Hydro power. Market might.

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Abstract

A central tenet of economic theory is that market power induces deadweight loss. This claim rests on an assumption that is difficult to verify empirically. Namely, dominant firms produce less than the social optimum. I provide evidence of such restrictive behaviour using a rich dataset of Norwegian hydropower firms. The research design exploits exogenous variation in the formation of localized electricity markets. Power plants are assigned to distinct sub-markets as the result of binding transmission constraints. This manifests as a shock to the market power that parent firms command in each sub-market. Further, the ubiquity of hydropower generation in Norway avoids empirical complications associated with marginal cost estimation and endogenous variation in the supply mix. This allows me to identify the causal impact of market power on firm behaviour without imposing strong structural assumptions on the data. I show that a one percent increase in market power causes firms to withhold production by as much as a 0.3 percent. My results suggest that even seemingly competitive markets are susceptible to manipulation and welfare losses.

JEL Codes: Q25, Q41, L12, L13

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1 Introduction

The great recession and its aftermath have reignited concerns about market power in the economy. Against a backdrop of rising income inequality and sluggish sectoral growth, a series of high-profile papers have argued that high industry concentrations and record markups are responsible for a variety of economic ills. These range from stagnant wages and falling labour productivity shares (e.g. Autor et al., 2017; Azar et al., 2017; Benmelech et al., 2018) to a slowdown in aggregate output (e.g. De Loecker and Eeckhout, 2017). Moreover, the signs of growing market power are being observed at both a national and global level (Azar et al., 2018; De Loecker and Eeckhout, 2018), as well as in both traditional and nascent markets (Benmelech et al., 2018; Dube et al., 2018).

The central mechanism by which market power induces deadweight loss to society is a reduction in output. Economic theory tells us that dominant firms will be incentivized to raise prices by restricting production, thereby ensuring themselves higher profits. Yet, as uncontroversial as this theory is among economists, it is remarkably hard to verify empirically. Firms do not enter, exit or come to dominate industries by chance. Nor do they acquire or merge with other firms at random. They do so, among other reasons, because of their expectations over future profits and market conditions. These factors are largely unobservable to the empirical researcher and thus require varying degrees of model parameterization, imposed structure, and ancillary assumptions.[1] It is consequently difficult to think of an empirical setting that would allow us to recover the parameters of interest directly from the data. The present paper describes such a rare setting and thereby attempts to bridge the gap between pure theory and empirics. While I will argue that my findings are generalisable to other industries afflicted by market power, I rely on a fortuitous confluence of factors that are manifest in a particular market; namely, the Norwegian hydropower sector.

Hydropower is the world's foremost source of non-fossil energy. It accounts for seven percent of global primary energy and 16 percent of global electricity generation (BP, 2016). This role is even more pronounced in countries like Norway — the setting for this paper — where it accounts for over 95 percent of national electricity generation.[2]

[1]The notion that dominant firms will restrict output may be regarded as a *precept* of structural industrial organization models, insofar as it arises directly from assumptions about profit maximization and equilibrium market behaviour (Reiss and Wolak, 2007).

[2]Other prominent examples include Venezuela (70 percent of electricity generation), Brazil (65 per-

Hydropower is also characterised by a unique set of production features that greatly simplify economic questions related to firm behaviour and output. Unlike traditional modes of electricity production, variable costs in a hydropower plant are negligible. Water arrives exogenously from nature, while employee wages and maintenance fees are best regarded as fixed costs independent of output. Hydropower is furthermore a dispatchable form of electricity production. Plants can easily increase or decrease output in response to market conditions. Electricity is then itself a homogeneous end-good, which further reduces potential complications related to product differentiation and branding effects.

With fuel costs irrelevant, production in a hydropower system is largely determined by the opportunity cost of water — the so-called *water value*. Reservoir inflows are seasonal and stochastic, and yet water is a durable good that can be stored for long periods of time. The producer's decision thus collapses into one of how much water to use today and how much to save for tomorrow. Together with variations in demand, this creates opportunities for exploiting market power via intertemporal price discrimination and the strategic reallocation of water resources. In particular, dominant hydropower firms can increase profits by withholding supply in periods with relatively inelastic demand, driving up prices when consumers are least responsive to such changes.

Here I provide empirical evidence of such strategic behaviour. An increase in market power among Norwegian hydropower firms leads to a modest, but distinctive, pattern of intertemporal resource shifting. I find that a one percent increase in local market share leads to a 0.2–0.3 increase in reservoir volumes during months when electricity demand is at its most inelastic, i.e. when dominant firms stand to profit most by withholding supply. Reverse effects of a similar magnitude are observed during relatively more elastic demand periods. Compared to previous studies, I use a much richer dataset that links individual firms to specific reservoirs, as well as broader market data such as electricity flows and capacities. Changes to bidding area definitions and binding transmission constraints provide exogenous variation in local market power, which allows me to cleanly identify the causal impact on firm behaviour. Indeed, the fact that individual hydropower plants are randomly assigned to separate bidding areas during different periods — and that these bidding areas themselves are changing over time — means that my empirical setting constitutes a rare natural experiment in which the actual *definition* of the market is constantly changing. Treatment is thus varying

cent), Canada (60 percent), and New Zealand (55 percent).

in both frequency (how often transmission constraints are binding) and distribution (how much market power is conferred to individual firms as a result).

These features allow me to make several contributions to the literature. First and foremost, rather than inferring noncompetitive outcomes through simulated counterfactuals or aggregate measures such as wholesale electricity prices, I am able to look at the behaviour of individual hydropower firms directly. The causal relationship between the producer's decision and market power is therefore determined at the firm (and, indeed, plant) level. This refinement not only establishes a close correspondence between the empirical set-up and underlying theory, but also permits the use of a conceptually straightforward regression framework in the form of panel fixed effects. My analysis imposes little-to-no structure on the data, nor does it hinge on strong assumptions about the market relationships in question. I also consider a much longer time period than previous studies, with my sample running from 2000 until the end of 2013. In so doing, I hope to shed light on the way that dominant firms strategically utilise their resources, not just in the short-term, but in response to changing market conditions over the course of months, seasons and years. To the best of my knowledge, this paper is the first to provide direct empirical evidence — absent structural assumptions or simulated counterfactuals — of firm's strategically withholding production in a dynamic market setting.

The remainder of the paper is organised as follows. Section 2 provides a brief overview of related studies and further contrasts their approaches with my own. Section 3 describes the key institutional features of the Norwegian electricity market, while section 4 covers the basic theoretical framework. Section 5 introduces the dataset and discusses how various source materials were merged into a unified set. Section 6 discusses the econometric strategy for causal inference. Section 7 presents the empirical results and section 8 concludes.

2 Related literature

Electricity markets feature prominently in the literature on empirical industrial organisation (e.g. Wolfram, 1999; Joskow and Tirole, 2000; Borenstein et al., 2000, 2002; Wolak, 2003; Müsgens, 2006; Sweeting, 2007; Puller, 2007; Mansur, 2007; Hortaçsu and Puller, 2008; Reguant, 2014; Davis and Hausman, 2016). In part this reflects electricity's fundamental importance to the overall economy, as well as the coincident wave of market liberalisation that swept the industry in the 1990s and 2000s (Joskow, 2008). However, it also speaks to the specific advantages that electricity offers as a subject for economic inquiry relative to other goods and sectors — product homogeneity, reduced complications in terms of branding, advertising, and so forth (Borenstein, 2016). Yet despite such advantages, much of this existing literature has still had to rely on a combination of aggregate data, simulation methods, model calibration and/or strong structural assumptions to support its findings. In contrast, my purely empirical approach leverages a mix of detailed plant-level data, hydropower's unique production characteristics and quasi-experimental variation in the economic parameters of interest, to identify evidence of noncompetitive behaviour in a dynamic market setting.

The studies closest to the present paper in terms of data richness and approach are those by Puller (2007), Hortaçsu and Puller (2008), Reguant (2014), and Davis and Hausman (2016). Both Puller and Davis and Hausman focus on the California electricity market, where they use plant-level data to document noncompetitive behaviour during the region's post-liberalisation energy crisis and following the shutdown of a major nuclear facility, respectively. Hortaçsu and Puller tread a similar path in evaluating the restructured Texas electricity market, where they find that larger firms are closer to (static) profit-maximising benchmarks than their smaller counterparts. In turn, Reguant uses Spanish data to show that startup costs in electricity generation can play an important role in rationalizing apparent deviations from optimal bidding behaviour.

Compared to these studies, the present work benefits from richer variation in market power over a longer period of time, as well as the specific empirical advantages afforded by my exclusive focus on hydropower generation. The firms in my dataset are directly and immediately comparable since they all use the same production technology and face the same (negligible) marginal costs. Similarly, while ignoring startup costs can lead to biased estimates of market power as per Reguant, the inherent dispatchability of hydropower renders such concerns moot in the present context. I would argue further that my identification strategy rests upon a more fundamental change in the parameters of interest. Rather than comparisons with simulated pricing data (Puller; Hortaçsu and Puller; Reguant) or a one-time shock to generation capacity (Davis and Hausman), I exploit recurring changes in the actual *definition* of the market being studied.[3] Despite these differences and the fact that we focus on different regions, the present analysis is

[3]This claim will be motivated in greater detail in subsequent sections of the paper.

still conducted in the same spirit as these four studies. Our collective ability to identify noncompetitive behaviour by firms is greatly enhanced by a combination of detailed data, quasi-experimental settings and transparent modeling approaches.

In addition to the studies named above, a number of authors have specifically examined the competitive structure of the Norwegian — and broader Nordic — electricity market. These include Johnsen et al. (1999), Hjalmarsson (2000), Steen (2004), Kauppi and Liski (2008), and Mirza and Bergland (2012). A review is provided by Fridolfsson and Tangerås (2009). The general finding is one of healthy competition, but with some scope for exercising local market power due to constraints in transmission capacities. I too focus on local market power that arises from transmission bottlenecks.[4] However, the richness of my dataset allows me to go much deeper by tracking firm-level responses to changing bidding area configurations over time. These changes provide a key source of additional variation in local market power that enable me to cleanly identify its impact on hydro firm behaviour *vis-à-vis* the management of individual reservoirs. Moreover, all previous studies of the Nordic market rely on aggregate data. This places strong restrictions on the methods that can be used to used to support causal inference. For example, several studies make use of the well-known Bresnahan (1982) and Lau (1982) framework for estimating market power in the absence of marginal cost data. Yet the Bresnahan-Lau model ultimately presumes that firms face a static production decision at each point in time. It is therefore of limited use for understanding the inherently dynamic nature of hydropower production. As Fridolfsson and Tangerås (2009, p. 3689) are led to remark in their review: "A lack of firm level data may explain why only the Bresnahan-Lau model or the even less demanding methodology proposed by Johnsen et al. [sc. 1999] has been applied to the Nordic power market. This suggests that more detailed data would be highly valuable for [determining] market power in the Nordic market for wholesale electricity."[5]

Finally, the empirical analyses of the Nordic and other electricity markets to date have tended to focus on short-run deviations from competitive prices. Or, they have taken the form of single event studies that compare market conditions before and after an eco-

[4] Theoretical contributions to this literature and related empirical applications in other electricity markets include those by Joskow and Tirole (2000), Borenstein et al. (2000), Davis and Hausman (2016), and Bigerna et al. (2016).

[5] Similarly, Kauppi and Liski (2008, p. 35): "Our approach to efficient allocations and those distorted by imperfect competition is aggregative. Analysis exploiting more detailed information on capacities, usage, and regional heterogeneity is therefore called for. If such data becomes available, one could potentially estimate hydro usage policies directly from the data[...]"

nomic shock. Relatively little is known about the strategic behaviour of dominant firms over the medium- to long-term, much less how they respond to changing conditions in their markets over time. I attempt to shed light on these dynamic uncertainties in the present paper.

3 The Norwegian electricity market

Following the enactment of the Energy Act of 1990, Norway become one of the first countries to deregulate and liberalise its electricity sector (Bye and Hope, 2005; Joskow, 2008). The other Nordic nations steadily followed suit and by 2000 Norway, Sweden, Finland, and Denmark had together formed the world's first — and still largest — multinational power exchange, *Nord Pool*. The primary market of the Nord Pool exchange is *Elspot*, a day-ahead market for the physical delivery of electricity. Elspot functions according to classic auction principles in which hourly supply and demand bids are first aggregated and then matched to determine a market clearing price, also known as the system price. In the absence of transmission constraints, all electricity is traded at the system price. However, when transmission constraints are binding, the Elspot market is split up into distinct bidding areas. During such periods, each bidding area effectively becomes its own market and is (typically) characterised by a distinct area price. This in turn confers potential local market power to dominant firms within those areas.

