

Supplemental Appendix

The Efficiency of Dynamic Electricity Prices

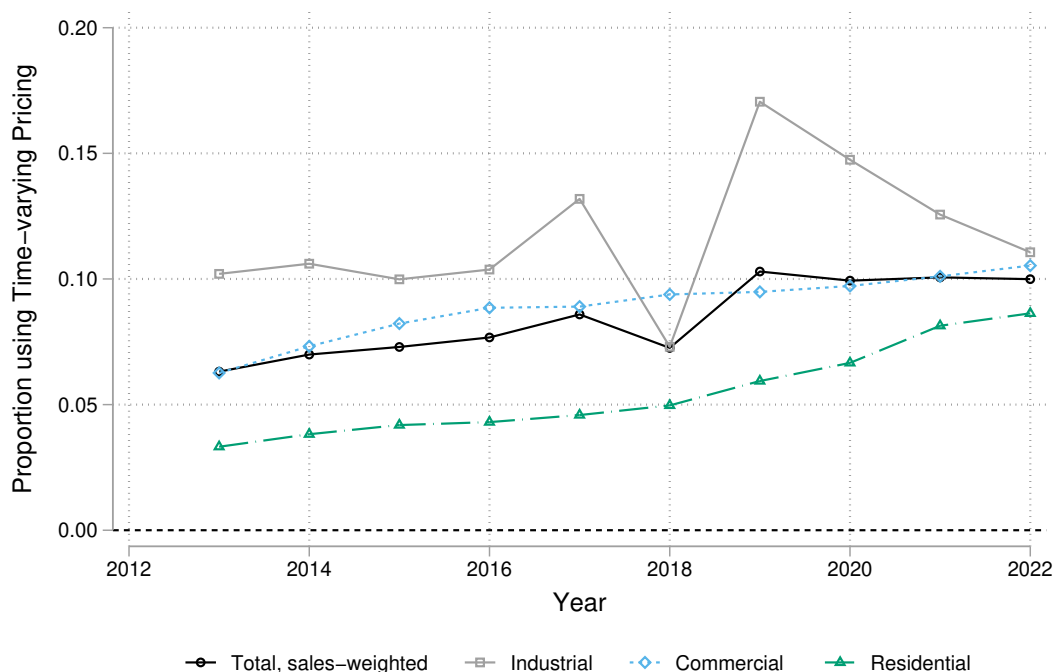
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A Appendix: Additional Methodological Details

A.1 Equilibrium Simulation

To define hourly demand curves we use a linear functional form. We calibrate the slope in each hour using observed average prices/quantities and an assumed elasticity of -0.2 (based on [Reguant \(2019\)](#)), which gives us a slope term of $-0.2(\frac{\bar{q}}{\bar{p}})$ for each hour in the data. We also consider values of -0.1 and -0.3 to assess sensitivity of results. We then calibrate the hourly intercept terms by aligning the observed load in each hour with the average price across the entire market-year. This is implicitly assuming that consumers were facing a flat tariff, set at average price, in the data. In reality most consumers do face flat tariffs, but industrial and commercial consumers are more likely to face time-varying prices than residential consumers. Figure [A.1](#) shows that only 5-10% of load in each year do not face flat prices, although this proportion is increasing modestly over time. Among consumers that do face time-varying prices, industrial consumers are relatively more likely to face true real-time prices and residential/commercial consumers are relatively more likely to face simple time-of-use prices.

Figure A.1: Proportion of Consumers Facing Time-Varying Prices



Note: Each point represents the proportion of consumers in the US that face time-varying prices (including time-of-use pricing, critical-peak pricing, critical-peak rebates, variable-peak pricing, and real-time pricing), calculated by sector. Total is an average of the sectoral estimates weighted by annual usage (in GWh). Source: Form EIA-861 (<https://www.eia.gov/electricity/data/eia861/>).

In light of this, we interpret our demand curve here as an overall response to retail electricity price changes, which is then an average of the demand response from each segment weighted according to its size and likelihood to face retail prices. We selected values based on estimates of residential, commercial, and industrial demand elasticities and shares. See Reguant (2019) (Table 2 and footnote 27) for a brief overview of these.

To generate hourly supply curves, we begin with market-year-level merit order curves. For ease of computation, we fit linear splines with knots at the 75th and 95th percentiles of quantity along the merit order. This specification was selected via grid search over every possible set of 1, 2, or 3 vigintile knots—this set explained the greatest proportion of the variance in our merit order data, with an average R^2 of 0.959 across all market-years. We then horizontally shift the supply curves such that they intersect demand at the observed price and quantity in each hour. This assumes that hourly shocks to the merit order all occur among the lowest marginal cost technologies (e.g., wind/solar). Table B.5 provides summary statistics of these implied hourly shocks, which can be caused by a variety of factors, including renewables intermittency, outages, maintenance, and imports/exports.

Finally, we generate the counterfactual hourly equilibria via the intersection of these two curves. We then simulate hourly policy equilibria by crossing the demand curve with a horizontal “enforced” supply curve set at the policy price. Deadweight losses caused by any given policy are computed by integrating to evaluate consumer and producer surpluses.

A.2 Peak-Hour Definition

To create our standard definition of peak vs. off-peak hours in each market, we find the pair of hours that, as a start and end hour for the peak period, on average, explain the greatest proportion of the variation in observed wholesale prices in that market. To do so, we employ an exhaustive search best-subsets selection algorithm, an out-of-sample variant of which we use in Section 6.1.

We define a peak policy by its start and end hour. This is any subset of {midnight, 1AM, 2AM, ..., 11PM} of size 2, where the peak period is defined as those hours weakly after the start hour and weakly before the end hour (or vice versa). There are $\binom{24}{2} = 276$ possible arrangements. For each market-year of our data, we calculate the in-sample R^2 from each of these possible peak definitions. We then collapse to the market-level median R^2 value for each peak definition (of which there are 276×7), and select the definition with the highest median R^2 value in each market as the 7 peak definitions in our analysis.³² The results of this exercise (local time) are shown in Table A.1. As is often practiced by utilities, peak hours usually run from sunrise until sundown, with the exceptions of ERCOT (which is more concentrated during the hottest hours of the day) and CAISO (which is shifted slightly later in the day).

Table A.1: Peak Hours for Each Market, Inclusive

Market	Start Hour	End Hour
PJM	6am	8pm
ISO-NE	6am	8pm
NYISO	7am	8pm
ERCOT	12pm	6pm
MISO	6am	8pm
SPP	6am	8pm
CAISO	10am	10pm

A.3 CPP Price Schedule Construction

To define in-sample CPP schedules (such as those in Figure 3 and Table 2), we first order days in the year by their mean of the observed real-time prices during their peak period. Then,

³²Selections using the market-level mean R^2 are qualitatively similar.

we define indicator variables for each of the top-20 peak periods and report the R^2 from the regression of real-time prices on those indicator variables. This creates a schedule consisting of the day-specific mean peak-period price during the top-20 peak periods (i.e., following what we call “event-level pricing” in Section 5.3) and the mean of all remaining real-time price observations in non-CPP hours.

To define out-of-sample CPP schedules, we begin similarly. In most cases, we sort days of the year by their peak period day-ahead price and define the top- n peak periods as critical-peak periods—in Figure 6, we also display results sorted by real-time price. Using the day-ahead market in this way gives our model an imperfect signal of the best CPP events to call given a fixed number of them. However, it is still an *ex post* solution to the true optimal-stopping problem utilities must solve in calling CPP events. We discuss this issue further in Section 5.3.

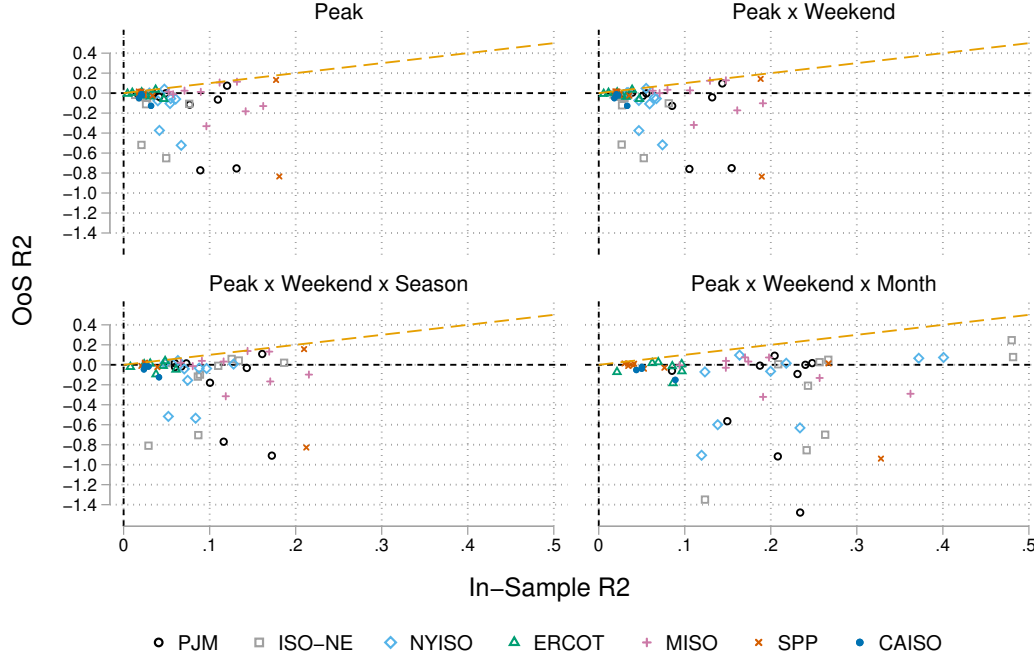
Then, we define either a single critical-peak price (averaged over all event-hours), event-level critical-peak prices (averaged over hours for each event), or hourly critical-peak prices (each critical-peak hour is priced individually) depending on the structure of the policy. Unless otherwise specified, we report results with event-level prices—Figure 5 compares these structures directly. When using event-level pricing, we define these critical-peak prices using predicted values from a regression of daily peak-period mean simulated equilibrium prices on day-ahead prices. This accounts for risk premia in the forward market and the equilibrium price effects of the critical-peak price. When using single pricing, we use the mean value of these event-level prices. When using hourly pricing, we instead use predicted values from a regression of simulated equilibrium prices on day-ahead prices during peak periods without collapsing to daily peak-period averages (although the regression coefficients are qualitatively similar). In Figure 6, we also display results priced in real-time—in those cases, we use the simulated equilibrium price directly in place of the predicted values based on the day-ahead market.

Finally, we must define prices during off-peak hours. Other than in Section 5.4, we use a flat price for these hours. To define this flat price, we take the mean of the previous three years’ simulated equilibrium prices, excluding the $3n$ highest-priced hours (where n is the number of yearly critical peak periods considered). This approximates excluding CPP event hours in the creation of off-peak prices.³³ In Section 5.4, we define TOU schedules underlying CPP policies in much the same way. We construct TOU policies using the simulated equilibrium prices from the three previous years, and exclude the $3n$ highest-priced hours from the training data.

³³We do not explicitly simulate what peak periods in the training sample would have been critical-peak events because it would require day-ahead data in the training sample, reducing our OoS analysis sample size by three years in each market.

