The Power of Substitution:
Short-Run Electricity Demand Flexibility*

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Abstract

We estimate short-run electricity demand responses to price changes for Norwegian households from 2023 to 2025, using continental solar and wind forecasts, and hydrological inflow to instrument supply-driven price variation. The presence of several instruments for the price changes allows us to explicitly test the margins at which substitution happens. Households' electricity substitution is real but coarse: households mostly choose between day and night consumption with a price elasticity of 0.073. Substitution across hours within these blocks, or across days, is more limited.

Keywords: Real-time pricing; Intertemporal substitution; Demand flexibility
JEL codes: D12; L94; Q41; Q48

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1 Introduction

Electricity systems must balance supply and demand in real time. As generation increasingly relies on intermittent wind and solar, balancing requires storage, backup generation, grid expansion, or flexible demand. Demand-side flexibility can therefore reduce the need for costly capacity and infrastructure investments. (Gorenstein Dedecca et al., 2025). The importance of household demand flexibility will grow as electrification raises household electricity use.

Real-time electricity prices can induce consumers to shift consumption away from periods of high scarcity, with efficiency gains increasing as renewable generation expands (see, e.g., Borenstein, 2005; Borenstein and Holland, 2005; Joskow and Wolfram, 2012; Imelda et al., 2024; Hinchberger et al., 2026). Yet, evidence on very short-run demand responses remains limited. Much of the existing literature estimates responses over longer horizons, such as months, or studies experimental pilots and special pricing programs. In particular, we have limited evidence on whether households facing hourly prices shift consumption across hours in settings with high electrification and widespread access to technologies that lower the cost of responding.

This paper provides such evidence. We estimate the short-run price responsiveness using hourly municipality-level residential electricity consumption covering nearly all Norwegian households from 2023 to 2025. Rather than imposing the relevant adjustment horizon, we let the data determine the time unit over which households substitute. Flexibility turns out to be real but coarse: households shift consumption mostly between day and night, rather than hour by hour, and total daily use barely responds to the price level.

The setting is particularly well suited for studying the potential for short-run household flexibility: 94.7 percent of households are on hourly spot-price contracts, 86 percent of household energy use is electric, and electric vehicles account for 27.4 percent of the passenger car fleet. Smart meters, price apps, smart chargers, smart water heaters, and other automation technologies make hourly price information and automated load shifting widely accessible.[1] The setting therefore provides evidence on the flexibility that may emerge as other economies electrify heating and transport and adopt technologies that lower the cost of responding to hourly prices.

A central empirical challenge is that hourly electricity prices are endogenous: prices are high precisely when electricity demand is high. We address this challenge using two complementary strategies. In our preferred specification, we instrument the day-night price gap with continental solar and wind forecasts and the daily price level with hydro-

[1]More information on the Norwegian electricity market is provided in Section 4.1.

logical inflow. In an alternative specification, we also estimate demand using detailed weather controls, including municipality-level temperature.

We combine this data-rich environment with a theoretical framework that separates two potential margins of adjustment: substitution across time blocks within the day and changes in total daily consumption in response to the overall price level. The within-day margin captures reallocation from high- to low-price periods while holding daily use largely fixed, and determines the gains from real-time pricing. The across-day margin matters when prices are high for an entire day or longer, including multi-day scarcity events such as a *dunkelflaute*.

The existence of several instruments allows us to explicitly test for which margin substitution happens. The estimated price elasticity should be similar irrespective of whether the induced price change comes from variation in continental solar or wind. This matters because solar generates strongly patterned within-day price variation, particularly through the midday dip, while wind-induced price variation is more diffuse across hours of the day. The two instruments agree on the elasticity only when we estimate the model as day (06-22) vs. night (22-06). Hence, our setting plausibly identifies the margin at which substitution happens. Moreover, the differences in estimated hourly substitution elasticities in the literature may stem from instruments inducing variation differently across this day–night margin.

In our preferred instrumental-variables specification, the day–night substitution elasticity is 0.073. Estimates using continental solar, wind, or both as instruments are statistically consistent, and ordinary least squares with weather controls give nearly the same results. Substitution across hours within the blocks is more limited where both instrument families have identifying power, and total daily use barely responds to the price level (an elasticity of at most 0.046 that falls to 0.021 under a lagged instrument). Households seem to shift schedulable consumption between day and night, but do not fine-tune much across hours within blocks.

Related literature. This paper contributes to the literature on household responses to real-time electricity prices in two ways: by studying a setting where hourly contracts are the norm and automation is widespread, and by estimating rather than imposing the time unit of the response. The latter helps reconcile seemingly conflicting findings in this literature.

Our decomposition helps explain the weak responses found in several closely related studies of real-time pricing: designs whose identifying price variation loads on the hourly or the daily margin should, given our estimates, find weak responses, because adjustment occurs primarily between day and night. Fabra et al. (2021) find zero or near-zero responses among Spanish households using day-ahead wind generation forecasts as instruments, which they attribute to limited consumer awareness and low price variation. Reanalyzing their data, Tiedemann (2025) argues that wind-based instruments identify only the response to high-frequency price surprises, and finds that the same consumers respond to expected price patterns. In Denmark, Adib et al. (2025) find small hourly but somewhat larger daily responses, while Andersen and Dietrich (2026) find weak or zero responses for many households and modest responses among others, emphasizing rational inattention.[2] Scarazzato (2025) likewise finds no significant response of Swiss end-user demand.[3] Our results provide a structural interpretation: wind-driven variation partly reshuffles prices across hours within blocks, where households respond little, so a wind-instrumented hourly design may tend to find near-zero responses even when block-level substitution is present.

Other studies find larger responses. Herrmann et al. (2026) find modest but statistically significant responses to hourly prices among Finnish households, although only about 31 percent of households face real-time prices by the end of their sample.[4] Similarly, Bobbio et al. (2025) estimate an own-price elasticity of 0.26 among British households who self-select into a dynamic tariff, with larger responses among owners of electric vehicles and other low-carbon technologies, emphasizing that these first movers differ from average consumers. Hirth et al. (2024) also find substantial responses in aggregate German electricity demand, likely driven mainly by industrial consumers.[5] We show that household flexibility in the very short run is real but coarse, even in a setting with high electrification and broad access to technologies that lower the cost of adjusting consumption. For the near-universal Norwegian population, the day–night substitution elasticity of 0.073 sits well below the own-price elasticity that Bobbio et al. (2025) find for self-selected first movers on a dynamic tariff in Great Britain, which suggests that the flexibility of such first movers should not yet be extrapolated population-wide.

In a recent contribution, Enrich et al. (2024) study time-of-use (TOU) pricing, where prices follow predictable schedules, and find substantial responses among Spanish house-

[2] Jessoe and Rapson (2014) also emphasize the importance of information as a determinant of household electricity-price responsiveness.

[3] Moreover, Hofmann and Lindberg (2024) find substantial conservation among Norwegian households during the 2021-2022 energy crises, but limited average short-run response to daily or hourly price variation. Our results suggest that using realized spot-price variation understates responsiveness because prices are correlated with contemporaneous demand shocks.

[4] Herrmann et al. (2026) show that wind-based price instruments can be upward biased when local wind affects heating demand, and therefore control for wind speed.

[5] A set of papers studies responses to real-time prices among commercial consumers; see, e.g., Choi et al. (2011); Møller and Andersen (2015).

holds. Because TOU prices are typically simple, salient, and known in advance, they may induce stronger demand responses than real-time prices.[6] Our results show that households can nevertheless respond to less predictable prices, especially if the price changes induce variation across the day–night margin.

Another strand of the literature studies household responses to hourly or within-day electricity prices in experimental settings.[7] We demonstrate that everyday, non-experimental flexibility exists without warnings or experimental salience, but that it operates by re-timing schedulable use between day and night rather than hour by hour.

Finally, a substantial literature estimates household electricity-demand responses over longer horizons, typically using monthly consumption data.[8] Evidence generally points to limited short- and medium-run responses, with substaintial heterogeneity across households (see Ahlvik et al., 2026 and Reiss and White, 2005). Long-run responses are larger as consumers have more time to adapt (Deryugina et al., 2020). We locate the short end of the horizon profile precisely: a day–night substitution elasticity of 0.073 within the day, and a total-demand response of at most 0.046 at the daily horizon.

Roadmap. The remainder of the paper is organized as follows. Section 2 sets up the two-tier demand system over day and night blocks and derives the estimating equation that separates the day–night substitution elasticity, σ, from the elasticity to the daily price level, η. Section 3 presents the empirical setups and the assumptions each requires. Section 4 describes the Norwegian electricity market and the data. Section 5 reports the results and relates them to the literature, and Section 6 concludes.

2 Theoretical Setup

We model the demand for electricity from households in municipality i, treated as a representative consumer, observed in hour h of day t. Electricity is priced at the level of the price zone, so the price, p_{iht} per megawatt-hour, faced by municipality i depends on i only through its zone, denoted $z(i)$, and within a zone there is no price variation.

The day is divided into two *blocks*: day, d (06–22), and night, n (22–06), following the grid tariffs partition. The households choose consumption consumption, q_{ibt}, $b \in \{d, n\}$,

[6] TOU pricing fails to reflect marginal-value differences across days and within pricing periods. Hinchberger et al. (2026) find that a typical TOU tariff eliminates only about 10 percent of the dead-weight loss from flat prices, relative to full real-time pricing.

