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Do Two Electricity Pricing Wrongs Make a Right? Cost Recovery, Externalities, and Efficiency

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Advocates of using market mechanisms for addressing greenhouse gases and other pollutants typically argue that it is a necessary step in pricing polluting goods at their social marginal cost (SMC). Retail electricity prices, however, deviate from social marginal cost for many reasons. Some cause prices to be too low–such as unpriced pollution externalities–while others cause prices to be too high–such as recovery of fixed costs. Furthermore, because electricity is not storable, marginal cost can fluctuate widely within even a day, while nearly all residential retail prices are static over weeks or months. We study the relationship between residential electricity prices and social marginal cost in the US, both on average and over time. We find that the difference between the standard residential electricity rate and the utility's average (over hours) social marginal cost exhibits large regional variation, with price well above average SMC in some areas and price well below average SMC in other areas. Furthermore, we find that for most utilities the largest source of difference between price and SMC is the failure of price to reflect variation in SMC over time. In a standard demand framework, total deadweight loss over a time period is proportional to the sum of squared differences between a constant price and SMC, which can be decomposed into the component due to price deviating from average SMC and the component due to the variation in SMC. Our estimates imply if demand elasticity were the same in response to hourly price variation as to changes in average price, then for most utilities the majority of deadweight loss would be attributable to the failure to adopt time-varying pricing. Nonetheless, in a few areas–led by California– price greatly exceeds average SMC causing the largest deadweight losses.

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The efficient functioning of markets relies on prices accurately reflecting the short-run social marginal cost of supply to both producers and consumers. However, in utility industries that have traditionally been viewed as natural monopolies, the theoretical ideal of marginal cost pricing has been elusive in practice. One stream of research dating back to Ramsey (1927) has examined how price discrimination and non-linear tariffs can be used to mitigate deadweight loss while still allowing a utility with declining average cost to recover its total costs. Another research literature, growing out of Pigou's (1920) seminal work, has shown that environmental externalities lead firms to charge prices below social marginal cost. A third and somewhat more recent literature – starting with Boiteaux (1960) and Steiner (1957) – has emphasized that the highly time-varying cost of delivering electricity, due to its high cost of storage, suggests the need for dynamic pricing in order to reflect the constantly changing cost.

In this paper, we examine the relationship between marginal retail prices and the social marginal cost of supply in the electricity industry from 2014 to 2016. We focus on the most common residential electricity tariffs. In the $174 billion residential market, the efficiency implications of a gap between the marginal cost of service and the marginal price paid by consumers are growing more serious with the increasing availability of substitute technologies such as rooftop solar photovoltaics and small-scale battery storage. These technologies make the demand of end-use consumers more price elastic, and therefore can magnify the deadweight loss from mis-pricing. Utilities around the world have expressed concern about the prospect of a "death-spiral," in which reduced consumption leads to higher regulated prices which in turn leads to more consumption decline (Costello and Hemphill 2014).

Retail pricing in electricity markets suffers from at least three distortions: (a) because neither buyers nor sellers bear the pollution costs of electricity generation, prices will tend to be below their optimal level, (b) because there are significant economies of scale in electricity distribution, and possibly other parts of the value chain, a linear price likely will need to exceed private marginal cost of the utility in order to recover its total costs, and (c) because electricity is not storable and demand fluctuates continuously, the private marginal cost changes by the constantly within a day, yet retail prices do not reflect those fluctuations. Notably, these distortions do not all work in the same direction and can at times potentially offset one another. Research on the electricity industry and the policies that impact it, however, has tended to focus on each of these distortions in isolation. Since at least Buchanan (1969) it has been well understood in economics that markets with multiple distortions may not be improved by addressing one of the distortions in isolation.

In this paper, we take a step towards a holistic view by attempting to measure, at high frequency, the departure of residential electricity prices from the economic ideal of short-run social marginal cost (SRSMC). We then decompose the depar-

was circulated under the title "Are Residential Electricity Prices Too High or Too Low? Or Both?".

ture from SRSMC into the component caused by charging a price that differs from the average SRSMC and the component caused by charging a constant price that does not vary over short time periods as SRSMC does. The analysis is primarily an exercise in measurement of various aspects of SRSMC and the marginal prices faced by customers. Some of these measures are available in public data, and some we estimate, because direct measures are not available.

We break the construction of price versus social marginal cost into three components: retail price, private marginal cost, and external marginal cost. Section II presents the residential electricity price data and our calculation of marginal electricity price. Section III discusses private marginal cost, for which we begin with wholesale electricity price data, but then make adjustments to incorporate time-varying costs associated with local distribution. Section IV brings in externalities, estimating marginal externality costs for the marginal consumption of electricity by region. In section V, we bring the three measures together to analyze the deviation of price from SRSMC, then calculate and decompose the implied deadweight loss. In section VI we discuss several potential policy implications of our calculation. We conclude in section VII with a discussion of the broader relevance of our findings.

I. Related Literature

This paper relates to three strands of literature that have examined electricity pricing from different perspectives. The first concerns itself with the central challenge of natural monopoly pricing: minimizing deadweight loss while ensuring the recovery of average costs (Brown and Sibley 1986, Kahn 1988, Braeutigam 1989, Borenstein 2016). Here the main concern has been the inclusion of fixed and sunk costs in volumetric prices, potentially driving prices above marginal cost. Various solutions have been proposed and at least partially implemented, including price discrimination with linear tarrifs (Ramsey 1927, Boiteux 1960, Boiteux 1971), two-part pricing (Feldstein 1972, Littlechild 1975), and more sophisticated nonlinear pricing (Wilson 1997, Laffont, Rey and Tirole 1998). Yet, despite a plethora of complex rate structures in use, there is a general perception that utility rates do not closely approximate (private) marginal costs (Friedman 1991, Puller and West 2013). In closely related papers, Davis and Muehleggar (2010) estimate marginal tariff rates for natural gas utilities and find that they do not adjust fully to fluctuations in wholesale gas supply costs, while Borenstein and Davis (2012) examine the equity effects of these departures from marginal cost pricing of natural gas and discuss the potential equity and efficiency effects of changing fixed charges. We are not aware of any comprehensive effort to measure the departure from marginal cost of retail electricity prices.

A second literature on electricity pricing is concerned with the variation of costs over time, particularly those driven by scarcity or capacity constraints. Early theory focused on forms of peak-load, or capacity, pricing that could at least partially capture scarcity effects in otherwise static tariff structures(Boiteux 1960, Steiner

1957, Joskow 1976, Oren, Smith and Wilson 1985, Crew and Kleindorfer 1976). The advent of advanced metering technology made feasible the prospect of dynamic electricity pricing (Borenstein 2005, Joskow and Wolfram 2012) that could capture scarcity costs through frequently varying linear prices. However, despite a growing literature on its practical effectiveness (Jessoe and Rapson 2014), dynamic pricing is still quite rare. As we describe below, only 4% of residential US customers are on a time-varying price, and the bulk of those customers are on static time-of-use prices. The lack of dynamic retail pricing has been widely cited as a source of inefficiency in the electricity industry (Borenstein and Holland 2005, Borenstein 2005, Joskow and Wolfram 2012, Puller and West 2013).

The most recently active strand of literature on the efficiency of electricity prices concerns their relationship with the external costs of electricity production and consumption (Cullen 2013, Graff Zivin, Kotchen and Mansur 2014, Novan 2015, Holland et al. 2016, Callaway, Fowlie and McCormick 2018). The environmental impacts of electricity supply, particularly with respect to climate change, are significant and have been the focus of policy activity for at least two decades. Environmental economists have generally advocated for the pricing of external costs, through either Pigouvian taxation or cap-and-trade systems, in this and other industries. However, alternative approaches, such as subsidies for clean energy through either tax credits or performance standards, and non-market interventions relating to energy efficiency have been more common in practice than the pricing of externalities.[1] These latter programs have been criticized by economists on several grounds.

Several papers have addressed the optimality of environmental policies with respect to consumer incentives. These studies have raised concerns about policies that limit the pass-through of externality costs. For example, the impact of intensity standards for limiting carbon emissions (Bushnell et al. 2017), the use of output-based allocation of allowances in cap-and-trade systems (Fischer and Fox 2012), and energy efficiency interventions (Allcott and Greenstone 2017). A common theme is that many "green" policies tend to promote over-consumption as they fail to properly reflect marginal environmental damages in electricity costs (Borenstein 2012). However, these papers address the design of optimal externality policies from an underlying assumption that retail prices accurately reflect private (but not social) marginal cost. To the extent that pre-existing distortions to retail prices, due to natural monopoly pricing for example, have already distorted retail prices, the optimal environmental policy can look very different from the one applied in a system with prices reflecting private marginal costs.

[1]For example, the Obama-era EPA regulatory initiative known as the Clean Power Plan offered States several options for compliance, including an intensity standard or direct subsidies of zero-carbon generation sources, as alternatives to carbon pricing (Fowlie et al. 2014).

II. Residential Electricity Pricing

The challenge in constructing data on residential electricity pricing is to accurately characterize the marginal price that a customer faces. While data on aggregate revenues and quantity sales to residential customers by utility are available, those data alone only allow inference about the average price paid by residential customers. In theory, however, customers should respond to the marginal price of electricity, not the average price. Thus, we must adjust the analysis in order to get a more accurate measure of marginal price.

Our primary source of utility sales data is the Energy Information Administration's Form EIA-861 survey (Energy Information Administration 2017*a*). The EIA-861 is an annual survey of electric utilities that covers many aspects of their commercial activities.[2] The EIA-861 data include for every utility/state annual total revenues from residential customers, total number of customers, and total kWh sold. Dividing total revenues by total kWh yields an average price.

However, many utilities have monthly fixed charges. In order to calculate the marginal price, we remove the fixed charges. The utility fixed charges for residential customers come from the National Renewable Energy Laboratory's Utility Rate Database (URDB) (National Renewable Energy Laboratory 2017*b*). The URDB is described in more detail in the appendix. It includes many residential rates for each utility. For each utility we chose what appeared to be the primary or basic rate (the process of determining this rate is described in the appendix) and took the fixed charge from that rate. We used this fixed charge to approximate fixed revenues – total customers multiplied by fixed charge – and subtracted that amount from the total residential revenues. We divided the remainder by kWh sold to get the average variable rate, which we take as our measure of marginal price.

In some parts of the country, the electricity sector has been restructured such that customers can choose their retail providers. This affects about 32% of residential customers in the US, and just under half of these actually have a retail provider that is not vertically integrated with their local distribution company. Data on sales and revenues for these customers are reported slightly differently in the EIA-861 as both the retail provider and the local distribution company report separately for their shared customers. Texas is an exception to this where only the retail provider reports. To incorporate such areas, we reformatted the EIA-861 data on sales and revenues and incorporated additional information from the Texas Public Utilities Commission (Public Utility Com-

[2]To be precise, our sample contains 2,104 utility/state combinations. Utilities report their operations separately by state to the EIA. For each utility/state combination, we calculate each measure separately for each year and then for the maps we take the average across the years for which the utility/state is in the dataset (which is 2014, 2015, and 2016 for almost all utility/states). See the appendix for further details. For simplicity, we refer to the unit of observation as a utility/state. A smaller number of major utilities are surveyed monthly, covering about two-thirds of the household customers in the annual survey (Energy Information Administration 2017*b*). In the appendix, we discuss a robustness check that we carry out using the monthly survey. We find very small seasonal changes in retail rates.

mission of Texas 2017*b*, Public Utility Commission of Texas 2017*a*). Rates for retail providers are also not available from the URDB. We therefore identified the largest retail providers in these markets and manually collected additional rate information on fixed charges directly from provider websites. Full details can be found in the appendix.

Removing the fixed component of customers' bills still does not fully capture marginal rates if those rates vary with the level of consumption, such as from increasing-block or decreasing-block pricing – under which marginal price rises or falls in steps as a household's consumption increases. Thus, some customers of a given utility are likely to have a higher marginal rate, and others a lower marginal rate, than the one we use. Based on the 1743 utilities with rates in the URDB, about 58% of residential customers are served by a utility for which it appears that the marginal price in the primary residential tariff varies with consumption, of which about 37% face increasing-block pricing and about 21% face decreasing block pricing.[3]

Similarly, we do not capture differences in static rates across customers of a utility. This occurs for most utilities because some customers are on rates targeted to low-income households. But it could also occur if a utility charges rates that vary by geographic region. It is worth noting, however, that the failure to reflect variations in marginal rates across customers that are not based on marginal cost is very likely to lead to understated estimates of the deadweight loss associated with residential rates. This is because deadweight loss increases more than proportionally with the difference between price and marginal cost. Thus, for linear pricing, if all customers have the same demand elasticity, deadweight loss is minimized by charging all customers the same linear price.

In all cases, we also have assumed that the primary residential rate had no time-varying component, including no time-of-use variation, no critical peak pricing, no demand charges, and no real-time pricing. The prevalance of these kinds of tariffs is very low among residential customers. During 2014-2016 about 4% of customers were on some form of time-varying pricing, and just under 6% of customers were part of some form of demand response rebate program.[4]

Our final dataset on residential electricity pricing covers an average of 128.2 million residential customers during 2014-2016, with average annual sales of 1.384 trillion kWhs and revenues of $174 billion. After incorporating our estimates of fixed charges we were able to calculate the average variable per-kWh price faced by just over 93% of residential customers and kWh sales.

[3]The share of *quantity* sold on non-linear pricing is somewhat smaller, as the retail providers utilizing increasing-block pricing serve smaller average residential demand per customer. Overall, providers serving larger numbers of customers are more likely to use increasing-block pricing. Of the 1743 retail electricity providers in our URDB sample, about 39% utilize non-linear marginal pricing, with about 15% using increasing-block pricing and about 24% using decreasing block pricing in their primary residential rates.

[4]The EIA-861 data that are the source of these figures do not allow one to calculate the overlap between these two sets of customers, but it is probably significant. Furthermore, a very large share of the customers on time-varying pricing are on simple peak/off-peak rates with fixed time periods and fairly small differentials between peak and off-peak.

A. *Is marginal price the correct measure?*

A number of papers, most recently Ito (2014), have challenged the belief that electricity consumers respond strictly to marginal price.[5] Ito finds that in the context of steeply increasing-block electricity pricing at two large utilities in California, consumers are more accurately characterized as responding to the average price they face, rather than the marginal price. These analyses, however, do not address the extent to which consumers are able to separate recurring fixed charges from volume-based charges.[6] Understanding and distinguishing a monthly fixed charge from volumetric pricing seems likely to be much less difficult than diagnosing which step of an increasing-block marginal price schedule the household is likely to end up on at the end of the month. Ito and Shuang (2018) is the only work of which we are aware that does address this question. They find that evidence that consumers do respond to changes in marginal prices apart from changes in fixed charges.

Luckily, for our analysis, the three large utilities in California that have steep increasing-block electricity price schedules, where the steps differ by more than 4 cents per kWh, are outliers in the US as a whole. Out of the 1743 utilities we study that are in the URDB, there are 673 with non-constant marginal price. Among those 673, the median absolute difference between the lowest and highest tier across all US utilities was 1.9 cents per kWh, with 75% of the rates showing a difference of less than 3.7 cents per kWh.

Furthermore, even in California the variation in marginal price across the steps has shrunk significantly in the last decade from a ratio of more than 3 to 1, to a ratio of less than 1.4 to 1 in 2017.[7] Nonetheless, the existence of marginal pricing that changes with consumption quantity should be recognized in interpreting our results.

B. *Residential Electricity Pricing Results*

We present many results graphically through maps of the contiguous United States with measures primarily at the ZIP Code level. Of course, nearly all utilities serve multiple ZIP Codes, so these are not independent observations. Rather, we use ZIP Codes to approximate the shapes of each utility's service territory as accurately as possible. Our primary source for this is information in the URDB on the ZIP Codes served by each utility (National Renewable Energy Laboratory 2017*a*). For utilities not included in the URDB ZIP Code lookups, we use county information from the EIA-861 and the US Census Bureau (US Census 2017*a*, US Census 2017*b*, US Census 2017*c*). The error created by imperfect matching to ZIP Codes affects only the visual presentation in the maps. The

[5]See also Shin (1985) and Borenstein (2009).

[6]The customers in Ito's sample faced increasing-block pricing, but no fixed charge.

[7]This is true for the vast majority of households. There remains a "superuser" rate that applies for usage over 400% of the baseline quantity, but that is relevant for just a few percent of households.

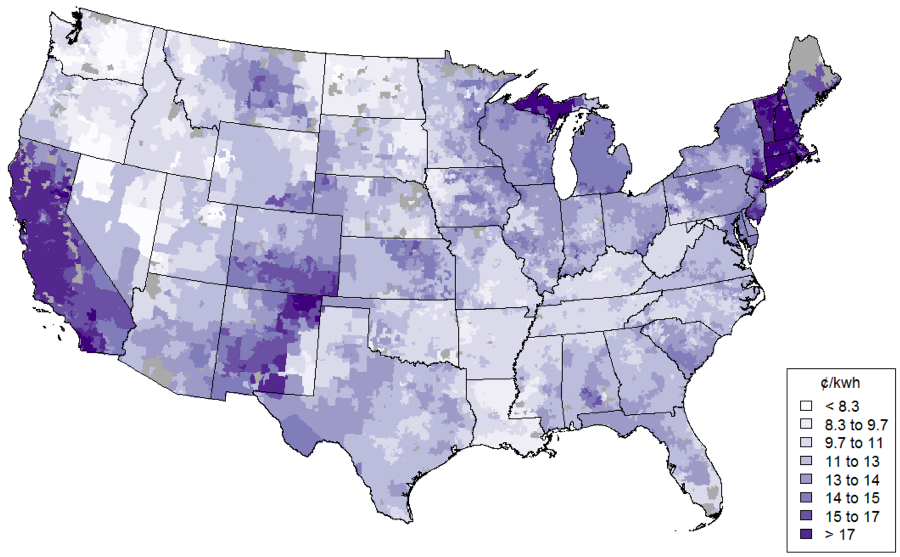


Figure 1: Average Price per kWh

other empirical analysis is by utility, so is not affected.[8]

Figure 1 presents the average price per kilowatt hour by ZIP code. (Here, and in all of the maps, areas with no data are represented by a dark gray shade, such as in northern Maine.) It shows, for instance, that California has among the highest average prices per kilowatt hour for residential customers, but that the very highest prices are in the Northeast. The lowest prices can be found in much of the Northwest and the South. It also shows that even in fairly high-priced states like California, New York, and Massachusetts, there are some areas with substantially lower prices.

