allow the different KB types to have a much greater influence on ultimate policy decisions.

There is still much to be done in developing an epistemology of KBs. However, we regard the initial results we have presented here as a launching-off point. Considered as a base case, our model establishes how the effects of KBs being part of a knowledge ecosystem are hidden when they are conceptualized only in terms of carefully delineated roles. In our model, all KBs have the same role. They all process and summarize scientific evidence in exactly the same way. Yet the consequences for policymakers'

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decision making are different by virtue of differences in dominant incentives and possible differences in influence. Moreover, our results indicate that facts about the overall composition of the brokering landscape nontrivially affect our strategizing for how, ultimately, to improve the quality of knowledge available in policymaking.

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