[7] See Garnache et al. (2025) on critical-peak pricing in Norway; Fowlie et al. (2021) on peak-hour pricing and time-of-use pricing in Sacramento; Prest (2020) on Irish households; and Wolak (2011) and Allcott (2011) on US consumers. Harding and Sexton (2017) review this literature.

[8] See, e.g., Ito (2014); Byrne et al. (2021). Labandeira et al. (2017) provide a review.

while within each block, consumption in each hour is a fixed proportion, reflecting that the profile of use inside a block is set by routines and appliance cycles rather than by hour-to-hour prices. This is not an assumption of convenience, but an empirical finding: substitution across hours *within* a block is negligible in the data, hourly and finer-block models are rejected by overidentification tests whichever instrument is used, and the day–night partition is the aggregation at which our two instruments agree (Section 5 and Appendices C.1–C.2).

Preferences. Preferences are weakly separable and take a two-tier constant-elasticity-of-substitution (CES) form. The outer tier aggregates an electricity composite Q_{it} and a numeraire bundle of all other goods z_{it} with constant elasticity of substitution, η, between electricity and other goods:

$$U_{it} = \left[\phi_{it}^{1/\eta} Q_{it}^{(\eta-1)/\eta} + (1-\phi_{it})^{1/\eta} z_{it}^{(\eta-1)/\eta}\right]^{\eta/(\eta-1)}. \tag{1}$$

The electricity composite Q_{it} is a CES aggregate over the two block quantities, with constant elasticity of substitution, $\sigma > 0$, between the blocks:

$$Q_{it} = \left(\sum_{b\in\{d,n\}} \alpha_{ibt}^{1/\sigma} q_{ibt}^{(\sigma-1)/\sigma}\right)^{\sigma/(\sigma-1)}. \tag{2}$$

Observed and unobserved demand shifters enter the CES weights multiplicatively. The electricity weight is $\phi_{it} = \phi \exp(\mathbf{m}_{it}'\lambda + \xi_{it})$, where $\mathbf{m}_{it}$ is a vector of period-level demand shifters (e.g., daily mean temperature, calendar-fixed effects) and ξ_{it} includes all unobserved demand shifters for municipality i at t. Similarly, the block weights are $\alpha_{ibt} = \alpha_b \exp(\mathbf{x}_{ibt}'\delta_b + \omega_{ibt})$, where $\mathbf{x}_{ibt}$ is the vector of block-level demand shifters (e.g., block temperature) and ω_{ibt} includes all unobserved block-level demand shifters. The two elasticities η and σ are the central structural parameters: σ governs the reallocation of electricity consumption between day and night in response to the relative block price, while η governs the response of total electricity use to the overall price level.

Budget constraints. Households choose to allocate their disposable income y_{it} into electricity consumption or other spending z_{it}. The preference system allows a flexible interpretation of z_{it} as either including only current consumption of goods (y_{it} includes saving) or current and future goods (y_{it} is current income, and z_{it} includes saving).[9]

[9] Interpreting y_{it} as current income and z_{it} as a current-and-future composite requires a constant intertemporal elasticity of substitution and weak separability of electricity from that composite.

The consumer maximizes (1) subject to the following budget constraint:

$$\sum_{b\in\{d,n\}} p_{ibt}\, q_{ibt} + z_{it} = y_{it}, \tag{3}$$

for all t, with the numeraire price normalized to one. p_{ibt} is the price of the block bundle: with the hours inside a block consumed in fixed proportions, the block price is the correspondingly weighted average of the hourly prices within the block, and we work with its logarithm (measured empirically as a fixed-weight index, Section 3).

The assumption of weak separability between the electricity composite and other goods permits two-stage budgeting (derivation in Appendices A.1–A.2). In the lower stage, the consumer allocates a given quantity of the electricity composite between the day and night blocks by cost minimization. The resulting associated unit cost is the CES price index

$$P_{it} = \Big(\sum_{b\in\{d,n\}} \alpha_{ibt}\, p_{ibt}^{1-\sigma}\Big)^{1/(1-\sigma)}, \tag{4}$$

and electricity expenditure equals $P_{it}Q_{it}$.

In the upper stage, the representative consumer divides its budget between electricity and other goods, yielding a demand for the composite that depends on P_{it} with constant elasticity (see Appendices A.1–A.2). It is convenient to summarize the daily price pair by its *level*, $\ell_{it} \equiv \ln P_{it}$, and its *shape*, $r_{ibt} \equiv \ln p_{ibt} - \ln P_{it}$. The within–day allocation responds only to the shape, i.e., to whether the day block is cheap or expensive relative to the night, with elasticity σ, whereas total electricity use responds to the level, i.e., to whether the full day is expensive or cheap.

Combining optimization in the two stages (Appendix A.3) yields the structural block demand, which we take to the data in the form

$$\ln q_{ibt} = a_b + \mu_i + \tau_{(\cdot)t} + \mathbf{w}'_{ibt}\boldsymbol{\delta} + \ln y_{it} - \sigma\, r_{ibt} - \eta\, \ell_{it} + u_{ibt}, \tag{5}$$

where a_b and μ_i are block and municipality fixed effects, $\mathbf{w}_{ibt}$ collects the observed demand shifters (temperature, wind, and rooftop-solar feed-in controls), $\tau_{(\cdot)t}$ is a time effect whose level of aggregation depends on the identification strategy described below,[10] and $u_{ibt} = \omega_{ibt} + \xi_{it}$ contains the unobserved demand shocks. The coefficient on the shape term is the substitution elasticity σ and that on the level term is η.[11] The two terms separate cleanly

[10]These time controls include municipality-by-day fixed effect and zone-by-block-by-month fixed effects in the block specification.

[11]In practice, P_{it} may be replaced by a share–weighted log price index built from predetermined expenditure shares.

in estimation: with municipality-by-day fixed effects, the level term (and everything else that varies at the day level) is absorbed and σ is identified from within-day variation alone, while η is estimated from a companion daily equation:

$$\ln Q_{it} = \mu_i + \tau_{(\cdot)t} - \eta \ell_{it} + \mathbf{w}_{it}' \boldsymbol{\delta} + u_{it}, \tag{6}$$

identified from variation across days where $\mathbf{w}_{it}$ includes wind, temperature, and rooftop-solar feed-in controls, and τ_t includes day-of-week-by-month fixed effects, month-by-year fixed effects, and zone-by-month fixed effects.

The simultaneity of prices and quantities complicates the identification of the elasticities. The unobserved demand shifters decompose into a spatially common, zone-wide component, $\bar{\omega}_{z(i),b,t}$ and $\bar{\xi}_{z(i),t}$, and an idiosyncratic one, $\tilde{\omega}_{ibt}$ and $\tilde{\xi}_{it}$:

$$\omega_{ibt} = \bar{\omega}_{z(i),b,t} + \tilde{\omega}_{ibt}, \qquad \xi_{it} = \bar{\xi}_{z(i),t} + \tilde{\xi}_{it}, \tag{7}$$

and likewise for the observed shifters. We will assume throughout that each municipality is small relative to its price zone, so that municipality-specific shocks do not move the zonal price. Hourly zonal prices clear a market in which the relevant demand is the aggregate of the same shocks, i.e.:

$$\ln p_{iht} = \Pi^*\Big(\underbrace{S_{z(i),h,t}}_{\text{zonal supply}}, \underbrace{\bar{\mathbf{x}}_{z(i),b,t}, \bar{\mathbf{m}}_{z(i),t}, \bar{\omega}_{z(i),b,t}, \bar{\xi}_{z(i),t}}_{\text{zonal aggregate demand}} \Big), \tag{8}$$

where S collects supply conditions, such as capacity, plant availability, and closures. Because the price moves with the zone-wide demand shocks, the shape and level terms in (5) are correlated with u_{ibt}, so that estimation of equation (5) is, in general, biased.

3 Empirical Setup

We estimate equation (5) on a municipality-day-block panel. The block price is a fixed-weight log price index, $p_{ibt} = \sum_{h \in b} \bar{\theta}_{z(i)hm} \ln p_{iht}$, where the weight $\bar{\theta}_{z(i)hm}$ is the average share of hour h in daily electricity expenditure in zone $z(i)$ and calendar month m over the full sample, renormalized within the block.[12] The shape $r_{ibt} = p_{ibt} - \ell_{it}$ is the block price relative to the daily index. The dependent variable is log block consumption per household. All

[12]Fixed weights keep the index predetermined with respect to the contemporaneous demand shock: a demand shock that shifts the within-day consumption profile on day t cannot move the weights, and hence cannot enter the price index mechanically. The daily level ℓ_{it} is the correspondingly weighted index over all 24 hours.

block specifications absorb municipality-by-day fixed effects, zone-by-block-by-month effects, a block-specific temperature spline, wind controls, and the rooftop-solar feed-in control of Section 4, and standard errors are clustered by municipality and by zone-day. The level elasticity η is estimated from the companion daily equation, with the same controls at the daily level.

3.1 Identification of elasticities

We follow two identification strategies to estimate equation (5) and recover the pair of elasticities (σ, η). The strategies share a common core of maintained assumptions and differ only regarding the orthogonality condition that delivers identification together with the auxiliary conditions each strategy brings with it. We state the common core first and then the specific assumptions made for each strategy. The conditions common across strategies are the following:

- **(C1) Correct structural specification.** Demand follows the two–tier CES system (1)–(2), so that (5) holds with an additive demand shock $u_{ibt} = \omega_{ibt} + \xi_{it}$.
- **(C2) Price–taking.** Each municipality is small relative to its price zone, so its own consumption does not move the zonal price. The only price–quantity simultaneity operates through the zone–wide demand shock in (8).
- **(C3) Rank condition.** The shape term r_{ibt} and the level term ℓ_{it} are moved independently by the identifying variation, so σ and η are separately identified.