Figure 2 presents monthly fixed charges as discussed above. Much of California

[8]The URDB ZIP Code assignments are based on service territory spatial data taken directly from individual utilities. However, it also appears to be the case that for many smaller utilities no such spatial data were available and so the lookups are based on the same county information taken from the EIA861 survey. Here all ZIP Codes within a county are designated as part of the utility's service territory. We have not searched the database to find all such county-level data. We also adopt the same approach of using the county-level information to fill in any remaining utilities that were not in the URDB lookups, although this is a fairly small number. In total there are 40,552 ZIP Codes in the contiguous United States as of 2016. Excluding those that have no associated area, such as large volume single site ZIP Codes (e.g. government, building, or organization addresses) we present results for 30,105 ZIP Codes, only three of which had no residential population (Environmental Systems Research Institute 2017). Of those, 40% are assigned to a single utility based on the matching described in the previous paragraph. For the remaining 60% we use the median value in any map plots.

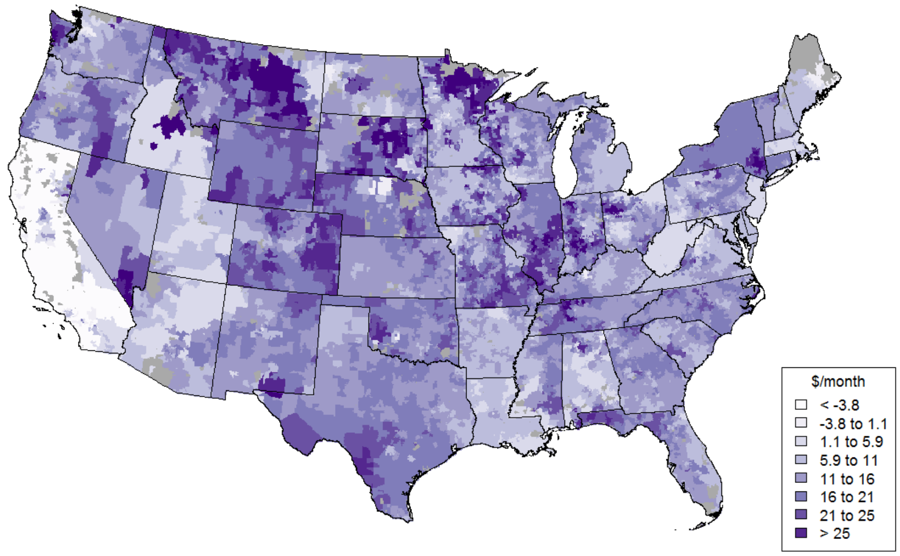


Figure 2: Fixed Monthly Charge

has zero or slightly negative fixed charges – which occurs because of a semi-annual "climate rebate" that each residential customer gets as part of the State's cap and trade program – while some utilities in the center of the country have fixed charges of $30 per month or higher.

Figure 3 shows the results from adjusting the average price for the monthly fixed charges to get an average variable price. We would expect this to be an accurate indicator of the marginal price that consumers face if the utility uses a simple two-part tariff. For those utilities that utilize increasing-block or decreasing-block pricing, as discussed earlier, this captures the average variable price across customers.[9] The average variable prices illustrated in this figure are used in our calculation of the gap between marginal price and social marginal cost.

The top panel of table 1 presents unweighted summary statistics on average price, fixed charge and average variable charge across the 6,215 utility/state years in the entire sample. The bottom panel presents the same statistics weighted by utility sales. For the maps, we calculate the statistics separately for each utility/state year it is in the data set, and then take the average of those years.

[9]How closely this reflects the average of the marginal prices faced by customers depends on the distribution of customers across the tiers of the block pricing. See Borenstein (2009) and Ito (2014) for further discussion.

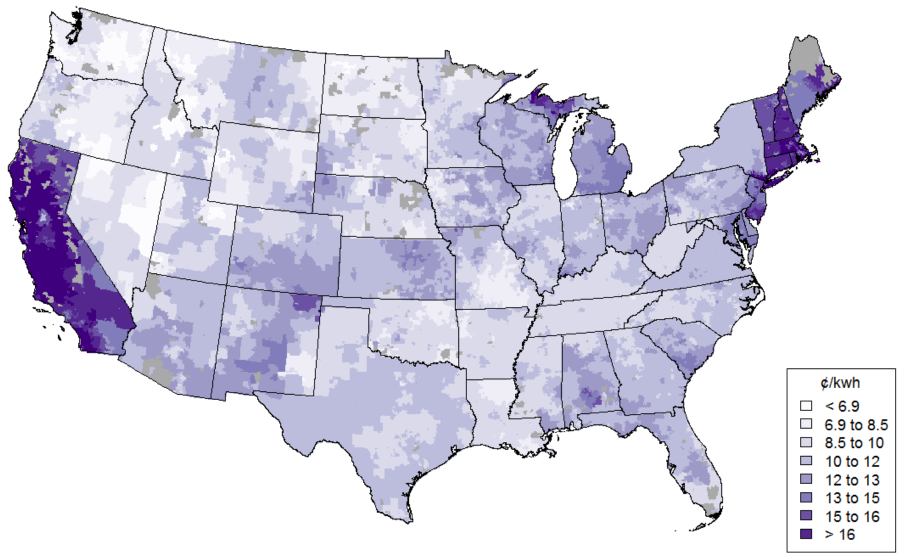


Figure 3: Marginal Price per kWh

	Mean	StDv	Min	P10	P90	Max
Retail Fixed Charge ($/month)	13.67	8.89	-26.11	4.30	25.35	75.53
Retail Variable Price (¢/kWh)	10.97	3.03	2.36	7.98	14.41	48.22
Retail Average Price (¢/kWh)	12.44	3.26	2.96	9.29	16.13	53.31
Retail Fixed Charge ($/month)	10.78	7.65	-26.11	2.53	20.00	75.53
Retail Variable Price (¢/kWh)	11.49	3.07	2.36	8.79	16.29	48.22
Retail Average Price (¢/kWh)	12.61	3.01	2.96	9.83	16.65	53.31

N=6215 (utility-state-years). Top panel is unweighted. Bottom panel is sales-weighted

Table 1: Summary Statistics of Residential Rates

III. Private Marginal Costs

Provided that wholesale electricity markets are competitive, the primary component of the private marginal cost of supplying electricity is captured in the wholesale price. We collected wholesale prices from regions that are part of Independent System Operator (ISO) control areas. ISOs calculate and report locational marginal prices (LMPs), which reflect the marginal cost of electricity generation plus high-voltage transmission congestion and losses. These prices literally represent the derivative of total system production cost with respect to a change in consumption at a given location (node), accounting for all relevant transmission, operating reserve, and unit-level operating constraints considered by the system operators.

Some parts of the country, particularly the Southeast, have large areas that are not covered by ISOs. In those areas, we collected data that grid operators are required to file to the Federal Energy Regulatory Commission as part of the FERC Form-714 survey (Federal Energy Regulatory Commission 2017). This survey includes a requirement to report the "system lambda", which is the engineering calculation of the shadow cost of changing production by one unit. Thus, ideally, it would correspond with the marginal cost, as reflected by a competitive market price, in the ISOs. In practice, however, much of the Form-714 data are obviously unreliable, exhibiting many consecutive hours of identical values and zero values where they are not plausible. As described in the appendix, we incorporate data for those areas where the Form-714 data seem to be most reliable. Nonetheless, the Form-714 data may understate the true private marginal cost, both because system lambda likely does not fully incorporate marginal transmission losses and congestion costs and because system lambdas may not fully incorporate scarcity rents in constrained hours.[10].

	Mean	Min	P10	P90	Max
CA	33.86	-150.00	17.47	52.38	1658.94
FRCC	25.87	-32.69	15.91	37.28	1043.18
MRO	25.94	-150.00	13.42	38.91	1858.24
NPCC	40.95	-150.00	13.27	76.17	1446.06
RFC	34.90	-150.00	17.95	52.66	1938.75
SERC	30.63	-150.00	17.09	41.75	2726.81
SPP	27.11	-150.00	14.97	38.43	4655.87
TRE	28.24	-110.47	15.20	40.15	4708.40
WECC	30.85	-150.00	15.28	48.07	2770.26

Weighted by Retail Sales.

Table 2: Wholesale Power Prices by NERC Region

We calculate private marginal cost based on LMP prices and/or system lambda values that are closest to the ZIP Codes served by a given utility, which should

[10]The wholesale prices in areas with ISOs are also imperfect measures, because they likely incorporate market power in some hours, although analysis by oversight divisions suggests very modest if any market power averaged over all periods (Bushnell et al. 2017). Unfortunately, comparing system lambdas to wholesale prices where they exist does not help to reveal the magnitude of these biases, because the ISOs typically report the market price for the system lambda.

allow those costs to include transmission losses and transmission congestion costs. Full details of this calculation can be found in the appendix. Table 2 summarizes the wholesale power cost, weighted by hourly consumption, by NERC region.[11] As we discuss later, average prices are below levels generally considered sufficient to cover long-run average cost of a modern combine-cycle natural gas power plant, even at today's very low gas prices. These averages, however, mask significant heterogeneity in prices both regionally and over time. When wholesale markets have experienced either scarcity conditions or high natural gas prices, wholesale prices have risen to extremely high levels. Each of our ISO based markets experienced prices in individual hours well above \$1000/MWh. This supports the viewpoint that market prices are capable of reflecting marginal costs that include significant scarcity rents when applicable, and that the relatively low average prices are reflective of a lack of scarcity, rather than a systemic suppression of wholesale price below marginal cost.

A. Distribution Losses

The private marginal costs calculated based on wholesale prices do not include the losses that occur on lower-voltage distribution lines downstream from the transmission grid. Losses from low-voltage distribution lines fall into two categories: a smaller share is attributed to "no-load" losses that occur in transformers, and a larger component is "resistive" losses that are a function of the flow on the line. No load losses are fairly constant for a utility and vary across utilities as a function of the size of their systems. Resistive losses change constantly scaling with the square of the flow on a line.[12] On average, around 25% of distribution losses are no-load with the remainder attributed to resistive losses.

A range of factors affect the magnitude of losses, including the distance electricity must be carried (approximately the inverse of geographic demand density), the density of load on circuits, the use of equipment to optimize voltage, and the volatility of demand. Demand volatility increases losses for a given average demand level due to the quadratic relationship between flow and resistive losses. Many of these factors are likely to differ between residential customers and commercial or industrial customers. Importantly, many industrial and some commercial customers take power from the distribution system at higher voltages than residential customers, which can substantially reduce the level of line losses.

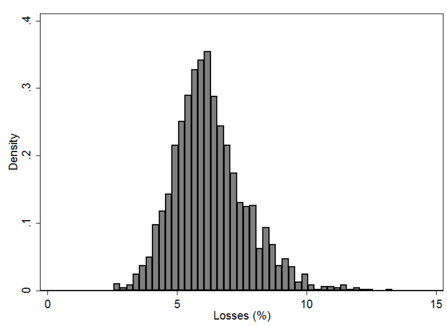
Unfortunately, the only systematic data available on distribution line losses are reported on an annual basis by utility in the EIA-861, with no breakdown by class of customers, or by hour. As we describe in the appendix, we approximate

[11] We Winsorize hourly prices at -\$150, because that is the minimum bid allowed in most ISO markets. A few observations of much lower prices appear in the data, but it is unclear whether they are data errors. Including all prices has a very small effect on average price calculations and the deadweight loss from price deviating from average SMC. But for a few utilities, extremely negative prices cause larger deadweight loss calculations from hourly SMC variation. We also did all calculations with hourly prices Winsorized at \$0, which has very little effect on any of the calculations compared to a -\$150 cutoff.

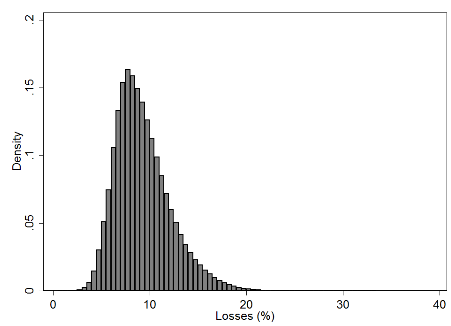
[12] Lazar and Baldwin (1997) have a very accessible discussion of distribution line losses.

hourly losses for service to residential customers by first estimating an equation for annual average losses, controlling for the factors mentioned in the previous paragraph, and then converting that average hourly rate to a time-varying hourly loss rate.

Utilizing the observable characteristics of each utility, we estimate the total annual losses for each utility attributable to residential customers. Using the standard engineering approximation that losses increase with the square of flow, we then calculate marginal losses in each hour for each utility assuming that 25% of losses are invariant to load and 75% are proportional to the square of load. The details are presented in the appendix. To do this, however, we need data on the pattern of hourly consumption by residential customers, which don't exist for most utilities. FERC Form-714 provides hourly data on total consumption of all customers from groups of utilities, known as planning areas. We use that load profile, scaled by the share of total demand that comes from residential customers, to approximate the residential demand in each hour. This is not ideal. The alternative, however, is to use data produced with an engineering model of residential energy use patterns, which also is highly imperfect. We conduct a sensitivity using engineering-model based data and it does not materially affect our results.



(a) Average annual residential distribution losses



(b) Marginal hourly residential distribution losses

Figure 4: Estimates of residential distribution losses

Distribution losses turn out to be significant in the overall analysis. Figure 4a presents the spread of average annual distribution losses from residential customers for the utilities in our analysis. Table 3 shows that on a sales-weighted basis the estimated average distribution loss rate is 6.2%. Furthermore, because the externalities associated with electricity consumption take place upstream from the distribution losses, the loss rate scales up both the private marginal cost and the external marginal cost. After assuming that 25% of losses are non-marginal and the other 75% vary with the square of load, figure 4b presents the distribution of marginal hourly distribution losses from residential service that we estimate. These average about 8.9%, but vary greatly hourly with load.

	Mean	StDv	Min	P10	P90	Max
Avg. Total Losses (%)	5.15	1.47	0.55	3.32	7.13	10.43
Avg. Res. Dist. Losses (%)	6.61	1.36	2.58	5.06	8.46	12.56
Marg. Res. Dist. Losses (%)	9.51	1.96	3.75	7.29	12.14	18.24
Avg. Total Losses (%)	4.90	1.34	0.55	3.36	6.56	10.43
Avg. Res. Dist. Losses (%)	6.20	1.26	2.58	4.84	7.84	12.56
Marg. Res. Dist. Losses (%)	8.87	1.83	3.75	6.94	11.15	18.24

N=6215 (utility-state-years). Top panel is unweighted. Bottom panel is sales-weighted

Table 3: Summary Statistics of Distribution Losses

B. Other private cost considerations

The energy costs captured by the LMP and system lambda data used in this analysis constitute the great majority of the average wholesale electricity costs that must be covered by customers over the year. The remainder is made up of capacity costs, ancillary services costs and other uplift payments. Across the seven ISOs energy costs comprised between 74% and 98% of the total wholesale cost of electricity in 2015, as shown in table 4. More detail on the source and interpretation of these costs is in the appendix.

	Energy	Capacity	Ancillary	Uplift
CAISO	89%	9%	1%	1%
PJM	74%	23%	2%	1%
ISO-NE	81%	15%	3%	1%
NYISO	74%	22%	3%	1%
ERCOT	92%	-	4%	4%
SPP	98%	-	1%	1%
MISO	95%	4%	0%	1%

Note: Percentages may not sum to 100 due to rounding

Table 4: Estimates of the composition of total wholesale costs by ISO

We do not include capacity costs in our calculation of short-run private marginal cost. In energy-only markets, such as ERCOT or SPP, there are no explicit capacity costs. In other markets that do have capacity requirements, the standards have to be adjusted in the medium or long run in response to variation in demand.

These costs can sometimes be substantial. In 2015 capacity costs comprised between 4% and 22% of the total wholesale cost of electricity at the five ISOs that make these payments. Importantly, these revenues move inversely to energy market revenues. When energy prices, reflecting short-run marginal costs, are high, capacity payments to generation implicitly or explicitly adjust to reflect the fact that resources are recovering more of their fixed costs through energy prices. In other words, capacity payments partially smooth the difference between long-run and short-run marginal cost.

The link between incremental consumption in a given hour and the capacity requirement is complex. However, conditioned upon the capacity at any point in time, the wholesale energy market price should reflect the true marginal resource cost of delivering one more kWh. Thus, from a strict economic efficiency vantage, longer-run investments triggered by current demand would not be a short-run marginal cost.[13]

We also do not incorporate short-run operating reserve, or "ancillary service", costs into our marginal cost calculation. LMPs are calculated in a process that simultaneously optimizes for meeting demand and reserve requirements. The LMP therefore already reflects the shadow costs imposed through reserve requirements. The primary marginal impact of reserves is reflected in the energy prices or system lambda values used to reflect cost. This is because most reserves operate as stand-by resources and do not incur marginal cost unless a contingency event occurs. The main cost impact of an expansion of reserves arises when lower cost units are held back to provide reserves, while more expensive units are deployed to supply energy in their place. However this effect is captured in the marginal energy price when the more expensive units set those prices. In any event, these costs are relatively small, even in aggregate. In 2015 ancillary service costs at the seven ISOs comprised between less than 1% and 4% of the total wholesale cost of electricity.

Finally, some non-convex incremental costs, such as generator "start-up" costs, that are incurred to supply energy are at times not captured in the energy price and are instead paid as "uplift" payments to specific units. We do not currently adjust our costs for these considerations. Again though, these costs are very small. In 2015 "uplift" payments range from less than 1% to 4% of the total wholesale cost of electricity.