As per Figure 1, Norway is currently composed of five Elspot bidding areas: NO1 (east), NO2 (south), NO3 (mid), NO4 (north), and NO5 (west). Importantly, this configuration of bidding areas has been changed multiple times over the last decade and a half (c.f. Appendix B). New bidding areas have been added or removed and the boundaries between existing areas have been redrawn, as the Norwegian system operator, Statnett, has tried to optimise electricity access under the inherent physical and technical constraints of large-scale power grid. I will discuss this issue in more depth in the empirical section of the paper. For the moment, it need simply be said that such "regime" changes provide an additional layer of plausibly exogenous variation in local market power and are thus highly advantageous from an empirical perspective. The evolving configuration of bidding areas, in concert with binding transmissions constraints and data on individual reservoirs, will ultimately allow me to identify the causal effect of local market power on hydro firm behaviour by randomly assigning individual plants

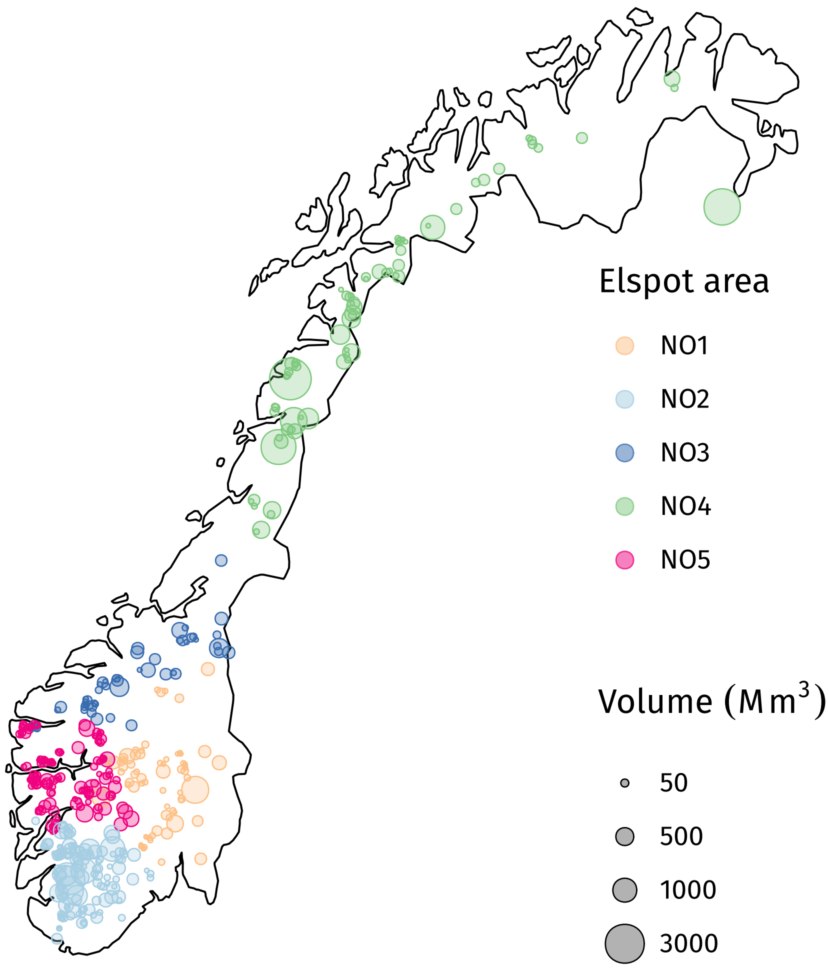


FIGURE 1: NORWEGIAN HYDROPOWER RESERVOIRS

Notes: Elspot bidding area configuration as of 2 December 2013 (i.e. regime Q).

to distinct markets.

Turning to the broader characteristics of the Norwegian electricity market, hydropower dominates at both the national and regional level. Norwegian reservoirs generated around 130 TWh of electricity in 2013. This corresponds to over 95 percent of national electricity generation and more than a third of the 380 TWh generated in the Nordic region as a whole (NordREG, 2014; SSB, 2015). For its part, Norwegian electricity demand tends to fluctuate significantly depending on the time of day, the day of week, and, indeed, the time of year. While large portions of this demand are not substitutable, the Norwegian electricity sector is designed to foster consumer responsiveness whenever conditions allow. Most buildings are equipped with in-house electricity meters that provide real-time information on consumption. Moreover, approximately 85–90% of end-user contracts are either tied directly to the spot price, or come in the form of variable price contracts that are highly-correlated with the spot price and may be terminated at short notice (Bye and Hansen, 2008). Norwegian consumers are thus directly exposed to the changes in the spot prices and can be expected to react accordingly.

The principal focus of this paper is strategic behaviour among hydropower firms over longer periods of time. It therefore makes sense to abstract from short-term fluctuations (e.g. day versus night, weekdays versus weekends) and concentrate on variations in demand over the course of months and seasons. With that in mind, winter electricity demand in Norway is approximately double that of summer, primarily because of indoor heating requirements. However, electrical heating is relatively easy to substitute with indoor fireplaces, fuel-burning heaters, warmer clothing, better insulation, etc. This permits greater flexibility among consumers, whereas summer electricity demand is dominated by technical end-uses that do not allow for easy substitution. These seasonal differences in substitution and adjustment possibilities contribute to a perhaps surprising finding: Demand elasticities are significantly *higher* during the Norwegian winter than they are during summer (Johnsen, 2001; Hansen, 2004; Bye and Hansen, 2008).[6] I confirm this finding using detailed bid curve data in Section 5.2. However, it is first useful to cover the theoretical basis of dominant hydro firm behaviour, and why seasonal variations in demand elasticities are fundamental to their strategy.

4 Theoretical framework

Førsund (2015) outlines the various ways in which market power affects producer behaviour in a hydropower system. The general result is to incentivise a reallocation of water from periods with relatively inelastic demand to periods with relatively more elastic demand. The contribution of this paper is empirical and, as such, I will not describe these theoretical permutations in detail. However, it will be useful to recapitulate a version of the simplest case — i.e. monopoly with no uncertainty, outside trade

[6] The phenomenon of a relatively more elastic winter electricity demand is quite common among high-latitude countries, where substitutable heating requirements account for a large portion of overall energy consumption, e.g. Canada (Genc, 2016).

or reservoir constraints — to get a sense of the underlying intuition.

Consider the profit maximization problem of a hydropower monopoly in a two period setting,

$$\begin{aligned} \max \sum_{t=1}^{2} p_t\left(q_t\right) \cdot q_t \\ \text{s.t.} \sum_{t=1}^{2} q_t \leq W, \end{aligned} \tag{1}$$

where $p_t\left(q_t\right)$ is an inverse demand function with standard properties (e.g. price decreasing in quantity), q_t is the quantity of electricity demanded by consumers (or, more precisely, its water equivalent), and W is the known water endowment for the monopolist's reservoir. Let us further assume that period 1 is summer and period 2 is winter. This assumption has no bearing on the theoretical results, but will become useful as a reference for the empirical setup later in the paper.

The necessary first order conditions for profit maximization are

$$\begin{aligned} \frac{\partial L}{\partial q_t} = {p_t}'\left(q_t\right) \cdot q_t + p_t\left(q_t\right) - \lambda \leq 0 \\ (\, = 0 \quad \text{for } q_t > 0) \end{aligned} \tag{2}$$

and

$$\begin{aligned} &\lambda \geq 0 \\ &(\, = 0 \quad \text{for } \sum_{t=1}^{2} q_t < W). \end{aligned} \tag{3}$$

The parameter λ denotes the shadow price on stored water, i.e. positive if the resource constraint in equation (1) is binding and zero otherwise. Without loss of generality, let us assume that the shadow price is positive and that the monopolist also produces in both periods.[7] The first order conditions may then be written as

$$p_1(q_1)\left(1+\frac{1}{\epsilon_1}\right) = p_2(q_2)\left(1+\frac{1}{\epsilon_2}\right) = \lambda, \tag{4}$$

where $\epsilon_t = \frac{p_t}{q_t}\frac{\partial q_t}{\partial p_t} < 0$ is the price elasticity of demand. Rearranging equation (4), it is easy to see that prices depend on the relative demand elasticities in each period. For example, we would have

$$p_1(q_1) > p_2(q_2) \quad \text{if} \quad |\epsilon_1(q_1)| < |\epsilon_2(q_2)|. \tag{5}$$

Since we have assumed a downward-sloping demand curve, the above corresponds to

$$q_1 < q_2 \quad \text{if} \quad |\epsilon_1(q_1)| < |\epsilon_2(q_2)|. \tag{6}$$

The monopolist solution thus involves a reallocation of production across periods, contingent on the elasticity of demand. This contrasts with the social solution that arises under perfect competition, where production and prices are equalised across periods.[8] We can further generalise the difference between monopoly and perfect competition in this simple setup as

$$q_t^M < q_t^C \text{ and } q_{\hat{t}}^M > q_{\hat{t}}^C \quad \text{if} \quad |\epsilon_t(q_t)| < |\epsilon_{\hat{t}}(q_{\hat{t}})|, \tag{7}$$

where the M and C superscripts denote the monopolist and competitive outcomes, respectively. The monopolist is able to recoup higher profits by withholding supply — hence driving up the electricity price — during the relatively inelastic period when consumers are least responsive to such changes. Market power not only causes electricity prices and quantities to diverge from their social optimums, but also implies an observable difference in the way that reservoirs are managed. Reservoirs belonging to dominant firms will tend to be relatively fuller during inelastic periods than they would

[7] If we instead assumed that the shadow price is zero (due to a non-binding resource constraint), then the ensuing results are largely unchanged but for some fraction of water that remains unused.

[8] By definition, the price elasticity of demand facing a competitive firm is always perfectly elastic, i.e. $\epsilon \to \infty$. That competition leads to equal prices and quantities across periods is easily shown by solving the above set-up as a social optimisation problem that maximizes total welfare. See Førsund (2015).

otherwise have been under competition. The reverse is true during more elastic periods.

The generalized version of the above model with more than two periods follows the same pattern. Producers maximize profits by reallocating production away from relatively inelastic demand periods. Moreover, the theoretical extensions that Førsund (2015) and others (e.g. Hansen, 2009; Mathiesen et al., 2013) explore beyond the simple case presented here may be regarded as variations on a theme. While each variation has the ability to ameliorate or exacerbate market distortions in its own way, the substantive result is largely unchanged.[9] Market power leads to a strategy of shifting water use away from relatively inelastic demand periods to relatively elastic ones. Moreover, as described in Section 3, electricity demand in Norway is relatively more inelastic during the summer months. Our testable hypothesis is therefore that dominant firms will tend to maintain fuller reservoirs in summer and lower reservoirs in winter.

5 Data

This paper uses a novel dataset of Norwegian hydropower firms, reservoirs and electricity data. The data have been constructed from a variety of sources — both public and proprietary — and are summarised in Table 1. Below I describe the original data sources in greater detail, as well as the methods that have been used to merge these disparate parts into a unified dataset.

5.1 Hydropower reservoirs, plants and firms

Time series data for a large number of Norwegian hydropower reservoirs — representing approximately 90 percent of total system capacity — were obtained from the Norwegian Water and Energy Directorate (NVE). Most reservoirs are observed at a daily resolution from January 2000 to December 2013, and contain water readings in terms of both volumes (million m^3) and levels (m). The reservoirs in my dataset are subject to regulation regarding their maximum and minimum holding capacities. Operating firms are legally required to keep their reservoirs within these limits so as to

[9]For example, trade with outside regions can moderate the intertemporal disparities yielded by the standard monopoly model. However, accounting for transmission constraints brings us back towards the original result.