The two-tier CES demand structure from section 2 is imposed by assumption C1, and ensures that the disagreements among the strategies below concern the exogeneity of prices rather than the shape of demand. Assumption C2 is plausible in this setting because all price zones contain many municipalities, so no single municipality's consumption substantially moves the zonal price. We show below that the identifying variation in each strategy is sufficient to satisfy the rank condition in assumption C3.

Strategy 1: OLS with weather controls. Because electric heating accounts for a large share of household electricity consumption for much of the year, weather is a key demand shifter in Norway. Our first strategy estimates the block equation by ordinary least squares with municipality-by-day fixed effects, μ_{it}, and detailed weather controls:

$$\ln q_{ibt} = a_b + \mu_{it} + \mathbf{w}'_{ibt}\boldsymbol{\delta} - \sigma\, r_{ibt} + u_{ibt}. \tag{9}$$

The fixed effects absorb the level term, income, and every other day-level shifter, so only σ remains. The elasticity is identified from the partial covariance of block consumption with the block relative price *within the day*: does the day–night split of consumption tilt toward the cheaper block? Consistency requires:

(OLS) Conditional price exogeneity: $\mathbb{E}[u_{ibt} \mid r_{ibt}, \mathbf{w}_{ibt}, \text{FE}] = 0$. The within-day price shape is mean-independent of the within-day demand shocks, conditional on the weather controls and the fixed effects.

The day fixed effects do most of the work here: any demand shock that operates at the day level (economic activity, most weather, local events) is absorbed, so the only threat is a shock that shifts the *composition* of demand between day and night and co-moves with the price shape. Weather with a daily profile is the leading candidate, which is why the temperature response is block-specific and wind enters directly. Additionally, the rooftop-solar feed-in control removes the metering channel described in Section 4.

Strategy 2: Instrumental variables with supply shifters. The endogenous prices are instrumented by exogenous, weather-driven supply shifters and estimated by two-stage least squares. In the block equation, the block price r_{ibt} is instrumented by *two independent families* of continental supply shifters: the day-ahead forecasts of solar and of wind generation in the interconnected continental market areas (Germany-Luxembourg, the Netherlands, and Denmark), averaged over the hours of each block and interacted with zone. The first stage thus loads each forecast separately in each zone. For both wind and solar, conditions in the interconnected continental markets are transmitted to southern Norwegian prices through the interconnectors, but they move prices in very different ways: solar deepens the midday dip, thereby cheapening the day block, while wind typically shifts prices diffusely across all hours of the day. In the companion daily equation, the level ℓ_{it} is instrumented by *hydrological inflow* (the deviation of modeled zone catchment runoff from its seasonal normal), which shifts the marginal cost of Norway's predominantly hydropower supply and hence the daily price level. The two key conditions for this strategy are:

(IV.1) Instrument exogeneity: $\mathbb{E}[u_{ibt} \mid \mathbf{Z}_{ibt}, \mathbf{w}_{ibt}, \text{FE}] = 0$, where $\mathbf{Z}_{ibt}$ collects the continental solar and wind shifters (and, in the daily equation, inflow).

(IV.2) Relevance: the continental forecasts shift the block price r_{ibt} and inflow shifts the level ℓ_{it}, giving first stages with full rank.

Using instruments weakens the requirement from price exogeneity: unobserved demand shocks may be correlated with the price, provided they are uncorrelated with the continental forecasts and with inflow, once the weather controls are conditioned on.

Having two instrument families for the same price is the paper's main specification device. Solar and wind generate price variation from different weather processes, so demand-side violations that could contaminate one (Norwegian sunshine for solar; Norwegian wind and cold for wind) would not contaminate the other in the same way. If both families are valid and the block model is correct, they must deliver the same σ. We test this using overidentification statistics (Hansen J-statistics, Hansen, 1982 and Hayashi, 2000, p. 217–218) and C-tests comparing each family against the other (Eichenbaum et al., 1988, Appendix C and Hayashi, 2000, p. 218–221).[13] The same tests, applied at the hourly frequency, *reject* the single-elasticity hourly model for any instrument family (Appendix C.3), and applied at finer partitions of the day, they reject those models as well (Appendix C.2). The day–night block is the unit at which the two quasi-experiments do not disagree.

The main threat to IV.1 is that Norwegian weather may correlate with the continental forecasts. For inflow, this is addressed by removing the seasonal cycle, by the temperature controls, and by a timing check that replaces contemporaneous runoff with accumulated lagged runoff (Table 2, Panel B, and Appendix C.4). For the continental forecasts, it is addressed by the block-specific temperature spline and wind controls, by the rooftop-solar feed-in control (Section 4), and by the seasonal-stability check of Appendix C.5. Because the instruments are persistent weather processes, day-to-day dependence in residual demand could in principle load neighboring days' responses onto today's price (Thams et al., 2024 and Tiedemann et al., 2024). The municipality-by-day fixed effects limit this channel to the within-day composition of demand, and Appendix C.6 verifies directly that it is inert: whitened instruments, one-day-lagged instruments added as overidentifying restrictions, and a lagged-outcome control all leave the estimate within one standard error of the baseline, indicating that the static coefficient is a contemporaneous response rather than a cumulated one.

The direction of the simultaneity bias. The comparison between the OLS and the instrumental-variables estimates is informative in its own right, because the simultaneity in (8) biases the OLS estimate in a known direction. A demand shock that tilts consumption toward the day block also raises the day-block price through the zonal market, so the block price is positively correlated with the error and OLS *understates* σ. With

[13]The C-test (difference-in-Hansen) removes a named block of instruments and asks whether the overidentification fit deteriorates, testing that block's validity conditional on the remaining instruments.

the municipality-by-day fixed effects, however, the scope for this bias is limited to the within-day composition of demand, and the zonal price shape is set largely by supply, so the gap between OLS and IV should be small. The gap is therefore a direct measure of the remaining simultaneity, and its near-disappearance in the block design (in contrast to hourly designs without day fixed effects, Appendix C.3) is itself suggestive evidence that the block model isolates supply-driven price variation.

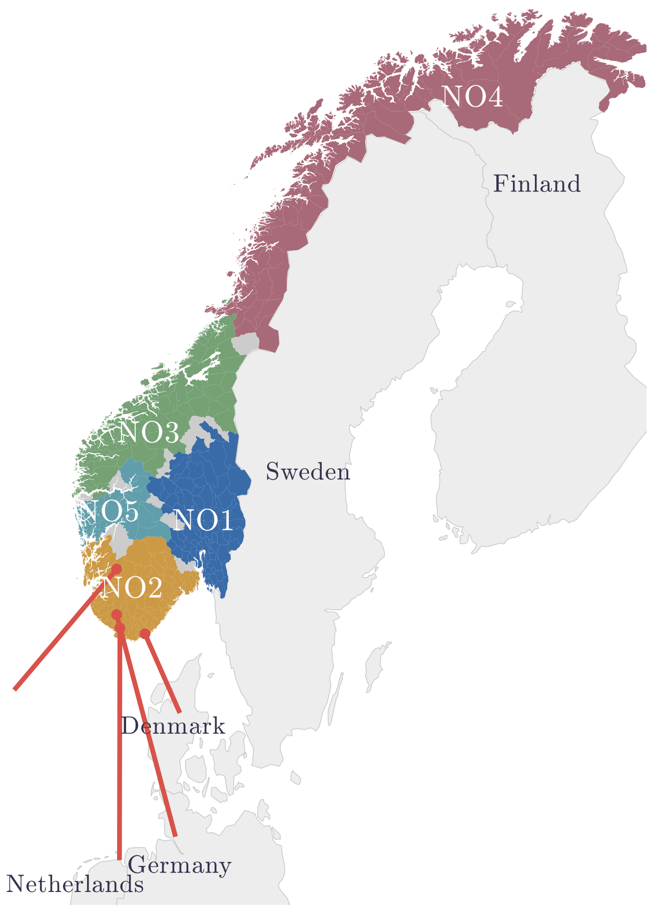
4 Data

We build an hourly panel of residential electricity demand from September 2023 to September 2025. Norway is divided into five bidding zones (NO1–NO5), each with an hourly day-ahead price. Combining all data sources yields 3,438,807 municipality-hour observations across 192 municipalities. Aggregated to the day and night blocks on which estimation takes place, the estimation sample contains 285,640 municipality-day-block observations.

4.1 The Norwegian electricity market

Bidding zones and the day-ahead market. Norway is divided into five bidding zones: NO1 (south-east), NO2 (south), NO3 (central), NO4 (north), and NO5 (west). Wholesale electricity is traded one day ahead on the Nord Pool exchange: for each hour of the following day, a single price clears in each zone where bids and offers balance. When the transmission grid between zones is uncongested, the zonal prices coincide. When an interconnector's capacity constraint binds, prices separate across the boundary. Within zones, generation is roughly 90% hydropower, so the marginal cost, and hence the price level, is mostly governed by water availability. The connection between (local) water availability and the price motivates the inflow instrument. The southern zone (NO2) is linked by interconnectors to Denmark, Germany-Luxembourg, the Netherlands, and Great Britain, so that continental supply conditions are transmitted to southern Norwegian prices, motivating the continental solar and wind instruments. Figure 1 maps the five zones together with the cables to the neighboring markets, which make landfall in NO2.

