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

Online Appendix

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Appendix for Online Publication

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). The last section covers the details of the deadweight loss calculations.

1. *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 2017a). 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.[1] 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.

[1]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, Pennsylvania 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 receiving "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.[2] Where there were discrepancies between the state totals for energy-only

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

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 discrepancies 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 utilities 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.[3] 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 2017b). These data were then matched with the retail choice providers using the same proportional allocation process used for the other retail choice states.

2. 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 individual 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 vary 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

are many local distribution companies that provide delivery service in the state. 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.

[3]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.

passed through to 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 2017b). 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 cleaned 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 2017a).[4]

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 residential tariffs. The average fixed charge paid by a given utility's residential 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 residential tariffs. We checked our selection of standard rates for 166 large utilities that report in FERC Form 1 the number of customers on each paragraph. For those utilities, 92% of our selected standard rates matched the rate with the most customers on FERC Form 1. Over 95% differed by less than

[4] 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.

$2 per month in absolute value.

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 the number of residential 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. To the extent that these data are held by individual utilities they are 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 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 2017b).[5] For this subset of utilities, we found that the variation is fairly small compared to average variable prices, with the vast majority of monthly implied average variable prices within 10% of the annual average variable price. 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. To look at the possibility of hourly variation in retail 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

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

the US are on tariffs 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.

3. *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 2017a). This provides a list of ZIP Codes served by each local distribution company. These lookups were created using a proprietary set of shape files 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).[6] 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

[6]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).

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 2017a, US Census 2017b, US Census 2017c). 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.

The matching of utility service territories to ZIP Codes, or counties, was used to assign LMPs and load to zip codes before aggregating the zip codes to the utility level (described below). For the final mapping of the data, we use utility service territory boundary shapefiles from HIFLD, as described in the paper.

affects only the visual representation of results in maps. It does not affect any of the underlying results by utility, or the calculations of deadweight loss and its decomposition.

4. 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).[7] 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 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.[8] 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

[7]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.

[8]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.

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 2017b). This is a proprietary source of financial data and market intelligence and includes a convenient centralised database of LMP data from all seven ISOs.[9] 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 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 saving time 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 saving time by visual inspection and the location of the reporting entity. We then manually corrected for this and adjusted to EST as

[9]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.

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%.

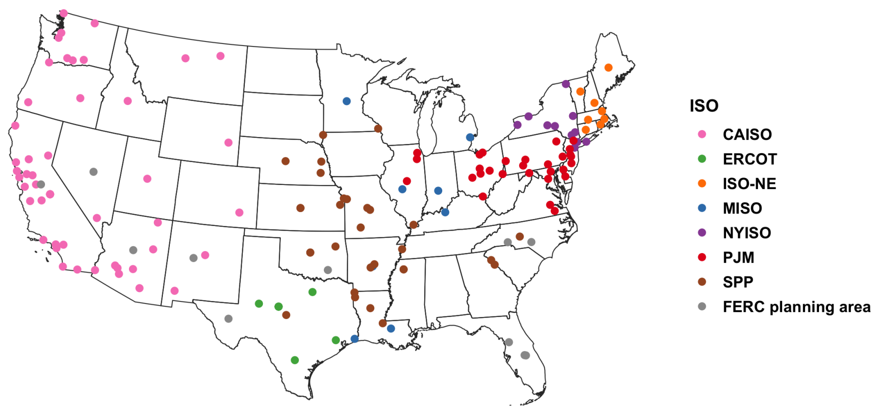


Figure A1: Locations of ISO zonal price points and Balancing Authority area system lambdas in 2015

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 in order to accurately assign wholesale prices within a utility service territory. We then aggregated the zip code level prices by taking population-weighted averages of the wholesale prices across the zip codes within a utility service territory. 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 2017a). 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 2017a). These spatial coordinates can be seen in Figure A1. Once these had been collected we calculated the distance to each ZIP Code centroid.[10] The price for each ZIP Code was then calculated as the inverse distance-weighted average of the prices at the three closest price nodes.[11] While the system lambda data can be considered a less accurate measurement of private marginal costs, less than 10% of utility-states (weighted by load) rely exclusively on system lambda pricing points. As another check, we also dropped all of the system lambda values and set prices for every utility purely on ISO pricing hubs. The results are almost indistinguishable from figure 9, though there are slight changes in some states, such as Florida, Georgia, South Carolina, Washington, Oregon, Idaho and Arizona. Comparing the results with and without system lambda values on a utility-by-utility basis, the (quantity-weighted) mean absolute difference in PMC is 0.07 cents, the 95th percentile is 0.49 cents and the maximum is 1.32 cents.