B Appendix: Additional Figures and Tables

Figure B.1: In-Sample versus Out-of-Sample Performance

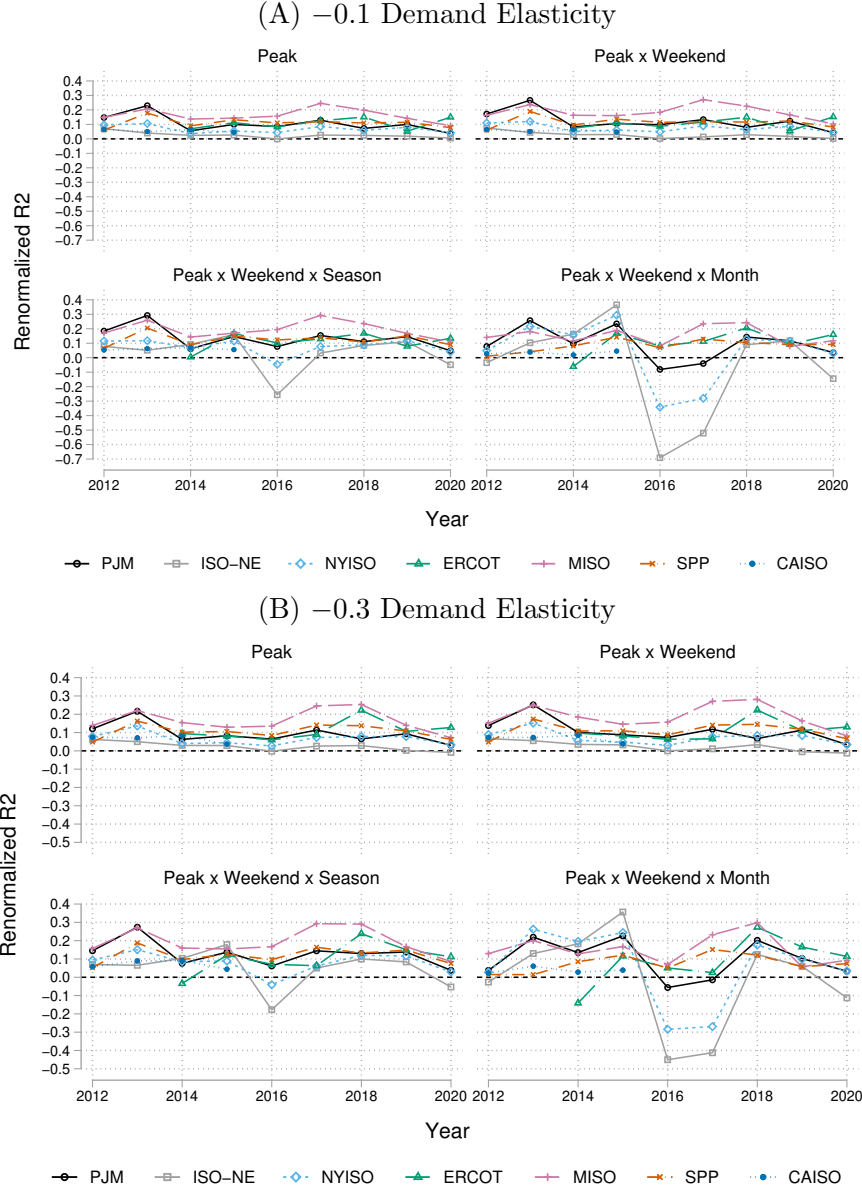


Note: Each point represents the in-sample and out-of-sample performance for a given policy in a given market-year. The horizontal axis represents the simple in-sample R^2 as in Section 5.1. The vertical axis represents the observed-basis out-of-sample R^2 as described in Section 4. 45-degree line shown in yellow. In-sample results are only shown when there are enough data to produce corresponding out-of-sample values.

Figure B.1 compares results from our observed-basis in-sample analysis to the raw observed-basis out-of-sample R^2 values. This differs from our primary out-of-sample analysis in that it uses the observed basis and is not renormalized, but has the useful property that welfare gains implied by the two axes are on the same scale. In each panel, we display the 45-degree line in yellow. Mechanically, all points will fall weakly below this line, but the vertical distance represents welfare gains that are lost due to prediction errors. Many points fall below the horizontal line at zero, indicating that an unbiased flat tariff performs better than many out-of-sample policies (even if constructing this hypothetical tariff requires information not yet known to the policymaker). Comparing panels, we see that more complex policies typically underperform expectations more strongly than simple policies do. Further, within each panel, when a greater proportion of the in-sample variation is explained by the policy, the greater the risk of overfitting. Strikingly, the correlation between in-sample and out-of-sample R^2 s is actually slightly negative, both across and within panels. This is consistent with in-sample

gains not being realized out-of-sample, even conditional on the tariff structure being used.

Figure B.2: Out-of-Sample Efficiency Gain of Different TOU Designs,
Varying Demand Elasticity

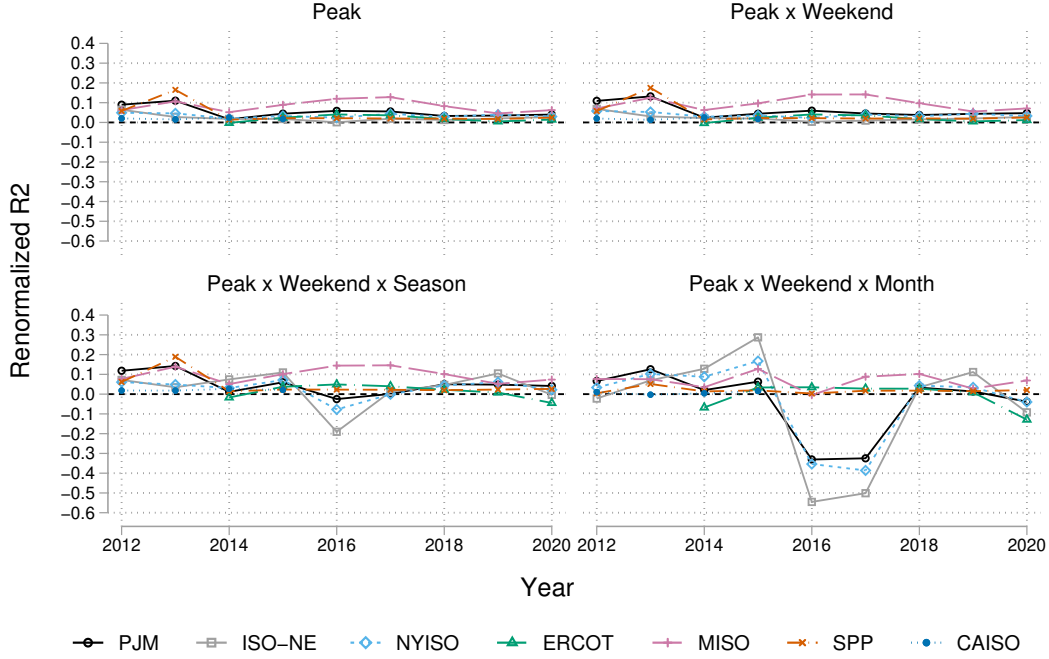


Note: Each point represents the equilibrium-basis renormalized R^2 for a given TOU policy in a given market-year, using the simulation methodology described in Section 4. Panel (A) uses a -0.1 demand elasticity and Panel (B) uses a -0.3 demand elasticity. Season splits the year into two 6-month periods, beginning in April and October. CAISO ends in 2015 and ERCOT begins in 2014 due to data availability issues. Main version using -0.2 demand elasticity available in Figure 4.

Figure B.2 shows a variation of our main results in Figure 4 assuming a demand elasticity

of -0.1 or -0.3 (as opposed to our base value of -0.2), in panels A and B respectively. This has little impact on the R^2 results, though it does affect the magnitude of total DWL. For example, while the peak policy creates a mean (median) DWL of 283 (195) million dollars across the market-years of our sample with an elasticity of -0.2, this same policy creates 168 (112) and 407 (274) million dollars of deadweight loss under a -0.1 and -0.3 elasticity, respectively.

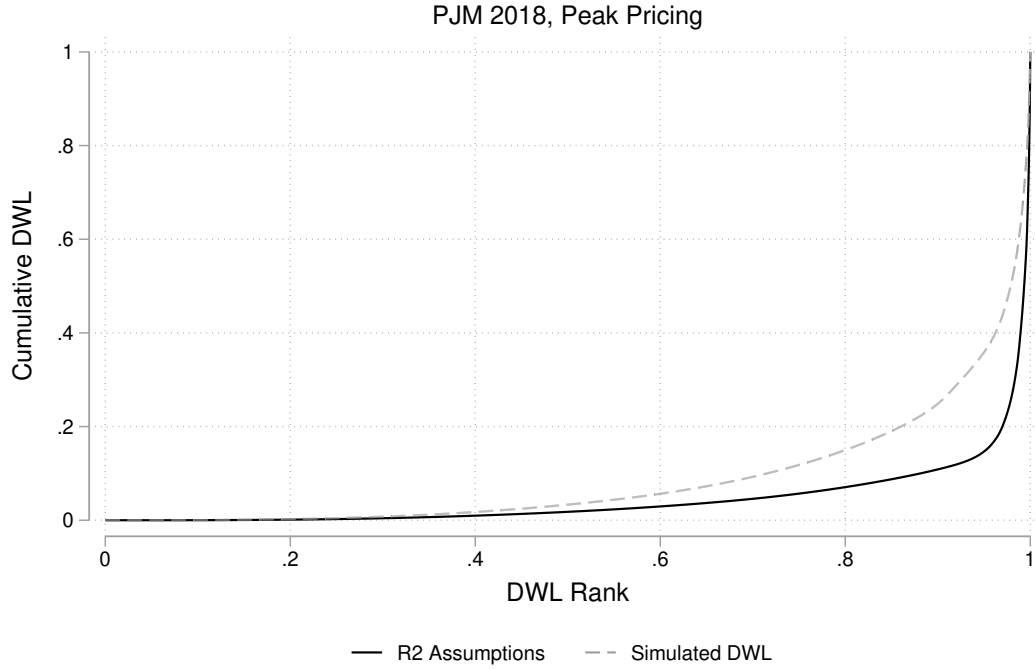
Figure B.3: Out-of-Sample Efficiency Gain of Different TOU Designs, Observed Basis



Note: Each point represents the observed-basis renormalized R^2 for a given TOU policy in a given market-year, using the simulation methodology described in Section 4. Season splits the year into two 6-month periods, beginning in April and October. CAISO ends in 2015 and ERCOT begins in 2014 due to data availability issues. Main version using the equilibrium basis available at Figure 4.

Figure B.3 demonstrates that the result that there are diminishing (and even negative) returns to TOU complexity is similar when using observed wholesale prices instead of simulated real-time prices. Note that, relative to the equilibrium-basis out-of-sample results, we have also changed the functional form of the supply curve: the equilibrium basis out-of-sample results in Figure 4 assume linear spline supply curves; the observed basis out-of-sample results here assume linear supply.

