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PAPER

Causal inference to scope environmental impact assessment of renewable energy projects and test competing mental models of decarbonization

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Abstract

Environmental impact assessment (EIA), life cycle analysis (LCA), and cost benefit analysis (CBA) embed crucial but subjective judgments over the extent of system boundaries and the range of impacts to consider as causally connected to an intervention, decision, or technology of interest. EIA is increasingly the site of legal, political, and social challenges to renewable energy projects proposed by utilities, developers, and governments, which, cumulatively, are slowing decarbonization. Environmental advocates in the United States have claimed that new electrical interties with Canada increase development of Canadian hydroelectric resources, leading to environmental and health impacts associated with new reservoirs. Assertions of such second-order impacts of two recently proposed 9.5 TWh yr^{-1} transborder transmission projects played a role in their cancellation. We recast these debates as conflicting mental models of decarbonization, in which values, beliefs, and interests lead different parties to hypothesize causal connections between interrelated processes (in this case, generation, transmission, and associated impacts). We demonstrate via Bayesian network modeling that development of Canadian hydroelectric resources is stimulated by price signals and domestic demand rather than increased export capacity per se. However, hydropower exports are increasingly arranged via long-term power purchase agreements that may promote new generation in a way that is not easily modeled with publicly available data. We demonstrate the utility of causal inference for structured analysis of sociotechnical systems featuring phenomena that are not easily modeled mechanistically. In the setting of decarbonization, such analysis can fill a gap in available energy systems models that focus on long-term optimum portfolios and do not generally represent questions of incremental causality of interest to stakeholders at the local level. More broadly, these tools can increase the evidentiary support required for consequentialist (as opposed to attributional) LCA and CBA, for example, in calculating indirect emissions of renewable energy projects.

1. Introduction

To limit global climate warming to within 1.5 °C of preindustrial averages, total greenhouse gas emissions will need to be offset by removal and sequestration ('net-zero') by 2050 (Huang and Zhai 2021, van Soest *et al* 2021, Dafnomilis *et al* 2024, United Nations 2024). This in turn will require investments in electrical generation and transmission infrastructure on the order of $4 trillion to $6 trillion beyond a business-as-usual scenario over the same period in the United States alone (National Academies of Sciences, Engineering, and Medicine 2021). Yet, in the United States and internationally, governments, utilities, and other stakeholders have faced major obstacles in achieving the rate of build-out of renewable energies necessary to meet these targets. As we describe below, a significant fraction of projects proposed for development are challenged using environmental impact assessment (EIA) legislation.

In this section, we recast EIA-centered debates as disagreements over causal 'mental models' and describe how causal inference methodologies may be used to evaluate the extent to which competing mental models are supported by available data. We describe how this may complement existing energy systems models which are not designed to elucidate questions of incremental causality at the local scale, and how these methods add to the literature on sociotechnical analysis of energy systems. We introduce the case study of controversial electrical interties between the United States and Canada, which provides a timely setting for characterization of advantages and limitations of these methods. We introduce the central claim we test in this analysis, that new electrical interties stimulate new reservoir development in Canada, and we describe why this question cannot be answered with currently available energy systems models.

1.1. Local sociopolitical dynamics complicate decarbonization planning

Notwithstanding major recent developments such as the U.S. Inflation Reduction Act, the pace of build-out of wind, solar, storage, and associated transmission infrastructure remains highly uncertain in the United States and internationally. These uncertainties arise from (1) quantifiable differences in model assumptions in the national and international economic and technological parameters driving technology uptake and the range of projects that are proposed (e.g. future costs for battery storage, availability of tax credits, etc) (Batel 2020, Moore *et al* 2022, Bistline *et al* 2024); and (2) the cumulative effect of less predictable sociopolitical processes at the individual to global scales that determine (among other things) the pace at which proposed projects are actually built (Batel 2020, Moore *et al* 2022), which is the focus of this analysis.

Realization of climate targets is jeopardized by the cumulative effects of localized rejection of renewable energy projects. In the United States and Canada, 17% and 18% respectively of wind projects proposed between 2000 and 2016 faced significant opposition, with this fraction increasing over time (Stokes *et al* 2023). Weise and Bhat (2024) report that 15% of U.S. counties have effectively halted new wind and/or solar projects, with half of solar bans having been passed in 2023 alone. Restrictions at the state level have more than doubled between 2023 and 2024 (Eisenson *et al* 2024). Environmental protection legislation the most common vehicle for these challenges, accounting for 1316 of the 2328 legal challenges against U.S. renewable energy projects inventoried by the Sabin Center for Climate Change Law as of September 2024 (Sabin Center for Climate Change Law 2024). Of these, challenges to under federal or state EIA legislation account for the majority (706 out of 1316). The land-use needs of renewable energies suggest that EIA will play an increasing role in debates over decarbonization decisions. For example, Lovering *et al* (2022) calculate future global land use requirements of roughly 207 Mha by 2050 to achieve the International Energy Agency's 2 °C warming scenario compared to 97 Mha in 2017, not counting land required for transmission infrastructure.

1.2. Disputes over EIA reflect conflicting beliefs about causal relationships in environmental, social, and technical systems

EIA provides a mechanism by which infrastructure and other projects will be evaluated in terms of foreseeable environmental impacts and is now required in some form for major generation, transmission, and many other types of projects in most countries (Morgan 2012, Glasson and Therivel 2013). In the United States, the National Environmental Policy Act (NEPA) requires evaluation of 'reasonably foreseeable' environmental consequences with a 'reasonably close' causal link to a federal action (e.g. permit issuance) even if these consequences fall outside the U.S., and even if they are second-order or indirect effects (Border Power Plant Working Group v. Department of Energy 2003, Council on Environmental Quality 2021). Recent updates to the regulations governing NEPA implementation reaffirm that relevant impacts may occur at a different time or place than the covered action while clarifying that simple 'but-for' causation is generally an insufficient standard (Council on Environmental Quality 2020). Executive agencies have broad discretion and latitude to apply their own judgments in scoping and interpreting environmental assessments and impact statements, even while their actions and findings under NEPA can be (and frequently are) reviewed by the courts (Colburn 2016).

There is increasing interest in (1) the extent to which EIA, life-cycle analysis (LCA), and similar tools embed critical but subjective and often inadequately justified judgments of developers or regulators, notably, in decisions over the geographic, temporal, and causal scope of the analysis (Dubois-Iorgulescu *et al* 2018, Cederlöf and Hornborg 2021, Das 2024); and (2) techniques to consider second- and higher-order effects in EIA, and particularly social effects or effects mediated through social responses (Börjesson Rivera *et al* 2014, Pohl *et al* 2019, Nilsson *et al* 2021). These questions are becoming increasingly urgent as widespread disagreements around EIA scope and adequacy combine to slow progress to decarbonization, but methodologies to resolve these controversies or build consensus among stakeholders remain elusive (Larsen *et al* 2018, Dutta *et al* 2021, Hall *et al* 2022, Zarzavilla *et al* 2022).

This work reports on controversies over the scope of EIA for transmission projects proposed to increase U.S. import capacity of Canadian hydropower in terms of contested 'mental models' and proposes causal inference methodologies as an avenue of resolution and consensus-building. Mental models encode beliefs about deterministic or probabilistic causal relations among physical and social phenomena and are increasingly deployed to analyze conflicts over environmental systems (Kolkman *et al* 2007, Khemlani *et al* 2014, Gaus *et al* 2023, Olofsson *et al* 2023). To our knowledge, this is the first work to evaluate how competing causal beliefs may be evaluated quantitatively in the setting of disputed EIA.

1.3. Debates over United States—Canada energy integration provide a case study for the use of Bayesian inference methodologies to address controversies in EIA

In the northeastern United States, state decarbonization plans have sought to leverage Canadian hydroelectric resources as firm lower-carbon capacity and to buffer intermittent wind and solar generation; however, of four (∼1 GW) large intertie projects proposed since 2018, two have been cancelled (2018 and 2024) and one was suspended in 2021 before a legal challenge allowed construction to resume (U.S. Department of Energy 2017, Gronendyke 2018, Appeal of Northern Pass Transmission, LLC & a 2019, Maine Department of Environmental Protection 2021, NECEC Transmission LLC et al. V. Bureau of Parks and Lands et al 2022, Dalton 2024).

A key feature of the opposition to these transmission projects is the claim that *increased transborder transmission* will stimulate *increased generation* in Canada and hence increase the environmental, social, and health impacts of large-reservoir hydropower (Rosenberg *et al* 1997, Calder *et al* 2016); this has been the basis for legal filings to the U.S. Department of Energy and others during the EIA process for these projects (Birchard 2017, Forest Society n.d., Appalachian Mountain Club 2018, Natural Resources Council of Maine 2018; Kurtz *et al* 2018, Riverkeeper, n.d.). Thus, debate over transborder electrical interties is in effect a debate over how to understand the causal relationship between transmission and generation infrastructure and whether to construe generation-side impacts as causally downstream from decisions over transmission. This is an example of a much broader category of disputes over EIA which center on the range of impacts that can be plausibly attributed to the action under consideration which differ between parties according to the mental model of each.

1.4. Quantitative tools are needed to bridge the gap between technical and sociotechnical conceptions of the evolving energy system

Such questions are not easily addressed by currently available mechanistic energy systems models. Available capacity expansion models (at least in the transborder context) do not have the resolution to describe, for example, how a decision about a transmission corridor affects the probability of new generation (Calder *et al* 2024). In general, energy systems research has tended to develop models that characterize optimal portfolios of assets without regard to contingencies or path-dependencies introduced at intermediate steps along the path to these portfolios (e.g. at the project-specific level) (Bouffard *et al* 2018, Dimanchev *et al* 2021, Rodríguez-Sarasty *et al* 2021, Ba *et al* 2024). This work may acknowledge social 'barriers' to implementation and support characterization of uncertainties around economic (but usually not other social) constraints or trends (Sovacool *et al* 2015, Geels *et al* 2017).

Conversely, a socio-technical framing interrogates the political, perceptual, legal, and behavioral mechanisms that combine to constrain and determine the evolution of the energy system in ways that are often overlooked in quantitative research (Sovacool 2009). In reality, the energy system evolves as a function of complex interdependencies between social (political, economic, etc) and technical processes that are difficult to simulate mechanistically (e.g. as in traditional energy systems models) (Geels 2005, Hess and Sovacool 2020, 2020), though the present work posits that retrospective quantitative analysis may nonetheless be possible. At the same time, there is increased interest in understanding conflict over renewable energy projects in terms of the set of tools used by, and range of projects proposed by, governments, developers, and utilities, notably with respect to public priorities, values, and interests (van de Grift and Cuppen 2022, Calder *et al* 2024).

There is a need for tools that allow for structured analysis of alternative worldviews as they pertain to the evolution of sociotechnical systems (notably, the range of impacts to consider in EIA, as analyzed here) in a way that provides empirical evidence for or against competing mental models. Such tools can provide a transparent basis for regulators to justify decisions over (for example) the scope of an analysis and can help other actors decide whether they will support or oppose a given project (for example, transmission projects that are contentious given their uncertain range of impacts). Here, we propose a role for tools that (1) complement rather than imitate the range of disciplinary-specific tools available to understand the performance of technical systems (e.g. tools to simulate the current electrical grid that operates almost independently of social dynamics) and (2) leverage data to describe the range of social and technical systems and sectors that combine to describe the evolution of energy systems using a sociotechnical framing.

There is for example increasing interest in the application of statistical causal inference tools to scope the range of environmental impacts attributable to biophysical perturbations (Paul 2011, Arif and MacNeil 2022). We have however not identified work exploring the use of these methodologies in the setting of impacts mediated by social systems, for example, to arrive at consensus of the range of second-order impacts that can plausibly be attributed to renewable energy projects. We demonstrate by way of case study that Bayesian inference methodologies can bridge the gap between (1) energy systems analysis, which is overwhelmingly quantitative and focused on the optimization of select technical endpoints, and (2) analysis of controversies regarding the scope of social and environmental impacts to consider.

This responds to a growing call within sociotechnical systems research to integrate causal inference methodologies to examine the intricate cause-and-effect relationships inherent in energy transitions (Geels *et al* 2016, Köhler *et al* 2019, Andersen and Geels 2023). By employing causal inference models, we can quantitatively assess how non-technical factors influence technical developments and vice versa, providing empirical evidence to support or challenge competing mental models (Pearl 2000, Sovacool *et al* 2021). This enables (1) a more nuanced understanding of contingencies and path dependencies (e.g. secondary impacts) that shape energy systems which is often neglected in mental models, and (2) the ability to curate effective and socially responsive energy policies by identifying critical causal relationships and potential intervention points to accelerate decarbonization (Kern and Rogge 2016).

More broadly, we posit that such methods may be informative for understanding the evidence underpinning competing mental models in other types of disputes. Impacts mediated through social systems, i.e. those which are conditional on an unknown future individual or social response, are virtually never addressed in EIA due to a lack of integrated modeling capacity or efforts by project proponents to limit EIA scope. This includes results of economic phenomena such as the 'rebound effect', where projects improving efficiency accelerate rather than arrest depletion of natural resources or environmental degradation (Owens *et al* 2022), and market actions of electricity suppliers following projects that increase transmission capacity, which is the focus of the present analysis (Border Power Plant Working Group v 2003).

2. Methods

2.1. Study area

Quebec, Canada has 37 590 MW of installed hydroelectric capacity (plus an exclusive power purchase agreement for 5428 MW of generation at Churchill Falls in Labrador), accounting for 94% of total generation (Hydro-Québec 2022a, Canada Energy Regulator 2024a). These resources are a large and generally growing source of electricity for the northeastern United States across borders with Maine, New Hampshire, New York, and Vermont: net exports to the U.S. averaged 22.5 TWh yr^{-1} between 2018–2023, compared to 11.9 TWh yr^{-1} between 1998–2003, and accounted for roughly half of Canada's net electricity exports to the U.S. in that period (Canada Energy Regulator 2024b). Energy systems models find that increased intertie capacity with Canada generally lowers overall costs of decarbonization in the United States, with Canadian hydropower either buffering intermittent supply of U.S. wind and solar or supplying base load (Dimanchev *et al* 2021, Calder *et al* 2022).

Development of large (>245 MW) hydroelectric facilities began with La Tuque (entry into service in 1955) and has continued to present day with Romaine-4 (2022). Locations of existing interties (corresponding to 25 incremental expansion projects undertaken since 1979) and large generation facilities are plotted in figure 1. The U.S. accounts for the large majority (i.e. >70% over 2018–2023) (Hydro-Québec 2018, 2019, 2020, 2022a, 2023, Canada Energy Regulator 2024a) of net exports from Quebec and is the site of the most significant controversy regarding transmission infrastructure and is thus the focus of our analysis.

The six states of New England share a common transmission system operator, ISO New England, though each state has different renewable energy targets and has historically managed renewable energy procurements individually. The electrical grid in New York is managed by ISO New York. We refer to New England and New York collectively as the northeastern United States (NE USA). Historically, surplus generation from Quebec has been sold on the short-term spot market to neighboring states and provinces (i.e. 90% of exports between 2014–19). However, recently, longer-term export contracts tied to large purpose-built infrastructure have been pursued. This includes a 10.4 TWh yr^{-1} (1.3 GW) corridor through New York recently completed, two 9.5 TWh yr^{-1} ($\sim$1 GW) corridors to Massachusetts via New Hampshire (cancelled) and Maine (suspended), and a $\sim$1 GW corridor through Vermont and New Hampshire (cancelled) (U.S. Department of Energy 2017, Gronendyke 2018, Appeal of Northern Pass Transmission, LLC

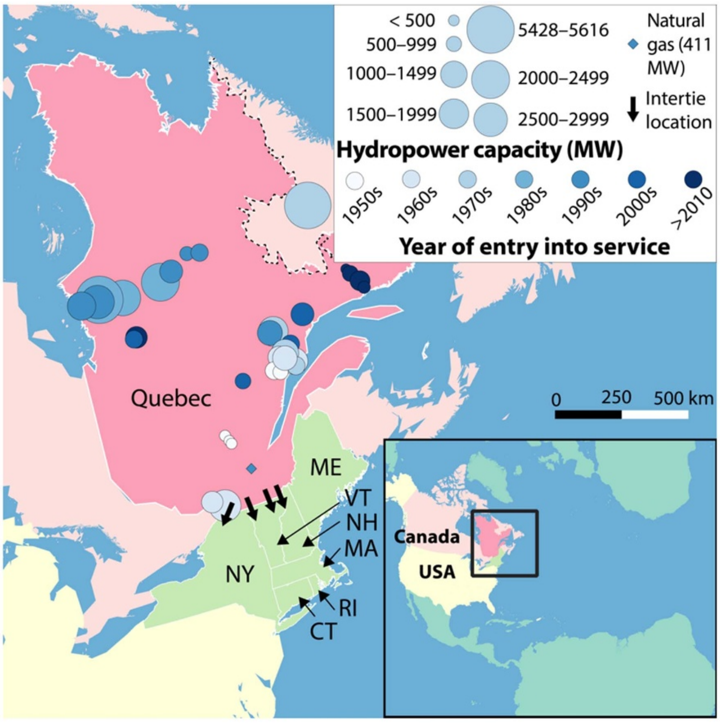

Figure 1. Large (>245 MW) generation and transborder transmission infrastructure in Quebec, Canada including Churchill Falls in Labrador due to exclusive power purchase agreement. New York (NY), New England states Connecticut (CT), Massachusetts (MA), Maine (ME), New Hampshire (NH), Rhode Island (RI), and Vermont (VT), and Quebec, Canada, are highlighted. Years of entry into service and installed capacity from Hydro-Québec (2023). Locations of infrastructure from Hydro-Québec (2020). Intertie locations represent 25 capacity expansion projects (∼4300 MW) undertaken since 1979.