Including all of the non-energy wholesale electricity costs would have a modest effect on the average wholesale price of electricity, and therefore on the gap between the marginal retail price and the average social marginal cost. It could, however, have a significant effect on the SMC during peak hours if reserve costs

[13] One complication to this interpretation of short-run marginal cost arises when there is scarcity of supply. When electricity systems experience short-term violations of operating constraints, such as unit ramping or transmission flow constraints, prices include penalty values to reflect the cost of the scarcity of appropriate supply. To the extent these values do not reflect the true underlying value of electricity to end-users, they are rough approximations of the short-run marginal costs in these periods. There were relatively few such periods during 2014-2016.

were considered marginal and were attributed entirely to the highest-demand hours. In that case, SMC would be more volatile than our analysis suggests and the deadweight loss of static pricing would be greater.

C. Private Marginal Cost Results

Figure 5 presents the private marginal cost calculations. Summary statistics on private marginal cost are presented in table 5 in the next section along with external marginal costs and total social marginal cost. As discussed above, these cost levels are below what many consider to be the long-run average cost of power supply. In part, that reflects the fact that much of the country had excess capacity during 2014 to 2016, and still does today, due to a combination of mistakes or bad luck in planning and policies of carrying large quantities of excess capacity. Consistent with such policies, this also reflects the fact that in most deregulated markets, power plant owners receive revenues from capacity payments as well as energy payments. Regardless of whether such capacity payments are appropriate, they do not reflect marginal cost and therefore can distort consumption when reflected in marginal consumer prices.

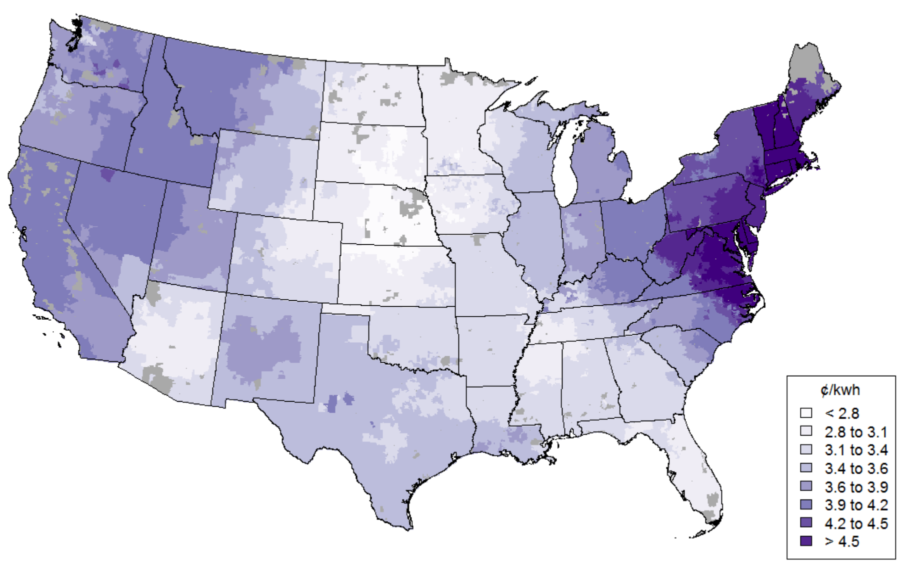


Figure 5: Average Private Marginal Cost per kWh

There is also significant variation over time in these levels. Figure 6 summarizes the average wholesale private marginal cost by NERC region.[14] During winter periods of high demand and gas prices, such as the 2014 polar vortex, prices rose to extremely high levels, raising monthly averages above $0.15/kWh in parts of the Mid-Atlantic (RFC) and northeast (NPCC) regions. This pattern reflects, on a longer time-scale, many of the issues raised in discussions of short-run dynamic electricity pricing. Marginal costs in power markets are quite volatile, even on a monthly or annual basis. The electricity industry has experienced repeated cycles where marginal costs move dramatically relative to average cost (Borenstein and Bushnell 2015), and retail prices, which are strongly linked to historical average cost, are significantly more rigid.

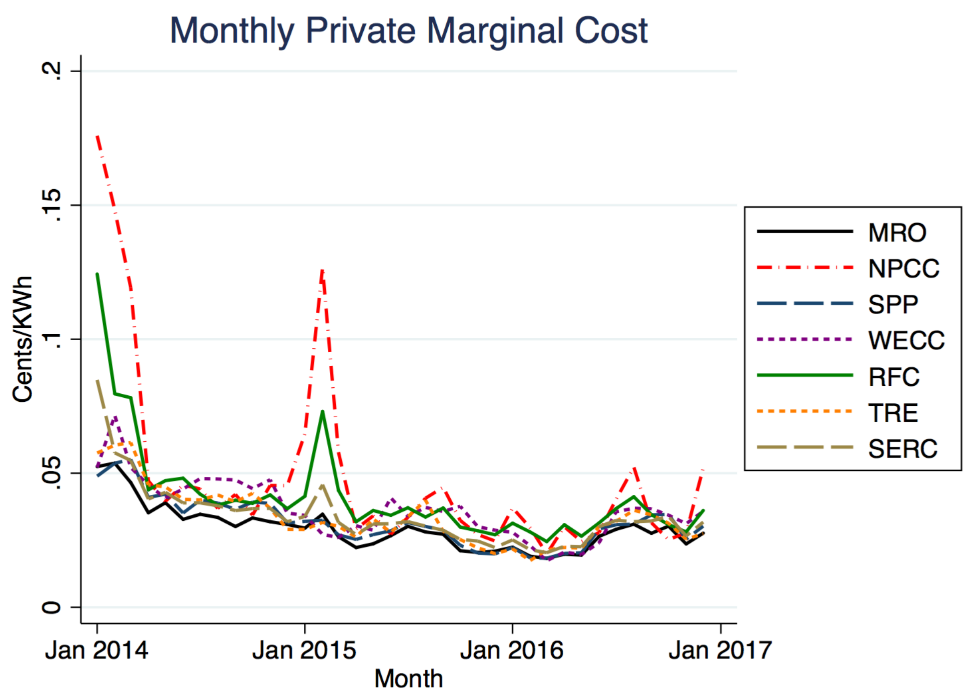


Figure 6: Monthly Private Marginal Cost by NERC Region

Wholesale prices (and implied private marginal costs) that remain for long periods below levels necessary to cover long-run average cost are certainly a concern for generators and policymakers. However, even if measured accurately, such a shortfall does not have direct bearing on our analysis of the efficiency of resi-

[14]We have combined California with the rest of the WECC and Florida (FPCC) with the neighboring SERC region in order to make the figure more readable. The regions that we combined have very similar price patterns.

dential retail marginal prices and their deviation from SRSMC. Economic theory dictates that if short-run marginal costs are indeed quite low, then efficient pricing should reflect that, even if such prices are not sufficient to cover average cost.[15] Furthermore, even if policymakers believe that additional revenue must be raised in order to cover the past investments of suppliers, such revenues need not come from marginal energy prices. Fixed charges, subscription charges (*e.g.,* based on the customer's circuit breaker capacity) and demand charges are among the alternatives that can be used to increase revenue collection without raising marginal price, though these alternatives can also create distortions.

IV. External Marginal Costs and Total Social Marginal Costs

For external marginal cost, we build on Graf Zivin, Kotchen and Mansur (2014) and Holland, Mansur, Muller, and Yates (2016), as well as the newer AP3 pollution damage model (see Clay, Jha, Muller and Walsh (2018)) to estimate the marginal damages associated with a change in load in nine U.S. regions. These regions are primarily based on reliability regions established North American Electricity Reliability Corporation (NERC). The details of the estimation are in the appendix. In brief, for each of the four major pollutants from electricity generation (CO_2, SO_2, NO_x, and $PM_{2.5}$), we create a variable that is total emissions damages by hour of the three-year sample for each of the nine regions, incorporating the operations of each fossil fuel power plant and the damages associated with emissions from each plant, based on the AP3 damage model for 2014.

We then regress each pollutant damage variable on piecewise linear functions of the load within the same region and the load in the other regions that are part of the same grid interconnect (Western, Eastern, and Texas). The regressions are estimated in 24-hour differenced form, so identification is based on the change in emissions from day to day in response to a change in load. The coefficients of these regressions can be interpreted as estimates of the marginal damage from a change in load in one region as a function of the load level in that and interconnected regions. We use these coefficients to construct the damage associated with marginal electricity consumption in each of the nine regions for each hour of the sample. We do make two small adjustment to these damage estimates. The first involves scaling up the calculations of pollution associated with a marginal end-use kWh to account for distribution losses as discussed above. The second involves adjusting down our estimates of external costs to account for any policies that incorporate externality costs into electricity prices, such as carbon cap-and-trade programs.

[15] And, conversely, if the marginal generation costs are quite high, yielding very high profits for producers (but without exercise of any market power), then efficient retail prices should reflect those high short-run marginal costs.

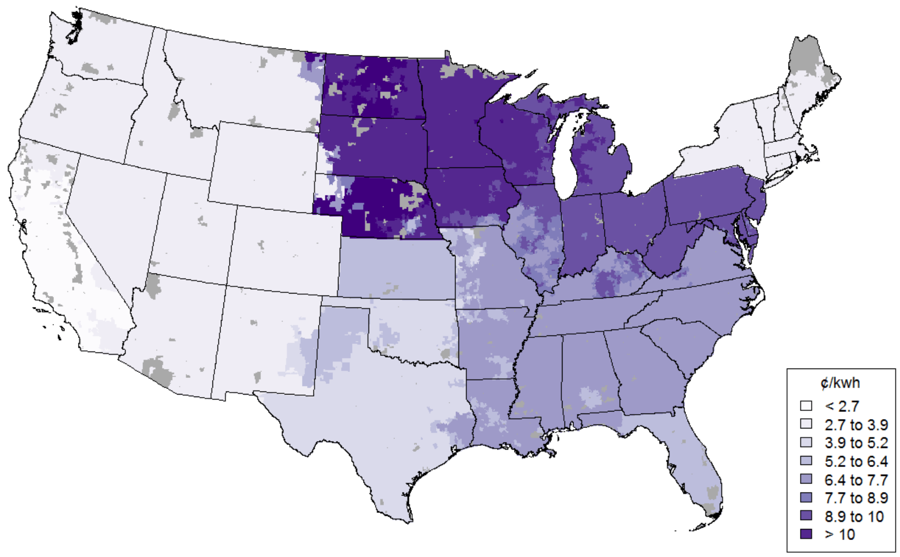


Figure 7: Average External Marginal Cost per kWh

A. External Marginal Cost Results

In figure 7, we show the average externality cost per kWh. The figure shows the average dollar-value externality cost associated with a marginal kWh of demand change in each location. The figure illustrates some coarseness in these data, because the analysis assumes that the same plants are marginal for any incremental demand within each of the nine regions for a given hour of the sample regardless of the location of the incremental demand in the region. Still, the figure demonstrates that externality costs vary widely and are particularly large in the areas where coal-fired power plants are most prevalent. Comparing the scales of figure 5 and figure 7 also indicates that the majority of the social marginal cost in our calculations in most locations is due to externalities, rather than the private marginal cost of generation.

B. Total Social Marginal Cost Results

Figure 8 then aggregates the data in figures 5 and 7 to present the social marginal cost. Though California has among the higher private marginal costs, the external marginal cost associated with that generation is much lower than in most of the U.S., causing it to have among the lowest SMCs. In contrast, the upper Midwest has low PMC, but such high EMC that it exhibits a very high

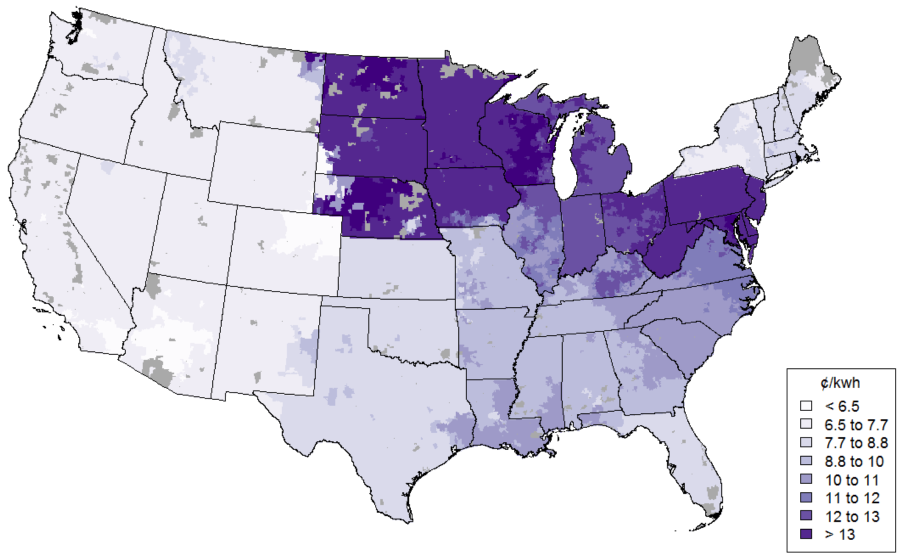


Figure 8: Average Social Marginal Cost per kWh

SMC. Table 5 shows that the average quantity-weighted social marginal cost is 9.9 cents per kWh, nearly two-thirds of which is due to external marginal costs.

	Mean	StDv	Min	P10	P90	Max
Private Marginal Cost (¢/kWh)	3.64	1.14	2.16	2.53	5.13	8.22
External Marginal Cost (¢/kWh)	7.13	2.78	2.49	3.45	11.26	12.12
Social Marginal Cost (¢/kWh)	10.77	2.88	5.14	6.68	14.45	17.71
Retail Variable Price - $\overline{\text{SMC}}$ (¢/kWh)	0.20	3.99	-9.39	-4.48	4.68	35.89
Private Marginal Cost (¢/kWh)	3.72	1.15	2.16	2.59	5.10	8.22
External Marginal Cost (¢/kWh)	6.21	2.38	2.49	3.04	9.37	12.12
Social Marginal Cost (¢/kWh)	9.93	2.67	5.14	6.51	13.72	17.71
Retail Variable Price - $\overline{\text{SMC}}$ (¢/kWh)	1.56	4.21	-9.39	-2.82	6.74	35.89

N=6215 (utility-state-years). Top panel is unweighted. Bottom panel is sales-weighted

Table 5: Summary Statistics of Marginal Costs

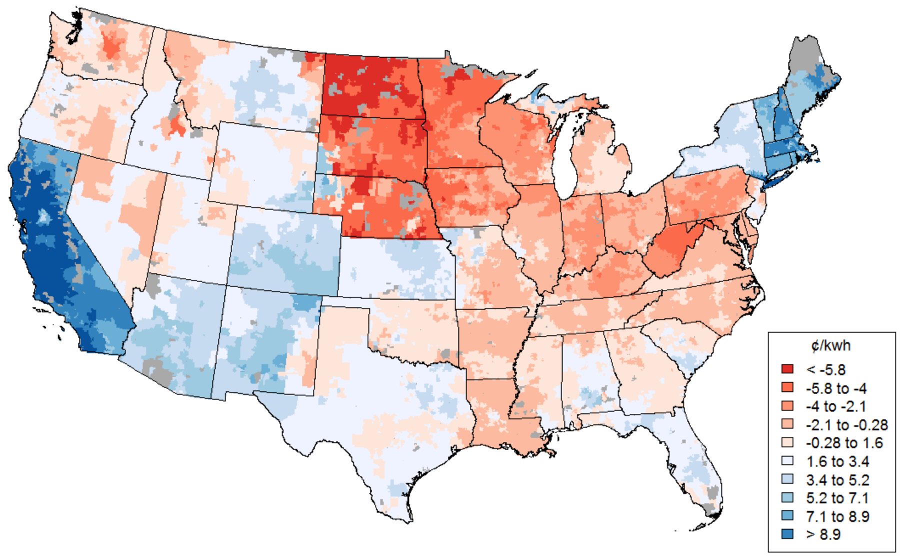


Figure 9: Marginal Price minus Average Social Marginal Cost per kWh

V. Mispricing and Deadweight Loss Decomposition

Figure 9 presents the marginal price minus average social marginal cost map. The bluer areas are pricing above average SMC, while the redder areas are pricing below average SMC. Much of the country has fairly light colors, indicating that the static marginal price that residential customers pay is fairly close to average SMC. California and parts of New England are notable for price being well above SMC, while parts of the Dakotas, Nebraska and Minnesota exhibit the largest price deviations below SMC.

Figure 9, however, captures only part of the story, because it does not include variation in SMC over time. The static price might reflect the average SMC well, but still create significant inefficiency because the SMC varies substantially hour-to-hour. Figure 10 shows histograms by state of the hourly price minus SMC, illustrating that SMC varies quite widely in some states, while it is much less volatile in others.