TABLE 1: Summary of data sources

Data	Description	Period	Frequency	Source
Reservoirs	Volumes and levels for the 500 largest reservoirs in Norway.	2000–2013	Daily	NVE[a]
Plants & firms	Regulatory limits, GIS data, etc.	N/A	N/A	NVE[b]
Elspot areas	Bidding area divisions and changes.	N/A	N/A	NVE[c], Nord Pool[d]
Electricity (I)	Prices, flows and transmission capacities.	2000-2013	Hourly	Nord Pool[e]
Electricity (II)	Bid curve data.	2014–2017	Hourly	Nord Pool[f]
Weather	Meteorological station data.	2000–2013	Hourly	NCDC[g]

[a] Available upon request. See: http://api.nve.no/doc/hydrologiske-data (Norwegian).
[b] http://gis3.nve.no/link/?link=vannkraft
[c] http://gis3.nve.no/link/?link=nettanlegg
[d] http://nordpoolspot.com/globalassets/download-center/elspot/elspot-area-change-log.pdf
[e] Proprietary. See: https://www.nordpoolgroup.com/services/Power-data-services/Product-details.
[f] https://www.nordpoolgroup.com/elspot-price-curves
[g] ftp://ftp.ncdc.noaa.gov/pub/data/noaa/

guard against flooding and environmental degradation. To ensure comparability between the different reservoir sizes in my dataset, the reservoir data are therefore normalised as percentages of their respective maximum regulated capacities. After various data cleaning steps described in Appendix A, I am left with a panel dataset of 500 Norwegian hydropower reservoirs that comprises nearly 2 million daily observations.

Each reservoir in my dataset is linked to a set of relevant covariates, including details about the specific hydropower plant that it supplies, the operating firm in question, and various pieces of geographic information. These data were also obtained from the NVE.[10] I define market power in this paper as the share of total generation capacity (in MW) that each producer wields within a designated bidding area. More specifically, the market share S of hydropower firm f, in a bidding area comprising F firms in total, is given as

$$S_f = \frac{\sum_{i=1} \overline{MW}_{if}}{\sum_{j=1}^{F} \sum_{i=1} \overline{MW}_{ij}}, \tag{8}$$

where $\overline{MW}_i$ is the maximum capacity of hydropower plant i. Note that this "share of overall capacity" definition of market power avoids the endogeneity problem associ-

[10] For example: http://gis3.nve.no/link/?link=vannkraft

ated with definitions that measure actual output. Namely, that changes in output have a direct impact on contemporaneous reservoir water volumes, which serve as the dependent variable in my econometric model.

Tracing the evolution of local market power as per equation (8) requires that each power plant and its associated reservoir(s) are mapped to the correct Elspot bidding areas at every point in time. The information needed to do perform this mapping does not readily exist. However, using the current Elspot allocation as a fixed starting point — together with coordinate information contained in my dataset, the Elspot change log document hosted by Nord Pool[11], a map of the Norwegian electricity grid components[12], and several other sources — I am able to manually back out the divisions of 16 earlier regimes going back to the beginning of 2000. These are depicted in Appendix B and denoted by the capitalised letters A to Q for convenience. The most recent Elspot regime, which went into effect on 2 December 2013, has already been highlighted in Figure 1.

Based on the above definitions, there are several ways that one could measure local market power within the Norwegian electricity system, and how this changes over time. Table 2 shows the Herfindahl index measures for the various Elspot bidding areas over time. As many as 35 of the 55 realised bidding areas can be characterised as highly concentrated ($H > 0.25$), while the remaining 20 are all moderately concentrated ($0.15 < H < 0.25$). No bidding areas would qualify as unconcentrated ($H < 0.15$). As an alternative to the Herfindahl index, we can also look at the market shares wielded by the top three producers in each area. These are shown in Appendix C and provide further evidence of potential market power at the regional level. The leading hydropower firm in some areas may command as much as 60 percent of available electricity generation, depending on the regime.

Two points are worth highlighting in relation to the overall empirical strategy before continuing. First, as can be seen from Table 2 and the maps in Appendix B, bidding areas are not consistently defined under the different regimes, even if they have been assigned the same area ID. For example, bidding area NO1 under regime A differs substantially in size and network coverage to bidding area NO1 under regime Q. In contrast, bidding area NO3 under regime B is exactly the same as bidding area NO4 under regimes M through Q. To ensure consistency, I henceforth adopt the term *zone* to

[11] http://nordpoolspot.com/globalassets/download-center/elspot/elspot-area-change-log.pdf
[12] http://gis3.nve.no/link/?link=nettanlegg

Table 2: Herfindahl index of the evolving Norwegian Elspot areas

Regime	Date	NO1	NO2	NO3	NO4	NO5
A	01 Jan 2000	0.174	0.381	–	–	–
B	02 Oct 2000	0.174	0.298	0.444	–	–
C	01 Jan 2001	0.174	0.381	–	–	–
D	12 Mar 2001	0.172	0.265	0.444	–	–
E	11 Jun 2001	0.174	0.381	–	–	–
F	16 Dec 2002	0.206	0.203	0.255	0.448	–
G	02 Jun 2003	0.174	0.381	–	–	–
H	13 Dec 2003	0.173	0.268	0.448	–	–
I	29 May 2004	0.174	0.381	–	–	–
J	18 Nov 2006	0.174	0.298	0.444	–	–
K	17 Nov 2008	0.174	0.381	–	–	–
L	13 Apr 2009	0.174	0.298	0.444	–	–
M	11 Jan 2010	0.200	0.228	0.298	0.444	–
N	15 Mar 2010	0.260	0.289	0.275	0.444	0.189
O	05 Sep 2011	0.260	0.257	0.275	0.444	0.249
P	05 Dec 2011	0.260	0.257	0.275	0.444	0.249
Q	02 Dec 2013	0.385	0.245	0.275	0.444	0.243

describe a unique (and potentially reoccurring) Elspot footprint. All told, there are 23 such zones. These will serve as key fixed effects units in the estimation procedure and are summarised in Table D.1 in the appendices.

Second, a practical question from an empirical perspective is whether my dataset contains enough variation to meaningfully identify the effect of changing market share (i.e. power) on firm behaviour. Figure 2 shows the relative distribution of these changes across all of the reservoirs in my dataset. Note that observations with approximately zero change have been excluded to aid visual inspection.[13] We can see that several hundred observations are characterised by significant jumps in market share. Producers may gain or lose as much 30–40% local market share overnight following the introduction of a new Elspot regime. It therefore seems fair to say that a lack of meaningful variation will not present an obstacle to the empirical analysis.

[13]These observations account for slightly more than half of the observations. The corresponding spike at zero thus makes it hard to judge the number of observations towards the tail ends of the distribution.

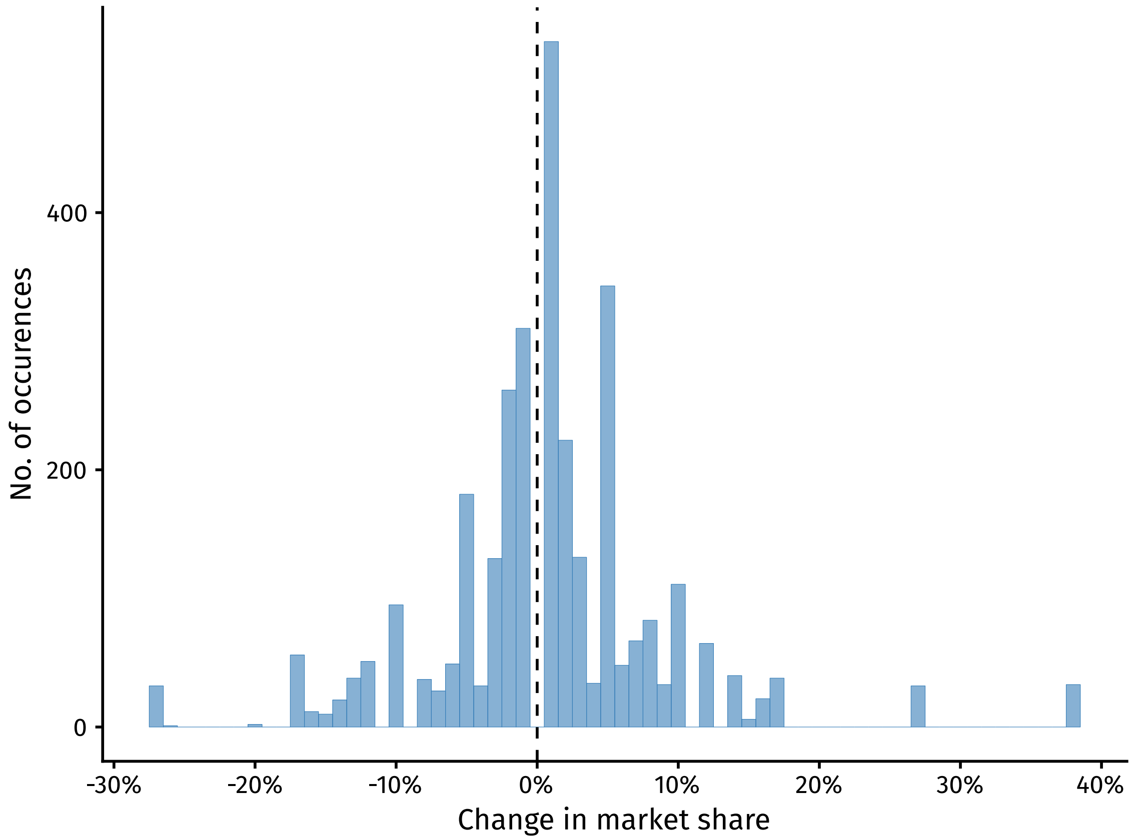


FIGURE 2: LOCAL MARKET SHARE CHANGE DUE TO ELSPOT RECONFIGURATION

Notes: Observations with approximately zero change, accounting for roughly half the sample distribution, have been excluded to aid visual inspection. These are represented by the dotted vertical line.

5.2 Electricity prices, flows and transmission constraints

All electricity data are obtained from Nord Pool. Electricity flows from one Elspot area to others via defined corridors and is limited by the capacity constraints of the transmission lines that make up those corridors. Similarly, a bidding area can have several corridors attached to it, depending on the number of neighbouring areas that it shares borders with. I use the phrase "in-use hours" as a shorthand for the total number of hours that electricity was flowing to or from a bidding area, across all of its corridors, in a single day. Consequently, it is possible for an area to experience more than 24 in-use hours during a day if it is connected via several corridors.

Electricity flow data for the individual Norwegian bidding areas are available at an

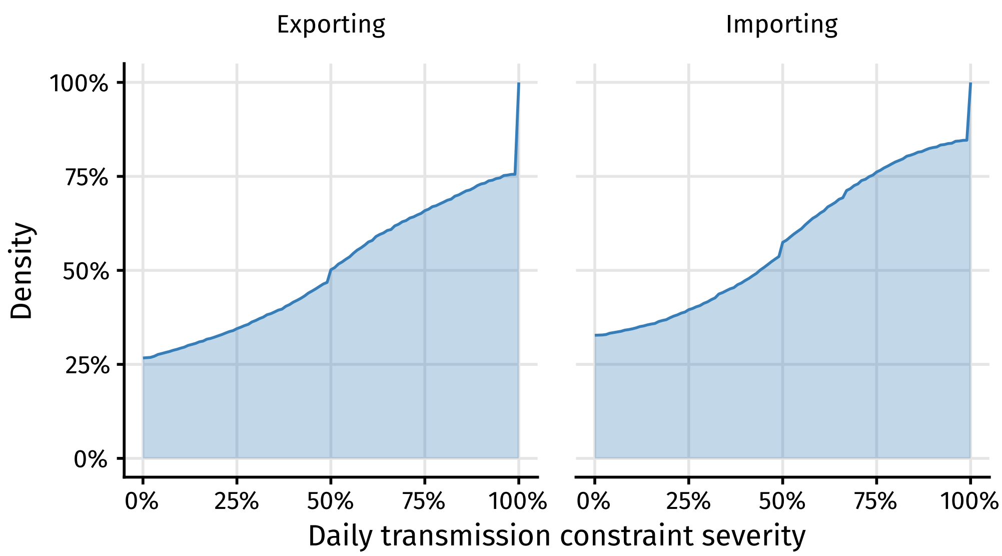


Figure 3: Cumulative distribution of transmission constraint severity

Notes: Severity reflects how often electricity flows to or from a bidding area were constrained by maximum transmission capacities.

hourly level, by corridor, from November 2000 onwards.[14] I match these flows to the maximum transmission capacities for the relevant corridors at each hour. I then define the transmission constraint on a corridor as binding whenever the hourly flows — whether importing or exporting — are equal to the maximum transmission capacity. It is furthermore possible to infer binding transmission constraints during the nine months prior to November 2000 by looking at differences in spot prices between neighbouring regions. For instance, if the price in NO2 is higher than NO1, then it is reasonable to infer that NO2 is importing electricity from NO1 and the transmission constraint is moreover binding. If the spot price between two regions is equal during this period, then I cannot infer much beyond the fact that the constraint is not binding. I cannot reliably say which area is exporting to which.

