

Cambridge Working Paper Economics

Cambridge Working Paper Economics: 1701

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9 January 2017

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EPRG Working Paper 1701

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Financial Support

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January 2017

Aalto Energy Efficiency Program and the Academy of
Finland program New Energy

www.eprg.group.cam.ac.uk

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December 7, 2016

Abstract

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1 Introduction

“For example, on wind energy, we get a tax credit if we build a lot of wind farms. That’s the only reason to build them. They don’t make sense without the tax credit.”

—Warren Buffett, *The Wall Street Journal*, May 4, 2014

This paper estimates the reduction in consumer prices attributable to the entry of wind power in an electricity market where the transition away from fossil-fuels has progressed exceptionally far — the Nordic market. With 5 % share of annual consumption, we estimate that the entry of wind power eliminates 25 % of the consumers’ electricity market expenditures. With 10 % market share for wind, consumers’ expenditures decline by one-half. Expenditures decline but the other side of coin is that consumers must cover part of the investment costs of the new entrants through subsidies. We find that the consumers’ estimated willingness to pay for subsidies to entry, defined through their impact on expenditures, exceeds the actual paid subsidies in this market.

The world is investing a quarter of trillion euros annually in renewable energy technologies (IEA, 2015). Subsidies to renewables are not only transfers to investors such as Warren Buffett. They lead to losses to old technologies and changes in the final cost of electricity to consumers. But the cost incidence of policies is far from obvious. In our empirical setting, consumers achieve a net gain: through equilibrium impacts, the cost of subsidies falls entirely on the incumbents in the market. Bringing attention to this extreme cost incidence allows drawing conclusions for climate policies more generally.

Fabra and Reguant (2014) show that the pass-through of emissions prices to the consumer side can be close to 100%. In contrast, phasing out fossil fuels with subsidies, as we show, implies a reversed cost incidence. In our empirical case, the (quasi-) rents of incumbents are sufficiently large to self-finance the transition away from fossil fuels, without resources needed from the consumers. Subsidizing the entry of technologies with zero marginal costs can thus have dramatic consequences for incumbents’ rents. Such rents are common in markets with a portfolio of technologies that have differing marginal costs.¹

The incidence of costs is an efficiency issue if industries can avoid the costs by relocating to other regions. The optimal policy in response to such a leakage should differentiate

¹One hypothesis is that the prevalence of rents, instead of efficiency improvements, explains the restructuring waves in electricity markets; see Borenstein and Bushnell (2015) for this argument, based on the US experience.

the cost burden across sectors that are differently exposed to competition from countries without climate policies (Hoel, 1996; see also e.g. Martin et al., 2014). The electricity sector produces the bulk of the carbon emissions, close to 30% of the total both in the EU and US,² and is thus important in transmitting the impacts of policies to the exposed sectors. However, the electricity sector itself is not exposed to competition from other regions, justifying a relatively high cost share of policies on electricity generators. According to our results, the rent shifting from generators to the exposed industries is quantitatively too important to be ignored in the transition towards cleaner technologies.

The Nordic electricity market with 25 million consumers offers a case for looking at what might be the future of electricity markets — intermittently available technologies combined with storable sources of energy. The market effectively pools together the available sources of hydroelectricity which, on average, covers 50% of annual consumption and provides a counterbalance for intermittent sources of supply. Without such a pre-existing counterbalance, scaling up the share of intermittent technologies can present a serious challenge to the current ways of organizing transmission, distribution, and production of electricity (Gowrisankaran, Reynolds and Samano, 2015).³ It may be necessary to invest trillions of dollars in energy storage in the US alone (Heal, 2016). Yet, empirical studies provide little guidance on the functioning of storage-dominated electricity markets.⁴ Much of the focus has been on the performance of the deregulated markets with traditional “static” technologies (for example, Borenstein, Bushnell, and Wolak, 2002; Fabra and Toro, 2005; Hortaçsu and Puller, 2009; Puller, 2007; Reguant, 2014). Markets dominated by storage and renewable energy technologies are fundamentally different since the storage creates dynamic linkages between hours, days, and even seasons of the year.

We develop an empirical identification strategy exploiting a basic property of renewables: their availability, after investment, is exogenous. With sufficient storage, the equilibrium division of labor between technologies depends merely on natural fundamentals such as temperature, wind, and rainfall. Because of the rich natural variation, the dynamic storage policies can be estimated directly from the observed actions.⁵ The

²US EPA (2015) and Eurostat (2015).

³Gowrisankaran et al. (2015) evaluate quantitatively the intermittency cost for southeastern Arizona. Ambec and Crampes (2012) study the optimal energy mix with reliable and intermittent energy sources.

⁴The existing studies build on simulation methods to evaluate the supply policies of hydroelectricity (for example, Bushnell, 2003). See also Kauppi, 2009; Kopsakangas-Savolainen and Svento, 2014. Fridolfsson and Tangerås (2008) review the simulation models used by the industry.

⁵We also verify the robustness of the estimates by quantification based on a model description of the market.

equilibrium outcomes are then generated by distributions that depend merely on the idiosyncrasies of the renewables. Some general results arise from this analysis.

First, replacing fossil-fuel technologies by renewables leads to more predictable market outcomes, not more uncertain, in a well-defined sense: preconditions for generation depend on idiosyncratic uncertainties rather than on the persistent uncertainties of fossil-fuel inputs.⁶ We explicitly quantify how the increased wind generation disconnects the market outcomes from the fossil-fuel inputs. For example, the pass-through of the EU Emissions Trading Scheme (EU-ETS) allowance costs to the final consumer price, as in Fabra and Reguant (2014), declines by one-half when the market share for wind reaches 10%. A deeper structural implication is that, all else equal, market price risks that are idiosyncratic, instead of persistent, lead to reduced investment frictions (Dixit and Pindyck, 1994).

Second, the market for storage in the electricity sector differs from that for standard storable commodities. Electricity storage is socially valuable because of both idiosyncratic and systematic variation of the natural fundamentals. Smoothing the impacts of the latter adds to the usual return from storage. We estimate a considerable trend return on holding the storable asset from low to high demand seasons. Such a return does not exist for standard storable goods (Williams and Wright, 1991, p. 46), turning the electricity storage partly into a natural resource, in the spirit of Hotelling (1931). Based on our results, the smoothing of predictable demand changes can be an important driver of investments in storage.⁷

Third, the setting provides methodological advantages for studying equilibrium storage decisions. The residual demand left for storage depends on the costs of the alternative supply sources that, in the electricity context, can be sharply characterized. In addition, the storage levels are precisely measured, not typical in the literature on storable-good markets.⁸ These properties allow us to use a dynamic-optimization approach to evaluate

⁶Generation based on wind, sun and rainfall follow distributions that are the same in this year and in the future. In contrast, generation depending on fossil-fuel inputs is fundamentally uncertain since, for example, “[...] changes in the real price of oil have historically tended to be (1) permanent, (2) difficult to predict, and (3) governed by very different regimes at different points in time” (Hamilton, 2009).

⁷Similar source of demand for storage arises, for example, in California where the high penetration of solar PV systems has led to a systematic mismatch between the daily peak demand and production, often illustrated by the so-called duck chart (Borenstein and Bushnell, 2015).

⁸The competitive storage model (Deaton and Laroque, 1992) has been designed to produce implications for price dynamics, without data on the underlying quantities. See Williams and Wright (1991) for an extensive treatment.

the robustness of the estimated results, including issues related to market power and capacity constraints in storage. With observed storage levels, we can generate long-run distributions relevant for the equilibrium analysis from the estimation results.⁹

The roadmap is the following. In Section 2, we shortly overview the policy incidence problem, with analysis in the Appendix. In Section 3, we describe the institutional setting. In the empirical analysis, Section 4, we first explicate the identification strategy used in the paper. Then, in Section 4.1, we state the theory arguments for the policies that are estimated in Section 4.2. The prices, in Section 4.3, are estimated for the historical market where the installed capacities have remained relatively stable. In Section 5, the capacities change as part of the counterfactual analysis. The rent transfer results follow from the estimated surplus generating process. Section 6 concludes and discusses the wider policy implications. The data used in the analysis and the code for replicating the results are available in a public folder.¹⁰

2 The policy cost incidence: a brief look

Ideally, clean technologies should not be subsidized if dirty technologies face the true social cost of their use; see, for example, Borenstein (2012). But subsidies, together with a price on emissions, may be needed in the transition to clean technologies if there are spillovers in technical change (for example, Acemoğlu, Akcigit, Hanley, and Kerr, 2015). Acknowledging these reasons for subsidies, we focus solely on the incidence of subsidy costs. This is an efficiency issue if climate policies do not have a global coverage so that policies may lead to relocation of industries (Hoel, 1996); it can also be a political-economy issue if consumer-voters care about the incidence, or a distributional issue if the set of distributional tools is limited.

Our results are consistent with the previous literature but, we believe, the gist of the cost incidence in our setting is dynamic and not present in this literature.¹¹ Fig. 1

⁹As in Roberts and Schlenker (2013), we could use instruments that are correlated with the storage levels but, without observing the stocks, the equilibrium analysis would not be implementable.

¹⁰https://www.dropbox.com/sh/be10c8pe14wq5fq/AABWSG-pjj_iMDd5EmaXdGIca?dl=0

¹¹The pass-through of a carbon price to the final consumer price can be close to 100%, as Fabra and Reguant (2014) demonstrate empirically. In contrast, Fischer (2010) notes that policies encouraging the adoption of new technologies through subsidies can lower the final consumer price; Böhringer and Rosendahl (2010) address the full set of resulting distortions. Newbery (2016) considers the optimal long-run market structure and the fraction of the subsidies that could be recovered from the consumers, taking in the account that consumers gain from “subsidized price reductions”. Green and Léautier (2015)

shows why carbon taxes and subsidies have a different immediate impact on incumbents' rents. For illustration, there are two steps in the incumbents' marginal costs; fossil fuels are used by the high-cost supply only. A tax on fossil fuels is passed on to the consumer price, evident from the Figure. In contrast, a subsidy to entry decreases the consumer price: entrants with zero marginal costs merely shift supply to the right or, as equivalently depicted, the residual demand for the incumbents' supply moves to the left. The consumer price falls, reversing the impact on the incumbents' rent. The final impact on the consumers depends on if the extracted rent is enough to cover the subsidy costs.

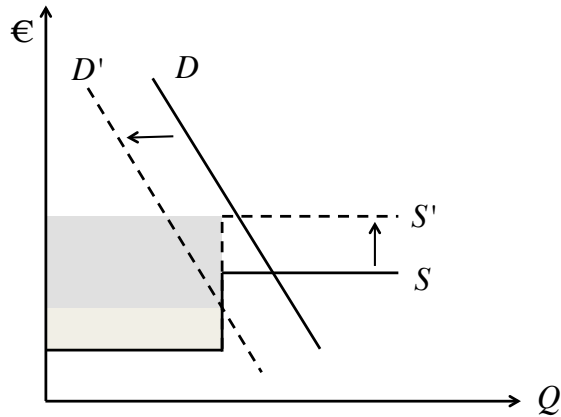


Figure 1: A schematic illustration of the policy cost incidence, with low and high cost of portions in supply. A tax on fuels increases the incumbent rents. Subsidies to new entrants shift the overall demand for the incumbent capacity to the left, and extract the rent.

But a sufficient penalty on fossil fuels will encourage entry too. It is not obvious why the incidence of costs is different in the two cases, if entry takes place in the end. The answer lies in the timing of incidence that is different under the two policies. We develop a simple model in Appendix H for the following mechanism. Assume that the investment cost for the new technology declines over time but is initially high enough to prevent entry to the market. A tax reflecting the true social cost of fossil-fuels will pass through to the consumer price because entry is not immediate; it is socially optimal to postpone investments and wait for lower investment costs. This waiting time protects the incumbents' rents.¹²

develop a rich model for similar issues with a detailed description of possible subsidy policies. Ritz (2016) looks at the total welfare implications from the entry of renewable energy in the presence of distortions such as incumbent market power.

¹²In the general equilibrium context, Nordhaus (e.g., 2008) has made the argument that climate policies

Subsidies bring new technologies to the market too early: the society pays too much for the investments and the consumption path becomes inefficiently front-loaded. But, as we show, the distortions vanish altogether if the consumer demand is inelastic enough. Then, subsidies become a pure distributional tool. Intuitively, subsidies merely eliminate the temporary rent protection for the incumbents, with a marginal distortion in the investment and consumption paths.

In the empirical case, we find that a relatively small subsidized entry of renewables leads to a large extraction of rents from the incumbents — to the extent that the consumers achieve a net gain. This is exactly what the theory model predicts.

3 The Nordic market

The Nordic market is a spot market for wholesale power, the Nord Pool Spot (NPS), owned jointly by the national transmission system operators in the Nordic region (Fig. 2).¹³ The NPS runs a day-ahead hourly market where supply and demand bids lead to a regional hourly price, the system price. This price becomes the actual transaction price if all trades are physically implementable; if this is not feasible, regional (zonal) prices are established. For example, Finland has at most one price zone, and Sweden has at most four zones.

The focus of our analysis is on how the regional price level is affected by persistent changes in wind generation. Although not all trades take place with the system price, it is yet a consistent measure of the price level and thus used for this purpose in our analysis. Historically, the system price has been the relevant longer-run reference price in the Nordic region (Juselius and Stenbacka, 2011). The price zones are indicative of difficulties in implementing all desired transactions but, historically, considerable part of the pressure on transmission links has been idiosyncratic. The degree of market integration varies across years depending on the availability of hydropower. Norway’s capacity is close to 100 per cent hydropower; Sweden has more equal shares of hydro and nuclear power; Finland has diversified between nuclear, thermal, and hydro power; Denmark has no hydropower but the largest share of wind (see Table A.1). In years of abundant hydro

should be gradually tightening for reasons related to income growth and consumption smoothing. Our model captures a different reason for gradualism, exogenous technical change, but the implications for the existing capital structure are similar: it should be phased out gradually. With endogenous technical change, a crash start could be optimal (Gerlagh, Kverndokk and Rosendahl 2009; and Acemoglu, Aghion, Bursztyn, and Hémous, 2012).

¹³Denmark, Finland, Norway and Sweden have been NPS members since 1999.

availability, the direction of exports is from the hydro-abundant regions (Norway and Sweden) to the rest of the market; the reverse holds in dry years.¹⁴

Market power concerns have not been as pressing as in many other early deregulated markets (for example, Wolfram 1999; Borenstein et al. 2002; Green and Newbery 1992). Rather, the question has been, as in the title of Amundsen and Bergman (2006), “Why Has the Nordic Electricity Market Worked So Well?” (see also Fehr, 2009).^{15 16}



Figure 2: The Nordic market area. The development of the inter-connection capacity is in Fig. A.4.

¹⁴The stability of the trading institution may be explained by the fact the division of labor between capacities changes from one year to another. In addition to the internal links, the Nordic market is also interconnected with the surrounding market areas. The main links are towards Germany, the Netherlands, the Baltic States and Russia which all are dominated by thermal power generation. The net supply from the neighboring regions is included in the analysis.

¹⁵Yet, it must be noted that the market performance of the Nordic market has not been as systemically evaluated as in other major electricity markets. One complication is the dynamic nature of hydro supply; another is that the NPS does not release the firm-level bid curves.

¹⁶According to NPS, there are 380 market participants, and over 90% of all electricity consumed is circulated through the NPS.

4 Empirical analysis

Our data covers years 2001-2014.¹⁷ The data is aggregated over regions to monthly observations. The aggregation over regions means that, for example, thermal power generation units form one fleet in the analysis of supply. The aggregation over the hourly market data to a monthly level produces rich seasonal variation that is essential for the empirical strategy in this paper.¹⁸ Appendix A provides the sources of data, with details on its construction.

Equation 1 shows the breakdown of supply.¹⁹ We will show that the monthly total demand depends on Nordic climatic conditions and thus is exogenous. The supply from WIND, combined heat and power (CHP), and NUCLEAR are also exogenous.²⁰ Then, by equation (1), the total residual demand left for HYDRO and THERMAL, denoted by d_t , can be taken as exogenous as well.²¹

$$\underbrace{\text{TOTAL.DEMAND}}_{=D_t} = \underbrace{\text{HYDRO} + \text{THERMAL}}_{=d_t} + \underbrace{\text{WIND} + \text{CHP} + \text{NUCLEAR}}_{\text{price insensitive}} \quad (1)$$

Our empirical strategy is to estimate the price-sensitive supply using exogenous demand shifters. Yet, we face a challenge since the decision to supply hydroelectricity is dynamic. With the danger of being overly pedantic, we use linear demand (q^d) and supply (q^s) to illustrate the empirical strategy:

$$\begin{aligned} q^d &= \alpha_0 + \alpha_1 p + u \\ q^s &= \beta_0 + \beta_1 p + v \\ q^d &= q^s \end{aligned}$$

¹⁷In this period, the definition of the market and the available capacity have been stable (Appendix A.10). Extending to 1990's would change the regional coverage of the market. We include the net trade with the neighboring regions in the analysis; the total supply is an aggregate that includes the supply coming from the other regions.

¹⁸In Section 4.3 we address the potential challenges follow from the use of monthly averages in the analysis.

¹⁹Term "load" is often used, instead of demand, to indicate that the quantity is given and needs to be procured from the suppliers in the market. We use the concepts interchangeably.

²⁰NUCLEAR is a must-run capacity. CHP units sell power to the market but the main obligation is to produce heat. WIND power output depends on climatic conditions.

²¹THERMAL includes traditional coal, gas, and oil fired power generation but also the price sensitive trade with other than Nordic countries is added to THERMAL.

with constants $(\alpha_0, \alpha_1, \beta_0, \beta_1)$, shocks (u, v) , and price p . If we can argue that demand q^d is exogenous ($\alpha_1 = 0$), we can use q^d as an instrument to identify the supply curve.²² Typically such exogenous variation can be thought of as arising from temperature-dependent final consumer demand. But it can also arise from renewable power determining the residual demand left for technologies with supply depending on out-of-pocket costs of production; thermal power is such a technology. Our setting is different. The current demand left for thermal power depends also on the forward-looking technology, hydro-electricity, with the opportunity of saving the hydro resource for some future demand situation. As in any dynamic market, the current equilibrium decisions must be solved jointly with the future equilibrium decisions; technically, through a fixed-point argument, the outcomes in the present and in the future are solved simultaneously. Then, the current decision, while dynamic, depends only on the current observables which can be taken as exogenous at time t .

