Efficient Pollution Abatement in Electricity Markets with Intermittent Renewable Energy

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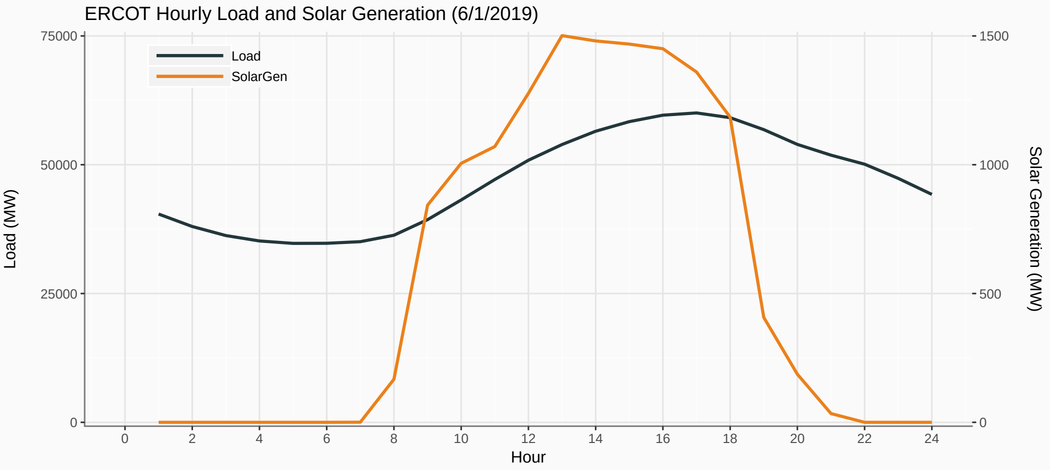
Motivation

What is intermittency?



Motivation

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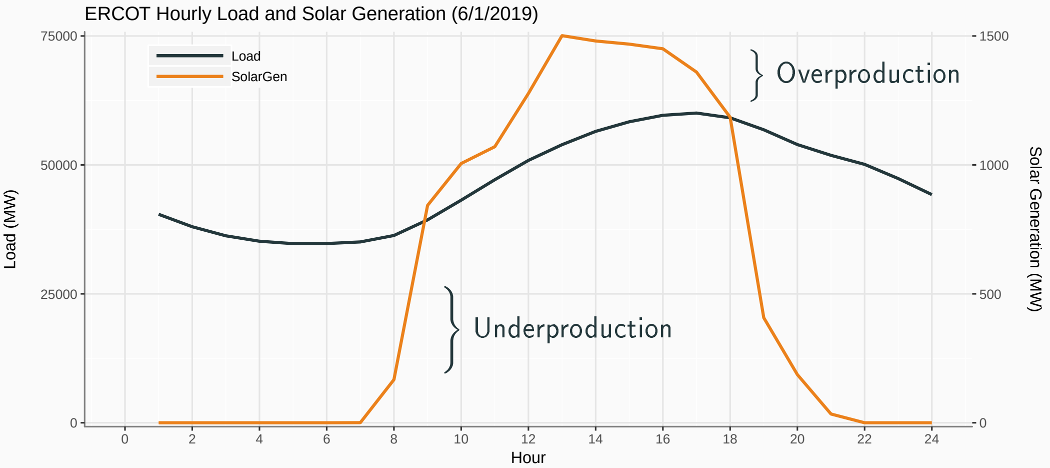
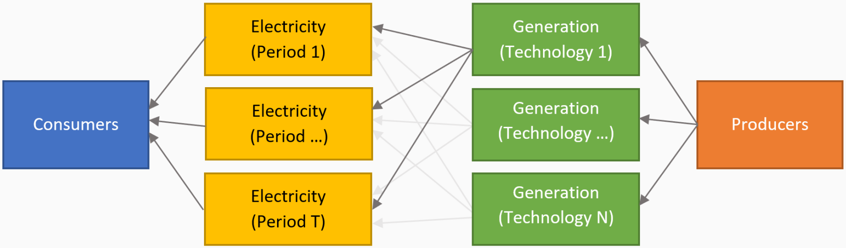


Motivation

How should we model intermittency?

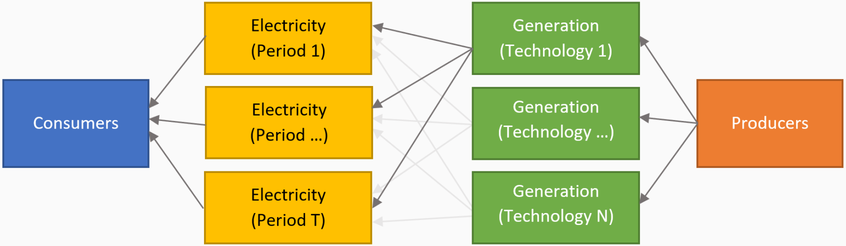
“*. . . the economics of all generating technologies, both intermittent and dispatchable, can be evaluated based on the expected market value of the electricity that they will supply, their total life-cycle costs, and their associated expected profitability. Such an analysis would reflect the actual expected production profiles of dispatchable and intermittent technologies, the value of electricity supplied at different times, and other costs of intermittency associated with reliable network integration.*” (Joskow, 2011)