& a 2019, Maine Department of Environmental Protection 2021, NECEC Transmission LLC *et al.* V. Bureau of Parks and Lands *et al* 2022, Dalton 2024).

Electricity trade between Quebec and Ontario display a balanced bilateral trade pattern that follows a seasonal cycle. Ontario's exports during the winter in Quebec help improve reliability and meet high electricity demands. In contrast, in the summer, there is a rise in exports from Quebec to Ontario due to the high demand for air conditioning (Independent Electricity System Operator n.d.).

2.2. Model conceptualization

We conceptualize the Quebec–New England–New York electricity market as generation, demand, transmission, and price phenomena connected via a causal network with uncertain structure and test structures corresponding to alternative mental models of various stakeholders. We develop a rich dataset covering the period 1979–2021, which we use to evaluate the plausibility of alternative causal structures represented by Bayesian networks (BNs). BNs are directed acyclic graphs (DAGs) used to evaluate the evidential support for the presence and directionality of causation among system variables (Pearl 1995, 2000, Spirtes *et al* 2001, Su *et al* 2013, Nogueira *et al* 2022, Hernan and Robins 2023).

Specifically, we interrogate the claim that transborder transmission infrastructure stimulates hydroelectric development in Canada. As described above, this claim has been the basis for legal filings arguing that DOE is required to consider generation-side environmental impacts in permitting transmission infrastructure and has contributed to opposition to these projects. We also characterize evidence for other asserted or hypothesized causal relations in this system and identify challenges inherent in the use of causal inference methodologies for complex sociotechnical systems more broadly.

As illustrated in figure 2, alternative model structures are composed of diverse hypothesized relationships. In general, evaluation of BNs test entire model structures rather than one-way relationships as in classical statistical methods.

We developed a conceptual model for generation, demand, transmission, and price variables, representing assumed and disputed causal connections in the Quebec and NE USA electricity markets (figure 2). Installed hydropower generation capacity is a function of current and projected demand and factors of safety to reflect uncertainties in future generation (governed by hydrologic conditions) and demand (Stedinger *et al* 1984, U.S. Department of Energy 2016). High-consequence dams require higher factors of safety for such uncertainties, increasing the probability of overdesign (Fell *et al* 2005, Herza *et al* 2018).

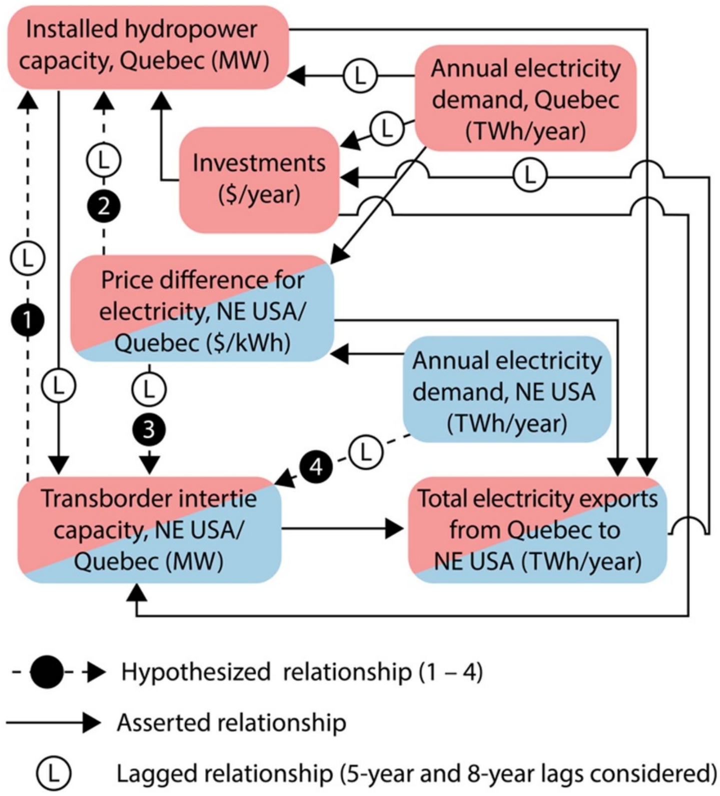

Figure 2. Conceptual diagram showing asserted and hypothesized relationships between generation, transmission, and demand variables in New York/New England (NE USA) and Quebec, Canada. Investments are a subset of revenues (omitted). Asserted and hypothesized relationships are described in the text. System variables are shaded red for Quebec, blue for the NE USA, and red/blue for transborder.

Exports are meanwhile determined by generation capacity, price signals resulting from the balance of supply and demand domestically and in export markets, and the capacity of available transmission infrastructure. Investments are necessary for increases in both installed generation and transmission. To our knowledge, these basic dynamics are not in debate and we have represented them as 'asserted relationships' in figure 2.

Development of transborder transmission capacity stimulated by U.S. electricity demand may accelerate the development of Canadian hydroelectric resources by enhancing opportunities for export. Historically, higher prices for electricity in the U.S. than in Canada have played a major role in the pursuit of export opportunities by Canadian utilities (Warner and Coppinger 1999). These export opportunities continue to be acknowledged in decision-making around new projects, for example, coupling the Maritime Link transmission project with the 824 MW Muskrat Falls hydroelectric project in Newfoundland & Labrador, developed in the 2010s (Government of Newfoundland and Labrador 2012). Meanwhile, public statements by Hydro-Québec, the government-owned utility that manages electrical generation and distribution in Quebec, Canada, suggest that the export market is necessary for profitability (Snyder 2018).

However, it is not clear that investments in transmission infrastructure decisions are themselves stimulating new generation beyond key drivers such as domestic demand and the export opportunities allowed by existing transmission. It is therefore not understood if, in the context of proposed transmission projects, potential new generation (and its associated environmental and social effects) can be construed as second-order consequences within the meaning of environmental impact, life cycle, or cost benefit analysis. Likewise, it is not clear how opposition to transborder transmission infrastructure affects the viability of new generation projects in Canada. While capacity expansion models can simulate the economics of new hydroelectric generation under different transborder transmission scenarios, currently available tools do not have the resolution to allow for simulations conditioned on individual projects (Calder *et al* in prep). Therefore, we apply causal inference to available data to better understand these questions.

The claim that increased transborder infrastructure leads to increased generating capacity in Canada is the central focus of this analysis and is represented as Hypothesis # 1 in figure 2. An affirmative finding would support the argument that generation-side impacts are 'reasonably foreseeable' consequences of transmission infrastructure and hence reviewable under environmental assessments and/or impact statements required by NEPA for federal permitting as previously argued to DOE (Birchard 2017).

Table 1. Summary of data aggregated for causal analysis, 1979–2021. Bolded variables correspond to conceptual figure 2 and include values derived from underlying data sources. Unbolded variables allow calculation of certain derived variables.

Variable name	Units	Description	References
EXPORTS	TWh yr^{-1}	Hydro-Québec's total exports	Hydro-Québec (1979-2017, 2018, 2019, 2020, 2021, 2022a, 2023)
DEMAND_QC	TWh yr^{-1}	Hydro-Québec's electricity sales to the Québec's market; equates to generation net of transmission losses	Idem
DEMAND_US	TWh yr^{-1}	Annual electricity sales to ultimate customers for NE USA (New England and New York).	U.S. Energy Information Administration (2022)
INVESTMENT	\$CAD yr^{-1}	Total investments in generation and transmission infrastructure made by Hydro-Québec	Hydro-Québec (1979-2017, 2018, 2019, 2020, 2021, 2022a, 2023)
INSTALLED	MW	Installed hydroelectric generation capacity in Quebec, Canada	Idem
INTERTIE	MW	Transborder intertie transmission capacity (see text for method to convert from kV)	U.S. DOE (1979–2021)
PRICE	\$CAD kWh^{-1}	Price difference between U.S. and Quebec [=PRICE_US × EX_RATE—PRICE_QC]—retail price used as a correlate for wholesale price	n/a
PRICE_QC	\$CAD kWh^{-1}	Annual average retail electricity prices for electricity in Quebec	(Hydro-Québec 2022b)
PRICE_US	\$USD kWh^{-1}	Annual estimate of average electricity price in NE USA	U.S. Energy Information Administration (2022)
EX_RATE	\$CAD $\$USD^{-1}$	Exchange rate between Canadian and U.S. dollars	Federal Reserve Board (2023)

Conversely, a negative (or null) finding may increase support among stakeholders who currently oppose transmission infrastructure on the basis of a supposed stimulating effect on generation (Webster 2022).

Beyond this central question, we evaluate other, non-mutually-exclusive relationships. Relationship # 2 holds that installed hydroelectric capacity is instead stimulated by the price difference between Quebec and the northeastern U.S. Other relationships evaluated represent potential drivers of transborder intertie capacity: Relationship # 3 hypothesizes that intertie capacity is stimulated by the same price difference, and Relationship # 4 hypothesizes that intertie capacity is stimulated by U.S. demand. These alternative hypotheses have fewer immediate implications for EIA but may provide an alternative causal framework by which to understand the temporal evolution of this system.

2.3. Variable definition and data aggregation

Table 1 summarizes the raw variables aggregated for this analysis with reference to the original data sources. Some variables are then transformed to reflect likely lags (represented in figure 2 and described in section 2.3). We selected the period 1979–2021, which maximizes data availability for relevant variables while covering all periods of major expansion of transborder transmission capacity.

Hydro-Québec's annual reports were consulted to acquire information regarding the company's generation capacity, its sales to the domestic market, its exports to outside markets, its annual revenues, and its investments in transmission and generation infrastructure. We quantify the rated capacity of transmission infrastructure developed (in MW) as a measure of transmission rather than the power exported in a given year (MWh) because this is more consistent with the physical properties of the infrastructure subjected to permitting and environmental review. Capacity of transmission lines was often reported in kV, which is not directly comparable to generation or transmission in MW. We converted transmission capacity to MW using the transmission line power-transfer capability curve commonly known as the St. Clair curve presented in supplemental information (SI) figure S1 (Gutman *et al* 1979), calibrated using eight available data points and applied to seven remaining points where capacity in MW was unknown (equation (1)). R^2 for the calibration curve was 0.998. Calibration and prediction data are included in SI table S1. The calibrated St. Clair curve is written as:

$$P = \alpha_1 V^2 + \alpha_2 V + \beta. \quad (1)$$

In equation (1), is the maximum loadability (capacity) in MW; V is the maximum voltage in kV; α_1 is a constant calculated via calibration as 0.004431; α_2 is a constant calculated via calibration as -0.5154; and β is a constant calculated via calibration as 20.82.

To represent the disparities in electricity prices between these regions, we calculated the retail price difference between Quebec vs NE USA based on average electricity price per kWh from both regions. We used retail price difference as a proxy for wholesale price difference since data for wholesale market prices was not available for the full period of our study (1979–2021). This approximation is justified by the strong correlation between retail and wholesale prices (Castro Pérez and Flores 2023). A causal connection between other variables in the proposed network (figure 2) and retail price would thus very likely imply a causal connection with wholesale price (or vice-versa). We tabulated other data related to climate, hydrology, and electricity sales to explore possible other correlations and identify potentially overlooked variables. These variables are described in SI table S2 but are not retained in the final causal model described below.

2.4. Variable transformations

Intertie capacity and installed generation capacity reflect large civil infrastructure projects with lead times of an average of 8.6 years between announcement and completion (Ansar *et al* 2014). We therefore expect that responses in the form of infrastructure expansion may be lagged with respect to their predictor variables (as represented in figure 2). However, infrastructure decisions are also made on the basis of forecasts and may be pursued in parallel with complementary components (intertie may expand in anticipation of new generation or vice versa). While many decades can elapse between first discussion of a hydroelectric project and its ultimate completion, the time between official sanction and project completion is substantially shorter; for example, the financing for Muskrat Falls was finalized in 2013 and the first power was generated in 2020. Therefore, for infrastructure outcomes, we consider lags in potential predictor variables of both 5 and 8 years. Because a lag period of t years reduces the size of the dataset by $t-1$ years, consideration of longer lag periods interferes with the ability of the model algorithm to identify coherent networks; nevertheless we also explored the use of lag periods up to 15 years.

Furthermore, we expect many variables represented in figure 2 to respond not necessarily to the absolute value of upstream nodes (i.e. their parents) but rather to changes in those variables over some preceding time period. For example, sudden increases in intertie capacity may stimulate expansion in generation (Hypothesis 1). Therefore, both generation and transmission were represented as the 5 or 8 year running average of changes (which serve as predictors lagged 5 or 8 years as described above). A lag is implemented for infrastructure variables serving as predictors but not when the same variable serves as an outcome. Thus, some variables may have more than one representation.

Finally, variables were transformed to respect the underlying assumptions for the structure and parameters of the BN approach used. BN models can be learned from data on continuous variables that are normally distributed, or on categorical variables. Therefore, if they are not already normally distributed, data may either be transformed to respect the assumption of normality or discretized. We thus evaluated each variable for normality using the Shapiro–Wilk test with a significance level of 0.05. Non-Gaussian variables (i.e. those that failed the Shapiro–Wilk test) were transformed using the Box–Cox method with the boxcox() function in the *MASS* package in *R* (Ripley and Venables 2003) to achieve normality where possible in order to retain maximum information.

After transforming the non-Gaussian variables, we reapplied the Shapiro–Wilk test to evaluate the effectiveness of the transformation. Variables that failed the Shapiro–Wilk test post-transformation were then discretized. Discretization of variables was done manually using the ordered cut() function in *R*; this means that continuous variables were converted to ordinal discrete variables. We used histogram plots to determine the cutting points for each variable to ensure a roughly equal distribution of observations across variable levels. Depending on the variable's definition (table 1) and its histogram, we discretized the variables according to three different schema: 1. 'low', 'medium', or 'high', 2. 'non-significant' or 'significant' and 3.

Table 2. Asserted and hypothesized causal relations indicating lagged (5 or 8 years), Box–Cox transformed and discretized variables. Relations are summarized in figure 2. Expanded figure showing all representations of variables included in SI figure S2A.

Response variable	Asserted causal (parent) variable(s)	Hypothesized causal (parent) variable(s)
INSTALLED[a,b]	$\text{DEMAND}_{\text{QC}}$[c], INVESTMENT[d,e]	INTERTIE[f,h,l], PRICE[g,b,l]
INTERTIE[a,h]	INVESTMENT[d,e], INSTALLED[i,e]	PRICE[g,b,l], $\text{DEMAND}_{\text{US}}$[c,l]
EXPORTS[j]	PRICE[j,b], INSTALLED[a,b], INTERTIE[a,h]	n/a
INVESTMENT[d,e]	EXPORTS[c,k], $\text{DEMAND}_{\text{QC}}$[c]	n/a
PRICE[j,b]	$\text{DEMAND}_{\text{US}}$[j,e], $\text{DEMAND}_{\text{QC}}$[j,e]	n/a

[a] Total expansion in 5 or 8 year period up to year *t*.
[b] Box–Cox transformed variable.
[c] 5 or 8 year lag of the 5 or 8 year moving average for the incremental expansion, i.e. value in year *t* minus value in year $t-1$.
[d] Average total investment in 5 or 8 year period up to year *t*.
[e] Discretized variable ('low', 'medium', 'high').
[f] 5 or 8 year lag of the total intertie capacity expansion in 5 or 8 year period up to year *t*.
[g] 5 or 8 year lag of price difference in 5 or 8 year period up to year *t*.
[h] Discretized variable ('non-significant', 'significant').
[i] 5 or 8 year lag of the total installed capacity expansion in 5 or 8 year period up to year *t*.
[j] Average expansion in 5 or 8 year period up to year *t*.
[k] Discretized variable ('negative', 'positive').
[l] Hypotheses 1, 2, 3 and 4.

'negative' or 'positive'. Implementation of a manual discretization protocol helps ensure production of meaningful and interpretable BN models (Beuzen *et al* 2018). All transformations are reported in table 2. Code for all variable manipulations and transformations is included in the reproduction information (RI).

2.5. BN modeling and evaluation of causal relations

We used BN modeling to test alternative model structures against data in order to evaluate the plausibility of asserted and hypothesized causal relations (section 2.1). BNs are probabilistic graphical models that represent sets of variables and their conditional dependencies in the form of DAGs (Scutari and Denis 2021). Compared to alternative approaches like vector autoregression, BNs make weaker assumptions about linearity and stationarity and are better suited to analysis of smaller datasets (Righetti 2022). DAG representation of these networks aids in illuminating possible causal relationships between variables, providing a clear illustration of how one variable or factor can affect others. BN models contain two major components: the network *structure,* which maps nodes and directed edges to create a DAG; and conditional probability distributions for each node, which are represented using *parameters*, describing the relative likelihood of values of response variables conditioned on the values of its direct causes. These tools are of particular value in the analysis of environmental or socioenvironmental systems defined by interacting, nonlinear processes incompatible with the assumptions of classical statistical techniques (Calder *et al* 2023).