A. Analyzing and Decomposing Deadweight Loss

In order to incorporate the mispricing both from price deviating from average social marginal cost and from charging a static price while the social marginal cost varies temporally, we move to analyzing deadweight loss directly. In the

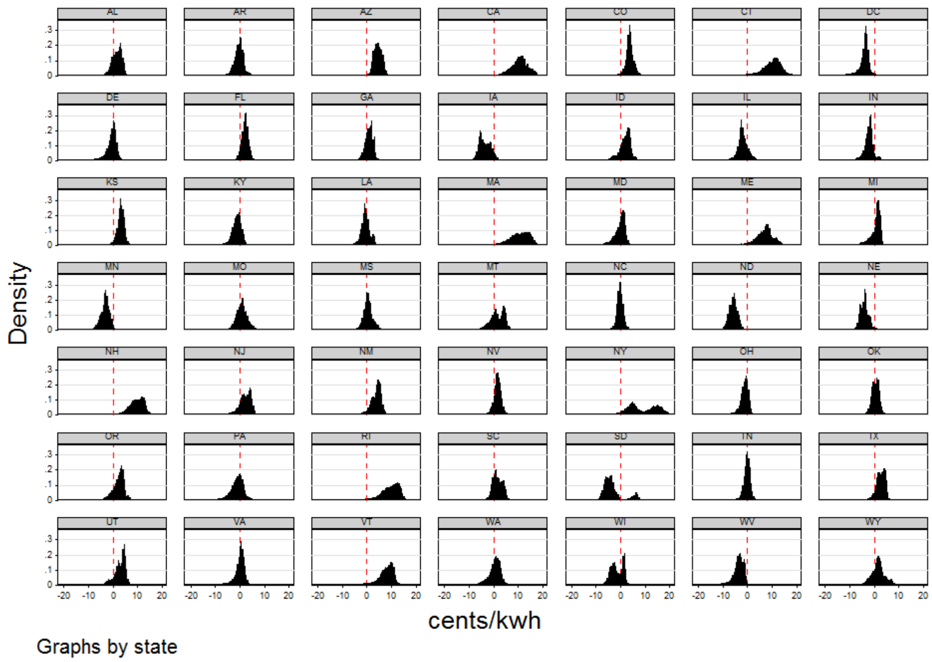


Figure 10: Marginal Price minus Hourly Social Marginal Cost by State

residential electricity market we model here, the seller charges the same price ($\bar{P}$) at all times, but SMC changes hour to hour. In the simplest model of this market, illustrated in figure 11, demand is the same in all hours and is (or can be approximated as) linear. For any hour h,

$$(1) \qquad DWL_h = \frac{1}{2}(\bar{P} - SMC) * \frac{(\bar{P} - SMC)}{s} = \frac{1}{2s}(\bar{P} - SMC)^2$$

where s is the slope of the inverse demand function, $\frac{dP}{dQ}$. So, the total DWL associated with charging a price, $\bar{P}$, is $\sum_h \frac{1}{2s}(\bar{P} - SMC_h)^2$. That is, DWL is proportional to the second uncentered moment of the distribution of $(\bar{P} - SMC)$. The result is the same if demand shifts hour to hour, but always has the same slope.

We can rewrite DWL as

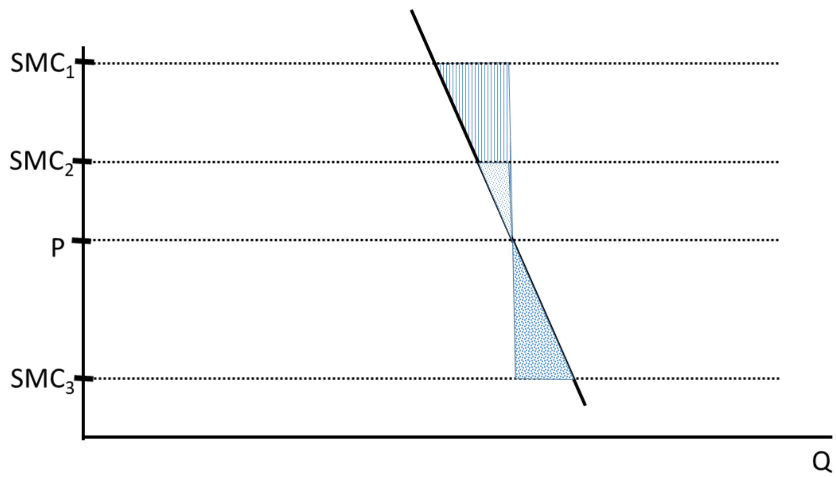


Figure 11: Illustration of Deadweight Loss in Hours with Varying SMC

$$
\begin{aligned}
(2) \qquad DWL &= \sum_h \frac{1}{2s}(\bar{P} - SMC_h)^2 \\
&= \frac{1}{2s}[H \cdot (\bar{P} - \overline{SMC})^2 + \sum_h (\overline{SMC} - SMC_h)^2]
\end{aligned}
$$

where H is the total number of hours covered by the DWL calculation. Under the assumption that s is the same for all hours, and would be the same for response to hourly price changes as to a longer-run change in the static price, equation (2) allows us to decompose DWL into the component resulting from price deviating from $\overline{SMC}$ and the component resulting from price failing to vary hour to hour as SMC changes.

Of course, a constant demand slope is not a benign, or even particularly reasonable, assumption, as it implies that the quantity response to a price change is the same regardless of the pre-change quantity. Instead, we adopt the more neutral assumption that all demands exhibits the same elasticity at $\bar{P}$, implying that the slope of inverse demand for hour h and utility i is $s_{hi} = \frac{\hat{s}_i}{Q(\bar{P}_i)}$. That is, $\hat{s}_i$ is a constant for each utility across all hours that is the slope of inverse demand per unit of quantity demanded at the utility's $\bar{P}$. Across utilities, this implies that a utility with twice as many customers would exhibit twice as much quantity response to a given change in price. Across hours, this implies that high-demand hours yield a larger quantity response to a given price change. Thus,

$$(3)\ DWL_{total} = \sum_h \frac{Q_h(\bar{P})}{2\hat{s}}(\bar{P} - SMC_h)^2$$
$$= \frac{1}{2\hat{s}}[\sum_h Q_h \cdot (\bar{P} - \overline{SMC_w})^2 + \sum_h Q_h \cdot (\overline{SMC_w} - SMC_h)^2]$$

where $\overline{SMC_w}$ is the quantity-weighted average of SMC,

$$\overline{SMC_w} = \frac{\sum_h Q_h \cdot SMC_h}{\sum_h Q_h} \quad (4)$$

We use equation (3) both to compare DWL of pricing across utilities, and to decompose the DWL into the share attributable to setting a constant price at the suboptimal level (given the constraint of charging a constant price) versus the share attributable to failing to adopt dynamic pricing.[16]

To evaluate the two components of mispricing – the deviation of average SMC from the static price and the residual volatility of SMC compared to the average SMC – we return to equation (3) and separate these two sources of deadweight loss.

$$DWL_{avg} = \frac{1}{2\hat{s}}[\sum_h Q_h \cdot (\bar{P} - \overline{SMC_w})^2] \quad (5)$$

$$DWL_{resid} = \frac{1}{2\hat{s}}[\sum_h Q_h \cdot (\overline{SMC_w} - SMC_h)^2], \quad (6)$$

where $\hat{s}$ has been defined so that the deadweight loss quantities are per unit of quantity demanded at the utility's $\bar{P}$, specifically assuming a linear demand curve with elasticity -0.2 at the utility's $\bar{P}$.[17]

Importantly, we are assuming, for now, the same price responsiveness to hour-to-hour price variation as to an overall shift in a static price.[18] As of 2018, it

[16] Borenstein and Holland (2005) show that the efficient constant price is equal to the quantity-weighted average marginal cost under the condition that demand elasticity is the same in all hours.

[17] $\epsilon = -P/Q * dQ/dP = -P/Qs \iff s = -P/Q\epsilon$. We are calculating s for a unit of quantity demanded ($Q = 1$) at $\bar{P}$ assuming $\epsilon = -0.2$, so $\hat{s} = -\bar{P}/0.2$.

[18] We are also assuming that all other goods in the economy are priced at their social marginal cost including, importantly, substitutes for electricity. That may not be a bad approximation for petroleum products, but natural gas is priced well above social marginal cost to residential customers (Davis and Muehlegger 2010, Borenstein and Davis 2012). Similarly, the welfare change from load shifting is a function of the difference in SMC at the two times and the consumer's difference in willingness to pay for the usage at the two times. Jacobsen, Knittel, Sallee and van Bentham (2016) make similar assumptions in their theoretical analysis of imperfect pricing and their application to dynamic electricity pricing. Focusing on what we term DWL_{resid}, they show that the R^2 an OLS regression can capture the share of

seems likely that actual price responsiveness is greater for a change in the static price than in response to hourly price changes. As technology evolves, however, it is quite possible that the ability to automate load shifting between hours could make the elasticity greater for response to hourly price variation.

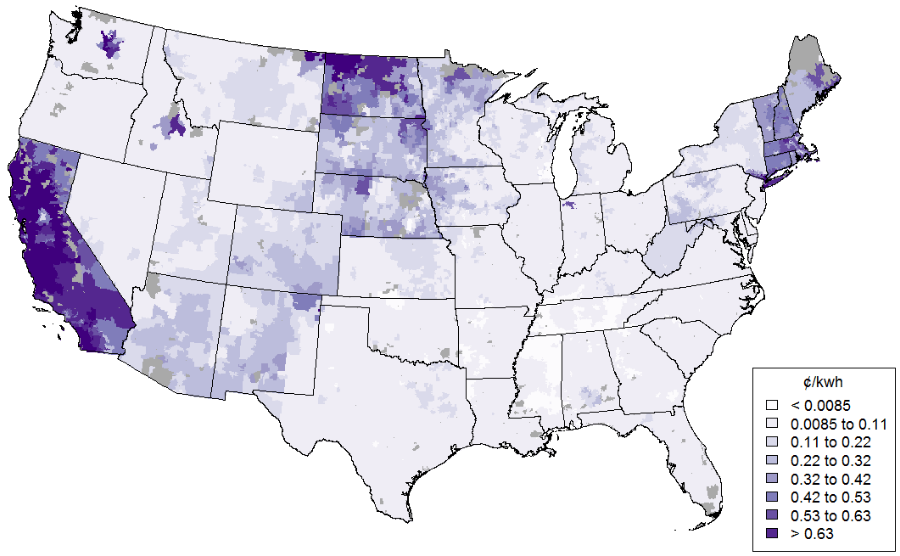


Figure 12: DWL Per Unit Demand Due to Price Differing from Average SMC

Figure 12 presents a map of DWL_{avg}. California is clearly the outlier. Though we saw that much of the Northeast has prices as high as California, the Northeast also has much higher SMC than California. While we have also seen that price is below SMC in much of the center of the country, the gaps to SMC are generally smaller than we find in California.

Figure 13 presents DWL_{resid}, the deadweight loss caused by charging a static price when SMC varies. The deadweight loss from SMC variation is most prevalent in Texas and the mid-Atlantic states, both areas with particularly volatile wholesale prices. Comparing figures 12 and 13 and their legends suggests, and table 6 confirms, that the most extreme DWL observations come from a few areas where retail price differs substantially from the average SMC, but the greater share of DWL for most utilities is from the failure to change retail price over time

deadweight loss that could be remediated through price variation that corresponds to only part of SMC variation.

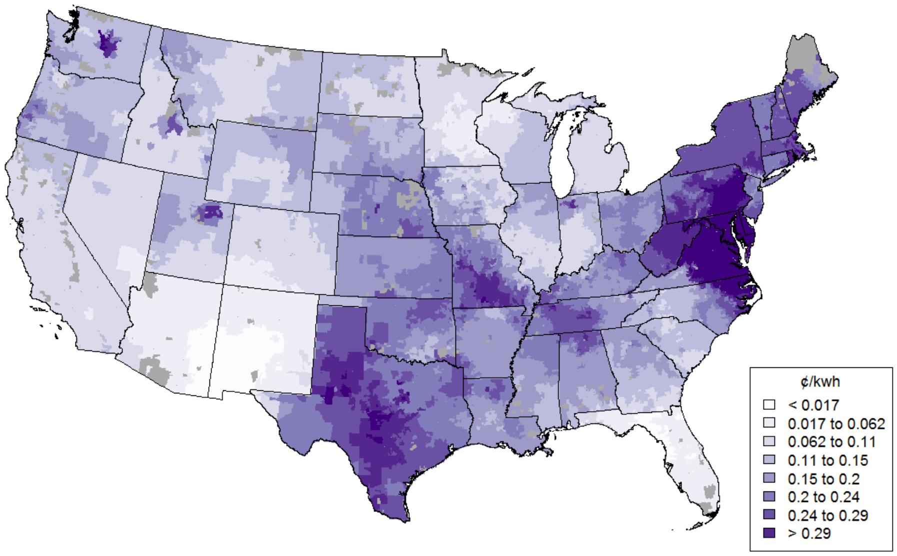


Figure 13: DWL Per Unit Demand Due to Time-Varying SMC and Static Price

as SMC varies. Again, this is under the important caveat that we are assuming the same elasticity for response to short-run and long-run price variation.

	Mean	StDv	Min	P10	P90	Max
DWL_{total} (¢/kWh)	0.31	0.30	0.01	0.06	0.68	4.57
DWL_{avg} (¢/kWh)	0.13	0.21	0.00	0.00	0.35	2.88
DWL_{resid} (¢/kWh)	0.19	0.21	0.01	0.03	0.46	1.98
DWL_{avg}/DWL_{total} (%)	35.60	30.77	0.00	0.87	82.15	98.81
DWL_{total} (¢/kWh)	0.31	0.32	0.01	0.05	0.78	4.57
DWL_{avg} (¢/kWh)	0.13	0.23	0.00	0.00	0.44	2.88
DWL_{resid} (¢/kWh)	0.18	0.23	0.01	0.02	0.44	1.98
DWL_{avg}/DWL_{total} (%)	37.36	32.26	0.00	1.24	88.10	98.81

N=6215 (utility-state-years). Top panel is unweighted. Bottom panel is sales-weighted

Table 6: Summary Statistics of Deadweight Loss Estimates Per Unit Demand

Table 6 presents summary statistics of the components and total deadweight loss per unit demand for the 2,104 utilities in the sample. It also presents the summary statistics for the ratio of DWL_{avg} to DWL_{total}. Whether weighted by sales or unweighted, the mean (and also the median, though it isn't shown) suggests that for most utilities, the largest deadweight loss is due to the failure to implement dynamic pricing, at least under the assumption of equal elasticities for all price variation.

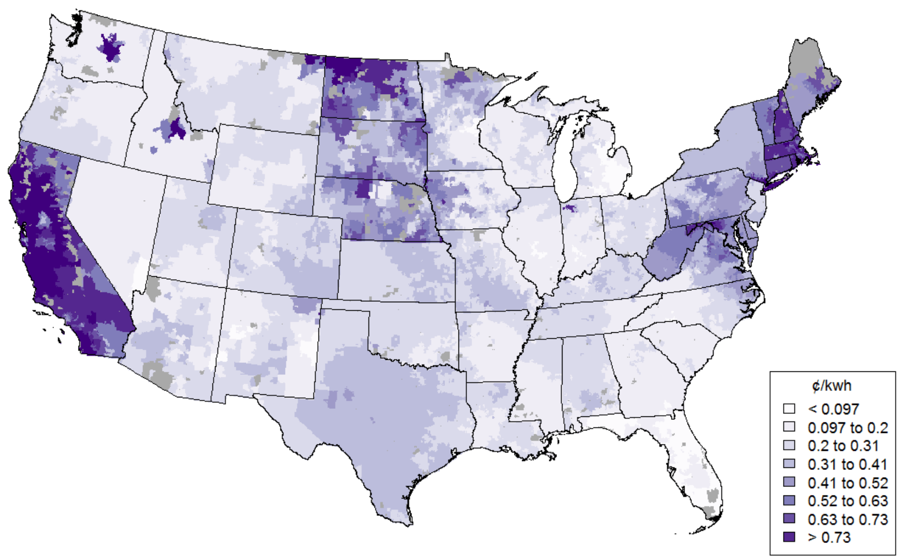


Figure 14: Total DWL Due to Price Differing from SMC

VI. Applications and Implications

Having calculated estimates of both the marginal prices and marginal social costs of electricity, we now consider some policy areas where such information ideally would be considered, and the implications of our calculation for the current desirability of such policies. One area where our calculation has potential relevance, but has received limited policy attention in the U.S., is the application of carbon pricing to the electricity sector. As discussed above, policy debates over the design of carbon pricing policies periodically invoke the Pigouvian ideal of capturing the marginal externality costs of greenhouse gasses in consumer energy prices. Mechanisms such as output-based updating of allowance allocation, and the application of intensity standards, have been criticized on the grounds that they dilute the externality cost faced by consumers ((Holland, Hughes and Knittel 2009, Fowlie 2011)).

However, if marginal prices are already well above social marginal cost, the additional externality signal only pushes prices further away from first best. It is worth noting that in the United States, carbon pricing - in the form of cap-and-trade - is currently applied to electricity only in California and the northeastern states comprising the Regional Greenhouse Gas Initiative. However, these are the collection of states where we have found average retail prices to be well above social marginal cost.

Still, it is important to recognize that our analysis focuses only on the distorted consumption incentives when residential retail price deviates from social marginal cost. We have not studied commercial and industrial rates, which are more complex, with greater use of time varying pricing and "demand charges" that determine (and distort) customer incentives. More importantly, our analysis does not consider the effect of market mechanisms for greenhouse gases and other pollution externalities on the mix of generation, between coal-fired generation, gas-fired generation, nuclear power, renewable generation and other sources. The efficiency value of pricing emissions at the wholesale level seems likely to be quite significant. Our findings, however, suggest that the argument for passing through those costs to residential rates is much weaker in some parts of the country.

Our findings also have direct implications for two other areas that have received considerable attention in the energy and economics literature: energy efficiency and distributed energy resource policy. We explore each of these in turn. We do not attempt here to perform a detailed calculation of the welfare implications of these policies, but rather present suggestive evidence that efforts in both areas may be significantly geographically misaligned with the benefits they can provide.

A. *Energy Efficiency*

The subject of energy efficiency in general, and its role in the electricity industry in particular, has been a topic of debate among economists and technologists for decades. Much of the debate has focused on whether these programs deliver the "negawatts" claimed by the utilities that implement them (Joskow and Marron 1992, Auffhammer, Blumstein and Fowlie 2008). Economists have also examined the specific behavioral, regulatory, and market channels that could justify energy efficiency policies (Allcott and Greenstone 2012, Gillingham and Palmer 2014). However, much of the literature on the "efficiency gap" has focused on what Gerarden, Newell and Stavins (2017) call the "private energy-efficiency gap" - the question of whether customers are making individually rational economic choices. They note that the more policy-relevant question of the social energy-efficiency gap hinges on many factors, including the relationship of energy prices to social marginal cost, a question they identify as a "relatively high priority" for further research. Indeed, well-informed consumers who face retail prices that are significantly above social marginal cost are already being given too much incentive to adopt energy efficiency measures. If consumers are able to make privately optimal energy-efficiency decisions, government programs to promote improved energy efficiency would be best aimed at areas where price is below social marginal cost.