Model – Overview



- Multi-period model with electricity consumers and producers
- Parametrize the model empirically
- Numerically evaluate the model to study its implications

Model – Preview of the Results

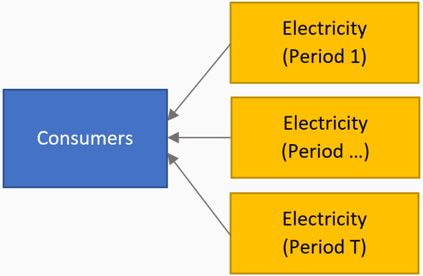


$\Longrightarrow$ Elasticity of substitution between renewables and fossil fuels is non-constant

$\Longrightarrow$ The importance of intermittency (in terms of welfare) increases with the intermittency of present generation

$\Longrightarrow$ Batteries can drastically increase the substitutability of renewables and fossil fuels

Model – Consumers



Consumer assumptions

- Representative consumer who purchases and uses electricity in each period
- Consumers prefer to use different amounts of electricity at different times
- Consumers will substitute electricity consumption across time periods based on relative prices

Model – Consumers

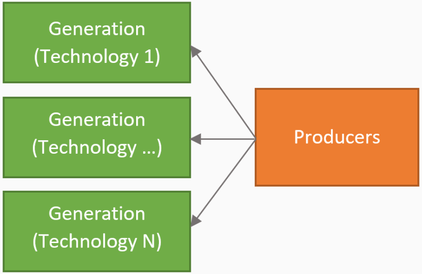
Consumer's Optimization Problem

$$\textbf{Utility}:\ U = \left(\sum_t \alpha_t Z_t^{\phi} \right)^{1/\phi}$$

$$\textbf{Budget Constraint}:\ I = \sum_t p_t Z_t$$

- α_t captures "time" preference
- $\sigma = 1/(1-\phi)$ is the intertemporal elasticity of substitution (IES)
- Total cost of electricity equals the cost of electricity consumed in each period

Model – Firms



Producer assumptions

- Representative firm that maximizes profit
- Firms build a fixed amount of capacity in different generation technologies
- Different technologies can access different fractions of their capacity in each period
- Output is not stochastic

Model – Firms

Firm's Optimization Problem

$$\textbf{Profit}: \Pi = p^T Z - c^T X$$
$$= p^T \xi X - c^T X$$

- Firms choose fixed quantities X_i of each generation technology i
- Technology i produces $\xi_{i,t}$ electricity per unit in period t
- Cost of building X_i units of generation technology i is $c_i X_i$
- Reminiscent of Joskow (2011) $\implies$ X is chosen "*. . . based on the expected market value of the electricity that they will supply, their total life-cycle costs, and their associated expected profitability. . .*"

Model – Solution

Equilibrium

$$\textbf{Utility Max:}\; Z_t = \left(\frac{\alpha_t}{p_t}\right)^{\sigma} \frac{I}{\sum_t \alpha_t^{\sigma} p_t^{1-\sigma}}$$

$$\textbf{Profit Max:}\quad p = \xi^{-1} c$$

- Consumer's optimum is the standard CES solution
- Analytically tractable only when $\sigma = 1$ and number of generation technologies equals the number of periods
- Can study the solution numerically by parametrizing ξ, c, α, and σ.

Empirical Methodology – Theory

Demand:

$$\overbrace{\ln(Z_{t,i}/Z_{s,i}) = -\sigma \ln(P_{t,i}/P_{s,i})}^{\text{CES First Order Condition}}$$

$$+ \underbrace{\gamma_{t,i} CDD_{t,i} + \omega_{t,i} HDD_{t,i} + \gamma_{s,i} CDD_{s,i} + \omega_{s,i} HDD_{s,i} + \eta \Delta_{t,s}}_{\text{Demand Controls}} + u_i$$

- $CDD_{t,i}$ = Cooling Degree Days
- $HDD_{t,i}$ = Heating Degree Days
- $\Delta_{t,s}$ = Difference in months between periods t and s

Empirical Methodology – Theory

Demand:

$$\ln(Z_{t,i}/Z_{s,i}) = -\sigma \ln(P_{t,i}/P_{s,i}) + \gamma_{t,i} CDD_{t,i} + \omega_{t,i} HDD_{t,i} + \gamma_{s,i} CDD_{s,i} + \omega_{s,i} HDD_{s,i} + \eta \Delta_{t,s} + u_i$$

Supply:

$$\ln(Z_{t,i}/Z_{s,i}) = \beta \ln(P_{t,i}/P_{s,i}) + \psi \ln(C_{t,i}/C_{s,i}) + v_i$$