Two types of data-training algorithms are available to evaluate network structures against a dataset: *score-based* and *constraint-based* (Su *et al* 2013). *Score-based* methods calculate a score for alternative structures, and the score reflects the ability of that structure to explain the observed data. Score-based methods are commonly favored for datasets that are small and contain noise (Cheng *et al* 2002). In score-based methods, the objective is to identify the configurations that yield high scores. Conversely, *constraint-based* methods seek to identify conditional independence (i.e. Markov condition) among variables. These methods use data to perform hypothesis testing regarding conditional independence to eliminate edges from a fully connected undirected graph. Subsequently, directions are assigned to edges in accordance with the *d-separation* criterion (Pearl 2000). It is also common to use hybrid algorithms that integrate the two types of methods to capture the benefits of each as a function of the properties of the dataset and the strength of hypotheses (Tsamardinos *et al* 2006).

We rely on a score-based method to evaluate the network structure against data because our dataset does not have a sufficient number of observations to effectively perform the hypothesis tests required of constraint-based methods. For example, many variables had to be discretized, resulting in a loss of information, and some variables were lagged, resulting in a loss of some years (described in section 2.3 and summarized in table 2). The score-based method employed uses the log-likelihood scoring criterion and employed a hill-climb algorithm using the hc() function in the *bnlearn* package for R to identify the highest scoring network (Scutari *et al* 2023). Generally, the log-likelihood criterion is the least restrictive (will admit the most relations), enabling us to most confidently rule out hypothesized (or asserted) relations if they do not appear in the best-fitting model structures.

To further assess the degree of confidence in returned relations, we also applied alternative scoring criteria (Akaike information criterion, or AIC, and Bayesian information criterion, or BIC) that penalize for the number of edges in the network. AIC and BIC results are discussed in greater detail in the SI. In all cases, the algorithm was initialized using the hypothesized network presented in table 2 and was constrained by a blacklist consisting of all illogical relations between variables (e.g. contemporary variables cannot influence lagged variables).

To interpret the network relations (i.e. assign a direction of effect) and measure the goodness of model fit for each variable in our DAG, we used the predict() function with the *bayes-lw* method (Needham *et al* 2007). The *bayes-lw* method performs both causal prediction and noncausal Bayesian inference using Monte Carlo methods. Further likelihood weighting ensures that predictions account for all possible values of variables accounting for their relative likelihood. To assess goodness of fit for continuous numerical variables, we calculated the coefficient of determination (r squared), while for discretized variables we calculated the proportion of correct predictions as a measure of model accuracy.

Finally, to further interrogate specific relations of interest, we used the d-separation criterion. Informally, the d-separation criterion states that, 'Each variable is independent of its non-descendants in the network given its parents' (Ding and Rebai 2010). More formally, the d-separation criterion specifies the set of conditional dependences and independences that are implied by a particular graph and subject to statistical hypothesis testing. Specifically, we used our data to test the independence of pairs of nodes by conditioning each pair on the pair's parents. If the p-value for an independence test is greater than the high threshold of 0.95, then the two variables are interpreted as 'Conditionally Independent'. If the p-value is smaller than the low threshold of 0.05, then this is labeled 'Potential Missing Link'. If the p-value is between the low and high thresholds, then the analysis is inconclusive. All functions mentioned in this section are reported in RI, including the functions that were developed by authors.

3. Results and discussion

3.1. Model structures returned by BN analysis

Using the log-likelihood criterion, the DAGs of the best fitting BNs were identical for the 5 year and 8 year formulations. Figure 3 shows the relations included in the best fitting BN (log-likelihood criterion) in comparison with the conceptual model presented in figure 2, where relations not included in the fitted BN are greyed out. Table 3 provides an indication of the accuracy of the fitted relations. As described in section 2.5, the log-likelihood criterion is generally more permissive than AIC and BIC and thus less likely to falsely rule out relationships. Thus, hypotheses rejected using the log-likelihood criterion are unlikely to exist. The identical model structure returned by both 5 and 8 year model formulations suggests that results are not sensitive to the averaging/lag period retained.

The best fitting BN does not indicate that installed generation capacity depends on intertie capacity (Hypothesis 1). The best fitting BN does indicate that price difference between the northeastern U.S. and Quebec has an influence on installed generation capacity (Hypothesis 2), but not on intertie capacity (Hypothesis 3). Intertie capacity also does not seem to be influenced by U.S. electricity demand (Hypothesis 4). D-separation results (table 4) confirm the conditional independence between intertie capacity and installed generation (Hypothesis 1). Other results are the same as presented in figure 3, with the exception of the relationship between electricity demand in Quebec and investments.

Therefore, the assertion that transborder intertie capacity directly 'causes' expansion of hydroelectric generation in Quebec is not supported by our analysis. We note, however, that expanded intertie capacity does influence electricity exports, which influences investments, and investments in turn influence installed capacity. Thus, expanded transborder intertie capacity appears to be one part of a broader evolving technological system with mutual interdependencies rather than a trigger of installed hydropower capacity per se. Yet, as described below, the ambiguous direction of effect along the causal path does not necessarily support the interpretation that expanded generation capacity is even a second- or higher-order result of expanded transmission.

AIC and BIC models broadly agree with the results presented here. In AIC and BIC models, 5 year formulations were more detailed, likely because fewer observations were discarded in the creation of 5 year-lagged variables than 8 year-lagged variables. In the BIC models, Hypothesis 1 was supported, but the direction of effect was negative. Model structures generated using the AIC and BIC criteria are available in SI figures S3(AIC) and S4(BIC). These figures demonstrate how stricter criteria, such as AIC or BIC, limit the model's ability to identify edges that can be discovered using our data.

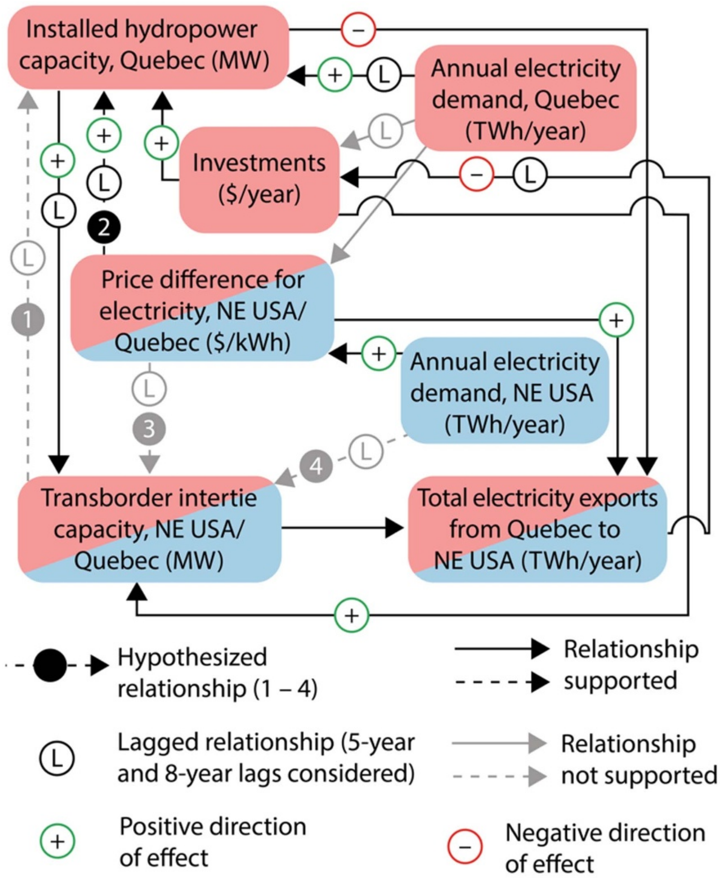

Figure 3. DAG that maximizes the log-likelihood scoring criterion (black lines) in comparison with the conceptual model in figure 2 (including light grey lines). The same structure applies to both 5 year and 8 year models. Intertie → Exports has an ambiguous direction of effect as described in section 3.2. Concept nodes are shaded red for Quebec, blue for the NE USA, and red/blue for transborder. Corresponding DAG is included in SI figure S2B.

Table 3. Summary of our BN modeling results: fitted relationships and corresponding performance metrics. Results generated using the AIC and BIC criteria are available in SI tables S3 & S4 (AIC), and S5 & S6 (BIC). Variables are transformed following footnotes in table 2.

Response	Causal (parent) variable(s)	5 year model		8 year model	
		r squared	Accuracy	*r* squared	Accuracy
INSTALLED	$\mathrm{DEMAND_{QC}}$, INVESTMENT, PRICE	0.76	—	0.96	—
INTERTIE	INVESTMENT, INSTALLED	—	0.70	—	0.89
EXPORTS	PRICE, INSTALLED, INTERTIE	0.78	—	0.92	—
INVESTMENT	EXPORTS	—	0.76	—	0.96
PRICE	$\mathrm{DEMAND_{US}}$	0.60	—	0.76	—

For all methods evaluated here, we explored the use of longer lag periods to account for longer average lead times between project sanction and development (e.g. up to 15 years). However, these models returned only fragmentary network structures, likely due to the significant amounts of data that must be discarded to calculate the first averaging period (see section 2.3). All code for these (and other) averaging periods is available via GitHub.

Figure 3 shows the signs of the fitted relations, indicating that most variables are positively influenced by their causal predictors. Supplemental figures characterizing the direction of effect of the different relations are included in the SI. SI figure S5 shows that installed generation capacity increases if any of its predictors increase. SI figure S6 shows that intertie capacity is positively impacted by increases in installed generation capacity and investment levels. SI figure S7 shows that price difference is positively impacted by increases of

Table 4. Summary of the results when conditioning on parents for the unsupported links presented in figure 2. Variables are transformed following footnotes in table 2.

Response	Causal (parent) variable	Conditional independence results
INSTALLED	INTERTIE	Conditionally independent
INTERTIE	$\text{DEMAND}_{\text{US}}$	Conditionally independent
INTERTIE	PRICE	Conditionally independent
INVESTMENT	$\text{DEMAND}_{\text{QC}}$	Potential missing link
PRICE	$\text{DEMAND}_{\text{QC}}$	Conditionally independent

average demand in the NE USA. By contrast, investments are negatively influenced by total exports in the previous time step, which in turn is negatively influenced by installed capacity (thus leading to an indirect positive relation between installed capacity and subsequent investments) as shown in SI figure S8. SI figure S9 shows that the relation between intertie capacity and total exports is ambiguous, being positive or negative depending on the values of the other predictors of total exports: installed generation capacity and price difference.

3.2. Temporal evolution of the generation-transmission system

Our analysis suggests that there is no direct association between increased intertie capacity and increased generation capacity (Hypothesis 1). There is an indirect link through exports and investment, meaning that increased exports facilitated by increased intertie capacity allows investments in both generation and transmission infrastructure. Therefore, intertie capacity appears to play at most an indirect, ancillary role in decisions around generation expansion.

Instead, this analysis reveals that investments in installed capacity are driven by a combination of domestic demand and price signals in the form of a difference between electricity prices in the northeastern United States and Quebec (Hypothesis 2). These price signals also drive export decisions over existing infrastructure. The significant reserve capacity of Hydro-Québec (up to 177 TWh) allows for selective exports at times of relative greater prices in the U.S (Hydro-Québec 2020).

While intertie capacity does not directly drive installed generation capacity, our analysis reveals that installed generation may partially drive intertie capacity. This may correspond to Hydro-Québec's seeking markets for excess supply; hydropower projects are likely to be overdesigned in order to guarantee the ability to meet local demand and to supply existing contracts, potentially posing a choice between non-revenue spills and pursuit of export opportunities. We do not find evidence that intertie capacity is the direct consequence of price signals (Hypothesis 3) or U.S. demand (Hypothesis 4). However, it may be a second-order consequence of these variables via the role of price signals on installed capacity.

As described earlier, the premise that increased transborder transmission capacity stimulates increased generation in Quebec has been used to argue for increased scope of assessments/statements under NEPA (Birchard 2017) and to attribute greenhouse gas emissions from reservoirs to proposed transmission projects (New York State Energy Research and Development Authority 2021). This premise has also adversely affected support for such projects among environmental stakeholders whose support is important for achieving decarbonization of the electrical sector (Webster 2022). Overall, this analysis supports a contrary view, i.e. that new transborder transmission projects should be considered independently from the suite of environmental and health impacts associated with reservoir construction.

Historically, electricity exports from Quebec have been overwhelmingly settled on the short-term spot market (i.e. between 86%–91% every year since 2001), which are the market behaviors captured by the causal model developed here. By contrast, several recently proposed projects tie long-term power purchase agreements to purpose-built infrastructure (Appeal of Northern Pass Transmission, LLC & a 2019, Maine Department of Environmental Protection 2021, BloombergNEF 2023). It is possible that power commitments via these long-term contracts will stimulate reservoir development in a way that we do not observe with historic export patterns, for example, by creating commitments that cannot be satisfied without new generation. In recent work, we described model and data gaps that make such situations difficult to identify and identified this as a priority area for model development given its importance in debates over environmental and social impacts (Calder *et al* 2024).

Theoretically, capacity expansion models can simulate how individual transmission projects affect the overall economics of new generation projects (and vice-versa) but in practice there are no publicly available models with project-scale resolution. Because Hydro-Québec does not publish reservoir levels, capacity factors, or other key statistics on the generation fleet, impacts of new long-term power purchase agreements on build-out of generation or on exports to other markets are currently speculative (Calder *et al* 2022, 2024). Overall, this analysis suggests that the new transmission infrastructure is not driving build-out of hydroelectric generation in Canada per se, but that a shift to long-term power purchase agreements may introduce pressures on electrical supply that are not currently easily modeled.

3.3. Strengths and limitations of causal inference methodologies for analysis of other socially mediated systems

This analysis suggests that formal causal inference methodologies may be used to understand evolving sociotechnical systems more broadly, for example, to scope environmental impact, life cycle, and cost-benefit analysis by building consensus on the range of relevant second-order effects. Because sociotechnical systems in general feature complex feedbacks, plausible narrative claims can be advanced for many alternative causal interpretations across a wide range of settings including the energy system (studied here), urban housing supply and affordability (Li 2021), and investments in resource conservation and protection of environmental resources (Owens *et al* 2022). We posited earlier that formal causal inference methodologies could help resolve debates around and build consensus over the most parsimonious causal structures to overlay on complex systems where 'everything is connected'.

We have demonstrated several modeling and interpretation approaches that may facilitate the use of BN analysis in other contexts. This includes the consideration of multiple BN algorithms, models and the interpretation of evidentiary support for hypothesized relationships on the basis of (1) agreement across models for a given hypothesized relationship and (2) whether it manifests as part of a causal structure with a plausible mechanistic interpretation. We have endeavored to describe evidence in support of potential causal relationships on the basis of a holistic analysis that considers multiple modeling choices and alternative causal structures, accepting that certain subjective choices may have significant effects on certain conclusions.

In certain cases, conclusions about features of the causal network may be robust to a wide variety of modeling choices. This was illustrated in this case study by our conclusion that hydroelectric generation in Canada is not the outcome of increased transborder intertie capacity, despite a plausible narrative claim advanced by expert stakeholders. In that case, our conclusions are robust to all possible models considered and thus seem robust enough to dismiss this assertion. For example, we failed to find evidence for this assertion across model formulations that varied in averaging/lag periods assumed and BN algorithm retained.

Conversely, our analysis suggests that these modeling choices can affect network structure in ways that could change the interpretation of causal dynamics in other settings. For example, our analysis based on the BIC criterion returns subtly different network structures when 5 year lag/averaging periods are considered vs 8 year periods (SI figure S10). In this analysis, data availability and the objective of ruling out asserted links suggested the BIC criterion was not well-suited. As in other types of quantitative modeling, professional judgment is required to exercise subjective decisions to interpret potentially contradictory results across model formulations.

The data available to parameterize a model clearly influence model predictions, and data are usually fragmentary and incomplete. In the setting of BNs, this may manifest as an unobserved counterfactual, creating uncertainties around a causal relationship between two nodes. For example, in the period 1979–2021, the price difference between Quebec and New York/New England was always positive (figure 4), even while the magnitude of this difference varied. This limits the range of conditions over which the model may be valid. The shapes of the distributions of available data furthermore required extensive transformation to respect the assumptions of Bayesian analysis as summarized in table 2 and described in section 2.2. These transformations, though necessary to respect the assumptions of Bayesian analysis, result in a loss of information that increase uncertainties in any model returned.

In the setting of the renewable energy transition, such unobserved counterfactuals may also manifest as changes to the relative value of different energy sources such as the increased value of hydropower in a heavily decarbonized system (Miller *et al* 2022). For a given model structure (e.g. figure 2), such changes may increase probability of hydropower construction all else being equal. As described in section 3.2, changes to the structure of underlying power purchase agreements can also change the relationship between variables represented in any causal model; however, such changes could be captured with the introduction of a new node.

