Adjustment on the Margin

Evaluating emissions reduction policies in the face of short-run adjustment costs

James Archsmith[1]

[1] University of Maryland, AREC

NBER Electricity Markets Workshop
May 29, 2019

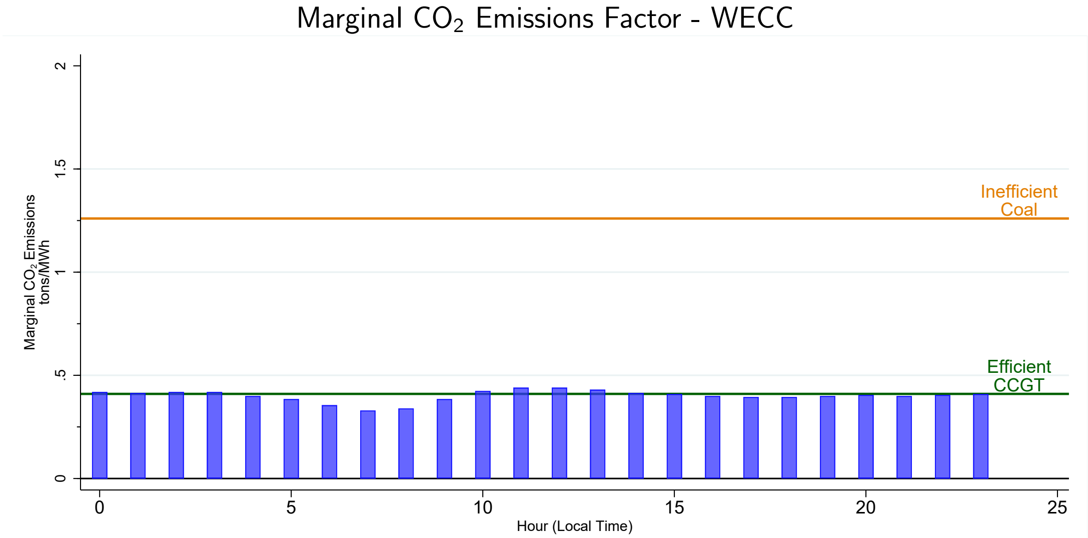
Motivation

1. Explicit goal of energy/renewables policy is to reduce carbon dioxide (CO_2) and local criteria pollutant (LCP) emissions
2. Policy instruments take many forms (RPS, storage mandates, DR)
3. Setting optimal policy requires understanding how emissions will change
4. Often rely on *ex ante* or *ex post* estimates of marginal emissions factors (MEFs)

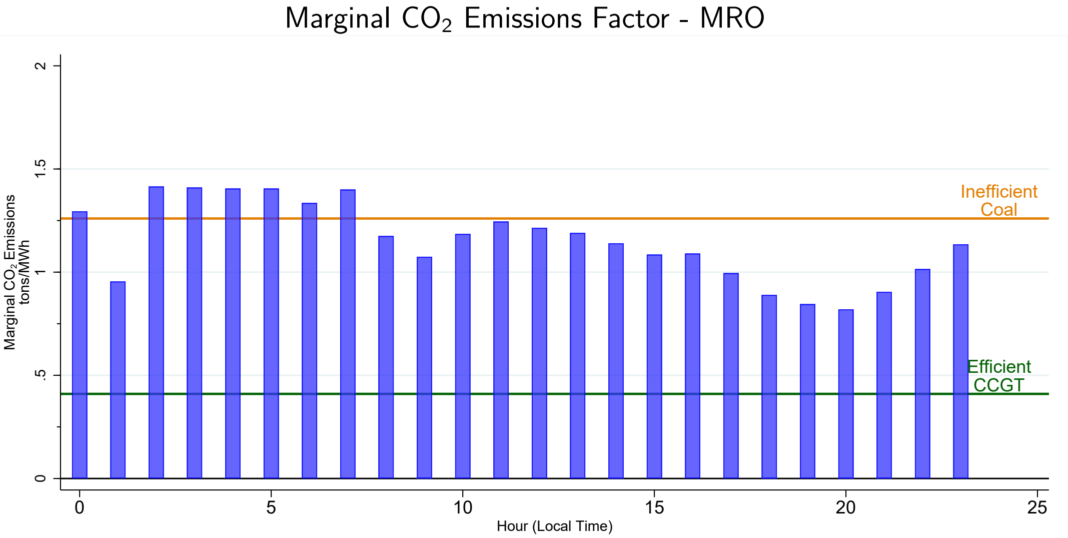
Computing MEFs

1. Extend methods for computing MEFs *ex post*
2. Account for the impact of foreseeable, short run adjustment in output by FF generation (ramping)
3. Ignoring ramping effects
    1. Overstates the emissions benefits of new solar PV
    2. Understates the emissions benefits of electricity storage

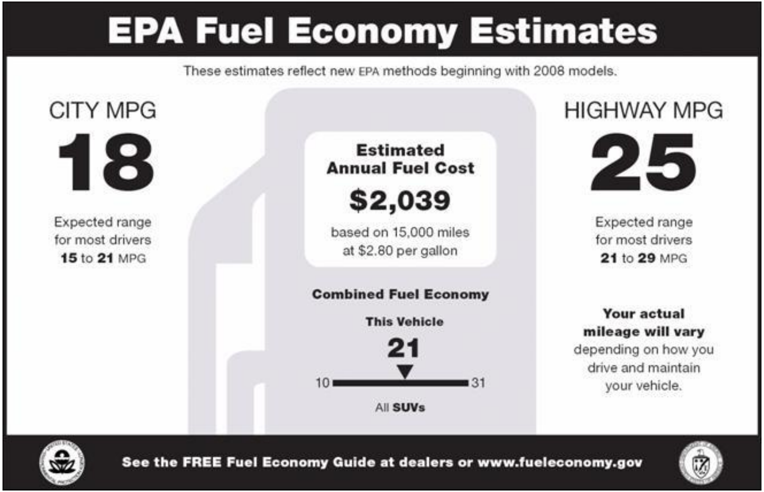
GZKM (2014) MEF WECC Interconnection



GZKM (2014) MEF MRO Region



Adjustment impacts vehicle fuel efficiency



EPA Fuel Economy Estimates

These estimates reflect new EPA methods beginning with 2008 models.

CITY MPG

18

Expected range
for most drivers
15 to **21** MPG

Estimated
Annual Fuel Cost

$2,039

based on 15,000 miles
at $2.80 per gallon

Combined Fuel Economy

This Vehicle

21

10 31

All **SUVs**

HIGHWAY MPG

25

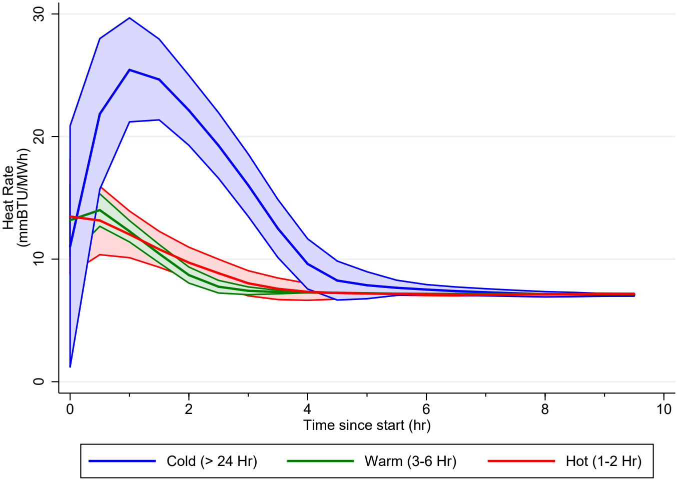
Expected range
for most drivers
21 to **29** MPG

Your actual
mileage will vary
depending on how you
drive and maintain
your vehicle.