- $\ln(C_{t,i}/C_{s,i})$ = Log difference in coal prices
- Coal prices affect the supply of electricity but not its demand
- Can use IV to handle endogeneity

Empirical Methodology – Approach

- Approach the problem using OLS, IV (2SLS), and a semiparametric regression
- **Semiparametric regression** - Partially Linear IV
  - Places controls (degree days, time) and instrument (coal prices) in smooth, unknown functions estimated using Kernel regressions
  - Error term assumed to be mean zero but may be non-Gaussian
  - Robust to misspecified functional forms on controls and instrument

Demand:

$$\ln(Z_{t,i}/Z_{s,i}) = -\sigma \ln(P_{t,i}/P_{s,i}) + f(CDD_{t,i}, HDD_{t,i}, CDD_{s,i}, HDD_{s,i}, \Delta_{t,s}) + u_i$$

Supply:

$$\ln(Z_{t,i}/Z_{s,i}) = \beta \ln(P_{t,i}/P_{s,i}) + g(C_{t,i}/C_{s,i}) + v_i$$

Data

- Panel consists of monthly data for each state in the US from 2011 to 2018
- Monthly retail electricity price and consumption data is obtained from the EIA
- Coal prices for the same period are also obtained from the EIA
- Degree day data is collected from the NOAA
- Each variable is trimmed by 1%

Results

Table 1: Partially Linear IV Regression Results

	Instrument: $\ln(C_{t,i}/C_{s,i})$		
	(1)	(2)	(3)
$\hat{\sigma}$	2.9976***	1.2123***	0.8847***
	(0.169)	(0.052)	(0.044)
Time Control			Yes
Degree Day Controls		Yes	Yes
Observations	6817	6817	6817

Note: The log difference in coal price between period t and s, $\ln(C_{t,i}/C_{s,i})$, is used as an instrument in these regressions. The sample covers all 50 US states from 2011 to 2018; outliers are removed by trimming 1% of each variable except $\Delta_{t,s}$. The unit of observation is a set (t, s, i) where $t \neq s$ are months and i is a state. Robust standard errors are reported in parentheses. *p<0.05, **p<0.01, ***p<0.001

Discussion

What are the practical implications of IES $\sigma = 0.88$?

- Consider our model in a setting with two periods (peak and off-peak) and two technologies (solar and coal)
- We parametrize our model using data on cost and efficiency from the EIA
- We then numerically evaluate the model

Discussion

Does intermittency motivate a CES relationship between renewables and fossil fuel technologies?

- Many papers assume electricity should be modeled as a CES function of renewable and fossil fuel capacity or capital
- Often something like: $\mathit{Electricity} = (\alpha \cdot \mathit{Renewables}^{\phi} + \beta \cdot \mathit{Fossils}^{\phi})^{1/\phi}$

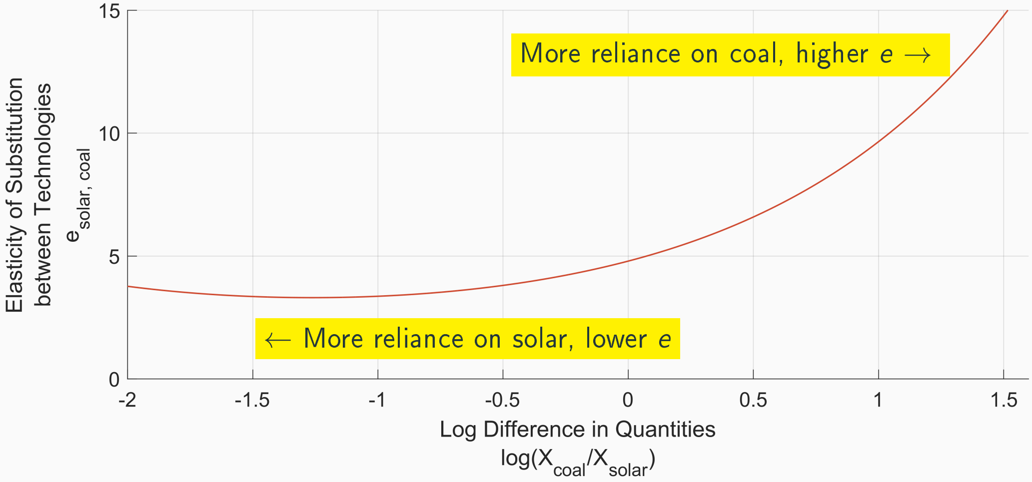
Discussion

Does intermittency motivate a CES relationship between renewables and fossil fuel technologies?