BN analysis is subject to the same limitations as any graphical modeling strategy, and the use of these tools to describe evolving sociotechnical and socioenvironmental systems presents several inherent challenges. In particular, such systems have no inherent temporal beginning or end, feature multiple feedbacks across temporal and spatial scales, are characterized by evidence generated by a range of methodological traditions, and feature 'mechanisms' that can be articulated at arbitrary levels of detail

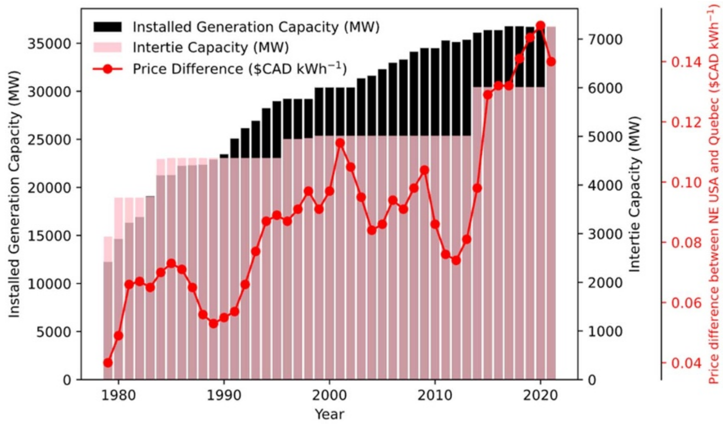

Figure 4. Time series of installed generation capacity and intertie capacity, and of retail electricity price differences between Quebec and New York and New England (average) 1979–2021.

(Calder *et al* 2020). Conceptual models for such systems thus necessarily reflect the judgments and specific decision context of the people who create these conceptual models.

As we have demonstrated here, these challenges can be compounded by the application of quantitative analysis, which necessarily embeds decisions made by modelers. This includes approaches to transforming and normalizing data and the selection of models, but also subjective elements of interpretation, for example, the description of results that conflict across model implementations with different BN learning algorithms. These are likely to be compounded by disagreements over the precise meaning of 'reasonably foreseeable' and 'reasonably close' in the application of NEPA and other institutional features that govern the interpretation of quantitative information, but that is outside the scope of this analysis.

3.4. Applications to life cycle and cost-benefit analysis

This analysis has demonstrated evaluated the utility of causal inference methodologies for structuring debates around the scope of EIA, which frequently reflect disagreements over the causal relationship between variables mediated by social systems. We note that analogous debates also complicate cost-benefit and LCA, with subjective judgments of the range of effects to attribute to an intervention, process, or technology often driving the outcome (Dubois-Iorgulescu *et al* 2018). In the setting of Canadian hydropower in northeast U.S. energy transitions, this has manifested as disagreements over the valuation of GHG emissions from reservoirs (the 'Scope 2' emissions of intertie projects in the terminology of the Greenhouse Gas Protocol) (Sotos 2015, Calder *et al* 2020).

In general, 'attributional' assessment of impacts (Ekvall 2019), whereby a fraction of the life cycle emissions of existing reservoirs is assigned to energy imported over new electrical interties, is common, even among prospective cost-benefit analyses (New York State Energy Research and Development Authority 2021). We have previously argued that this has the effect of underestimating net benefits from incremental expansion in transmission when these projects have no causal connection to new reservoir development (Calder *et al* 2022). Indeed, a 'consequentialist' perspective, whereby alternative interventions are compared in terms of the impacts causally connected to each candidate intervention, is better suited to decision support but rarely used in energy systems analysis due in part to difficulties in causal analysis (Curran *et al* 2005). Thus, causal inference methodologies such as those proposed here may promote the uptake of the consequentialist frame of reference in energy systems decision analysis.

Data availability statement

Data and computer code are available via GitHub. For the latest updates, visit this project's GitHub page.

The data that support the findings of this study are openly available at the following URL/DOI: https://github.com/amirgazar/Environmental-Impact-Assessment.

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Conflict of interest

The authors declare no competing interests.

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Author contribution statement

A.M.G. contributed to conceptualization, data collection, data analysis, methodology, visualization, computer code development and manuscript development (drafting, reviewing, and editing). M.E.B. contributed to data analysis, methodology, computer code development and manuscript development (reviewing and editing). R.S.D.C. contributed to conceptualization, data analysis, visualization, computer code development, manuscript development (drafting, reviewing, and editing), management and supervision.

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Reproduction Information

Causal inference to scope environmental impact assessment of renewable energy projects and test competing mental models of decarbonization

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Contents

1 Configuration and Setup

This document presents a comprehensive guide outlining the sequential process required to execute and replicate the causal inference modeling methodology presented in our article. Additionally, we supplied the pseudocode overview of code functionality in Section 3.

- To execute the supplied code refer to Section 2 of this document.
- To replicate this code refer to Sections 3 to 13 of this document.

1.1 Hardware and Operating System

We utilized a MacBook Pro with an Apple M1 Pro chip, featuring an 8-core CPU and 16 GB of memory. The startup disk is the Macintosh HD. The system operates on macOS 13.2.1 (22D68) `Ventura`.

1.2 Software Versions and Dependencies

We used R version 4.3.1 (2023-06-16) `Beagle Scouts` for the x86_64-apple-darwin20 platform. Furthermore, we used the RStudio environment, version 2023.06.2+561 to execute the our code. Table 1 below shows packages and versions utilized in this code.

Table 1: Package Version

Package	Version
Rgraphviz	2.44.0
bnlearn	4.8.3
gRain	1.3.13
visNetwork	2.1.2
ggplot2	3.4.2
zoo	1.8.12
scales	1.2.1
gridExtra	2.3
dplyr	1.1.2
MASS	7.3.60
svglite	2.1.1
tidyverse	2.0.0

1.3 Install Time

Installation of RStudio and R is contingent upon the specific hardware and operating system in use. This also holds true for the packages employed within the code. However, the packages used in this code typically take a few minutes to install.

1.4 Run Time

The run time on our operating system for this code is approximately 15 seconds.

2 Full code execution instructions

Following the instruction below, you can execute our code for the 5-year lag period and generate DAGs and conditional dependency graphs. This code is in turn broken up into an annotated and justified workflow in Sections 5 to 13. The expected outputs for this code are visualized DAGs presented in the `viewer` tab in RStudio and conditional dependency plots are saved as `.svg` files in the `repository` folder. Additional results are printed in the `console` in RStudio.

1. Download the `repository` files available in GitHub via this link..
2. Unzip the `repository` files.
3. Open the `Hydro EIA Code 5-year model.R` and `Graph_Generator.R` in RStudio.

4. Install any required packages and load them, refer to Section 5.1.

5. Set the working directory to the `repository` folder. See Section 5.2. Ensure the working directory in both R files is correctly set.

6. Execute the code.

7. The conditional dependency figures will be saved automatically in the `repository` folder. The DAGs will be displayed in the `viewer`, all other results are displayed in the `console`.

3 Pseudocode Overview

Here we provide the pseudocode overview of our algorithm.

Algorithm 1 Pseudocode Overview of Code Functionality

START
INITIALIZE the R environment:
    a. Install and load required packages.
    b. Set the working directory.
DEFINE required functions:
    a. DAG visualizer.
    b. Box-Cox transformer.
    c. Goodness of fit test.
    d. D-separation test.
PREPARE the data:
    a. Generate delta and lags.
    b. Create averaged and lagged variables.
    c. Ensure data is numeric.
    d. Check for Gaussian distribution.
    e. Transform non-Gaussian variables.
    f. Discretize variables.
    g. Create the final data-frame.
CREATE a blacklist.
VISUALIZE the hypothesized DAG.
CONSTRUCT score-based DAGs.
PLOT conditional dependency results.
TEST goodness of fit for each node.
PERFORM d-separation analysis.
END

4 Algorithm Overview

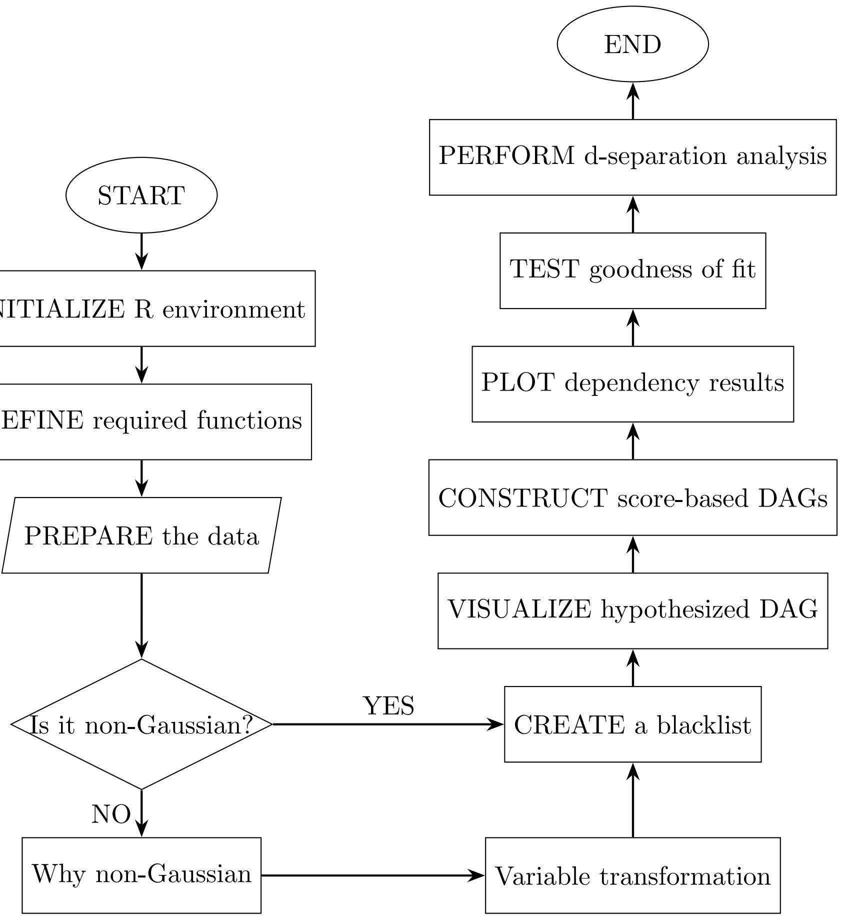

Figure 1: Algorithm to construct and evaluate BN models.

5 Preparing the R Environment

5.1 Install and Load the Required Packages

We use the following packages throughout the code. The core package that must be installed is the `bnlearn` package[1].

```
# Install Rgraphviz from Bioconductor
if (!requireNamespace("BiocManager", quietly = TRUE))
    install.packages("BiocManager")
BiocManager::install("Rgraphviz")

# List of other packages to install
packages <- c("bnlearn", "gRain", "visNetwork", "ggplot2",
              "zoo", "scales", "gridExtra", "dplyr", "MASS", "svglite", "tidyverse")

# Install packages
install.packages(packages)

# Load all the required packages
invisible(lapply(c("Rgraphviz", "bnlearn", "gRain", "visNetwork", "ggplot2",
```

[1] Scutari, M., Silander, T., and Ness, R. (2023). Bayesian Network Structure Learning, Parameter Learning and Inference (4.8.3) [R]. Available: `https://www.bnlearn.com/`

```
                  "stats", "zoo", "scales", "gridExtra", "dplyr", "MASS", "svglite", ...
                      "tidyverse"), library, character.only = TRUE))
```

5.2 Set Working Directory

Set the working directory and read in the data. Make sure to adjust the directory path to match your setup.

```
# Set Working Directory (change for your setup)
setwd("/Users/Documents/Hydro EIA Code")

# Read the data-set
hydro.data <- read.csv("hydro_var_aug23.csv")
```

6 Required Functions

We have created the following functions that will assist in creation and evaluation of our causal directed acyclic graphs (DAGs).

6.1 DAG Visualizer

Visualizes and returns DAGs created by the `bnlearn` package.

```
plot.network <- function(structure, ht = "400px", title){

  # Unique nodes from the arcs of the structure are identified.
  nodes.uniq <- unique(c(structure$arcs[,1], structure$arcs[,2]))

  # A data frame for nodes is created with attributes like id, label, color, and shadow.
  nodes <- data.frame(id = nodes.uniq,
                      label = nodes.uniq,
                      color = "maroon",
                      shadow = TRUE)

  # A data frame for edges is created with attributes like source, target, arrow ...
      direction, and other visual properties.
  edges <- data.frame(from = structure$arcs[,1],
                      to = structure$arcs[,2],
                      arrows = "to",
                      smooth = TRUE,
                      shadow = TRUE,
                      color = "black")

  # The network is visualized using the visNetwork function and returned.
  return(visNetwork(nodes, edges, height = ht, width = "100%"))
}
```

6.2 Box-Cox Transformer

Evaluates the data-set and checks for normality (using Shapiro-Wilk test), transforms the non-Gaussian variables using Box-Cox transformation. Re-evaluates the transformed variables with the Shapiro-Wilk test and checks for normality. Returns the results.

```
transform_and_test <- function(df, non_gaussian_vars){

  # Lists to store variables that remain non-Gaussian after transformation and those that ...
      were successfully transformed.
  still_non_gaussian <- vector("list")
  transformed_vars <- vector("list")
  df_new = df

  # Each non-Gaussian variable is processed.
  for (var in non_gaussian_vars) {

    # The minimum value of the variable is determined.
    min_value <- min(df[[var]], na.rm = TRUE)

    # If the minimum value is less than or equal to zero, a constant is added to make it ...
        positive.
```

```
    if (min_value ≤ 0) {
      constant <- abs(min_value) + 1
      df[[var]] <- df[[var]] + constant
    }

    # The Box-Cox transformation parameter (lambda) is estimated.
    bc <- boxcox(df[[var]] ¬ 1, plotit = FALSE)
    lambda <- bc$x[which.max(bc$y)]

    # Depending on the value of lambda, the variable is transformed.
    if(abs(lambda) ≤ 1e-5){
      transformed_var <- log(df[[var]])
    } else {
      transformed_var <- (df[[var]]^lambda - 1) / lambda
    }

    # The transformed variable is tested for normality using the Shapiro-Wilk test.
    shapiro_test <- shapiro.test(transformed_var)

    # Based on the p-value, the variable is categorized as still non-Gaussian or ...
        successfully transformed.
    if (shapiro_test$p.value < 0.05) {
      still_non_gaussian <- c(still_non_gaussian, var)
    } else {
      df_new[[var]] <- transformed_var
      transformed_vars <- c(transformed_vars, var)
    }
  }

  # The modified data frame, list of still non-Gaussian variables, and list of transformed ...
      variables are returned.
  list(df = df_new, still_non_gaussian = still_non_gaussian, transformed = transformed_vars)
}
```

6.3 Goodness of Fit Test

Evaluates each variable's goodness of fit for the DAGs produced by the `bnlearn` package.

Function to compute the R^2 (r-squared) metric for continuous variables, representing the proportion of variance in the dependent variable that's predictable from the independent variable.

```
evaluate_fit_continuous <- function(actual, predicted) {

  # An empty list for metrics is initialized.
  metrics <- list()
  # The r-squared metric is computed and stored in the metrics list.
  metrics$rsquared <- 1 - sum((predicted - actual)^2) / sum((actual - mean(actual))^2)
  # The metrics list is returned.
  return(metrics)
}
```

Function to compute the accuracy metric for discrete variables, defined as the ratio of correctly predicted values to the total number of values.

```
evaluate_fit_discrete <- function(actual, predicted) {

  # An empty list for metrics is initialized.
  metrics <- list()
  # The accuracy metric is computed and stored in the metrics list.
  metrics$accuracy <- sum(actual == predicted) / length(actual)
  # The metrics list is returned.
  return(metrics)
}
```

6.4 D-Separation Test

Uses conditional dependence test to evaluate relationships between independent nodes in the DAG produced by the `bnlearn` package while factoring in the available data.

We have created the `dsep.dag` function that can evaluate d-separation for any given node pair. This function uses the optimized DAG results to identify the following for each node pair and then calculates conditional independence: 1. Parents, 2. Neighbors (i.e., parents and children for each node) and 3. Markov-Blanket (i.e., parents, children and parents of children for each node). Furthermore, this function uses data to evaluate d-separation in addition to the results of DAG discovery. This combines the functionalities of the `ci.test` and `dsep` functions available in the `bnlearn` package. Where, `ci.test` exclusively utilizes data, while `dsep` solely employs DAGs.

6.4.1 Function Usage

The `dsep.dag` function is used as follows:

```
dsep.dag(x, data, z)
```

6.4.2 Parameters

The `dsep.dag` function accepts the following parameters:

- `x`: an object of class `bn`
- `data`: a data frame containing the variables in the model
- `z`: a list, where each element is a character vector representing a pair of node labels

Available conditioning sets (that are printed automatically) are:

1. **parents**: set of causal variables for each node
2. **neighbors**: set of causal and response variables for each node
3. **markov_blanket**: set of causal and response variables including causal variables of responses for each node

6.4.3 Return Value

The `dsep.dag` function returns the following for each node pair:

- `Results for parents`: a character string
- `Results for neighbors`: a character string
- `Results for markov_blanket`: a character string

The character string can yield one of the following values, representing the outcome of the d-separation analysis:

1. **Conditionally Independent**: The variables are independent given the observed variables.
2. **Potential Missing Link**: There might be a missing link between the variables.
3. **Uncertain - Further Analysis Needed**: The relationship between the variables is uncertain, necessitating further analysis.
4. **NA**: The node pair is either not available in the DAG, or they are connected, implying conditional dependence.