Average wholesale electricity prices are made up of payments for energy, capacity, ancillary services and other cost covered in 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).[12]

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.

5. *External Marginal Costs*

The AP3 model (see (Clay et al. 2018)) provides estimated marginal damage by county/pollutant/smoke stack height for 2014. This is an updated version of

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

[11]Prior to calculating these averages we winsorized any extermely negative prices at a cutoff of -$0.150/kWh. 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.

[12]These values are taken from the annual reports of each ISO. The one exception to this is capacity payments 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 payments received by the ISO. To account for this we have calculated capacity payments using data from the CPUC's Resource Adequacy Report (California Public Utilities Commission 2015). This yields an additional capacity payment of approximately $0.004/kWh, or approximately 9% of total wholesale costs.

the AP2 model used in Holland, Mansur, Muller, and Yates (2016). The model does not differentiate marginal damage by season or time of day, or by location within county. The data contain estimates of the environmental externality costs in dollars per marginal ton for 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). 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 2018a). 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 (output-weighted) 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 2018c). 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 2018b).[13]

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 discussed above 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

[13]For a map of these NERC regions, see https://19january2017snapshot.epa.gov/energy/north-american-reliability-corporation-nerc-region-representational-map_.html. We do not include Alaska or Hawaii, and California is carved out of WECC as a separate region in our analysis.

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 the regressions to estimate marginal dollar per kWh damages we first combine the hourly emissions data for each plant with the relevant dollar per ton of 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 in each hour by marginal pollutant damages to get hourly dollar damages by pollutant 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. We aggregate damages by pollutant to the region level, because we do not differentiate the location of load within a region for the marginal generation and emissions.

The basic externality regressions are, for each region and pollutant, a regression of the dollar-value damage of the pollutant in a given hour on the level of load in that region and the aggregate level of load in all other regions that are in the same interconnect (except for Texas, where there is no other region in the interconnect). In all, we estimated four regressions – one for each pollutant – for each of the nine NERC regions. Because the generation technology that provides marginal output varies systematically with the level of output in the region, we allowed the marginal pollution damages to be a nonlinear function of the "own region" and "other region" loads. We split the "own" region load data into terciles and created 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. To be precise, if we define Q^{33}_{own} and Q^{67}_{own} as the 33.3rd and 66.7th percentiles in the distribution of "own region" load, and Q_{own} as the own region load, then the three variables used to estimate a piecewise linear function are:
$Q_1 = min\{Q_{own}, Q^{33}_{own}\}$
$Q_2 = 0 \ if \ Q_{own} < Q^{33}_{own} \ else \ Q_2 = min\{Q_{own} - Q^{33}_{own}, Q^{67}_{own} - Q^{33}_{own}\}$
$Q_3 = 0 \ if \ Q_{own} < Q^{67}_{own} \ else \ Q_3 = Q_{own} - Q^{67}_{own}$

We handle the terciles of "other-region" load differently, because we assume that own-region load is the primary determinant of the impact of incremental generation in a region on pollution. Thus, other region load is assigned to one of

three variables depending on the tercile into which own-region load falls in that hour:
$Q_4 = Q_{other}\ if\ Q_{own} < Q_{own}^{33}\ else\ Q_4 = 0$
$Q_5 = Q_{other}\ if\ Q_{own}^{33} \leq Q_{own} < Q_{own}^{67}\ else\ Q_5 = 0$
$Q_6 = Q_{other}\ if\ Q_{own} \geq Q_{own}^{67}\ else\ Q_6 = 0$

While we could estimate each of the 36 regressions separately, we instead estimate the coefficients in a single "stacked" regression. That is, define y_{prt} to be the damage from pollutant p released in region r in sample hour t. And define I_r to be an indicator variable that is equal to 1 if the dependent variable is from region r. Then the regression can be written as:

$$y_{prt} = \sum_{r=1}^{9} I_r \cdot (\sum_{j=1}^{6} \beta_{jpr} Q_{jrt})$$

where j indexes the quantities defined above and their associated coefficients. We then cluster the standard errors on the day of sample, thereby accounting for correlated errors within the day for a given region/pollutant, and correlated errors across regions/pollutants on a given day. We do this because the errors are almost certain to be correlated across the regions/pollutants. Furthermore, as explained below, we need to construct estimates and standard errors of parameters that are linear functions of coefficients from different regressions. Unbiased estimates of the standard errors require accounting for the error correlation across regressions and the covariances of the coefficient estimates, which is straightforward to do in a stacked regression.