Denoting the hydro output by function $a(\mathbf{s}_t)$, where \mathbf{s}_t is a state vector collecting the current exogenous observables relevant for the dynamic hydro use decision, the demand left for thermal power becomes $d_t - a(\mathbf{s}_t)$. If there is enough variation in the observables \mathbf{s}_t , independent of the thermal power costs, the state can be used to identify the thermal supply curve. We establish the theory arguments for the dependence of the hydro output only on the current observables in Section 4.1. This theory serves two purposes. First, it gives the formal basis for using of the estimated policy function in the second-stage regression for recovering the equilibrium prices (Section 4.3). Second, the theory provides also a tool for direct quantification, and, as explained in Section 4.1, we use this quantification tool for addressing robustness challenges to the analysis.

In the empirical strategy just outlined, total demand D_t in eq. (1) is not responsive to prices. This assumption would not be true at the hourly level where within-the-day price differences lead to some demand responsiveness.²³ This arbitrage rests on the idea that, for example, the energy saved in an hour is bought back in a near-future hour. Such an arbitrage is inconceivable for the demand loads over the seasons of the year. These loads are driven by exogenously changing Nordic climatic conditions, demonstrated in Table 1.

Table 1 shows the results from regressing the total monthly demand on: seasons

²²This is the approach sometimes used in electricity market analysis. See Bushnell et al. (2008).

²³The NPS aggregate demand and supply curves show that the short-run demand can to some extent response to price differentials across hours. For example, industrial demands and pumped-hydro technologies are two possible sources of responsiveness.

Table 1

	(1)	(2)
Temperature		0.50 (0.03)***
Jan	38.89 (0.36)***	28.98 (0.60)***
Feb	38.68 (0.38)***	28.72 (0.63)***
Mar	35.62 (0.41)***	27.36 (0.55)***
Apr	31.00 (0.33)***	25.96 (0.39)***
May	27.46 (0.19)***	25.92 (0.21)***
Jun	25.58 (0.21)***	25.45 (0.22)***
Jul	23.99 (0.21)***	23.99 (0.20)***
Aug	25.55 (0.16)***	25.46 (0.15)***
Sep	27.56 (0.21)***	26.13 (0.18)***
Oct	31.12 (0.25)***	26.23 (0.31)***
Nov	34.74 (0.34)***	27.58 (0.46)***
Dec	37.32 (0.55)***	28.15 (0.54)***
R ²	0.95	0.98
Adjusted R ²	0.95	0.98
Observations	168	168

Note: *p<0.1; **p<0.05; ***p<0.01

The table reports total demand D_t (measured in TWh) regressed on: seasons (column 1); seasons and temperatures (column 2). The temperature measured in Nordic heating degree days (HDD, Appendix A). Robust standard errors in parentheses.

(column 1); seasons and temperature (column 2). The season fixed effects give the mean aggregate demand per month in TWh. The temperature measure is in heating degree days (HDD) in the Nordic region.²⁴ If the temperature decreases by one degree Celsius, the demand increases by .50 TWh/month. With $R^2 = .98$, the Nordic climatic conditions explain almost all of the variation in the seasonal demand (see also Fig. A.3).

4.1 Allocation policies: theory

We now formalize the dynamic planning problem. Under standard assumptions, the planning outcome can be decentralized to represent the market outcome.²⁵

²⁴Temperature affects demand mainly through electric heating. Cooling needs in the Nordic summer are much more sporadic and coincide with the summer holiday season. Including an estimate for cooling degree days does not change the results.

²⁵To extend the argument to the case of imperfect competition, we could introduce a Markov structure for the strategic interactions as, for example, in Bajari et al. (2007). An explicit model of imperfect competition allows studying if the observed allocations deviate from the first best allocations. The market power analysis is beyond the scope of the current paper, but we address the issue in two ways. First, in the robustness analysis of Appendix F, we solve the dynamic program for the efficient allocation and provide a quantitative assessment. The analysis is suggestive that the estimated policies come close

Time $t = 0, 1, 2, \dots$ is discrete and extends to infinity. State is vector

$$\mathbf{s}_t = (s_t, r_t, d_t, \omega_t, \theta_t),$$

where s_t is the amount water in the storage, r_t is inflow, d_t is the residual demand realization as defined in eq. (1) above, ω_t is the recurring season of the year, and θ_t is a process capturing exogenous changes in the environment. State transition is a stationary and bounded Markov process, with “action” denoted by a_t :

$$P(\mathbf{s}_{t+1}|\mathbf{s}_t, a_t).$$

Action $a_t \in A(\mathbf{s}_t)$ is the use from the stock, and the choice is constrained by set $A(\mathbf{s}_t)$, capturing, for example, storage and other capacity constraints. The payoff in period t from action a_t is

$$\pi(\mathbf{s}_t, a_t) = -C(d_t - a_t, \omega_t, \theta_t),$$

where $C(d_t - a_t, \omega_t, \theta_t)$ is the cost of meeting the demand with the alternative technology. The cost is increasing in the first argument, bounded, and positive. Under relatively mild assumptions, it follows that there exists a stationary policy function to the planning problem.²⁶ With discount factor $\delta < 1$, the optimal policy maximizes the expected discounted sum of gains:

$$V(\mathbf{s}_t) = \max_{\{a_\tau\}} \mathbb{E} \left[\sum_{\tau=t}^{\infty} \delta^{\tau-t} \pi(\mathbf{s}_\tau, a_\tau) | \mathbf{s}_t \right],$$

where the value of the program satisfies the Bellman equation

$$V(\mathbf{s}_t) = \max_{a_t \in A(\mathbf{s}_t)} \{ \pi(\mathbf{s}_t, a_t) + \delta \mathbb{E}[V(\mathbf{s}_{t+1}) | \mathbf{s}_t, a_t] \}.$$

PROPERTIES:

1. The optimal policy is a function of the state: $a_t = a(\mathbf{s}_t)$
2. The policy generates invariant distributions for state elements through $P(\mathbf{s}_{t+1}|\mathbf{s}_t, a(\mathbf{s}_t)) = P(\mathbf{s}_{t+1}|\mathbf{s}_t)$.

to the competitive outcome. Second, in Appendix G, we develop an indirect measure of market power in storage based on seasonal price differences. We discuss the results of this analysis in Section 4.4.

²⁶ In particular, the following assumptions are sufficient: (i) stationary rewards and transitions, (ii) bounded rewards, (iii) discounting, and (iv) discrete state space. See Puterman (1994), Chapter 6. Of course, item (iv) can be relaxed (Stokey and Lucas, 1993).

The optimal policy thus minimizes the cost of meeting the expected demands. Importantly, if we observe the policy, $a_t = a(s_t, r_t, d_t, \omega_t, \theta_t)$, it already contains information about the cost of the alternative technology. The policy captures the general fundamentals of the alternative such as its availability in different seasons ω_t and potential technical change or input price changes that can enter through θ_t .

The elements of the state are observable so we can estimate the policy directly. Before proceeding to this estimation in Section 4.2 just below, note that the dynamic program is presented not only for conceptual clarity. We also solve the policy implied by this program quantitatively, after estimating the function for gains $\pi(\mathbf{s}_t, a_t)$ and other primitives (see Appendix F). The dynamic policy is thus obtained in two ways, by direct estimation and dynamic programming. This allows us to quantitatively address two basic robustness challenges. First, we can compare the estimated and optimized policies. For the comparison, we consider invariant seasonal mean outputs from the long-run output distributions generated by the policies. Such seasonal means can be obtained from the estimated or optimized policies (Appendix F). The approaches produce very similar seasonal outcomes. Also, since the dynamic program identifies the efficient allocation, this robustness analysis provides indirect evidence for concluding that the estimated policy is not necessarily in conflict with competitive behavior.²⁷

Second, solving the dynamic program allows analyzing if the use of the estimated policies in the counterfactual analysis is justified. The counterfactual wind generation patterns change the primitives of the dynamic allocation task: state transition $P(\mathbf{s}_{t+1}|\mathbf{s}_t, a_t)$ will be altered because a persistent increase in wind generation leads to new season-specific demand distributions. The policy is thus estimated for an environment that differs from the one in the counterfactual analysis. To address this challenge to the analysis, we solve the dynamic program under different wind counterfactuals (Appendix F). We find that the seasonal growth of the wind generation has minor quantitative impacts on the optimized seasonal hydro allocations; the economic reasoning for this result is elaborated in Section 4.4 where we discuss the seasonal dynamics of this market. This gives grounds for using the estimated policies in the counterfactual analysis.²⁸

²⁷The potential exercise of market power is further elaborated in Section 4.4.

²⁸For transparency and tractability, we prefer to use the estimated policies in the analysis presented in the main text, and use the dynamic program in supporting robustness analysis.

4.2 Allocation policies: estimation

To estimate $a(s_t, r_t, d_t, \omega_t, \theta_t)$, we regress the monthly output of hydroelectricity on: monthly storage level, inflow, residual demand d_t , seasonal month fixed effects ω_t , and distinct month time trend θ_t . To emphasize the exogenous nature of demand, we define variable “residual demand d_t ” as follows. For each month, we construct the temperature deviation from the mean per month (both measured as HDD), which we transform to TWhs using the regression results from Table 1. From this temperature dependent total demand, we subtract the wind and nuclear power mean deviations. The resulting quantity is our measure of demand d_t in the regressions below (the descriptives of the data are in Figs. A.1-A.2; the mean deviations and variable d_t are in Figs. A.11).²⁹

Table 2

	(1)	(2)	(3)	(4)
Inflow		-0.001	0.05***	0.04**
Reservoir		0.15***	0.16***	0.16***
Demand dt			0.57***	0.57***
Trend				0.10***
Month FE	YES	YES	YES	YES
R ²	0.63	0.86	0.91	0.92
Adjusted R ²	0.60	0.84	0.90	0.91
F Statistic	1109.4	2441.7	3507.4	3940.3
Observations	168	168	168	168

Note: *p<0.1; **p<0.05; ***p<0.01

Notes: Linear regression of the hydro output on the following variables. Column (1): seasonal dummies. Column (2): seasonal dummies + inflow + reservoir. Column (3): seasonal dummies + inflow + reservoir + residual demand. Column (4): seasonal dummies + inflow + reservoir+residual demand+trend. Units: inflow, reservoir, demand, and production are measured TWhs. Variables "inflow", "reservoir" and "demand" are expressed as deviations from seasonal mean values. Robust standard errors for estimates in column 4: inflow 0.02, reservoir 0.01, demand 0.05, and trend 0.01. See Table B.3 for the values of the month fixed effects.

Quantities are measured in TWhs per month. In Table 2, we report the estimation results of a linear regression adding four sets of covariates successively. Column (1) shows

²⁹There is a positive trend for wind and a negative trend for nuclear, so the mean deviations are constructed from the respective trends. The net effect of the trends implies a downward drift for the absolute level of the residual demand. In the robustness analysis that is discussed shortly, we find no support for changes in the hydro policy over time: the systematic demand change has not affected the hydro usage policies in the data period. The results are also robust to using demand variable as defined by $d_t = D_t - WIND - CHP - NUCLEAR$.

the strong seasonality of the hydroelectricity output: 60 % of the variation in the policies can be explained by seasons only. The sum of the monthly dummies is the total mean annual availability of the resource, close to 200 TWh, about 50 per cent of the total mean annual demand in this market (see the expanded Table B.3).

Column (2) adds the most important natural variation for the policies, inflows and reservoirs: R^2 increases to .84. Changes in availability is a source of large deviations from the seasonal mean hydro outputs (see Figs. B.6-B.7 for visualization).

In column (3), we add the residual demand realization as explained above. Finally, in Column (4), we include the trend which is precisely estimated but quantitatively small: over 168 months, hydroelectricity production has increased about 1.4 TWh (.4 % of the market size).³⁰

One standard deviation of variable “reservoir” is approximately 10 TWh per month. Monthly production increases only by 1.6 TWh per one standard deviation increase in availability, indicating a strong propensity to store. For comparison, one standard deviation of demand d_t is approximately 1.3 TWh per month; 57% of such a demand increase is covered by hydroelectricity, according to the point estimate. Fig. 3 (upper panel) depicts the actual and estimated hydro outputs over the sample years.

The simple linear relationship between the hydro output and natural covariates is compelling but the robustness of this particular form is still open. First, we have left out the cost measures of the alternative technology. Intuitively, the more costly is the alternative, the greater is the incentive to use hydroelectricity as a substitute. Yet, the marginal cost measures of thermal power turn out to have no impact on the estimated hydro usage patterns (see Table B.3). To understand this finding, note that the total amount of hydro output is exogenously given by the natural fundamentals and thus cannot be affected by the cost of the alternatives. But when the inputs for thermal power become more costly, the same endowment could be reallocated across seasons; for example, there could be more storage from Summer to Winter seasons. In Section 4.4, we discuss storage constraints that can explain why the input prices do not significantly influence the seasonal hydro usage pattern.

Second, interaction terms such as *reservoir* \times *month* seem economically meaningful, as they reveal whether the propensity to store additional availability changes over the seasons of the year. The seasonal dynamics is such that the scarcity is expected to disappear in the Spring with a new endowment of water. The propensity to use an

³⁰The capacity of the hydroelectricity has increased (see Appendix A.10), as a result of upgrades in the turbine technology.

extra unit of water in the reservoir for consumption should be become larger as we move towards the end of Winter. The estimated interactions in Table E.5 confirm this economic intuition. Yet, the interactions are statistically and economically insignificant.³¹

Third, we redefined monthly fixed effects as quarterly. The point estimates presented remain unaffected by the granularity of the seasons. With quarterly seasons, there are more degrees of freedom to add all remaining interactions to the model (Table E.6). We find that the simple linear model remains robust. In particular, the interactions between the overall time trends and seasons show that the seasonal pattern of hydro use has remained stable over the time period considered.³²

Finally, we want to address if the estimated policy is dynamically consistent. We take the initial reservoir level (in Jan 2001) as data and generate the subsequent reservoir levels from the estimated policy. There is a striking consistency between the actual monthly reservoir in the data and the fictitious reservoir that unfolds from the policy (see Fig. E.9).

Table 3

	(1)	(2)	(3)	(4)
Inflow		-0.09***	-0.06***	-0.05***
Reservoir		-0.10***	-0.10***	-0.10***
Demand dt			0.21***	0.20***
Trend				-0.13***
Month FE	YES	YES	YES	YES
R ²	0.11	0.67	0.69	0.8
Adjusted R ²	0.04	0.64	0.67	0.78
F Statistic	34.5	97.7	98.9	143.5
Observations	168	168	168	168

Note: *p<0.1; **p<0.05; ***p<0.01

Notes: Linear regression of the thermal output on the following variables. Column (1): seasonal dummies. Column (2): seasonal dummies + inflow + reservoir. Column (3): seasonal dummies + inflow + reservoir + trend. Column (4): seasonal dummies + inflow + reservoir+trend+temperature. Units: inflow, reservoir, demand, and production are measured TWhs. Variables "inflow", "reservoir", and "demand" are expressed as deviations from seasonal mean values. Robust standard errors for estimates in column 4: inflow 0.02, reservoir 0.01, demand 0.04, and trend 0.01.

After estimating the hydro policy (Table 2), we obtain an estimate for the monthly thermal power simply as residual $d_t - a(\mathbf{s}_t)$. However, it is more straightforward to regress

³¹According to F-test, the interactions should not be included in the model. We conducted the full analysis of this paper with the interactions. They do not impact the results; see Table E.8.

³²The stability of the policy addresses the concern discussed in footnote 29.

the monthly thermal output directly on the same covariates. We report in Table 3 the estimation results of a linear regression of thermal power output on the set of covariates just discussed above. The point estimates for “inflow”, “reservoir”, and “demand” are mirror images of those obtained for hydro policies, as expected.³³

To visualize the actual and estimated thermal outputs over the sample years, see Fig. 3 (lower panel).³⁴ The variation of the thermal power output can be explained to a remarkable extent by natural covariates, without any monetary measures.³⁵ We turn next to prices.

4.3 Recovering prices

The estimation above captures the dependence of thermal power on exogenously changing climatic and hydrological conditions but it is yet silent about prices that support the division of labor between the technologies: the output price must cover the running costs of the active thermal units. We estimate next a price-supply relationship for thermal power.

Denote the estimated dependence of thermal on the state by $q^{TH}(\mathbf{s}_t) = q^{TH}(s_t, r_t, d_t, \omega_t, \theta_t)$. As, for example in Bushnell et al. (2008), we can regress (the log of) the spot price on (log of) of the index of marginal costs, denoted by mc_t , and on $q^{TH}(\mathbf{s}_t)$:³⁶

$$\ln p_t = \alpha_0 + \alpha_1 \ln mc_t + \alpha_2 q^{TH}(\mathbf{s}_t) + \epsilon_t. \quad (2)$$

The marginal cost index depends on input prices, average rates for efficiency in using

³³Yet, note that the two estimates for “demand” in Tables 2 and 3 do not sum to unity; the theory assumption that the two technologies (thermal and hydro) share the residual demand does not seem to hold. This is due to our definition of the variable “demand”, which does not exactly correspond to the theory definition of the residual demand.

³⁴Recall that we include the trade with other than Nordic countries in the thermal output. Thus, exports explain the observations with negative thermal output.

³⁵Note the deviation of the fitted thermal from the observations in years 2007–2008 (and the corresponding deviation on the hydro side). This can be explained by the temporal incentives to save the European Emission Trading System (ETS) allowances through hydro storage: the ETS allowances were not storable between the ETS Phase I (2005–2007) and Phase II (2008–2012). Temporarily, the thermal output expanded above the level predicted in Fall 2007 to exhaust the Phase I surplus allowances. Effectively, the emissions allowances were saved through hydro storage.