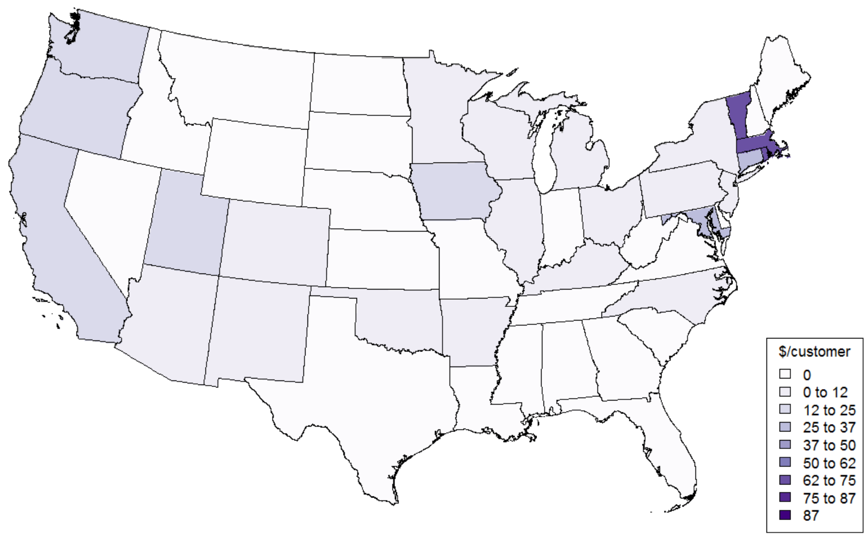


Figure 15: Electric Utility Expenditures on Energy Efficiency Programs

Several recent papers have attempted to address aspects of the relationship between energy efficiency programs and the social benefits they provide. Both Novan and Smith (2016) and Boomhower and Davis (2017) examine the impact of energy efficiency programs on the hourly profile of energy use, and compare those impacts to wholesale power costs and environmental impacts.

Using state-level data from the Consortium for Energy Efficiency,[19] we examine per-customer reported expenditures on residential energy efficiency programs.[20] This includes both energy efficiency programs run through utilities and those run through non-utility organizations, which play a significant role in New York, Oregon, Vermont, and parts of California, for instance. Other efficiency measures, such as appliance and building standards, impose costs on firms and consumers that are also not captured in these data. Still the data presented here are strongly reflective of the relative emphasis that different jurisdictions place upon energy efficiency measures. Figure 15 illustrates the regional expenditures per customer of electric utilities on energy efficiency programs. The largest expenditures are

[19]https://www.cee1.org/annual-industry-reports

[20]Our thanks to Hunt Allcott for suggesting this comparison.

focused on the coasts, with particular intensity in California and the northeast. According to our calculations, these are the regions where marginal energy efficiency expenditures provide the least, possible even negative, social value. Clearly, the distribution of spending on energy efficiency within the US is suboptimal at best.

B. *Distributed Energy Resources*

Another area of energy policy that is directly impacted by the relationship between retail prices and marginal cost is the deployment of small-scale distributed energy resources. Small scale generation resources, currently overwhelming comprised of rooftop solar photovoltaic (PV) installations, are deployed "behind the meter" and generally eligible for "net metering." When a customer's production exceeds consumption, the excess production in one hour is allowed for billing purposes to offset excess demand in other hours. In this way, residential customers with distributed generation can offset the full retail price of electricity, rather than the marginal replacement cost of the energy that is produced. Where retail variable prices substantially exceed the marginal cost, residential solar is considerably more attractive for consumers. In California, Borenstein (2017) calculates that the gap between retail and wholesale marginal electricity prices provides about as large an incentive for residential solar as the 30% federal investment tax credit.

Drawing again from the EIA Form-861, we aggregate the capacity of distributed resources that is subject to net metering by utility reporting area. Figure 16 illustrates the capacity of distributed generation (in Watts) per customer for the utility systems that report this statistic to the EIA. California, with over 40% of the residential solar capacity in the nation, again dominates this calculation.

The map reflects the union of at least three sets of attributes: significant solar incentives (*e.g.,* New Jersey), solar potential (desert southwest), and high retail prices. Comparing figure 16 to figure 10, the strong relationship between high retail prices and solar deployment again stands out. A full calculation of the welfare implications of retail tariffs on DG would require a decomposition of rate effects from other incentives, as well as estimates of the relative efficiency of solar deployment in different locations. However, figure 16 does suggest that expenditures on distributed solar are strongly associated with retail price incentives that greatly exceed the social value of distributed generation.

The deployment of distributed energy resources, and the resulting reduction in metered consumption, or "load defection" is a growing threat to the finances of distribution utilities who have been recovering capital cost though volumetric rates. Critics of small-scale DG have pointed to net-metering policies as a target for changes to rectify the situation, but net-metering policies lose their relevance if the marginal retail rate reflect social marginal cost. Recognizing this fact, utilities are increasingly seeking to adjust their rate structures to increase monthly fixed charges and reduce their volumetric prices. While not a panacea (Borenstein 2016)

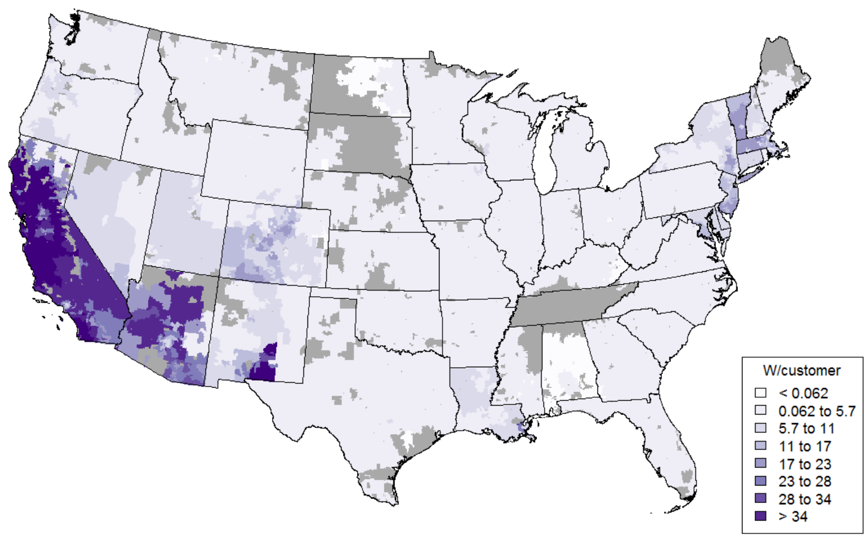


Figure 16: Installed Distributed Generation Capacity Subject to Net Metering

a shift toward larger fixed fees, particularly in states like California where they are modest to non-existent, would partially insulate utilities from the loss of customer load and reduce the marginal private reward of solar deployment for customers.

Consideration of distributed generation also raises questions of their potential impact on distribution losses and other costs associated with distribution networks, such as voltage support. As discussed above, marginal distribution losses can be significant, reaching over 20% at times, which DG could mitigate or exacerbate depending on location and timing of production. More generally, the degree to which optimized location and control of distributed resources could change the cost of distribution remains an important area of research. Collection of distribution-level data with higher temporal and locational resolution could help address these questions.

VII. Conclusion

Most policy recommendations from economists for responding to the challenge of climate change focus on "getting the prices right." But in electricity, the prices are wrong for many reasons beyond greenhouse gas emissions. In this paper, we have analyzed the direction and degree of mispricing in residential electricity.

We find that with the current generation capacity and remuneration mechanisms for generation, the short-run private marginal cost was quite low during

2014-2016, averaging less than 4 cents per kWh, which is below most estimates of the long-run average cost that generation must cover to support new investment. Estimates of the average externalities associated with generation are approximately twice the level of private marginal costs. We show that distribution-level marginal line losses significantly increase both of these costs, by more than 9% on average. Accounting for private and external marginal costs, and adjusting for distribution line losses, we find large variation in full societal marginal cost from a (sales-weighted) 10th percentile of 6.5 cents per kWh to a 90th percentile of 13.7 cents per kWh.

Somewhat surprisingly, we find that across the country about 39% of residential sales at a time-invariant marginal electricity price are below the utility's average social marginal cost of providing electricity. But we find wide variation, with prices well above average SMC in California and the Northeast, and below in much of the Midwest and the South.

That comparison, however, captures only part of the inefficiency, because social marginal cost varies hour to hour while price does not for nearly all residential customers. We show that the full inefficiency can be decomposed into a component due to the gap between price and average social marginal cost and a component due to static pricing when SMC varies. Under the strong assumption that the elasticity of residential demand is the same for these two types of price variation, we show that for most utilities more of the deadweight loss is due to failure to capture volatile SMC. Nonetheless, the largest DWL results from a small number of utilities, mostly in California, setting prices well above average SMC.

Our findings have implications not just for standard deadweight loss analysis of consumption, but also for common related policies on residential energy efficiency and distributed generation. Many states have aggressive programs to encourage such investments, but if prices already exceed social marginal cost, the value of additional investments beyond those that well-informed individuals would already choose to make is open to question. It is perhaps not politically surprising, but nonetheless economically concerning, that we find these programs are most prevalent in areas where retail prices are already substantially above social marginal cost.

VIII. Appendix

The data used in this analysis come from a diverse range of sources. The construction of the data necessary for this analysis can be divided into the following categories:

- The annual sales of electricity to residential customers
- The marginal retail price paid by residential customers
- The location of residential customers as determined by utility service territories
- The private marginal costs of serving electricity demand
- The external marginal costs of serving electricity demand
- The hourly load shapes to distribute annual residential demand throughout the year
- The losses associated with distributing electricity from the transmission grid to residential customers

Each of these categories is covered by a section below. All results were converted to constant 2016 dollars using Consumer Price Index data (US Census 2018).

A. Residential Electricity Sales

The starting point for this analysis was the Form EIA-861 survey published by the US Energy Information Administration (EIA) (Energy Information Administration 2017*a*). This survey collects a range of valuable annual data on every electric utility in the US. Of primary interest for this work was the dataset on "Sales to Ultimate Customers" which contains annual data on kilowatt-hour sales of electricity, numbers of customers and retail revenues. These data are broken down by state, so there can be multiple entries for a single utility if it has customers in multiple states. These data are also broken down by customer class, such that the sales, revenues and customer numbers are reported separately for residential, commercial and industrial customer types.[21] There is also some other key information available through the EIA-861 including data on the ownership structure of a utility (*e.g.,* Investor Owned, Municipal, Cooperative, etc.); the various regulatory regimes each utility belongs to (*e.g.,* reliability regions or balancing authorities); the counties that are part of a given utility's service territory; and operational data such as the peak load in each utility's service territory, numbers of distribution circuits and line losses.

[21]Strictly speaking a Transportation customer class is also included, although during our analysis period this represents a negligible volume and so is largely ignored.

The analysis here is focused on residential customers, so all information on industrial and commercial customers was dropped. Only utility-state pairs serving at least some residential customers were retained. The analysis here also focuses on the continental 48 states and the District of Columbia because the necessary private and external marginal cost data are not available for Hawaii, Alaska or the US territories. We also opted to drop the very small number of utilities that were classed as "Behind the Meter" as we are interested in comparing residential customers receiving a standard electricity service throughout the US.

Finally, the data were reformatted to appropriately deal with the different ways that residential customers receive their electricity. Roughly 85% of customers still receive their electricity through a vertically integrated utility that provides "bundled" service. This means the utility that is procuring the electricity that customers consume is also the company that owns and operates the distribution network that delivers the electricity to customers homes. However, in some states the electricity sector has been restructured such that customers can choose their electricity provider. In this case the service has been "unbundled" such that one company provides the electricity procurement service (*i.e.,* the "energy" service) and another company distributes the electricity to the customer (*i.e.,* the "delivery" service). The company providing the energy service is subject to competition from other providers, and will be referred to here as the "retail choice provider". The utility providing the delivery service continues to be a public or regulated monopoly and will be referred to hear as the "local distribution company". Various states take different approaches to handling which of these two entities is in charge of the other aspects of electricity service, such as billing and customer service. Roughly 32% of customers have the option to receive their electricity this way, although only about half of these actually do have a retail provider that is not integrated with their local distribution company. A large number of these customers are concentrated in a few states such as Texas, Ohio, Pennsylvannia and New Jersey.

To ensure these customers can be correctly incorporated into the analysis, the data were reformatted such that each entry had a "delivery" utility and an "energy" utility. For vertically integrated utilities providing "bundled" service these two entries were the same. For customers recieving "unbundled" electricity service these two entries would necessarily differ. Unfortunately, the EIA-861 data do not include information on how a given retail choice provider's customers and sales are divided among the various local distribution companies that are providing delivery-only service in a given state. As such, new entries were created for all possible state-by-state combinations of retail choice providers and local distribution companies. The sales and customer numbers were then allocated proportionally. In the limited cases where we had prior knowledge about the operations of a retail provider this was included before any proportional allocation.[22] Where there were discrepencies between the state totals for energy-only

[22]For example, Marin Clean Energy is effectively a retail choice provider in California and there are

and delivery-only customer numbers and sales the convention was adopted that the energy service totals were correct and the delivery service totals were re-scaled accordingly. In general any discrepencies were relatively small and likely due to errors in reporting.

One final wrinkle in completing this reformatting was the approach taken to reporting in the EIA-861 by utilities in Texas. Unfortunately, the Texas utilties do not break out their reporting between "energy" and "delivery" service. Instead, the retail choice provider reports the sales, customer numbers and revenues as if they were providing a complete "bundled" service. This also means that the six local distribution companies that offer delivery services to the retail choice providers in Texas do not report any information in this part of the survey.[23] To remedy this and make the data for Texas consistent with the other retail choice states, additional data were collected from the Texas Public Utilities Commission on the residential customer numbers, sales and revenues for these six missing local distribution utilities (Public Utility Commission of Texas 2017*b*). These data were then matched with the retail choice providers using the same proportional allocation process used for the other retail choice states.

B. Residential Marginal Retail Prices

Once the EIA-861 data were collected and reformatted, it was then straightforward to calculate the annual average retail price paid by every residential customer. To do this, total revenues were divided by total kWh sales to get the average cents per kWh price. However, this is almost certainly not a good reflection of the marginal retail price faced by each customer for three reasons. First, electricity tariffs are usually designed as two part tariffs, with a fixed monthly charge and a variable per-kWh charge. Because fixed charges are so prevalent and can comprise a substantial portion of customers' bills, simply using the average price would overstate the marginal rate customers actually face. Second, for many utilities, there is variation in the variable per-kWh price customers pay even after accounting for fixed charges. The most common reason is that the per-kWh price a customer pays depends on the amount that a customer consumes (i.e. tiered rates where prices increase or decrease in discrete blocks of cumulative consumption). Less common reasons are that the price may very by time of day (*i.e.,* "time-of-use" or "dynamic" pricing), or time of year (*i.e.,* seasonal pricing where winter and summer rates differ). Third, the structure of retail tariffs themselves are also not static over time and are updated as utilities' new regulatory cases are approved, as changes in certain costs are automatically passed through to

three local distribution companies that provide delivery service in the state: Southern California Edison, San Diego Gas & Electric and Pacific Gas & Electric. However, Marin Clean Energy's operations are limited to Marin County and nearby counties, so delivery service is only provided to its customers by Pacific Gas & Electric.

[23]These six utilities are Oncor Electric Delivery Company LLC, CenterPoint Energy, AEP Texas Central Company, AEP Texas North Company, Texas-New Mexico Power Company and Sharyland Utilities LP.

customers or as retail choice providers alter their tariffs in an effort to win new customers.

To deal with fixed charges, we have collected information on the retail tariffs actually offered by utilities and extracted the monthly fixed charges. Our main source for this information is the National Renewable Energy Laboratory's Utility Rate Database (URDB) (National Renewable Energy Laboratory 2017*b*). This is an open-access repository for rate structure information for utilities operating in the US. The fixed charges for residential tariffs active during our analysis period were extracted, and the utility names were cleared up so that their corresponding identifiers and states matched those in the EIA-861 data. At the time of writing, the URDB only contained tariffs for utilities providing "bundled" service. This presented us with a similar challenge to the EIA-861 data in dealing with the roughly 15% of customers with a retail choice provider that differs from their local distribution company. To resolve this, we manually collected additional fixed charge information for the largest retail choice providers in the states with substantial numbers of retail choice customers (Public Utility Commission of Texas 2017*a*).[24]

Once we had finished collecting all the necessary data on fixed charges we found that it was almost always the case that a given utility operating in a given state had many different tariffs. The average fixed charge paid by a given utility's customers must therefore be some weighted average of the fixed charges in each of these tariffs, with the weights determined by the number of customers on each tariff. Unfortunately we know of no comprehensive data source that could give us this breakdown of customers by tariff. As such we summarized the fixed charges in these tariffs by identifying the standard tariffs that were most likely to have many customers on them, as compared to the more niche non-standard tariffs that few customers were likely to be on. We did this by searching for keywords in the names of the tariffs. Tariffs containing words like "vehicle", "solar", "medical" or "three-phase" were identified as non-standard. This tended to leave us with a set of more standard tariffs with names containing words like "default", "residential" and "general". Full details of the keywords used can be found in the accompanying code. Once these standard tariffs had been identified, we took the median, giving us a single estimate of the residential fixed charge for each utility-state pair. We considered other approaches to combining these (e.g. mean or mode), but this did not significantly affect our results. It was also often the case that utilities had similar or identical fixed charges on many or all of their tariffs. Once this exercise was complete, these rates were matched with the utility-state pairs in our reformatted version of the EIA-861 data. At this point it was now possible to estimate the second part of the two part tariff - namely the average variable per kWh price. To do this the fixed charge was multiplied by

[24] In collecting these data we sought to capture whether the fixed charges offered by a given retail choice provider varied depending on the local distribution company whose service territory their customer was located in. In general though we found very little evidence of utilities having much variation in their fixed charges for this reason.

the number of customers to get fixed revenues, these were subtracted from total revenues to get variable revenues, and these were then divided by total kWh sales to get the average variable cents per kWh price.