The household bill and the grid tariff. 94.7 percent of Norwegian households are on hourly spot price contracts (Statistics Norway, 2025b) and all households have had smart meters installed since 2018 (Statistics Norway, 2019), implying that almost all Norwegian



Notes: Each municipality is colored by its bidding zone (NO1–NO5). Municipalities that a zone border cuts through, for which no single zonal price applies, are left unassigned (mid grey). The red lines are the high-voltage direct-current cables to the Continent and Great Britain: Skagerrak (Denmark), NorNed (the Netherlands), NordLink (Germany), and the North Sea Link (Great Britain), all of which make landfall in the southern zone NO2.

Figure 1: Norwegian price zones and foreign interconnectors.

households face the hourly spot price contract.[14]

The price a household pays per kilowatt-hour is the wholesale spot price plus the regulated network tariff (*nettleie*), the electricity excise and the Enova levy, and value-added tax, less the electricity subsidy (see below). The distribution grid is a regulated local monopoly: each municipality is served by a single network company, and households pay that company a *nettleie* composed of a fixed (capacity) charge and an energy term in øre per kilowatt-hour, the latter typically differentiated between day and night and across

[14]The Norwegian market is also particular as 86 percent of household energy use is electric, including heating (Statistics Norway, 2025c), fully electric vehicles (EVs) account for 27.4 percent of the Norwegian passenger car fleet and 88.9 percent of new cars sold in 2024 (Opplysningsrådet for veitrafikken, 2025; Statistics Norway, 2026), and automation technologies are widely adapted (for example, the national energy market IT platform Elhub has made high-frequency consumption data broadly available to Norwegian households and third-party service providers, see `elhub.no`).

seasons.

Electricity-support schemes over time. The government introduced an electricity-support scheme (*strømstøtte*) in December 2021. Under the scheme, the state reimburses households for a large share (raised over time to about 90%) of the part of the spot price that exceeds a threshold of 70 øre per kilowatt-hour (excluding VAT), up to a monthly consumption cap. The scheme's design changed twice in ways central to our strategy. Until August 2023, the reimbursement was based on the *monthly average* spot price, and as a result, the hourly price signal at the margin was muted. From 1 September 2023, the support was placed on an *hourly* basis, computed for each hour from that hour's spot price, so that the marginal price in a given hour equals the spot price net of the per-hour subsidy rate. From 1 October 2025 a further scheme, *Norgespris*, was introduced. This scheme offers households a subsidized fixed price, again decoupling the marginal price from the hourly spot price. Our sample is the window between these last two reforms. Because the subsidy reimburses a large share of the spot price above the threshold, it strongly compresses the pass-through of the spot price to the *level* of the consumer price.

4.2 Data sources and construction

Consumption. Hourly metered electricity consumption by municipality and consumer group comes from Elhub (Elhub, 2025), Norway's national power-market data hub. We use the private-household group and observe, for each municipality and hour, the total metered volume and the number of metering points. Our dependent variable is consumption per household, q_{iht}, the metered volume divided by the number of metering points. All timestamps are expressed in Norwegian standard time (UTC+1), so no hour is lost or duplicated at the daylight-saving transitions. The metered volume is the electricity a household draws from the grid. Electricity generated and consumed on-site by households with rooftop solar is unmetered, while surplus feed-inis registered separately as production. Metered consumption therefore understates electricity use in homes with panels, especially on sunny days.

Rooftop solar. Hourly metered solar production by pricing zone also comes from Elhub (Elhub, 2025). We include it, interacted with zone indicators, as a control in the regressions. On sunny days, households with panels draw less from the grid precisely when continental solar also lowers midday prices. Metered consumption then falls with the price for reasons unrelated to behavior, which hides part of the true substitution and biases the shape of elasticity toward zero. Because the elasticity we are after concerns the electricity households use (self-produced power runs the same appliances), this is a measurement problem, rather than a demand response. Hourly zone feed-in moves closely with the sunshine and therefore absorbs this channel. [15]

Prices. The consumer price is built from the zonal day-ahead (spot) price (Nord Pool, 2025) and the regulated components that households actually pay:

$$p_{iht} = \left(\text{spot}^{\text{sub}}_{iht} + \text{tax}_{it} + \text{nettleie}_{iht} + \text{enova}\right) \times (1 + \text{VAT}_i),$$

where spot^{sub} is the spot price net of the electricity subsidy, tax is the electricity excise, nettleie is the energy term of the grid tariff (Norwegian Water Resources and Energy Directorate (NVE), 2025a), enova is a fixed levy, and VAT is value-added tax. Due to the subsidy scheme, the consumer price is a compressed transformation of the market spot price. The municipalities in Nord-Troms and Finnmark are exempt from VAT and the excise. The daily price level ℓ_{it} and the block price indices p_{ibt} are constructed from p_{iht} with fixed expenditure-share weights, as described in Section 3.

Weather. Hourly air temperature, wind speed, and precipitation are taken from the Frost archive of the Norwegian Meteorological Institute (Norwegian Meteorological Institute, 2025). Station observations are aggregated to municipality-hour means. Temperature enters through block-specific splines, wind speed through a spline and an interaction with temperature, and precipitation is used in the exclusion check for the level instrument (Appendix C.4).

Supply instruments. The *level* is instrumented by *hydrological inflow*. For each price zone, we take the seNorge gridded water-balance model runoff (*Avrenning*) of the Norwegian Water Resources and Energy Directorate (NVE) (Norwegian Water Resources and Energy Directorate (NVE), 2025b) at three interior hydropower catchments in each zone, and average it to a daily zone series in millimeters.[16] We next subtract that zone's day-of-year seasonal normal (the median runoff for each calendar day over 2014–2022, smoothed with

[15] Rooftop capacity roughly doubled within our sample window (in NO1, metered solar feed-in grew from 80 gigawatt-hours in 2023 to 164 in 2025), so the correction is growing in importance and will matter even more in later samples.

[16] seNorge (senorge.no) is the national gridded environmental dataset for Norway, maintained by the Norwegian Meteorological Institute, NVE, and the Norwegian Mapping Authority. It interpolates station observations of temperature and precipitation onto a 1×1 km grid and runs them through NVE's operational water-balance model, from which the modeled runoff (*Avrenning*) is taken. Runoff is thus simulated water supply on a uniform grid rather than gauged river flow, which makes it comparable across catchments and zones.

a fifteen-day centered window). The inflow anomaly is therefore a zone-specific deviation from the local seasonal cycle, measured in millimeters of runoff. It is de-meaned within the zone through the seasonal normalization, and it is constant across the hours of a day and across the municipalities of a zone.

The *block price* is instrumented by *continental solar and wind*. We take the raw day-ahead solar and wind generation forecasts from the ENTSO-E Transparency Platform (ENTSO-E, 2025) for the continental market areas, Germany-Luxembourg, the Netherlands, and Denmark, and sum each into a single continental total.[17] From each total we subtract its within-day mean, keeping only the within-day profile, rescale to gigawatts, and average over the hours of each block. These continental series are common to all of Norway. To let the price response differ across zones, we interact each with the zone indicators, giving one solar and one wind instrument for each of the five zones (ten instruments in all). Thus, the first stage estimates a separate loading in every zone. As Table B.1 in Appendix B shows, the loadings are concentrated in the southern zones (NO1, NO2, and NO5). Keeping the solar and wind families separate, rather than pooling them, is deliberate: they are driven by different weather processes, so agreement between them (formally tested with C-statistics) provides validity evidence that a single pooled instrument could not provide.

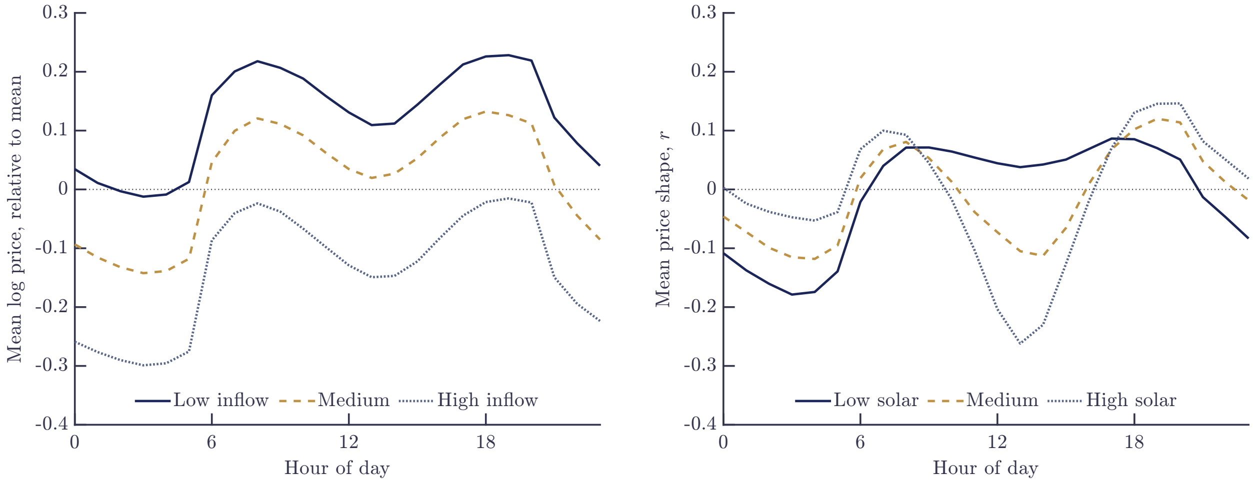
Income. Municipal median household income after tax is taken from Statistics Norway (Statistics Norway, 2025a), harmonized to current municipality codes using the official classification crosswalk for the 2024 boundary reform.