Once the dependent and independent variables are constructed in this manner, we 24-hour difference the data.[14] We estimate the linear regressions with three years of hourly observations (26,304 hours) for each of the 36 region/pollutants.[15] Due to the 24-hour differencing, the regression does not include a constant term, or hour-of-day or month-of-sample fixed effects.

From this regression, we then construct the marginal pollution damage due to marginal load in each region for each hour. The marginal pollution damage from marginal load in region A is the sum of the marginal pollution caused by that load from generation in region A and the marginal pollution caused by that load from generation in all other regions that are part of the same interconnect as region A. In each case, the appropriate coefficient is determined by the tercile of the load in which the generation resides.

For instance, assume that in hour h the CA region load is in tercile 1 (lowest) and the $WECC$ region load is in tercile 2. Then the marginal damage from

[14]So for example, the dependent and all of the independent variables for hour 3 today are differenced with their values from hour 3 yesterday.

[15]One minor modification, as noted earlier: the Texas region is not interconnected with any other regions, so the variables Q_4, Q_5, Q_6 are zero when the dependent variable is a pollutant in Texas.

marginal load in CA from that pollutant would be $\beta_1^{CA} + \beta_5^{WECC}$, where the superscripts indicate the regressions from which each coefficient is taken.[16]

[16]To possibly belabor the point, but hopefully avoid confusion in the much more complicated Eastern interconnect, assume that in hour h, the $NPCC$ region is in tercile 1 (lowest), $FRCC$ is in tercile 2, MRO is in tercile 3, RFC is in tercile 1, $SERC$ is in tercile 2, and SPP is in tercile 3. Then the marginal damage from marginal load in $NPCC$ from the pollutant would be $\beta_1^{NPCC} + \beta_5^{FRCC} + \beta_6^{MRO} + \beta_4^{RFC} + \beta_5^{SERC} + \beta_6^{SPP}$. And the marginal damage from marginal load in SPP from the pollutant would be $\beta_4^{NPCC} + \beta_5^{FRCC} + \beta_6^{MRO} + \beta_4^{RFC} + \beta_5^{SERC} + \beta_3^{SPP}$.

The estimated marginal damage (in dollars per megawatt-hour) from marginal load with demand in each tercile is presented in table A1.

These calculations produced values for the dollar-value marginal external damage per kWh for each region for each hour. We made 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 Northeastern US. Our external marginal cost estimates were created using a social cost of carbon (SCC) 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 from CO_2 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.[17]

Another potential complication is the impact of zero-carbon renewable energy resources that produce intermittently and with seasonally varying patterns. Note that our primary specification differences our variables of interest with the value from 24 hours prior. This accounts for any systematic seasonal variation in renewable energy output. However, to confirm that our analysis was not being affected by fluctuations in 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.[18] Once

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

[18] The CA region used CAISO for wind and 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.