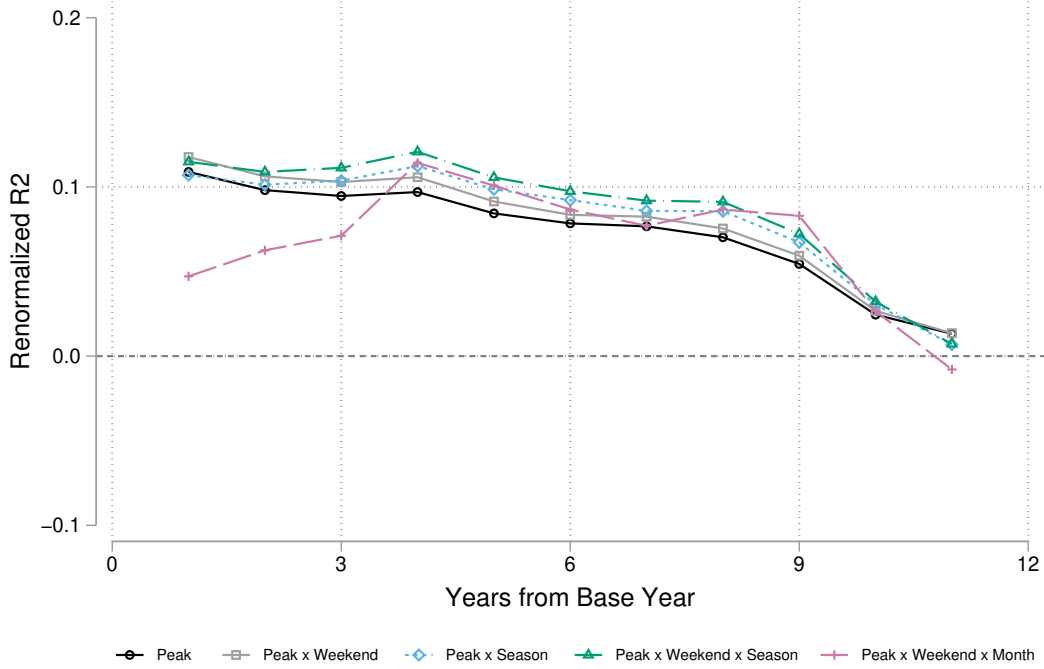
Figure B.4: Cumulative Distribution of In-Sample DWL - PJM - 2018



Note: This figure shows the cumulative distribution function of deadweight loss across hours of the year under linear supply/demand with observed wholesale prices as the benchmark (solid black line) and with spline supply/linear demand with simulated equilibrium prices as the benchmark (dashed grey line), for an in-sample peak/off-peak policy in the PJM market in 2018.

Under the observed wholesale basis, the “target” price schedule is the observed marginal cost of generation. However, the first-best equilibrium price is that which would have been reached under full real-time pricing. When the supply curve is sloped, these two prices are generally not the same. The observed wholesale basis overweights the deadweight loss associated with the most extreme outlier hours, which, under real-time pricing, would have experienced a large reduction in load due to demand response to the higher price. Simulated equilibrium prices have a smaller variance than observed wholesale prices, so the estimated deadweight loss from an intermediary policy is more evenly distributed across hours (Figure B.4).

Figure B.5: Varying the Size of the Training Sample

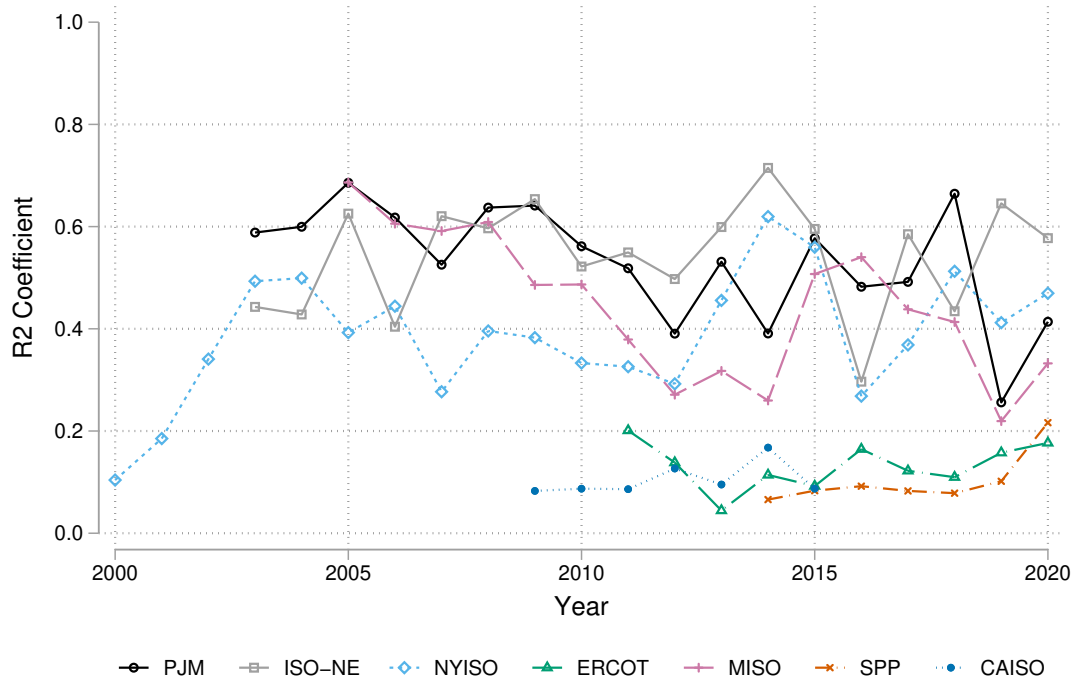


Note: Each point represents the mean renormalized R^2 across all markets with a given policy and number of years of training data, using the simulation methodology described in Section 4. Pre-collapsed data is unbalanced across markets due to varying data availability and unbalanced across levels of the horizontal axis because, with a temporally finite sample, fewer years can support larger training samples.

Figure B.5 presents the mean renormalized R^2 across all market-years of five different TOU policies while varying the size of the training sample. The horizontal axis denotes the number of prior years that constitutes the training sample—note that our inclusion of all possible years of test data causes the panel of results to be unbalanced (with smaller values on the horizontal axis containing more R^2 observations). Our main specification corresponds to a value of 3 along the horizontal axis. We do not see a significant positive or negative trend in R^2 from expanding or contracting the number of years of training data around this point. We do see a decline after 8 years, but this excludes most potential years of test data, especially from CAISO and ERCOT (which can respectively support at most 6 and 9 years of training in our data). Additionally, any reasonable weighting of the training data would prioritize more recent information, so we do not consider this a threat to our empirical strategy. Finally, we also notice that the most complex policy studied (peak $\times$ weekend $\times$ month) improves both in absolute terms and relative to the other policies significantly when moving from 1 to 4 years of pre-period data. This is because, with few years of training data, large spikes in the observed prices can be extremely influential on the policy price on particular tariff levels, causing overfitting. After enough years of data

have been added, this policy is “smoothed” significantly, and more closely resembles the policy prices from simpler policies (e.g., peak $\times$ weekend $\times$ season).

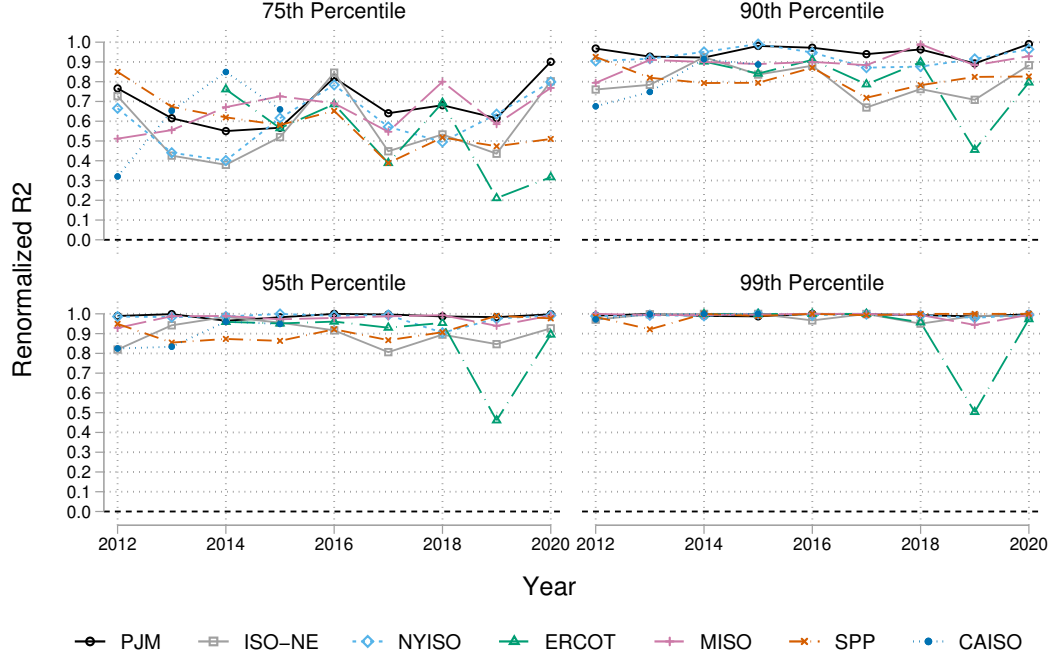
Figure B.6: R^2 Coefficients from a Regression of Real-Time on Day-Ahead Prices



Note: Each point represents the R^2 from a regression of ISO-level real-time prices on day-ahead prices for PJM, ISO-NE, NYISO, ERCOT, MISO, SPP, and CAISO over the period 2000-2020 (with data coverage varying as described in Section 3).

Figure B.6 shows the R^2 from regressions of ISO-level real-time prices on day-ahead prices. These values are significantly below 1, which indicates that there is still significant variation in real-time prices that cannot be predicted even a day in advance. As is visually apparent, certain ISOs’ forward markets explain more of the variation in spot prices than others. For example, SPP’s base load has a large wind generation share, which is difficult to predict, whereas ISO-NE has larger nuclear and hydroelectric generation shares, which are more predictable. This may partially explain differences in expected efficiency gains from CPP policies. There is typically a small difference in mean between these two market prices—this is a risk premium. Our interest is in whether or not day-ahead prices can accurately *predict* real-time prices, so, as long as this risk premium is consistent in expectation, this is not an issue.

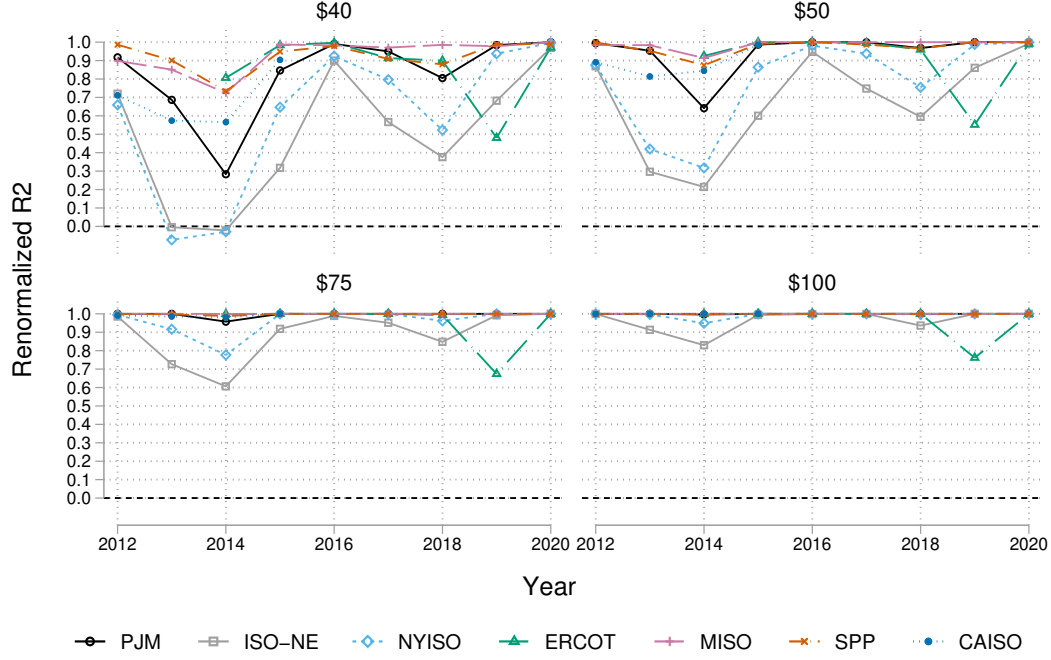
Figure B.7: Real-Time Pricing with Price Caps – In-Sample Caps



Note: Each point represents the equilibrium-basis renormalized R^2 for real-time pricing with a given price cap in a given market-year, using the simulation methodology described in Section 4. CAISO ends in 2015 and ERCOT begins in 2014 due to data availability issues. Panels represent real-time pricing schedules with price caps set at the 75th, 90th, 95th, and 99th percentiles of simulated equilibrium prices from the current year, respectively. A version using out-of-sample price caps appears in Figure 8. A version using flat price caps appears in Figure B.8.