See the FREE Fuel Economy Guide at dealers or www.fueleconomy.gov

Source: fueleconomy.gov

Adjustment impacts power plant efficiency



Heat rate by hours in operation for a CCGT

Operational data from CEMS

Analogy

Motivation

1. Emissions depend on both the level and change in demand
2. Past and expected future states matter
3. Particularly important for policies that alter the *pattern* of demand falling on FF generators
    1. e.g., Solar PV, electricity storage, CPP, demand response
    2. Consider the impacts of predictable, short run changes in demand on emissions

Adjustment on the Margin

1. Small component of overall emissions
2. Large factor on the margin
3. Median ERCOT load: 38,770 MW
4. Median ERCOT hourly change in load: 1,079 MW
5. 10 MW represents 0.025% of median load but 1% of ramp

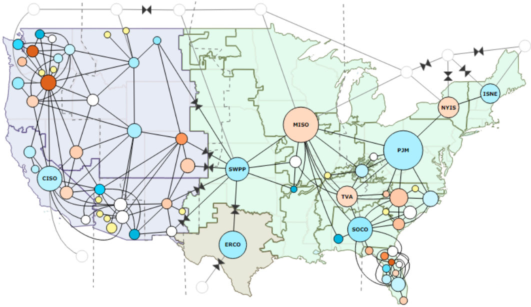
Adjustments to the Margin

1. Incremental changes to generation will impact the margin
2. New solar PV
    1. Reduces the level of fossil fuel generation
    2. Increases hour-to-hour change in fossil fuel generation
3. New electricity storage
    1. Time-shifts levels of fossil fuel generation
    2. Can reduce hour-to-hour change in fossil fuel generation
4. Demand and supply-side policies can target level and/or ramp

Data

1. Electricity hourly supply and demand (EIA-930)
2. For each lower-48 balancing authority
   1. Demand, generation, and interchange
   2. Day-ahead demand forecasts
   3. Generation by energy source (since June 2018)
3. Available 2016-Present, near real-time

EIA-930 Balancing Authorities



Bigger

Linear FE Estimates of MEFs

1. Compute *ex post* estimates of the marginal impact of electricty demand on emissions
2. Follow Graff Zivin, Kotchen, and Mansur (2014) and others
3. CO_2 emissions from plants in an interconnection are a linear function of demand for each region within the interconnection
    1. Assumes electricity flows between regions, not interconnections
    2. Estimate separate parameters for each hour of day
    3. Use time fixed effects to control for unobservables
    4. Here regions are aggregations of EIA-930 balancing authorities

Demand Level

1. Impact of contemporaneous demand level similar to previous work
2. Q^D_{tr} - Demand at time t in region r
3. Q^N_{tr} - Non-fossil fuel supply at time t in region r

$$E_t = \sum_{h \in H} \sum_{r \in R} \left(\beta^0_{rh} Q^D_{tr} - \gamma_{rh} \mathbf{E}_{t-1} \left[Q^N_{tr} \right] \right)$$

Future Ramp

1. Include expected changes in demand/supply in the future

$$\sum_{h\in H}\sum_{r\in R}\sum_{s=1}^{S}\left(\beta_{rh}^{s}\mathbf{E}_t\left[\Delta Q_{t+s,r}^{D}\right]-\gamma_{rh}^{s}\mathbf{E}_t\left[\Delta Q_{t+s,r}^{N}\right]\right)$$

Past Ramp

1. Include past changes in demand/supply
2. Decompose changes between $t - s$ and s into components anticipated or unanticiapated at $t - s$

$$Q_t^D - Q_{t-s}^D = \underbrace{Q_t^D - \mathbf{E}_{t-s}[Q_t^D]}_{\text{Unanticipated Shock } (S_t^D)} + \underbrace{\mathbf{E}_{t-s}[Q_t^D] - Q_{t-s}^D}_{\text{Anticipated Change } (A_t^D)}$$

Past Ramp

1. Include past anticipated and unanticipated changes in demand/supply

$$\sum_{h \in H} \sum_{r \in R} \left(\phi^{*}_{rh} S^{D}_{t} + \psi^{*}_{rh} S^{N}_{t} \right)$$

$$+ \sum_{h \in H} \sum_{r \in R} \sum_{s=1}^{S} \left(\beta^{s}_{rh} \mathbf{E}_{t} \left[\Delta Q^{D}_{t+s,r} \right] - \gamma^{s}_{rh} \mathbf{E}_{t} \left[\Delta Q^{N}_{t+s,r} \right] + \phi^{-s}_{rh} A^{D}_{t} + \psi^{-s}_{rh} A^{N}_{t} \right)$$

Forward Demand

1. Effects of forward ramp require forecasts of future demand
2. Actual forward demand is uncertain
3. EIA-930 provides day-ahead forecasts
4. Information is revealed as forecast horizons decrease

Forward Demand Forecasts

1. Estimate forward demand using day-ahead forecast and information revealed since the forecast
    1. Day-ahead forecast demand
    2. Current level of demand
    3. Deviations from previous forecasts
2. Possibly complicated relationships
3. Compute forecasts using random forests
    1. All forecasts predicted out-of-sample
4. Similar methods to predict non-fossil fuel generation Details

Graphs

Linear Specification

1. Combine current, future, and past components into linear model
2. Include month-of-year, hour-of-day, and year fixed effects
3. Large space of potential covariates
4. Choose between models using out-of-sample fit
5. Also consider models quarterly parameters

Model Selection/Cross Validation

1. Begin with the current demand model
2. Train and evaluate model out-of-sample using 10-fold cross validation
3. Add a lead or lag component and repeat
4. Prefer models with the lowest out-of-sample MSPE

Linear Model Selection - ERCOT

FE Out-of-Sample Forecast Error by Model (ERCOT)

Model Name	RMSE	Free Params
FE Only	3,116.69	290
Slope+FE	1,118.80	292
Hourly Slope	1,116.65	338
Future Ramp	1,112.18	386
Past Ramp	1,091.36	434
Past/Future	1,091.05	482
Past/Future Quarterly	1,125.80	1,058