6.4.4 Underpinning Functions

To construct and utilize the `dsep.dag` function, we implemented the following functions sequentially:

Function to check if a directed arc exists between two nodes in a given set of arcs. This eliminates manually checking the arcs in an existing DAG.

```
arc_exists <- function(from, to, existing_arcs) {
  # The existence of the arc is checked and the result is returned.
  return(any(existing_arcs[existing_arcs[, "from"] == from, "to"] == to))
}
```

Function to perform d-separation tests on all non-adjacent pairs of nodes in a given DAG using the dataset provided.

```
perform_dsep_tests <- function(dag, data) {
  # Existing arcs in the DAG are extracted.
  existing_arcs <- arcs(dag)

  # An internal function to check for arc existence is defined.
  arc_exists <- function(from, to, existing_arcs) {
    return(any(existing_arcs[existing_arcs[, "from"] == from, "to"] == to))
  }

  # A list for non-adjacent node pairs is initialized.
  non_adj_pairs <- list()

  # Non-adjacent node pairs are identified.
  for (node1 in node.ordering(dag)) {
    for (node2 in node.ordering(dag)) {
      if (!arc_exists(node1, node2, existing_arcs) && !arc_exists(node2, node1, ...
          existing_arcs) && node1 != node2) {
        non_adj_pairs <- append(non_adj_pairs, list(c(node1, node2)))
      }
    }
  }

  # A list for test results is initialized.
  results_parents <- list()
  results_nbr <- list()
  results_mb <- list()

  # D-separation tests are performed for each non-adjacent pair.
  for (pair in non_adj_pairs) {
    # Conditioning on parents of a node
    conditioning_set <- setdiff(unique(c(bnlearn::parents(dag, pair[1]), ...
        bnlearn::parents(dag, pair[2]))), pair)  # Combined Markov blanket excluding x and y
    test <- ci.test(pair[1], pair[2], conditioning_set, data = data)
    results_parents[[paste0(pair[1], "_", pair[2])]] <- test$p.value
    # Conditioning on immediate neighbors of a node
    conditioning_set <- setdiff(unique(c(nbr(dag, pair[1]), nbr(dag, pair[2]))), pair)  # ...
        Combined Markov blanket excluding x and y
    test <- ci.test(pair[1], pair[2], conditioning_set, data = data)
    results_nbr[[paste0(pair[1], "_", pair[2])]] <- test$p.value
    # Conditioning on Markov Blanket of a node
    conditioning_set <- setdiff(unique(c(mb(dag, pair[1]), mb(dag, pair[2]))), pair)  # ...
        Combined Markov blanket excluding x and y
    test <- ci.test(pair[1], pair[2], conditioning_set, data = data)
    results_mb[[paste0(pair[1], "_", pair[2])]] <- test$p.value
  }

  return(list(parents = results_parents, neighbors = results_nbr, markov_blanket = ...
      results_mb))

}
```

Function to categorize the p-values from d-separation tests into three categories: "Conditionally Independent", "Potential Missing Link", and "Uncertain - Further Analysis Needed".

```
interpret_dsep_pvalues <- function(pvalues, threshold_low = 0.05, threshold_high = 0.95) {
  # P-values are categorized based on predefined thresholds.
  categories <- sapply(pvalues, function(p) {
    if (p > threshold_high) {
      return("Conditionally Independent")
    } else if (p < threshold_low) {
      return("Potential Missing Link")
    } else {
      return("Uncertain - Further Analysis Needed")
    }
  })
  return(categories)
}
```

Function to organize and print the interpret_dsep_pvalues function results.

```
interpret_print <- function(node1, node2, interpretations_list) {
  # Constructing the key string from the node names
  key <- paste0(node1, "_", node2)

  interpretations <- lapply(interpretations_list, function(interpretation) {
    interpretation[key]
  })
  names(interpretations) <- c("parents", "neighbors", "markov_blanket")
  # Printing the results
  cat("From", node1, "To", node2, ":\n")
  for (name in names(interpretations)) {
    cat("Results for", name, ":\n")
    cat(interpretations[[name]], "\n\n")  # Directly prints the value without the key
  }
}
```

Function that wraps all of the previous functions into one concise function, i.e., the `dsep.dag` function.

```
dsep.dag <- function(dag, data, node_pairs) {
  # Performing D-separation tests
  dsep_results <- perform_dsep_tests(dag, data)

  # Translating the results
  interpretations_list <- lapply(dsep_results, interpret_dsep_pvalues)

  # Initializing a list to hold the interpreted results for each node pair
  interpreted_results <- list()

  for (node_pair in node_pairs) {
    key <- paste0(node_pair[1], "_", node_pair[2])
    interpret_print(node_pair[1], node_pair[2], interpretations_list)
    interpreted_results[[key]] <- lapply(interpretations_list, function(interpretation) ...
        interpretation[key])
  }

  # Returning the list of interpreted results
  return(interpreted_results)
}
```

7 Data Preparation

Modify the variables as needed, we introduced lags and deltas to ensure we capture the temporal difference of causality for our variables. Refer to the main document for further information. Note that in this section we only show the code for some variables transformations. Refer to the main document for further details for each transformation.

7.1 Generating delta and lags

We manually introduced deltas and lags into our variables based on the hypothesized model.

```
{
  # New intertie capacity in every year
  hydro.data$INTERTIE_new = NA
  for(i in 2:nrow(hydro.data)){
    hydro.data$INTERTIE_new[i] = hydro.data$INTERTIE[i] -
      hydro.data$INTERTIE[i-1]
  }
  # Sum of new intertie capacity in preceding 5 years
  hydro.data$INTERTIE_5y = NA
  for(i in 5:nrow(hydro.data)){
    hydro.data$INTERTIE_5y[i] = sum(hydro.data$INTERTIE_new[(i-4):i],na.rm=T)
  }
  # Sum of new intertie capacity in preceding 5 years lagged by 5 years
  hydro.data$INTERTIE_5y_lag_5y = NA
  for(i in 10:nrow(hydro.data)){
    hydro.data$INTERTIE_5y_lag_5y[i] = hydro.data$INTERTIE_5y[i-5]
  }
}
```

7.2 Creating averaged and lagged variables

We used loops to generate new variables that represent 5-year averages and their respective lags.

```
lag_periods <- c(5)
new_vars <- c("INTERTIE", "INSTALLED", "DEMAND_QC", "DEMAND_US", "INVESTMENT", "EXPORTS", ...
    "PRICE")

for (var in new_vars) {
  var_new <- paste0(var, "_new")

  for (lag_period in lag_periods) {
    # moving average
    var_avg <- paste0(var_new, "_avg_", lag_period, "y")
    hydro.data[[var_avg]] <- zoo::rollapplyr(hydro.data[[var_new]], width = lag_period, ...
        FUN = mean, fill = NA)

    # lagged average
    var_lag_avg <- paste0(var_avg, "_lag_", lag_period, "y")
    hydro.data[[var_lag_avg]] <- dplyr::lag(hydro.data[[var_avg]], lag_period)
  }
}
```

7.3 Creating a subset for averaged and lagged variables

We subset our data-set to only retain 5-year averaged and lagged variables.

```
vars.exclude.5y = c(1:8,grep("_new$",colnames(hydro.data)))
hydro.data.subset.5y =
  hydro.data[,setdiff(1:ncol(hydro.data),
                      vars.exclude.5y)]
```

7.4 Ensuring data-set is numeric

It is critical to ensure that the data-set is numeric before proceeding to perform any further analysis.

```
for(i in 1:ncol(hydro.data.subset.5y)){
  hydro.data.subset.5y[,i] = as.numeric(hydro.data.subset.5y[,i])
}
```

7.5 Creating a new data-frame

After preparing our data-set we create a new data-frame that excludes rows with missing values. It must be noted that introducing lags and deltas will result in some information loss, therefore selecting an optimum lag period is imperative.

```
# Create new dataframe
df.5y = hydro.data.subset.5y
```

```

# Creating new data frames with minimum number of rows cut off
lag.cols.5y = grep("lag",colnames(df.5y))
df.5y.no.lags = df.5y[,setdiff(1:ncol(df.5y),
                               lag.cols.5y)]
df.5y.rows.to.cut = which(apply(df.5y,1,function(x) sum(is.na(x))>0))
df.5y.no.lags.rows.to.cut = which(apply(df.5y.no.lags,1,function(x) sum(is.na(x))>0))
df.5y.with.lags.no.NA = df.5y[setdiff(1:nrow(df.5y),
                                      df.5y.rows.to.cut),]
```

7.6 Check for Gaussian distribution

We perform the Shapiro-Wilk test to check for normality across our variables. Bayesian models we use in this analysis require normality to ensure an accurate estimation. Variables that don't pass the Shapiro-Wilk test a p-value less than the specified significance level (0.05) are considered non-Gaussian and are stored in a list.

```
significance_level <- 0.05
non_gaussian_5y_lag <- vector("list")
for (var in colnames(df.5y.with.lags.no.NA)) {
  # Shapiro-Wilk Test
  shapiro_test <- shapiro.test(df.5y.with.lags.no.NA[[var]])
  print(paste("Shapiro-Wilk Test for", var, "- p-value:", shapiro_test$p.value))

  if (shapiro_test$p.value < significance_level) {
    non_gaussian_5y_lag <- c(non_gaussian_5y_lag, var)
  }
}
```

7.7 Transforming non-Gaussian variables

We transform the variables that are non-Gaussian, obtained from the previous step. We use the 'transform_and_test' function created in Section 6.2 to transform the variables using Box-Cox transformation. If the variables are still non-Gaussian after transformation the function reverts them to their original state.

```
result_5y_lag <- transform_and_test(df.5y.with.lags.no.NA, non_gaussian_5y_lag)
df.5y.with.lags.no.NA <- result_5y_lag$df
still_non_gaussian_5y_lag <- result_5y_lag$still_non_gaussian
```

7.8 Discretizing variables

Variables that cannot be transformed using the Box-Cox transformation are then discretized into categories based on their values and histograms.

```
df.5y.with.lags.no.NA$EXPORTS_new_avg_5y <- cut(df.5y.with.lags.no.NA$EXPORTS_new_avg_5y, ...
    breaks = c(min(df.5y.with.lags.no.NA$EXPORTS_new_avg_5y,na.rm=T), 0, ...
    max(df.5y.with.lags.no.NA$EXPORTS_new_avg_5y,na.rm=T)), labels = c("negative", ...
    "positive"), include.lowest = TRUE, ordered_result = TRUE)
```

7.9 Creating the final data-frame

We drop the variables that are identical after transformations. Finally we create the final data-frame by subsetting the current data-frame.

```
# Drop the variables
var.drop = c("INSTALLED_new_avg_5y", "INTERTIE_new_avg_5y","INSTALLED_new_avg_5y_lag_5y", ...
    "INTERTIE_new_avg_5y_lag_5y", "INSTALLED_lag_5y", "INTERTIE_lag_5y")
# Subset the dataset
df.5y.with.lags.no.NA =
  df.5y.with.lags.no.NA[,setdiff(1:ncol(df.5y.with.lags.no.NA),
                                 match(var.drop,colnames(df.5y.with.lags.no.NA)))]

# Selecting columns of interest
selected.columns <- c('INSTALLED_5y_lag_5y', 'INSTALLED_5y', ...
    'DEMAND_QC_new_avg_5y_lag_5y', 'INVESTMENT_5y', 'PRICE_5y_lag_5y',
                      'INTERTIE_5y_lag_5y', 'INTERTIE_5y', 'DEMAND_US_new_avg_5y_lag_5y', ...
                          'PRICE_5y',
```

```
                        'EXPORTS_new_avg_5y_lag_5y', 'EXPORTS_5y', 'DEMAND_QC_5y', ...
                            'DEMAND_US_5y')

# Subsetting the dataframe and creating the final dataframe
df.expert.5y <- df.5y.with.lags.no.NA[, selected.columns]
```

8 Creating a Blacklist

We have to set the parameters and boundaries for our Bayesian model. We do this by creating an allowable list of arcs derived from our hypothesized "expert" model. Using a for-loop we then convert this allowable list to a blacklist.

```
# The allow list is initialized with specific variable pairs.
allow.list.expert =
  data.frame(matrix(c(
    # Various variable pairs are listed here.
    "INVESTMENT_5y","INSTALLED_5y",
    ...
    "DEMAND_US_5y","PRICE_5y"),
    ncol = 2,byrow=TRUE))

# Column names for the allow list are assigned.
colnames(allow.list.expert) = c("From","To")

# The black list is initialized with a placeholder value.
black.list.expert = NA

# For each pair of variables in the final data-frame, a check is performed.
# If the pair is not found in the allow list, it is added to the black list.
for(i in 1:ncol(df.expert.5y)){
  for(j in 1:ncol(df.expert.5y)){
    from.test = colnames(df.expert.5y)[i]
    to.test = colnames(df.expert.5y)[j]

    if(length(which(allow.list.expert$From==from.test&
                    allow.list.expert$To==to.test))==0){
      black.list.expert =
        rbind(black.list.expert,c(from.test,to.test))
    }
  }
}

# Column names for the black list are assigned.
colnames(black.list.expert) = c("From","To")

# The placeholder value in the black list is removed.
black.list.expert = black.list.expert[2:nrow(black.list.expert),]
```

9 Visualizing the Hypothesized DAG

We construct the hypothesized "expert" DAG using the **'model2network'** function from the **bnlearn** package. We visualize this DAG using **'plot.network'** function that we created in Section 6.1. Figure 2 shows the visualized expert DAG.

```
# A DAG is constructed using expert knowledge.
dag.expert.5y <- model2network("[INSTALLED_5y_lag_5y][DEMAND_QC_new_avg_5y_lag_5y]
[PRICE_5y_lag_5y][INTERTIE_5y_lag_5y][DEMAND_US_new_avg_5y_lag_5y][EXPORTS_new_avg_5y_lag_5y]
[DEMAND_QC_5y][DEMAND_US_5y]
[INSTALLED_5y|DEMAND_QC_new_avg_5y_lag_5y:INVESTMENT_5y:PRICE_5y_lag_5y:INTERTIE_5y_lag_5y]
[INTERTIE_5y|INSTALLED_5y_lag_5y:INVESTMENT_5y:DEMAND_US_new_avg_5y_lag_5y:PRICE_5y_lag_5y]
[INVESTMENT_5y|DEMAND_QC_new_avg_5y_lag_5y:EXPORTS_new_avg_5y_lag_5y]
[EXPORTS_5y|INTERTIE_5y:INSTALLED_5y:PRICE_5y]
[PRICE_5y|DEMAND_QC_5y:DEMAND_US_5y]")

# The constructed DAG is visualized with a specified height.
plot.network(dag.expert.5y, ht = "600px")
```

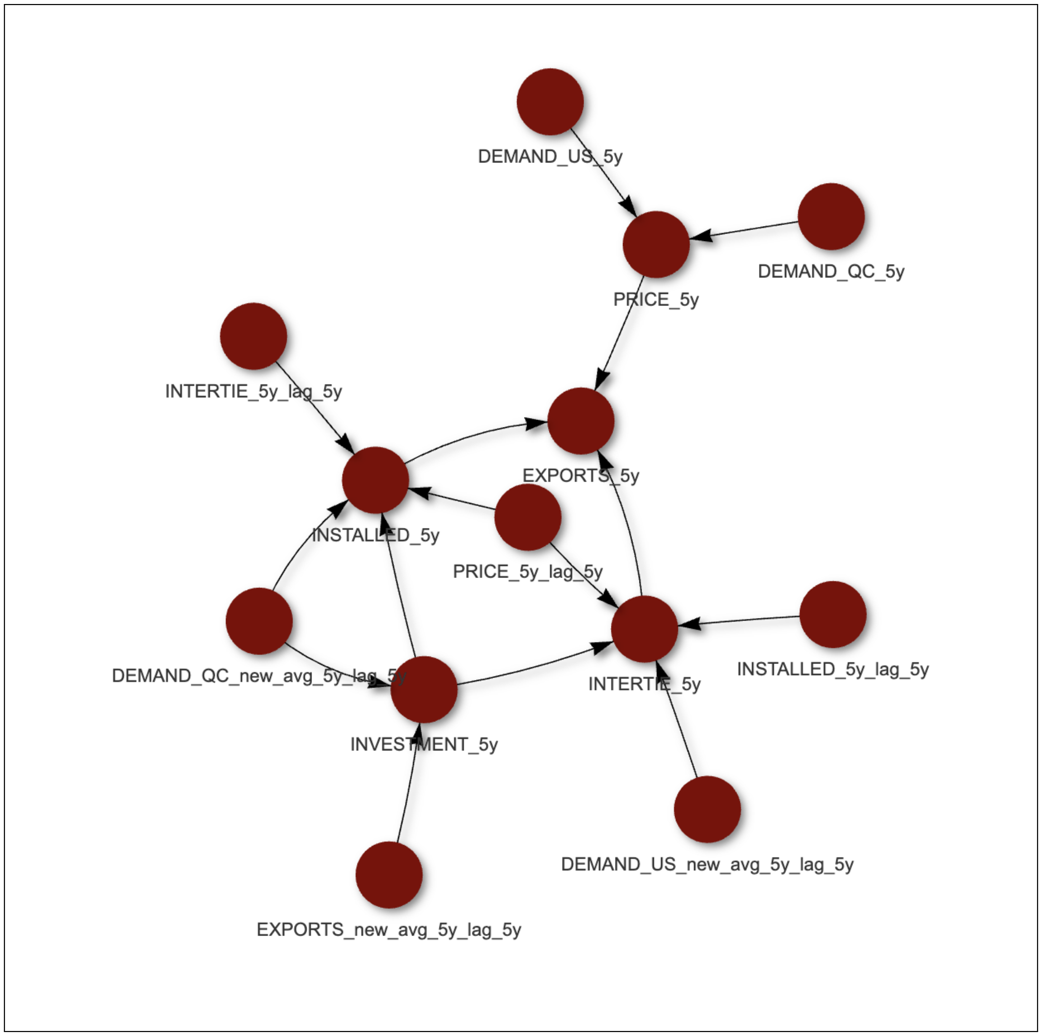

Figure 2: Hypothesized DAG visualization.