Figure B.7 presents a variation on our analysis of real-time pricing with price caps, instead defining price caps using percentiles of in-sample equilibrium prices. This is not achievable in practice and therefore not a realistic possibility, unlike the results presented in Figure 8—indeed, we are using information that the policymaker does not have access to in order to set these caps. However, the use of this is that we have fixed the proportion of hours affected by the price cap to be equal to exactly $(100 - x)\%$ of hours in each panel. These four panels have mean (median) R^2 values of 0.605, 0.863, 0.937, and 0.981 (0.616, 0.888, 0.96, 0.994), respectively. Based on this, we conclude that real-time pricing with price caps binding less than 10% of the time still recover the overwhelming majority of deadweight loss compared to a flat baseline.

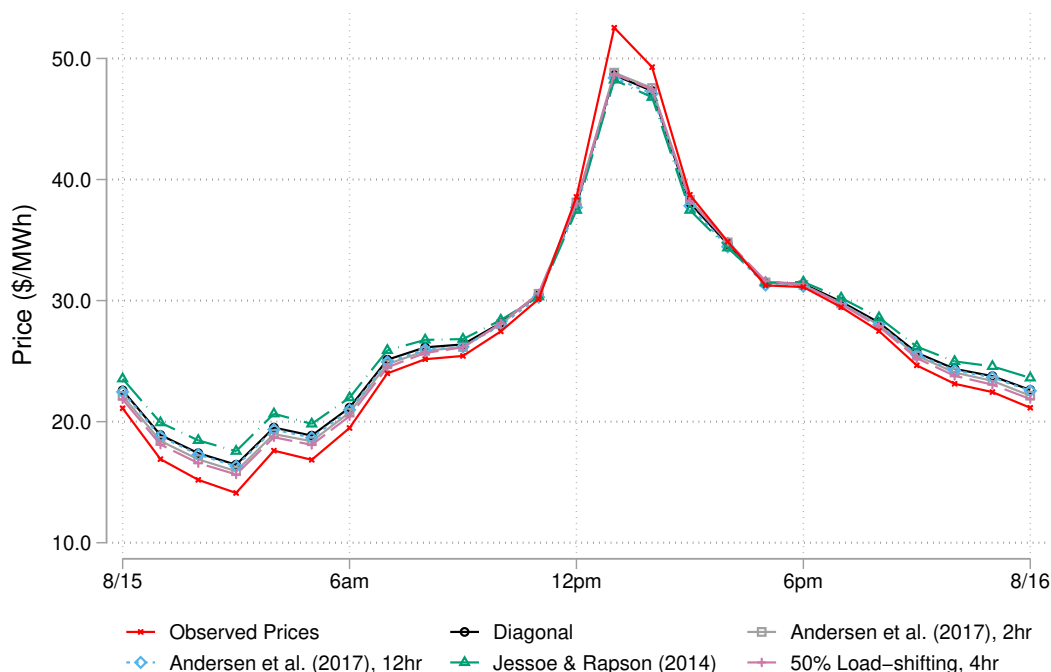
Figure B.8: Real-Time Pricing with Price Caps – Flat Caps



Note: Each point represents the equilibrium-basis renormalized R^2 for real-time pricing with a given price cap in a given market-year, using the simulation methodology described in Section 4. CAISO ends in 2015 and ERCOT begins in 2014 due to data availability issues. A version using out-of-sample price caps appears in Figure 8. A version using in-sample price caps appears in Figure B.7.

Similarly, Figure B.8 presents a variation of our real-time pricing with fixed-value price caps set at \$40, \$50, \$75, and \$100. As Table B.1 shows, the distribution of prices varies significantly across the years of our sample. Therefore, the proportion of hours in which the cap binds is variable, as in Figure 8. Some market-years using the \$40 cap result in negative R^2 values—this is because the cap is binding in many hours during those market-years (in some cases, the cap is below the median price).

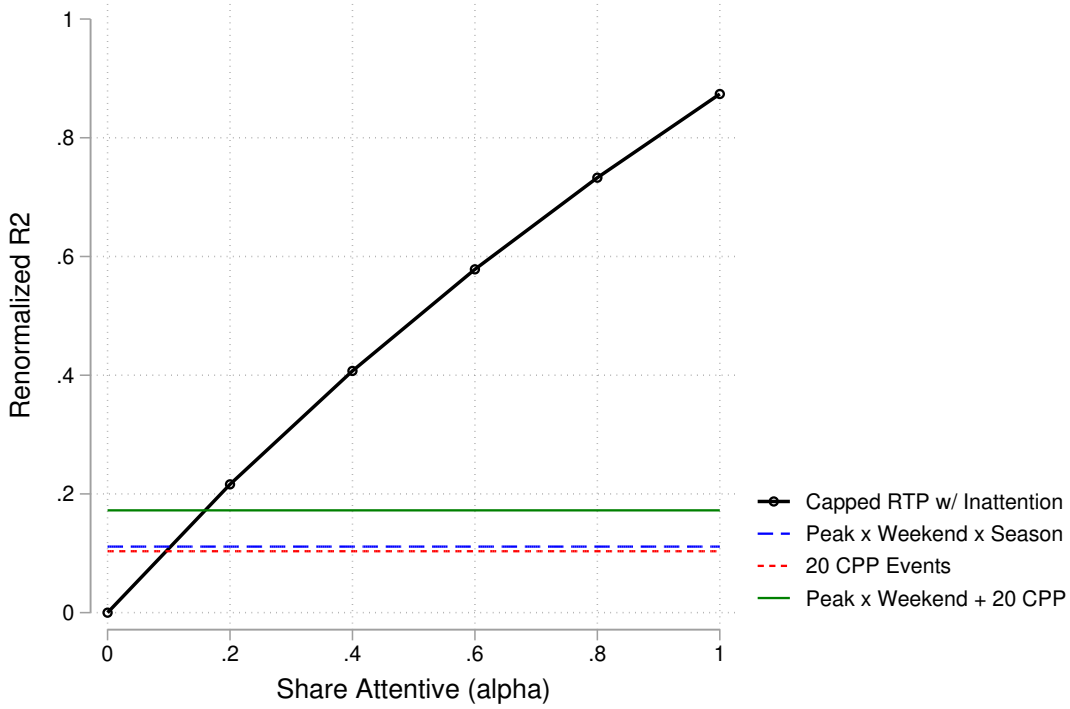
Figure B.9: Simulated Prices with Various Load-Shifting Patterns - PJM - August 15, 2015



Note: Each point represents an hourly simulated equilibrium price of electricity under true real-time pricing from PJM on August 15, 2015. Different colors represent different shoulder substitution patterns, corresponding to different estimates from the literature. Points in red represent observed wholesale prices directly from the data.

Figure B.9 shows a comparison of simulated real-time prices under different shoulder-substitution patterns alongside observed wholesale prices from an example day. We find that these simulated equilibrium prices broadly follow the observed wholesale price, and even more so strongly bunch together with each other. These different calibrations typically diverge in price more during periods of low demand and bunch more tightly in periods of high demand. During those peak hours, any simulation that passes real-time prices onto retail consumers will see a stark response to avoid progressing too far on the steep portion of the merit order curve. Compared to the other calibrations, simulations using [Jessoe and Rapson \(2014\)](#) typically fall on the opposite side of the no-shoulder substitution (diagonal) case—this is because they find that electricity in adjacent hours are complements, where the other studies found that them to be substitutes.

Figure B.10: Capped RTP with Inattentive Consumers



Note: Each point along the black line represents the equilibrium-basis renormalized R^2 for real-time pricing with a price cap at the 90th percentile of the previous three years' equilibrium prices, averaged over all market-years in our sample, with α proportion of consumers that are inattentive, as described below. Horizontal lines represent the average renormalized R^2 from the associated policies with fully attentive consumers. TOU policies are set out-of-sample, and CPP events are called and priced based on event-level day-ahead prices.

One prescient concern with (capped) real-time pricing is that consumers are imperfectly attentive to it. That is, even if the policy better matches wholesale price variation, consumers may be less responsive to it than a simpler policy. We investigate the welfare consequences of this possibility by modeling capped real-time pricing with $1 - \alpha$ consumers responding to the policy price and α consumers responding as if they face an out-of-sample flat price. Behaviorally, this is as if, due to the complexity of the policy, α consumers “give up” on responding to the price signal. This generates a very simple total demand curve of $\tilde{Q}^d(P) = (1 - \alpha)Q^d(P) + \alpha Q^d(\bar{P})$, which, since $Q^d(\cdot)$ is linear, simplifies into another, less elastic, linear demand curve. We then combine our hourly supply curves with $\tilde{Q}^d$ to calculate an equilibrium price schedule with α inattentive consumers, keeping track of attentive consumers' load, inattentive consumers' load, and total load. We then apply price caps, recalculate load, and calculate deadweight loss benchmarked against the first-best prices with fully attentive consumers.³⁴

³⁴Note that, with inattentive consumers, the policy price schedule for an RTP policy will not equal the first-best price schedule, even in hours where the cap does not bind. To calculate lost PS, we take the area between

Figure B.10 displays the results for a real-time pricing policy with a cap at the OoS 90th percentile. Increasing the share of inattentive consumers decreases R^2 in near one-for-one. This is intuitive—since attentive consumers face (capped) real time prices ($R^2 \approx 1$) and inattentive consumers face flat prices ($R^2 = 0$), a reasonable conjecture for the R^2 with α inattentive consumers is $\alpha \cdot 0 + (1 - \alpha) \cdot 1 = 1 - \alpha$.³⁵ We can use this framework to compare the welfare gains at different levels of customer confusion. We plot horizontal lines at the average R^2 value for a Peak x Weekend x Season TOU policy, a CPP policy with 20 events, and a Peak x Weekend TOU combined with 20 CPP events, all with $\alpha = 1$ (i.e., assuming that consumers are fully responsive to these policies). Comparing the two analyses, we conclude that consumers would need to be less than one-fifth as responsive to the capped RTP policy for its welfare gains to be lower than the simpler policies.

Table B.1: Percentiles of Simulated Equilibrium Prices

Market	75th	90th	95th	99th
PJM	35.83	47.92	55.13	57.17
ISO-NE	43.86	59.36	69.97	96.47
NYISO	41.11	60.1	71.77	79.07
ERCOT	28.35	36.71	42.27	51.9
MISO	29.82	37.89	44.7	51.95
SPP	27.91	33.8	39.19	55.07
CAISO	38.7	45.96	53.5	78.04

Note: Table shows the 75th, 90th, 95th, and 99th percentiles of simulated equilibrium prices averaged across the years of our sample for each market in dollars per megawatt hour.