All told, binding transmission constraints are a common occurrence. Figure 3 presents a normalized measure of constraint severity: The fraction of daily in-use hours that are constrained for individual bidding areas, expressed as a cumulative distribution. To summarize, just over a quarter of daily exporting periods (and a third of daily importing periods) in the sample experience no binding constraint. However, the severity rate

[14]Real-time flows can be viewed on the Statnett website: http://www.statnett.no/en/Market-and-operations/Data-from-the-power-system/Nordic-power-flow

rises to 50 percent — one constrained hour for every two in-use hours — for at least half the sample. Moreover, a full quarter of daily exporting periods (and 15 percent of daily importing periods) are completely constrained. That is to say, the transmission capacities available to bidding areas in this category were always binding, so that electricity flows along all corridors were constrained during every single hour of the day that they were in use.

5.3 Elasticity of electricity demand and implied reservoir volumes

A great advantage of working with market-based electricity data in recent years is the availability of detailed bid curve histories. Recovering demand and supply elasticities directly from the data is then a simple matter of estimating the relevant arc elasticities (e.g. Wolak, 2003; Bigerna et al., 2016). Which is to say, we need merely trace deviations from a clearing price along the demand (supply) curve and calculate the resulting slope changes as per any introductory economics textbook. The arc elasticity approach not only benefits from being relatively easy to execute, but should also yield more precise estimates than alternative approaches.[15]

Nord Pool has made anonomized bid curve data available since mid-2014 and I have obtained the hourly bid sheets until mid-2017.[16] While this three-year period falls after my primary study period (i.e. 2000-2013), the fact that I am interested in persistent differences in seasonal elasticities allows me to proceed apace. I begin by defining an arbitrary arc segment of 5 EUR on either side of the hourly clearing prices.[17] I then calculate the corresponding arc elasticity of demand (ϵ_D) for each hour and aggregate these up into daily means. Finally, I regress these daily elasticities on month dummies and various other calendar effects. The key finding from this regression is summarized in Figure 4. The predicted demand elasticities exhibit a clear seasonal trend, with ϵ_D at its smallest absolute value in June and largest absolute value in November. These results correspond closely to the general finding of previous studies, which rely on alternate

[15]To the best of my knowledge, existing estimates of the elasticity of electricity demand in Norway — and, indeed, the wider Nordics — rely on indirect approaches such as instrumental variables, model simulation, and parameterization (e.g. Johnsen, 2001; Hansen, 2004; Bye and Hansen, 2008). Likely, this is because the advent of detailed bid curve data is a relatively new advent.

[16]https://www.nordpoolgroup.com/elspot-price-curves. See Figure E.1 in the appendices for a detailed comparison of hourly bid curve data across two representative summer and winter dates.

[17]Experimenting with different segment lengths yields very similar answers to the ones presented here. As a reference, the average Nord Pool clearing price over 2014–2017 was 25 EUR.

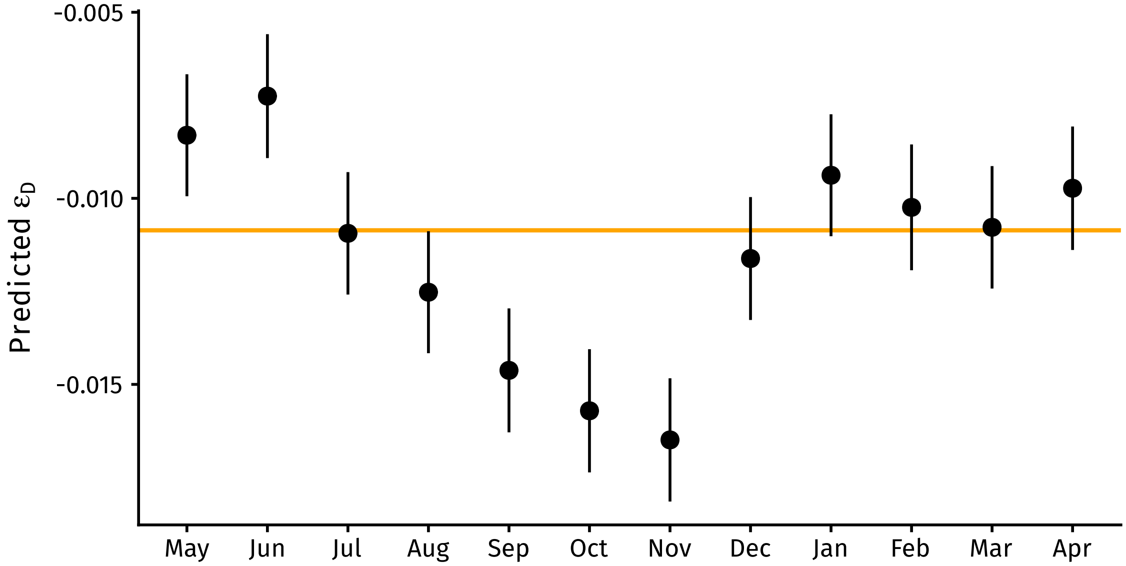
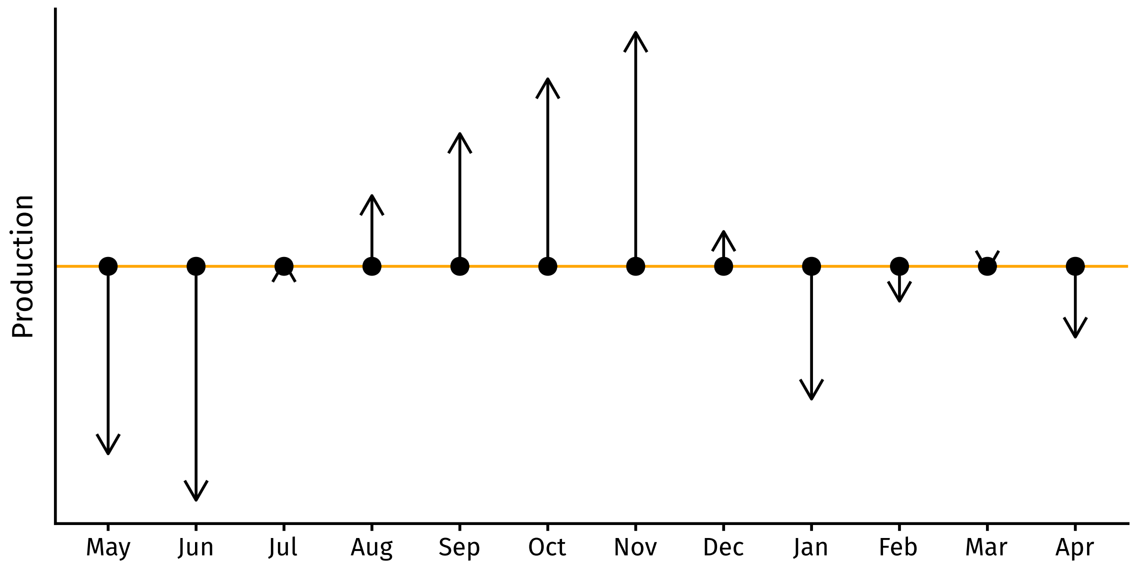


FIGURE 4: DEMAND ELASTICITY ESTIMATES

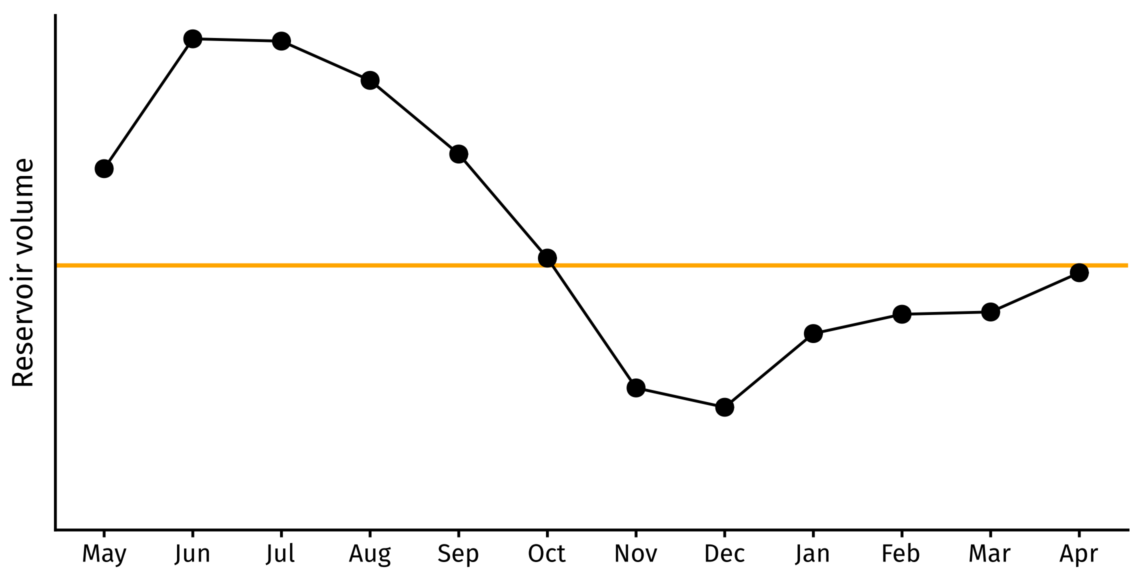
Notes: Estimates are obtained by regressing daily arc elasticity values, obtained from bid curve data over 2014–2017, on monthly dummies and other control variables. Dots denote point estimates and error bars denote 95 percent confidence intervals. The orange horizontal line highlights the median estimate and, following equation (6), serves as a reference case for periods when dominant firms would withold theoretically production (above the line) or oversupply (below the line) relative to the competitive outcome.

methods for estimating Norwegian electricity demand elasticities (e.g. Johnsen, 2001; Hansen, 2004; Bye and Hansen, 2008). We can therefore say with some confidence that electricity demand in Norway is at its most inelastic in the early summer months and at its most elastic in the early winter months (or, late autumn months).

Importantly, these elasticity estimates provide the empirical link to a theory-motivated prediction of when (and how) variations in market power will cause deviations in reservoir management. Following equation (6), dominant hydropower firms will reallocate their water resources so as to withhold production during the relatively inelastic periods of the year. The opposite is true during the relatively elastic periods of the year. All other things being equal, the cumulative effect of this (proportional) production reallocation should lead dominant Norwegian firms to maintain relatively higher reservoir volumes in the summer months and relatively lower reservoir volumes in the winter months. Figure 5 maps out these implied deviations in production and reservoir volumes in stylised fashion, taking the theory of Section 4 and my empirical ϵ_D estimates



(A) Implied deviation in production



(B) Implied deviation in reservoir volume

Figure 5: Stylised implications of market power

Notes: Implied deviations are relative to a competitive outcome (orange lines) and based upon the empirical demand elasticity estimates shown in Figure 4. Panel (A) assumes that production follows a dominant hydropower firm's optimal allocation rule as per equation (6). Panel (B) takes this production allocation as given and maps it to reservoir volumes, assuming an approximate May-April hydro year.

here as given. The figure encapsulates the testable hypothesis that I shall subject my data to. If the theory about market power in a hydropower setting is correct, then my main regression analysis should yield coefficients that look roughly similar to the sinusoidal shape of Figure 5(B).

5.4 Weather data

Weather data are obtained from the National Climate Data Center (NCDC).[18] In order to derive a vector of daily weather data that is unique to each reservoir in my dataset, I follow a simple inverse-distance rule. Each reservoir is matched to its three nearest meteorological stations and weather conditions are assumed to be a weighted average of the conditions at these three stations. While this "nearest neighbours" approach is conceptually straightforward, there are two additional points worth noting. First, while snow depth and glacial melt are potentially valuable data for understanding Norwegian reservoir dynamics, these series are only available for a small subset (both temporally and spatially) of the meteorological stations that I have access to. I have thus excluded them from the analysis and focus predominantly on temperature and rainfall data. Second, the meteorological station dataset is unbalanced, with new stations coming into operation during the study period and others falling out of the NCDC records. Appendix A describes this issue in more depth, as well as the approach that I favour in dealing with the unbalanced station data. The upshot is that I determine the three nearest neighbours for each station on a per-year basis, according to which stations were operational during that year. This yields a dataset of 201 stations from which I derive the reservoir-specific weather data. A map showing the relative geographic distribution of these meteorological stations, as well as their years of availability relative to the full study period, is shown in Figure F.1.