Linear Model Selection - CAISO

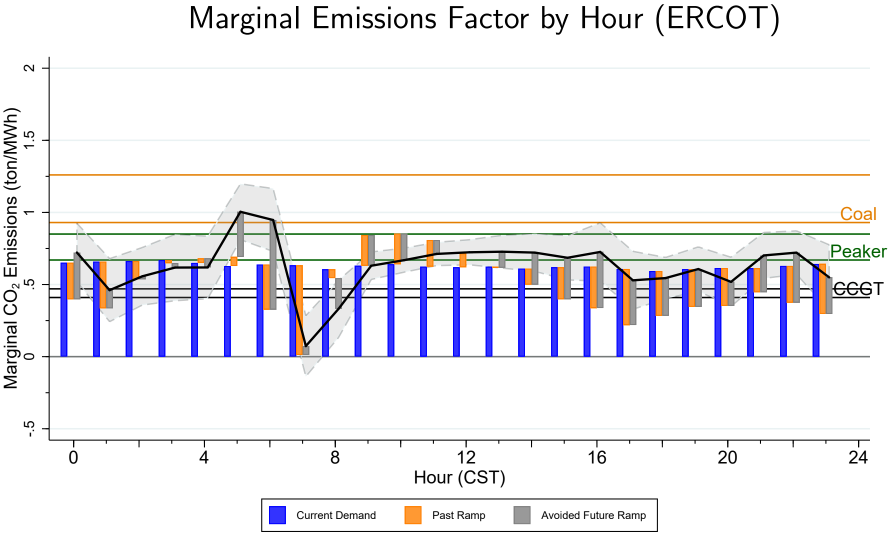
FE Out-of-Sample Forecast Error by Model (CAISO)

Model Name	RMSE	Free Params
FE Only	2,998.93	290
Slope+FE	1,328.62	298
Hourly Slope	1,306.60	434
Future Ramp	1,275.65	578
Past Ramp	1,257.80	722
Past/Future	1,246.58	866
Past/Future Quarterly	1,204.42	2,594

Linear Model Fit

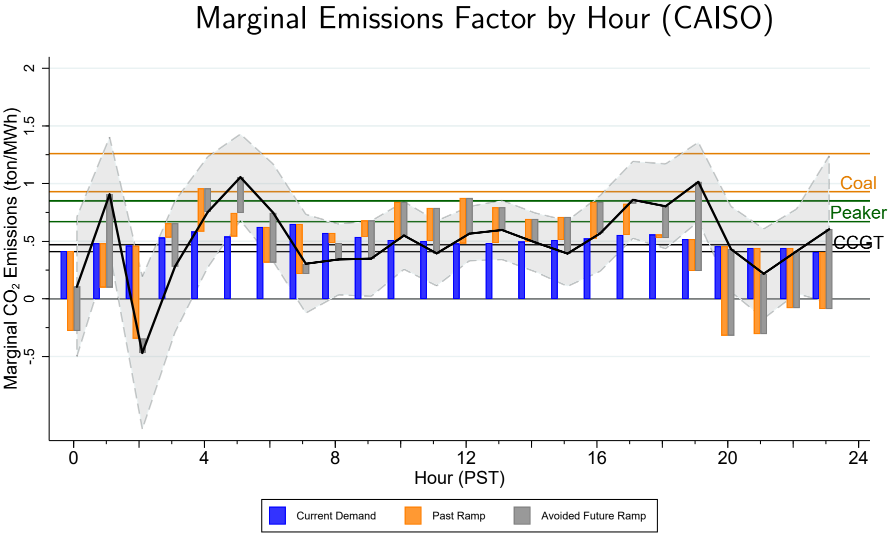
1. Models including ramp have superior out-of-sample fit
2. Additional leads and lags do not improve fit
3. Improvements in fit from adding past ramp larger than adding hourly coefficients
4. Ramp may be as important as hour-to-hour heterogeneity