Table B.1 gives the mean across all years of the sample of the 75th, 90th, 95th, and 99th percentiles of simulated equilibrium prices for each market. This (roughly) gives the average value of the price caps being implemented in Figures 8 and B.7 for each market.

the supply curve and the policy price between the first-best and policy total loads (e.g., $Q^d(P^{FB})$ and $\tilde{Q}^d(P^{Pol})$). To calculate lost CS from attentive consumers, we take the $(1 - \alpha) \cdot 0.5 \cdot |Q^d(P^{Pol}) - Q^d(P^{FB})| \cdot |P^{Pol} - P^{FB}|$, where Q^d is the true demand curve. To calculate lost CS from inattentive consumers, we take $\alpha \cdot 0.5 \cdot |Q^d(\bar{P}) - Q^d(P^{FB})| \cdot |\bar{P} - P^{FB}|$ (i.e. α times the lost CS from the OoS flat policy).

³⁵This conjecture is not exactly true, even without caps and with linear supply curves, because inattentive consumers change equilibrium prices, causing surplus losses for attentive consumers.

Table B.2: Variable Cost Recovery

Market	Flat	Peak	20 CPP	Peak + 20 CPP	RTP 90 Cap
PJM	-5027	-3654	-3403	-2638	-998
ISO-NE	-1063	-916	-798	-714	-550
NYISO	-1083	-859	-742	-616	-322
ERCOT	-16616	-11229	-12918	-9936	-1953
MISO	-1497	-886	-1164	-692	-623
SPP	-1052	-753	-973	-725	-416
CAISO	-1730	-1331	-1611	-1303	-655

Note: Table shows the mean annual variable profits for the utility under various pricing schemes in millions of dollars. All values used come from the in-sample equilibrium basis, critical peak pricing policies price and call on day-ahead prices, and RTP uses an in-sample 90th percentile price cap, as in Appendix Figure B.7.

Table B.2 shows the cost recovery performance of four in-sample policies in each market, averaged across the years of the sample. To do this, we calculate the variable profits (e.g., policy price minus wholesale equilibrium price times equilibrium quantity) for each policy in our sample for the in-sample flat policy.³⁶ Notably, all these averages are negative³⁷—this is because the flat tariff is an unweighted average of simulated RTP prices, not a load-weighted one (and similarly in a regression context for TOU/CPP). In our earlier welfare analyses, these losses are assumed to be recovered through the fixed charge (or through some other nondistortionary tax instrument). However, we also find that, for all the policies we consider, no market-years simulated result in shortfalls relative to the flat policy, and the additional variable profits from time-varying pricing are significant in magnitude. This is as expected for TOU/CPP: a mean-preserving change to a flat tariff that increases (decreases) prices during higher (lower) marginal cost hours shifts load away from hours where the utility suffers losses and towards hours where they make profits. For RTP with a price cap, we are instead eliminating all profitable hours and most unprofitable hours, and limiting losses in the most unprofitable hours. Even though this mechanically results in losses for the utility, these are below the average losses with any other policy. Overall, this leads us to conclude that the implementation of these policies would not result in significant shortfalls for utilities—in fact, we predict that the opposite will occur.

³⁶We focus on in-sample policies to avoid significant differences in mean prices between TOU/CPP and capped RTP policies.

³⁷Dividing the losses for the flat tariff in this table by total annual load results in losses well below \$10/MWh, with the exception of ERCOT.

Table B.3: Peak Load Avoided (MW)

Market	Obs. Max	Peak	20 CPP	Peak + 20 CPP	RTP 90 Cap
PJM	147551	1945	3086	4081	3988
ISO-NE	25045	244	155	291	356
NYISO	30897	426	605	879	661
ERCOT	71868	1375	1367	1821	1832
MISO	112269	1583	3518	3978	2510
SPP	48581	584	571	964	814
CAISO	46244	415	834	1100	1509

Note: Table shows the mean difference in yearly maximum load between the listed policy and a flat tariff. “Obs. Max” column shows the average observed annual maximum load across years of our sample, which is equivalent to our simulated flat tariff load (see Appendix A.1). All values used come from the out-of-sample equilibrium basis, critical peak pricing policies price and call on day-ahead prices, and RTP uses an in-sample 90th percentile price cap, as in Appendix Figure B.7.

One potential benefit of dynamic pricing policies beyond avoided deadweight loss from short-run mispricing is that, if the policy incentivizes reductions in load during the highest demand hours of the year, utilities may be able to avoid costly investments in capacity. To this end, Table B.3 shows the difference in average annual maximum load between a flat tariff and four different dynamic policies. Notably, these policies are not clearly ranked across markets along this metric. CPP policies are designed to reduce extreme peak load. However, utilities do not have perfect foresight about the highest n peaks. Further, even if CPP correctly targeted exactly those hours, it may leave some nearly-as-high load hours unaffected. Peak pricing, on the other hand, applies a much smaller price change to all peak hours in the year. This policy will affect nearly all the highest load hours relative to CPP, but will obviously reduce load in these hours by less. Similarly, the capped RTP policy is certain to affect all of the highest-load hours, but the price cap will bind in the hours we most want to be targeting.

Regardless of the relative ranking, it is apparent that all of the policies we propose have the potential to reduce peak load. On average, these policies are reducing peak load by 1-3%. To quantify the economic benefits of long-run reductions in capacity requirements, we turn to a metric called the annualized cost of new entry (CONE). Utilities calculate this number as the annualized capital cost in dollars per megawatt of increasing the system capacity. Typically, this figure falls around \$100,000 per MW of generation capacity per year (Newell et al. 2018). Multiplying the numbers in Table B.3 by this figure implies long-run savings of the same order of magnitude as our static welfare gains explored in the body of the paper. Then dividing

these numbers by the average static deadweight losses in Table 3, we would find welfare gains from avoided investment equivalent to a policy that yielded an R^2 of between 6% and 170% across markets, typically falling between 20-60%. However, we caution that this is a back of the envelope calculation that ignores important spatial reliability concerns, and this disinvestment would also change the slope of the merit order (and would thus affect our static welfare calculations). It is also important to note that, in our analysis, we are targeting price variation. If, for example, a utility instead targeted CPP events not at the highest *price* hours but at the highest *load* hours, they may be able to reduce investment by even more than what is suggested here. Therefore, we interpret these findings as suggestive only.

Table B.4: Predicting Welfare Gains with Covariates

	Peak				Peak x Weekend x Season			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Fossil Share	0.190 (5.25)		0.103 (1.24)	0.033 (0.18)	0.194 (3.46)		0.093 (0.75)	-0.322 (-1.00)
Solar/Wind/Geo Share	-0.065 (-0.49)		-0.109 (-0.75)	0.325 (1.36)	-0.042 (-0.21)		-0.035 (-0.16)	0.213 (0.51)
Nuclear Share	-0.096 (-1.19)		-0.228 (-2.12)	-0.233 (-0.52)	-0.020 (-0.16)		-0.316 (-1.98)	-0.560 (-0.72)
Hydro Share	-0.048 (-0.40)		-0.078 (-0.58)	0.308 (0.64)	-0.117 (-0.63)		-0.151 (-0.75)	0.220 (0.26)
Cooling Degree Days		0.043 (4.36)	0.013 (0.51)	0.028 (0.25)		0.029 (2.01)	-0.011 (-0.31)	0.206 (1.06)
Heating Degree Days		0.013 (1.69)	0.003 (0.24)	-0.025 (-0.91)		0.005 (0.42)	-0.006 (-0.32)	0.000 (0.01)
Precipitation		-0.001 (-0.45)	0.002 (1.07)	0.000 (0.27)		0.001 (0.83)	0.004 (2.10)	0.002 (1.15)
Observations	56	56	56	56	56	56	56	56
Year + Market FEs	No	No	No	Yes	No	No	No	Yes

Note: t -statistics in parentheses. Regressand is the renormalized equilibrium-basis R^2 of the policy listed in the header. Regressors are generation shares (in proportions), ISO-average cooling/heating degree days and inches of precipitation, and ISO and market fixed effects. All regressions run without a constant, as the generation shares sum to 1. Fossil generation includes coal, natural gas, and oil.

We may be interested in explaining why the welfare benefits of these policies are heterogeneous across market-years, especially given the ongoing energy transition. To this end, we have collected two additional datasets. First, from the plant-level EIA Forms 860 and 923, we generate fuel mixes for each of the market-years in our sample. As fossil generation is flexible and dispatchable while nuclear, hydro, solar and wind are not, one might expect wholesale market pricing volatility to decrease in fossil generation and vice versa. Second, we construct market-year level weather data from the NOAA nClimDiv state files ([NOAA 2014](#)). In particular, for each ISO, we generate annual average cooling degree days, heating degree days, and precipitation, weighted by state population served by the ISO. One might expect that markets with more extreme weather exhibit more volatile pricing. These two data sources roughly correspond to changes on the supply and demand side of the market, respectively. Therefore, we can regress our renormalized R^2 metric on these supply and demand shifters in an attempt to explain how welfare benefits of adopting these policies vary across markets.

Table [B.4](#) presents the results of these regressions for two separate policies: peak pricing and peak by weekend by season pricing. For the cross-market regressions in columns 1-3, we find that the coefficients on fossil fuel share are positive and significantly greater than the negative coefficients on renewables, nuclear, and hydro. This is true for both policies, if slightly weaker for the more complex tariff in columns 5-7. This is exactly as expected, as flexible fossil generation might reduce variance in supply, reducing variance in wholesale prices which, all else equal, increases the R^2 . The opposite might be true for intermittent renewables or inflexible nuclear. This would suggest that, as the energy transition progresses and fossil generation declines, we will see smaller relative welfare gains from an intermediary time-varying pricing scheme, strengthening the case for true real-time pricing. However, as is visible in columns 4 and 8, we do not observe this relationship within market over time (and after netting out a common time trend across markets). There are many other market-varying or time-varying factors that influence the effectiveness of these policies (imports/exports, changes to the shape of the load curve, etc.), so we interpret these findings with caution. For the weather variables, we do not find a particularly consistent or compelling relationship across specifications.

Table B.5: Descriptive Statistics of Supply Shocks (GW)

Market	Mean	SD	P25	P75	Summer Mean	Capacity	Low-MC Capacity
PJM	−8.94	27.09	−19.08	8.57	−5.60	211.03	48.14
ISO-NE	−2.24	5.81	−7.11	2.10	−0.73	36.22	9.24
NYISO	0.94	6.50	−1.38	5.07	2.58	44.41	13.05
ERCOT	−1.90	13.78	−6.91	6.30	0.20	96.46	13.64
MISO	4.73	24.95	−6.15	22.32	5.85	164.01	23.30
SPP	2.50	8.90	−0.46	7.27	3.81	76.23	12.01
CAISO	−4.19	9.95	−10.24	2.21	−1.74	67.47	19.14

Note: Table shows descriptive statistics of supply shocks for all hours of all years for each market (in GWh). Supply shocks are defined as the horizontal distance needed to shift the base merit order curve in order to rationalize the observed (price, load) pair. Positive (negative) values constitute rightward (leftward) shifts of the base merit order. Summer includes months April through September. Capacity gives the maximum capacity of the base merit order, averaged across years for each market. Low-MC is defined as wind, solar, hydro, and nuclear.

In our data, we have base merit orders for each market-year, which we shift horizontally to justify the observed price and quantity in each hour (see Appendix A.1 for further details). Table B.5 gives descriptive statistics of the implied hourly supply shocks. Several details of note emerge. First, the mean supply shock is generally not zero, although this mean is small relative to the total capacity of the market. Across markets, the share of supply shocks that are negative ranges from 27% (SPP) to 66% (CAISO). The variance of these shifts is also large—this could be due to many factors, including renewables intermittency, outages, maintenance, congestion constraints, ramping costs, and imports/exports. Our use of these shocks is most consistent with changes to the availability of low marginal cost units. Across markets, the standard deviation of the shocks is on average half the capacity of low-MC (wind, solar, hydro, and nuclear) units, and the interquartile range is on average slightly smaller than that capacity. This suggests that intermittency plays a role but cannot explain all of our observed supply shocks. Reassuringly, the summer mean is in all cases greater than the unconditional mean, consistent with greater renewable generation in those months.