Table A1: Marginal External Costs by Region and Load Tercile

Region	Tercile	Marginal Damages				
		CO_2	NO_X	SO_2	$PM_{2.5}$	Total
CA	1	17.25	1.29	0.82	4.36	23.72
		(0.92)	(0.19)	(0.21)	(1.62)	(2.08)
CA	2	16.87	1.40	0.83	5.29	24.40
		(0.82)	(0.19)	(0.21)	(1.16)	(1.60)
CA	3	20.66	1.84	0.91	9.57	32.98
		(0.77)	(0.23)	(0.21)	(1.15)	(1.60)
FRCC	1	25.76	2.51	14.48	2.78	45.53
		(0.54)	(0.17)	(1.37)	(0.09)	(1.82)
FRCC	2	25.82	3.26	15.57	2.72	47.37
		(0.53)	(0.19)	(1.34)	(0.09)	(1.80)
FRCC	3	26.39	4.88	16.49	2.91	50.67
		(0.53)	(0.20)	(1.43)	(0.09)	(1.86)
MRO	1	58.85	9.78	43.66	2.08	114.38
		(3.71)	(0.71)	(2.76)	(0.14)	(6.89)
MRO	2	52.45	9.77	43.55	1.88	107.65
		(3.67)	(0.78)	(2.92)	(0.14)	(7.08)
MRO	3	42.19	8.71	31.75	1.69	84.33
		(2.84)	(0.64)	(2.65)	(0.13)	(5.80)
NPCC	1	15.25	1.58	0.72	2.80	20.34
		(0.63)	(0.22)	(1.43)	(0.13)	(2.03)
NPCC	2	17.52	2.30	4.40	2.97	27.19
		(0.62)	(0.24)	(1.39)	(0.13)	(1.96)
NPCC	3	20.59	5.32	11.48	3.67	41.06
		(0.62)	(0.34)	(1.44)	(0.15)	(2.14)
RFC	1	29.88	5.99	44.04	3.99	83.90
		(0.77)	(0.25)	(2.52)	(0.15)	(3.23)
RFC	2	29.39	6.21	44.55	4.24	84.40
		(0.92)	(0.26)	(2.69)	(0.19)	(3.58)
RFC	3	27.01	6.69	39.44	4.97	78.11
		(0.65)	(0.26)	(2.28)	(0.16)	(2.81)
SERC	1	27.12	3.92	22.53	2.00	55.56
		(0.65)	(0.22)	(1.70)	(0.12)	(2.28)
SERC	2	28.41	4.42	26.34	2.20	61.38
		(0.64)	(0.23)	(1.78)	(0.12)	(2.40)
SERC	3	28.67	5.65	24.23	2.24	60.78
		(0.67)	(0.38)	(2.05)	(0.13)	(2.89)
SPP	1	27.72	4.30	18.05	1.44	51.51
		(1.34)	(0.25)	(1.51)	(0.10)	(2.71)
SPP	2	25.80	4.64	15.57	1.40	47.42
		(1.41)	(0.27)	(1.47)	(0.10)	(2.76)
SPP	3	22.46	5.01	12.34	1.33	41.14
		(1.06)	(0.25)	(1.37)	(0.10)	(2.29)
TRE	1	26.86	2.14	17.23	2.03	48.25
		(1.26)	(0.12)	(1.15)	(0.11)	(2.45)
TRE	2	24.88	1.84	13.38	1.84	41.95
		(0.96)	(0.11)	(0.95)	(0.08)	(1.92)
TRE	3	24.69	3.14	6.38	1.60	35.82
		(0.71)	(0.12)	(0.69)	(0.06)	(1.29)
WECC	1	26.48	4.94	4.80	1.23	37.45
		(0.91)	(0.20)	(0.26)	(0.72)	(1.46)
WECC	2	22.82	4.13	3.97	1.14	32.06
		(1.04)	(0.23)	(0.32)	(0.73)	(1.65)
WECC	3	18.82	2.91	2.61	0.98	25.32
		(0.96)	(0.22)	(0.28)	(0.73)	(1.53)

we had assembled these data on renewables we conducted a sensitivity analysis 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.

As of 2021, it appears that the most common estimates of the SCC, around \$50/ton, may be revised upward significantly as our understanding of climate change continues to evolve. For comparison purposes, we have recalculated externalities and the gap between price and SMC based on a \$100/ton SCC. Figure A2 presents the gap under this assumption. Though it obviously shifts the colors to be redder than in figure 9, the change in the bluer areas is more modest, because these are areas with relatively low marginal CO_2 emissions to begin with.

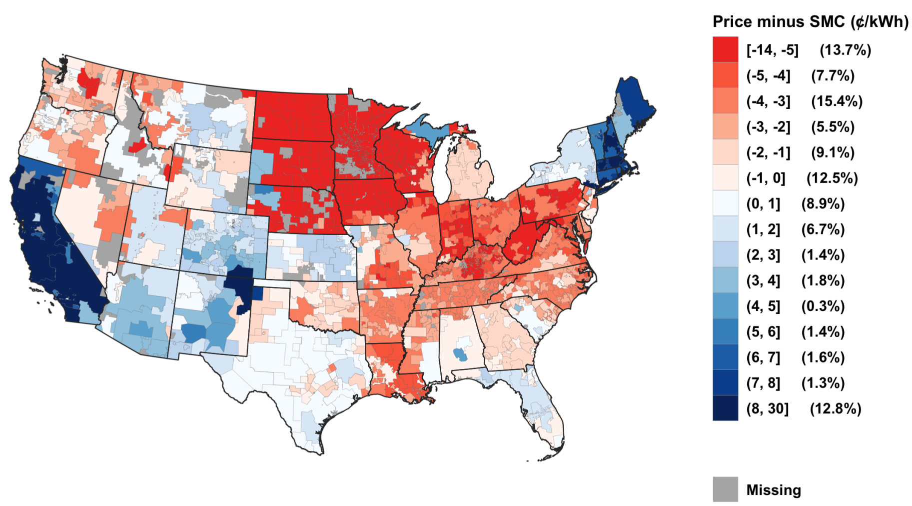


Figure A2: Marginal Price minus Average SMC per kWh with SCC=\$100/ton

6. *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 2017b). 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.[19] 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 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 2017a, Department of Homeland Security 2017b). These spatial coordinates can be seen in Figure A3.[20] We then calculated load shares for each ZIP Code using the inverse distance-weighted averages of the three nearest load points.