³⁶Some may find it more natural to regress the output on the price. In particular, if one uses in a 2SLS regression demand shifters correlated with the price but not with the production costs, this order of presenting variables is natural. Obviously, reversing the order does not affect the results. Given that we first estimate the stand-alone policy rules, it is convenient to work with equation (2).

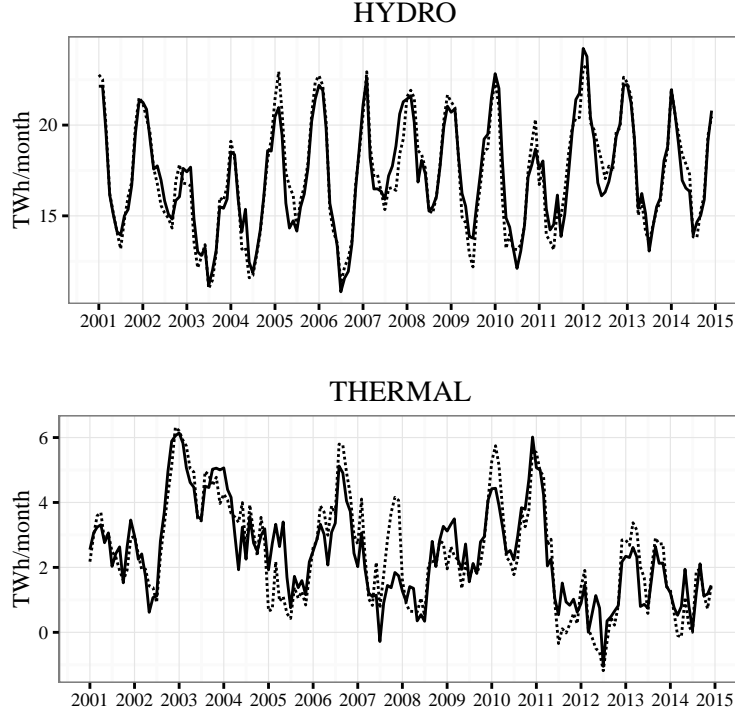


Figure 3: Actual (dotted lines) and the estimated (solid lines) hydro and thermal power policies (TWh/month) in years 2001–2014.

the inputs, and emissions rates.³⁷ We may regress the price on the fitted thermal policy directly as in (2) but, more appropriately, we use the state vector as instrument for the endogenous thermal output (to obtain almost identical point estimates).³⁸ We use the IV estimates in the analysis, reported in Table 4. For this specification, 1 TWh increase in output per month, that is, a change corresponding to a nuclear power unit, is associated with a 19 per cent increase in the output price. The actual historical and fitted prices from the estimation are depicted in Fig. 4.

The linear regression has conceptual advantages but it faces a number of practical challenges. Electricity supply is characterized by sharp short-run capacity constraints, and also must-run units with willingness to supply even with negative prices. The lin-

³⁷See Appendix A.5 for the detailed numbers and sources of data. A measurement error in marginal cost can lead to biased estimates. The problem is arguably less severe in electricity markets than in many other markets because there is relatively good expert knowledge of the technology (see, for example, Wolfram, 1999). The problem is also alleviated by the stability of the technologies and capacities during the time period considered (see Appendix A.10).

³⁸The IV just adds marginal cost information to the first stage regression. Note that estimated policy $q^{TH}(\mathbf{s}_t)$ already captures the systematic variation in the thermal power costs, arising from the availability of different types of capacity units during the seasons of the year.

Table 4

log(mc)	0.52 (0.03)***
Thermal	0.19 (0.01)***
Constant	1.25 (0.11)***
Observations	168
R ²	0.79
Adjusted R ²	0.79

Note: *p<0.1; **p<0.05; ***p<0.01

The table reports the IV estimates of the coefficients of the thermal supply. Standard errors are reported in parentheses. Marginal cost measure mc is a function of the input prices (Appendix A.5). The coefficient on Thermal reported per TWh of output. All data: monthly observations in years 2001–2014.

ear supply (the semi-log specification) ignores such nonlinearities but still captures the monthly price-quantity relationship quite well. We can see two explanations. First, a cross-border market is not a strictly closed system and, thereby, steeply rising or falling prices tend to lead to trade with the neighboring regions, which can take the edge off the capacity constraints. Second, strict capacity commitments at the hourly level are stipulated by the vagaries of the short-term market clearing but, at the monthly level, the capacities are more flexible.³⁹

Additionally, the monthly averages can in principle be driven by extreme events that might have become more frequent with increased wind power generation, potentially due to exercise of market power. We analyze the volatility of monthly prices constructed from the hourly observations in Appendix C. We find no systematic change in volatility over time, and, perhaps surprisingly, we also find that the increased wind generation has not at all contributed to the volatility.⁴⁰

Finally, although the volatility analysis is not indicative of systematic changes in the spot price distribution, the estimated supply may still not represent competitive bidding. Note that the empirical analysis as such does not require the assumption of competitive behavior; the same variation could also identify a non-competitive supply.

³⁹We have experimented with semi-parametric supply functions and flexible parametric forms to evaluate if allowing for nonlinearities changes the results. They do not. Linearity arises from these regressions as well, excluding the extremes ends of the supply where the departures from the linear shape are driven by a few observations.

⁴⁰In fact, the analysis suggests that prices have become more stable over time. One explanation is that after the forced entry of the subsidized wind generation, demand and supply meet more frequently on the flat rather than on the increasing part the supply curve.

But the counterfactual analysis can change, if the policies are highly sensitive to the market structure assumption. We return to this question after introducing the expected seasonal prices in the next Section.

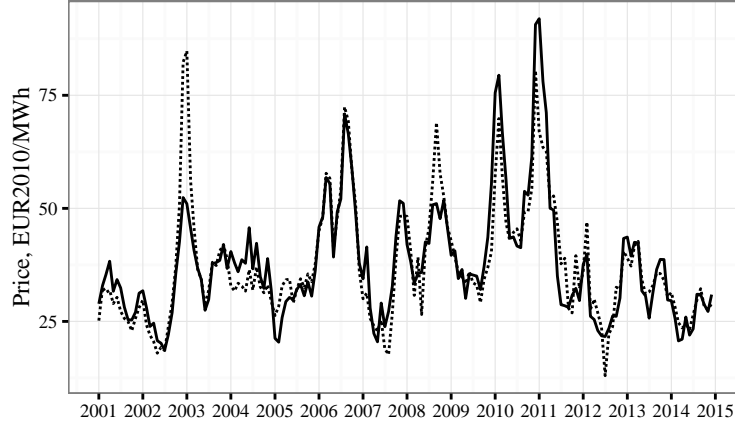


Figure 4: The historical (dotted lines) and fitted prices (solid lines) from the second-stage regression in equation (2), measured in 2010 €/MWh.

4.4 Invariant prices

The entry of wind power leads to changes in the output produced by the incumbents and prices in the market. To quantify the persistent changes, we consider how the expected seasonal outputs and prices are impacted. The expectations can be in principle obtained as follows: the policies estimated in the first stage generate invariant distributions for the state elements through $P(\mathbf{s}_{t+1}|\mathbf{s}_t, a(\mathbf{s}_t)) = P(\mathbf{s}_{t+1}|\mathbf{s}_t)$ (see Section 4.1). The outputs (first stage regression) and prices (second stage regression) follow from this invariant distribution. They are the key inputs to the quantitative assessment in the next Section; they also provide interesting insights to the dynamics of this market.

In Fig. 5, we depict the seasonal mean prices from the invariant distribution together with two confidence intervals, representing the parameter uncertainty (tighter interval) and also the state variation (wider interval).⁴¹ The trend in expected prices reflects the increase in scarcity as we move from Summer to Winter. Interestingly, as in Hotelling

⁴¹The practical evaluation of the seasonal mean prices can be done in three ways. (i) Taking the historical mean values for the elements in the state and computing the expected monthly price from the second-stage price equation gives the expected price conditional on the mean state. See Appendix D for the formal procedure for dealing with the error term distribution that impacts the conditional mean price. (ii) Specifying distributions for the elements in the state, such as inflows and demands, allows computing

(1931), there is a recurring trend return on holding the asset (inflow accumulated to the storage) from Summer to the end of the year; the price increase gives the return from holding the asset rather than using it. The positive expected return differentiates a natural resource from a storable good, illustrating empirically the observation in Williams and Wright (1991, p. 46). Hydroelectricity in this market is thus a natural resource within a year but a storable good over the years: storage to the next hydrological cycle can take place if the availability relative to the demand is good in the end of Winter. In other words, the prices are not expected to systematically increase over the Summer-Summer cycle; otherwise, there would be expected increase in scarcity over the years.

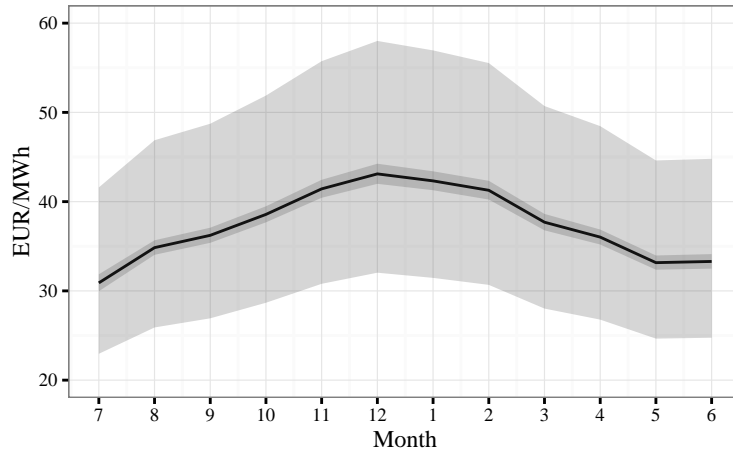


Figure 5: The monthly expected prices (in 2010 Euros/MWh), 95 % confidence interval (darker band) and 95 % prediction interval.

The seasonal price dynamics is important for the analysis. First, any given wind capacity generates relatively more power during the Fall and Winter than in other seasons (see Fig. 6, discussed below). This impacts the returns from saving the hydro resource for these seasons; thus, the storage policies could change if more wind power enters the market. The robustness analysis does not support this conclusion: the quantification using the dynamic program shows that the relative values of using the resource in different the state-contingent prices from the second-stage price equation and thus the price expectation. (iii) Historical realizations for the state lead to a sample of state-contingent prices, again from the second-stage price equation, with mean prices as estimates for the expected prices. Approach (ii), because of the imposed structure on the distributions, is less transparent than the other two approaches. We use approach (i) in the analysis, although the principle of certainty equivalence does not hold in our model. Approach (iii) produces almost equivalent results, suggesting that the practical evaluation of the expected price at the mean state comes close to evaluating the expected price over the sampled state space.

months do not change much (Appendix F). The explanation for this result follows from the next observation.

Second, in Fig. 5, we observe that the return from holding the resource in some months is greater than in others; the Hotelling model says that the return should be the same, equal to the earning from comparable assets.⁴² What explains the differential returns over the months? According to one hypothesis, capacity constraints in storage and potentially also other operational constraints prevent the equalization of returns over the seasons. Under suitably specified constraints, the observed returns can be reconciled with efficiency. Storage constraints mean that, in expectations, some fraction of the inflow that would be stored if the capacity allowed must be dumped on the market. This tends to depress the prices during the heavy inflow (Spring and Summer), relative to the unconstrained situation. The constraints cannot be directly observed but, in the analysis of Appendix F, we let the observed historical the minimum and maximum storage levels to define the capacities for storage.⁴³ The constraints can resolve the puzzle. They are indeed necessary for the efficient dynamic program to produce a seasonal pattern similar to the one estimated. Moreover, the constraints provide one explanation for why the policies are insensitive to wind generation: as a response to wind generation, the producers would have to allocate more output to months where the inflow of water is already forcing outputs to systematically exceed the levels prevailing in the absence of constraints.

According to another hypothesis, the seasonal price differences can be exacerbated by the exercise of market power by the storage holders. Crampes and Moreaux (2001) show that differential demand elasticities in the seasons lead to an overuse of the resource in some periods, increasing the scarcity and prices in other periods. In the quantitative assessment of Appendix F, we find that the planner would save somewhat more of the resource to the high demand season (Winter) than the estimated policies imply. Yet, this argument alone cannot identify market power since the same observational outcome results if we slightly modify the storage constraints.⁴⁴

⁴²This argument does not apply in the Spring since the scarcity gradually disappears by the arrival of the new endowment.

⁴³A detailed structural approach would need to capture the microstructure of constraints and reservoirs since the effective aggregate bite of the constraints depends on how the resource is distributed among the hundreds of reservoirs in the system.

⁴⁴One potential route to detecting market power is to consider empirically if the entry of wind power has affected the observed pricing pattern. All else equal, the entry of wind power changes the residual demand for the hydroelectricity. This has a different implication for the annual price increase depending on if competition is perfect or, alternatively, if there is a dominant resource holder who can influence the



Figure 6: The figure shows the historical mean monthly wind output (dotted line) and the fitted wind output (solid line) from a regression of wind generation on monthly dummies and time trend. Units are in TWh/month. Data from years 2001–2014.

5 Analysis of the rent transfer

We turn now to quantify the impacts of wind power entry on the consumers’ and incumbents’ surpluses. To capture the persistent incidence of impacts, the quantification looks at changes in the invariant prices and outputs, that is, in the seasonal means discussed above. The analysis builds on the following premises:

- I. To measure the pressure on the incumbent assets, we assume that the installed inframarginal capacity, other than wind, remains fixed.⁴⁵ Thus, the analysis assumes that there is no exit from or entry to the fleet of inframarginal units.⁴⁶

price. Under competition, the price difference between any two months should not change because of the demand change since, in equilibrium, this gap is fixed by the return achievable elsewhere. In contrast, under marker power, the price gap is sensitive to the change in the demand. We develop this argument formally in Appendix G. The above reasoning suggest an approach for detecting market power: has the entry of wind power observed so far impacted the seasonal price differences in the market? We look at the months in the end of year where the storage constraints are less likely to dominate. We take the observed spot prices at a given state and then produce the expected price for the next month using the observed state transitions in our price estimate. The few observations that we have are not suggestive of market power in storage (see Fig. G.13 in Appendix G).

⁴⁵The installed capacity has remained stable during the period 2001–2014 (see Appendix A.10). Wind generation has a historical rate of increase equal to one per cent per month (Fig. 6).

⁴⁶Hydro is a fixed factor and can evade the policy only if there is a political decision to restructure the market area. Nuclear can respond to policies by the timing of phasedowns. That nuclear is not strictly a fixed factor shapes the long-term interpretations of the estimates but it is not a problem for the gist

- II. It is assumed that the marginal generation (i.e., thermal) responds, on average, one-to-one to *permanent* increases in the wind generation: 10% increase in the annual wind generation must reduce the long-run thermal output by the same amount. Notice that temporary, short-run, changes in the wind output contribute to the residual demand variation, with a supply response captured by the estimates (Section 4.2). However, the long-run response of the incumbent supply cannot be obtained from the estimates. The annual hydro output cannot adjust by permanently saving inflows, so thermal power must be the adjusting margin.⁴⁷
- III. We increase the annual wind generation and allocate any given annual increase according to the estimated wind power monthly profile (see Fig. 6). Note that the entry profile of wind generation over the year is important for the evaluation because of the strong seasonality of the prices; see Section 4.4.
- IV. We consider wind scenarios ranging between 0–50 TWh of annual generation. The benchmark is 20 TWh of annual generation, about 5% of the market size and coming close to the mean generation over the past few years. Scenarios reflect the change of capacity underway. We take 50 TWh as the upper bound for the increase.⁴⁸ The current 20 TWh is the main case; 0 TWh provides a benchmark for evaluating the change in the market that has already taken place. Scenarios 30-50 TWh are for the forthcoming projects in the pipeline.⁴⁹
- V. The input prices are fixed and set equal to the historical averages in the data period.

of the analysis: we quantify the immediate pressure on the assets.

⁴⁷The total availability of hydro over time can be reduced only by spilling of water. However, spilling is regulated. We provide some description of the regulations regarding spilling in Appendix F; see also Kauppi (2009).

⁴⁸The actual wind power generation in 2015 was about 36 TWh. TEM (2012) has compiled, from various sources, the estimated increase for the total wind generation in the Nordic countries: 48 TWh in 2020.

⁴⁹ The results beyond 50 TWh are from *terra incognita*. The supply curve that we have estimated identifies a price-quantity relationship for generating units that have been active in the historical data. Since the entry of wind displaces exactly these marginal price-setting units, a sufficient entry implies that the price-setting units will be different from those observed in the past. Thus, the estimation does not identify a price-quantity relationship when the price-setting margin sufficiently evolves. 50 TWh of annual wind generation comes close to this limit. Because the reservation price for production is likely to drop faster than implied by the estimates if wind generation exceeds 50 TWh, the results close to this limit represent a conservative lower bound of the price reduction attributable to the wind power expansion.

Following steps I–V, we can obtain the seasonal mean prices (as in Section 4.4) and the associated annual mean prices for any given level of annual wind generation. This price is depicted in the Fig. 7. Only 2.5% market share for wind (10 TWh of 400 TWh) leads to a permanent mean price reduction of ca. 15%. A market share of 5% reduces the prices by 28%; the price level is cut by half when the share of the total generation for wind reaches 10%.

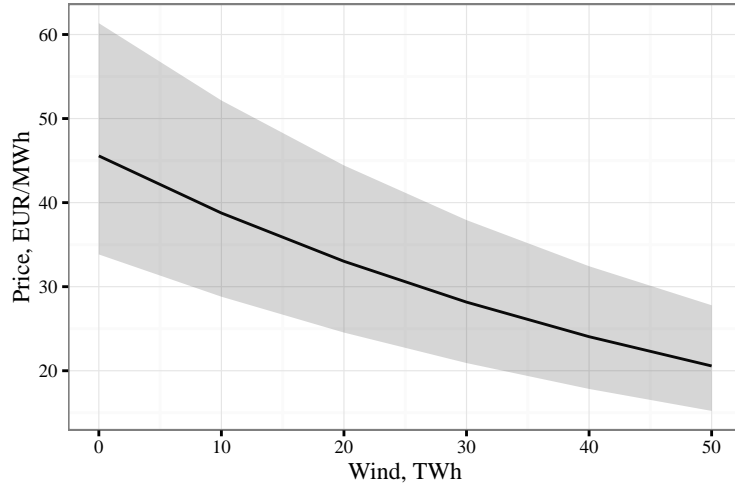


Figure 7: Annual mean prices (EUR/MWh) for varied annual wind generation levels (TWh/year). Confidence band is defined by 95% prediction interval for any given level of wind.