MEF By Hour - ERCOT



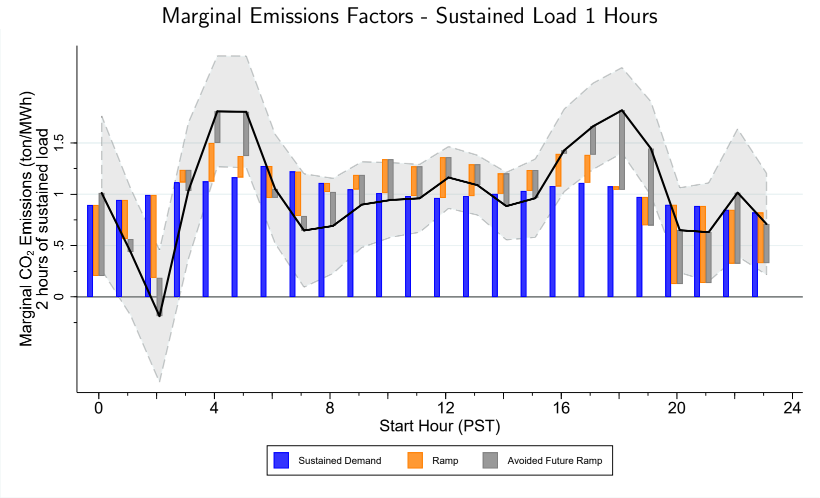
No Ramp

MEF By Hour - CAISO

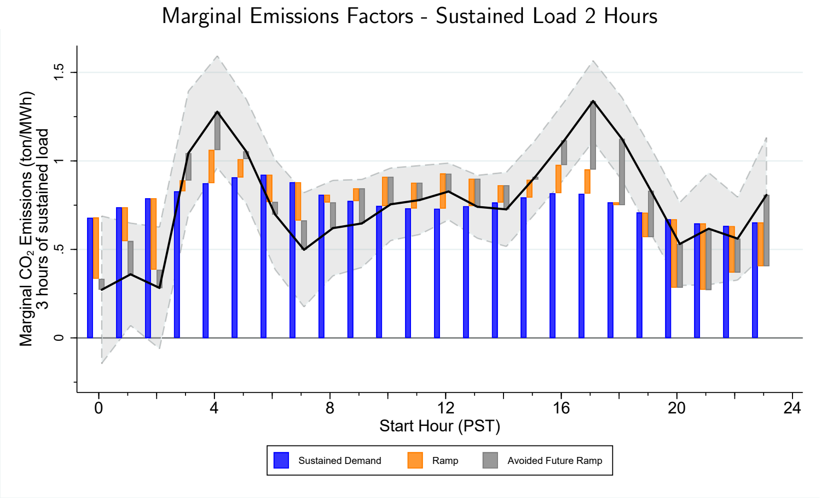


No Ramp

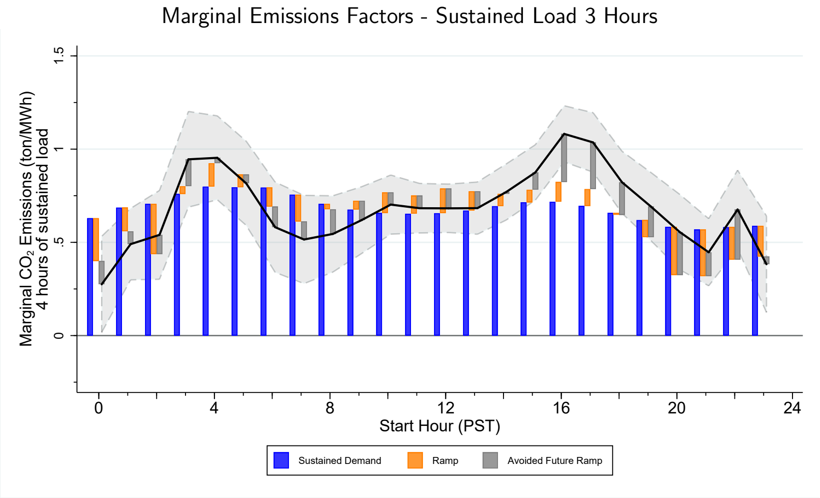
MEF for Sustained Load By Hour - CAISO



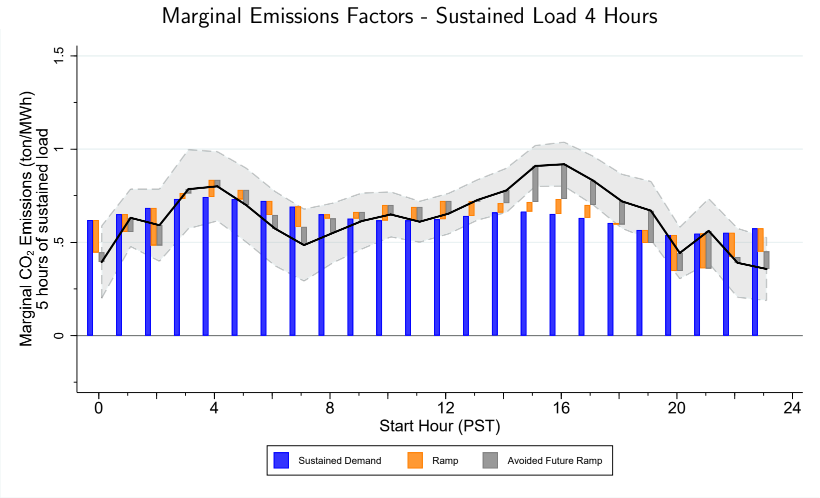
MEF for Sustained Load By Hour - CAISO



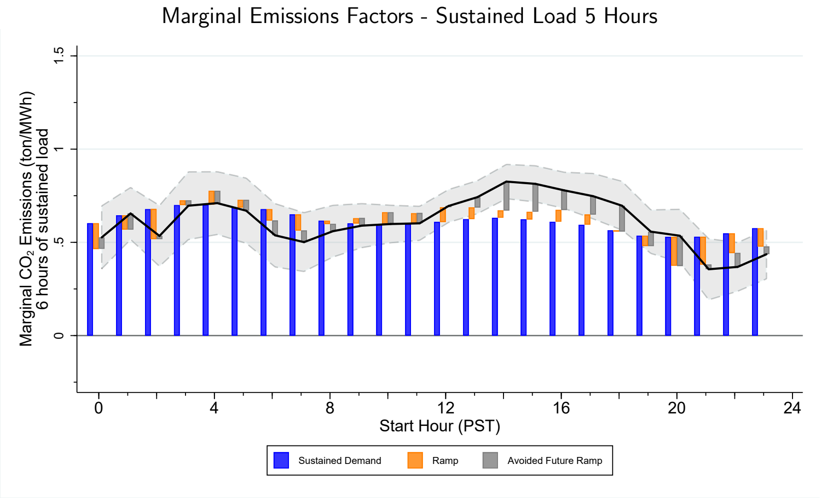
MEF for Sustained Load By Hour - CAISO



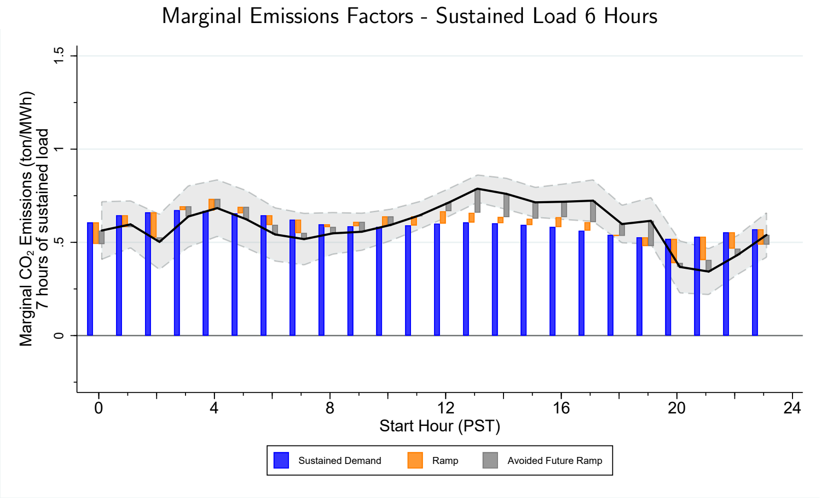
MEF for Sustained Load By Hour - CAISO



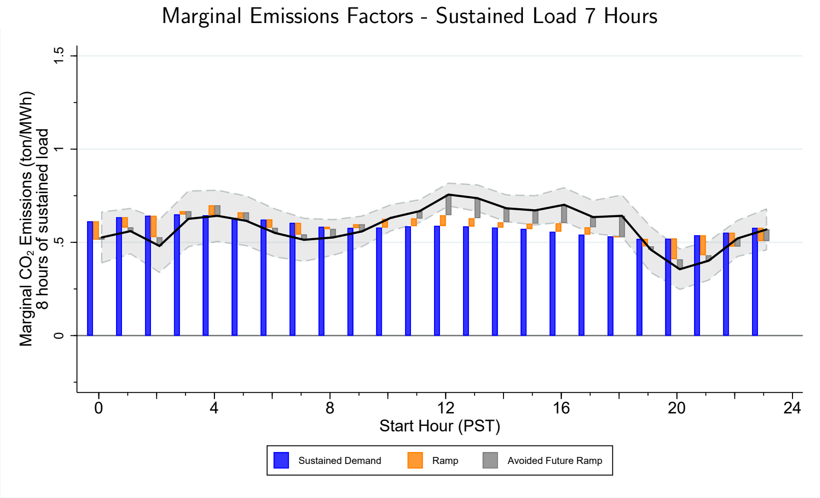
MEF for Sustained Load By Hour - CAISO



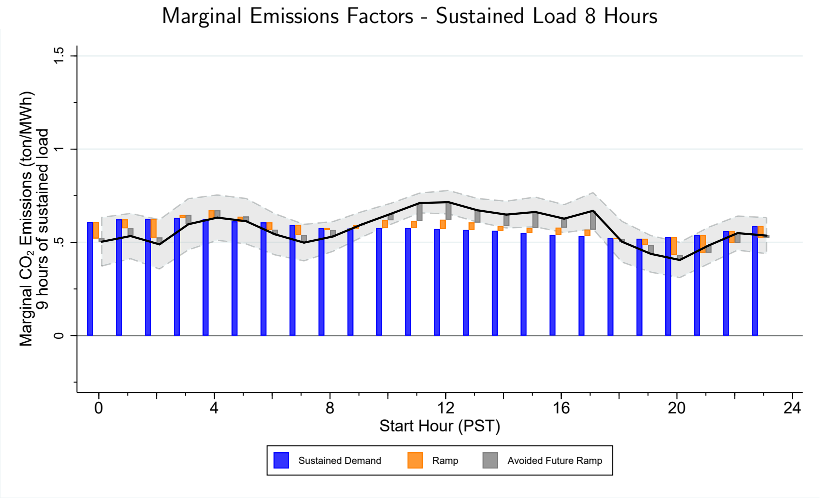
MEF for Sustained Load By Hour - CAISO



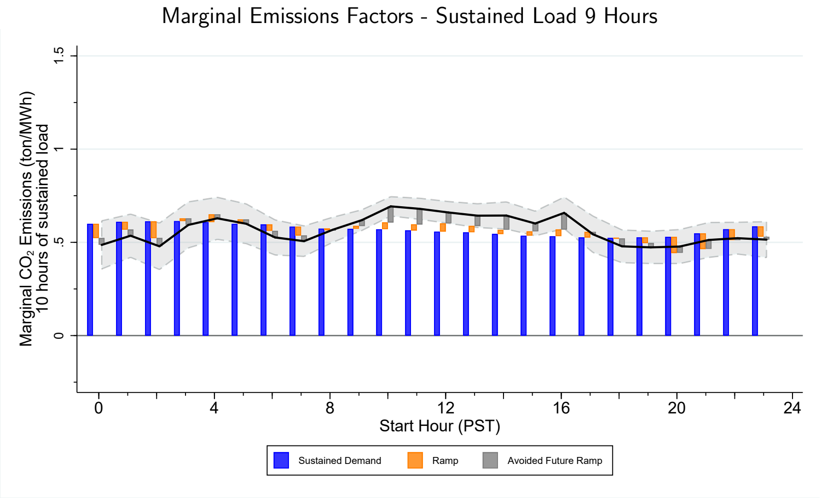
MEF for Sustained Load By Hour - CAISO



MEF for Sustained Load By Hour - CAISO



MEF for Sustained Load By Hour - CAISO



Simulating Emissions Benefits

1. Models provide a MEF for both the level and rate of change in demand in every hour
2. Marginal changes to electricity generation impact both, e.g.,
    1. New solar PV offsets some FF generation, but also induces ramp as it increases and decreases output each day
    2. Electricity storage can offset high-cost generation, or high-cost ramping
3. I simulate the total change in emissions for a hypothetical change in generation stock Details

Simulated Emissions Benefits

Simulated Emissions Benefits - ERCOT

Generation Technology	Marginal Change tons CO_2 per MWh		Percent Difference
	No Ramp	With Ramp	
Onshore Wind	-0.634	-0.632	0.2%
Solar PV	-0.625	-0.626	-0.2%
Storage	0.000	-0.252	-

Simulated Emissions Benefits

Simulated Emissions Benefits - CAISO

Generation Technology	Marginal Change tons CO_2 per MWh No Ramp	 With Ramp	Percent Difference
Onshore Wind	-0.588	-0.564	4.2%
Solar PV	-0.537	-0.461	16.3%
Storage	-0.144	-1.735	-91.7%

Simulated Emissions Benefits