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

[19]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.

[20]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)

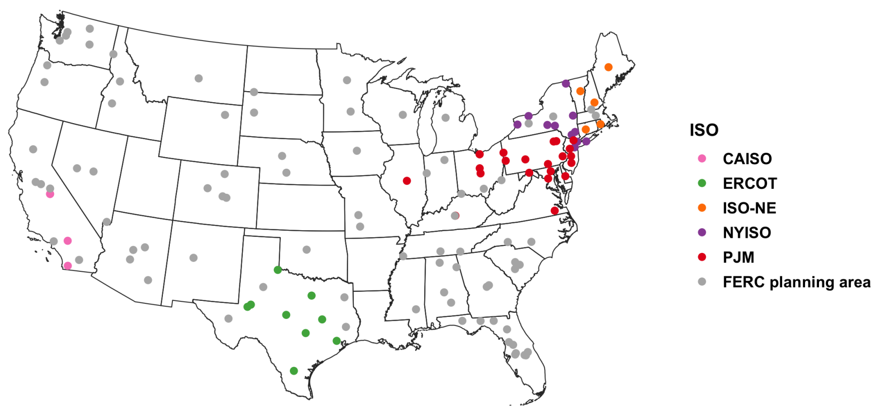


Figure A3: Locations of ISO load zones and load Planning Areas in 2015

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 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.

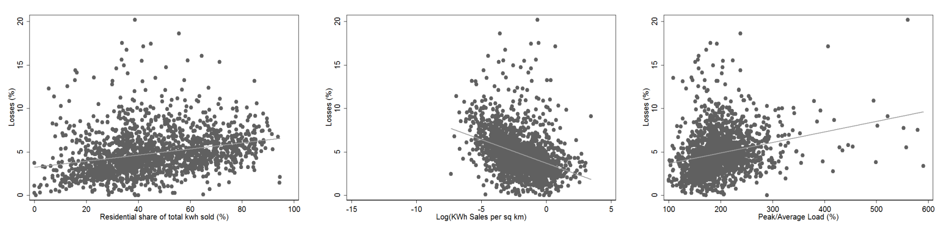
To test the robustness of using these system load profiles as a proxy for residential load profiles, we conducted a sensitivity analysis using an alternative source of residential load profile data. For this, we collected modeled residential load profiles produced by NREL (National Renewable Energy Laboratory 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 modeling 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.

7. *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 A4: 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.[21] 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, $Transmission_i$.[22] Table A2 presents summary

[21]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.

[22]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

statistics on these variables.

Table A2: Summary Statistics of Variables in the Distribution Losses Regression

	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)

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

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

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 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 (1) with respect to $Qres$ (recognizing that $dQtot/dQres = 1$) would then give the change in annual losses from delivering one additional unit of electricity.

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.

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

Equation (1), however, would be highly heteroskedastic in the form shown, so we normalize (1) by total quantity and estimate

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

where the interpretation of the coefficients is the same as in (1) and (2).

We estimate (3) 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 A3, 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.[23]

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 $Qres_i/Qtot_i = 1$, $Qcom_i/Qtot_i = 0$ and $Transmission_i = 0$.[24] The vast majority of our estimates fall between 4% and 8%, as can be seen in the histogram below.

Clearly, this is an imperfect approximation to average distribution losses for residential customers. It assumes implicitly that the relative losses of residential versus commercial and industrial customers are the same for all utilities. Fur-

[23]Even though this is a (short) panel, it is worth noting that identification of the parameters in this regression comes almost entirely from the cross-sectional variation. If one includes utility fixed effects, only the density effect remains statistically significant.

[24]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.

Table A3: Estimates of Average Distribution Losses

	$L_{\text{i}}/Qtot_{\text{i}}$
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
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

thermore, 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.