5.1 Consumer surplus

For the benchmark of 20 TWh of annual wind generation, we estimate that the consumers in the Nordic countries spend 12.61 billion euros annually on the wholesale electricity (Table 5). This estimate is obtained from the seasonal consumption profile and the invariant seasonal price profile for 20 TWh of annual wind generation.⁵⁰

The invariant mean expenditures have declined by 5 billion euros per year, attributable to new wind generation: without the wind generation already in place, the estimated expenditure would be 17.59 billion euros annually. This relatively small increase in new generation cuts the consumer expenditure by prodigious 28 %, almost equivalent to the price decline quantified in the previous Section. With 10 % market share for wind of the total, the expenditure declines by about one-half. The impact is economically significant

⁵⁰The confidence interval [9.37, 16.96] reflects to a large extent the variation in the monthly price distribution; the annual consumption profile are relatively stable and thus contributes relatively little to the variation in expenditures.

Table 5

TWh WIND	low estimate	mean	high estimate
0	13,059	17,586	23,685
10	11,059	14,880	20,022
20	9,369	12,606	16,962
30	7,940	10,693	14,397
40	6,734	9,079	12,244
50	5,712	7,719	10,433

The table reports the total annual invariant electricity market expenditures in the Nordic countries in millions of 2010 euros for TWh wind power generated. Low and high estimates from the 95 per cent confidence interval (invariant distribution).

— the Nordic region spends ca. one per cent of the regional GDP on procuring wholesale electricity.

The breakdown of expenditures across countries is in Table 6. The savings in expenditures are shared between the countries in proportion to consumptions. Majority of the new wind power locates in Sweden which, as the largest economy, is also the biggest consumer.

Table 6

TWh Wind	0	10	20	30	40	50
DEN	1,630	1,379	1,169	991	842	716
FIN	3,529	2,986	2,529	2,145	1,822	1,549
NOR	5,744	4,861	4,118	3,493	2,966	2,521
SWE	6,683	5,654	4,790	4,063	3,450	2,933
Total	17,586	14,880	12,606	10,692	9,080	7,719

The table reports the annual invariant electricity market expenditures by country in millions of 2010 euros for TWh wind power generated. Mean values reported.

The reduction in the expenditures defines the consumer side willingness to pay for the new wind generation units: how much consumers could subsidize every MWh generated by the new technologies without consumer-side budgetary implications? To obtain a measure for the consumers' willingness to pay, we take the expenditure reduction and divide it by the cumulative addition of wind generation. The results are reported in Table 7. Looking at the last row of the table, the Nordic consumers are willing to pay 271 euros per MWh of new generation for the first 10 TWh increment. This number exceeds by a large margin the subsidies seen in this region and elsewhere. In Finland, the feed-in tariff

sets a minimum price for the wind generators; it is currently at 83 €/MWh.⁵¹ Sweden together with Norway implement a subsidy scheme based on “green certificates”; each MWh renewable energy generated produces a certificate that can be sold to non-green producers. The subsidy payment is thus not collected directly from consumers. In 2003–2013, the certificate price has fluctuated between 20 and 30 €/MWh (Fridolfsson and Tangerås, 2013). It seems safe to conclude that consumers gain from subsidizing the new output up to 20 TWh per year; the willingness to pay is likely to exceed the actual paid subsidies up to 30-40 TWh of annual generation.

Table 7

TWh	10	20	30	40	50
DEN	25	10	6	4	3
FIN	54	23	13	8	5
NOR	88	37	21	13	9
SWE	103	43	24	15	10
Total	271	114	64	40	27

Consumer-side willingness to pay for MWh of wind generation: annual expenditure reduction (in 2010 euros) divided by the cumulative addition of wind generation (MWh), start from zero. Mean values reported.

5.2 Producer surplus by technology

Losses on the producer side present a mirror image of the consumer side gains.⁵² The hydro output presents about 50 per cent of total output on average, with around 7 billion annual invariant revenue in the 20 TWh wind scenario. The current wind power in the market has lowered prices by close to 30 per cent, leading to a loss of the same magnitude for the hydroelectricity producers (Table 8). Since this technology has low or non-existing out-of-pocket marginal costs, the estimated loss gives the loss of rents. The near-term wind projects in the pipeline (30-50 TWh of annual wind generation) imply another almost 3 billion annual loss of hydro rents. Recall that wind output increases most during Winter, which tends to compress the price differences between the seasons. Hydro operators lose both because of lower prices throughout the year and also because of lower returns from storage within the year. Nuclear power is a must-run capacity; it loses revenue in the same proportions as the hydro technology. Thermal power revenue

⁵¹The subsidy is scheduled to decline (TEM, 2012).

⁵²The difference in the producer and consumer side numbers is due to trade links.

is eliminated after 50 TWh of annual wind power generation.

Table 8

	0	10	20	30	40	50
HYDRO	9,588	8,119	6,883	5,843	4,966	4,226
NUCLEAR	3,943	3,343	2,839	2,413	2,051	1,751
CHP	2,323	1,958	1,649	1,391	1,176	992
THERMAL	1,927	1,229	708	314	26	0
WIND	0	395	672	852	961	1,021
Total	17,781	15,044	12,751	10,813	9,180	7,990

Annual invariant electricity market revenue losses by technology in millions of 2010 euros for Terawatt-hours WIND generated. Mean values reported.

5.3 Pass-through of emission allowance costs

The EU Emissions Trading Scheme (EU-ETS) sets a price on emissions that is factored into the supply reservation price for those units that use fossil fuels. As shown in Reguant and Fabra (2014), the pass-through of the emission cost can be close to 100%. We quantify next how the pass-through changes when the subsidized wind generation enters the market.

The EU ETS price affects the marginal cost through the amount of emissions from coal generation, 0.341 kgCO₂/MWh, and the assumed average efficiency of 36 %. Assuming no wind output, and increasing EU ETS from 0 EUR/tCO₂ to 50 EUR/tCO₂ leads to an estimated price increase of 24.18 EUR/MWh (Table 9). Given annual wind output of 50 TWh, the corresponding price increase is reduced to 10.94 EUR/MWh. Loosely, the result illustrates the disconnection between output prices and fossil-fuel input costs that will take place by year 2020. Historical prices (until year 2016) have been below 30 EUR/tCO₂.

The result is another side of the same coin that is the central theme of the paper: the incidence of subsidy costs following from subsidies is opposite to that under a market mechanism that sets a price on emissions. Moreover, as a result of subsidized entry to the market, the EU ETS may become redundant as an instrument for investments in clean technologies; the reward for investing in emissions-free technologies arises because of the pass-through. The development is consistent with the experience from the U.S. SO₂ trading program where overlapping regulations led to a similar demand destruction and to a final collapse of emissions allowance prices. (Stavins and Schmalensee, 2013).

Table 9

Wind TWh	EU ETS price (EUR/tCO ₂)					Change 0 → 50
	0	5	10	20	50	
0	39.76	42.80	45.64	50.84	63.93	24.18
10	33.84	36.43	38.84	43.27	54.41	20.58
20	28.83	31.04	33.10	36.87	46.37	17.54
30	24.60	26.49	28.25	31.46	39.57	14.96
40	21.02	22.63	24.13	26.88	33.80	12.78
50	17.98	19.36	20.64	22.99	28.91	10.94

Invariant electricity prices (EUR/MWh) for varied annual wind generation (TWh/year) and prices of emission rights (EUR/tCO₂) in the EU Emissions Trading Scheme (EU ETS).

6 Conclusions

Who bears the costs of climate policies in the end? If industries have to pay a lion's share of the costs, businesses may relocate, potentially undermining the acceptability of climate policies. The electricity sector produces the bulk of the carbon emissions and is among the first sectors facing policy-determined penalties on using fossil fuels. By familiar tax incidence arguments, these costs are further passed on to the consumer side if the consumer demand is inelastic which is typically the case in electricity markets.

We show that the cost incidence is reversed if, instead of pricing emissions, policies provide support for clean technologies: the electricity producers, rather than the consumers, end up paying a major part of the final cost of the new technologies. Subsidies to technologies that, once installed, operate with zero marginal costs—such as wind and solar power—lead to reduced final prices for outputs. If incumbent technologies earn scarcity rents and, in addition, cannot evade the policies that lower the output prices, part of the rents are transferred to the consumers. The rent transfer can be so complete that the climate policy cost falls entirely on the incumbents.

The argument in this paper is unorthodox. To what extent can it be expected to hold in other contexts as well? In general, subsidizing market entry implies changes (i) in the division of a given surplus from trading but also (ii) in the total surplus achievable. The Nordic setting is clean since it allows us to focus on the first item: the efficient dispatch of technologies is not distorted by subsidies. This is because the most expensive units to run are also the ones with the highest emissions intensity. The entrant technologies thus replace those incumbent technologies that should be replaced. The same conclusion does not apply, for example, in Germany, the leading nation supporting renewable energy.

More generally, policies have had significant adverse impacts also for relatively low-carbon assets in the EU. According to Caldecott and McDaniels (2014), the total low-carbon asset write-down of major EU utilities in 2010-2012, amounts to €22 billion. Similarly, The Economist writes (Oct. 12th 2013), in an article titled *How to lose half a trillion euros*, “Renewable, low-carbon energy accounts for an ever-greater share of production. It is helping push wholesale electricity prices down. For established utilities, though, this is a disaster. Their gas plants are being shouldered aside by renewable-energy sources.”

The problem with the asset destruction statements, as just above, is that the distributional and efficiency ramifications of climate policies remain indistinct. We have provided a clean quantification of the distributional effect that, we believe, is strongly present in other contexts as well. We see that our results present a challenge to future impact quantifications in other markets: the pure wealth transfer part of the policies should be isolated from the part of the asset destruction that is inefficient. Otherwise, the quantitative basis for evaluating the costs of policies implementing the energy transition remains unclear.

Finally, the results provide some insights on technology complementarities that are likely to shape future electricity markets — storage technologies combined with intermittently available sources of supply. Our case is special in that the storage precedes the entry of renewable power to the market. More commonly, the increased intermittency creates demand for the services of storage technologies. While the dynamics of entry of the two complementary technologies is not the focus of the current paper, such analysis cannot be performed before understanding how the technologies interact, once they coexist. We want to underscore that different storage technologies serve different purposes, and that a significant part of the social value in energy storage may arise from the ability to turn predictable but temporally available energy into a natural resource. This differentiates energy storage from standard commodity storage.

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ONLINE APPENDIX

A Appendix: data

Data used together with the code for replicating the results can be uploaded from: https://www.dropbox.com/sh/bel0c8pe14wq5fq/AABWSG-pjj_iMDd5EmaXdGIca?dl=0

A.1 Data sources

We have used the following sources of data:

1. DENMARK: Energinet.dk, the Danish Transmission System Operator (TSO)
<http://www.energinet.dk/en/el/engrosmarked/udtraek-af-markedsdata/Sider/default.aspx>
2. FINLAND: The Finnish Energy Industries
<http://energia.fi/tilastot/sahkon-kuukausitilastot-2014-2015>
3. NORWAY: Statistics Norway
<https://www.ssb.no/en/energi-og-industri/statistikker/elektrisitet/maaned/>
4. SWEDEN: Statistics Sweden
http://www.scb.se/sv_/Hitta-statistik/Statistik-efter-amne/Energi/Tillforsel-och-Manatlig-elstatistik/
5. NORD POOL: Nord Pool Spot AS, the Power Exchange
<https://www.nordpoolspot.com/globalassets/download-center/power-data-services/outline-nord-pool-spot-ftp-server.pdf>
6. EUROPEAN CLIMATE ASSESSMENT & DATASET (ECA&D)
file created on 13-01-2015. Klein Tank, A.M.G. and Coauthors, 2002. Daily dataset of 20th-century surface air temperature and precipitation series for the European Climate Assessment. Int. J. of Climatol., 22, 1441-1453. Data and metadata is available at: <http://www.ecad.eu>
7. THE FINNISH METEOROLOGICAL INSTITUTE
http://ilmatieteenlaitos.fi/c/document_library/get_file?uuid=827685fa-942d-4727-a&groupId=30106
8. EUROPEAN ENERGY EXCHANGE AG
Emission allowance prices

9. ENTSO-E (European Network of Transmission System Operators for Electricity)
Interconnection information

<https://www.entsoe.eu/publications/order-maps-and-publications/electronic-grid-maps/Pages/default.aspx>

10. THOMSON REUTERS
Input price data

DATA PERIOD: 2001–2014

The maximum time period for which the full data is available at the time of writing.

A.2 Data quality

The generation data in the analysis is at the monthly level, and all data has been corrected to 30 day months to remove the variations caused by shorter (e.g. February) and longer months. We also correct for the number of working days within a month. Electricity demand is higher during the working days (Mon-Fri) than during weekends and public holidays.

A.3 Supply

Equation 1 in the text provides the breakdown of output by technology, reproduced here

$$TOTAL.DEMAND = HYDRO + THERMAL + WIND + CHP + NUCLEAR.$$

HYDRO, WIND, and NUCLEAR is compiled from data sources 1-4. Combined Heat and Power (CHP) reported in data sources 2-4 is taken as traditional CHP that is run against heat or industrial load. In data source 1, CHP and THERMAL requires manual separation due to ambiguities in statistics. We have carefully implemented this separation through a breakdown of the Danish data reporting system (details available on request). We have also compared our CHP-THERMAL division to the one used by the industry analysts. Note that CHP can to some extent respond to prices in the hourly market. At the monthly level the CHP is driven by heat and industrial loads.

THERMAL includes trade with the neighboring regions (from data source 5). We add traded quantities as net supply (can be negative) to the thermal output in the Nordic region.

A.4 Demand

We use Heating Degree Days (HDD) as a measure of temperature in demand regressions. We construct “Nordic HDD” by using a weighted average of the HDD in the Nordic capitals, with weights defined by average consumptions. Source 6 provides the temperature data and source 7 the construction guidelines for the HDD.

A.5 Marginal costs

Short-run marginal cost (SRMC) is calculated as follows:

$$SRMC = \frac{COAL.PRICE + EUETS \times .341}{.36}$$

where EUETS is the emissions trading price (European Energy Exchange AG). Coal emission rate is 0.341 gCO_2/kWh (Statistics Finland), and the average power efficiency of condensing power plants is assumed to be 36 % (Statistics Finland). COAL.PRICE is from HWWI Coal Eurozone price index at Thompson Reuters Datastream.

A.6 Generation by technology

Table A.1

	HYDRO	THERMAL	CHP	WIND	NUCLEAR
DEN	0	20	7	8.1	0
FIN	13.4	12.1	25.6	0.5	22.2
NOR	127.5	0	2.5	1	0
SWE	66.6	0.8	13.2	4.3	62.7
Total	207.5	32.9	48.3	13.9	84.9

Annual generation in TWh/year by technology in the Nordic region. Average value in period 2001–2014. Thermal includes generation from condensing power plants and trade to thermal dominant regions.

Table A.2

	HYDRO	THERMAL	CHP	WIND	NUCLEAR
2001	213.3	31.4	45.0	4.9	91.2
2002	207.0	34.3	47.0	5.6	87.1
2003	169.2	57.9	49.5	6.5	87.3
2004	183.6	41.1	50.2	7.8	96.6
2005	222.8	12.9	47.5	8.2	91.9
2006	193.1	47.3	49.3	7.9	87.1
2007	215.7	30.5	48.7	9.7	86.7
2008	225.9	17.9	48.1	10.1	83.1
2009	205.6	27.2	51.4	10.5	72.8
2010	197.6	44.8	59.6	12.5	77.5
2011	200.8	22.6	52.8	17.7	80.3
2012	237.6	5.0	46.7	19.4	83.2
2013	203.3	28.1	46.2	23.6	86.4
2014	214.6	10.1	42.1	27.9	84.9

Annual generation in TWh/year by technology and year in the Nordic market. Thermal includes generation from condensing power plants and trade to thermal dominant regions.

A.7 Supply by source in the Nordic market

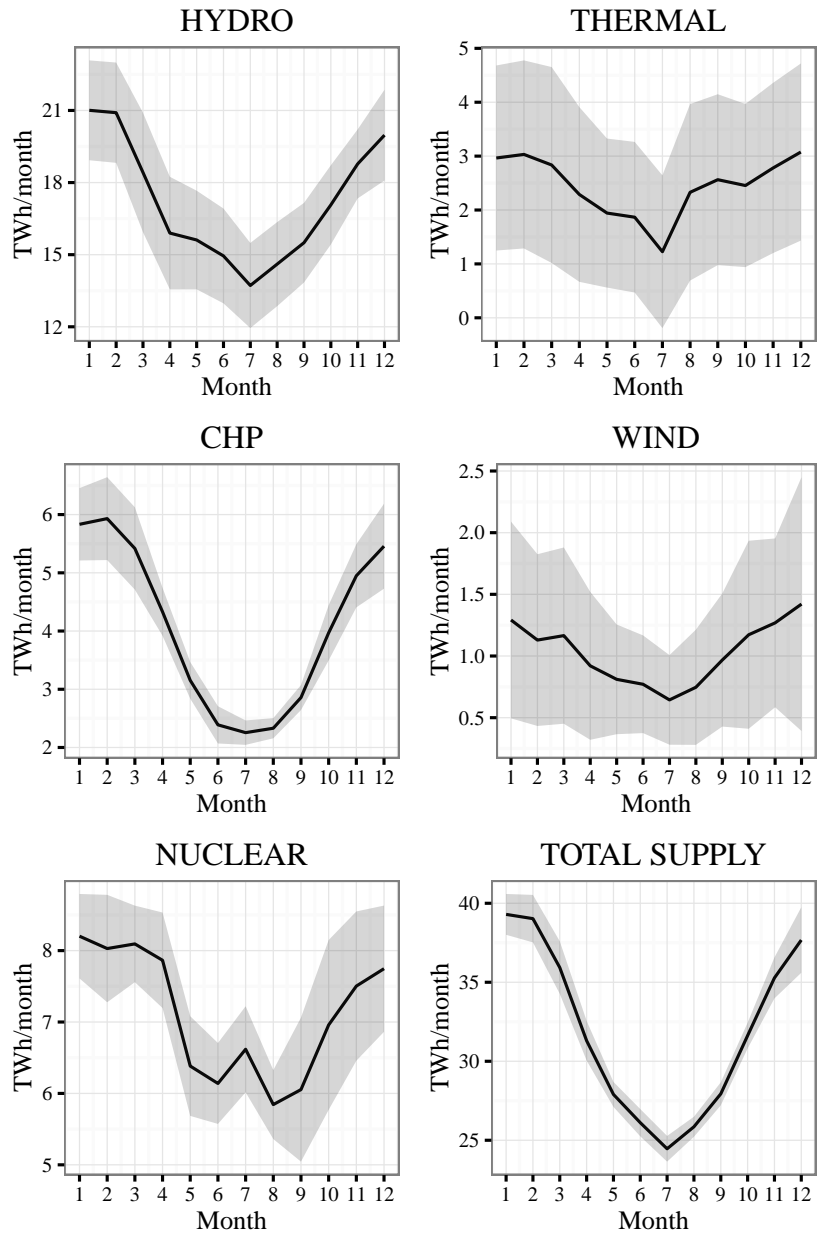


Figure A.1: Mean monthly supplies by source in TWh and +/- st. dev. bands in 2001–2014 in the Nordic market area. Thermal includes generation from condensing power plants and trade to thermal dominant regions.