Failing to account for ramp

1. Overstates the emissions benefits of solar PV by 16% in CAISO
2. Vastly understates the *potential* emissions benefits of electricity storage
3. Emissions minimizing electricity storage would not operate in ERCOT

Accounting for ramp 1 MWh of electricity storage in CAISO can reduce emissions more than eliminating 1 MWh of coal generation

Assumptions of the Linear FE Model

1. Linear FE models include terms for level of demand and hour-to-hour changes
2. Assumes the marginal impact of ramp does not vary with quantity of ramp
3. True marginal effect of ramp may be non-linear
   1. Larger output changes generally less efficient
   2. Large demand changes may require additional unit commitment or curtailment
4. Difficult to *a priori* pin down the precise functional form

Non-Linear Effects

1. Goal: Compute estimates of MEFs
    1. Accounting for non-linearities in both demand and ramp
    2. Agnostic to the precise functional form
2. Estimate MEFs using local linear forests (LLFs) from Friedberg et al. (2018)
    1. LLFs are an extension of random forests
    2. Replace “mean-only” predictions with a linear model in each leaf

Details

Local Linear Forest Model Selection - ERCOT

LLF Out-of-Sample Forecast Error by Model (ERCOT)

Model Name	RMSE
No Ramp	1,029.59
1-hr Past/Future	1,011.98
2-hr Past/Future	990.44
3-hr Past/Future	1,003.52
4-hr Past/Future	1,015.87

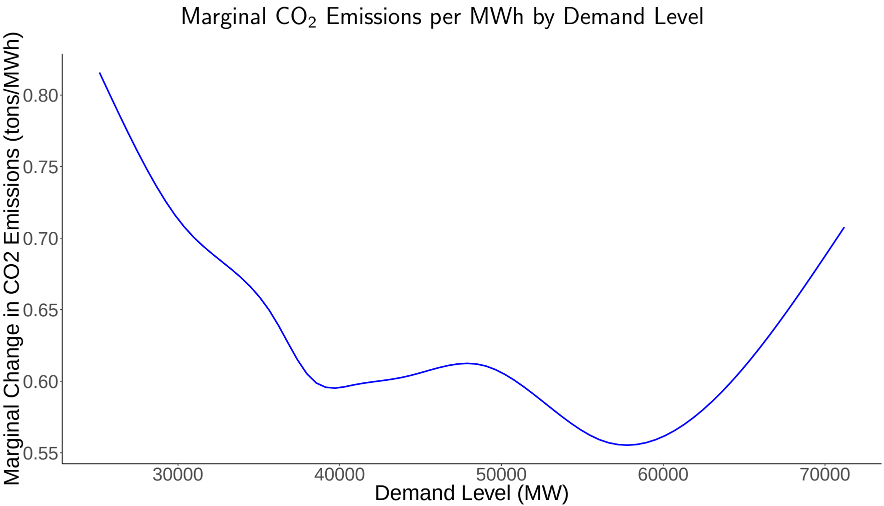
LLF vs. Linear FE Models

1. LLF models have superior out-of-sample forecast performance
2. Best case reduction of 10% in root mean forecast error
3. Prefer models with more leads/lags of demand
4. Likely non-linearities in MEF across levels of demand and ramp

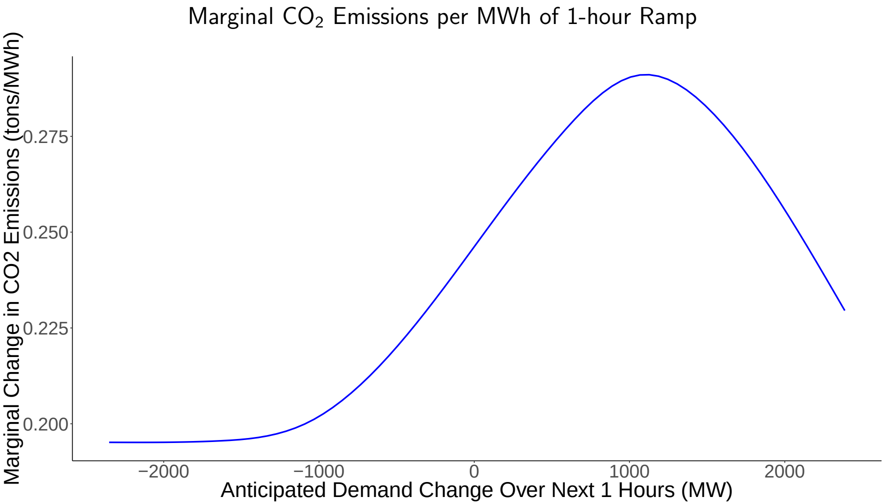
Calculation of Marginal Emissions Factors from a LLF