- Many papers assume electricity should be modeled as a CES function of renewable and fossil fuel capacity or capital
- Often something like: $\mathit{Electricity} = (\alpha \cdot \mathit{Renewables}^{\phi} + \beta \cdot \mathit{Fossils}^{\phi})^{1/\phi}$
- Does this relationship arise in our model? Is the elasticity of substitution (e) between these technologies constant?
- We numerically estimate the elasticity of substitution e between solar and coal in our model

Discussion

The elasticity of substitution between technologies is not constant



Discussion

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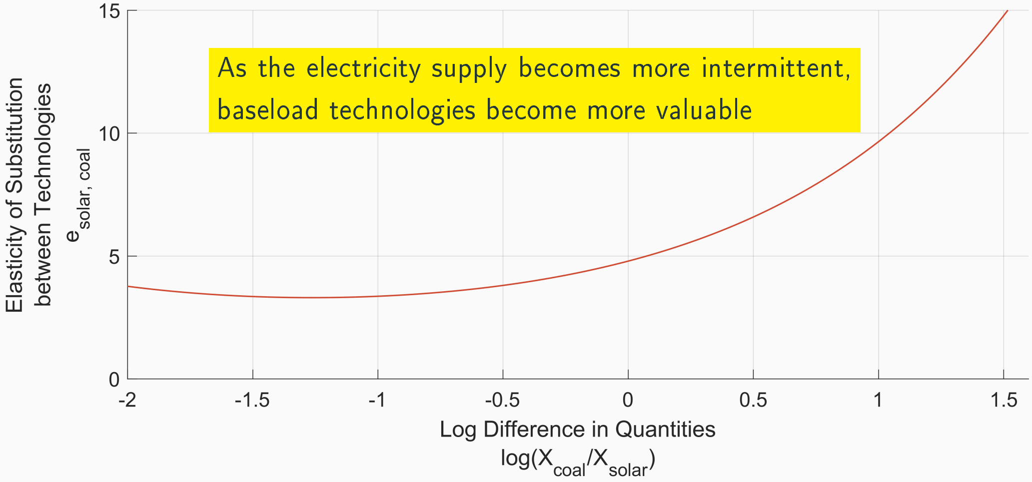
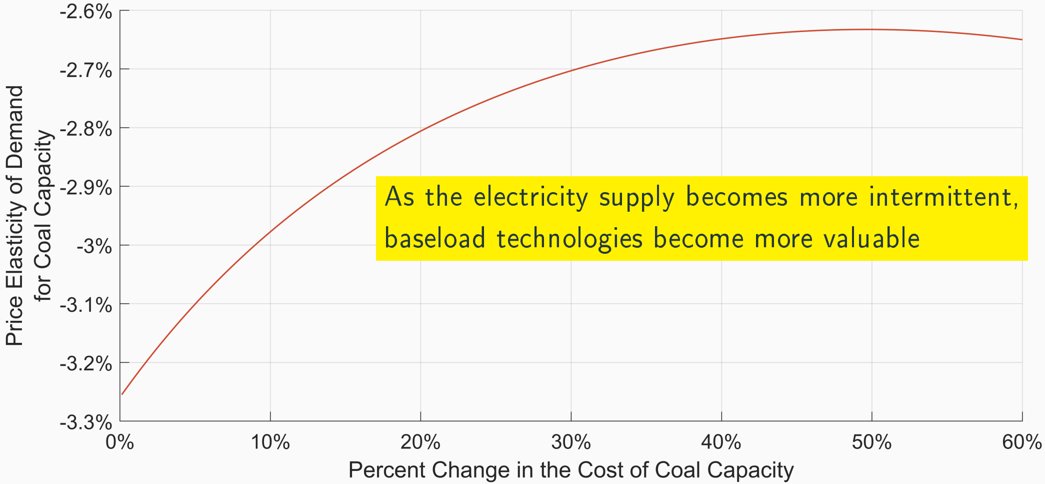


Discussion

Demand for base load capacity becomes more inelastic with its price



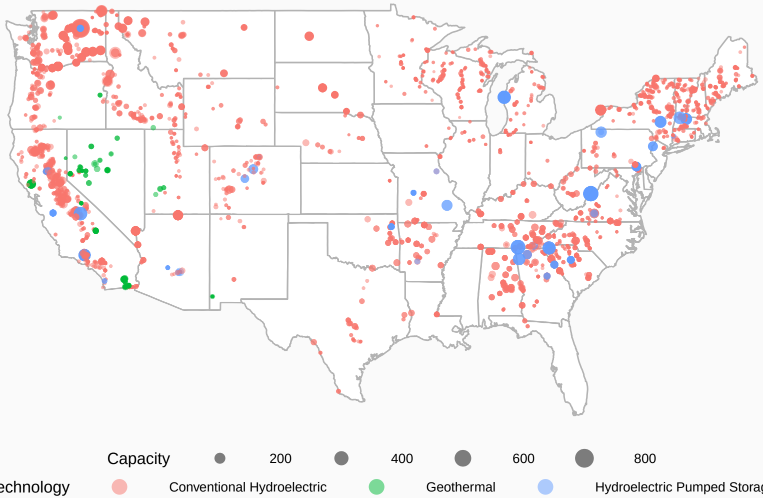
Discussion

How should we handle pollution abatement when generation is intermittent?