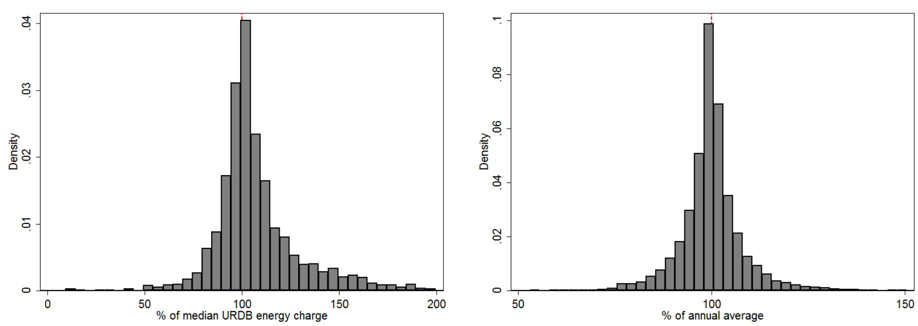
The second issue in identifying the marginal retail price was dealing with the fact that utility tariffs often do not contain just a single flat per-kWh variable price. This could mean that the average variable per kWh price calculated using the fixed charge information described above does not reflect the actual marginal price paid by customers. The URDB does in fact contain some information on the structure of the per kWh prices in each tariff (e.g. tier sizes and prices for increasing- or decreasing-block rates, or peak vs off-peak rates and timings for time-of-use pricing). However, these data are necessarily complex, and they are less complete than the fixed charge information we had already extracted. As already noted, these data also don't cover retail choice providers, so significant additional manual collection would be required to make these data complete. Furthermore, to properly use this information we would need to know both how many customers are on each tariff and the consumption patterns of the customers on each tariff. As was noted before, we know of no comprehensive source of these data, and to the extent that these data are held by individual utilities it is almost certainly confidential.

Thus, we have opted here to conduct the analysis assuming that all utilities charge a single flat variable per kWh price. While this is obviously not strictly true, we believe it is not an unreasonable assumption for the purposes of our analysis. To investigate this, we conducted the following robustness checks. First, we compared our derived estimates of average variable per-kWh prices with the \$/kWh energy charges recorded in the URDB. Where rates had multiple energy charges (e.g. for tiered or time-varying rates) we conducted our comparison against the median. Figure 17a indicates that our estimates do broadly match up with the rates recorded in the URDB. Second, to look at the issue of variation in prices due to seasonal factors changing flat or tiered rate structures we calculated monthly estimates of the variable per kWh rate. To do this we used the EIA-861M survey which is a monthly version of the annual EIA-861 survey that covers a sample of the complete population of utilities (Energy Information Administration 2017*b*).[25] Figure 17b suggests that the variation is likely to be fairly small, and given the cost drivers and regulatory arrangements in the electricity sector, it is unclear whether accounting for more frequent retail rate changes would align retail rates with contemporaneous marginal cost more closely. Third, to look at the issue of hourly variation in prices during the day we examined evidence from the "Demand Response" and "Dynamic Pricing" sections of the EIA-861 survey. These sections provide data on the numbers of customers participating in demand response programs or subject to some form of dynamic pricing tariff. We find that around 4% of residential customers in the US are on tariffs

[25] In 2015 the EIA-861M contained information on utilities accounting for 67% of residential customers and sales.

with time-varying prices. This includes time-of-use, real time, variable peak and critical peak tariffs. Demand response programs are also limited in scope with less than 6% of customers enrolled in a demand response rebate program during 2014-2016. There is also likely substantial overlap in the customers exposed to these two forms of price variability. Roughly three quarters of the customers on tariffs with time-varying prices or in demand response programs are served by the same set of 96 utilities.

A closely related issue for many utilities is that a share of customers are on low-income rates, which in many cases are lower marginal rates than the standard tariff. Our analysis captures the average variable payment (assuming that we have correctly characterized the fixed charges), but it is possible that some customers pay a higher marginal rate and others pay a lower marginal rate. We are not able to capture such variation in marginal rates across customers. It is worth noting, however, that because DWL increases with the square of the price deviation, such variation would almost certainly mean that our analysis understates the deadweight loss associated with marginal rates deviating from average SRSMC.



(a) Correspondence between estimated variable prices and median URDB energy charges

(b) Variability in monthly variable per kWh retail prices relative to the annual average

Figure 17: Robustness of use of constant variable charge

C. Utility Service Territories

To match up our data on retail rates with information on social marginal costs, we had to represent the spatial distribution of residential customers. For this we used information on the service territories of the local distribution companies that distribute electricity to end consumers.

Our main source for this was a lookup file provided as part of the URDB (National Renewable Energy Laboratory 2017*a*). This provides a list of ZIP Codes served by each local distribution company. These lookups were created using a proprietary set of shapefiles detailing the actual service territories of major electric utilities, which were converted to a list of ZIP Codes falling within those service territories. Unfortunately the ZIP Code lookups did not cover all the utilities in our dataset. To fill in any gaps we relied on the "Service Territory" section in the EIA-861 survey. This provides a list of counties served by each local distribution company. For consistency these were converted to ZIP Code lookups by assuming any local distribution company serving a given county also served all the ZIP Codes in that county. Our spatial data on US ZIP Codes were downloaded from Environmental Systems Research Institute and included polygons for 30,105 ZIP Code areas, and central coordinates for the full universe of 40,552 ZIP Codes (Environmental Systems Research Institute 2017).[26] These data were used as they were more comprehensive than the Zip Code Tabulation Area data available from the US Census Bureau.

To increase the accuracy of our geographic allocation of residential customers within a given service territory we also collected data on population counts by ZIP Code. The vast majority of these data were from the ESRI spatial data we downloaded, as this also included estimates of population for each ZIP Code based on ESRI's analysis of US Census Bureau data. However, there were a few ZIP Codes where the population data were missing but where we were confident that people lived. To remedy this, county-level population data were downloaded from the US Census Bureau, along with spatial data on US counties and a set of lookups from counties to ZIP Codes (US Census 2017*a*, US Census 2017*b*, US Census 2017*c*). The ZIP Codes with missing data were then assumed to have a population density equivalent to the county they belonged to. Missing ZIP Code population counts were then calculated as the county-level population density multiplied by the ZIP Code area.

It is important to emphasize that the matching of utility service territories to ZIP Codes, or counties, affects only the construction of the maps shown in the results. It does not affect any of the summary statistics by utility, or the calculations of deadweight loss and its decomposition.

D. Private Marginal Costs

The primary source of the data for calculating private marginal costs was the price information provided by the seven major US Independent System Operators (ISOs).[27] These are Electric Reliability Corporation Texas (ERCOT), the New England ISO (ISO-NE), the New York ISO (NYISO), the California ISO (CAISO), the Southwestern Power Pool (SPP), the Midcontinent ISO (MISO) and the PJM Interconnection (PJM). Each of these manages the operation of the electricity transmission grid over a large geographic area, most encompassing multiple states. These organizations calculate wholesale locational marginal

[26] The latter is larger because it includes ZIP Codes that have no associated area such as post office box ZIP Codes and single site ZIP Codes (e.g. government, building, or large volume customer).

[27] Strictly speaking some of these, such as PJM, are classed as Regional Transmission Organizations (RTOs) but for the purpose of this paper the distinction is largely immaterial, so we refer to all as ISOs.

prices (LMPs) for major locations in their covered territories, reflecting the value of electricity supplied at different points in the power grid. Each ISO has LMPs for thousands of pricing nodes within their system, such that across all seven ISOs there are in excess of 30,000 nodes with hourly price data available.[28] We did not consider it necessary to utilize data from all these nodes in our analysis. This was in part because prices at nodes located very close to one another are usually very highly correlated, so selecting a smaller number should still allow us to create a sufficiently robust picture of the main spatial and temporal variation. In light of this we selected a total of 157 key LMPs. All of these were aggregated "zonal" LMPs that represent averages of many individual nodal prices. In selecting these we were also mindful that different nodes can refer to a range of important locations in the power grid, such as power stations, load substations or major interconnection points with neighboring systems. Wherever possible our selection focused on zones that were aggregates of load nodes or were used by regulators in their determinations of utilities' wholesale costs for supplying their customers. This clearly fits with our interest in finding the marginal cost of serving residential customer demand. These data were downloaded from SNL Financial (SNL Financial 2017*b*). This is a proprietary source of financial data and market intelligence and includes a convenient centralised database of LMP data from all seven ISOs.[29] All data were converted to Eastern Standard Time (EST) for consistency.

These seven ISOs cover large parts of the US. However, their coverage is not complete and they are most notably absent from the most of the Southeastern U.S. To remedy this and provide a secondary source of corroborating data we also used data from the Federal Energy Regulatory Commission's Form-714 survey (Federal Energy Regulatory Commission 2017). This survey collects data from electric utility balancing authorities (or control areas) in the United States. The seven ISOs are also classed as balancing authorities, so their aggregate system-wide data appear in the FERC-714 data. Importantly though, balancing authorities also include approximately 200 additional utilities and regulatory entities that undertake a similar electricity system operation role. This includes major utilities in the Southeastern U.S. The FERC-714 data used are the hourly system lambda data. Here respondents are supposed to report hourly values of the incremental cost of energy in their system. In principal this seems ideal. In practice, a check of the data reported by the ISOs shows that ISOs simply report LMPs as the system lambdas at various locations. Unfortunately, visual inspection of the system lambda data provided by the other balancing authorities reveals a range of suspect data, including respondents providing no data, respondents providing all zeros, respondents providing data that remain unchanged over long periods, and respondents providing data that differ substantially from LMPs at nodes in

[28]Often pricing data are available at even finer temporal resolutions (*e.g.,* 15 minute) but for this analysis we have used hourly data as they are consistently available across all seven ISOs.

[29]It should be noted that these data are freely available directly from each ISO. We have opted to utilize SNL Financial's database purely due to ease of accessing and compiling the data.

nearby ISOs. To deal with these weaknesses in the system lambda data, each series was individually inspected to determine if it was sufficiently robust to be included. This left just 19 balancing authorities (besides the seven ISOs) with reliable system lambda data. Fortunately this still included a number of balancing authorities in Southeastern states such as Florida and Alabama. As with the ISO data, all series were converted to EST for consistency. Unfortunately the quality of the reporting of time zones and daylight savings for these data is often unreliable such that it is not always clear what time format these data are in. In some cases respondents even left the time zone section blank. Where there were clear errors or gaps we sought to identify the reporting time zone and the presence of daylight savings by visual inspection and the location of the reporting entity. We then manually corrected for this and adjusted to EST as appropriate. Lastly, the system lambda data do not account for transmission losses, while LMP data implicitly do. To remedy this all system lambda prices were increased by an assumed transmission loss rate of 2%.

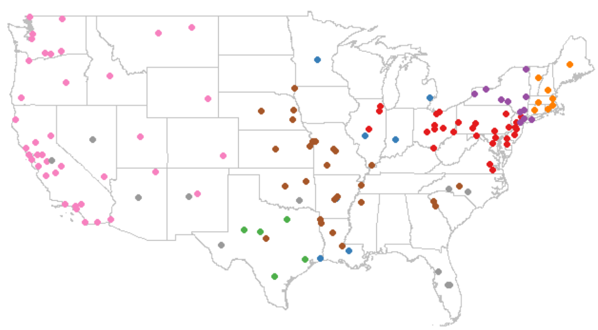


Figure 18: Locations of ISO zonal price points and Balancing Authority area system lambdas in 2015

Once the ISO and balancing authority data had been collected, we next sought to use these data to calculate hourly ZIP Code level estimates of the marginal private costs of supplying electricity. We chose to do this at the ZIP Code level because our intention is to combine these outputs with the EIA-861 data described earlier, and as mentioned in the previous section, our representation of utility service territories is based on ZIP Codes. To begin this process of creating ZIP Code-level prices we first had to determine where each ISO zone or balancing authority area was located. Unfortunately, we were unable to get access to the necessary spatial polygon data files detailing the areas covered by the ISO zones. Instead SNL Financial were able to provide us with a list of coordinates they use to represent the location of each ISO node, including the zonal nodes we had chosen for this analysis (SNL Financial 2017*a*). Strictly speaking, the ISO zonal nodes are themselves representing many individual nodes, but for our purposes the central coordinates of these zones are likely sufficient. For consistency we also represented the locations of the FERC-714 balancing authorities using the central coordinates of their respective network areas. These coordinates were calculated using the polygon centroid from spatial data on electricity balancing authorities downloaded from the Homeland Infrastructure Foundation-Level Data website, which is part of the US Department of Homeland Security (Department of Homeland Security 2017*a*). These spatial coordinates can be seen in Figure 18.[30] Once these had been collected we calculated the distance to each ZIP Code centroid.[31] The price for each ZIP Code was then calculated as the inverse distance-weighted average of the prices at the three closest price nodes.[32]

Average wholesale electricity costs are made up of energy costs, capacity costs, ancillary services costs and other uplift payments. Our use of LMP and system lambda data captures the energy cost component. Table 4 shows the relative contributions of each of these four categories across the seven ISOs (Electric Reliability Council of Texas 2015, California Independent System Operator 2016, Independent System Operator New England 2016, Midwest Independent System Operator 2015, New York Independent System Operator 2016, PJM Interconnection 2016, Southwest Power Pool 2016).[33]

The end product of the private marginal cost data collection process was a dataset of hourly estimates for each US ZIP Code. These data were then merged with the reformatted retail rates data using the information on the ZIP Codes served by each local distribution company. The hourly price assigned to a utility-state was an average of each of the ZIP Code prices, weighted by the total population of each ZIP Code.

[30] The figure depicts selected price points for ISO-NE (orange), NYISO (purple), PJM (red), MISO (blue), SPP (brown), ERCOT (green), CAISO (pink) and FERC planning areas (grey).

[31] This was done using the geodesic on a WGS84 ellipsoid to properly account for the curvature of the earth.

[32] Prior to calculating these averages we winsorized any extermely negative prices at a cutoff of -\$150/MWh. This only affected prices at a few nodes in a small number of hours and was done to avoid the calculations of deadweight loss being distorted by unusual outliers.

[33] These values are taken from the annual reports of each ISO. The one exception to this is capacity costs in the CAISO. Capacity payments in California are primarily agreed through bilateral contracts overseen by the CPUC's Resource Adequacy program, so do not show up as capacity costs levied by the ISO. To account for this we have calculated capacity costs using data from the CPUC's Resource Adequacy Report (California Public Utilities Commission 2015). This yields an additional capacity cost of approximately \$4/MWh, or approximately 9% of total wholesale costs.

E. External Marginal Costs

The data on marginal pollution damages are from the AP3 model (see (Clay et al. 2018)). This is an updated version of the AP2 model used in Holland, Mansur, Muller, and Yates (2016). The data contain estimates of the environmental externality costs in \$/ton marginal damages from four pollutants associated with the generation and supply of electricity: particulate matter (PM), nitrogen oxides (NO_x), sulphur dioxide (SO_2) and carbon dioxide (CO_2). There are different values of damages for emissions within each county. Baseline damages assume pollutants are emitted at a height of 200-500m. This is classed as a "medium" height in the model and is in line with the smoke stack height for most fossil fuel power plants. The dataset also then has individual plant-specific marginal damage values for a small number of large power plants that have "tall" smoke stacks.

The data on power plant emissions are from the Environmental Protection Agency (EPA) Continuous Emissions Monitoring System (CEMS) (Environmental Protection Agency 2018*a*). The data are comprised of hourly emissions of NO_x, SO_2 and CO_2 from large stationary sources. For our purposes this includes more than 90% of the fossil fuel power plants in the US. As well as emissions, the CEMS data also include hourly information on fuel energy inputs and electricity generated. These data do not include hourly emissions of PM. To resolve this we follow an approach suggested by Holland, Mansur, Muller, and Yates (2016). We use annual total emissions data by power plant from the EPA's National Emissions Inventory (NEI) (Environmental Protection Agency 2018*c*). We divide annual PM emissions by annual fuel energy inputs to get a PM emissions rate for each power plant. We then use the hourly fuel energy inputs information in the CEMS data to calculate hourly PM emissions, thereby assuming the annual rate is constant throughout the year. To match plants to counties and NERC regions we use plant characteristics data from EPA's Emissions & Generation Resource Integrated Database (eGRID) (Environmental Protection Agency 2018*b*).

The data on hourly load are from the FERC-714 survey described earlier (Federal Energy Regulatory Commission 2017). It contains hourly load data for planning areas in the US. These planning areas have a regulatory responsibility to ensure resources are available to meet customer load. There is considerable overlap with the balancing authorities used earlier for the system lambda data. The coverage and quality of the planning area load data are much better than for the balancing authority system lambda data, resulting in 122 planning areas with usable load data. Again we converted all data to EST using the same approach as the one set out above for the price and system lambda data. We then divided the contiguous U.S. into nine regions, in line with the approach taken by Holland, Mansur, Muller, and Yates (2016). These correspond to the eight reliability regions of the North American Electric Reliability Coorporation (NERC), with the exception of the Western Interconnection region which is split into a California region and a non-California region. Each planning area was then assigned to one of the nine regions - the regions cover the Eastern Interconnection (NPCC, RFC, MRO, SERC, SPP, FRCC), the Western Interconnection (CA, non-CA-WECC) and Texas (TRE). Each planning area was assigned to one of the nine regions. The one exception here was MISO which actually spans several regions in the Eastern interconnect. To deal with this we collected data on kWh sales from the EIA-861 survey described earlier. We then identified both whether a given utility was in MISO, and also which of our nine regions it was in. We then used this to proportionally allocate the hourly MISO load across our nine regions. This primarily resulted in MISO being split fairly evenly between MRO, RFC and SERC.