Table B.6: Comparing Different Inefficiencies

Inefficiency	DWL	Price Wedge Mean	Price Wedge SD
Flat Pricing	12.03	0	29.22
Carbon Externalities	19.21	-26.86	18.74
Fixed Cost Recovery	91.62	77.70	0
Carbon + Fixed Costs	47.76	50.84	18.74
All Three	54.19	50.84	29.22

Note: Table shows the average annual deadweight loss (in billions of dollars) summed across markets from various inefficient pricing policies and the mean and standard deviation of the price wedge in dollars per MWh (averaged across market-years). All policies are benchmarked against a price schedule that internalizes carbon externalities, recovers fixed costs through the fixed charge, and passes through real-time variation in prices to consumers.

There are three major inefficiencies present in retail electricity pricing. We focus solely on the failure of retail prices to pass real-time price variation onto end users. In doing so, we abstract from both externalities from pollution and inefficient recovery of fixed costs through volumetric rates. We now investigate the size of each of these inefficiencies in isolation, as well as the extent to which they may offset each other.

To do so, note that consideration of pollution externalities requires us to generate a social marginal cost curve and a new socially optimal price schedule. Our merit order data includes CO2 emissions rates, which we combine with a a \$190 social cost of carbon. For simplicity, we re-sort units according to their social marginal cost and estimate a spline approximation of the SMC curve, much like with the private marginal cost curves considered previously.³⁸ We then shift this base SMC curve using the same supply shocks as before and cross it with our hourly demand curve to generate the socially optimal price schedule. We then can vary policies along our three inefficiencies. First, we can price either hourly, or collapse to an annual mean. Second, we can set prices according to the PMC curve or the SMC curve. Finally, we can either pass fixed costs onto consumers using fixed fees or add them into volumetric rates. To implement this, we add \$77.7 per MWh to the price in each hour, taken as the mean difference between marginal prices and marginal costs in Table 5 of [Borenstein and Bushnell \(2022a\)](#).

The first three rows of Table B.6 presents the three inefficiencies taken individually. We find that the deadweight loss from flat pricing is significant, somewhat smaller than the inefficiency from failing to price carbon emissions, though substantially smaller than that from inefficient cost recovery. However, the source of these inefficiencies is different. Inefficient cost recovery creates a large price wedge on average, but by the same amount in each hour. Flat pricing,

³⁸This resorting ignores allocative inefficiencies, but is much more tractable.

however, is correct on average, but creates wedges with the same variance as the socially optimal price schedule. Marginal damages from carbon emissions are on average positive, but also vary hour-by-hour—externalities cannot be fully internalized without time-varying prices, so row 1 includes environmental inefficiencies even though the average marginal damage is included in the price.³⁹ Additionally, note that inefficient cost recovery and the average externality partially offset each other—naturally, their average price wedges sum. Row 4 shows a lower deadweight loss than row 3.⁴⁰ However, the variance of the price wedges in this policy is inherited from carbon damages, although this variance is lower than the variance of price wedges from flat pricing alone (because MD and PMC are positively correlated).

In sum, we conclude that deadweight loss from flat pricing is smaller than the deadweight loss created by inefficient cost recovery or pollution externalities in isolation. However, this deadweight loss is still economically large in its own right, it is not subject to “two wrongs making a right” on average, and correcting the flat pricing inefficiency is necessary to fully internalize pollution damages.

³⁹One may note that the average DWL from flat pricing is approximately six times larger in Appendix Table B.6 than in Table 3. This is because the variance in first-best prices (i.e., the variance of the price wedges) when considering pollution damages is much larger than when ignoring it, and because the slope of the SMC curve is usually larger than the slope of the PMC curve.

⁴⁰Note that we have assumed damages from local externalities such as SO₂ and NO_x emissions, which are correlated with carbon damages, are internalized by other policies (e.g., the acid rain program). [Borenstein and Bushnell \(2022a\)](#), who do not do this, find a price wedge mean which is much closer to 0.

C Appendix: Repeated Exhibits

Table C.1: ISO-level R^2 from In-Sample Electricity Tariff Regressions, Part 1

Panel A: PJM										
Pricing Scheme	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Flat Tariff	.	.	0	0	0	0	0	0	0	0
Peak	.	.	.261	.216	.206	.136	.171	.199	.127	.128
Peak x Weekend	.	.	.291	.245	.240	.160	.192	.208	.143	.141
Peak x Season	.	.	.277	.225	.216	.150	.185	.282	.207	.153
Peak x Weekend x Season	.	.	.308	.257	.250	.177	.207	.291	.224	.168
Peak x Weekend x Month	.	.	.365	.335	.437	.282	.263	.391	.370	.293
Hour x DoW x Month	.	.	.601	.601	.665	.481	.490	.611	.558	.493
CPP, 20 Events	.	.	.168	.123	.158	.305	.177	.172	.231	.259
Pricing Scheme	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Flat Tariff	0	0	0	0	0	0	0	0	0	0
Peak	.092	.114	.120	.017	.050	.131	.075	.034	.041	.089
Peak x Weekend	.108	.136	.143	.029	.057	.153	.085	.039	.052	.105
Peak x Season	.125	.125	.137	.050	.070	.150	.089	.054	.048	.100
Peak x Weekend x Season	.143	.149	.160	.067	.078	.172	.101	.061	.059	.115
Peak x Weekend x Month	.206	.236	.204	.187	.246	.232	.150	.240	.086	.208
Hour x DoW x Month	.411	.437	.398	.349	.444	.500	.356	.361	.312	.453
CPP, 20 Events	.360	.308	.349	.493	.382	.193	.263	.365	.174	.143
Panel B: ISO-NE										
Pricing Scheme	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Flat Tariff	.	.	0	0	0	0	0	0	0	0
Peak	.	.	.131	.130	.130	.099	.189	.119	.092	.097
Peak x Weekend	.	.	.135	.141	.136	.110	.199	.125	.096	.106
Peak x Season	.	.	.147	.146	.134	.103	.201	.230	.236	.102
Peak x Weekend x Season	.	.	.151	.158	.141	.116	.212	.237	.240	.116
Peak x Weekend x Month	.	.	.248	.258	.488	.164	.340	.414	.437	.286
Hour x DoW x Month	.	.	.453	.460	.646	.351	.516	.554	.576	.470
CPP, 20 Events	.	.	.281	.365	.172	.305	.197	.266	.224	.274
Pricing Scheme	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Flat Tariff	0	0	0	0	0	0	0	0	0	0
Peak	.067	.076	.031	.02	.029	.029	.032	.015	.029	.050
Peak x Weekend	.074	.081	.034	.028	.032	.036	.033	.019	.032	.053
Peak x Season	.068	.084	.106	.169	.117	.032	.083	.048	.126	.082
Peak x Weekend x Season	.075	.089	.110	.179	.121	.039	.088	.053	.132	.085
Peak x Weekend x Month	.252	.243	.257	.478	.461	.128	.260	.208	.259	.242
Hour x DoW x Month	.402	.443	.385	.572	.581	.334	.382	.349	.401	.412
CPP, 20 Events	.371	.280	.323	.321	.264	.314	.392	.344	.336	.318

Note: Cells of this table present R^2 values for regressions of the hourly ISO-average price of electricity observed in the wholesale market in a given year (given by the column) and a given set of independent variables which define a time-of-use or critical-peak price schedule (given by the row).

Table C.1: ISO-level R^2 from In-Sample Electricity Tariff Regressions, Part 2

Panel C: NYISO											
Pricing Scheme	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Flat Tariff	0	0	0	0	0	0	0	0	0	0	0
Peak	.069	.070	.072	.138	.204	.088	.089	.102	.087	.074	.072
Peak x Weekend	.072	.080	.087	.147	.219	.096	.105	.111	.090	.081	.077
Peak x Season	.073	.087	.081	.140	.212	.098	.095	.105	.157	.145	.078
Peak x Weekend x Season	.076	.098	.099	.150	.227	.106	.113	.116	.161	.153	.085
Peak x Weekend x Month	.142	.184	.235	.307	.295	.295	.179	.147	.296	.261	.184
Hour x DoW x Month	.327	.357	.417	.494	.530	.480	.364	.340	.454	.459	.393
CPP, 20 Events	.303	.386	.279	.218	.211	.247	.408	.291	.207	.168	.209
Pricing Scheme	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	
Flat Tariff	0	0	0	0	0	0	0	0	0	0	
Peak	.053	.057	.049	.021	.041	.042	.054	.031	.061	.067	
Peak x Weekend	.060	.066	.056	.035	.048	.047	.060	.033	.067	.074	
Peak x Season	.059	.062	.057	.110	.081	.046	.067	.045	.088	.076	
Peak x Weekend x Season	.066	.073	.064	.128	.089	.051	.075	.049	.097	.084	
Peak x Weekend x Month	.139	.125	.164	.373	.401	.117	.136	.219	.197	.234	
Hour x DoW x Month	.337	.338	.314	.482	.551	.334	.345	.351	.378	.433	
CPP, 20 Events	.316	.317	.396	.434	.291	.241	.250	.347	.232	.236	
Panel D: ERCOT											
Pricing Scheme	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	
Flat Tariff	.	.	.	.	.	.	.	.	.	.	
Peak	.	.	.	.	.	.	.	.	.	.	
Peak x Weekend	.	.	.	.	.	.	.	.	.	.	
Peak x Season	.	.	.	.	.	.	.	.	.	.	
Peak x Weekend x Season	.	.	.	.	.	.	.	.	.	.	
Peak x Weekend x Month	.	.	.	.	.	.	.	.	.	.	
Hour x DoW x Month	.	.	.	.	.	.	.	.	.	.	
CPP, 20 Events	.	.	.	.	.	.	.	.	.	.	
Pricing Scheme	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	
Flat Tariff	0	0	0	0	0	0	0	0	0	0	
Peak	.014	.025	.016	.004	.027	.050	.037	.020	.009	.032	
Peak x Weekend	.017	.026	.017	.006	.028	.050	.039	.021	.010	.032	
Peak x Season	.030	.028	.023	.006	.045	.061	.046	.028	.019	.035	
Peak x Weekend x Season	.037	.032	.025	.008	.046	.064	.050	.030	.024	.039	
Peak x Weekend x Month	.138	.048	.043	.020	.086	.101	.070	.063	.097	.086	
Hour x DoW x Month	.361	.264	.317	.256	.310	.312	.289	.268	.280	.319	
CPP, 20 Events	.345	.317	.208	.035	.275	.291	.282	.266	.485	.349	

Note: Cells of this table present R^2 values for regressions of the hourly ISO-average price of electricity observed in the wholesale market in a given year (given by the column) and a given set of independent variables which define a time-of-use or critical-peak price schedule (given by the row).