- Carbon taxes and renewable subsidies still work
- Should also account for its distributional effects
- Welfare effects depend on access to non-intermittent renewables
- Keep equity-efficiency trade-off in mind

Discussion

Distribution of Hydrothermal and Geothermal Plants (EIA, 2019)



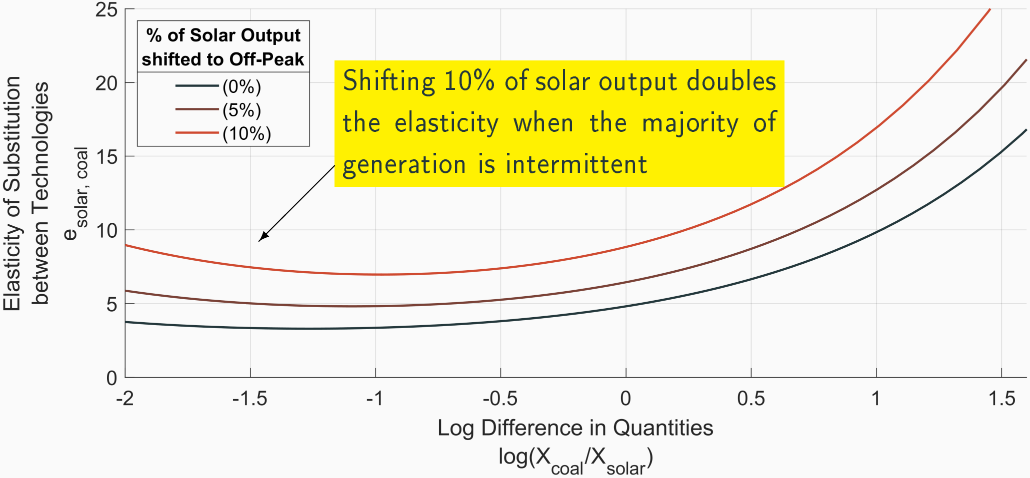
Discussion – Batteries

Researching battery technology can make a significant difference

- Reducing the intermittency of renewables greatly increases their substitutability
- Mitigates the distributional side effects of intermittency + policy
- Can roughly approximate the effects of batteries in our model by shifting solar output to the off-peak period when it under-produces

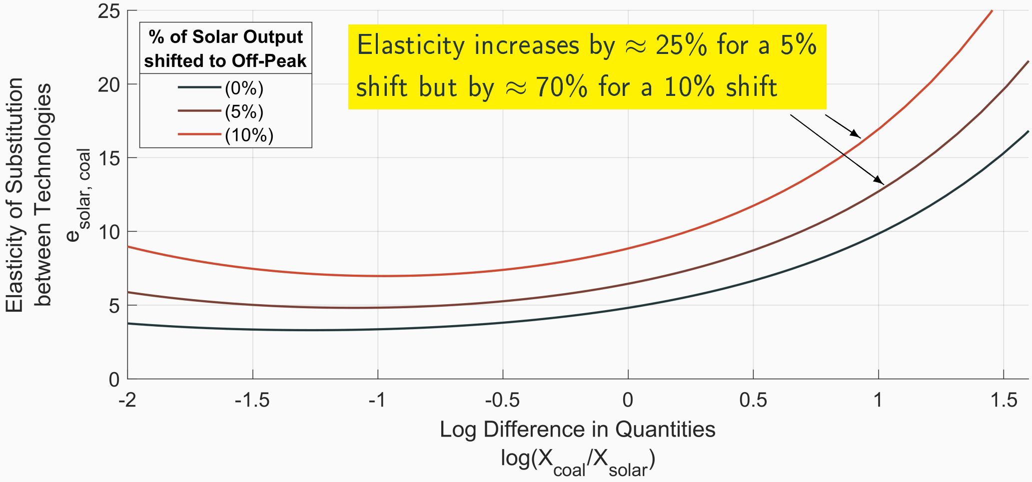
Discussion – Batteries

Using batteries to shift solar output greatly increases its substitutability



Discussion – Batteries

Initially, increasing returns to batteries and substitutability



Conclusion

- Welfare effects of carbon taxes and renewable subsidies depend on the intermittency of renewables
- Geographic heterogeneity in intermittency can create a trade-off between efficiently and equitably preventing climate change
- Subsidizing battery research can complement other policies by increasing the substitutability of renewable and fossil energy while mitigating their unintentional distributional consequences

Questions?