[18] ftp://ftp.ncdc.noaa.gov/pub/data/noaa/

6 Empirical strategy

6.1 Regression specification and identification strategy

Consider a fixed effects model that estimates water volumes in reservoir i $(i, ..., N)$, belonging to hydropower firm f $(f = 1, ..., F)$, at time t $(t = 1, ..., T)$. The primary observation unit is the reservoir, while the secondary observation unit is the firm. Following the notation of Abowd et al. (2008), the reservoir–firm relationship may be conceptualised through a link function, $f = F(i, t)$, which indicates that firm f is managing reservoir i at time t. The regression model may thus be written as

$$V_{it} = \sum_{m=1}^{12} \beta_m M_{mt} + \sum_{m=1}^{12} \gamma_m M_{mt} \cdot S_{it,F(it)} + \boldsymbol{X\beta_X} + a_i + v_{it}, \tag{9}$$

where V is reservoir volume as a percentage of maximum regulated capacity, M_m is set of month dummies, and S is the market share wielded by the operating firm as per equation (8). By interacting S with M_m, we are allowing for the fact that market share can have a differential effect on reservoir volumes, depending on how the price elasticity of demand varies by period.[19] The regression model is completed by a set of additional controls such as temperature and precipitation data, $\boldsymbol{X}$, while the first component of the composite error term, $a_i + v_{it}$, denotes an unobservable reservoir-specific effect — e.g. idiosyncratic operating characteristics or hydrological conditions — that we eliminate from the model via within group transformation. The key parameters of interest in the above regression model are the γ_m coefficients pertaining to the interacted market share terms. Given the observed variations in Norwegian demand elasticities (Johnsen, 2001; Hansen, 2004; Bye and Hansen, 2008), we would expect a positive sign on these coefficients during the summer months, as dominant producers withhold their production in the face of relatively more inelastic demand. Similarly, we expect these coefficients to then turn negative during the winter months as demand elasticities increase.

While the naive specification of regression equation (9) captures the essence of the

[19]Following Balli and Sørensen (2013), it is also advisable to demean the reservoir-specific market shares before running the regression, so as to safeguard against possibly spurious results in the interaction term. That is, the estimated model becomes $V_{it} = \sum_{m=1}^{12} \beta_m M_{mt} + \sum_{m=1}^{12} \gamma_m M_{mt} \cdot (S_{it,F(it)} - \overline{S}_i) + a_i + \epsilon_{it}$. Given that the underlying logic of the model is unchanged, I shall nonetheless continue using the notation of equation (9) for simplicity.

underlying theory, it suffers from two related conceptual limitations. First, it does not explicitly account for the conditions that make local market power possible. Second, it does not address a potential identification problem related to changing demand. As it turns out, however, the nature of my dataset allows me to correct for both limitations by simply adding a few additional controls to the model. To see why this is the case, it is worth taking a step back to consider some of the specific empirical advantages of my dataset and its institutional context.

A key assumption of my empirical strategy is that changes to Norway's Elspot bidding areas over time provide a plausibly exogenous source of variation in local market power. My identification strategy thus relies on the fact that (i) the Elspot area divisions are determined by outside factors, and (ii) they affect a hydropower firm's production decision only via changes in market share. It is relatively straightforward to argue for the former. The reason that separate bidding areas exist in the first place is that geographical and technical constraints limit the flow of electricity that is physically possible between two regions (Steen, 2004; Mirza and Bergland, 2012; ENTSOE, 2015, etc.). That these bidding areas have been redrawn over time is in of itself testament to the underlying physical constraints, as Statnett (the system operator) seeks to best manage internal congestion problems, outages and scheduled maintenance periods, litigation procedures, and the laying out of new cables.[20]

The second component of my identification strategy — i.e. changes to the Elspot bidding areas only affect producer behaviour through changes in market share — is potentially complicated by the fact that the demand will also change with the redrawing of bidding areas. Yet, the demand complication is ultimately dealt with fairly easily through the inclusion of zone fixed effects. (Recall that a zone denotes a bidding area under a particular Elspot regime.) This controls for demand by grouping reservoirs at the zone level. Any residual differences between otherwise similar reservoirs can thus be interpreted as a causal result of market share, since producers within the same zone will always face the *same* demand, irrespective of whether transmission constraints are binding or not.

It is worth noting that this latter claim would not necessarily hold true if we were to

[20]The abuse of market power is not listed by Statnett as a reason for the redrawing of bidding areas. Instead, their communications to Nord Pool participants makes it clear that their decisions are based on exogenous factors like climate (e.g. drought) and the gradual completion of long-term grid connectivity objectives (e.g. subsea cables to new regions).

compare plants with different production technologies (e.g. hydro versus nuclear). Electricity in modern power systems is dispatched according to the merit order of production, with plants ranked in ascending order of their marginal costs. Depending on the supply characteristics of the redrawn bidding areas, the relative positions that two plants occupy along the merit curve would likely change if they did not have the same production technology. In other words, the probability of a producer serving a particular consumer — or, at least, the relative probability — would change and we would not be able to control for demand effectively. Fortunately, my exclusive focus on hydropower plants means that I am able to neatly sidestep this problem.[21] Not only am I always comparing like with like, but recall that the marginal costs of hydropower production are moreover negligible. These plants necessarily occupy the lower rungs of the merit curve irrespective of other production technologies. Such factors further help to simplify the econometric analysis and again speak to the unique empirical advantages of hydropower in general and my dataset in particular.

Having considered the issues of identification and regional market conditions, let us return to the regression model. Equation (10) expands on the earlier specification in equation (9) by explicitly introducing zone and regime dummies into model.[22] Employing a reservoir–firm link function as per before, we now estimate water volumes of hydropower reservoir i, belonging to firm f, in zone z, and at time t as

$$\begin{aligned} V_{it} = \sum_{m=1}^{12} \beta_m M_{mt} + \sum_{m=1}^{12} \gamma_m M_{mt} \cdot S_{it,F(it)} \\ + \sum_{r=1}^{17} \delta_r R_{rt} + \sum_{z=1}^{23} \eta_z Z_{it} + \boldsymbol{X}\boldsymbol{\beta}_{\boldsymbol{X}} + a_i + v_{it}, \end{aligned} \tag{10}$$

where R_r is a set of regime dummies, Z_z is a set of zone (i.e. regime-area) dummies, and the remaining parameters are as before. Given that producers will be able to exploit

[21] At the very least, other studies that do not benefit from this unique institutional setting must control for varying plant types and bidding curves explicitly. For example, Puller (2007), Mansur (2007), Hortaçsu and Puller (2008), and Davis and Hausman (2016) rely on marginal cost estimates for different generation technologies to infer bidding behaviour.

[22] Including regime dummies alongside the zone dummies might seem redundant at first, since zones already denote the specific regime-area combinations. However, in so doing, we are allowing for the possibility that the configuration of bidding areas under a particular regime may bring about an aggregate effect. For example, some regimes may comprise a less efficient configuration of bidding areas, which raises the possibility of transmission bottlenecks and congestion within the system as a whole. This would have potential knock-on effects beyond the individual constraints pertaining to any one zone.

their local market power most effectively when transmission constraint are binding, we may also wish to additionally interact this term with a measure of constraint severity. I explore the implications of such a threeway interaction term in the results section. Finally, since a common treatment is shared by all reservoirs belonging to a single firm in a specific zone, I will be clustering my standard errors at the firm-zone level.

6.2 Accounting for firm expectations and market formations

An empirical complication that I have elided over so far is the fact that, strictly speaking, strategic behaviour in this market should correspond not to a firm's realised market power, but rather their *expected* market power. (Recall that the Elspot market is a day-ahead auction market, where firms are obliged to submit their supply bids by noon of the preceding day.) Broadly speaking, I adopt three approaches to accurately model firm expectations about their market power.

The first "local-only" approach simply assumes that firms base their expectations solely on the local market power that they command in their respective bid areas (i.e. zones). In other words, they ignore the variable impact of intraday transmission constraints and only recalibrate their expectations when they are "permanently" re-assigned to a new bidding area following the reconfiguration of a new Elspot regime.[23] While such an approach may seem overly myopic, it is not necessarily unrealistic given the frequency with which transmission constraints are binding in this market (Figure 3). Moreover, we can additionally control for non-linear responses to particularly constrained periods of the year by interacting local market share with a term that measures constraint severity.

The second "constraint-weighted" approach weights expectations according to the relative frequency with which transmission constraints were binding for that day. For example, if the transmission corridors attached to a particular bidding area were constrained for 50 percent of all operating hours, then each firm's weighted market share is calculated as the simple mean of its local market share and the market share that it commands within the Norwegian system as a whole. (Similarly, if the electricity flows were entirely unconstrained, then the weighted market share is only based on its system-

[23] Yet another way to put this is that we are not distinguishing between the two layers of exogenous variation — transmission constraints and reconfigured Elspot regimes — as separate forms of treatment.

wide market share. And so forth.) This approach arguably improves upon the local-only approach, insofar as it treats transmission constraints and Elspot regime reconfiguration as separate sources of exogenous variation. However, it implicitly assumes that firms accurately predict the degree to which transmission will be constrained on the following day. This may not be an overly burdensome assumption given the inertia in modern electric power systems, the availability of accurate near-term weather forecasts, and so on. Nevertheless, we might additionally control for expectations by modeling market share as, say, a rolling mean of the previous seven days.

The third and final "price-based" approach treads a similar path to the constraint-weighted approach above. However, rather than weighing market share as some combination of a firm's market share in its (immediate) bidding area and the system as a whole, it is based on the actual formation of common price markets. These may comprise one or several bidding areas — including the system as a whole when there are no transmission constraints. This approach has the advantage of accounting for constrained periods that may not be obvious when comparing electricity flows and capacities at bidding area's immediate borders. For example, a bidding area may be part of a larger segmented market arising from a bottleneck elsewhere in the system, even though electricity is freely flowing across its own corridors. On the other hand, because this price-based measure of common markets is no longer precisely constrained by the physical capacities and flows on transmission corridors, we cannot be sure that it is entirely exogenous. For example, prices may be diverging because a firm is exercising market power, which is the very thing we want to measure. We should henceforth regard this measure with caution and view it as a sanity check more than anything else.

7 Results

My primary regression results are presented in Table 3 and Figure 6. While each column in the table depicts a different model specification, the highlighted coefficients may all be interpreted in the same way. These correspond to the γ_m parameters described in regression equations (9) and (10), and show the marginal effect of increasing market share on reservoir volumes, contingent on month. Economic theory, together with my estimates of Norwegian electricity demand elasticities in Section 5.3, suggests that the sign on these variables should be positive during the summer months and negative