Sample. The sample *begins* on 1 September 2023, when the subsidy switched from compensating households on the basis of the *monthly average* spot price to an *hourly* basis. It *ends* on 30 September 2025, the day before the introduction of *Norgespris*. Within this window, the estimation sample is the intersection of the sources above, covering the five price zones and the 192 municipalities with weather coverage.[18]

Summary statistics. Table 1 reports summary statistics for the hourly panel and for the day/night block objects the estimation uses. Two features matter for what follows. Households consume almost three times as much during the day block (06–22) as during the night block, so there is room to shift schedulable load. And the day–night block

[17]Great Britain, although connected to NO2 by the North Sea Link, is not covered by the ENTSO-E Transparency Platform following its departure from the EU internal energy market, and is therefore excluded from the instruments.

[18]There are originally 357 consistent municipalities in Norway during our sample period. The main constraint is that we require weather measurement stations with temperature, wind, and precipitation data in each municipality.



(a) Inflow shifts the level

(b) Solar tilts the shape

Notes: Each panel plots the mean hourly price profile across terciles of an instrument. Panel (a) uses the hydrological-inflow terciles, with the mean log price expressed relative to its overall mean. The profile shifts up or down with inflow while its within-day shape is unchanged. Panel (b) uses the continental-solar terciles for the southern zones (NO1, NO2, and NO5) and plots the within-day price shape r_{iht}, which is zero on average by construction. Higher solar tilts the profile, depressing the midday price, while leaving the daily average intact. In contrast, the continental wind forecast (not shown) shifts prices more diffusely across the hours of the day.

Figure 2: Supply shifters move the level and the shape.

price gap is economically large: it averages about 16 log points and reaches 38 on high-spread days (the 90th percentile), so the relative-price variation identifying the substitution elasticity is neither rare nor marginal.

	Mean	SD	p10	Median	p90
Consumption and prices (hourly)					
Consumption, kWh per household-hour	1.64	0.81	0.80	1.50	2.63
Consumer price, øre/kWh	83.89	38.93	34.99	79.67	139.15
Price level, ℓ_{it}	4.30	0.58	3.59	4.39	4.90
Price shape, hourly	-0.01	0.18	-0.23	0.02	0.15
Demand shifters					
Temperature, °C	5.7	8.2	-4.9	5.8	15.9
Median household income, 1000 NOK	650.8	55.5	587.0	647.9	720.1
Households per municipality	10613.9	29541.5	921.0	4107.0	19375.0
Instruments and supply controls					
Inflow anomaly, mm/day	0.67	3.44	-2.62	0.11	4.69
Continental solar, within-day dev., GW	0.00	12.18	-13.87	-2.38	19.28
Continental wind, within-day dev., GW	0.00	5.03	-5.67	-0.31	6.12
Rooftop-solar feed-in, GWh	0.01	0.02	0.00	0.00	0.01
Day/night blocks					
Day-block consumption (06–22), kWh	28.69	13.60	14.90	26.30	45.28
Night-block consumption (22–06), kWh	10.64	5.50	5.01	9.76	17.28
Day–night block log-price gap	0.17	0.18	-0.01	0.15	0.39

Notes: Hourly municipality-level observations over the subsidy period, across 192 municipalities and the five price zones. The final panel reports the day/night block objects used in estimation. The price level ℓ_{it}, the hourly shape, and the block price indices are constructed from the hourly consumer price using fixed expenditure-share weights (hour-of-day shares at the zone-month level over the full sample).

Table 1: Summary statistics.

5 Results

Table 2 contains our main results. Households substitute between the day and night blocks: in our preferred specification, column (4) of Panel A, the substitution elasticity is $\hat{\sigma} = 0.073$ (standard error 0.018). Total daily consumption, by contrast, barely responds to the price level: the elasticity in Panel B is at most 0.046 and indistinguishable from zero under the timing-robust lagged instrument in column (3). Together with the absence of substitution across hours within the blocks (Appendix C.1), these results say that short-run flexibility is real but coarse. Households mostly choose when to run schedulable loads at the resolution of the tariff calendar's day and night periods, rather than hour by hour, and they mostly do not change their total use.

Panel A: day–night substitution, σ (municipality-day-block panel)

		Instrumental variables		
	(1) OLS	(2) Solar	(3) Wind	(4) Both
Block price, p_{ibt} $(-\sigma)$	-0.062***	-0.097***	-0.061***	-0.073***
	(0.007)	(0.036)	(0.022)	(0.018)
Kleibergen-Paap F		14.4	22.1	20.7
Hansen J (p)		0.386	0.727	0.539
C-test wind block (p)				0.590
C-test solar block (p)				0.312
Observations	285,640	285,640	285,640	285,640

Panel B: daily level, η (municipality-day panel)

	(1) OLS	(2) IV (inflow)	(3) IV (lagged inflow)
Daily price, p_{it} $(-\eta)$	-0.013***	-0.046***	-0.021
	(0.005)	(0.015)	(0.021)
Kleibergen-Paap F		241.5	96.2
Observations	108,836	108,836	108,836

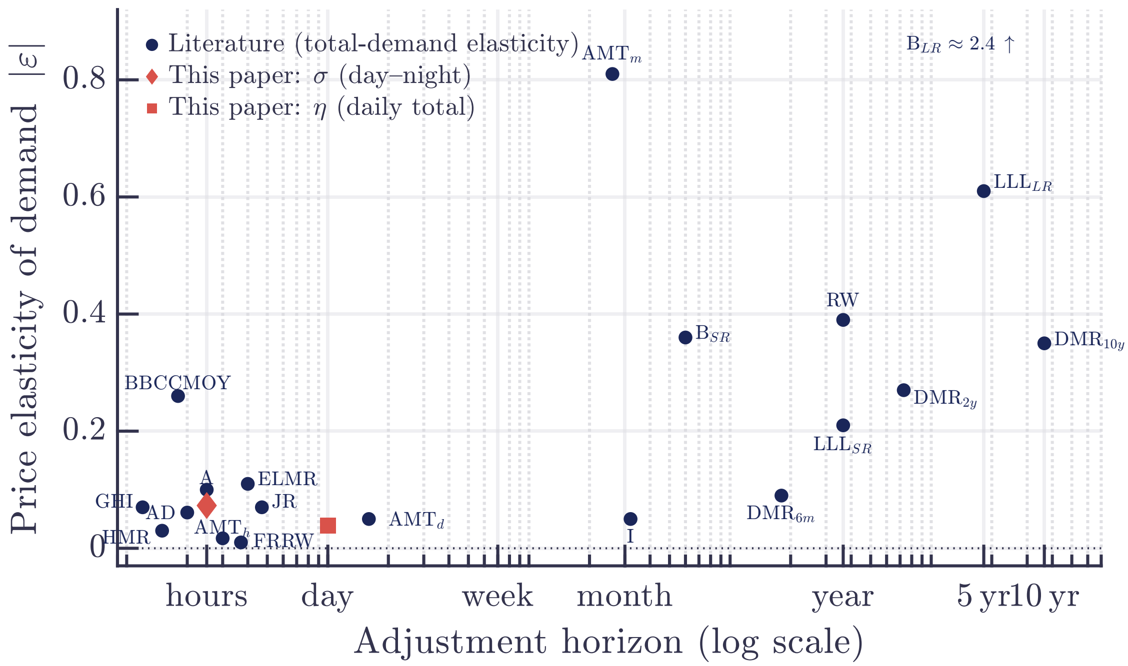
Notes: Panel A: the unit of observation is a municipality-day-block, where the blocks are day (06–22) and night (22–06), the partition used by the grid tariffs. The dependent variable is log block consumption per household and σ is minus the coefficient on the fixed-weight block log-price index. All columns carry municipality-by-day fixed effects (which absorb the daily price level and every day-level demand shifter), zone-by-block-by-month effects, a block-specific temperature spline, wind controls, and the zone-interacted rooftop-solar feed-in control. Column (1) is OLS. Columns (2)–(4) instrument the block price with block means of the continental solar forecast, the continental wind forecast, or both, each interacted with zone. The C-tests examine each instrument family against the other. Panel B: the unit of observation is a municipality-day. The dependent variable is log daily consumption per household and η is minus the coefficient on the fixed-weight daily log-price index, with municipality, day-of-week by month, year-month, and zone-by-month effects and the daily analogues of the weather and rooftop-solar controls. Column (2) instruments the daily price with the hydrological inflow anomaly. First stages are reported in Appendix B. Standard errors are clustered by municipality and zone-day. Each panel uses a common sample across its columns.

Table 2: Main estimates.

The within-day substitution margin. The four columns of Panel A provide similar estimates, although based on different variation. Ordinary least squares gives 0.062. Because the municipality-by-day fixed effects control for every day-level demand shocks, the only remaining simultaneity is the within-day co-movement of demand and the price shape, which is small: the shape of the zonal price is mostly determined by supply. Instrumenting with the continental solar family gives 0.097, with the wind family 0.061, and with both 0.073. A day–night substitution elasticity of 0.073 means that when the day block becomes one percent more expensive relative to the night, households shift about 0.07 percent of the day–night consumption ratio.