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References i

- Acemoglu, D., Aghion, P., Bursztyn, L., & Hemous, D. (2012). The Environment and Directed Technical Change. American Economic Review, 102(1), 131–166. https://doi.org/10.1257/aer.102.1.131
- Adelman, M. A. (1995). The genie out of the bottle: World oil since 1970. MIT Press.
- Ambec, S., & Crampes, C. (2012). Electricity provision with intermittent sources of energy. Resource and Energy Economics, 34(3), 319–336. https://doi.org/10.1016/j.reseneeco.2012.01.001
- Aubin, C., Fougere, D., Husson, E., & Ivaldi, M. (1995). Real-time pricing of electricity for residential customers: Econometric analysis of an experiment. Journal Of Applied Econometrics, 10, S171–S191.
- Borenstein, S. (2012). The Private and Public Economics of Renewable Electricity Generation. Journal of Economic Perspectives, 26(1), 67–92. https://doi.org/10.1257/jep.26.1.67
- Chao, H. (2011). Efficient pricing and investment in electricity markets with intermittent resources. Energy Policy, 39(7), 3945–3953. https://doi.org/10.1016/j.enpol.2011.01.010
- Climate Prediction Center (2019). Degree Days Statistics. National Oceanic and Atmospheric Administration. https://www.cpc.ncep.noaa.gov/products/analysis_monitoring/cdus/degree_days/
- Delarue, E., De Jonghe, C., Belmans, R., & D'Haeseleer, W. (2010). Applying portfolio theory to the electricity sector: Energy versus power. Energy Economics, 33(1), 12–23. https://doi.org/10.1016/j.eneco.2010.05.003
- Deryugina, T., Mackay, A., & Reif, J. (2017). The Long-Run Dynamics of Electricity Demand: Evidence from Municipal Aggregation. NBER Working Paper Series. https://doi.org/10.3386/w23483
- Electricity Information Administration (2019a). Net generation, United States, all sectors, annual. Electricity Data Browser. https://www.eia.gov/electricity/data/browser

References ii

- Electricity Information Administration (2019b). Levelized Cost and Levelized Avoided Cost of New Generation. Annual Energy Outlook 2019. https://www.eia.gov/outlooks/aeo/pdf/electricity_generation.pdf
- Electricity Information Administration (2019c). U.S. renewable electricity generation has doubled since 2008. Today in Energy. https://www.eia.gov/todayinenergy/detail.php?id=38752
- Fan, S., & Hyndman, R. (2011). The price elasticity of electricity demand in South Australia. Energy Policy, 39(6), 3709–3719. https://doi.org/10.1016/j.enpol.2011.03.080
- Foley, A., Leahy, P., Marvuglia, A., & Mckeogh, E. (2012). Current methods and advances in forecasting of wind power generation. Renewable Energy, 37(1), 1–8. https://doi.org/10.1016/j.renene.2011.05.033
- Geroski, P. (2000). Models of technology diffusion. Research Policy. Elsevier B.V. https://doi.org/10.1016/S0048-7333(99)00092-X
- Helm, C., & Mier, M. (2019). On the efficient market diffusion of intermittent renewable energies. Energy Economics, 80, 812–830. https://doi.org/10.1016/j.eneco.2019.01.017
- Herriges, J., Baladi, S., Caves, D., & Neenan, B. (1993). The Response of Industrial Customers to Electric Rates Based Upon Dynamic Marginal Costs. The Review of Economics and Statistics, 75(3), 446. https://doi.org/10.2307/2109458
- Joskow, P. (2011). Comparing the Costs of Intermittent and Dispatchable Electricity Generating Technologies. American Economic Review, 101(3), 238–241. https://doi.org/10.1257/aer.101.3.238
- King, Kathleen, and Peter Shatrawka (1994). "Customer Response to a Permanent Time- Varying Pricing Program in the United Kingdom." Laurits R. Christensen Associates, Madison, Wisconsin.
- Mohajeryami, S., Moghaddam, I., Doostan, M., Vatani, B., & Schwarz, P. (2016). A novel economic model for price-based demand response. Electric Power Systems Research, 135, 1–9. https://doi.org/10.1016/j.epsr.2016.03.026

References iii

- Musgens, F., & Neuhoff, K. (2006). Modelling Dynamic Constraints in Electricity Markets and the Costs of Uncertain Wind Output. Faculty of Economics.
- Neuhoff, K., Cust, J. & Keats, K. (2007). Implications of intermittency and transmission constraints for renewables deployment. Cambridge Working Papers in Economics 0711, Faculty of Economics, University of Cambridge.
- Newey, W. (1990). Efficient Instrumental Variables Estimation of Non-linear Models. Econometrica, 58(4), 809–837. https://doi.org/10.2307/2938351
- ORNL (2004). Measurement practices for reliability and power quality. A toolkit of reliability measurement practices. U.S. Department of Energy. https://info.ornl.gov/sites/publications/Files/Pub57467.pdf
- Papageorgiou, C., Saarn, M., & Schulte, P. (2017). Substitution between clean and dirty energy inputs: a macroeconomic perspective.(Author abstract). Review of Economics and Statistics, 99(2), 201–212. https://doi.org/10.1162/REST_a_00623
- Reiss, P., & White, M. (2005). Household Electricity Demand, Revisited. The Review of Economic Studies, 72(252), 853. Retrieved from http://search.proquest.com/docview/204335314/
- Revankar, N. (1971). A Class of Variable Elasticity of Substitution Production Functions. Econometrica, 39(1), 61–71. https://doi.org/10.2307/1909140
- Schwarz, P., Taylor, T., Birmingham, M., & Dardan, S. (2002). Industrial response to electricity real-time prices: short run and long run. Economic Inquiry, 40(4), 597–610. https://doi.org/10.1093/ei/40.4.597
- Shahriari, M., & Blumsack, S. (2018). The capacity value of optimal wind and solar portfolios. Energy, 148, 992–1005. https://doi.org/10.1016/j.energy.2017.12.121
- Silverman, B. (1986). Density estimation for statistics and data analysis. London; Chapman and Hall.