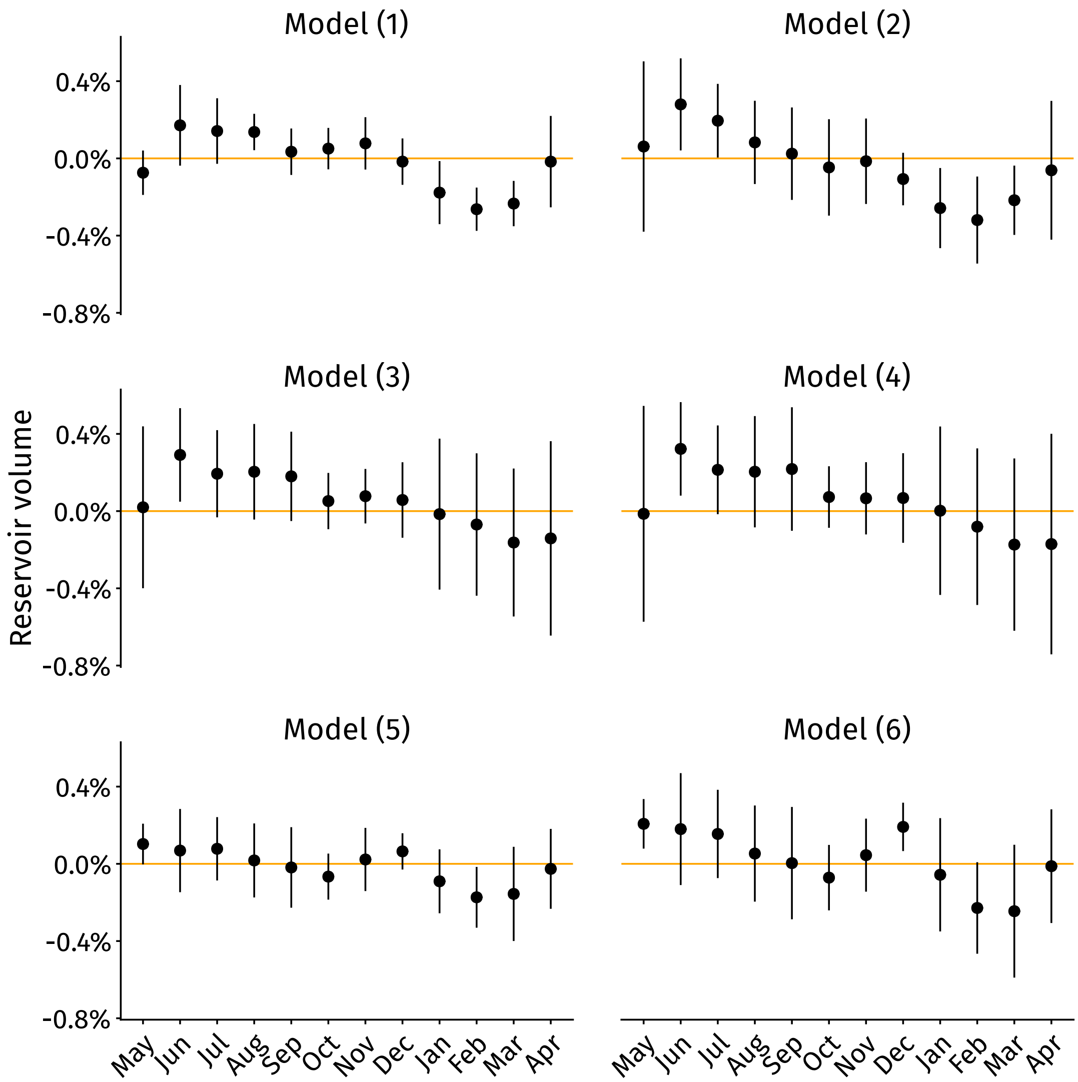


FIGURE 6: CHANGE IN RESERVOIR VOLUMES DUE TO INCREASING MARKET POWER

Notes: Marginal effect of a one percent increase in producer market share on reservoir volumes by month. Dots denote point estimates and the error bars show 95 percent confidence intervals. See Table 3 and the text for details.

during the winter months. Moreover, since both reservoir volume and market share are measured in percentages, these coefficients should be read as elasticities. While the remaining coefficients and controls have been omitted from the table for brevity, these are all jointly significant and, where applicable, of the expected sign and magnitude.

Model (1) is a direct application of equation (10), using the "local-only" measure of market power discussed in the previous section. The results are immediately encour-

Table 3: Regression results

Dependent Variable: Reservoir volume

	Local-only		Constraint-weighted		Price-based	
	(1)	(2)	(3)	(4)	(5)	(6)
Summer months						
May	-0.074	0.061	0.020	-0.014	0.103^{*}	0.207^{***}
	(0.059)	(0.225)	(0.214)	(0.285)	(0.054)	(0.065)
June	0.171	0.280^{**}	0.291^{**}	0.322^{***}	0.069	0.180
	(0.107)	(0.122)	(0.124)	(0.124)	(0.110)	(0.148)
July	0.142	0.195^{**}	0.194^{*}	0.214^{*}	0.078	0.155
	(0.087)	(0.097)	(0.115)	(0.117)	(0.084)	(0.117)
August	0.137^{***}	0.083	0.204	0.204	0.018	0.053
	(0.048)	(0.110)	(0.126)	(0.147)	(0.098)	(0.127)
September	0.035	0.024	0.180	0.218	-0.019	0.004
	(0.061)	(0.122)	(0.118)	(0.163)	(0.106)	(0.148)
October	0.051	-0.047	0.052	0.073	-0.066	-0.072
	(0.055)	(0.127)	(0.074)	(0.081)	(0.061)	(0.086)
Winter months						
November	0.078	-0.015	0.077	0.066	0.023	0.045
	(0.069)	(0.113)	(0.072)	(0.095)	(0.083)	(0.097)
December	-0.017	-0.107	0.058	0.068	0.064	0.191^{***}
	(0.061)	(0.069)	(0.100)	(0.118)	(0.048)	(0.064)
January	-0.177^{**}	-0.257^{**}	-0.016	0.002	-0.090	-0.057
	(0.083)	(0.106)	(0.199)	(0.223)	(0.084)	(0.150)
February	-0.263^{***}	-0.319^{***}	-0.069	-0.081	-0.173^{**}	-0.229^{*}
	(0.057)	(0.115)	(0.188)	(0.207)	(0.080)	(0.121)
March	-0.234^{***}	-0.217^{**}	-0.163	-0.173	-0.156	-0.245
	(0.060)	(0.092)	(0.195)	(0.228)	(0.124)	(0.176)
April	-0.017	-0.062	-0.141	-0.171	-0.026	-0.012
	(0.121)	(0.183)	(0.257)	(0.291)	(0.106)	(0.150)
Constraint interaction	No	Yes	No	No	No	No
Rolling mean	No	No	No	Yes	No	Yes
Clusters	425	425	425	425	2359	2359
N	1,911,492	1,872,899	1,872,899	1,842,299	1,910,113	1,907,447
Adjusted R^2	0.512	0.512	0.512	0.513	0.511	0.511

The table shows the marginal effect of a one percent increase in producer market share on reservoir volumes, conditional on month (season) of the year. The dependent variable is daily individual reservoir volume, expressed as a percentage of the reservoir's maximum capacity. Standard errors (in parentheses) are clustered at the producer:zone level (or, where appropriate, producer:price-zone level). All models include reservoir, power plant, firm, Elspot regime, and Elspot zone fixed effects, as well as an ensemble of calendar fixed effects (day of week, week of year, month, and year). In addition, the models control for meterological conditions using a mix of temperature and preciptation covariates, which are jointly significant albeit omitted for brevity. Model (1) uses local (i.e. zone-level) market share that only changes with the reconfiguration of a new Elsopt regime. Model (2) follows Model (1), but interacts market share with a constrained transmission (>50 percent of operating hours) dummy variable. Note that unconstrained periods from this model are omitted for brevity. Models (3) and (4) weight local and system-wide market share according to the severity of transmission constraints, with the latter using a 7-day rolling mean. Models (5) and (6) establishe market share according to common price zones, with the latter using a 7-day rolling mean. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

aging with respect to our theoretical predictions. We see that higher market share generally leads to a rise in reservoir volumes (i.e. decreased production) during summer and the opposite in winter. Model (2) builds upon this first specification by adding an interaction term to account for periods when transmission constraints are binding for at 50 percent of the day. This specification even more closely resembles the predicted sinusoidal shape that we saw in Figure 5(B). Taking the summer month of June as an example, a one percent increase in producer market share corresponds to 0.3 percent increase reservoir volumes on average. Conversely, the same change in market share yields a 0.2 percent mean decrease in volumes during the winter month of February.

Models (3) and (4) both follow the "constraint-weighted" approach to measuring market power, with the latter using a seven-day rolling mean to account for expectation formation. Interestingly, this pair of regression models produces larger standard errors than our first two models. This possibly reflects the fact that producers are not consistently or (accurately) re-optimizing for the specific market conditions of each day. While the general patten of higher reservoir volumes in summer and lower volumes in winter appears to hold, the latter point estimates are not statistically significant at conventional levels. Nevertheless, the key insight that gaining market shares appears to trigger a withholding of production during the inelastic summer months passes through intact.

Finally, Models (5) and (6) following the "price-based" approach to measuring market power. Here again, we see a rough continuation of the same sinusoidal pattern across seasons. However, we should heed our earlier observation about this series potentially being endogenous and should therefore view it as a sanity check as much as anything else

It should be said that the comparative impact of this market share effect on reservoir volumes is modest next to the role of other factors like snow-melt runoff and changes in aggregate electricity demand. Reservoir volumes typically vary over a range of 70 to 85 percent of maximum regulated capacity as one moves from the pre-melt trough in early spring to the autumn peak. Yet, it still suggests that firms within the same bidding area will operate their reservoirs in meaningfully distinct ways when the differences in local market share are large enough.

Finally, as welfare exercise, consider the following thought experiment: How much higher are prices because of local market power versus a counterfactual scenario where

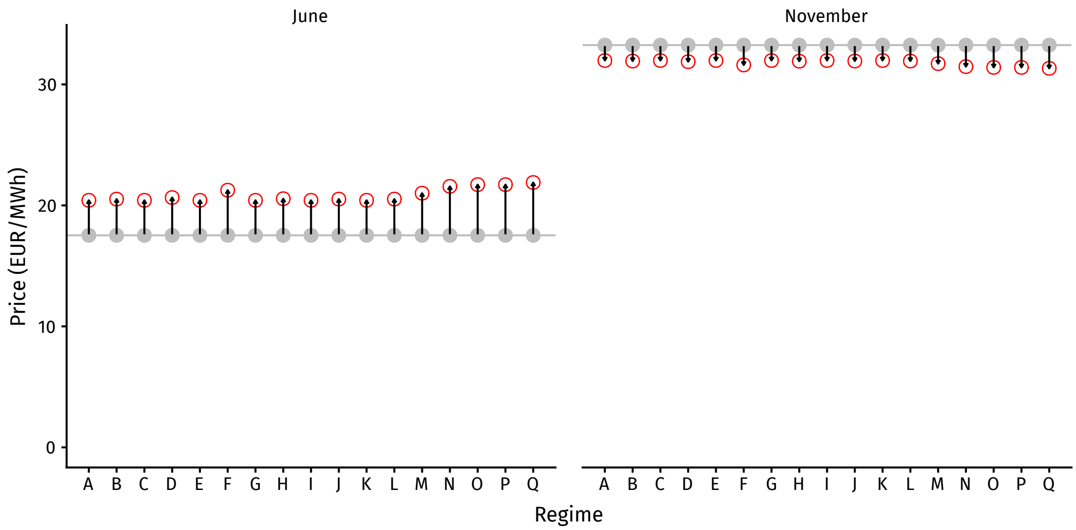


FIGURE 7: WELFARE EXERCISE

Notes: Grey dots denote a simulated counterfactual where transmission constraints are never binding.The red circles

transmission constraints are never binding? Figure 7 provides the results from such a thought experiment, concentrating on the months of June and November. The figure shows the estimated difference in average equilibrium prices (red circles) versus a counterfactual state where transmission constraints are never binding (grey dots). A comparison is provided for each of the different Elspot regimes ("A" to "Q"). In summary, prices are as much as 4 EUR/MWh higher in June (i.e. most inelastic demand month), depending on the Elspot regime. In contrast, they are as much as 2 EUR/MWh lower in November (i.e. most elastic demand month).

8 Concluding remarks

How does market power affect firm behaviour? Microeconomic theory provides the answer familiar to every economist: Dominant firms will produce less than the social optimum (thereby raising prices and ensuring themselves higher profits). However, this fundamental tenet is surprisingly hard to verify with empirical data. A host of complications — from the unobserved factors underlying the decision to enter or exit a market, to uncertainties about marginal cost curves — prohibit us from causally identifying such behaviour among real-world firms. In the specific case of a hydro-based electricity system, theory tells us that dominant hydropower firms will reallocate their water resources away from periods with relatively inelastic demand for electricity to periods with relatively elastic demand. This would allow them to recoup higher profits by restricting supply when consumers are least responsive to the resulting price increase.

I test this hypothesis using a novel data set of Norwegian hydropower reservoirs, power plants and electricity flows. Changes to bidding area divisions and binding transmission constraints provide the additional layers of exogenous variation that allow me to cleanly identify the causal impact of market power on firm behaviour. Consistent with the predictions of theory, I find that increased market power leads to a modest, yet definitive, intertemporal shifting of water resources. Taking Model (2) as a benchmark, a one percent increase in producer market share yields a 0.3 increase in reservoir volumes during summer and a similar percent decrease during winter. This market share effect is distinct from the regular seasonal patterns in reservoir volumes that arise from annual snow-melt inflows and so forth. The qualitative results are also robust to various specifications and model formulations.

Constructing a large dataset such as this from disparate sources entails numerous choices in how one compiles the data. For instance, an implicit simplifying assumption in my empirical analysis has been that firm ownership of reservoirs remains constant over the review period. This may not be an entirely benign assumption and could mask some important results if there was significant merger and acquisition activity during that time. On the other hand, the Norwegian electricity sector had already been liberalised for nearly two decades by the start of my review period. The maturity of the market should give us at least some confidence regarding its stability and competitive structure. In a similar vein, the effects of partial- and cross-ownership have not been considered (c.f. Amundsen and Bergman, 2002). Fully accounting for these issues is a potentially fruitful topic for future research.