A.8 Total and residual demands in the Nordic market

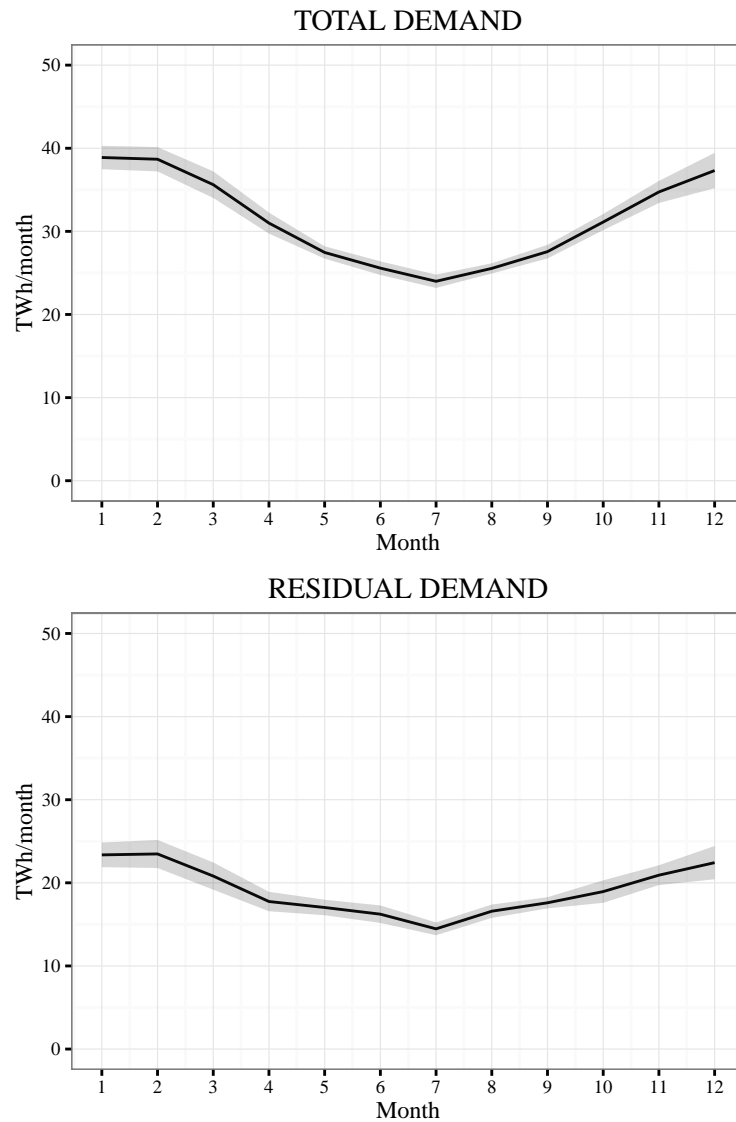


Figure A.2: Mean monthly total (D_t) and residual demands (d_t) in TWWhs, and \pm st. dev. bands in 2001–2014 in the Nordic region. The residual demand is defined by equation (1): $d_t = D_t - WIND - CHP - NUCLEAR$.

A.9 Total demand: regression fitted

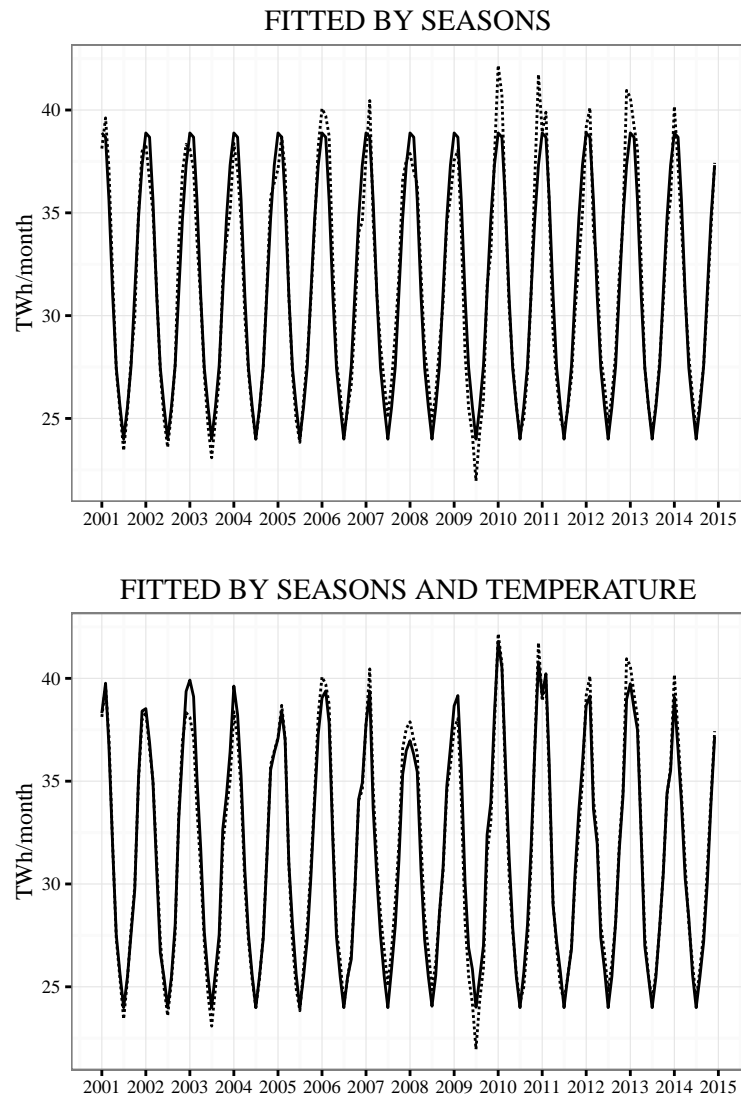


Figure A.3: Actual (dotted lines) and the estimated TOTAL DEMAND (solid lines) (TWWh/month) in years 2001–2014. Upper panel: actual and fitted values from TOTAL DEMAND regressed on seasons (column 1 of Table 1). Lower panel: actual and fitted values from TOTAL DEMAND regressed on seasons and temperature (column 2 of Table 1).

A.10 Installed capacity

In this Appendix we report the total quantity of the installed capacity in Gigawatts for different technologies in Denmark, Finland, Norway, and Sweden, and the interconnection capacities from and to Nord Pool area. The reported numbers are based on the authors' own calculations, using data obtained from the national system operators.

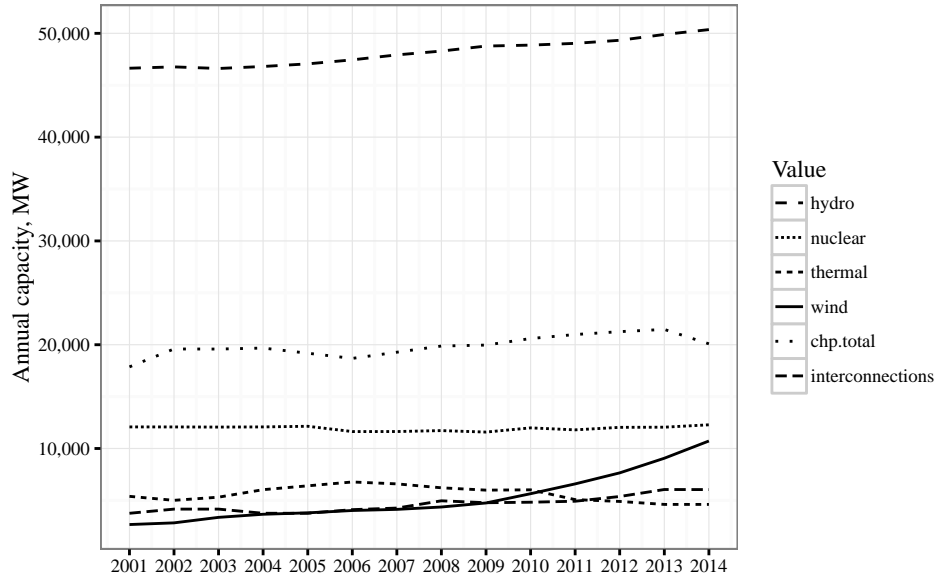


Figure A.4: The Figure depicts the development of the installed capacity in the Nordic countries in period 2001–2014 (measured at the beginning of the year). Transmission interconnections are for import capacity to the region. Authors' own calculations from variety sources, including the sources listed in Appendix A.

A.11 Mean deviations: data used in the first stage regression

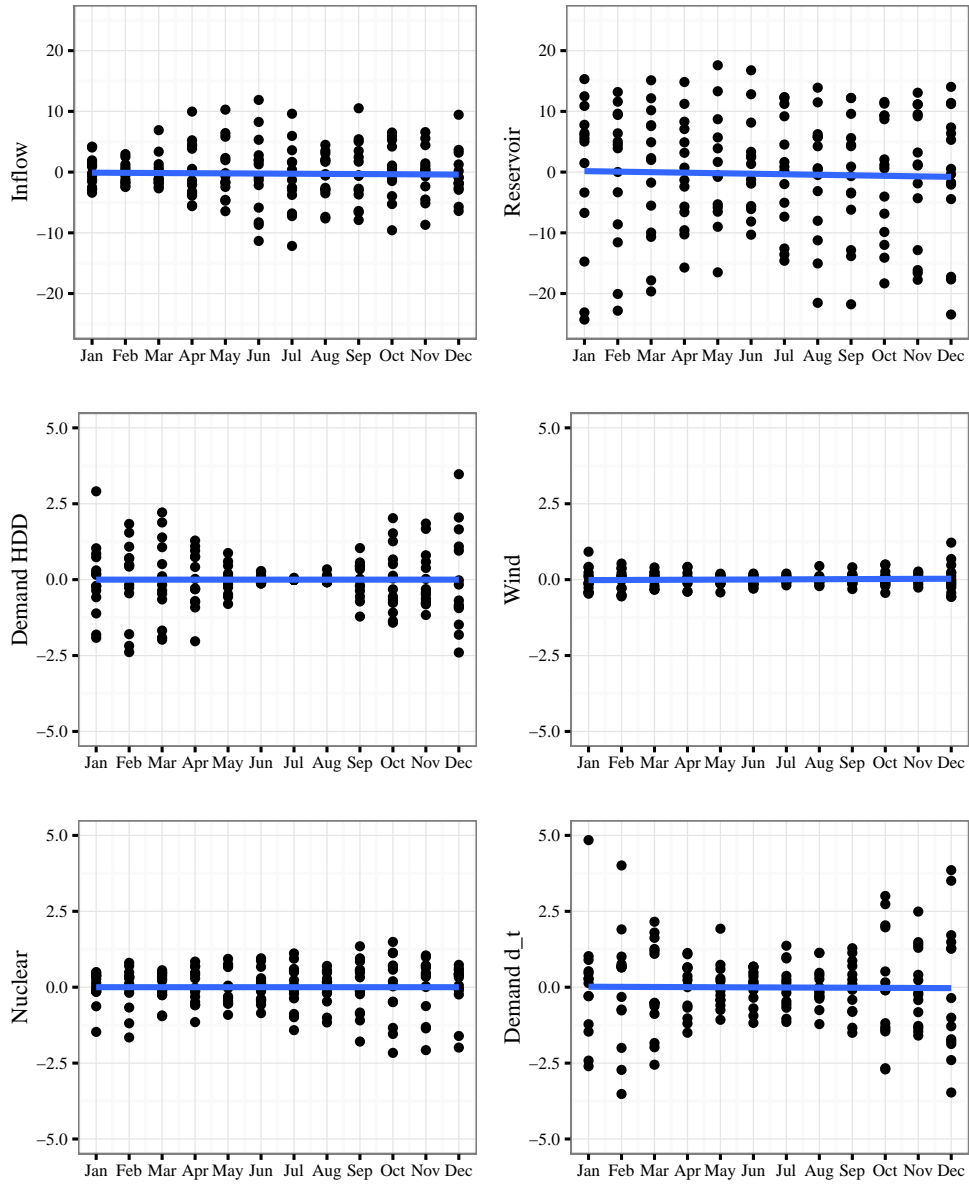


Figure A.5: Overview of the data used in the first stage regression. Top row shows the deviations of inflow from monthly mean values (left) and deviations of reservoir from mean values (right). Deviations in residual demand (bottom right) are constructed from temperature (middle left), wind (middle right), and nuclear (bottom left) deviations from their respective monthly means.

B Appendix: Hydro policy regression expanded

Table B.3

	(1)	(2)	(3)	(4)	(5)
Inflow		-0.001	0.05***	0.04**	0.04**
Reservoir		0.15***	0.16***	0.16***	0.16***
Demand dt			0.57***	0.57***	0.56***
Trend				0.10***	0.08***
log(mc)					0.25
Jan	21.01***	21.02***	21.02***	20.38***	19.60***
Feb	20.91***	20.93***	20.93***	20.28***	19.50***
Mar	18.42***	18.46***	18.48***	17.82***	17.04***
Apr	15.90***	15.91***	15.92***	15.25***	14.47***
May	15.61***	15.55***	15.52***	14.85***	14.08***
Jun	14.95***	14.86***	14.85***	14.17***	13.38***
Jul	13.72***	13.75***	13.82***	13.11***	12.33***
Aug	14.61***	14.72***	14.78***	14.07***	13.29***
Sep	15.50***	15.63***	15.66***	14.95***	14.18***
Oct	17.07***	17.19***	17.21***	16.50***	15.73***
Nov	18.77***	18.88***	18.89***	18.17***	17.41***
Dec	19.97***	20.08***	20.15***	19.42***	18.65***
R ²	0.63	0.86	0.91	0.92	0.92
Adjusted R ²	0.6	0.84	0.9	0.91	0.91
F Statistic	1109.4	2441.7	3507.3	3940.3	3718.6
Observations	168	168	168	168	168

Note: *p<0.1; **p<0.05; ***p<0.01

Hydro policy regressed on different sets of parameters. Column (1): seasonal dummies. Column (2): seasonal dummies + inflow + reservoir. Column (3): seasonal dummies + inflow + reservoir + trend. Column (4): seasonal dummies + inflow + reservoir + trend + temperature. Column (5): seasonal dummies + inflow + reservoir + trend + temperature + marginal cost. Units: inflow, reservoir, demand, and production is measured Terawatt hours. Variables "demand" and "reservoir" expressed as deviations from seasonal mean values. Robust standard errors for estimates in column 4: inflow 0.02, reservoir 0.01, demand 0.05, trend 0.01, and the month dummies in range 0.18 - 0.33. Note that inclusion of marginal cost in (5) does not affect point estimates in comparison to other columns, the estimate of log-valued marginal cost is relatively small, and the F Statistic decreases compared to model (4).

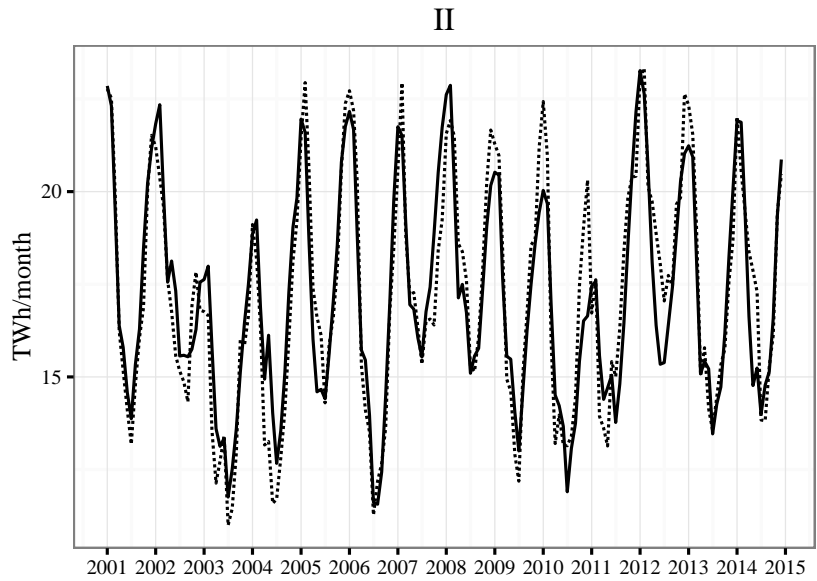
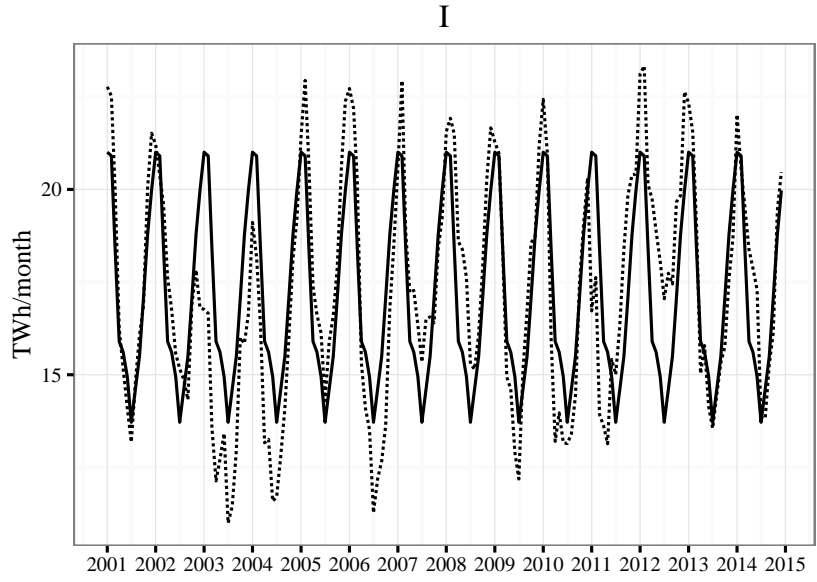


Figure B.6: Estimation results from Table 2. Solid lines = fitted values, dotted lines=actual. Hydro policies estimated on four sets of explanatory variables (TWh/month) in years 2001–2014. I: seasons. II: seasons+inflow+reservoir. Continues in Fig. B.7.