1. LLFs compute a prediction for each observation
2. Compute MEF as the centered finite difference at each out-of-sample observation
    1. Computing MEFs is computationally demanding
3. Aggregate marginal effects as the simple average across observations

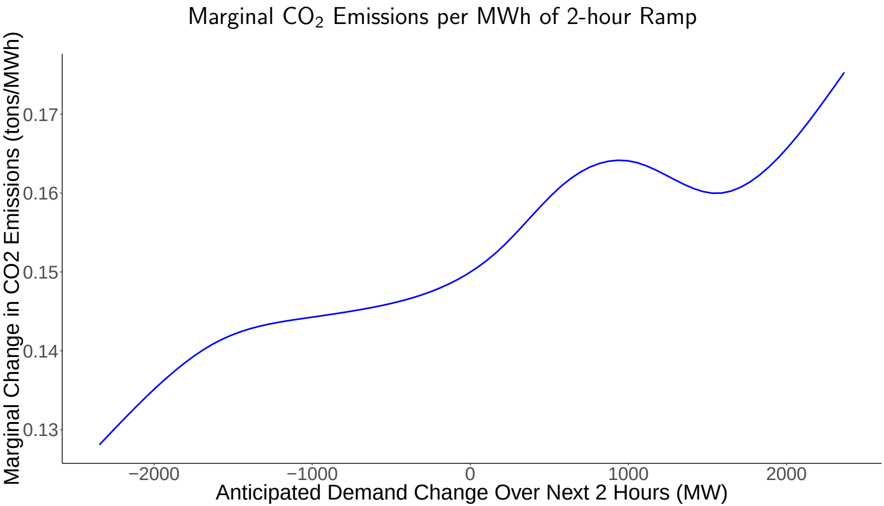
MEF by Demand Level (ERCOT)



MEF of 1-hour Ramp (ERCOT)



MEF of 2-hour Ramp (ERCOT)



LLF Models Summary

1. LLFs prefer models with more leads and lags of ramp than linear FE models
2. Variable importance measures suggest
    1. **Most:** Demand level, non-FF generation, and their changes
    2. **Medium:** Time of year
    3. **Less:** Time of day, day of week

Emissions Benefits of Electricity Storage

1. LLFs compute a marginal effect for each observation
2. Combine with hourly price data to estimate how profit-maximizing storage would change emissions
    1. Storage technology identical to previous simulations
    2. Storage operators have perfect foresight over future prices
3. Several analyses caution storage could *increase* emissions
    1. e.g., Carson and Novan (2013), Babacan et al. (2018)

Emissions Benefits of Electricity Storage (ERCOT)

Emissions Benefits of Simulated Electricity Storage Per MWh Consumed

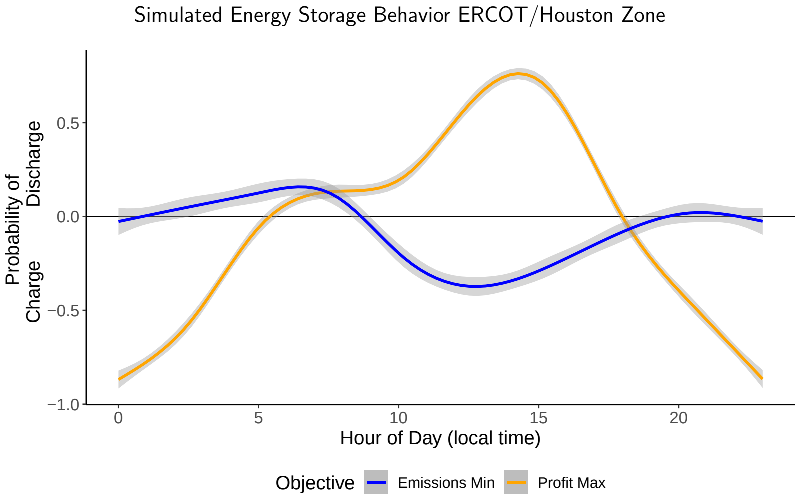
	Marginal Change in CO_2 Emissions per MWh					
	Profit Max			Emissions Min		
ERCOT Region	No Ramp	With Ramp	Difference	No Ramp	With Ramp	Difference
HOUSTON	0.1730	-0.1605	207.8%	-0.2911	-0.6277	53.6%
SOUTH	0.1793	-0.1674	207.1%	-0.2911	-0.6277	53.6%
WEST	0.1721	-0.1634	205.3%	-0.2911	-0.6277	53.6%

Emissions Benefits of Electricity Storage (ERCOT)

For profit-maximizing storage operators

1. Failing to account for ramp suggests storage would increase CO_2 emissions
2. Accounting for ramp, emissions modestly decrease
3. Emissions reductions still fall far short of theoretical maximum

Simulated Storage Behavior in ERCOT by Hour



With Tax

Summary

1. Short-run adjustment is an important component of emissions on the margin
2. Marginal changes to the generating mix induce systematic demand for ramp by FF generation
3. Ignoring ramping effects
    1. Overstates emissions benefits of solar PV by 16%
    2. Understates the emissions benefits of electricity storage
    3. Other demand/supply-side policies (e.g., DR) could target both level and ramp

Moving forward

1. Expand framework here to Eastern Interconnection
2. Marginal emissions of local criteria pollutants
    1. As in Holland, Mansur, Muller, and Yates (2016) requires plant-level analysis
    2. LLFs can identify plant attributes contributing to emissions
3. Role of ramping on marginal cost and entry incentives