Such caveats notwithstanding, the results of this paper may be interpreted as empirical vindication of the underlying theory. More to the point, they can help guide competition authorities in effectively regulating electricity markets like the Nordic system, where hydropower comprises a major share of generation. Or, where transmission constraints create opportunities for producers to exercise local market power. To the best of my knowledge, this paper is one of the first studies to provide direct empirical evidence — absent structural assumptions or simulated counterfactuals — of noncompetitive behaviour in a dynamic market setting. While the magnitude of the effects that I identity here are modest, it is worth remembering that the Nordic system is generally regarded as a paragon among liberalised electricity markets. I therefore interpret my results as a lower bound on the extent to which market power is being exercised more generally in the economy. Any empirical advantages provided by the institutional features of this particular market should be tempered by these considerations. A larger lesson is that even our most advanced markets may be susceptible to the abuse of market power under relatively common conditions.

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Appendices

A Data cleaning and and merging

A.1 Hydropower reservoirs, plants and firms

As noted in the main text, reservoir data are normalised in terms of their maximum regulated capacities. While this normalisation procedure is generally straightforward, a number of reservoirs in the dataset suffer from discrete jumps in measurement values, while others have conflicting regulatory limits ascribed to them. These anomalies may reflect adjustments to the base measurement value (e.g., metres above sea level versus a local reference point), regulatory changes, and, in some rare cases, building out of extra capacity. To account and correct for such anomalies, the data are filtered to detect large, discrete jumps in measurement values and other outliers. These are then corrected as best as possible by reconciling the data with the various regulatory limits, and by comparing the volume and levels series for consistency.[24]

A related problem is that some reservoirs exhibit distinctly unnatural trends. Most obviously, long streaks of the same recurring value. This issue is effectively limited to small reservoirs in the dataset and almost certainly constitutes measurement error. Streaks extending over 10 or more consecutive observations are thus discarded from the analysis. As a final check, time-series plots of all 500 individual reservoirs are examined manually to check for abnormalities that the automated filters may have missed, leaving a handful of cases to be corrected as per the above. Any remaining data anomalies that could not be reconciled in a satisfactory manner, or rationally accounted for, have been dropped from the analysis.

A.2 Weather data

The major issue with respect to the weather data used in this study is the fact that the NCDC panel dataset is unbalanced. While some Norwegian meteorological stations in the dataset are operational over the entire 2000–2013 study period, others come in

[24]While the data analysis part of this study does not utilise the levels series, it nonetheless provides a very useful counterpoint to the volumes series for this reason.

and out of existence. This presents a challenge insofar as I have to decide between two contrasting approaches for determining the (three) nearest neighbour stations to each reservoir, which are in turn used for calculating a reservoir's weather data vector via the inverse-distance weighted average rule. The first approach is to consider only meteorological stations that are available over the full 14-year study period. However, this excludes approximately 90 percent of the stations that would qualify as a "nearest neighbour" during the period when they were operational. I therefore favour a second approach, which is to proceed year-by-year and base the nearest neighbour rule on the stations that were operational for that particular year. This latter approach ensures that as much useful information is retained as possible and that the weather data for every reservoir in my dataset is as accurate as it can be. Experimentation shows that this choice has a negligible effect on the main findings.

B Previous Elspot regimes

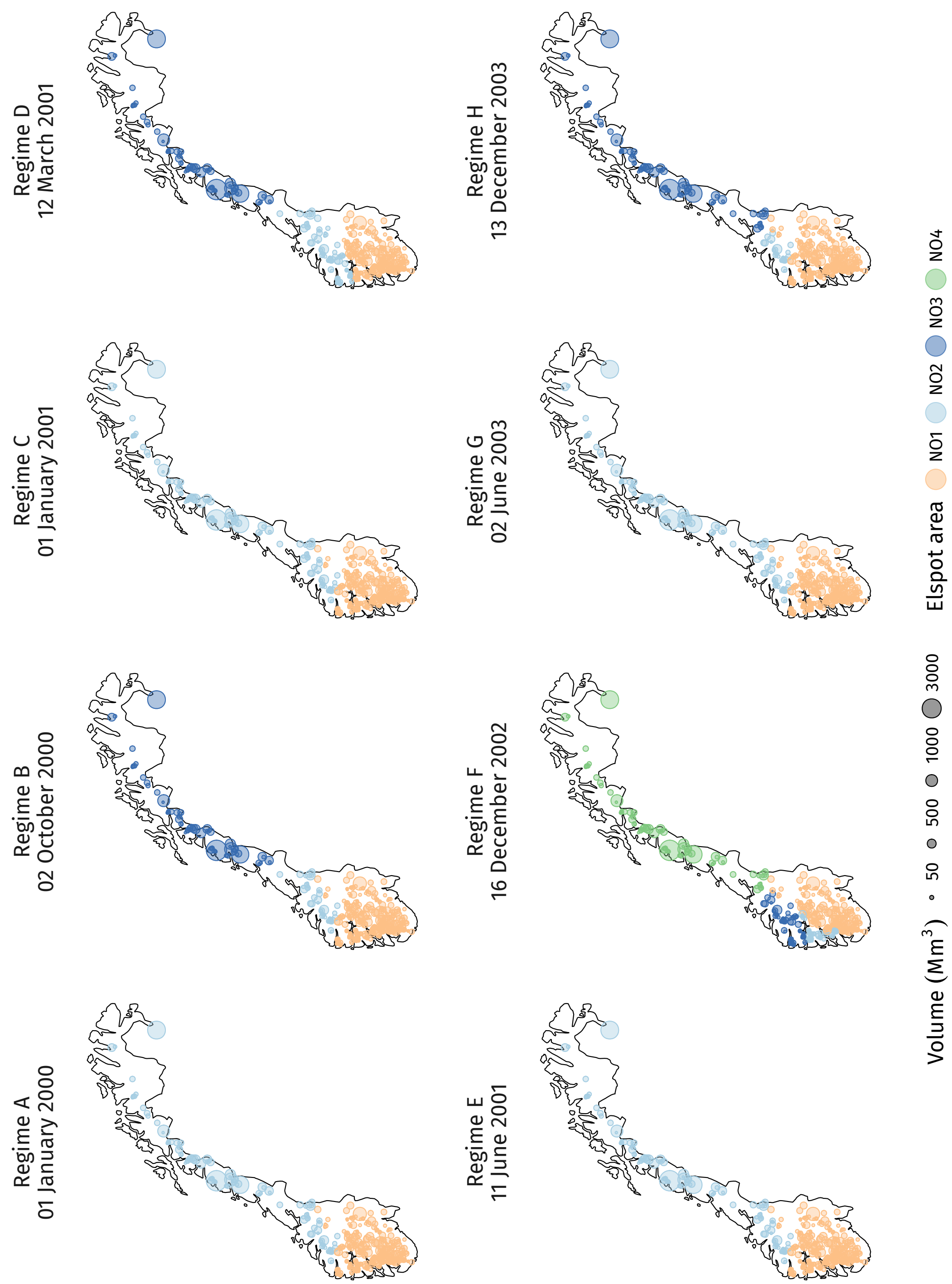

FIGURE B.1: ELSPOT REGIMES A – H (1 JANUARY 2000 – 13 DECEMBER 2003)

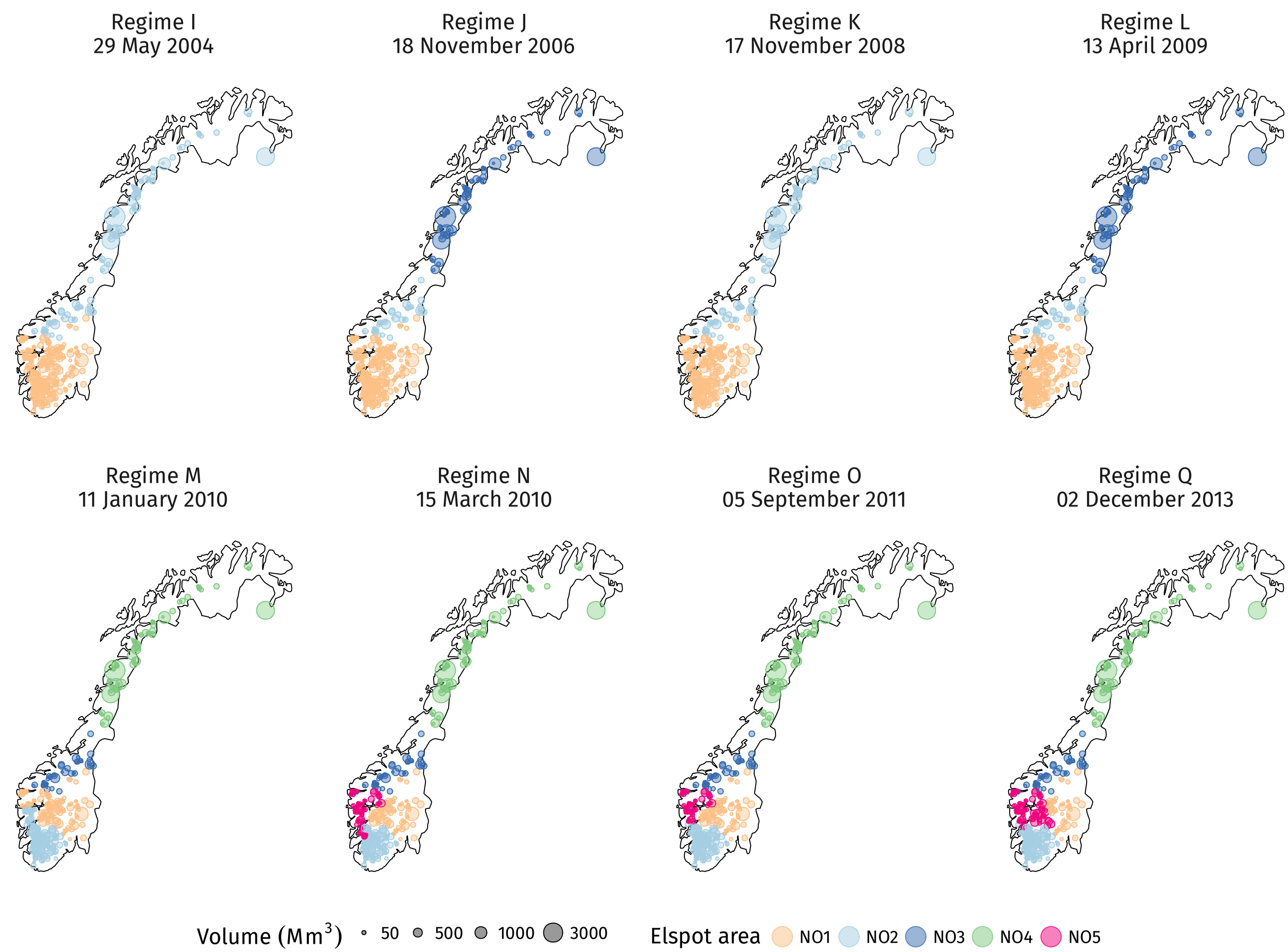

Figure B.2: Elspot regimes I – Q (29 May 2004 – 5 December 2011)

C Market shares of top three producers

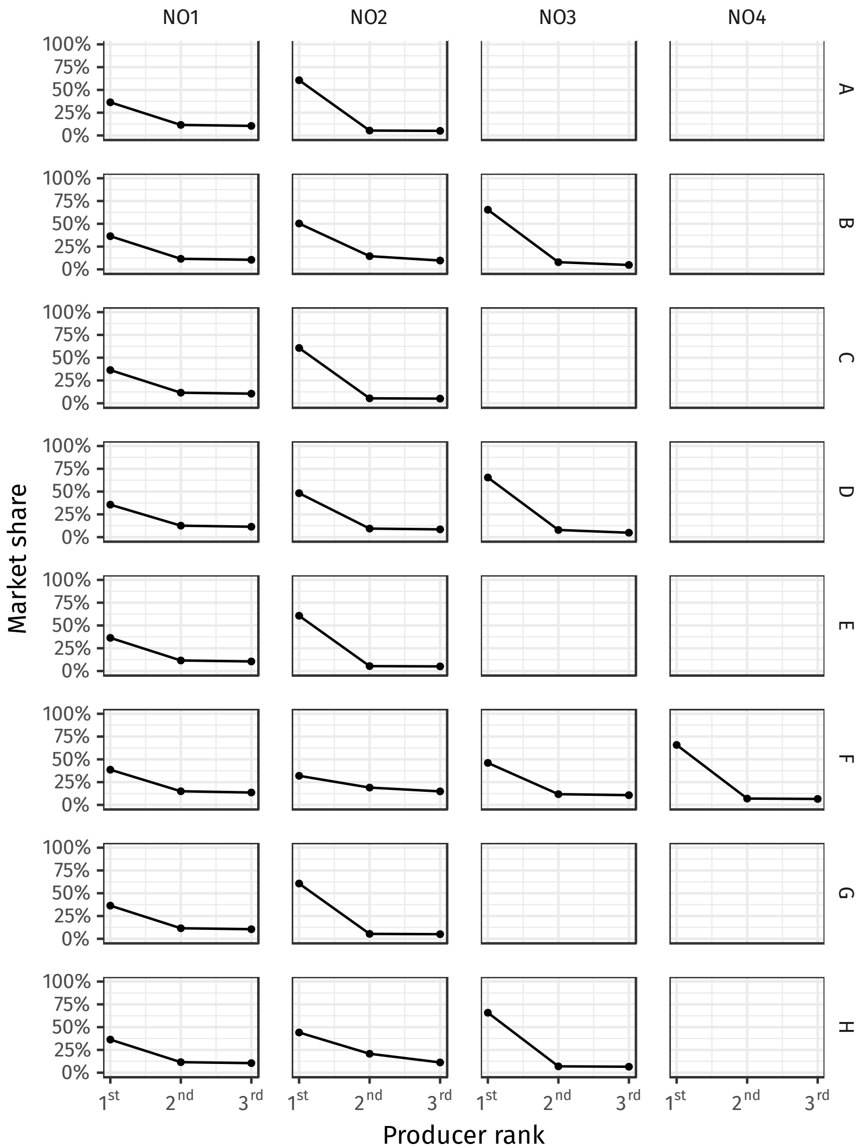

FIGURE C.1: TOP THREE PRODUCERS PER ELSPOT REGIME BY BIDDING AREA

Notes: Ranked by local market share. Elspot regimes A – H.