10 Constructing Score-Based DAGs

We construct DAGs using the score-based hill-climb (HC) algorithm. W use the `'hc'` and `'bn.fit'` functions from the `bnlearn` package. We visualize this DAG using `'plot.network'` and `'graphviz.chart'` functions. We use three different scoring functions; 1. `'loglik-cg'`, 2. `'aic-cg` and 3. `'bic-cg'`.

```
# DAG created using the loglik-cg score function and HC algorithm
dag.expert.5y.emp <- hc(df.expert.5y, score = "loglik-cg", blacklist = black.list.expert, ...
    debug = FALSE)
par(mar=c(1,1,1,1))
# Fitting the model
model.expert.5y.emp = bn.fit(dag.expert.5y.emp, df.expert.5y)
#Visualizing model's conditional probabilities using the graphviz.chart
graphviz.chart(model.expert.5y.emp,  type = "barprob", grid = TRUE, bar.col = "darkgreen",
               strip.bg = "lightskyblue")
dev.off()
# Network visualized using plot.network
plot.network(dag.expert.5y.emp, ht = "600px")

# DAG created using the aic-cg score function and HC algorithm
dag.expert.5y.emp.aic <- hc(df.expert.5y, score = "aic-cg", blacklist = black.list.expert)
plot.network(dag.expert.5y.emp.aic, ht = "600px")
par(mar=c(1,1,1,1))
```

```
model.expert.5y.emp.aic = bn.fit(dag.expert.5y.emp.aic, df.expert.5y)
graphviz.chart(model.expert.5y.emp.aic,  type = "barprob", grid = TRUE, bar.col = "darkgreen",
               strip.bg = "lightskyblue")
dev.off()

# DAG created using the bic-cg score function and HC algorithm
dag.expert.5y.emp.bic <- hc(df.expert.5y, score = "bic-cg", blacklist = black.list.expert)
plot.network(dag.expert.5y.emp.bic, ht = "600px")
par(mar=c(1,1,1,1))
model.expert.5y.emp.bic = bn.fit(dag.expert.5y.emp.bic, df.expert.5y)
graphviz.chart(model.expert.5y.emp.bic,  type = "barprob", grid = TRUE, bar.col = "darkgreen",
               strip.bg = "lightskyblue")
dev.off()
```

11 Plotting Conditional Dependency Results

We used the conditional probability results from the DAG model to evaluate the relationship between various nodes. We used visualization to plot these dependencies. This was achieved by creating a separate R code called **Graph_Generator.R** located in the same directory as the main code. This code is then recalled using the **source** function.

It must be noted that the type of each plot is dependant on the type of each node and the number of its parents. Therefore, here we only present one node's results as an example. Refer to the supplemental information document for further details for each node. Figure 3 shows the results for this plot.

11.1 Running the Graph_Generator.R Code

We use the following code to recall the **Graph_Generator.R** code from the directory. This will run that code in the background.

```
source("Graph_Generator.R")
```

11.2 Snippet of Graph_Generator.R Code

Here is an snippet of **Graph_Generator.R** code where graphs are defined for nodes of interest and they're saved in the **.svg** format automatically when this code is called.

```
# 5. Conditional density: EXPORTS_5y | INSTALLED_5y + INTERTIE_5y + PRICE_5y
# Makind predictions for the node EXPORTS_5y using 'predict' function from the 'bnlearn' ...
    package.
df.expert.5y$EXPORTS_5y_pred = predict(model.expert.5y.emp, node = "EXPORTS_5y", data = ...
    df.expert.5y, method = "bayes-lw")
p<- ggplot(df.expert.5y, aes(x = PRICE_5y, y = INSTALLED_5y, size = EXPORTS_5y_pred, color ...
    = as.factor(INTERTIE_5y))) +
  geom_point() +
  labs(x = "PRICE",
       y = "INSTALLED",
       size = "Predicted EXPORTS",
       color = "INTERTIE") +
  scale_color_manual(values = palette)
ggsave(filename = "fig_8.svg", plot = p, device = "svg")
```

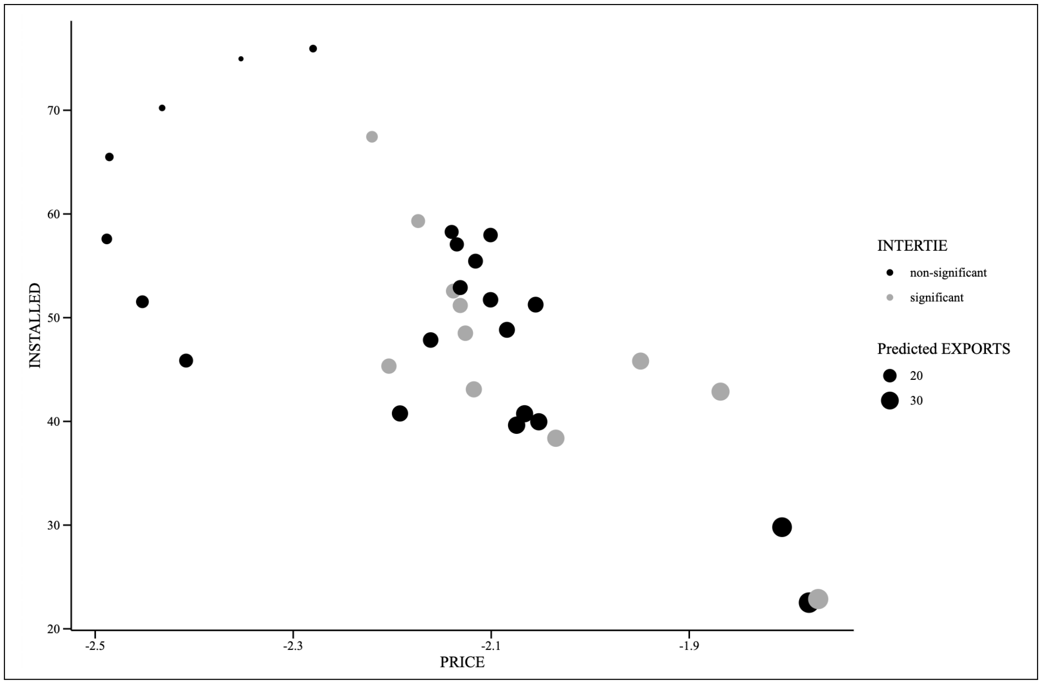

Figure 3: 5-year model's conditional dependency results for the exports node.

12 Goodness of Fit for Each Node

Here we use the `'evaluate_fit_discrete'` and `'evaluate_fit_continuous'` functions created in Section 6.3 to evaluate the goodness of fit for nodes with parent(s). We use the `predict()` function from the `bnlearn` package. Additionally we utilize Monte Carlo posterior inference method using the `bayes-lw` with 5000 parameters.

```
# identify discreet and continiuous variables
discrete_vars <- c("INTERTIE_5y", "INVESTMENT_5y")
continuous_vars <- setdiff(colnames(df.expert.5y), c(discrete_vars, value = TRUE))
# Create a blank results list
results_loglik <- list()

# Looping over each node to generate its prediction using the 'predict' function from the ...
    'bnlearn' package.
for (var in colnames(df.expert.5y)) {
  if (!grepl("_pred$", var)) {
    pred_column <- paste(var, "pred", sep = "_")
    df.expert.5y[[pred_column]] <- predict(model.expert.5y.emp, node = var, data = ...
        df.expert.5y, method = "bayes-lw", n = 5000)
    actual_values <- df.expert.5y[[var]]
    predicted_values <- df.expert.5y[[pred_column]]

    # Calculate the goodness of fit for different type of variables using the functions we ...
        created previously
    if (var %in% continuous_vars) {
      results_loglik[[var]] <- evaluate_fit_continuous(actual_values, predicted_values)
    } else if (var %in% discrete_vars) {
      results_loglik[[var]] <- evaluate_fit_discrete(actual_values, predicted_values)
    }
  }
}
```

13 D-Separation Analysis

Here we use the `'arc_exists'`, `'perform_dsep_tests'` and `'interpret_dsep_pvalues'` functions created in Section 6.4 to evaluate the conditional dependence of nodes of interest if needed. This step helps resolve any discrepancies or nuances that we might witness in different models.

```
# Defining the node_pairs list to identify nodes of interest where we want to perform ...
    d-separation. Note that this list contains node in a "from", "to" format.
different_edges <- compare(dag.expert.5y.emp, dag.expert.5y, arcs = TRUE)
node_pairs <- different_edges$fp
print(node_pairs)
node_pairs <- lapply(seq_len(nrow(node_pairs)), function(i) as.character(node_pairs[i, ]))

# Using the dsep.dag function to calculate conditional dependency for each pair
dsep_log <- dsep.dag(dag.expert.5y.emp, df.expert.5y, node_pairs)
```

Supplemental Information

Causal inference to scope environmental impact assessment of renewable energy projects and test competing mental models of decarbonization

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Supporting tables

Supporting Figures

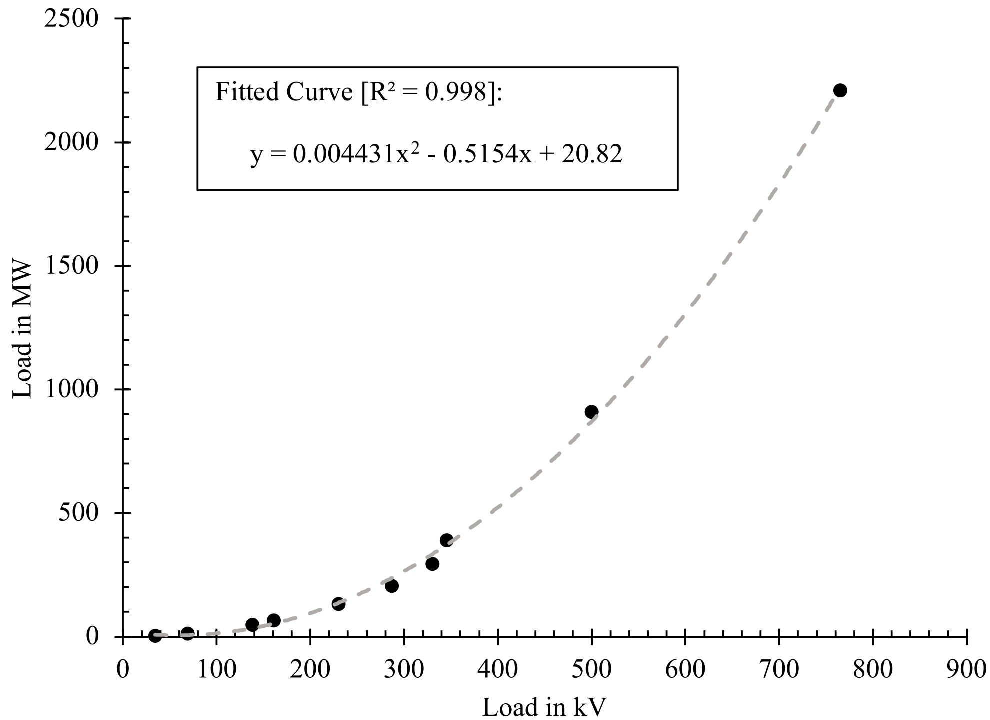


Figure S1: Calibrated curve for the New England/New York/Quebec intertie transmission network

Table S1: Capacity information for transborder transmission infrastructure (U.S. Department of Energy, 1979–2021). Bolded lines had capacity reported in kV and MW and were used to calibrate the St. Clair curve (Figure S1) except for DC lines noted with * where St. Clair curve does not apply. Unbolded lines had capacity reported in kV, and MW was calculated using St. Clair curve.

Docket No.	Presidential permit labeled by company name	Date issued (YYYY-MM-DD)	Capacity (kV)	Total estimated capacity (MW) using St. Clair curve
PP-11-2	Fraser Papers	1999-02-28	6.6	0
PP-11-2	**Fraser Papers**	**1999-02-28**	**138**	**48**
PP-12	Maine	1963-12-05	**69**	**12**
PP-12	Maine	1948-01-03	**69**	**12**
PP-13	Niagara Mohawk Corporation	1948-01-31	38	7
PP-31	Niagara Mohawk Corporation	1958-02-28	**230**	**132**
PP-190	Niagara Mohawk Corporation	1958-02-28	115	19
PP-190	Niagara Mohawk Corporation	1958-02-28	**69**	**12**
PP-190	Niagara Mohawk Corporation	1958-02-28	**69**	**12**
PP-190	Niagara Mohawk Corporation	1958-02-28	38	7
PP-190	Niagara Mohawk Corporation	1958-02-28	12 (13 units)	47
PP-190	Niagara Mohawk Corporation	1998-12-22	115	19
PP-24	Long Sault	1980-06-06	115	19
PP-29	Maine Public Service	1968-03-22	**138**	**48**
PP-32	Eastern Maine	1959-02-05	**69**	**12**
PP-362	Champlain Hudson Power Express, Inc.	2014-10-06	**320 DC***	**1,000***
PP-43	Maine Electric	1969-07-25	**345**	**390**
PP-56	NYPA Ft Covington	1974-09-13	**765**	**2,210**
PP-66	Citizens Derby	1979-06-21	120	21
PP-74	NYPA	1980-11-24	**345 (2 units)**	**780**
PP-76	VETCO	1984-04-05	**450 DC***	**775***
PP-80	Citizens Vermont	1983-08-05	25 (2 units)	20
PP-82	Joint Owners of the Highgate	1985-05-14	120	21
PP-89	Bangor Hydro	1996-01-22	**345**	**390**
PP-438	NECEC Transmission LLC	2021-01-14	**1,250 DC***	**1,250***

Table S2: Summary of supplemental variables (1979-2021) aggregated to explore possible correlations, covariates, and confounders but not included in final causal analysis

Variable name	Units	Description	References
REVENUE	CAD year^{-1}	Annual revenues to Hydro-Québec	Hydro-Québec (2018–2023)
PRICE_QC	$CAD kWh^{-1}	Annual average retail electricity prices for electricity in Quebec	Hydro-Québec (2022)
PRICE_US	$USD kWh^{-1}	Annual estimate of average electricity price in northeastern U.S.	U.S. Energy Information Administration (2022)
POP_US, POP_QC	millions	Population of New England - New York (POP_US) and Quebec (POP_QC)	Institut de la statistique du Québec (2022); U.S. Census Bureau (2023)
DSNW_US, DSNW_QC	days	Number of days in calendar year with snowfall ≥ 25 mm at any weather station in the northeastern U.S.[1] or Quebec[2].	Lawrimore et al. (2016a)
DP10_US, DP10_QC	days	Number of days with rainfall more than 2.5 mm at any weather station in the northeastern U.S.[1] or Quebec[2].	Idem
TMIN_US, TMIN_QC	ºC	Average minimum temperature in calendar year. Average of the mean monthly minimum temperatures at any weather station in the northeastern U.S.[1] or Quebec[2].	Idem
TMAX_US, TMAX_QC	ºC	Average maximum temperature in calendar year. Average of the mean monthly maximum temperatures at any weather station in the northeastern U.S.[1] or Quebec[2]	Idem
TAVG_US, TAVG_QC	ºC	Average temperature in calendar year. Average of at any weather station in the northeastern U.S.[1] or Quebec[2]	Idem
CLDD_US, CLDD_QC	ºC	Cooling Degree Days. Computed when daily average temperature is more than 18.3 degrees Celsius [CDD = mean daily temperature – 18.3 degrees Celsius]. Daily CDDs are summed to produce an annual total. Annual totals are computed based on a calendar year in Northern Hemisphere at any weather station in the northeastern U.S.[1] or Quebec[2] and averaged.	Idem

[1] Weather station IDs for "_US" variables: USC00308600; USW00014605; USW00014606; USW00014607; USW00014732; USW00014733; USW00014739; USW00014742; USW00014750; USW00014755; USW00014764; USW00014771; USW00094705; USW00094725; USW00094746; USW00094765; USW00094789; USW00094790 (Lawrimore et al., 2016b).