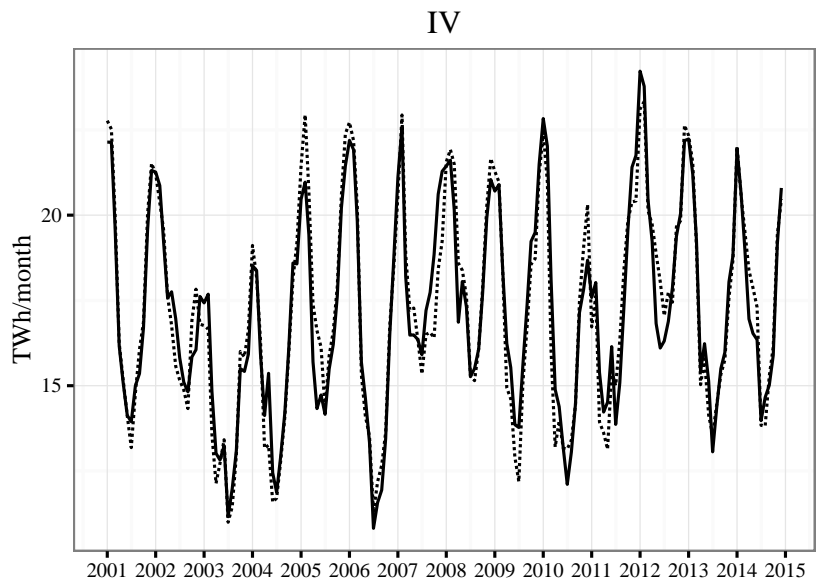
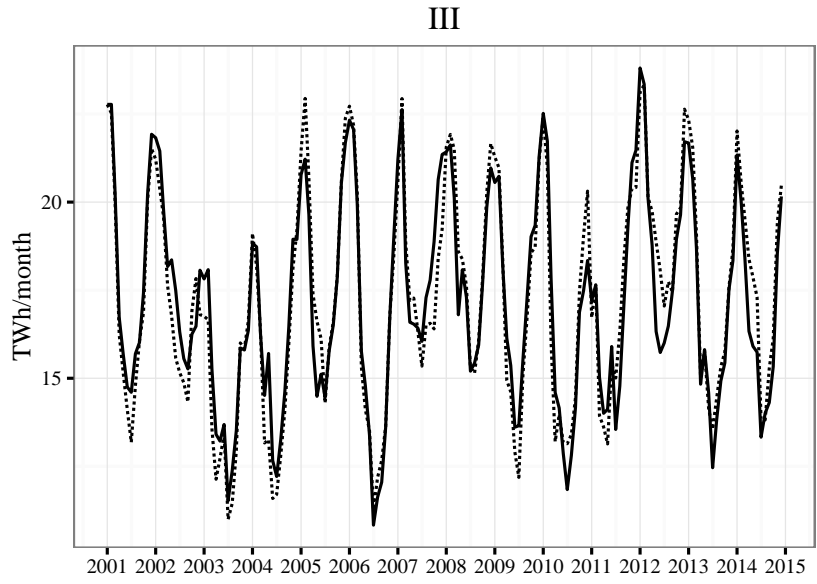


Figure B.7: Estimation results from Table 2. Solid lines = fitted values, dotted lines=actual. Hydro policies estimated on four sets of explanatory variables (TWh/month) in years 2001–2014. III: seasons+inflow+reservoir+demand. IV: seasons+inflow+reservoir+demand+trend.

C Appendix: Spot market volatility

If capacity concerns or market power become more important when there is more wind power generation, there should be changes in the hourly spot price volatility. We analyze next the determinants of the spot price volatility. Fig. C.8 plots the standard volatility measure constructed from the hourly observations for each month. The left panel shows the volatility over the data period: we do not observe a systematic increase or decrease in the volatility. The right panel ranks the months in the order of wind generation in each month and shows the volatility for each level of wind: we do not observe a relationship between wind generation and volatility.

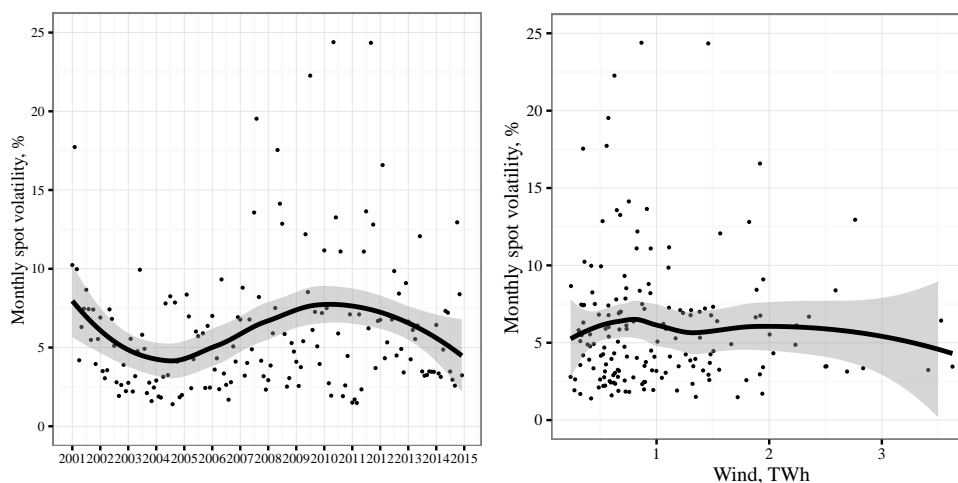


Figure C.8: Monthly spot price volatility in 2001–2014 (left panel) and monthly spot price volatility against WIND output during the same time period. Monthly spot price volatility is measured from the hourly spot price data, $\sigma^2 = \frac{1}{n-2} \sum_{i \in 2, \dots, n} (r_i - \bar{r})^2$, where $r_i = p_i/p_{i-1}$, \bar{r} is the mean of returns of the month, p_i spot price for the hour i , and n the number of hours in a month.

We then look more systematically at the determinants of volatility in Table C.4. Wind generation does not correlate with volatility, given the six sets of covariates presented in the Table. The variables are defined as in the main text. High inflows and cold temperatures seem to correlate with volatility. The wind and trend coefficients are small and not significant.

Table C.4: Regression of monthly volatility.

	(1)	(2)	(3)	(4)	(5)	(6)
Wind		0.10	0.02	0.06	-0.02	0.0002
Inflow			0.04***	0.06***	0.06***	0.06***
Reservoir			0.01***	0.02***	0.02***	0.02***
HDD				0.12***	0.11***	0.11***
Trend					0.01	0.01
MC						0.001
Jan	1.62***	1.49***	1.60***	-0.74*	-0.66	-0.69
Feb	1.60***	1.48***	1.59***	-0.76*	-0.68	-0.72
Mar	1.31***	1.19***	1.30***	-0.66*	-0.60	-0.63
Apr	1.39***	1.30***	1.37***	0.17	0.18	0.15
May	2.02***	1.94***	1.99***	1.59***	1.57***	1.54***
Jun	2.01***	1.93***	2.00***	1.95***	1.92***	1.89***
Jul	1.99***	1.92***	2.03***	2.03***	1.98***	1.95***
Aug	1.54***	1.47***	1.57***	1.54***	1.50***	1.47***
Sep	1.51***	1.41***	1.51***	1.15***	1.14***	1.10***
Oct	1.50***	1.38***	1.49***	0.31	0.34	0.30
Nov	1.33***	1.21***	1.33***	-0.37	-0.32	-0.35
Dec	1.41***	1.27***	1.42***	-0.74*	-0.66	-0.70
R ²	0.17	0.18	0.37	0.46	0.46	0.46
Adjusted R ²	0.11	0.11	0.31	0.4	0.4	0.4
F Statistic	109.2	101.6	115.7	127.1	119.4	112.2
Observations	168	168	168	168	168	168

Note:

*p<0.1; **p<0.05; ***p<0.01

D Appendix: Expected seasonal price

Using equation (2) and taking the expectations of log-price for given state \mathbf{s}_t yields

$$\begin{aligned} E[\ln p_t] &= E[\alpha_0 + \alpha_1 \ln mc_t + \alpha_2 q^{TH}(\mathbf{s}_t) + \epsilon_t] \\ &= \alpha_0 + \alpha_1 E[\ln mc_t] + \alpha_2 E[q^{TH}(\mathbf{s}_t)] \end{aligned}$$

The expectations of price is

$$E[p_t] = E[e^{\alpha_0} mc_t^{\alpha_1} e^{\alpha_2 q^{TH}(\mathbf{s}_t)} e^{\epsilon_t}].$$

If we assume normal error term, then this becomes a standard log-normal to normal transformation with $\sigma^2/2$. But if not, then the expectations of price for given a state, say the mean state $\bar{\mathbf{s}}_t$, needs to be corrected with $E[e^{\epsilon_t}]$ (for each month separately). This follows Duan, N., 1983. Smearing estimate: A nonparametric retransformation method. *Journal of the American Statistical Association*, 78, 605-610. We obtain

$$\begin{aligned} E[p_t | \bar{\mathbf{s}}_t] &= E[e^{\alpha_0} mc_t^{\alpha_1} e^{\alpha_2 q^{TH}(\bar{\mathbf{s}}_t)} e^{\epsilon_t} | \bar{\mathbf{s}}_t] \\ &= e^{\alpha_0} mc_t^{\alpha_1} e^{\alpha_2 q^{TH}(\bar{\mathbf{s}}_t)} E[e^{\epsilon_t} | \bar{\mathbf{s}}_t] \\ &= e^{\alpha_0} mc_t^{\alpha_1} e^{\alpha_2 q^{TH}(\bar{\mathbf{s}}_t)} E[e^{\epsilon_t}] \end{aligned}$$

We implement this in the analysis by obtaining $E[e^{\epsilon_t}]$ from the residuals for each month.

E Appendix: Robustness analysis

Table E.5

	(1)	(2)	(3)	(4)	(5)
Inflow		-0.001	0.05***	0.04**	0.05***
Reservoir		0.15***	0.16***	0.16***	0.12***
Demand dt			0.57***	0.57***	0.57***
Trend				0.10***	0.10***
Jan					0.05*
Feb					0.07**
Mar					0.10***
Apr					0.12***
May					0.03
Jun					0.03
Jul					0.02
Aug					0.03
Sep					0.02
Oct					0.004
Nov					-0.02
Dec					
Month FE	YES	YES	YES	YES	YES
R ²	0.63	0.86	0.91	0.92	0.94
Adjusted R ²	0.6	0.84	0.9	0.91	0.93
F Statistic	1109.4	2441.7	3507.3	3940.3	2696.8
Observations	168	168	168	168	168

*p<0.1; **p<0.05; ***p<0.01

Notes: Linear regression of the hydro output on the same sets of covariates as in Table 2 but the interactions between the reservoir and month added in column (5). The interactions for March and April confirm the economic reasoning explained in the main text. However, according to F-test, these interactions should not be included in the model.

Table E.6

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Inflow		0.001	0.06**	0.05*	-0.03	-0.003	0.01	0.01
Reservoir		0.15***	0.16***	0.16***	0.15***	0.12***	0.12***	0.12***
Demand dt			0.57***	0.57***	0.54***	0.50***	0.55***	0.56***
Trend				0.10***	0.10***	0.10***	0.10***	0.09*
Q1	20.11***	20.14***	20.14***	19.49***	19.48***	19.44***	19.45***	19.78***
Q2	15.49***	15.44***	15.43***	14.76***	14.74***	14.70***	14.72***	14.44***
Q3	14.61***	14.70***	14.75***	14.05***	14.04***	14.01***	14.03***	13.85***
Q4	18.61***	18.72***	18.75***	18.02***	17.99***	17.94***	17.97***	18.08***
inflow:Q1					0.12	-0.07	-0.15	-0.14
inflow:Q2					0.10	0.05	0.05	0.04
inflow:Q3					0.10	0.09	0.07	0.07
inflow:Q4								
reservoir:Q1						0.08***	0.08***	0.08***
reservoir:Q2						0.06*	0.06*	0.06*
reservoir:Q3						0.01	0.01	0.01
reservoir:Q4								
residual:Q1							-0.15	-0.14
residual:Q2							0.30	0.29
residual:Q3							-0.30	-0.27
residual:Q4								
trend:Q1								-0.03
trend:Q2								0.06
trend:Q3								0.04
trend:Q4								
Quarterly FE	YES	YES	YES	YES	YES	YES	YES	YES
R ²	0.53	0.76	0.81	0.83	0.83	0.84	0.84	0.84
Adjusted R ²	0.52	0.75	0.8	0.82	0.82	0.83	0.83	0.82
F Statistic	2790.9	3601.6	3908.3	3716.7	2702.1	2201.3	1811.1	1528.8
Observations	168	168	168	168	168	168	168	168

*p<0.1; **p<0.05; ***p<0.01

Notes: Linear regression of the hydro output on the same sets of covariates as in Table 2 of the main text but (i) monthly fixed effects replaced by quarterly fixed effects and (ii) full set of interactions added. Columns (1)-(4) reproduce the results from the main specification, Table 2. The point estimates remain robust to changes in the definition of the seasonal fixed effects. Columns (5)-(8) add the remaining interactions. According to F-test, the interactions should not be included in the model.

Table E.7

	Monthly 2001–2014	Quarterly 2001–2014
log(mc)	0.52 (0.03) ^{***}	0.53 (0.03) ^{***}
Thermal	0.19 (0.01) ^{***}	0.19 (0.01) ^{***}
Constant	1.25 (0.11) ^{***}	1.23 (0.11) ^{***}
Observations	168	168
R ²	0.79	0.79
Adjusted R ²	0.79	0.79

*p<0.1; **p<0.05; ***p<0.01

The table reports IV estimates of the coefficients of the thermal supply, with seasonal fixed effects specified as months (left) and quarters (right). Standard errors are reported in parentheses. Marginal cost measure mc is a function of the input prices. The coefficient on Thermal reported per TWh of output. All data: monthly observations in years 2001–2014.

Table E.8

	(1)	(2)
log(mc)	0.52(0.03) ^{***}	0.52 (0.03) ^{***}
Thermal	0.19(0.01) ^{***}	0.19 (0.01) ^{***}
Constant	1.25(0.11) ^{***}	1.26 (0.11) ^{***}
Observations	168	168
R ²	0.79	0.79
Adjusted R ²	0.79	0.79

The table reports IV estimates of the coefficients of the thermal supply, without (1) and with (2) interactions in the first stage regression. Standard errors are reported in parentheses. Marginal cost measure mc is a function of the input prices. The coefficient on Thermal reported per TWh of output. All data: monthly observations in years 2001–2014.

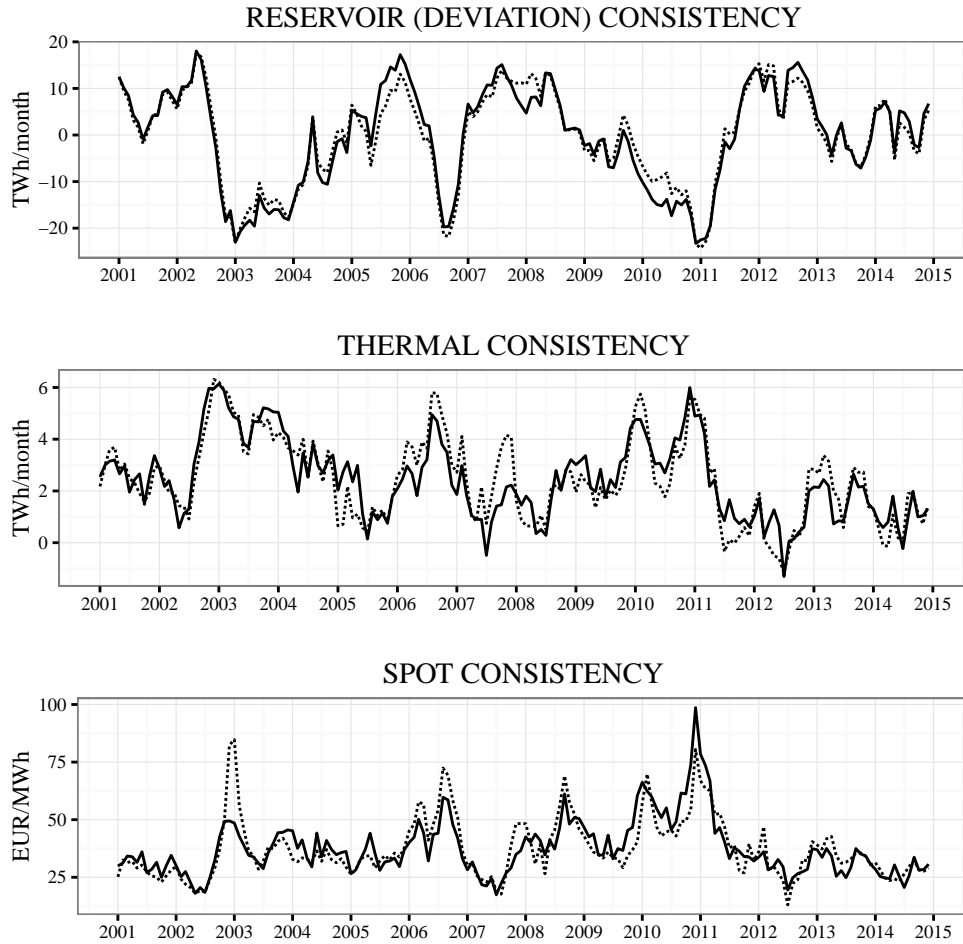


Figure E.9: The panel reports a consistency of check of the estimated policies. Here we do not take the observed hydro reservoir as data but we let the estimated hydro policy to generate the reservoir level for all months, except for the first month in the data (Jan 2001). The upper panel reports the actual and policy-generated change (Delta reservoir) in the storage level measured in TWh/month in 2001–2014. Both data series assume the same inflow data. The middle panel reports the thermal policy when we estimate the thermal policy using not the actual reservoir data but the data generated by the hydro policy. The lower panel reports the fitted spot price based on the thermal output from the middle panel and actual spot price.