The paper's central specification result is the relative agreement between the two instrument families. Solar and wind generate very different price variation (solar deepens the midday dip, wind moves prices diffusely across the day), so they could disagree in many ways, and at any finer time resolution they do: the same battery of tests, applied to the hourly single-elasticity design in our own data, rejects the two families against each other for every choice of instruments (Appendices C.2 and C.3). At the day–night aggregation the Kleibergen-Paap F is 20.7, the Hansen test does not reject ($p = 0.54$), and the C-tests cannot reject either family against the other ($p = 0.59$ and 0.31). The tests stop rejecting when, and only when, the model aggregates the day into the two tariff blocks. We read them as informative about the structure of demand, not as a nuisance. The first stage coefficients are reported in Table B.1 in Appendix B, with loadings concentrated in the southern zones (NO1, NO2, and NO5) closest to the continental interconnectors.

The level margin. Panel B estimates the companion daily equation: log daily consumption per household on the fixed-weight daily price index, instrumented by the hydrological inflow anomaly, with municipality, day-of-week by month, year-month, and zone-by-month effects and the daily analogues of the weather and rooftop-solar controls. The instrument strongly predicts the price (Kleibergen-Paap F of 241.5) and the estimate is $\hat{\eta} = 0.046$ (standard error 0.015): small, but statistically distinguishable from zero. We read it as an upper bound. The key concern is timing: contemporaneous runoff is rain, and rain may co-move with heating-adjacent demand on the same day, biasing η away from zero. Column (3) therefore instruments with runoff accumulated over days $t - 32$ to $t - 3$, which moves today's reservoir-driven price but cannot be correlated with today's weather-driven demand. The estimate falls to 0.021 (standard error 0.021) and is indistinguishable from zero. Appendix C.4 reaches the same conclusion with direct precipitation controls. Daily electricity demand therefore seems to be relatively inelastic.



Notes: Price elasticity of demand by adjustment horizon (log scale). The day–night substitution σ (within the day) and daily total-demand η (day) of this paper are in red. Horizontal placements of the literature are approximate. Studies, by author initials: FRRW: Fabra et al. (2021); A: Allcott (2011); AMT: Adib et al. (2025); AD: Andersen and Dietrich (2026); HMR: Herrmann et al. (2026); JR: Jessoe and Rapson (2014); GHI: Garnache et al. (2025); I: Ito (2014); DMR: Deryugina et al. (2020); RW: Reiss and White (2005); LLL: Labandeira et al. (2017); B: Buchsbaum (2022); ELMR: Enrich et al. (2024); BBCCMOY: Bobbio et al. (2025).

Figure 3: Price elasticity of electricity demand by adjustment horizon.

Relation to the literature. Figure 3 places our two elasticities in the demand literature by the horizon of adjustment each estimate captures. The existing evidence traces a response that builds slowly with the horizon: hourly and daily responses in well-identified designs are small, the canonical monthly estimates remain modest, and the elasticity reaches 0.3 to 0.6 only over several years. Our estimates fit this pattern and sharpen its short end. The day–night substitution elasticity of 0.073 is of the same order as several hourly studies, while the daily total-demand elasticity is close to zero. Our decomposition may explain why the short end looks the way it does: what some studies see as a small hourly response is a moderate response on one specific margin (the timing of schedulable use between day and night) and essentially nothing on the others. Studies whose identifying price variation mostly loads on the within-block or the daily margin will measure close to zero, and studies whose variation mostly loads across blocks (the day–night margin) will measure something closer to 0.07, even in the same population. The apparent disagreement in the literature may be, in part, a matter of which margin the design happens to weight.

6 Conclusion

We estimate the short-run price responsiveness of residential electricity demand in Norway, separating the margins that demand structure makes distinct: the timing of consumption within the day and the response of total daily use to the price level. The central finding is that within-day flexibility is real but coarse. Households shift consumption between the day and night blocks of the tariff calendar, with a substitution elasticity of 0.073. They do not seem to fine-tune much which hour within a block they consume in, and they barely change how much they consume in total when the daily price level moves.

Along the way, we show that the time unit of choice can be estimated rather than assumed. Two independent instrument families (continental solar and continental wind, which move Norwegian prices through the interconnectors in very different within-day patterns) disagree sharply about the hourly elasticity, and the standard overidentification tests reject the hourly model outright. Both objections disappear when the day is aggregated into the two blocks households actually schedule over.

Our estimates place household flexibility in a range comparable to existing evidence, and the Norwegian setting is favorable for finding it: hourly spot-price contracts are the norm, electricity accounts for a large share of household energy use, electric vehicles are common, and price apps and automated controls are relatively widely available. The day–night margin we measure is often the one automation targets.

Our findings have direct policy implications, and the decomposition matters for how they read. Real-time pricing moves household demand, but mostly on the day–night margin rather than hour by hour. A back-of-the-envelope calculation illustrates the magnitude: with a substitution elasticity of 0.073 and a day–night price gap that averages about 17 log points and reaches 39 on high-spread days (Table 1), real-time pricing shifts roughly one percent of daytime consumption into the night on such days relative to a flat tariff (ignoring general equilibrium effects).[19] Because hours within a block move together, pricing schemes that sharpen the day–night contrast (or automation that widens the set of loads scheduled on it) will do more for the system than ever-finer hourly signals, and the within-hour peaks themselves are better addressed by storage, grid expansion, and backup capacity than by household prices alone.

[19]The calculation holds total daily consumption Q_{it} and the price index P_{it} fixed and opens a day–night log-price gap Δ from a flat tariff. When $\ln(q_{idt}/q_{int})$ falls by $\sigma_B \Delta$, holding the index fixed implies that the day price rises by only the night expenditure share of the gap, $w_n \Delta$. Hence, *daytime* consumption falls by approximately $\sigma_B w_n \Delta$. With $\sigma_B = 0.073$, $w_n \approx 0.24$ (the night block's share of daily electricity expenditure implied by Table 1), and $\Delta \approx 0.39$, this gives $0.073 \times 0.24 \times 0.39 \approx 0.007$, i.e., roughly one percent of daytime consumption.

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Online Appendix for "The Power of Substitution"

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August 2026

A Derivations

Throughout, the index i denotes a municipality, treated as a representative consumer, and the subscripts i, t are suppressed where unambiguous.

A.1 Stage 2: within–day allocation

For a given Q_{it} the consumer chooses $\{q_{ibt}\}$ to minimize cost $\sum_b p_b q_b$ subject to (2), with Lagrangian

$$\mathcal{L} = \sum_b p_b q_b + \psi\Big(Q - \Big(\textstyle\sum_b \alpha_b^{1/\sigma} q_b^{(\sigma-1)/\sigma}\Big)^{\sigma/(\sigma-1)}\Big),$$

Writing $B = \sum_b \alpha_b^{1/\sigma} q_b^{(\sigma-1)/\sigma}$ so $Q = B^{\sigma/(\sigma-1)}$, the marginal product is

$$\frac{\partial Q}{\partial q_b} = \tfrac{\sigma}{\sigma-1} B^{\frac{1}{\sigma-1}}\, \alpha_b^{1/\sigma} \tfrac{\sigma-1}{\sigma} q_b^{-1/\sigma} = Q^{1/\sigma} \alpha_b^{1/\sigma} q_b^{-1/\sigma},$$

using $B^{1/(\sigma-1)} = Q^{1/\sigma}$. The first-order condition, $p_b = \psi\, \partial Q/\partial q_b$, rearranges to $q_b = \psi^\sigma \alpha_b Q\, p_b^{-\sigma}$. Substituting back into B gives $Q = \psi^\sigma Q\Big(\sum_b \alpha_b p_b^{1-\sigma}\Big)^{\sigma/(\sigma-1)}$, which forces the multiplier to equal the inner CES unit cost, i.e., $\psi = P_{it}$ as given in (4). Hence, the conditional block demands, their log form, and total electricity expenditure can be expressed as:

$$q_b = \alpha_b\Big(p_b/P\Big)^{-\sigma} Q, \tag{A.1}$$

$$\ln q_b = \ln \alpha_b + \ln Q - \sigma\Big(\ln p_b - \ln P\Big), \tag{A.2}$$

$$\textstyle\sum_b p_b q_b = PQ, \tag{A.3}$$

the last using $\sum_b \alpha_b p_b^{1-\sigma} = P^{1-\sigma}$. The block-$b$ expenditure share and the index derivative are

$$w_b = \frac{p_b q_b}{PQ} = \frac{\alpha_b p_b^{1-\sigma}}{\sum_{b'} \alpha_{b'} p_{b'}^{1-\sigma}}, \qquad \frac{\partial \ln P}{\partial \ln p_b} = \frac{\alpha_b p_b^{1-\sigma}}{P^{1-\sigma}} = w_b,$$

the second obtained by differentiating $P^{1-\sigma} = \sum_b \alpha_b p_b^{1-\sigma}$.