To run our regressions to estimate marginal dollar per kWh damages we first combine the hourly emissions data for each plant with the relevant dollar per ton marginal damages. For most plants this merge is done based on the county the plant is located in. For the small number of large plants with taller smoke stacks this is done using a plant-specific identifier. We then multiply emissions by marginal damages to get hourly dollar damages for each plant. Next we sum together damages by pollutant for all plants in a given region, yielding a total dollar damages value for each region in each hour. This forms our dependent variable in our regressions. The independent variables are constructed from the hourly load data. First we construct the "other" (*i.e.,* rest-of-interconnect) load variable for each region. We then split the "own" region load data into terciles and create three variables that allow us to estimate a piecewise linear response to own region load with separate slopes for the lowest, middle, and highest terciles of load. In most of the regressions, the coefficients on the three terciles are statistically different though the magnitude differences are mostly fairly small. Estimating with a larger number of linear components did not materially alter our findings. We then split the "other" region load variables into terciles in a similar way, except the tercile of other region load is determined by the tercile of own-region load for the same hour (*i.e.,* if "own" is in the second tercile, the total value for "other" region is allocated to its own second tercile variable). The reasoning behind this approach is that the dispatch of a particular plant depends on the local level of demand for energy, which we are approximating with the own-region demand. To the extent that demand from other regions changes the dispatch of a plant, it is through the impact of that other-region end-use demand on the local production demand for energy around that plant.

Once the dependent and independent variables are constructed in this manner we 24-hour difference the data.[34] We then estimate our regressions by pollutant and by region, clustering at the hour-of-sample level. In all, we estimated four regressions (one for each pollutant) for each of the nine NERC regions. All of the regressions, except those for Texas (TRE) included piecewise linear (terciles) functions of own-region and other-region loads.

Once the estimation produced final values for the marginal dollar per KWh

[34]So for example, 2am today is differenced with 2am yesterday

damages for each region, these results were merged with the reformatted retail rates data using information in the EIA-861 survey on the NERC region that each local distribution utility belongs to.[35] The final damage results also vary by terciles of load within a given region, so the allocation across hours was determined by the tercile of load that that hour fell into.

We make a small set of adjustments to our estimates of external marginal costs to avoid double counting. This can arise where the private marginal costs data already incorporate some portion of external marginal costs due to environmental policies that put a price on externalities. The two main instances of this that are relevant here are California's Cap and Trade Program and the Regional Greenhouse Gas Initiative (RGGI) that covers nine states in the north-eastern US. Our external marginal cost estimates were created using a social cost of carbon of \$50/ton of CO_2. The California and RGGI carbon prices in 2014-2016 averaged \$12.70/ton and \$6.00/ton respectively. We therefore multiply the \$/kWh external damages by approximately $(\$50 - \$12.70)/\$50 = 75\%$ for the state of California and by approximately $(\$50 - \$6.00)/\$50 = 88\%$ for the states that participate in the RGGI.[36]

Lastly, to ensure that our analysis was not being affected by fluctuations in zero-emissions renewable generation we also gathered data on hourly renewables (wind and solar) for each of our nine regions. First we downloaded monthly generation data by plant from the EIA-923 survey (Energy Information Administration 2018). This includes generation from all plants including wind and solar (unlike the CEMS data which is focused on fossil fuel plants). We then matched information on the state and NERC region each plant is located in to aggregate the plant-level values and get monthly total wind and solar generation for our nine regions. Next, we used hourly data on renewable generation from the ISOs to allocate this monthly generation across the hours of each month and get our desired estimates of hourly renewable generation by region (Electric Reliability Council of Texas 2018, California Independent System Operator 2018, Midwest Independent System Operator 2018, Southwest Power Pool 2018, New York Independent System Operator 2018, PJM Interconnection 2018, Independent System Operator New England 2018). For each region we identified the most relevant ISO (or combination of ISOs) with which to do this within-month allocation.[37] Once we had assembled these data on renewables we conducted a sensitivity analysis

[35]The exception here was the California and non-California regions that the Western Interconnection was divided into. Here the data were matched by the combination of both NERC region and state identifiers.

[36]These are Conneticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New York, Rhode Island and Vermont.

[37]The CA region used CAISO for wind and CAISO solar. The TRE region used ERCOT for wind and solar. The SPP region used SPP for wind and solar. The MRO region used MISO for wind but solar was assumed negligible. For the SERC region both wind and solar were assumed negligible. The RFC region used PJM for wind and solar was assumed negligible. For the FRCC region both wind and solar were assumed negligible. The NPCC region used ISONE for wind (2014-2015) and combined NYISO/ISONE for wind (2016) but solar assumed was negligible. The non-CA-WECC region used combined CAISO/MISO for wind and combined CAISO/SPP for solar.

by subtracting from hourly total load to get load net of renewables (i.e. "net load"). We then repeated our regression analysis using net load instead of load. Reassuringly this did not meaningfully alter our estimates of marginal dollar per kWh damages, so the analysis presented here just uses load as the independent variable in all regressions.

F. Hourly Load Shapes

Residential customer demand for electricity is not constant, nor is the deviation between residential retail price and the social marginal costs of supplying electricity. In fact, it is likely the case that these will sometimes be strongly correlated (*e.g.,* periods of peak wholesale electricity prices tend to coincide with peak residential electricity demand). It is therefore important to be able to determine how annual residential sales are distributed across the hours in our analysis period. The ideal dataset for this would likely be some form of hourly metered consumption data for the universe of residential households in the US. Clearly such a dataset does not exist - customers' meter data are confidential and held by their individual utility, and many residential households still do not even have meters that can record this information at an hourly frequency. To tackle this challenge our preferred approach involved using hourly load data from a selection of ISO zonal nodes and planning areas. These data were used to represent the shape of hourly residential load profiles at the ZIP Code level up to a scale factor, and then once again we used our dataset of ZIP Code service territory lookups to match these up to utilities.

To do this, we again used the ISO zonal data from SNL Financial (SNL Financial 2017*b*). Unlike pricing nodes, load is only available for a limited number of zonal nodes, and is not available for the many thousands of individual load nodes where LMPs are calculated. Fortunately many of these are the same nodes that we already chose to use in our selection of LMPs. In total this gave us load data for 66 ISO zonal nodes. The FERC-714 survey was then used to supplement this with additional hourly load data for planning areas. All series were then normalized to hourly shares of annual load by dividing each hour by the annual total for that ISO zone or planning area.[38] On average this would mean the load share in a single hour should be 1/8760, or 0.0114%. Above average hours (*e.g.,* 6pm on weekdays) should be above this and below average hours (*e.g.,* 3am on weekends) should be below this. Normalizing the data in this way helped account for the fact that ISOs and planning areas differ massively in size (as measured by total load) and is also consistent with our intended use of these data to apportion annual kWh sales across each hour of the year. As with the private marginal cost

[38]There were some series with data missing for some hours of the year. If an ISO zone or FERC balancing authority had more than 10% of the hours in a year missing, shares were not calculated and that series was dropped. The concern here was that shares calculated using a subset of the hours in the year may not produce accurate shares if the hours for which there were missing data were not representative of all hours. This only led to data for 3 planning areas being dropped.

data, these shares of annual load needed to be assigned to the utility-state entries in our reformatted retail rates dataset. We employ the same approach as for the private marginal costs analysis. This involves assigning each ISO zone or planning area series to a central coordinate (SNL Financial 2017*a*, Department of Homeland Security 2017*b*). These spatial coordinates can be seen in Figure 19.[39] We then calculated load shares for each ZIP Code using the inverse distance-weighted averages of the three nearest load points.

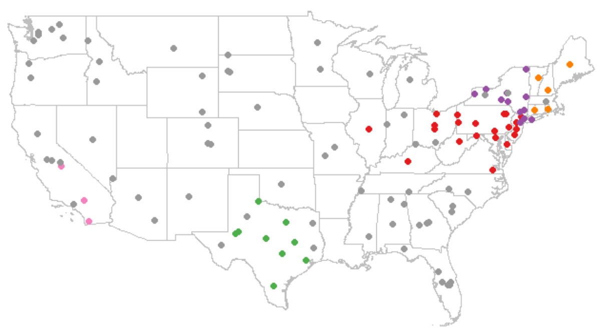


Figure 19: Locations of ISO load zones and load Planning Areas in 2015

The end product of the residential load profile data collection process was a dataset of estimates of hourly shares of annual residential electricity demand for each US ZIP Code. These data were then merged with the reformatted retail rates data using the information on the ZIP Codes served by each local distribution company. Where a utility served multiple ZIP Codes in a given state, we again weighted the ZIP Code values for the load shares by the total population of each ZIP Code. A final adjustment was made to ensure that each of the newly created series correctly summed to one over the year.

It is important to note that our preferred approach of using system load profiles as a proxy for residential load profiles has a clear drawback in that it likely underestimates the peakiness of residential load. This is because system load is made up of all demand for electricity from residential, commercial and industrial customers. Differences in the load profiles of residential versus commercial and industrial customers mean that the combination of these three customer classes

[39]The figure depicts selected load points for ISO-NE (orange), NYISO (purple), PJM (red), MISO (blue), SPP (brown), ERCOT (green), CAISO (pink) and FERC planning areas (grey)

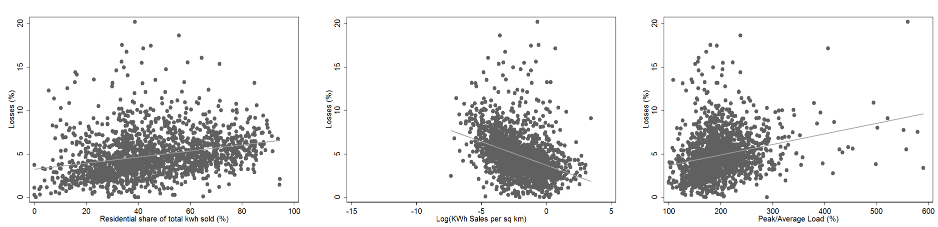
tends to lead to a smoother total system load profile. It is true that residential customers make up the largest customer class, accounting for over 37% of all kWh sales in 2015, so are an important driver of total system load. Even so, where commercial and industrial customers have significantly different load profiles to residential customers and where they make up a significant portion of total load, our hourly allocation of residential load will almost certainly be biased towards less volatility.

To test the robustness of using these system load profiles as a proxy for residential load profiles, we conducted a sensitivity analysis using an alternative source of residential load profile data. For this, we collected modelled residential load profiles produced by NREL (National Renewable Energy Laboratory 2013). This dataset uses an engineering model to estimate hourly residential electricity demand profiles for a set of representative residential households at different locations throughout the US. To construct the dataset NREL classified the US into five climate zones and made assumptions about building characteristics that varied by climate zone (*e.g.,* source of space heating, presence of air conditioning, square footage, construction materials etc.). NREL also made additional assumptions about operational conditions, such as occupancy rates and weather. An hourly weather profile was used based on NREL's "typical meteorological year" (TMY3) dataset. This provides hourly averages for a range of weather variables (*e.g.,* temperature, humidity, precipitation etc.) based on up to 30 years of historical data from 1976 to 2005. The engineering model then takes these assumptions and weather data and estimates a residential electricity demand profile at over 1,400 TMY3 locations throughout the US (National Renewable Energy Laboratory 2008). The clear advantage of the NREL dataset is that it is a more explicit measure of fluctuations in *residential* load, rather than system load. The main disadvantages are twofold. First, the dataset is comprised of estimates of residential load based on a 2008 engineering model that necessarily makes strong assumptions about building performance, customer behavior and the nature of the housing stock. As such this may be a poor proxy for the performance of the actual housing stock in our analysis period. Second, the dataset is produced using averaged weather data from well before our chosen period of analysis. As such the weather profile used may differ substantially from the actual weather that prevailed during our analysis period.

To conduct our sensitivity analysis we carried out the same processing steps described earlier to get a second set of estimates of residential load profiles for each US ZIP Code, in this case based on the NREL simulation data. To assess the actual performance of the load profiles based on the NREL dataset relative to our load profiles based on observed system load we compared both approaches against the very few datasets of actual metered residential load we were able to find. In general we found that the load profiles based on system load understated the peakiness of residential load and the load profiles based on the NREL modelling data overstated the peakiness of residential load. We also found some limited evidence that the profiles based on system load were more strongly correlated with the actual residential load data. Finally, we conducted the entire analysis using both approaches to estimating the residential load profile to see how this would move the results. We found that the choice of residential load profile had a very small impact on the final results (*e.g.,* on the extent of estimated deadweight loss) so we have opted throughout to use the approach based on system load.

G. Distribution Losses

Our estimation of private and external marginal costs gives the marginal cost of electricity delivered in the high-voltage transmission system. However, our analysis is concerned with the marginal costs of serving residential customers. It is therefore important that we account for losses incurred as power is carried through the low-voltage distribution system to residential households. We estimate average annual residential distribution losses for each local distribution company using data in the EIA-861 survey. Unfortunately, the only data on losses that are available report total losses for a given utility across all types of customers (*i.e.,* residential, commercial and industrial). This is problematic because losses to residential customers are likely higher than for any other customer type. This is because residential customers are located at the furthest ends of the distribution network at the lowest voltage levels. Industrial customers, on the other hand, likely have the lowest losses because they are connected to more centralized portions of the distribution network at higher voltage levels. Sometimes industrial customers are even connected directly to the transmission network, so incur zero distribution losses. A second issue with these data on total losses is that they are not exclusively distribution system losses; some utilities own and operate both transmission and distribution system infrastructure, so their reported losses cover both these parts of the power grid.



(a) Residential share (b) Density of load (c) Peak/average load

Figure 20: Losses plotted against three key covariates

To address these shortcomings, we estimate average annual residential distribution losses. We compile data on the following variables for each local distribution company, i: total losses in kWh, L_i; total sales in kWh, Q_i, sales for residential customers in kWh, $Qres_i$, commercial customers, $Qcom_i$, and industrial customers, $Qind_i$; the density of customer load, D_i, as measured by the log of total kWh sales divided by the service territory area in square kilometers; the share of distribution circuits with voltage optimization, $VoltOpt_i$, and the ratio of peak load to average load, P_i.[40] We also created dummies for each state, $State_{si}$, utility type, $UtilityType_{ui}$, and a dummy variable representing whether the utility is involved in electricity transmission, $Transmission_i$.[41] Table 7 presents summary statistics on these variables.

	Mean	StDv	Min	Max	N
Avg. Proportion Total Losses	0.05	0.03	0.00	0.27	5088
Share of Sales (Residential)	0.46	0.21	0.00	1.00	5796
Share of Sales (Commercial)	0.30	0.17	0.00	1.00	5796
Share of Sales (Industrial)	0.24	0.23	0.00	1.00	5796
Log(Sales per sq. km)	-2.29	2.02	-12.73	3.44	5791
Share of Circuits w. Volt. Optim.	0.23	0.39	0.00	1.00	5761
Ratio of Peak to Average Load	1.97	0.49	1.00	5.90	5184
Transmission	0.17	0.38	0.00	1.00	5274

5001 out of 5796 observations have complete information (observations are utility-state-years)

Table 7: Summary Statistics of Variables in the Distribution Losses Regression

The equation for annual losses of a utility could be written as

$$
\begin{aligned}
(7) \qquad L_i &= \alpha_0 Qtot_i + \alpha_1 Qres_i + \alpha_2 Qcom_i + \alpha_3 Qtot_i Density_i \\
&+ \alpha_4 Qtot_i VoltOpt_i + \alpha_5 Qtot_i (Qpeak/Qavg_i) \\
&+ \alpha_6 Qtot_i Transmission_i \\
&+ \sum_{u=1}^{U} \gamma_u UtilityType_{ui} Qtot_i + \sum_{s=1}^{S} \beta_s State_{si} Qtot_i + \epsilon_i
\end{aligned}
$$

where the Qs are total, residential, and commercial electricity delivered, $Density$ is $\log(Qtot/area)$, $VoltOpt$ is the share of circuits with voltage optimization equipment, $Qpeak/Qavg_i$ is the ratio of the utility's peak to average load, and $Transmission_i$ is an indicator that the utility also owns transmission lines (and reported

[40] The log of the density of kWh sales was used as it provided a much better fit, likely due to the very large range of density values in the data.

[41] All utilities in our sample were involved in distribution. We also chose to aggregate the State, Federal and Political Subdivision utility types into a single "Other Public" category as some of these classifications only contained a very small number of observations. The Retail Power Marketer utility type was also not relevant for this analysis because we are focused on local distribution companies. This left us with four utility type categories for our distribution losses analysis: Investor Owned, Cooperative, Municipal, Other Public.

losses include losses from transmission). The equation includes fixed effects for type of utility (investor-owned, municipal, cooperative, etc.) and state. The coefficient α_0 alone would represent the losses associated with an additional unit of electricity delivered to an industrial customer. The derivative of equation (7) with respect to $Qres$ (recognizing that $dQtot/dQres = 1$) would then give the change in annual losses from delivering one additional unit of electricity.

$$
\begin{aligned}
(8) \qquad dL_i/dQres_i &= \alpha_0 + \alpha_1 + \alpha_3 Density_i \\
&+ \alpha_4 VoltOpt_i + \alpha_5 (Qpeak/Qavg_i) \\
&+ \alpha_6 Transmission_i \\
&+ \sum_{u=1}^{U} \gamma_u UtilityType_{ui} + \sum_{s=1}^{S} \beta_s State_{si} + \epsilon_i
\end{aligned}
$$

Equation (7), however, would be highly heteroskedastic in the form shown, so we normalize (7) by total quantity and estimate

$$
\begin{aligned}
(9) \qquad Lavg_i &= \alpha_0 + \alpha_1 Qres_i/Qtot_i + \alpha_2 Qcom_i/Qtot_i + \alpha_3 Density_i \\
&+ \alpha_4 VoltOpt_i + \alpha_5 (Qpeak/Qavg_i) \\
&+ \alpha_6 Q_t ot_i Transmission_i \\
&+ \sum_{u=1}^{U} \gamma_u UtilityType_{ui} + \sum_{s=1}^{S} \beta_s State_{si} + \epsilon_i
\end{aligned}
$$

where the interpretation of the coefficients is the same as in (7) and (8).

We estimate (9) on annual observations for the 1669 distribution utilities for which these data are available for the years 2014 through 2016. A few of the utilities are not in the data for all three years, so the total number of observations is 5001. The results, presented in table 8, suggest that distribution to residential customers exhibits about 3 percentage point higher losses than to industrial customers, and that higher geographic density of customers significantly lowers distribution losses. Voltage optimization also lowers distribution losses, while more volatile load raises distribution losses for a given average level of load. Utilities that also own transmission may exhibit somewhat higher losses, though that effect is not estimated precisely.