F Appendix: Stochastic programming solution for the allocation problem

Solution strategy

To recap, we consider time $t = 0, 1, 2, \dots$ that is discrete and extends to infinity. State is vector

$$\mathbf{s}_t = (s_t, r_t, d_t, \omega_t, \theta_t),$$

where s_t is the amount of the water in storage, r_t is inflow, d_t is the residual demand, ω_t is the recurring season of the year, and θ_t exogenous state such as the input price. The value of the planner's program satisfies the Bellman equation,

$$V(\mathbf{s}_t) = \max_{a_t \in A(\mathbf{s}_t)} \{ \pi(\mathbf{s}_t, a_t) + \delta \mathbb{E}[V(\mathbf{s}_{t+1}) | \mathbf{s}_t, a_t] \},$$

where $\pi(\mathbf{s}_t, a_t) = -C(d_t - a_t, \omega_t, \theta_t)$ is the cost of meeting demand with the alternative technology. On a yearly level, the standard interpretation of the Bellman equation is that the marginal value of water in storage this year is the same as the discounted value next year (formulated early on in Little, 1955; and Lindqvist, 1962).⁵³ Within the year, the allocation takes into account the value of saving within the year, expectations for demand and inflows during the year, and the operational constraints for use of hydropower. Our implementation strategy breaks the problem precisely this way, to the year-to-year (outer problem) and the within-the-year problem (inner problem).

Formally, we optimize the actions in each state of the inner problem, taking as given the state-dependent value of water in the end of the year, coming from the outer problem. Value function iteration is applied to the outer problem to match the beginning and end of the year values.

First, we explain the detailed approach to the inner problem; the outer problem values are strongly dependent on these details. We face a trade-off between (i) the detailed inclusion of stochasticity and operational constraints, and (ii) the increase in dimensionality. We discretize the set of possible events (but not state space), and solve the resulting stochastic optimization problem. Second, we explain the quantitative choices regarding the primitives such as the transition probabilities, cost function, discounting, and the constraint sets. Finally, we report the quantitative results.

⁵³Lindqvist, J. 1962. "Operation of a Hydrothermal Electric System: A Multistage Decision Process." Transactions of the American Institute of Electrical Engineers. Part III: Power Apparatus and Systems, 81(3): 1-6. Little, John D. C. 1955. "The Use of Storage Water in a Hydroelectric System." Journal of the Operations Research Society of America, 3(2): 187-197.

Within-the-year allocation: the inner problem

We discretize the set of events. Formally, the uncertainty is modeled by a non-recombining discrete time scenario tree, \mathcal{K} , whose states, or nodes, are denoted by $k \in \mathcal{K}$. Expectation are calculated using probability measure P that defines for each node in the tree probability p_k . With these probabilities, the planner can obtain the probability of each contingency defined by the tree. The year is divided to months, $\omega \in \mathcal{T}$. \mathcal{K}_ω denotes the set of nodes $k \in \mathcal{K}$ at time ω and $\tau(k)$ gives the time step of the node k . Let $\tau(k) = \bar{t}$ denote the last time step in the year; $\mathcal{K}_{\bar{t}}$ is the set of nodes at the last step. Node k_0 is the root node. Each node k , except the root node, has an unique ancestor node given by $h(k)$. In the numerical implementation we define the tree structure such that the initial node is in the past so that the tree has a structure rich enough for the calibration of events in all months.

The decisions at each node are *non-anticipatory*. That is, given the resource inherited from the previous node, decisions are made before the information about inflow and demand has become known. The set of feasible hydropower generation strategies $\mathcal{A}(k)$ consists of those actions that fulfil the storage dynamics and operational boundaries, for $i = 1, \dots, N$ reservoirs:

$$\begin{aligned} s_k^i &= s_{h(k)}^i + r_k^i - a_k^i - q_k^i, & \forall k \\ \underline{s}_{\tau(k)}^i &\leq s_k^i \leq \bar{s}_{\tau(k)}^i, & \forall k \\ \underline{a}_{\tau(k)}^i &\leq a_k^i \leq \bar{a}_{\tau(k)}^i, & \forall k, \end{aligned}$$

where r_k^i indicates the inflow to the storage i in node k , a_k^i the energy used, and q_k^i the spillage. Variable q_k^i must be included since, in some states, there is a minimum flow of water through the system, due to environmental regulations, for example. Note that the operational constraints are depend on the time step, rather than on the state; the constraint is the same for all nodes in that time step.⁵⁴

The gains are defined by the cost function of the alternative technology. In addition, the part of the water that is not allocated for the year at hand is valued at the end of the year. Given the stochastic structure, the optimal allocation solves:

$$\min_{a_k^1, \dots, a_k^N \in \mathcal{A}} \sum_{k \in \mathcal{K}} p_k \delta^{\tau(k)} C(d_k - \mathbf{a}_k, \tau(k), \theta) - \sum_{k \in \mathcal{K}_{\bar{t}}} \delta^{\tau(k)} p_k \sigma_k, \quad (3)$$

where \mathbf{a}_k is the sum of usage in node k , p_k is the probability of a node and σ_k is the value of water at the final stage. The cash flows are discounted to time $t = 0$ with factor

⁵⁴This is due to our calibration where we let the historical minimum and maximum values determine the seasonal constraints.

δ . The value of this program defines the value function at the beginning of the year; the outer-problem value iteration matches the final and initial values of the program.

To obtain a sufficient description of the stochasticity, the number of scenarios in the stochastic tree needs to be large enough. We solve the stochastic problem directly by using a binary tree with up to 21 time-periods or over 2 million scenarios⁵⁵. The allocation problem is solved within R by using AMPL stochastic programming language and MOSEK solver. Thus, we solve the inner problem as a nonlinear convex stochastic optimization problem (see, e.g., Birge and Louveaux, 1997) since we find it easier to handle the dimensions of the problem this way than using dynamic programming.⁵⁶ Conceptually, there is no difference to the dynamic programming outcome in our setting; straightforwardly, the methods in Stokey and Lucas (1993) apply in a discrete tree structure.

Quantitative choices

Operational constraints for hydropower are set by the physical size of a storage and installed generation capacity. In addition, hydropower generation possibilities are limited by operational and environmental regulations⁵⁷. The regulatory boundaries for the hydropower are often time-dependent. On a detailed level, hydropower river systems can be very complex, e.g. generation from one power plant can be dependent on another further upstream. In our aggregated framework, constraints are set on the basis of observed aggregate history for usage and storage in period 2001–2014 (data sources: Appendix A). The Nordic market area is modelled on a high level aggregation with one reservoir system for each country (Denmark, Finland, Norway, and Sweden). Thus, there are four reservoirs, $i = 1, \dots, 4$. In practice the outcome is determined only by the Norwegian and Swedish reservoirs, as Denmark’s hydro resource are almost non-existent and the optimization of Finnish hydropower is very limited.

We assume that both demand and hydrological inflows distributions have seasonality within the year but over the years the distributions remain the same. We obtain these dis-

⁵⁵The scenarios are constructed by setting the start month earlier than the start of the year, so that there is enough variation at the start of the value iteration.

⁵⁶Birge, J.R., and F. Louveaux. 1997. *Introduction to Stochastic Programming*. Springer-Verlag, New York.

⁵⁷Hydropower changes the natural fluctuations in river flows and water reservoir levels. These changes cause external effects to the environment and the society, including erosion of river banks, changes in flooding, degraded juvenile and spawning habitats for fish and nesting habitats for birds, and decreased possibilities for recreational uses of rivers and lakes.

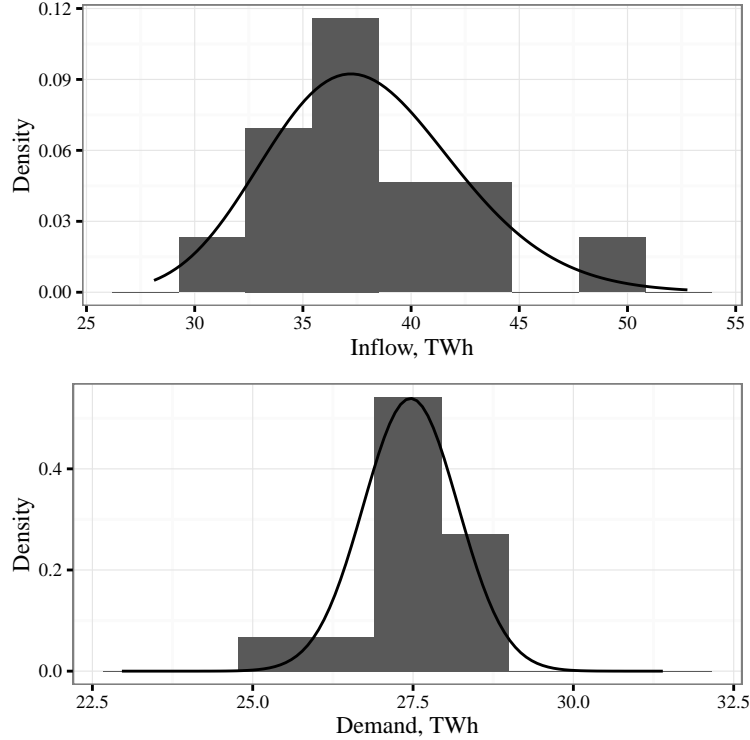


Figure F.10: An illustration of inflow and demand frequencies in one month (May), obtained from data for years 2001–2014.

tributions from the data for years 2001–2014. For demand, we consider residual demand for the hydro directly and work with monthly distributions, assumed to be Gaussian with first and second moments matched to the data. Similarly, we match monthly inflow distributions, assumed to be log-normal. Fig. F.10 illustrate the inflow and demand frequencies in one region (Norway) for in one month (May).

Cost function $C(d_t - a_t, \omega_t, \theta_t)$ is obtained from our empirical analysis. That is, the second-stage regression analysis identifies a relationship between prices and thermal quantities,

$$\ln p_t = \alpha_0 + \alpha_1 \ln mc_t + \alpha_2 q^{TH}(\mathbf{s}_t) + \epsilon_t.$$

We evaluate the supply curve using the estimated parameters, and, through integration, obtain the cost function to be used in computations.

Discount factor corresponds to 4 % discount rate for annual returns. The results are not very sensitive to the choice of the discount rate, as long as we remain below 10 %. Intuitively, the stochasticity and operational constraints within the year are strongly shaping the storage dynamics; the savings for the longer term are less important.

To clarify a potential source of confusion, it should be noted that the first-stage estimate hydro policy does not enter the simulation exercise set up here but the only the

estimated supply curve for thermal power. In the computational exercise, we only use the estimated parameters and let the optimal solution to determine how much thermal and hydro power should be used in each month.

Quantitative results

The quantification seeks to answer two questions.

1. Does the estimated policy function and optimal policy from the dynamic program resemble each other? This question addresses the robustness of the estimation.
2. Does the policy from the dynamic program change when we add more wind power to the system. This second question addresses the robustness of the counterfactual analysis: adding more wind to the market changes the seasonal distributions for the residual demand left for hydro and thermal power. If the optimized policy is not quantitatively sensitive to such changes, more trust can be placed on the analysis building on the estimated policy.

Considering the first question, recall that the policies estimated in the first stage generate invariant distributions for the state elements through $P(\mathbf{s}_{t+1}|\mathbf{s}_t, a(\mathbf{s}_t)) = P(\mathbf{s}_{t+1}|\mathbf{s}_t)$. We proceed now as in Section 5 (counterfactual analysis), except that we fix the monthly wind generation patterns so that the annual generation is 20 TWh/year. Then, we use the estimated hydro policy to produce invariant hydro outputs per month. The result is depicted in see Fig. F.11 that shows the monthly output (together with the 95% confidence bounds from the estimation). The optimized policy generates predictions that are within the confidence bounds for the estimated policy, excluding a deviation in the Summer months.⁵⁸

Considering the second question, we produce the expected seasonal outputs from the optimization model for different levels of annual wind generation. We scale up the wind generation as in the main text (Section 5), and report the seasonal hydro generation patterns in Table F.9. The seasonal pattern remains stable. This stability is explained by the operational constraints of the hydro technology, as discussed in the main text.

⁵⁸The deviation can be explained by constraints that may in reality be more complex than those assumed. The optimized storage level is higher (hydro generation lower) than in the estimated policy because of minimum flow constraints for outputs: there is a chance of very low inflows during the winter that would lead to a breach of the minimum constraints. The constraint forces the optimization model to store more water prior to the Winter months.

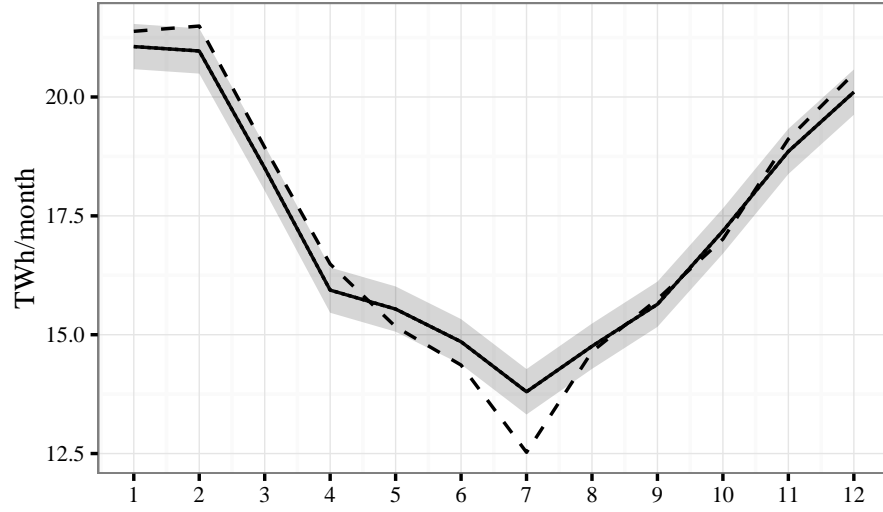


Figure F.11: The invariant thermal output obtained from the estimated thermal policy (solid line and 95 % prediction interval) compared to the mean seasonal output generated by the optimization model (dashed line).

		TWh/year					
mo	0	10	20	30	40	50	
1	21.6	21.4	21.2	21	20.8	20.6	
2	21.6	21.5	21.5	21.4	21.4	21.4	
3	19.0	18.9	18.8	18.7	18.6	18.5	
4	16.4	16.5	16.5	16.6	16.7	16.9	
5	15.0	15.2	15.2	15.3	15.3	15.3	
6	14.2	14.4	14.4	14.5	14.6	14.7	
7	12.3	12.5	12.5	13.0	13.2	13.3	
8	14.5	14.6	14.8	15.0	15.1	15.3	
9	15.7	15.8	15.8	15.8	15.9	15.9	
10	17.1	17.0	17.0	16.9	16.9	16.8	
11	19.2	19.1	19.0	18.9	18.9	18.8	
12	20.9	20.5	20.5	20.4	20.3	20.1	
Tot.	207.4	207.4	207.4	207.6	207.7	207.6	

Table F.9: In the table we scale up the annual wind generation following the steps outlined in the main text (Section 5), and report the mean monthly output generated by the optimization model.

G Appendix: analysis of demand changes on storage and market power

The allocation problem: efficient solution

Consider a simplistic setting for allocating a given output capacity over two periods, $t = 1, 2$. We intent to model a storage decision where a given remaining capacity is to be allocated between the current period (Fall) with known demand and the end of year (Winter) with uncertain demand. We want to understand how a change in the riskiness of demand at $t = 2$ impacts the allocation; this is a thought experiment where the expected (residual) demand for the hydro resource becomes more volatile due to the entry of wind power.

Let y denote the quantity of output from the perfectly storable good (hydro), allocated to $t = 2$. Price at $t = 2$, for given demand x , is

$$p_2 = \begin{cases} 0 & \text{if } x \leq y \\ c & \text{if } x > y \end{cases} \quad (4)$$

where 0 arises because the storage available exceeds the demand; $c > 0$ is the marginal cost of reproducible output to be used in case of demand exceeding storage.⁵⁹ Let $F(x)$ denote the cumulative distribution function for x , defined on \mathcal{R}_+ , and satisfying the monotone hazard rate assumption: $h(x) = \frac{f(x)}{1-F(x)}$ is monotonically increasing.

Let $p_1 > 0$ be a given fixed output price at $t = 1$. Price p_1 is taken as given since, implicitly, there is abundant capacity to meet the demand at $t = 1$. The idea is that just before the winter ($t = 1$) there is typically plenty of capacity relative to the demand, and the supply price of this capacity fixes price p_1 . But the availability cannot be taken for granted in the winter, and this motivates storage to $t = 2$.⁶⁰

With this setting in mind, consider the expected price from allocation y committed to $t = 2$

$$\mathbb{E}p_2 = (1 - F(y))c \quad (5)$$

so that efficient allocation must satisfy, in the absence of discounting,

$$p_1 = \mathbb{E}p_2 \Rightarrow p_1 = (1 - F(y))c. \quad (6)$$

⁵⁹In reality, the potential excess storage is not wasted but kept in reservoirs over the Winter to the Spring where the endowment for the next year arrives. Thus, 0 is a normalization, capturing the idea that scarcity may disappear in the Winter, instead of the Spring.