A.2 Stage 1: total electricity demand

Using $P_{it}Q_{it}$ as electricity expenditure, the consumer maximizes (1) subject to $P_{it}Q_{it} + z_{it} = y_{it}$. The tangency condition equates the marginal rate of substitution to the price ratio,

$$P_{it} = \left(\tfrac{\phi_{it}}{1-\phi_{it}}\right)^{1/\eta}\left(\tfrac{z_{it}}{Q_{it}}\right)^{1/\eta}, \tag{A.4}$$

which solves to $z_{it} = Q_{it}P_{it}^{\eta}(1-\phi_{it})/\phi_{it}$. Substituting into the budget constraint, the demand for the composite can be expressed as:

$$Q_{it} = \phi_{it}\, P_{it}^{-\eta}\, \Pi_{it}^{\eta-1}\, y_{it}, \qquad \Pi_{it} = \left[\phi_{it}P_{it}^{1-\eta} + (1-\phi_{it})\right]^{1/(1-\eta)}, \tag{A.5}$$

where Π_{it} is the outer price index, and in logs, with $\gamma = \ln \phi$,

$$\ln Q_{it} = \gamma + \mathbf{m}_{it}'\lambda - \eta \ln P_{it} + (\eta - 1)\ln \Pi_{it} + \ln y_{it} + \xi_{it}. \tag{A.6}$$

Differentiating $\Pi^{1-\eta} = \phi P^{1-\eta} + (1-\phi)$ gives $\partial \ln \Pi/\partial \ln P = \phi(P/\Pi)^{1-\eta} = s_{it}^E$, the electricity budget share (indeed $s_{it}^E = P_{it}Q_{it}/y_{it}$). The implied price elasticity of total electricity demand is therefore

$$\widetilde{\eta}_{it} \equiv -\frac{\partial \ln Q_{it}}{\partial \ln P_{it}} = \eta - (\eta-1)s_{it}^E = \eta(1-s_{it}^E) + s_{it}^E. \tag{A.7}$$

A.3 Block demand, the estimating equation, and the elasticities

Substituting (A.6) into (A.2) gives the structural block demand

$$\ln q_{ibt} = \ln \alpha_b + \mathbf{x}_{ibt}'\delta_b + \mathbf{m}_{it}'\lambda + \gamma + \ln y_{it} - \sigma \ln p_{ibt} + (\sigma - \eta)\ln P_{it} + (\eta-1)\ln \Pi_{it} + u_{ibt}, \tag{A.8}$$

where $u_{ibt} = \omega_{ibt} + \xi_{it}$. With $r_{ibt} = \ln p_{ibt} - \ln P_{it}$ and $\ell_{it} = \ln P_{it}$, the price terms satisfy $-\sigma \ln p_{ibt} + (\sigma-\eta)\ln P_{it} = -\sigma r_{ibt} - \eta \ell_{it}$, which yields the estimating equation (5) once the demand shifters are collected in $\mathbf{w}_{ibt}$ and the fixed effects are introduced. The term $(\eta-1)\ln \Pi_{it}$ is nearly constant in P_{it} when s_{it}^E is small and is absorbed by the fixed effects, or constructed from (A.5) for the exact specification. Differentiating (A.8) with respect to $\ln p_{ibt}$, and using $\partial \ln P_{it}/\partial \ln p_{ib't} = w_{ib't}$ and $\partial \ln \Pi/\partial \ln p_{b'} = s^E w_{ib't}$,

$$\varepsilon_{b,b} = -\sigma + w_b\Big[\sigma - \eta(1-s^E) - s^E\Big] = -\sigma(1-w_b) - \widetilde{\eta}\, w_b, \qquad \varepsilon_{b,b'} = (\sigma - \widetilde{\eta})\, w_{b'} \;\; (b' \neq b),$$

which are the own-price and cross-price elasticities of block demand.

B First stages

This appendix reports the first stages behind Table 2. Table B.1 regresses the block price index on the zone-interacted block means of the continental solar and wind forecasts (Panel A of Table 2). Table B.2 regresses the daily price index on the hydrological inflow anomaly (Panel B).

	(1) Solar	(2) Wind	(3) Both
Continental solar, block mean (GW) × NO1	-0.006***		-0.008***
	(0.002)		(0.002)
Continental solar, block mean (GW) × NO2	-0.009***		-0.011***
	(0.001)		(0.001)
Continental solar, block mean (GW) × NO3	-0.000		-0.001
	(0.001)		(0.001)
Continental solar, block mean (GW) × NO4	0.002		0.002
	(0.001)		(0.001)
Continental solar, block mean (GW) × NO5	-0.004***		-0.005***
	(0.001)		(0.001)
Continental wind, block mean (GW) × NO1		-0.005***	-0.005***
		(0.001)	(0.001)
Continental wind, block mean (GW) × NO2		-0.007***	-0.008***
		(0.001)	(0.001)
Continental wind, block mean (GW) × NO3		-0.002**	-0.002**
		(0.001)	(0.001)
Continental wind, block mean (GW) × NO4		-0.001	-0.001
		(0.001)	(0.001)
Continental wind, block mean (GW) × NO5		-0.003***	-0.004***
		(0.001)	(0.001)
Joint F (excluded instruments)	14.4	22.1	20.7
Observations	285,640	285,640	285,640

Notes: The block price index regressed on the excluded instruments (block means of the continental solar and wind forecasts, each interacted with zone), with the same fixed effects and controls as Table 2. Standard errors clustered by municipality and zone-day. The joint F of the excluded instruments is reported for each column.

Table B.1: First stage: the block price on the continental instruments

	(1) Daily price, p_{it}
Inflow anomaly, mm/day	-0.019***
	(0.001)
F (excluded instrument)	248.2
Observations	113,732

Notes: The daily price index regressed on the hydrological inflow anomaly, with the fixed effects and controls of Table 2, Panel B. Standard errors clustered by municipality and zone-day.

Table B.2: First stage: the daily price on inflow

C Robustness

This appendix collects a series of robustness checks on the block design: the absence of substitution within the blocks (C.1), the robustness of the day–night partition (C.2), the rejection of the hourly single-elasticity design (C.3), the exclusion check for the level instrument (C.4), the seasonal stability of the block elasticity (C.5), and the lead-lag exogeneity of the persistent instruments (C.6).

	Night (22–06)			Day (06–22)		
	(1) Wind	(2) Solar	(3) Both	(4) Wind	(5) Solar	(6) Both
Hourly price, r_{iht} $(-\sigma_W)$	-0.007	0.078	-0.007	0.017	-0.136***	-0.054***
	(0.011)	(0.086)	(0.011)	(0.024)	(0.034)	(0.017)
Kleibergen-Paap F	73.0	1.5	37.1	26.3	22.3	34.7
Hansen J (p)	0.012	0.294	0.036	0.277	0.138	0.015
C-test wind block (p)			0.020			0.016
C-test solar block (p)			0.420			0.008
Observations	998,803	998,803	998,803	2,425,952	2,425,952	2,425,952

Notes: Hourly panel with municipality-by-day-by-block fixed effects, zone-by-hour-by-month effects, an hour-interacted temperature spline, wind controls, and the rooftop-solar feed-in control. The coefficient is the negative of the within-block elasticity of hourly consumption with respect to the hourly relative price. Columns are restricted to night hours (22–06) or day hours (06–22) and instrument with the wind family, the solar family, or both. Standard errors clustered by municipality and zone-day.

Table C.1: Robustness: substitution within the blocks

C.1 No substitution within the blocks

The block model treats the hours inside a block as consumed in fixed proportions: a household may shift consumption between day and night, but the hourly profile *within* the day block, and within the night block, is assumed rigid. If households in fact reallocate across hours inside a block, then the two-block CES is the wrong aggregator: the block price indices would mismeasure the price households actually respond to, and σ_B would mix the between-block margin with an unmodeled within-block one.

Table C.1 tests the assumption directly on the hourly panel. The specification includes municipality-by-day-by-block fixed effects, which absorb every block-level object so the only variation that remains is the allocation of consumption across hours inside a block, and the only price variation that remains is the hourly deviation from the block price. A nonzero coefficient can therefore only reflect within-block reallocation. We estimate this symmetrically for the night and day blocks, instrumenting with the wind family, the solar family, and both, so each family's verdict can be checked against the other's.

Within the night block, the elasticity is precisely zero, while the wind family provides ample variation (the night solar columns are weakly identified by construction). Within the day block, the two families disagree: wind finds nothing, solar finds a response of about 0.14 concentrated on its own midday pattern, and the C-tests flag the conflict. We consider the within-day-block margin as unidentified given this response rather than estimated. What is robust is that no instrument family finds within-block reallocation that the other confirms, while both confirm the block margin of Table 2.

	Day 06–22	Day 08–20	Three 8-hour blocks	
	(1) Both	(2) Both	(3) Solar	(4) Wind
Block price, p_{ibt} $(-\sigma)$	-0.073***	-0.117***	-0.118***	-0.010
	(0.018)	(0.029)	(0.035)	(0.020)
Kleibergen-Paap F	20.7	22.2	19.1	35.6
Hansen J (p)	0.539	0.861	0.667	0.162
Observations	285,640	285,632	428,410	428,410

Notes: The specification of Table 2 with alternative partitions of the day. Columns (1)–(2): day/night with boundaries 06–22 (the main specification) and 08–20, both instrument families. Columns (3)–(4): three 8-hour blocks (23–07, 07–15, 15–23), solar and wind families separately. Fixed effects, controls, and clustering as in Table 2, with block-specific temperature splines throughout.

Table C.2: Robustness: the block partition

C.2 The partition is day/night

The day–night partition is itself an assumption. The 06–22 boundary is inherited from the grid-tariff calendar, not estimated, and the worry runs in two directions: the estimate could depend on where exactly the boundary is drawn, or households could in fact operate on a finer partition — morning, midday, evening — that the two-block structure conceals, in which case σ_B would be an artifact of aggregation rather than a structural margin.

Table C.2 varies the block structure in both directions. Columns (1)–(2) move the boundary to 08–20 and re-estimate the two-block model with both instrument families.