Thank You

James Archsmith
`archsmit@umd.edu`

Working paper available soon at econjim.com/WP1802

Appendix

Example: Measuring Fuel Economy

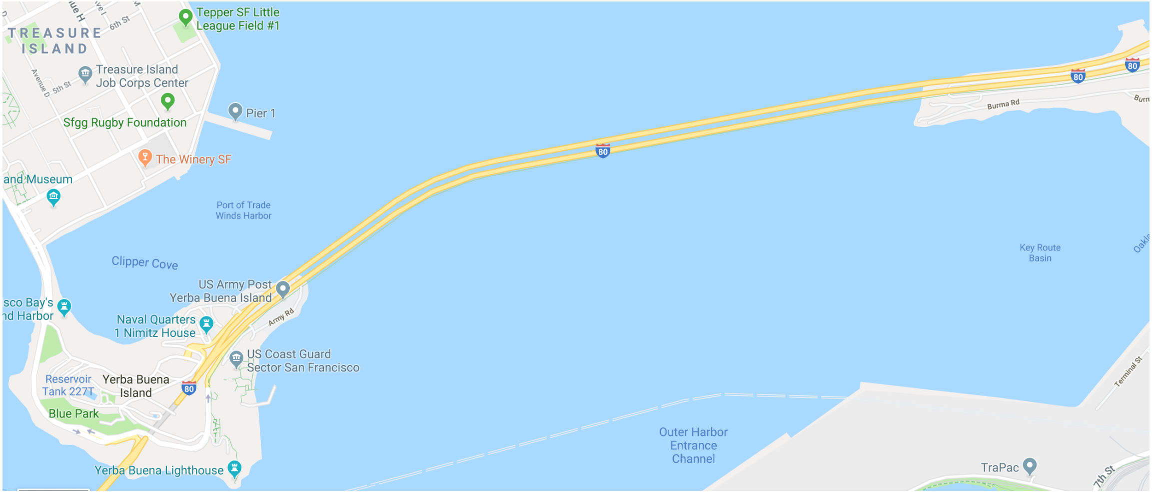


Image Source Google Maps. Traffic data simulated. Back

Example: Measuring Fuel Economy

Image Source Google Maps. Traffic data simulated. Back

Example: Measuring Fuel Economy

Image Source Google Maps. Traffic data simulated.