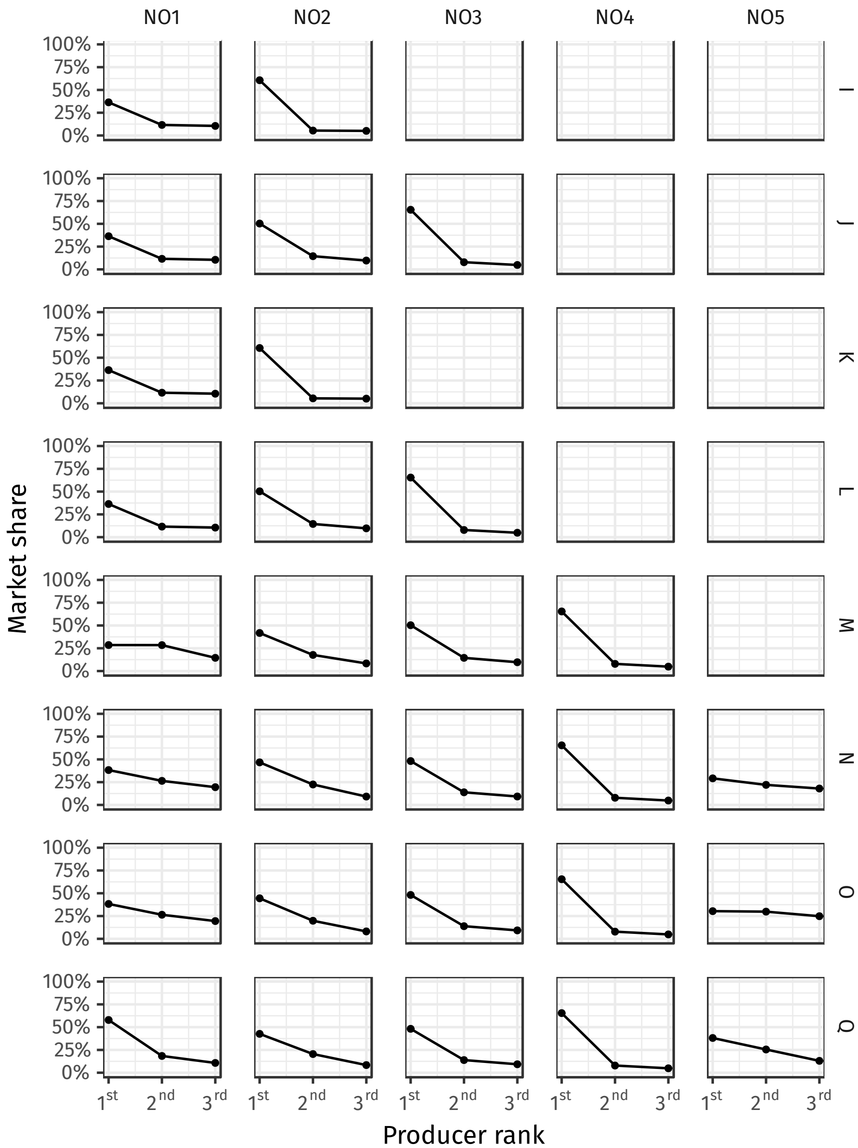

FIGURE C.2: TOP THREE PRODUCERS PER ELSPOT REGIME BY BIDDING AREA (CONT.)

Notes: Ranked by local market share. Elspot regimes I – Q. Regime P is identical to regime O and is thus excluded.

D Elpsot zones

Table D.1: Elspot zones

Zone	First instance	Repeat instances
1	A (NO1)	B (NO1); C (NO1); E (NO1); G (NO1); I (NO1); J (NO1); K (NO1); L (NO1)
2	A (NO2)	C (NO2); E (NO2); G (NO2); I (NO2); K (NO2)
3	J (NO2)	L (NO2); M (NO3)
4	B (NO3)	D (NO3); J (NO3); L (NO3); M (NO4); N (NO4); O (NO4); P (NO4); Q (NO4)
5	D (NO1)	–
6	D (NO2)	–
7	F (NO1)	–
8	F (NO3)	–
9	F (NO2)	H (NO3)
10	F (NO4)	–
11	H (NO1)	–
12	H (NO2)	–
13	M (NO1)	–
14	M (NO2)	–
15	N (NO1)	O (NO1); P (NO1)
16	N (NO3)	O (NO3); P (NO3); Q (NO3)
17	N (NO2)	–
18	N (NO5)	–
19	O (NO2)	P (NO2)
20	O (NO5)	P (NO5)
21	Q (NO1)	–
22	Q (NO5)	–
23	Q (NO2)	–

Notes: Zones describe particular geographic and network extents, which may be common to multiple Elspot bidding areas under different regimes A–Q. See main text for additional details.

E Bid curves

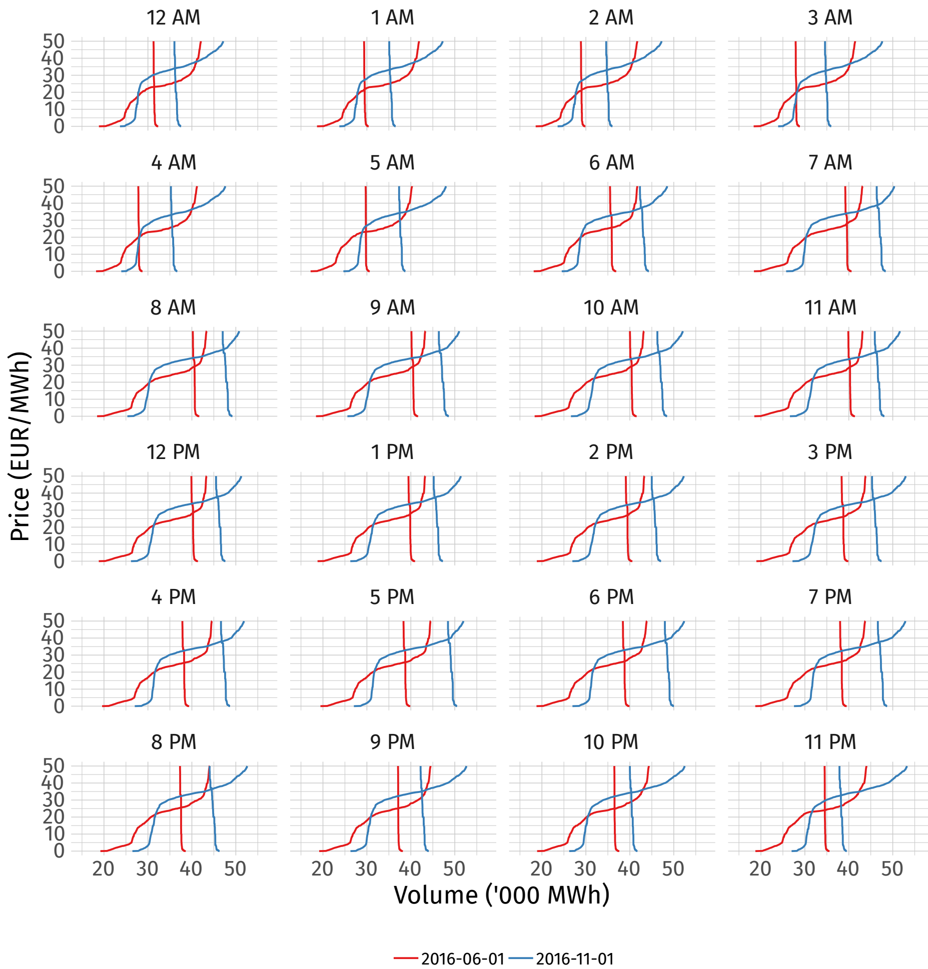

FIGURE E.1: HOURLY ELSPOT BID CURVES

Notes: June 1st (red) and November 1st (blue) are selected as representative days from the months where electricity demand is respectively at its the most inelastic and elastic. The y-axes have been truncated at 0 and 50 EUR/MWh to aid visual inspection.

F Meteorological stations

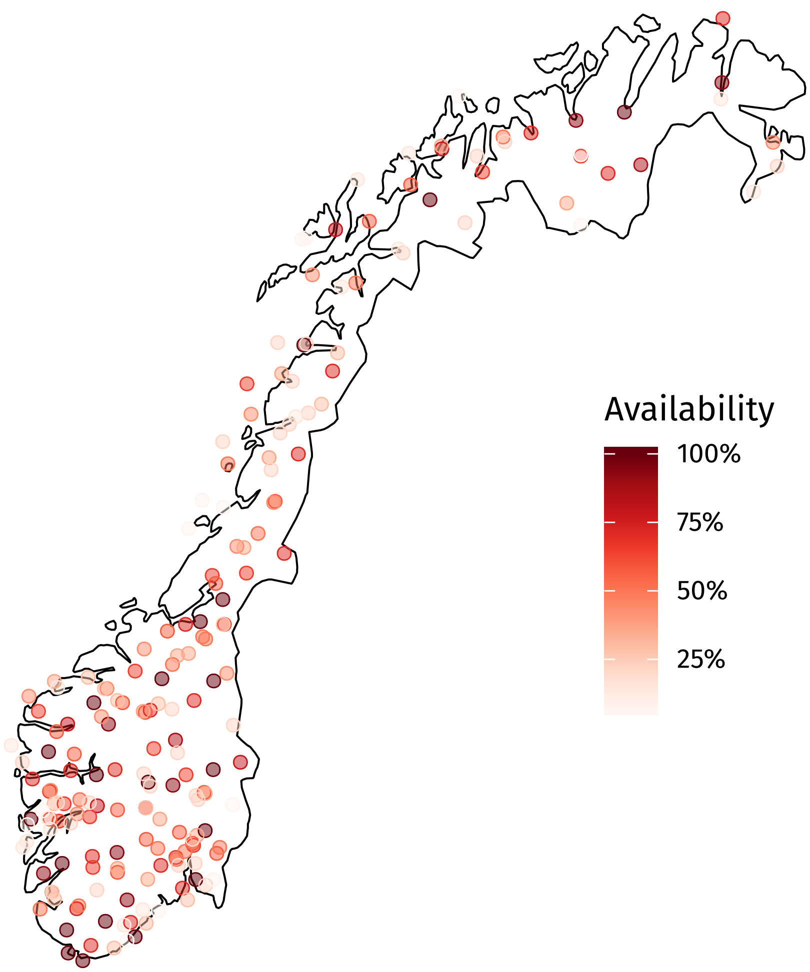

Figure F.1: Meteorological stations

Notes: Stations are colour-coded by years of availability relative to the full study period of 2000–2013. A station with 100% availability thus provides weather records for all 14 years, while a station with 50% availability only provides records for seven years.