Table C.1: ISO-level R^2 from In-Sample Electricity Tariff Regressions, Part 3

Panel E: MISO										
Pricing Scheme	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Flat Tariff	.	.	.	.	0	0	0	0	0	0
Peak	.	.	.	.	.240	.203	.220	.221	.209	.197
Peak x Weekend	.	.	.	.	.298	.244	.265	.259	.230	.217
Peak x Season	.	.	.	.	.247	.211	.228	.248	.253	.211
Peak x Weekend x Season	.	.	.	.	.309	.253	.276	.287	.275	.232
Peak x Weekend x Month	.	.	.	.	.418	.321	.320	.385	.323	.315
Hour x DoW x Month	.	.	.	.	.623	.554	.567	.630	.533	.557
CPP, 20 Events	.	.	.	.	.199	.208	.132	.150	.124	.148
Pricing Scheme	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Flat Tariff	0	0	0	0	0	0	0	0	0	0
Peak	.140	.077	.114	.058	.144	.164	.132	.090	.052	.098
Peak x Weekend	.157	.086	.132	.072	.164	.192	.148	.106	.063	.113
Peak x Season	.157	.086	.127	.068	.153	.188	.152	.100	.055	.107
Peak x Weekend x Season	.173	.097	.147	.082	.173	.217	.169	.116	.066	.122
Peak x Weekend x Month	.225	.154	.174	.149	.259	.363	.198	.174	.094	.194
Hour x DoW x Month	.463	.370	.397	.398	.470	.583	.415	.389	.313	.422
CPP, 20 Events	.203	.243	.136	.268	.184	.243	.198	.205	.204	.153
Panel F: SPP										
Pricing Scheme	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Flat Tariff	.	.	.	.	.	.	0	0	0	0
Peak	.	.	.	.	.	.	.204	.189	.096	.145
Peak x Weekend	.	.	.	.	.	.	.214	.205	.108	.155
Peak x Season	.	.	.	.	.	.	.212	.301	.133	.160
Peak x Weekend x Season	.	.	.	.	.	.	.223	.317	.146	.170
Peak x Weekend x Month	.	.	.	.	.	.	.260	.508	.202	.296
Hour x DoW x Month	.	.	.	.	.	.	.560	.731	.451	.558
CPP, 20 Events	.	.	.	.	.	.	.127	.114	.116	.099
Pricing Scheme	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Flat Tariff	0	0	0	0	0	0	0	0	0	0
Peak	.163	.176	.170	.019	.029	.029	.034	.024	.028	.065
Peak x Weekend	.170	.184	.182	.021	.030	.030	.034	.025	.030	.068
Peak x Season	.229	.196	.188	.021	.031	.031	.038	.025	.033	.068
Peak x Weekend x Season	.236	.204	.203	.023	.032	.032	.038	.028	.035	.072
Peak x Weekend x Month	.332	.312	.257	.036	.047	.061	.050	.044	.041	.114
Hour x DoW x Month	.568	.547	.512	.289	.326	.286	.273	.263	.284	.328
CPP, 20 Events	.112	.144	.094	.113	.075	.113	.077	.097	.083	.125

Note: Cells of this table present R^2 values for regressions of the hourly ISO-average price of electricity observed in the wholesale market in a given year (given by the column) and a given set of independent variables which define a time-of-use or critical-peak price schedule (given by the row).

Table C.1: ISO-level R^2 from In-Sample Electricity Tariff Regressions, Part 4

Panel G: CAISO										
Pricing Scheme	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Flat Tariff	.	.	.	.	.	.	.	.	0	0
Peak	.	.	.	.	.	.	.	.	.036	.039
Peak x Weekend	.	.	.	.	.	.	.	.	.037	.040
Peak x Season	.	.	.	.	.	.	.	.	.056	.045
Peak x Weekend x Season	.	.	.	.	.	.	.	.	.058	.047
Peak x Weekend x Month	.	.	.	.	.	.	.	.	.080	.064
Hour x DoW x Month	.	.	.	.	.	.	.	.	.345	.306
CPP, 20 Events	.	.	.	.	.	.	.	.	.155	.101
Pricing Scheme	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Flat Tariff	0	0	0	0	0	.	.	.	.	.
Peak	.029	.027	.027	.035	.016	.	.	.	.	.
Peak x Weekend	.030	.027	.029	.038	.016	.	.	.	.	.
Peak x Season	.034	.032	.037	.043	.021	.	.	.	.	.
Peak x Weekend x Season	.036	.032	.039	.046	.023	.	.	.	.	.
Peak x Weekend x Month	.060	.058	.061	.090	.047	.	.	.	.	.
Hour x DoW x Month	.310	.271	.292	.331	.273	.	.	.	.	.
CPP, 20 Events	.082	.152	.103	.101	.128	.	.	.	.	.

Note: Cells of this table present R^2 values for regressions of the hourly ISO-average price of electricity observed in the wholesale market in a given year (given by the column) and a given set of independent variables which define a time-of-use or critical-peak price schedule (given by the row).

Table C.2: Node-Level R^2 from Electricity Tariff Regressions, Part 1

Panel A: PJM										
Pricing Scheme	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Flat Tariff	.	.	0	0	0	0	0	0	0	0
Peak	.	.	.228	.166	.153	.103	.113	.130	.087	.080
Peak x Weekend	.	.	.254	.189	.179	.121	.127	.136	.098	.088
Peak x Season	.	.	.244	.173	.160	.113	.122	.185	.140	.096
Peak x Weekend x Season	.	.	.270	.199	.186	.133	.136	.191	.152	.105
Hour x DoW x Month	.	.	.527	.451	.487	.362	.324	.400	.378	.306
County	.	.	.000	.016	.004	.001	.003	.006	.005	.003
Pricing Scheme	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Flat Tariff	0	0	0	0	0	0	0	0	0	0
Peak	.067	.081	.059	.013	.031	.062	.042	.022	.023	.025
Peak x Weekend	.079	.096	.071	.023	.035	.072	.047	.026	.028	.030
Peak x Season	.093	.088	.068	.038	.041	.070	.049	.035	.027	.028
Peak x Weekend x Season	.105	.105	.079	.051	.046	.081	.056	.039	.033	.033
Hour x DoW x Month	.300	.308	.195	.271	.262	.235	.196	.230	.172	.128
County	.002	.001	.001	.000	.000	.000	.000	.000	.000	.000
Panel B: ISO-NE										
Pricing Scheme	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Flat Tariff	.	.	0	0	0	0	0	0	0	0
Peak	.	.	.120	.123	.111	.083	.148	.113	.091	.093
Peak x Weekend	.	.	.124	.133	.116	.092	.156	.119	.094	.102
Peak x Season	.	.	.134	.138	.115	.086	.158	.219	.230	.097
Peak x Weekend x Season	.	.	.139	.149	.121	.097	.167	.225	.234	.111
Hour x DoW x Month	.	.	.416	.435	.552	.294	.405	.527	.564	.451
County	.	.	.001	.000	.001	.001	.002	.001	.000	.000
Pricing Scheme	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Flat Tariff	0	0	0	0	0	0	0	0	0	0
Peak	.065	.068	.030	.020	.028	.028	.030	.014	.028	.048
Peak x Weekend	.071	.072	.034	.028	.031	.036	.031	.019	.031	.051
Peak x Season	.066	.074	.104	.164	.115	.031	.077	.047	.123	.080
Peak x Weekend x Season	.072	.079	.108	.174	.119	.039	.082	.052	.129	.083
Hour x DoW x Month	.386	.393	.378	.563	.575	.328	.357	.340	.392	.399
County	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000

Note: Cells of this table present in-sample R^2 values for regressions of the hourly price of electricity observed in each node in the wholesale market in a given year (given by the column) and a given set of independent variables which define a time-of-use price schedule (given by the row).

Table C.2: Node-Level R^2 from Electricity Tariff Regressions, Part 2

Panel C: NYISO											
Pricing Scheme	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Flat Tariff	0	0	0	0	0	0	0	0	0	0	0
Peak	.042	.051	.055	.087	.117	.054	.058	.064	.038	.041	.045
Peak x Weekend	.044	.058	.067	.092	.125	.059	.068	.070	.040	.045	.048
Peak x Season	.044	.064	.062	.088	.121	.060	.062	.066	.070	.080	.049
Peak x Weekend x Season	.046	.073	.076	.094	.130	.065	.074	.072	.072	.085	.053
Hour x DoW x Month	.199	.263	.320	.311	.304	.294	.236	.213	.202	.254	.246
County	.001	.002	.001	.001	.000	.001	.003	.001	.000	.001	.001
Pricing Scheme	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	
Flat Tariff	0	0	0	0	0	0	0	0	0	0	
Peak	.035	.036	.028	.017	.026	.020	.031	.021	.024	.027	
Peak x Weekend	.040	.043	.032	.028	.031	.023	.034	.023	.027	.029	
Peak x Season	.039	.040	.032	.088	.052	.023	.039	.031	.035	.030	
Peak x Weekend x Season	.044	.047	.037	.103	.057	.025	.043	.034	.039	.033	
Hour x DoW x Month	.223	.217	.178	.387	.355	.161	.199	.240	.151	.171	
County	.001	.001	.001	.000	.001	.000	.001	.000	.001	.002	
Panel D: ERCOT											
Pricing Scheme	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	
Flat Tariff	.	.	.	.	.	.	.	.	.	.	
Peak	.	.	.	.	.	.	.	.	.	.	
Peak x Weekend	.	.	.	.	.	.	.	.	.	.	
Peak x Season	.	.	.	.	.	.	.	.	.	.	
Peak x Weekend x Season	.	.	.	.	.	.	.	.	.	.	
Hour x DoW x Month	.	.	.	.	.	.	.	.	.	.	
County	.	.	.	.	.	.	.	.	.	.	
Pricing Scheme	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	
Flat Tariff	0	0	0	0	0	0	0	0	0	0	
Peak	.014	.017	.012	.004	.019	.025	.012	.013	.010	.016	
Peak x Weekend	.016	.018	.014	.005	.019	.026	.013	.013	.011	.017	
Peak x Season	.030	.019	.017	.005	.031	.031	.015	.018	.020	.018	
Peak x Weekend x Season	.035	.022	.019	.007	.032	.033	.016	.019	.023	.020	
Hour x DoW x Month	.341	.179	.242	.217	.212	.158	.093	.165	.269	.162	
County	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	

Note: Cells of this table present in-sample R^2 values for regressions of the hourly price of electricity observed in each node in the wholesale market in a given year (given by the column) and a given set of independent variables which define a time-of-use price schedule (given by the row).

Table C.2: Node-Level R^2 from Electricity Tariff Regressions, Part 3

Panel E: MISO										
Pricing Scheme	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Flat Tariff	.	.	.	.	0	0	0	0	0	0
Peak	.	.	.	.	.166	.126	.138	.164	.107	.099
Peak x Weekend	.	.	.	.	.207	.152	.166	.191	.118	.108
Peak x Season	.	.	.	.	.171	.131	.143	.186	.129	.106
Peak x Weekend x Season	.	.	.	.	.214	.157	.173	.214	.141	.116
Hour x DoW x Month	.	.	.	.	.430	.344	.355	.466	.274	.279
County	.	.	.	.	.000	.001	.001	.000	.000	.000
Pricing Scheme	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Flat Tariff	0	0	0	0	0	0	0	0	0	0
Peak	.070	.038	.041	.028	.044	.057	.044	.041	.028	.028
Peak x Weekend	.078	.043	.048	.034	.050	.066	.049	.048	.034	.032
Peak x Season	.078	.043	.046	.032	.047	.065	.050	.045	.03	.031
Peak x Weekend x Season	.086	.048	.053	.039	.053	.075	.056	.053	.036	.035
Hour x DoW x Month	.231	.183	.143	.188	.144	.200	.138	.177	.168	.121
County	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
Panel F: SPP										
Pricing Scheme	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Flat Tariff	.	.	.	.	.	.	0	0	0	0
Peak	.	.	.	.	.	.	.056	.097	.037	.066
Peak x Weekend	.	.	.	.	.	.	.059	.106	.042	.071
Peak x Season	.	.	.	.	.	.	.058	.156	.052	.073
Peak x Weekend x Season	.	.	.	.	.	.	.061	.164	.057	.077
Hour x DoW x Month	.	.	.	.	.	.	.154	.379	.175	.255
County	.	.	.	.	.	.	.000	.000	.000	.000
Pricing Scheme	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Flat Tariff	0	0	0	0	0	0	0	0	0	0
Peak	.102	.084	.092	.016	.023	.021	.022	.016	.019	.031
Peak x Weekend	.107	.087	.098	.018	.024	.022	.022	.018	.020	.033
Peak x Season	.144	.093	.102	.018	.024	.022	.025	.018	.023	.033
Peak x Weekend x Season	.148	.097	.110	.019	.025	.023	.025	.019	.024	.035
Hour x DoW x Month	.356	.259	.276	.244	.248	.206	.179	.181	.193	.159
County	.001	.000	.000	.000	.000	.000	.000	.000	.000	.000

Note: Cells of this table present in-sample R^2 values for regressions of the hourly price of electricity observed in each node in the wholesale market in a given year (given by the column) and a given set of independent variables which define a time-of-use price schedule (given by the row).