From this regression, we then impute average distribution losses for residential customers of all utilities in the dataset by calculating the predicted value of $Lavg_i$ with $Qres_i/Qtot_i = 1$ and $Qcom_i/Qtot_i = 0$.[42] Clearly, this is an imperfect approximation to average distribution losses for residential customers. It assumes

[42]Summary statistics of the variables are presented in the appendix. We predict losses for all utilities in the data set. For those for which some of the right-hand side variables are not available, we use the average value of the variable from the 1669 utilities in the regression.

implicitly that the relative losses of residential versus commercial and industrial customers are the same for all utilities. Furthermore, we have no information on the extent to which voltage optimization or variation in hourly sales relates to residential circuits. Without making very strong assumptions about the correlates of residential losses, it is unclear how to improve on this estimate.

	$L_{\text{i}}/Qtot_{\text{i}}$
Share of Sales (Residential)	0.0284***
	(0.0064)
Share of Sales (Commercial)	0.0059*
	(0.0034)
Log(Sales per sq. km)	−0.0065***
	(0.0006)
Share of Circuits w. Volt. Optim.	−0.0019*
	(0.0010)
Ratio of Peak to Average Load	0.0076***
	(0.0020)
Transmission	0.0022
	(0.0015)
R^2	0.2916

Standard errors in parentheses

N=5001 (observations are utility-state-years)

Dependent Variable: Avg. Proportion Total Losses

Fixed Effects: State, Utility Type and Year

Cluster Variable: State

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Estimates of Average Distribution Losses

We then generated predicted values from this regression. However, in order for these predictions to be for annual *distribution* losses for *residential* customers, we generate our predicted values after altering the underlying dataset such that each utility's load is 100% residential and that each utility is only engaged in distribution. This meant setting the commercial and industrial shares to zero and the transmission dummy to zero. The result was a set of predictions of average annual distribution losses for residential customers for each local distribution company. The vast majority of our estimates fall between 4% and 8%, as can be seen in the histogram below.

Once we had estimates for average annual distribution losses for residential customers, the final step was to convert these to marginal losses and account for how losses vary throughout the year. As explained in the paper, we use the common characterization that 25% of losses are independent of flow on the line –

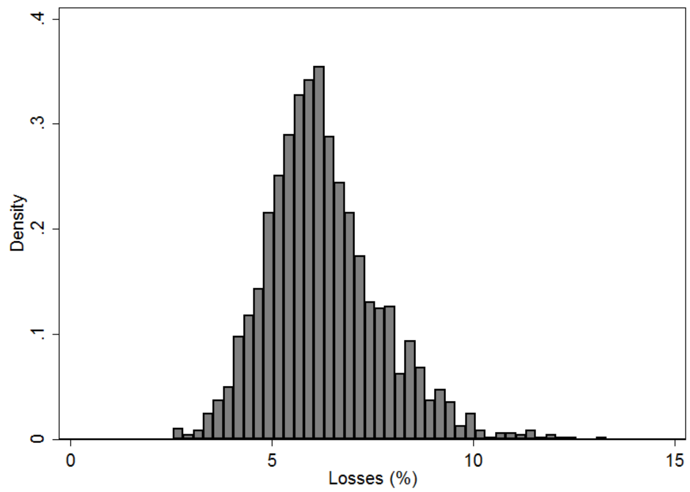


Figure 21: Histogram of Predicted Average Residential Distribution Losses

and therefore not associated with any marginal losses from increased consumption – and the engineering result that the other 75% resistive losses increase with the square of flow on the line.[43]

We adapt the approach taken in Borenstein (2008) and assume that utility i's losses in each hour are:

$$L_{it} = \alpha_{i1} + \alpha_{i2} Q_{it}^2 \tag{10}$$

We have already estimated average annual losses for each local distribution company, which we call γ_i. Because the α terms are constant across all hours we can convert the equation to annual sums and substiute for L_{it}. If we also assume that the static no-load losses, as represented by the α_{i1} term, constitute a quarter of a utility's total losses, we can then solve for α_2 for each local distribution company.

$$\sum_{t=1}^{T} L_{it} = \gamma_i \sum_{t=1}^{T} Q_{it} = \alpha_{i1} + \alpha_{i2} \sum_{t=1}^{T} Q_{it}^2 \iff \alpha_{i2} = (1 - 0.25)\gamma_i \frac{\sum_{t=1}^{T} Q_{it}}{\sum_{t=1}^{T} Q_{it}^2} \tag{11}$$

Finally, our interest is in marginal losses so we take the derivative of our original

[43]See Lazar and Baldwin (1997) and Southern California Edison's methodology for calculating Distribution Loss Factors, as set out in filings to the California Public Utilities Commission (California Public Utilities Commission 1997).

losses expression such that:

$$\frac{dL_{it}}{dQ_{it}} = 2\alpha_{i2}Q_{it} \tag{12}$$

Thus, equation (12) produces our estimate of marginal line losses as a fraction of energy that enters the distribution system of utility i in hour t. For each hour, private and external marginal costs were then scaled up by $\frac{1}{1-dL_{it}/dQ_{it}}$ to give our complete estimate of the social marginal cost of residential electricity consumption.

REFERENCES

Allcott, Hunt, and Michael Greenstone. 2012. "Is there an energy efficiency gap?" *Journal of Economic Perspectives*, 26(1): 3–28.

Allcott, Hunt, and Michael Greenstone. 2017. "Measuring the Welfare Effects of Residential Energy Efficiency Programs." National Bureau of Economic Research Working Paper #23386.

Auffhammer, Maximilian, Carl Blumstein, and Meredith Fowlie. 2008. "Demand-side management and energy efficiency revisited." *The Energy Journal*, 91–104.

Boiteux, M. 1960. "Peak-Load Pricing." *The Journal of Business*, 33(2): 157–179.

Boiteux, M. 1971. "On the management of public monopolies subject to budgetary constraints." *Journal of Economic Theory*, 3(3): 219 – 240.

Boomhower, Judson P, and Lucas W Davis. 2017. "Do Energy Efficiency Investments Deliver at the Right Time?" National Bureau of Economic Research.

Borenstein, Severin. 2005. "The Long-Run Efficiency of Real-Time Electricity Pricing." *The Energy Journal*, 26(3): 93–116.

Borenstein, Severin. 2008. "The Market Value and Cost of Solar Photovoltaic Electricity Production." University of California Energy Institute, Center for the Study of Energy Markets Working Paper #176.

Borenstein, Severin. 2009. "To What Electricity Price Do Consumers Respond? Residential Demand Elasticity Under Increasing-Block Pricing." *Paper presented at NBER Summer Institute.*

Borenstein, Severin. 2012. "The Private and Public Economics of Renewable Electricity Generation." *Journal of Economic Perspectives*, 26(1): 67–92.

Borenstein, Severin. 2016. "The economics of fixed cost recovery by utilities." *The Electricity Journal*, 29(7): 5–12.

Borenstein, Severin. 2017. "Private net benefits of residential solar PV: the role of electricity tariffs, tax incentives, and rebates." *Journal of the Association of Environmental and Resource Economists*, 4(S1): S85–S122.

Borenstein, Severin, and James Bushnell. 2015. "The US electricity industry after 20 years of restructuring." *Annu. Rev. Econ.*, 7(1): 437–463.

Borenstein, Severin, and Lucas W. Davis. 2012. "The equity and efficiency of two-part tariffs in US natural gas markets." *The Journal of Law and Economics*, 55(1): 75–128.

Borenstein, Severin, and Stephen Holland. 2005. "On the Efficiency of Competitive Electricity Markets with Time-Invariant Retail Prices." *RAND Journal of Economics*, 36(Autumn): 469–493.

Braeutigam, Ronald R. 1989. "Optimal policies for natural monopolies." In

Handbook of Industrial Organization. Vol. 2. 1 ed., , ed. R. Schmalensee and R. Willig, Chapter 23, 1289–1346. Elsevier.

Brown, Stephen J., and David Sumner Sibley. 1986. *The Theory of Public Utility Pricing.* Cambridge University Press.

Buchanan, James. 1969. "External Diseconomies, Corrective Taxes, and Market Structure." *American Economic Review*, 59(1): 174–77.

Bushnell, James B., Stephen P. Holland, Jonathan E. Hughes, and Christopher R. Knittel. 2017. "Strategic Policy Choice in State-Level Regulation: The EPA's Clean Power Plan." *American Economic Journal: Economic Policy*, 9(2): 57–90.

California Independent System Operator. 2016. "Annual Report on Market Issues and Performance."

California Independent System Operator. 2018. "Renewables Watch Reports."

California Public Utilities Commission. 1997. "Distribution Loss Factors, Supplement to the July 25th 1997 Workshop Report on Retail Settlement and Information Flows."

California Public Utilities Commission. 2015. "Resource Adequacy Report."

Callaway, Duncan S, Meredith Fowlie, and Gavin McCormick. 2018. "Location, location, location: The variable value of renewable energy and demand-side efficiency resources." *Journal of the Association of Environmental and Resource Economists*, 5(1): 39–75.

Clay, Karen, Akshaya Jha, Nicholas Z Muller, and Randy Walsh. 2018. "The External Costs of Shipping Petroleum Products by Pipeline and Rail: Evidence of Shipments of Crude Oil from North Dakota." *Energy Journal*, forthcoming.

Costello, Kenneth W., and Ross C. Hemphill. 2014. "Electric Utilities Death Spiral: Hyperbole or Reality?" *The Electricity Journal*, 27(10): 7–26.

Crew, Michael A., and Paul R. Kleindorfer. 1976. "Peak Load Pricing with a Diverse Technology." *Bell Journal of Economics*, 7(1): 207–231.

Cullen, Joseph. 2013. "Measuring the environmental benefits of wind-generated electricity." *American Economic Journal: Economic Policy*, 5(4): 107–33.

Davis, Lucas W, and Erich Muehlegger. 2010. "Do Americans consume too little natural gas? An empirical test of marginal cost pricing." *The RAND Journal of Economics*, 41(4): 791–810.

Department of Homeland Security. 2017*a*. "Electric Control Area boundary files."

Department of Homeland Security. 2017*b*. "Electric Planning Area boundary files."

Electric Reliability Council of Texas. 2015. "State of the Market Report."

Electric Reliability Council of Texas. 2018. "Generation by Fuel."

Energy Information Administration. 2017*a*. "Form EIA-861 "Annual Electric Power Industry Report"."

Energy Information Administration. 2017*b*. "Form EIA-861M "Monthly Electric Power Industry Report"."

Energy Information Administration. 2018. "Form EIA-923 "Power Plant Operations Report"."

Environmental Protection Agency. 2018*a*. "Continuous Emissions Monitoring Data."

Environmental Protection Agency. 2018*b*. "Emissions & Generation Resource Integrated Database."

Environmental Protection Agency. 2018*c*. "National Emissions Inventory."

Environmental Systems Research Institute. 2017. "USA ZIP Code Areas."

Federal Energy Regulatory Commission. 2017. "Form-714 - Annual Electric Balancing Authority Area and Planning Area Report."

Feldstein, Martin S. 1972. "Distributional equity and the optimal structure of public prices." *The American Economic Review*, 62(1/2): 32–36.

Fischer, Carolyn, and Alan Fox. 2012. "Comparing policies to combat emissions leakage: Border carbon adjustments versus rebates." *Journal of Environmental Economics and Management*, 64(2): 199–216.

Fowlie, Meredith. 2011. "Updating the Allocation of Greenhouse Gas Emissions Permits in a Federal Cap-and-Trade Program." In *The Design and Implementation of US Climate Policy.* , ed. D. Fullerton and C. Wolfram, 157–171. University of Chicago Press.

Fowlie, Meredith, Lawrence Goulder, Matthew Kotchen, et al. 2014. "An economic perspective on the EPA's Clean Power Plan." *Science*, 346(6211): 815–816.

Friedman, Lee S. 1991. "Energy utility pricing and customer response: the recent record in California." In *Regulatory Choices: A Perspective on Developments in Energy Policy.* , ed. R.J. Gilbert, Chapter 2, 10–62. University of California Press.

Gerarden, Todd D, Richard G Newell, and Robert N Stavins. 2017. "Assessing the energy-efficiency gap." *Journal of Economic Literature*, 55(4): 1486–1525.

Gillingham, Kenneth, and Karen Palmer. 2014. "Bridging the energy efficiency gap: Policy insights from economic theory and empirical evidence." *Review of Environmental Economics and Policy*, 8(1): 18–38.

Graff Zivin, Joshua S, Matthew J Kotchen, and Erin T Mansur. 2014. "Spatial and temporal heterogeneity of marginal emissions: Implications for electric cars and other electricity-shifting policies." *Journal of Economic Behavior & Organization*, 107: 248–268.

Holland, Stephen P, Erin T Mansur, Nicholas Z Muller, and Andrew J

Yates. 2016. "Are there environmental benefits from driving electric vehicles? The importance of local factors." *American Economic Review*, 106(12): 3700–3729.

Holland, Stephen P, Jonathan E Hughes, and Christopher R Knittel. 2009. "Greenhouse gas reductions under low carbon fuel standards?" *American Economic Journal: Economic Policy*, 1(1): 106–46.

Independent System Operator New England. 2016. "State of the Market Report."

Independent System Operator New England. 2018. "Hourly Historical Renewables."

Ito, Koichiro. 2014. "Do Consumers Respond to Marginal or Average Price? Evidence from Nonlinear Electricity Pricing." *American Economic Review*, 104(2): 537–63.

Ito, Koichiro, and Shuang Zhang. 2018. "Do Consumers Distinguish Marginal Cost from Fixed Cost? Evidence from Heating Price Reform in China." National Bureau of Economic Research Conference Paper.

Jacobsen, Mark R., Christopher R. Knittel, James M. Sallee, and Arthur A. van Benthem. 2016. "Sufficient Statistics for Imperfect Externality-Correcting Policies." National Bureau of Economic Research Working Paper 22063.

Jessoe, Katrina, and David Rapson. 2014. "Knowledge Is (Less) Power: Experimental Evidence from Residential Energy Use." *American Economic Review*, 104(4): 1417–38.

Joskow, Paul L. 1976. "Contributions to the Theory of Marginal Cost Pricing." *The Bell Journal of Economics*, 7(1): 197–206.

Joskow, Paul L., and Catherine D. Wolfram. 2012. "Dynamic Pricing of Electricity." *American Economic Review*, 102(3): 381–85.

Joskow, Paul L, and Donald B Marron. 1992. "What does a negawatt really cost? Evidence from utility conservation programs." *The Energy Journal*, 41–74.

Kahn, Alfred Edward. 1988. *The economics of regulation: principles and institutions.* Vol. 1, MIT Press.

Laffont, Jean-Jacques, Patrick Rey, and Jean Tirole. 1998. "Network Competition: II. Price Discrimination." *RAND Journal of Economics*, 29(1): 38–56.

Lazar, Jim, and Xavier Baldwin. 1997. "Valuing the Contribution of Energy Efficiency to Avoided Marginal Line Losses and Reserve Requirements." Regulatory Assistance Project discussion paper.

Littlechild, Stephen C. 1975. "Two-part tariffs and consumption externalities." *The Bell Journal of Economics*, 6(2): 661–670.

Midwest Independent System Operator. 2015. "State of the Market Report."

Midwest Independent System Operator. 2018. "Historical Generation Fuel Mix."

National Renewable Energy Laboratory. 2008. "National Solar Radiation Data Base, 1991- 2005 Update: Typical Meteorological Year 3 Stations Metadata."

National Renewable Energy Laboratory. 2013. "Commercial and Residential Hourly Load Profiles for all Typical Meteorological Year 3 Locations in the United States."

National Renewable Energy Laboratory. 2017*a*. "U.S. Electric Utility Companies and Rates: Look-up by ZIP Code."

National Renewable Energy Laboratory. 2017*b*. "Utility Rate Database."

New York Independent System Operator. 2016. "State of the Market Report."

New York Independent System Operator. 2018. "Real-Time Fuel Mix."

Novan, Kevin. 2015. "Valuing the wind: renewable energy policies and air pollution avoided." *American Economic Journal: Economic Policy*, 7(3): 291–326.

Novan, Kevin, and Aaron Smith. 2016. "The Incentive to Overinvest in Energy Efficiency: Evidence From Hourly Smart-Meter Data." *Journal of the Association of Energy and Resource Economists*, Forthcoming.

Oren, Shmuel, Stephen Smith, and Robert Wilson. 1985. "Capacity Pricing." *Econometrica*, 53(3): 545–566.

Pigou, Arthur C. 1920. *The Economics of Welfare.* Palgrave Macmillan.

PJM Interconnection. 2016. "State of the Market Report."

PJM Interconnection. 2018. "Data Miner Wind Generation."

Public Utility Commission of Texas. 2017*a*. "Average Annual Rate Comparison for Residential Electric Service."

Public Utility Commission of Texas. 2017*b*. "Report Cards on Retail Competition and Summary of Market Share Data."

Puller, Steven L., and Jeremy West. 2013. "Efficient Retail Pricing in Electricity and Natural Gas Markets." *The American Economic Review*, 103(3): 350–355.

Ramsey, Frank P. 1927. "A Contribution to the Theory of Taxation." *The Economic Journal*, 37(145): 47–61.

Shin, Jeong-Shik. 1985. "Perception of Price When Price Information Is Costly: Evidence from Residential Electricity Demand." *The Review of Economics and Statistics*, 67(4): 591–598.

SNL Financial. 2017*a*. "ISO LMP Node Coordinates."

SNL Financial. 2017*b*. "ISO Price and Load Data Repository."

Southwest Power Pool. 2016. "State of the Market Report."

Southwest Power Pool. 2018. "Generation Mix Historical."

Steiner, Peter O. 1957. "Peak loads and efficient pricing." *The Quarterly Journal of Economics*, 71(4): 585–610.

US Census. 2017*a*. "Cartographic County Boundary Shapefiles."

US Census. 2017*b*. "County Population Estimates."

US Census. 2017*c*. "Zip Code Tabulation Area to County Relationship File."

US Census. 2018. "Annual Average Bureau of Labor Statistics Consumer Price Index Research Series."

Wilson, Robert. 1997. *Nonlinear Pricing.* Oxford University Press.