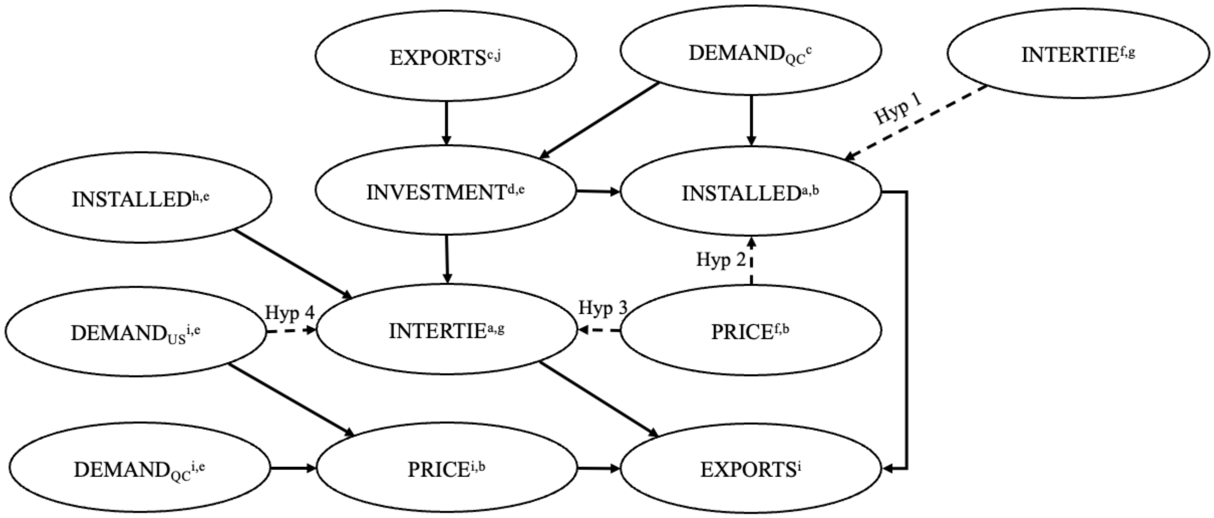
[2] Weather station IDs for "_QC" variables: CA006085700; CA007014160; CA007014629; CA007015730; CA007020828; CA007020860; CA007024280; CA007060400; CA007066820; CA007080468; CA007091299; CA007091305; CA007091401; CA007091404; CA007093716; CA007093GJ3; CA007103536; CA00710S005 (Lawrimore et al., 2016b).

Table S2 (cont'd): Summary of data (1979-2021) for variables aggregated to explore correlations and possibly overlooked covariates and confounders but not included in final causal analysis

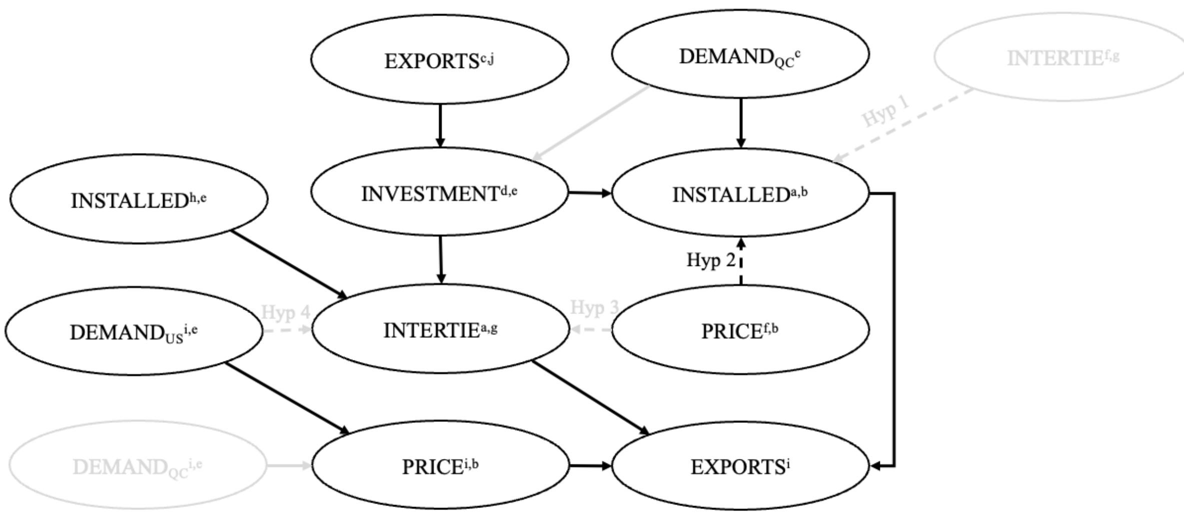
Variable name	Units	Description	References
PRCP_US, PRCP_QC	mm	Total annual precipitation averaged across weather stations in the northeastern U.S.[1] or Quebec[2]	Idem
SNOW_US, SNOW_QC	mm	Total annual snowfall averaged across weather stations in the northeastern U.S.[1] or Quebec[2]	Idem

[1] Weather station IDs for "_US" variables: USC00308600; USW00014605; USW00014606; USW00014607; USW00014732; USW00014733; USW00014739; USW00014742; USW00014750; USW00014755; USW00014764; USW00014771; USW00094705; USW00094725; USW00094746; USW00094765; USW00094789; USW00094790 (Lawrimore et al., 2016b).

[2] Weather station IDs for "_QC" variables: CA006085700; CA007014160; CA007014629; CA007015730; CA007020828; CA007020860; CA007024280; CA007060400; CA007066820; CA007080468; CA007091299; CA007091305; CA007091401; CA007091404; CA007093716; CA007093GJ3; CA007103536; CA00710S005 (Lawrimore et al., 2016b).



(A)



(B)

Figure S2: Hypothesized DAG (Panel A) and 5- and 8-year BN model DAG from loglik scoring (Panel B). Identical model structures returned under 5- and 8-year model versions. Models are expanded versions of structures presented in Figures 2 (Panel A) and 3 (Panel B) representing lag-transformed variables separately. Grayed our links are not supported. [a] Total expansion in 5 or 8-year period up to year *t*; [b] Box-Cox transformed variable; [c] 5-year lag of the 5 or 8-year moving average for the incremental expansion, i.e., value in year *t* minus value in year *t-1*; [d] Average total investment in 5 or 8-year period up to year *t;* [e] Discretized variable ("low", "medium", "high"); [f] 5 or 8-year lag of the total intertie capacity expansion/price difference in 5 or 8-year period up to year t; [g] Discretized variable ("non-significant", "significant"); [h] 5 or 8-year lag of the total expansion in 5 or 8-year period up to year *t;* [i] Average expansion in 5 or 8-year period up to year *t*; [j] Discretized variable ("negative", "positive").

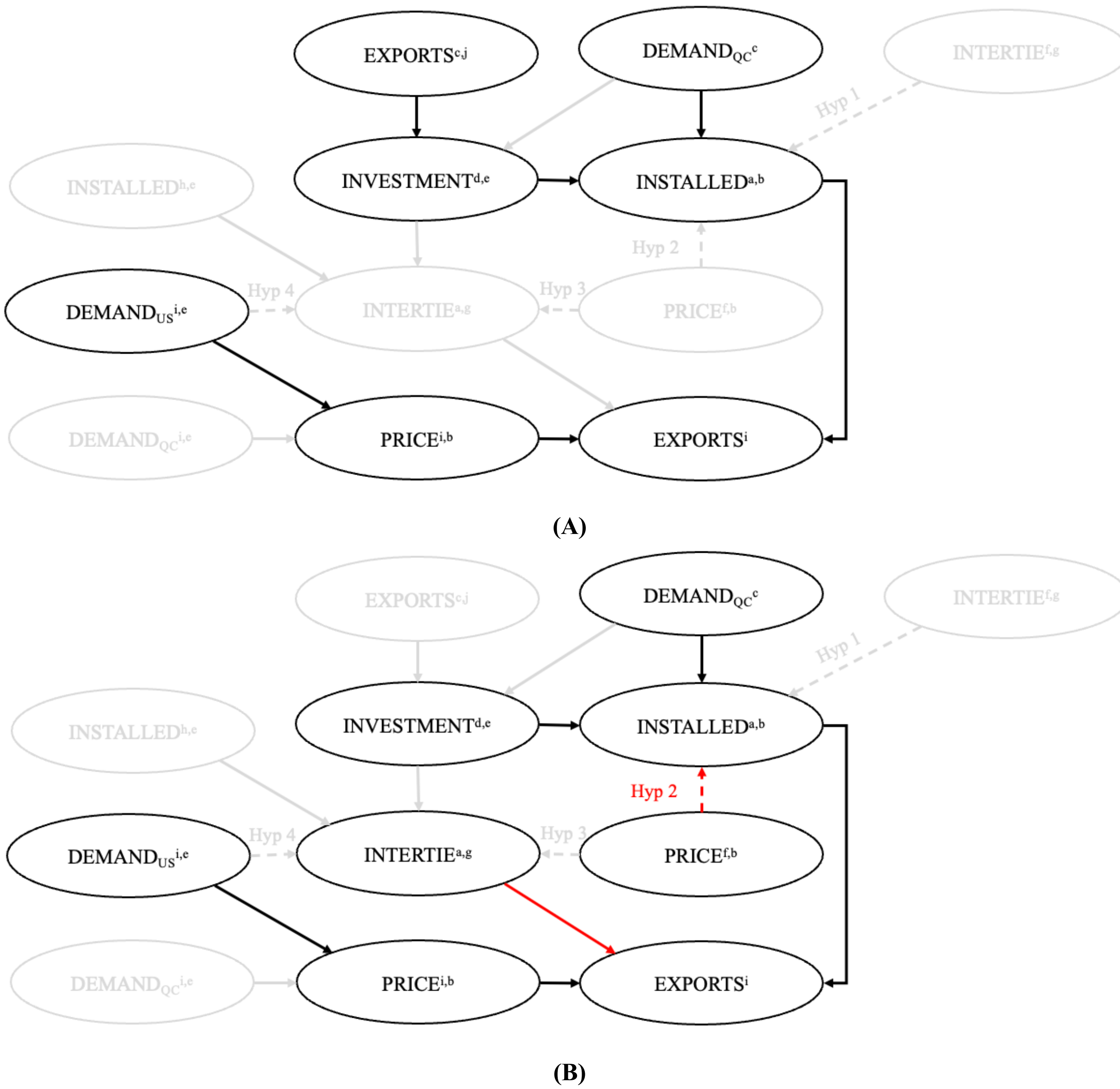
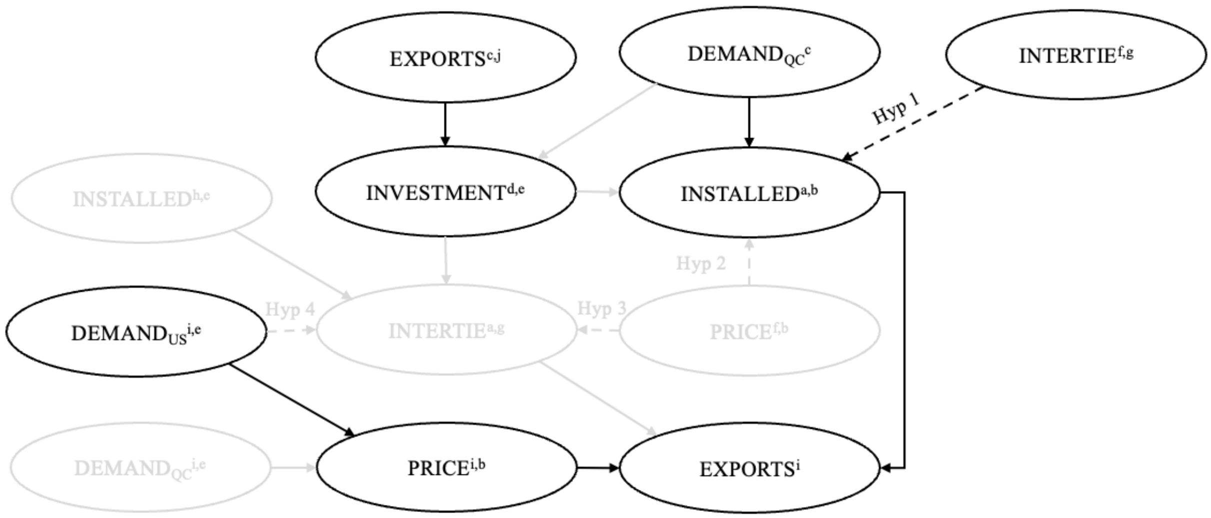
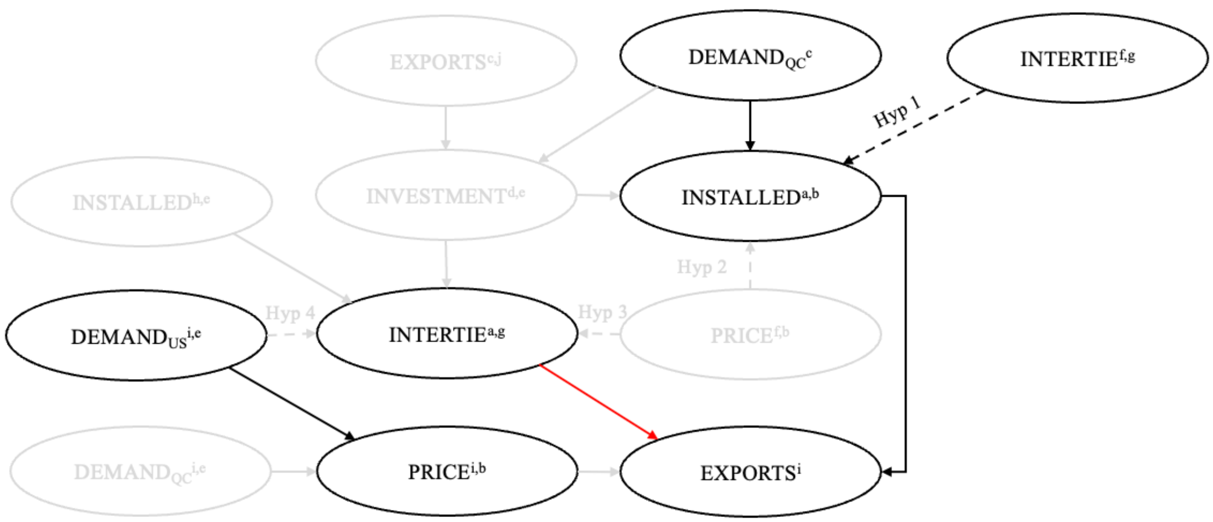


Figure S3: 5-year (Panel A) and 8-year (Panel B) BN model DAG (AIC scoring). Grayed our links are not supported. [a] Total expansion in 5 or 8-year period up to year *t*; [b] Box-Cox transformed variable; [c] 5-year lag of the 5 or 8-year moving average for the incremental expansion, i.e., value in year *t* minus value in year *t-1*; [d] Average total investment in 5 or 8-year period up to year *t;* [e] Discretized variable ("low", "medium", "high"); [f] 5 or 8-year lag of the total intertie capacity expansion/price difference in 5 or 8-year period up to year t; [g] Discretized variable ("non-significant", "significant"); [h] 5 or 8-year lag of the total expansion in 5 or 8-year period up to year *t;* [i] Average expansion in 5 or 8-year period up to year *t*; [j] Discretized variable ("negative", "positive").



(A)



(B)

Figure S4: 5-year (Panel A) and 8-year (Panel B) BN model DAG (BIC scoring). Grayed our links are not supported. [a] Total expansion in 5 or 8-year period up to year *t*; [b] Box-Cox transformed variable; [c] 5-year lag of the 5 or 8-year moving average for the incremental expansion, i.e., value in year *t* minus value in year *t-1*; [d] Average total investment in 5 or 8-year period up to year *t;* [e] Discretized variable ("low", "medium", "high"); [f] 5 or 8-year lag of the total intertie capacity expansion/price difference in 5 or 8-year period up to year t; [g] Discretized variable ("non-significant", "significant"); [h] 5 or 8-year lag of the total expansion in 5 or 8-year period up to year *t;* [i] Average expansion in 5 or 8-year period up to year *t*; [j] Discretized variable ("negative", "positive").