Columns (3)–(4) split the day into three 8-hour blocks (23–07, 07–15, 15–23) and estimate the implied block elasticity with the solar and the wind family separately, since a genuine finer margin should be visible to both families.

The result is that moving the boundary leaves the estimate similar. Splitting more finely does not survive the two-family standard: with three 8-hour blocks the solar family estimates a block elasticity of about 0.12 while the wind family estimates zero, and the same divergence appears at every finer partition we have examined: substitution between sub-day blocks other than day versus night is detected only by solar-shaped price variation and never confirmed by wind. The day–night partition is the coarsest one with no internal substitution and the only one on which the two families agree.

	(1) OLS	(2) Solar	(3) Wind	(4) Both
Hourly price, r_{iht} $(-\sigma)$	-0.060***	-0.125***	-0.014	-0.052***
	(0.004)	(0.029)	(0.014)	(0.012)
Kleibergen-Paap F		25.4	59.0	53.2
Hansen J (p)		0.330	0.093	0.019
C-test wind block (p)				0.009
C-test solar block (p)				0.028
Observations	3,424,822	3,424,822	3,424,822	3,424,822

Notes: Hourly panel. The endogenous regressors are the hourly relative price and the daily level, with one elasticity assumed across all hours (the design of the hourly literature). All columns include zone-by-hour-by-month effects, an hour-interacted temperature spline, wind controls, and the rooftop-solar feed-in control. Instruments are the zone-interacted continental solar family, the wind family, or both, plus inflow for the level. The final column instruments with solar under municipality-by-day fixed effects, so that only within-day variation identifies. Standard errors clustered by municipality and zone-day.

Table C.3: Robustness: the hourly single-elasticity design

C.3 The hourly single-elasticity design rejects itself

Most studies of hourly electricity demand regress hourly consumption on a single hourly price, instrumented by a weather-driven supply shifter, and assume one elasticity common to all hours. In our decomposition, that assumption is misspecified by construction: within a day, demand has a day–night margin and a within-block margin, and these are different objects — the first is σ_B, the second is absent (Appendix C.1). A single hourly coefficient is then a weighted mixture of the margins, with weights set by the within-day shape of whichever instrument is used, so two valid instruments with different shapes should deliver different "elasticities" while each looks internally consistent on its own.

Table C.3 estimates the hourly design in our data, giving it the best possible chance: our richest controls (an hour-interacted temperature spline, the wind spline and wind-temperature interaction, the rooftop-PV feed-in control, and zone-by-hour-by-month effects), including municipality-by-day fixed effects in every column, so that the daily price level is absorbed and only within-day variation identifies as in the block design. Column (1) is OLS, columns (2) and (3) instrument the hourly relative price with the solar and the wind family separately, and column (4) uses both families and adds the C-tests of each family against the other.

The result is that the two families disagree sharply — the solar family delivers an elasticity of about 0.13 while the wind family finds a near-zero 0.01, each internally consistent (neither family's own Hansen test rejects at the five percent level) yet mutually incompatible (the C-tests in the both-family column reject each family against the other, $p = 0.009$ and $p = 0.028$). No choice of instruments rescues the hourly model.

	(1) Inflow + precip.	(2) Lagged inflow + precip.
Daily price, p_{it} $(-\eta)$	-0.038**	-0.013
	(0.016)	(0.023)
Kleibergen-Paap F	232.2	86.0
Observations	89,584	89,584

Notes: The daily equation of Table 2, Panel B, with daily precipitation controls added (level, square, and an any-rain indicator). Column (1) instruments with the contemporaneous inflow anomaly and column (2) with runoff accumulated over days $t-32$ to $t-3$. Fixed effects, controls, and clustering as in Table 2, Panel B. Common sample across columns.

Table C.4: Robustness: exclusion of the level instrument

C.4 Exclusion of the level instrument

The level instrument is contemporaneous runoff into the hydro reservoirs, and contemporaneous runoff is same-day weather: precipitation and melt in the reservoir catchments. The exclusion concern is therefore one of timing. A wet day moves the price through supply, but the same weather may also move demand directly that day. Hence, conditional on the temperature controls, wet days may keep households indoors and raise electricity use. In that case, the instrument carries demand-side variation and biases the estimated level elasticity.

We probe the concern from two sides. First, timing: Panel B of Table 2 replaces today's runoff with runoff accumulated over days $t-32$ to $t-3$. Past inflow determines today's reservoir stock and hence today's price, and has a limited correlation with today's weather-driven demand, so the gap between the contemporaneous and the lagged estimate bounds the same-day contamination. Second, the channel: Table C.4 adds daily local precipitation controls (level, square, and an any-rain indicator) to both specifications. If the contamination runs through local rain shifting demand, the controls should absorb it and move the estimates.

The result is that the timing check lowers the estimate from 0.046 to an insignificant 0.021, while the precipitation controls move neither estimate, so local rain itself is not the channel. What separates the contemporaneous from the lagged estimate is either catchment-level weather that municipal controls cannot absorb or sampling variation. On either reading, the contemporaneous 0.046 is an upper bound, and the timing-robust estimate implies a level response indistinguishable from zero.

	(1) Full sample	(2) Winter (Oct–Mar)	(3) Summer (Apr–Sep)
Block price, p_{ibt} $(-\sigma)$	-0.073***	-0.080***	-0.068**
	(0.018)	(0.021)	(0.026)
Kleibergen-Paap F	20.7	8.8	13.1
Hansen J (p)	0.539	0.077	0.285
Observations	285,640	136,470	149,170

Notes: The preferred specification of Table 2, column (4) (both instrument families), re-estimated on the winter (October–March) and summer (April–September) half-years alongside the full sample. Fixed effects, controls, and clustering as in Table 2.

Table C.5: Robustness: seasonal stability of the block elasticity

C.5 Seasonal stability

The leading threat to the continental instruments is spatial correlation in weather. Solar radiation over the Continent and sunshine over southern Norway are not independent, and Norwegian sunshine can move Norwegian demand directly, so the solar family could in part be picking up a sunshine effect on consumption rather than a price response. This correlation would bias the block elasticity toward the solar instrument's own within-day pattern.

We evaluate the potential for this bias by exploiting the Nordic winter as a built-in placebo. From October to March, southern Norway has very little daylight, so any sunshine-to-demand channel is largely switched off. Continental solar, however, still varies enough to tilt the within-day price profile through imports. If the estimate reflects a price response, it should survive the winter. In contrast, if it reflects correlated Norwegian sunshine, it should collapse. Table C.5 therefore re-estimates the preferred column of Table 2 separately on the winter (October–March) and summer (April–September) half-years.

The results show that the block elasticity is essentially the same in both halves of the year and matches the full-sample estimate—the winter estimate does not collapse. The first stage weakens in winter, as expected when the solar dip is shallow.

	(1) Baseline	(2) Whitened	(3) + Lagged IVs	(4) Whitened + lag y
Block price gap, $p_{idt} - p_{int}$ $(-\sigma)$	-0.079***	-0.052**	-0.075***	-0.057***
	(0.015)	(0.021)	(0.015)	(0.020)
Kleibergen-Paap F	26.0	11.3	14.1	11.3
Hansen J (p)	0.101	0.230	0.109	0.279
Observations	142,254	142,254	142,254	142,254

Notes: The block equation in ratio form: the log day/night consumption ratio on the day–night block price gap, one observation per municipality-day (so the observation count is half the block count of Table 2, less the first days of each municipality's series, which the lags require), with municipality, day-of-week by month, year-month, and zone-by-month effects and the daily analogues of the weather and rooftop-solar controls. Column (1) instruments the gap with both continental families (zone-interacted). Column (2) replaces the instruments by their zone-level AR(3) innovations. Column (3) adds the one-day-lagged instruments as extra overidentifying restrictions. Column (4) adds the lagged outcome as a control alongside the whitened instruments. The innovations are generated instruments. The standard errors do not adjust for the first-step estimation. Standard errors clustered by municipality and zone-day. Common sample across columns.

Table C.6: Robustness: lead-lag exogeneity of the block design

C.6 Lead-lag exogeneity

Both continental forecasts are persistent weather processes: sunny and windy spells last for days. If the within-day composition of residual demand were serially dependent as well, the static coefficient could pick up more than the contemporaneous response — a household reacting today to yesterday's price gap, or a demand composition that drifts over the weather spell itself, would load onto persistent instruments, so the estimate would cumulate responses over the spell rather than measure a one-day response (Thams et al., 2024; Tiedemann et al., 2024).

Table C.6 runs the block equation in ratio form (the log day/night consumption ratio on the day–night price gap, one observation per municipality-day) under three dynamics checks of increasing sharpness. Column (2) whitens the instruments, replacing the day–night instrument gaps with their autoregressive innovations, which are unrelated to their own past by construction, so persistence cannot carry anything into the coefficient. Column (3) adds the one-day-lagged instruments as extra overidentifying restrictions. This is the sharpest test: if households responded to yesterday's gap, the lagged instruments would enter the outcome directly and be invalid, so the Hansen test becomes a direct test of dynamic contamination. Column (4) conditions on the lagged outcome alongside the whitened instruments, a combination in which the lagged outcome is a valid control.

Table C.6 includes three observations: (i) whitening leaves the estimate within one standard error of the baseline, at the cost of a weaker first stage; (ii) the lagged-instrument Hansen test does not reject; and (iii) conditioning on the lagged outcome changes little. Hence, the static block coefficient is a contemporaneous response.