References iv

- Zhou, S. & Teng, F., (2013). Estimation of urban residential electricity demand in China using household survey data.(Statistical data). Energy Policy, 61, 394–402.
- Staiger, D., & Stock, J. (1997). Instrumental Variables Regression with Weak Instruments. Econometrica, 65(3), 557–586. https://doi.org/10.2307/2171753
- U.S. Bureau of Economic Analysis (2019). Personal consumption expenditures: chain-type price index. FRED, Federal Reserve Bank of St. Louis. https://fred.stlouisfed.org/series/PCEPI, April 27, 2019.
- Wolak, F., & Patrick, R. (2001). The Impact of Market Rules and Market Structure on the Price Determination Process in the England and Wales Electricity Market. NBER Working Paper Series. https://doi.org/10.3386/w8248
- Woo, C., Chow, P., & Horowitz, I. (1996). Optional real-time pricing of electricity for industrial firms. Pacific Economic Review, 1(1), 79–92. https://doi.org/10.1111/j.1468-0106.1996.tb00175.x
- Zarnikau, J. (1990). Customer Responsiveness to Real-Time Pricing of Electricity. The Energy Journal, 11(4), 99. https://doi.org/10.5547/ISSN0195-6574-EJ-Vol11-No4-6

Appendix – VES

How can future models of energy generation substitutability be improved?

- Assuming a constant elasticity of substitution between renewables and fossil fuels does not accurately capture intermittency
- Empirical estimates of the elasticity of substitution may be incorrect since the functional form (CES) does not seem to be appropriate
- Directly implementing our model may not allow for analytical tractability

[1] The VES function was first defined in Revankar (1971).

Appendix – VES

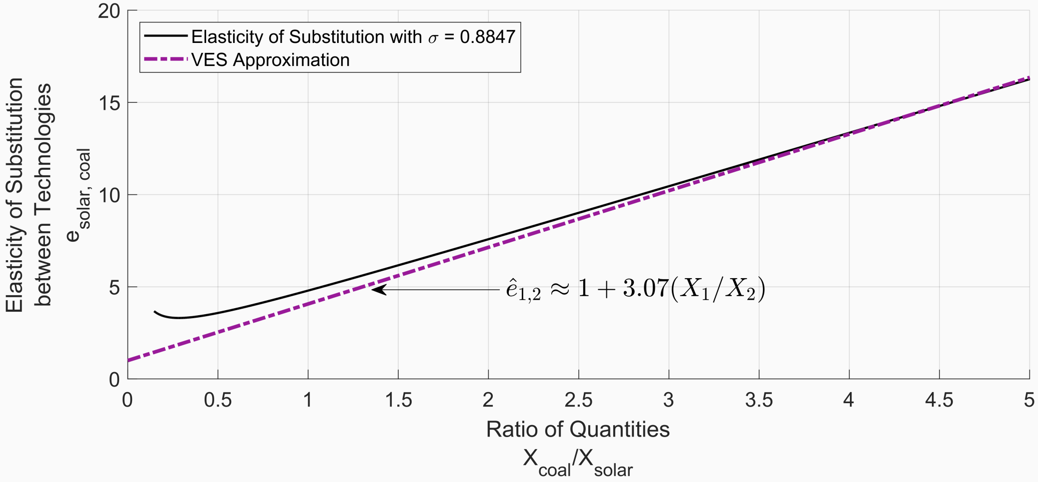
How can future models of energy generation substitutability be improved?

- Assuming a constant elasticity of substitution between renewables and fossil fuels does not accurately capture intermittency
- Empirical estimates of the elasticity of substitution may be incorrect since the functional form (CES) does not seem to be appropriate
- Directly implementing our model may not allow for analytical tractability
- Can try the variable elasticity of substitution (VES) form instead[1]

[1] The VES function was first defined in Revankar (1971).

Appendix – VES

VES approximation of the relationship between solar and coal



Appendix – VES

What exactly is the VES function?