Table S3: Summary of BN model when using AIC scoring criterion (5-year average and lag)

Child	Parent(s)	r squared	Accuracy
INSTALLED[a,b]	DEMAND$_{QC}$[c], INVESTMENT[d,e]	0.77	n/a
EXPORTS[f]	PRICE[f,b], INSTALLED[a,b]	0.78	n/a
INVESTMENT[d,e]	EXPORTS[c,g]	n/a	0.60
PRICE[f,b]	DEMAND$_{US}$[h,e]	0.58	n/a

[a] Total expansion in 5-year period up to year *t*
[b] Box-Cox transformed variable
[c] 5-year lag of the 5-year moving average for the incremental expansion, i.e., value in year *t* minus value in year *t-1*
[d] Average total investment in 5-year period up to year *t*
[e] Discretized variable ("low", "medium", "high")
[f] Average expansion in 5-year period up to year *t*
[g] Discretized variable ("negative", "positive")
[h] 5-year lag of the average expansion in 5-year period up to year *t*

Table S4: Summary of BN model when using AIC scoring criterion (8-year average and lag)

Child	Parent(s)	r squared	Accuracy
INSTALLED[a,b]	DEMAND$_{QC}$[c], INVESTMENT[d,e], PRICE[f,b]	0.96	n/a
EXPORTS[g]	PRICE[g,b], INSTALLED[a,b], INTERTIE[a,h]	0.92	n/a
PRICE[g,b]	DEMAND$_{US}$[i,e]	0.76	n/a

[a] Total expansion in 5-year period up to year *t*
[b] Box-Cox transformed variable
[c] 5-year lag of the 5-year moving average for the incremental expansion, i.e., value in year *t* minus value in year *t-1*
[d] Average total investment in 5-year period up to year *t*
[e] Discretized variable ("low", "medium", "high")
[f] 5 or 8-year lag of the total intertie capacity expansion/price difference in 5 or 8-year period up to year *t*
[g] Average expansion in 5-year period up to year *t*
[h] Discretized variable ("non-significant", "significant")
[i] 5-year lag of the average expansion in 5-year period up to year *t*

Table S5: Summary of BN model when using BIC scoring criterion (5-year average and lag)

Child	**Parent(s)**	**r squared**	**Accuracy**
INSTALLED[a,b]	$DEMAND_{QC}$[c], INTERTIE[d,e]	0.72	n/a
EXPORTS[f]	PRICE[f,b], INSTALLED[a,b]	0.78	n/a
INVESTMENT[g,h]	EXPORTS[c,i]	n/a	0.45
PRICE[f,b]	$DEMAND_{US}$[g,h]	0.59	n/a

[a] Total expansion in 5-year period up to year *t*
[b] Box-Cox transformed variable
[c] 5-year lag of the 5-year moving average for the incremental expansion, i.e., value in year *t* minus value in year *t-1*
[d] 5-year lag of the average expansion in 5-year period up to year *t*
[e] Discretized variable ("non-significant", "significant")
[f] Average expansion in 5-year period up to year *t*
[g] Average total investment in 5-year period up to year *t*
[h] Discretized variable ("low", "medium", "high")
[i] Discretized variable ("negative", "positive")

Table S6: Summary of BN model when using BIC scoring criterion (8-year average and lag)

Child	**Parent(s)**	**r squared**	**Accuracy**
INSTALLED[a,b]	$DEMAND_{QC}$[c], INTERTIE[d,e]	0.94	n/a
EXPORTS[f]	INSTALLED[a,b], INTERTIE[a,e]	0.91	n/a
PRICE[f,b]	$DEMAND_{US}$[g,h]	0.53	n/a

[a] Total expansion in 5-year period up to year *t*
[b] Box-Cox transformed variable
[c] 5-year lag of the 5-year moving average for the incremental expansion, i.e., value in year *t* minus value in year *t-1*
[d] 5 or 8-year lag of the total intertie capacity expansion/price difference in 5 or 8-year period up to year *t*
[e] Discretized variable ("non-significant", "significant")
[f] Average expansion in 5-year period up to year *t*
[g] 5-year lag of the average expansion in 5-year period up to year *t*
[h] Discretized variable ("low", "medium", "high")

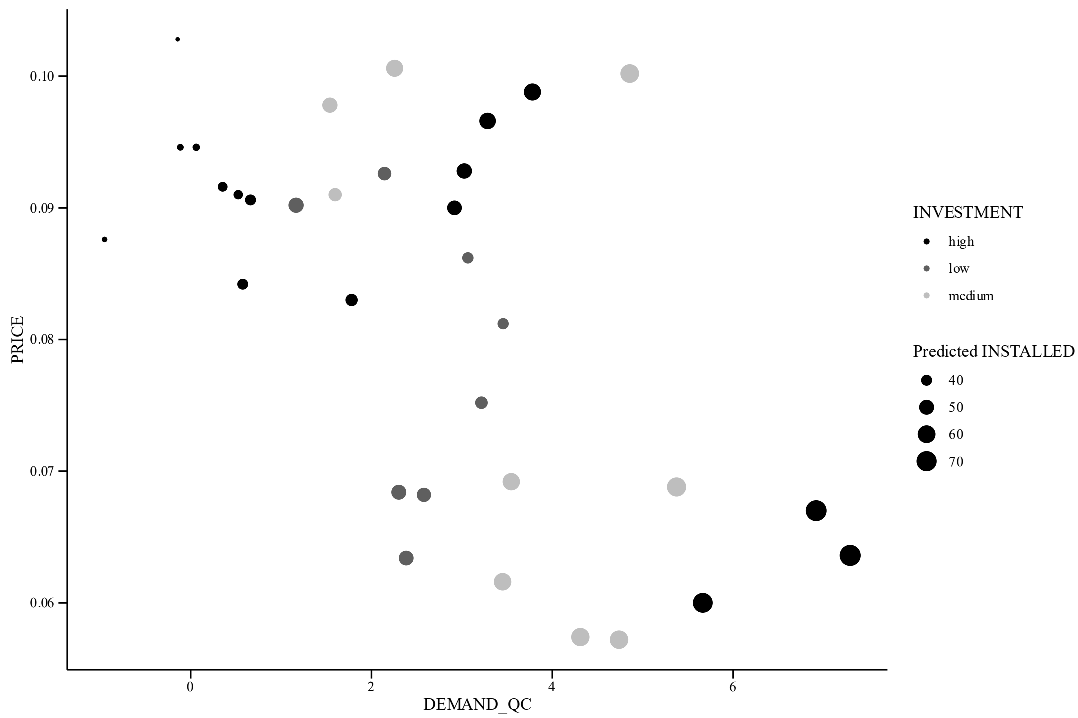


Figure S5: 5-year model results graph for installed generation capacity; child of total investments, lagged price difference and lagged new demand in Quebec.

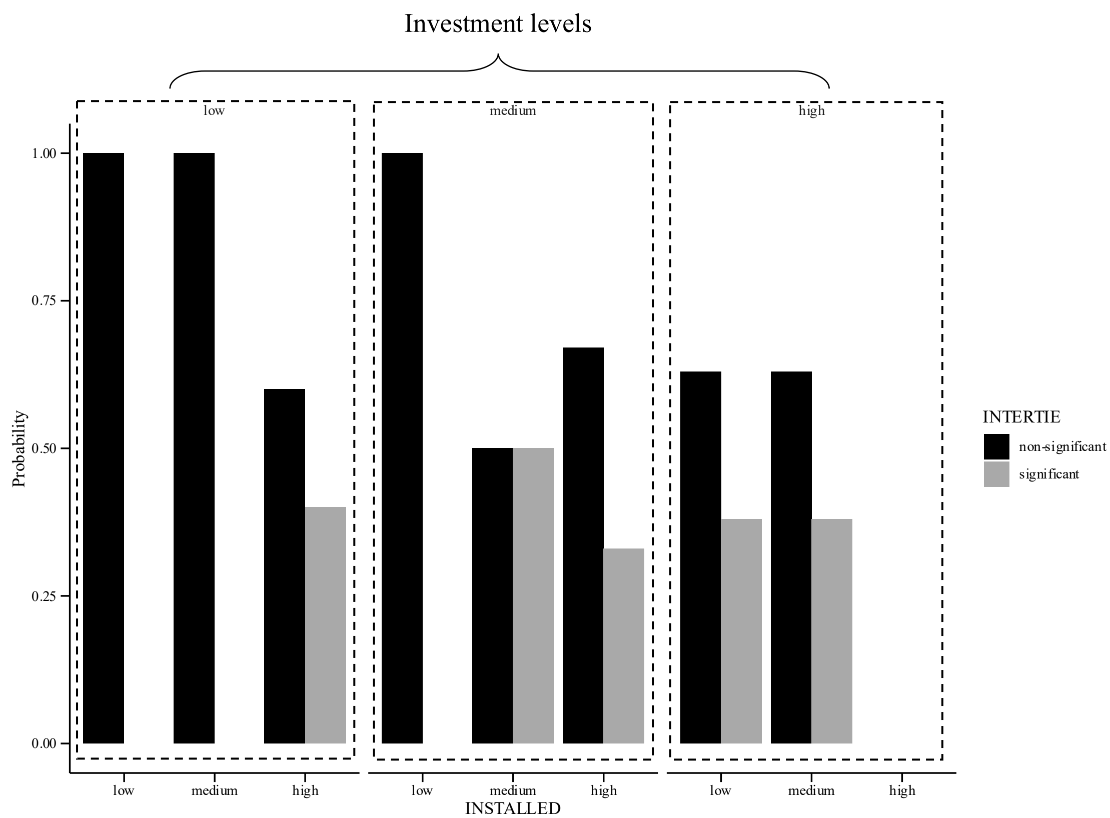


Figure S6: 5-year model results graph for intertie capacity; child of lagged installed generation capacity and total investments.

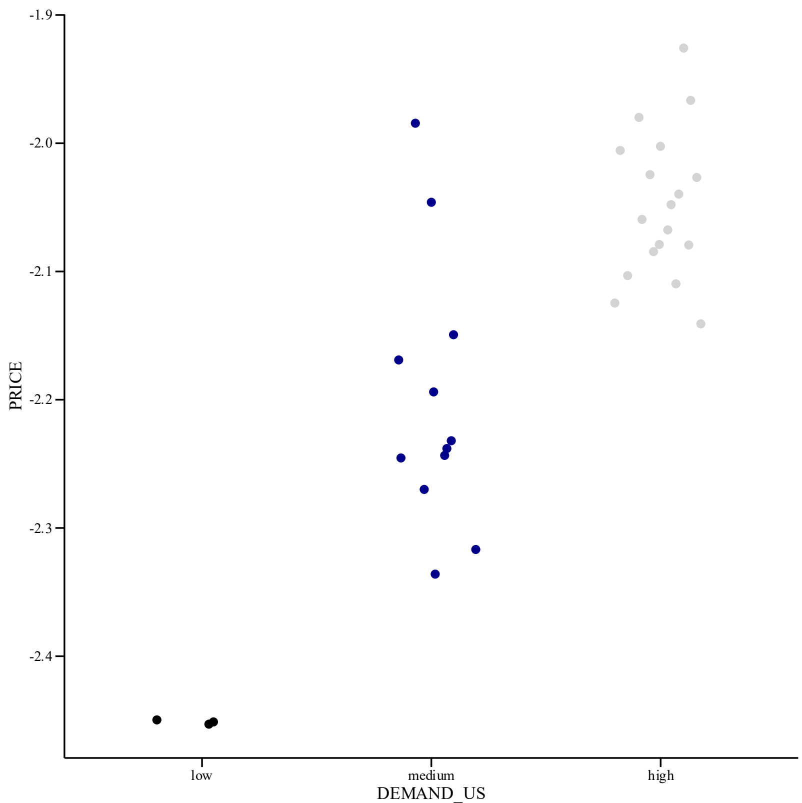


Figure S7: 5-year model results graph for price difference; child of average demand in the U.S.

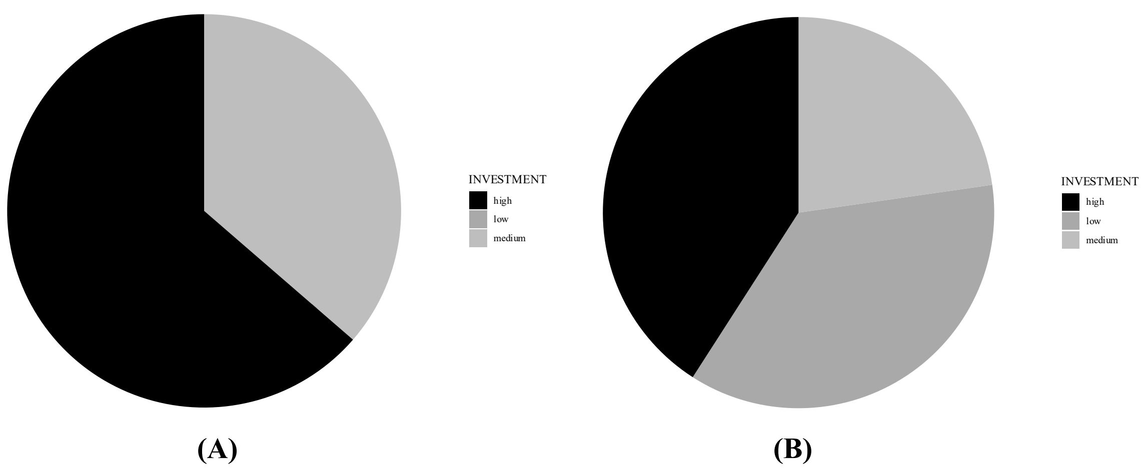


Figure S8: 5-year model results graph for total investment; child of lagged new total exports. **A:** Negative exports, **B:** Positive exports.

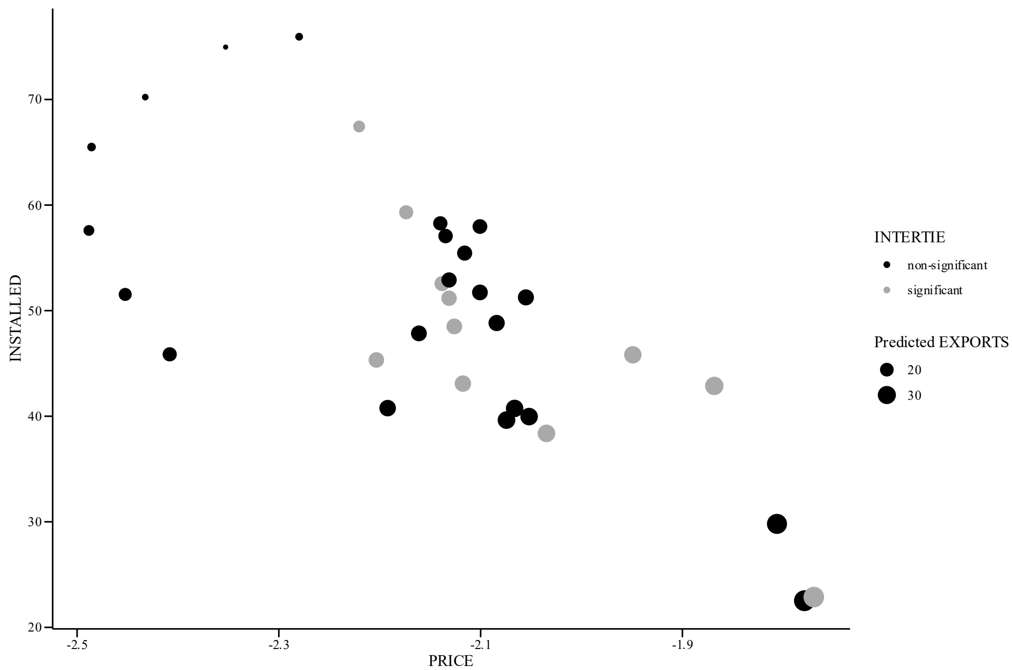


Figure S9: 5-year model results graph for exports; child of total expansion of intertie capacity, installed generation capacity and price difference.

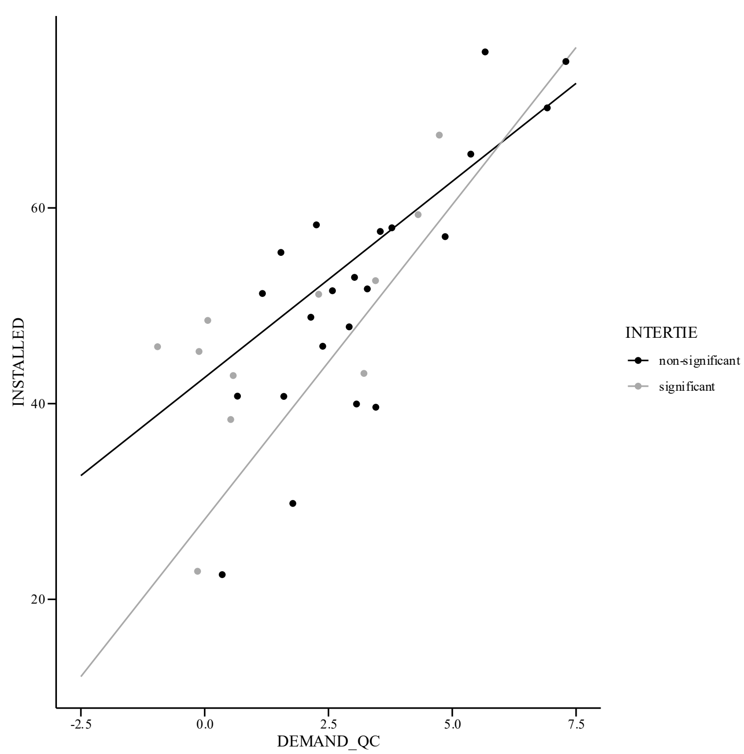


Figure S10: 5-year model results graph for installed generation capacity (BIC scoring); child of lagged intertie capacity expansion and lagged new average demand levels in Quebec.

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