Table C.2: Node-Level R^2 from Electricity Tariff Regressions, Part 4

Panel G: CAISO										
Pricing Scheme	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Flat Tariff	.	.	.	.	.	.	.	.	0	0
Peak	.	.	.	.	.	.	.	.	.024	.033
Peak x Weekend	.	.	.	.	.	.	.	.	.025	.034
Peak x Season	.	.	.	.	.	.	.	.	.039	.037
Peak x Weekend x Season	.	.	.	.	.	.	.	.	.040	.039
Hour x DoW x Month	.	.	.	.	.	.	.	.	.236	.256
County	.	.	.	.	.	.	.	.	.	.
Pricing Scheme	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Flat Tariff	0	0	0	0	0	.	.	.	.	.
Peak	.024	.013	.015	.025	.010	.	.	.	.	.
Peak x Weekend	.025	.013	.017	.027	.010	.	.	.	.	.
Peak x Season	.029	.016	.021	.032	.014	.	.	.	.	.
Peak x Weekend x Season	.030	.016	.023	.034	.015	.	.	.	.	.
Hour x DoW x Month	.258	.132	.168	.241	.174	.	.	.	.	.
County	.	.	.	.	.	.	.	.	.	.

Note: Cells of this table present in-sample R^2 values for regressions of the hourly price of electricity observed in each node in the wholesale market in a given year (given by the column) and a given set of independent variables which define a time-of-use price schedule (given by the row).

Figure C.1: Locational Pricing - ISO-NE

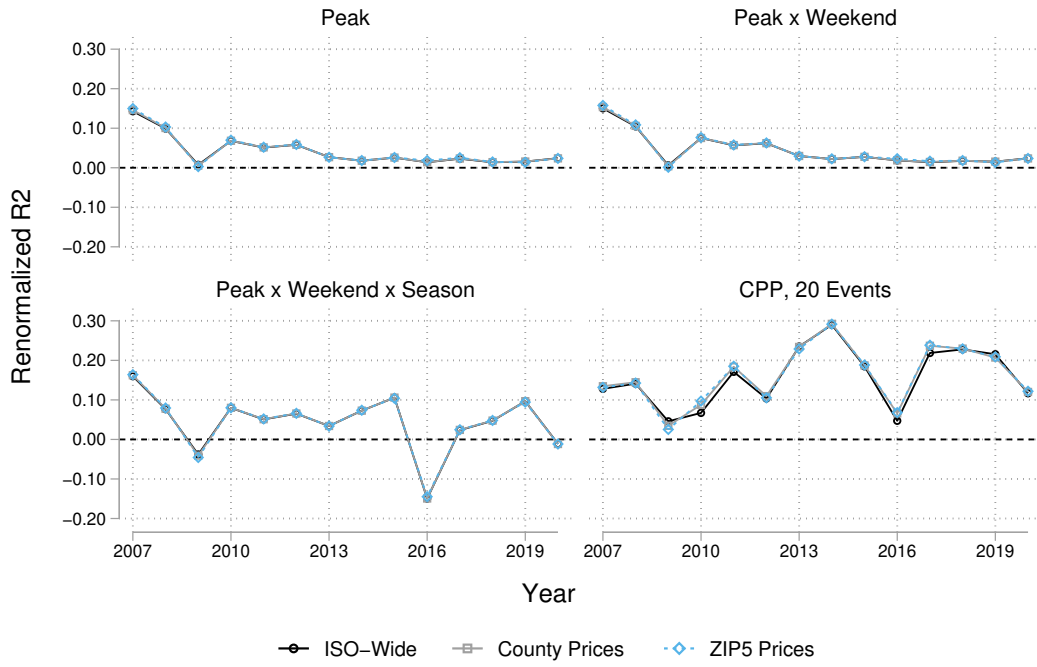


Figure C.2: Locational Pricing - NYISO

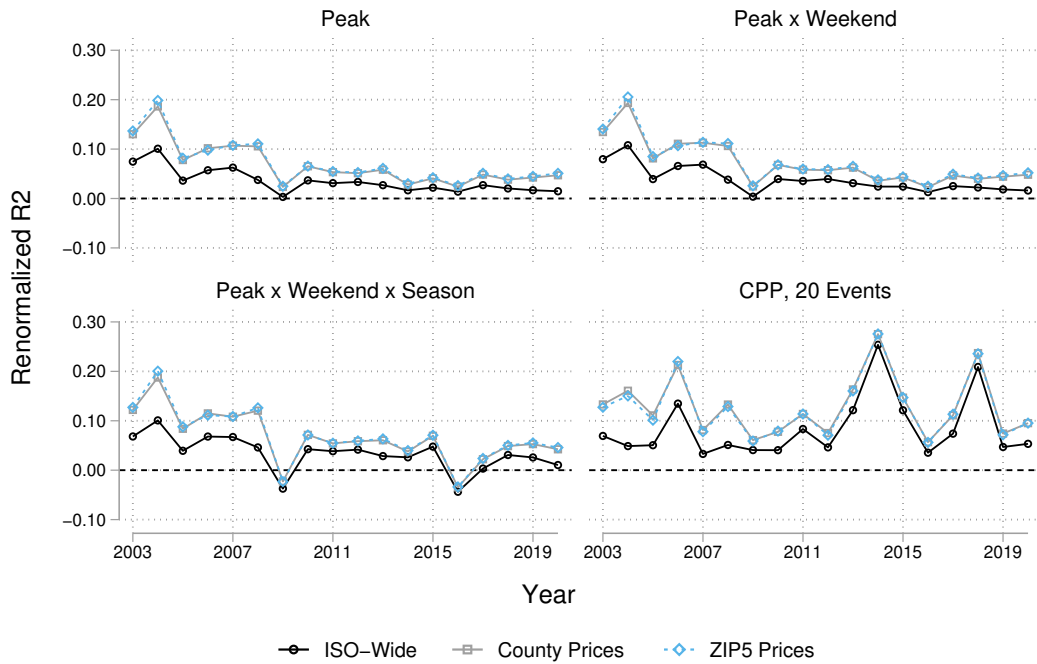


Figure C.3: Locational Pricing - ERCOT

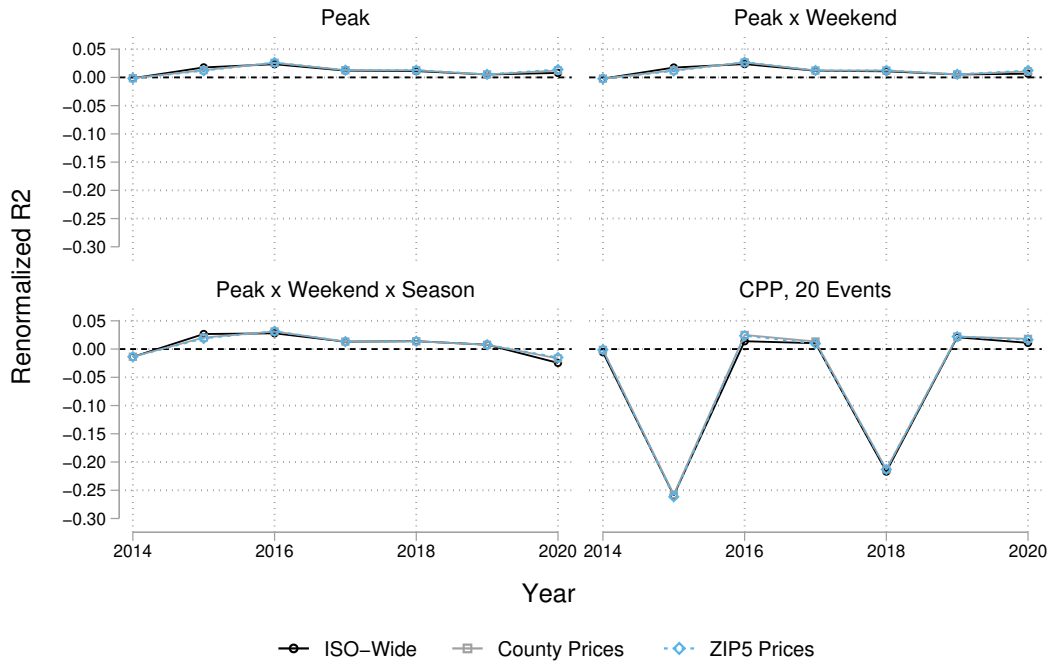


Figure C.4: Locational Pricing - MISO

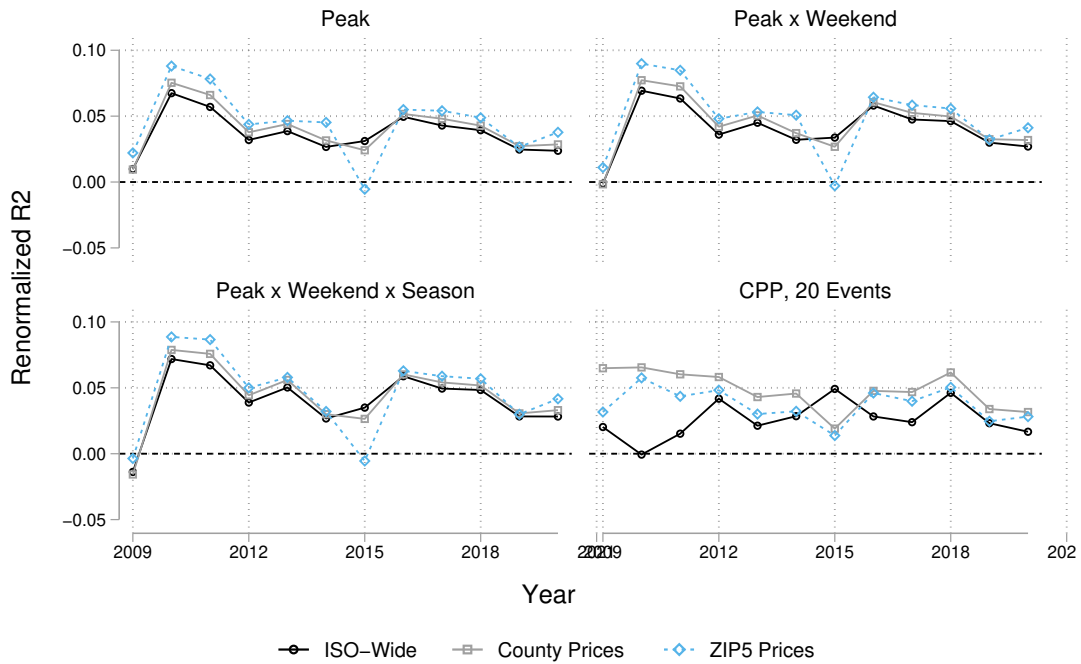


Figure C.5: Locational Pricing - SPP