- Assumes that the elasticity of substitution between factors varies as a linear function of their quantities
- Can be empirically estimated
- Simpler to implement in a theoretical or numerical framework than our model

$$Z = \gamma X_1^{\omega(1-\delta\rho)} \left(X_2 + (\rho - 1)X_1\right)^{\omega\delta\rho}$$

$$e = 1 + \beta(X_1/X_2)$$

$$\beta = (\rho - 1)/(1 - \delta\rho)$$

$$\gamma > 0, \quad \omega > 0, \quad 0 < \delta < 1, \quad 0 \leq \delta\rho \leq 1, \quad (X_2/X_1) > -\beta$$

Appendix – Literature

- Some literature approach the problem by numerically optimizing the capacity of intermittent renewables given reliability constraints [2]
- Other papers study how intermittent technologies affect the market itself [3]
- A common top-down approach is to model intermittency through a CES function between different energy technologies [4]
- Our model is closest to Helm and Mier (2019)

[2] (Musgens & Neuhoff, 2006), (Neuhoff et al., 2007)
[3] (Ambec & Crampes, 2012), (Chao, 2011), (Borenstein, 2012)
[4] See Papageorgiou et al. (2017) for a survey of the literature taking this approach

Appendix – OLS Results

	Dependent variable: $\ln(Z_{t,i}/Z_{s,i})$					
	(1)	(2)	(3)	(4)	(5)	(6)
$-\ln(P_{t,i}/P_{s,i})$	0.937***	1.075***	1.098***	1.074***	1.263***	1.305***
	(0.030)	(0.026)	(0.026)	(0.224)	(0.172)	(0.169)
$\Delta_{t,s}$			0.0005***			0.0065*
			(0.0001)			(0.0003)
CDD_t		1.156***	1.163***		1.164***	1.174***
$(\times 1000^{-1})$		(0.017)	(0.017)		(0.072)	(0.075)
CDD_s		−1.143***	−1.158***		−1.200***	−1.224***
$(\times 1000^{-1})$		(0.025)	(0.026)		(0.096)	(0.098)
HDD_t		0.246***	0.245***		0.237***	0.236***
$(\times 1000^{-1})$		(0.007)	(0.007)		(0.031)	(0.031)
HDD_s		−0.267***	−0.265***		−0.268***	−0.263***
$(\times 1000^{-1})$		(0.008)	(0.008)		(0.038)	(0.038)
Intercept	0.028***	0.012*	0.026***			
	(0.004)	(0.006)	(0.007)			
State FEs				Yes	Yes	Yes
Observations	6,817	6,817	6,817	6,817	6,817	6,817
Adjusted R^2	0.079	0.506	0.508	0.085	0.518	0.520
F Statistic	582***	1399***	1172***	685***	1474***	1241***

Appendix – IV Results

	First-Stage *Dep. Variable:* $\ln(P_{t,i}/P_{s,i})$			Second-Stage *Dep. Variable:* $\ln(Z_{t,i}/Z_{s,i})$		
	(A.1)	(B.1)	(C.1)	(A.2)	(B.2)	(C.2)
$\ln(C_{t,i}/C_{s,i})$	-0.042^{***}	-0.018^{***}	-0.018^{***}			
	(0.002)	(0.002)	(0.002)			
$-\ln(P_{t,i}/P_{s,i})$				2.978^{***}	5.896^{***}	5.818^{***}
				(0.180)	(0.548)	(0.524)
$\Delta_{t,s}$			0.001^{***}			0.003^{***}
			(0.00004)			(0.0004)
CDD_t ($\times 1000^{-1}$)		0.100^{***}	0.105^{***}		1.637^{***}	1.657^{***}
		(0.006)	(0.006)		(0.068)	(0.067)
CDD_s ($\times 1000^{-1}$)		-0.096^{***}	-0.114^{***}		-1.688^{***}	-1.783^{***}
		(0.009)	(0.009)		(0.079)	(0.084)
HDD_t ($\times 1000^{-1}$)		-0.048^{***}	-0.048^{***}		0.001	0.007
		(0.003)	(0.003)		(0.031)	(0.030)
HDD_s ($\times 1000^{-1}$)		0.053^{***}	0.055^{***}		0.0001	0.007
		(0.003)	(0.003)		(0.035)	(0.034)
State FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6817	6817	6817	6817	6817	6817
Adjusted R^2	0.061	0.264	0.293			
F Statistic	443^{***}	489^{***}	472^{***}			

Appendix – Model Parameters

$$\underbrace{\alpha_t = 0.6,\ \alpha_s = 0.4}_{Demand\ parameters},\ \underbrace{\xi_1 = (1,\ 1),\ \xi_2 = (1,\ 0.1)}_{Output\ parameters},\ \underbrace{c_1 = 104.3,\ c_2 = 60}_{Cost\ parameters}$$

- We normalize quantity units in terms of capacity, so cost is given in \$/MWh and output is given as the fraction of capacity available in each period
- EIA LCOE estimates for 2023 for "Coal with 30% CCS" and "Solar PV" are 104.3\$/MWh and 60\$/MWh $\implies c_1 = 104.3,\ c_2 = 60$
- Based on the graph of ERCOT loads from earlier, consumers prefer that $\approx 60\%$ of their energy arrive between 900-2400 $\implies (\alpha_t, \alpha_s) = (0.6, 0.4)$
- For same periods, solar output seems to be $\approx 10:1 \implies \xi_2 = (1,\ 0.1)$
- Coal output is assumed to be constant over both periods $\implies \xi_1 = (1,\ 1)$