⁶⁰The overall price level for $t = 1, 2$ is endogenous in the full model; here, only the price at $t = 2$ is endogenous. This simplification is not relevant for the analysis in this Appendix.

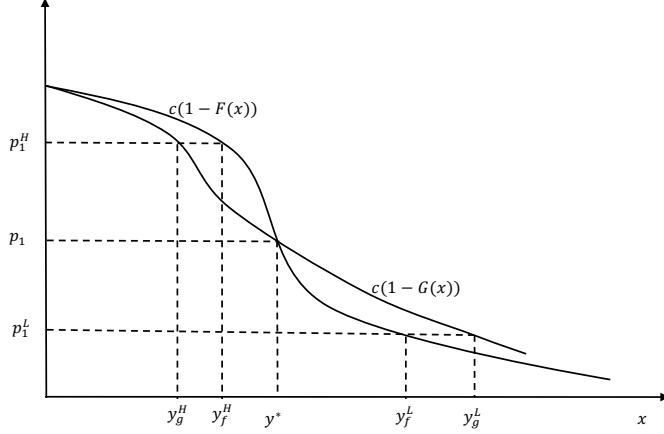


Figure G.12: The result in Proposition 1 illustrated.

Denote the solution to (6) by y^* . We now construct a mean-preserving spread around y^* by monotonic transformation $\alpha(x)$, satisfying

$$G(x) = F(\alpha(x)) \quad (7)$$

$$\int x dG(x) = \int x dF(x), \quad (8)$$

and $G(x) \neq F(x)$ for all x but $x = y^*$. Thus, distribution G is more risky with more mass on the tails: both very low and very high realizations of demand are more likely than under F .

We are interested in the implications of changes in risk, as captured by G , on the efficient storage. To this end, we vary period $t = 1$ base price from p_1 . This is important since the risk has a different impact depending on whether the overall availability of capacity is poor or good. Call the market tight when the availability is poor and the first period price is high: $p_1^H > p_1$. The market is slack if $p_1^L < p_1$.

Proposition 1 *Consider efficient market allocation for the two distributions, G and F . For a tight market ($p_1^H > p_1$),*

$$p_1^H = (1 - G(y_g^H))c = (1 - F(y_f^L))c \Rightarrow y_g^H < y_f^H \quad (9)$$

For a slack market ($p_1^L < p_1$),

$$p_1^L = (1 - G(y_g^L))c = (1 - F(y_f^L))c \Rightarrow y_g^L > y_f^L. \quad (10)$$

The proof is illustrated in Fig G.12. Thus, quantities respond to the increase in the riskiness in the opposite directions in the two cases, and there are no observational implications for the prices: an outside observer could not infer from the prices alone the perception of risk that the market is holding. Moreover, if we think that p_1 represents *ex ante* expectation of the market tightness, the deviations are expected to occur in both directions – whether the increased risk systematically increases the overall savings does not follow from the first principles but requires a quantitative assessment.

Market power

We continue with the same setting but assume now that the storage decision is made by a monopolist. We are interested if the exercise of market power is detectable from the market prices when the distribution changes from F to G .

Let us denote the quantity saved by the monopoly to period $t = 2$ by q . The monopoly evaluates the expected marginal revenue from saving q :

$$\frac{\partial \mathbb{E}[p_2 q]}{\partial q} = (1 - F(q))c - F'(q)cq = (1 - F(q))c[1 - h(q)q]. \quad (11)$$

For given p_1 , the monopoly allocation is given by

$$p_1 = \frac{\partial \mathbb{E}[p_2 q]}{\partial q} \Rightarrow p_1 = (1 - F(q))c[1 - h(q)q] \quad (12)$$

Let $\mathcal{G}(q) = \mathbb{E}p_2 - p_1$ denote the gap between the current price and the expected next period price. Clearly, for the efficient allocation, we have $\mathcal{G}(q^*) = 0$. The next result shows that the price gap is positive for the monopoly, and also that the gap varies with the perception of risk, captured by the two distributions F, G (the allocations are denoted with q^f, q^g , respectively).

Proposition 2 *For the monopoly, there is shortage of savings, $q < y^*$, leading to a price gap, $\mathcal{G}(q) > 0$. The price gap varies with risk: $\mathcal{G}(q^f) \neq \mathcal{G}(q^g)$.*

For the proof, note that hazard rate $h(q)$ is increasing so q is well defined. That $q < y^*$ follows from comparing the optimality conditions. Using definitions, the price gap can be written as $\mathcal{G}(q^f) = f(q^f)q^f c$, and $\mathcal{G}(q^g) = g(q^g)q^g c$ for distributions F, G , respectively. Thus, the gap reflects directly the slope of the marginal revenue curve which is different in the two cases.

The result is nothing more than the standard observation that market power is detectable if pricing outcomes are responsive to demand changes. The competitive outcome

always equalizes the expected price with cost that in our context is the opportunity cost of selling with price p_1 . The monopoly deviates from this principle by optimally allowing the expected price to respond to changes in demand (i.e., changes in riskiness).

Forecast for the first quarter of the year, Q1 in Fig. G.13, is the expected value for the spot price based on the estimated policy and price functions. We calculate the expected value with Monte Carlo simulation. The starting point is fixed as state s_t in November, after which we sample random deviates for inflow and residual demand. We then use estimated functions to calculate the *HYDRO* and *THERMAL* policies and price. *HYDRO* policy is used to update the reservoir state in s_t . The limited data is not suggestive of changes in the gap between the current and Q1 expected prices over the years depicted.

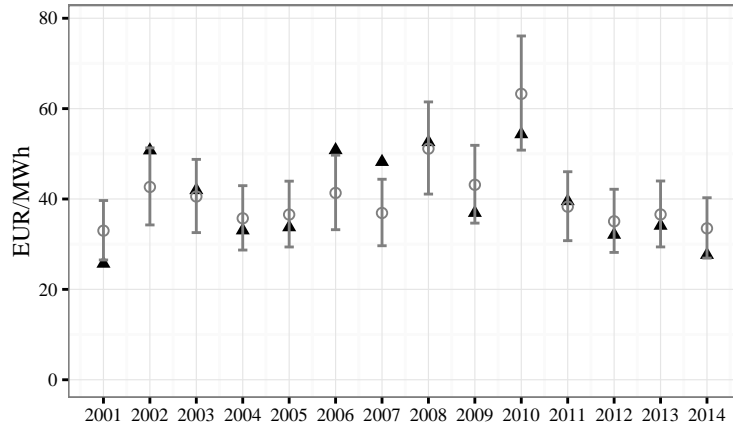


Figure G.13: Comparison of actual spot in November (black triangle) to forecast for Q1 the following year (mean and 95 % confidence interval).

H Appendix: A model of the policy cost incidence

Section 2 lays out a distributional argument for subsidies, relying on a dynamic model of renewable energy. We develop such a model in this Appendix. Time $t \in [0, \infty)$ is a continuous variable. It is first suppressed in the description of demand and supply (Section H.1).

H.1 Demand and supply before entry

Quantity demanded is given by a strictly downward sloping and continuously differentiable demand function $D(p)$, with p denoting the price. Let $S(Q)$ denote the inverse

supply, with two distinct segments:

$$S(Q) = \begin{cases} c, & Q \leq K \\ c + x, & Q > K. \end{cases}$$

Parameter $c > 0$ denotes the supply reservation price (marginal cost) for the low cost capacity of size K . Parameter $x > 0$ measures the cost disadvantage of the higher cost capacity. Capacity K is carbon free while any production $Q - K$ releases one unit of carbon per output. We denote $F = Q - K$ (where F stands for 'fossil'). Also, we assume

$$D(c + x) > K$$

which implies that the market price satisfies $p = x + c = D^{-1}(Q) = S(Q)$, with positive carbon output $F > 0$. Further, x includes not only the private cost of the carbon technology but also the social cost of carbon: x is the carbon price. To emphasize, x includes all social costs of the input use. Rent to the carbon free capacity is $(p - c)K = xK$, if $F > 0$. This rent attracts new entry to the market.

H.2 Entry of non-carbon technologies

We assume unlimited mass of potential entrants. Each marginal entrant faces an entry cost I_t at time t , per unit of installed capacity. We denote the installed capacity at time t by R_t (where ' R ' stands for renewables). Specifically, the investment cost evolves according to

$$I_t = I^\infty + \Delta \exp(-\theta t)$$

where $I^\infty > 0$ is the final long-run entry cost and Δ is the cost mark-up over the long-run cost. The cost mark-up declines at rate $\theta > 0$. Once installed the new unit can produce energy for free for unlimited time interval of time.⁶¹ Time discount rate is $\delta > 0$. We assume further assume that

$$\delta I^\infty > c \tag{13}$$

The equality ensures that the new technology cannot replace capacity K in the long-run: the price needed to cover the lowest possible investment cost, $p^\infty = I^\infty/\delta$, assuming that this price prevails forever, exceeds the reservation price of production K . Below, we make further assumptions for the entry to take place.

⁶¹Intermittency could be easily added explicitly as availability shock. Intermittency is important for reasons discussed in the main text but it is not central to the incidence argument here, and is therefore left out for simplicity.

H.3 Equilibrium: the first-best allocation

The equilibrium is a path $(p_t, R_t)_{t \geq 0}$ such that for all t :

$$(i) \quad I_t \geq V_t \equiv \int_t^\infty p_\tau \exp(-\delta(\tau - t)) d\tau$$

$$(ii) \quad D(p_t) = K + R_t + F_t.$$

With entry $dR_t/dt > 0$, and condition (i) must hold as equality; otherwise, the value of entering unit would exceed the investment cost. We first assume a continuous entry path so that $dR_t/dt > 0$ over some interval $[0, T)$ with possibly $T = +\infty$, and then we show that the assumption is correct. From (i), $I_t = V_t$ which, when differentiating both sides w.r.t. time, gives

$$-\theta \Delta \exp(-\theta t) = -p_t + \delta V_t.$$

Differentiating for the second time gives, after substitutions and rearranging,

$$dp_t/dt = \gamma \exp(-\theta t)$$

where $\gamma \equiv -\Delta\theta(\delta + \theta) < 0$. We obtain the price path, conditional on $dR_t/dt > 0$, as

$$p_t = p_0 + \frac{\gamma}{\theta}(1 - \exp(-\theta t)). \quad (14)$$

We assumed $dR_t/dt > 0$ for $[0, T)$ and derived the above price equation from the equilibrium zero-profit condition for entrants. Finite T cannot arise in equilibrium: the last entrant would gain by waiting for further cost reductions if the price froze at p_T . Considering the limit $T \rightarrow \infty$, it must be the case that $\lim_{T \rightarrow \infty} p_T = \delta I^\infty$: the last entrant must cover its costs. This boundary condition pins down the initial price,

$$p_0 = \Delta(\delta + \theta) + \delta I^\infty$$

and the full price path,

$$p_t = \delta I^\infty + \Delta(\delta + \theta) \exp(-\theta t). \quad (15)$$

It proves useful to define carbon price x as high, moderate, or low relative to the investment costs, respectively:

$$\delta I^\infty - c + \Delta(\delta + \theta) < x \quad (16)$$

$$\delta I^\infty - c < x < \delta I^\infty - c + \Delta(\delta + \theta) \quad (17)$$

$$x < \delta I^\infty - c. \quad (18)$$

Proposition 3 *Let τ measure the time passed since the first entry. For all $\tau > 0$, the equilibrium entry path is continuous with $dR_\tau/d\tau > 0$ and $(p_\tau, R_\tau)_{\tau>0}$ given by*

$$p_\tau = \delta I^\infty + \Delta(\delta + \theta) \exp(-\theta\tau) \quad (19)$$

$$R_\tau = D(p_\tau) - K. \quad (20)$$

The entry is immediate for a high carbon price (16), follows after a waiting period if carbon price is moderate (17), and never takes place for a low carbon price (18).

Proof.

Case (16): conditions (19)-(20) define (p_0, R_0) with $p_0 < c + x$ and $R_0 > 0$. Thus, there is mass entry at $t = 0$, and the price drops below the reservation price of F at $t = 0$. A continuous path (p_τ, R_τ) for all $\tau > 0$ is uniquely defined by (19)-(20).

Case (17): price (15) defines $p_t = c + x$ for some finite $t > 0$. At that moment, conditions (19)-(20) define (p_0, R_0) with $p_0 = c + x$, and $R_0 = F$. After that point, the entry continues as in the first case.

Case (18): no entry takes place since even the lowest investment cost remains above the reservation price for fossil output.

By construction, the last investor at any given t who foresees the equilibrium price path is indifferent between entering or staying out. Since all investors have the same constant returns to scale investment technology, the same conclusion applies to all entrants that make the quantity R_t . All entrants are indifferent at all times. ■

Remark 1 *The equilibrium path $(p_t, R_t)_{t \geq 0}$ in Proposition 3 is socially optimal.*

The value V_t measures the marginal social surplus attributable to one marginal unit of capital. Since all entrants receive this surplus as compensation, they invest resources to marginally equate costs and the social value of the investments.

H.4 The rent-extraction path

From now on, we assume that entry starts at $t = 0$, so $\tau = t$, without loss of generality. Consider now subsidies to entry. Clearly, since the starting point is the first-best path, they must introduce distortions. We can describe an interesting limit where the distortions vanish but the redistributive impact remains large.

In the dynamic setting, subsidies can be designed in multiple payoff-equivalent ways since it is the present value of the subsidies that matters, not the precise timing of the

subsidy payments. For simplicity, we consider subsidies paid at the investment time:

$$S_t = s\Delta \exp(-\theta t)$$

with $s \in [0, 1]$. This subsidy can be thought of as compensating the investor for accepting a less than mature technology. Thus, the investment cost, net of the subsidy payment, evolves as

$$I(S_t) = I^\infty + \Delta(1 - s) \exp(-\theta t).$$

Proposition 4 *The present-value rent extracted by subsidy policy S_t from the installed carbon free capacity K at time t is*

$$Ks\Delta \exp(-\theta t). \quad (21)$$

Proof. Let \hat{p}_t denote the price path induced by the subsidy policy. By the equilibrium condition $I_t = V_t$ that must hold with and without subsidies, we have a closed form expression for the price impact:

$$\int_t^\infty p_\tau \exp(-\delta(\tau - t))d\tau - \int_t^\infty \hat{p}_\tau \exp(-\delta(\tau - t))d\tau \quad (22)$$

$$= I_t - I(S_t) \quad (23)$$

$$= s\Delta \exp(-\theta t). \quad (24)$$

Multiplying by the size of the rent-earning capacity, remaining constant over time, gives the total rent extracted. ■

What is then the effect on the consumer side, taking into account the subsidy costs?

Proposition 5 *For demand elasticity sufficiently small, the consumer side net gain (=consumption expenditure gain - subsidy costs) from unit subsidy s is approximately equal to the rent loss (21).*

Proof. Let $\epsilon_{dp} = \frac{D'(p)p}{D(p)}$ denote the price elasticity of demand. It follows

$$\frac{dR_t}{dt} = D'(p_t) \frac{dp_t}{dt} \Rightarrow \frac{dR_t}{dt} = \epsilon_{dp} \frac{dp_t}{dt} \frac{D(p_t)}{p_t}. \quad (25)$$

Note that path $(p_t)_{t \geq 0}$ follows from Proposition 3; in particular, in equilibrium $(p_t)_{t \geq 0}$ is independent of the demand, ϵ_{dp} . Therefore, we can consider variations in demand without impacts on the price path. Since (D, p) are strictly positive and bounded, making elasticity sufficiently small, $\epsilon_{dp} \rightarrow 0$, implies that the rate of entry induced by the price

path becomes small, $\frac{dR_t}{dt} \rightarrow 0$. Keeping this result in mind, we look at the total consumer expenditure in the market:

$$W_t = \int_t^\infty D(p_\tau)p_\tau \exp(-\delta(\tau - t))d\tau \quad (26)$$

$$= K \int_t^\infty p_\tau \exp(-\delta(\tau - t))d\tau + \int_t^\infty R_\tau p_\tau \exp(-\delta(\tau - t))d\tau. \quad (27)$$

Let $W(S_t)$ denote the subsidy-induced consumer expenditures. Then, for $\epsilon_{dp} \rightarrow 0$,

$$W_t - W(S_t) \quad (28)$$

$$\approx K \int_t^\infty p_\tau \exp(-\delta(\tau - t))d\tau - K \int_t^\infty \hat{p}_\tau \exp(-\delta(\tau - t))d\tau \quad (29)$$

$$= K[I_t - I(S_t)] \quad (30)$$

$$= Ks\Delta \exp(-\theta t). \quad (31)$$

Finally, we need to consider the the subsidy payment flow:

$$S_t \frac{dR_t}{dt} = s\Delta \exp(-\theta t) D'(p_t) \frac{dp_t}{dt} = \epsilon_{dp} \frac{dp_t}{dt} \frac{D(p_t)}{p_t}. \quad (32)$$

Again, $\epsilon_{dp} \rightarrow 0$ implies that the subsidy costs vanish.

■

The result shows when the demand is inelastic, the subsidy merely redistributes rents. Intuitively, after the initial entry, the subsequent entry rate is small but enough to induce large price reductions. The result identifies a limit that, by continuity, shows that there is room for rent extraction even with more reasonable descriptions of the demand: the lower is the demand elasticity, the smaller is the quantitative change in R_t that is associated with the equilibrium price path p_t . Off the limiting case, there will be inefficiencies. First, the allocative inefficiency arises. The expedited investment path distorts cost minimization: the total producer surplus from producing a given demand is strictly larger without subsidies. Second, the subsidies bring the entrants online too early. The expedited investment path distorts consumption if demand is price responsive: consumption path is too front-loaded from the social point of view.