Back

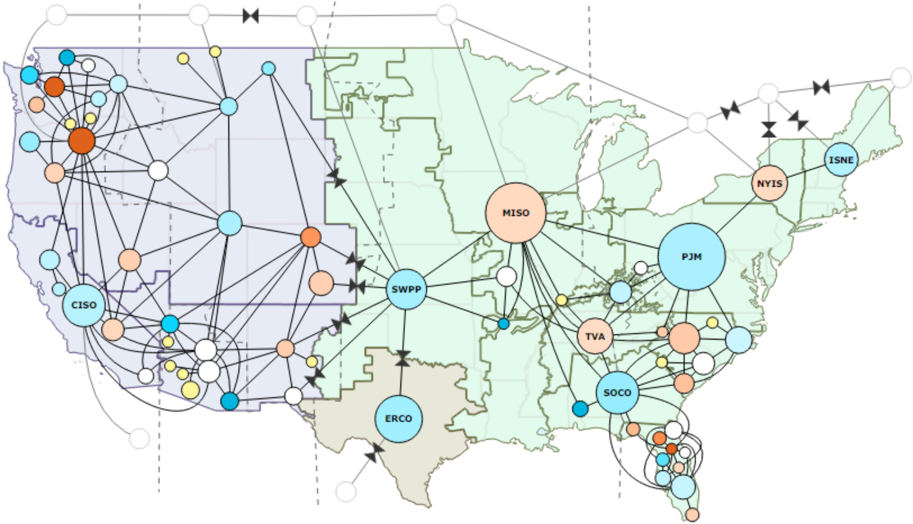
Example: Measuring Fuel Economy

Image Source Google Maps. Traffic data simulated. Back

Example: Measuring Fuel Economy

Image Source Google Maps. Traffic data simulated. Back

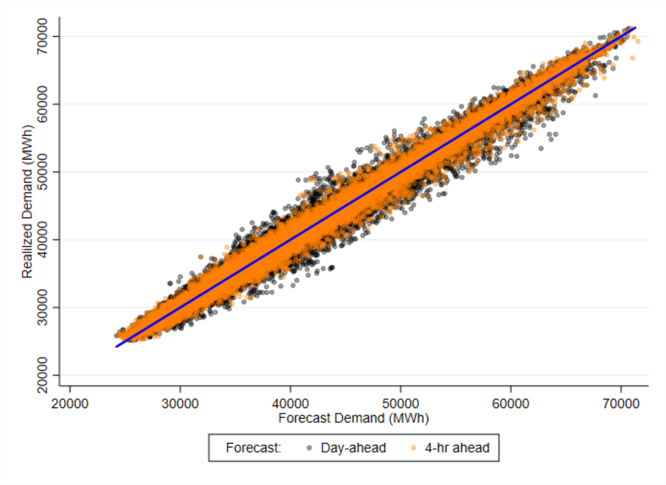
EIA-930 Balancing Authorities



Back

Forward Demand Forecasts - ERCOT

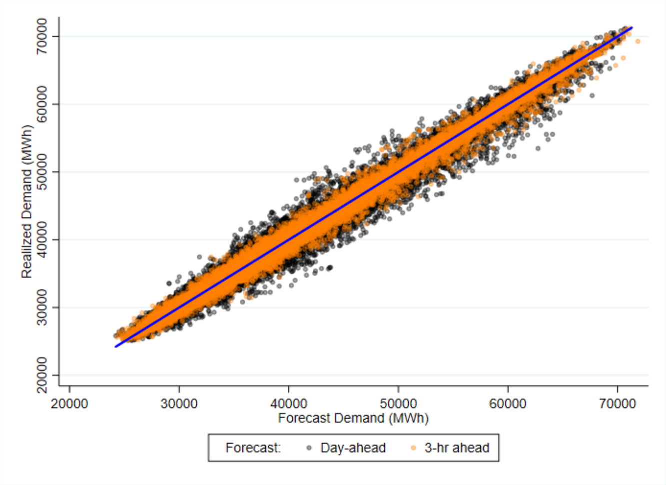
$t + 4$ hour forecast vs. day-ahead



Back

Forward Demand Forecasts - ERCOT

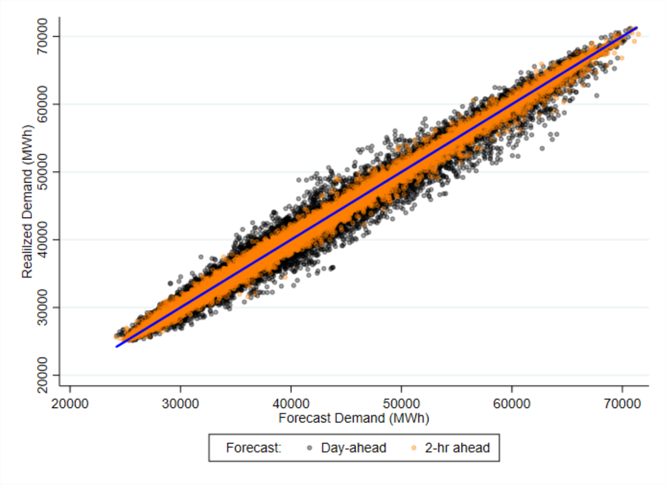
$t + 3$ hour forecast vs. day-ahead



Back

Forward Demand Forecasts - ERCOT

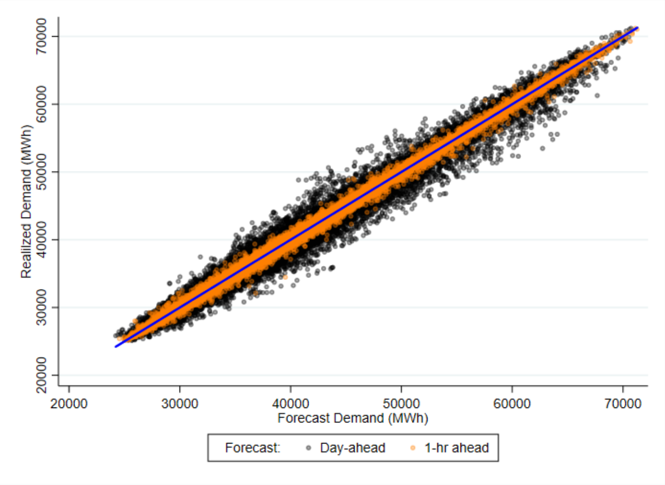
$t + 2$ hour forecast vs. day-ahead



Back

Forward Demand Forecasts - ERCOT

$t+1$ hour forecast vs. day-ahead



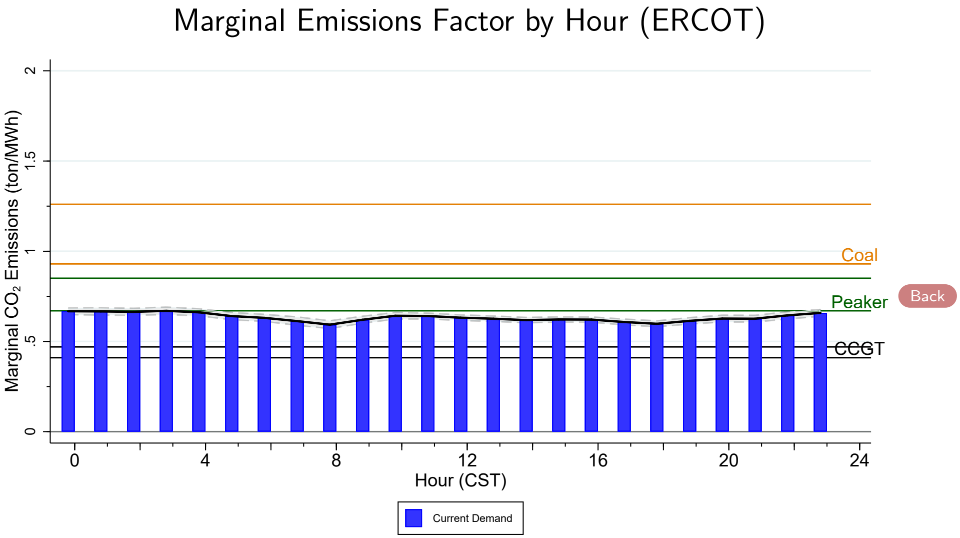
Back

Forward Non-Fossil Fuel Forecasts

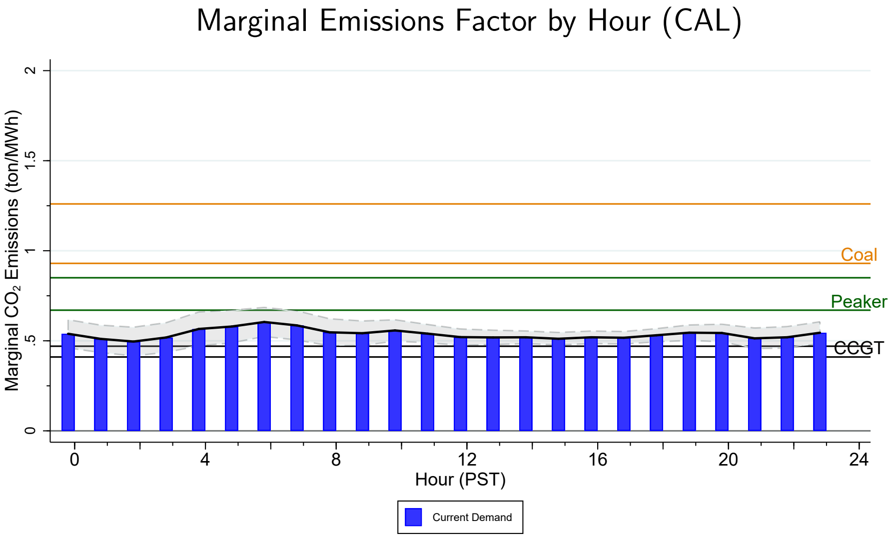
1. Forecasts of non-fossil fuel generation computed using random forests
    1. Lagged level of demand
    2. Lagged non-fossil fuel generation
    3. Day of week, hour-of-day, solar year date
2. Compute forecasts using random forests
    1. All forecasts predicted out-of-sample
3. Identical method used to predict contemporaneous value

Back

MEF By Hour - ERCOT



MEF By Hour - CAL



Back

Simulating Emissions Benefits

1. Compute both level and ramping effects
2. Requires knowing how generation varies over time
    1. Solar PV - Mean hourly solar output per MW of capacity from CAISO
    2. Wind - Mean hourly on-shore wind ouput per MW of capacity from CAISO
    3. Electricity Storage - Assume emissions-minimizing objective and 80% roundtrip efficiency

Back

Local Linear Forests

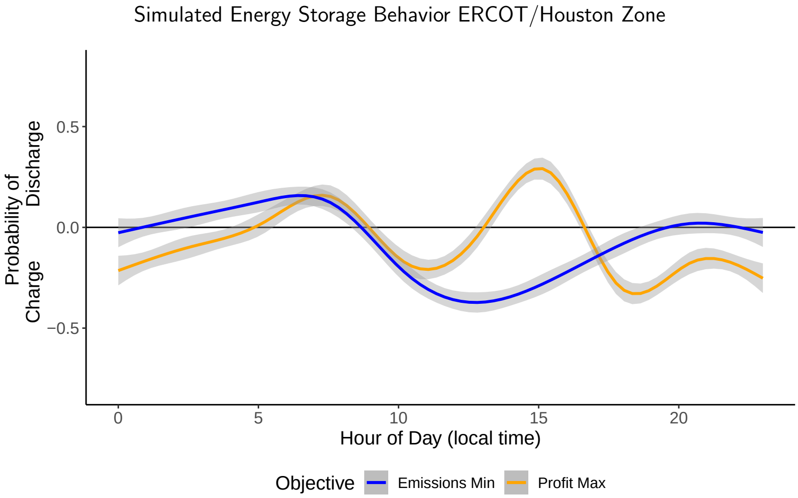
1. LLFs are an extension of random forests
2. Replace "mean-only" predictions with a linear model in each leaf
3. Follow Athey, Tibshirani, and Wagner (2019) method for generalized random forests
    1. Subsample data and variables
    2. Find the split that minimizes out-of-bag forecast error in a linear model (leaves)
    3. Continue splitting leaves until a stopping criterion is reached (trees)
    4. Grow many trees (forest)
    5. Model for a given set of covariates is the average across all trees

Local Linear Forests

1. Athey, Tibshirani, and Wagner (2019) demonstrate GRFs are consistent and asymptotically normal
2. LLFs are a case of GRFs
    1. Leaf's moment condition is a linear model as opposed to mean-only
    2. Leaves divided to maximize the difference in a regression parameter
    3. "Similar" observations are grouped into the same leaf
    4. Equivalent to a weighted regression where a tree-based estimator chooses the weights
    5. Separate model for each observation

Back

Simulated Storage Behavior in ERCOT by Hour



Back