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 – 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.[25]

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

$$L_{it} = \alpha_{i1} + \alpha_{i2} Q_{it}^2 \tag{4}$$

[25]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).

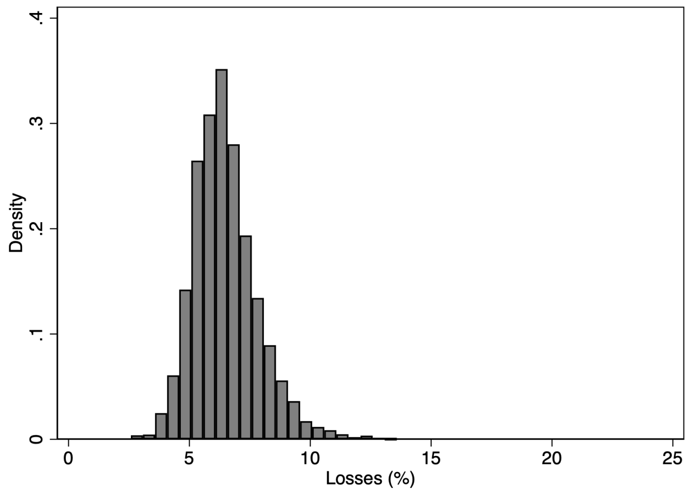


Figure A5: Histogram of Predicted Average Residential Distribution Losses

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 substitute 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.

$$(5)\qquad \sum_{t=1}^{T} L_{it} = \gamma_i \sum_{t=1}^{T} Q_{it} = \alpha_{i1} + \alpha_{i2} \sum_{t=1}^{T} Q_{it}^2 \iff \alpha_{i2} = (1-0.25)\gamma_i \frac{\sum_{t=1}^{T} Q_{it}}{\sum_{t=1}^{T} Q_{it}^2}$$

Finally, our interest is in marginal losses so we take the derivative of our original losses expression such that:

$$(6)\qquad \frac{dL_{it}}{dQ_{it}} = 2\alpha_{i2} Q_{it}$$

Thus, equation (6) 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.

8. Calculation of Deadweight Loss in the Short Run and the Long Run

To evaluate DWL while recognizing that short-run and long-run demand elasticities for electricity may differ substantially, we consider a two-stage consumer decision process. In the first stage, the consumer chooses the devices to buy, energy efficiency investments to make, and household habits for using the devices, all based on the average price they expect to face.[26] We refer to all of these choices collectively as the consumer's investment in devices. In the second stage, the customer uses the devices, responding to hourly prices, which will generally deviate from the average price.

Figure A6 illustrates the short-run demand functions that a household might have during a specific hour for the electricity to use individual devices 1, 2, 3, and 4. The household makes the long-run investment decisions – adding, removing or shifting a short-run demand function for a type of device – by comparing the price, energy efficiency and other device attributes with the consumer surplus that the household expects to receive by owning it. The consumer's gross consumer surplus from a device is calculated as the area under the short-run demand out to the quantity consumed, aggregated over the life of the device. We assume that the long-run demand elasticity reflects the household's optimized response to different average prices through the device investments they make and the extent to which they use them on average. The short-run demand elasticity reflects the household's change in hourly usage in response to changing hourly prices.

Efficient purchase and hourly usage of devices results when the hourly price is set equal to hourly social marginal cost, which implies that the average price is the average social marginal cost. In figure A6, assume that when that occurs the household purchases devices 1, 3, and 4, and has a household short-run demand function of D_{134} for this specific hour. The household's demand function varies hour to hour, but in the short run it will always reflect owning devices 1, 3, and 4.

The change in total surplus from a change in pricing regime is equal to:

$$\begin{aligned}\Delta\ Total\ Surplus = {} & \Delta\ Gross\ Consumer\ Surplus \\ & - \Delta\ Variable\ Costs - \Delta\ Investment\ Costs\end{aligned}$$

where Δ *Gross Consumer Surplus* occurs as a result of changing usage of current devices in the short run and changing the household's device investments in the long run. Measurement of the first two terms is fairly straightforward given assumptions about electricity price and costs, along with long-run and short-run demand elasticities. Recognizing that consumers will make investments only

[26]We implement this using the quantity-weighted average price for the utility. A sophisticated buyer facing time-varying prices could do a more granular calculation, taking into account the timing of their expected device usage and ability to shift consumption in response to price differences, but we abstract from this for simplicity, and because none of the long-run demand elasticity estimates in the literature reflect such optimization.

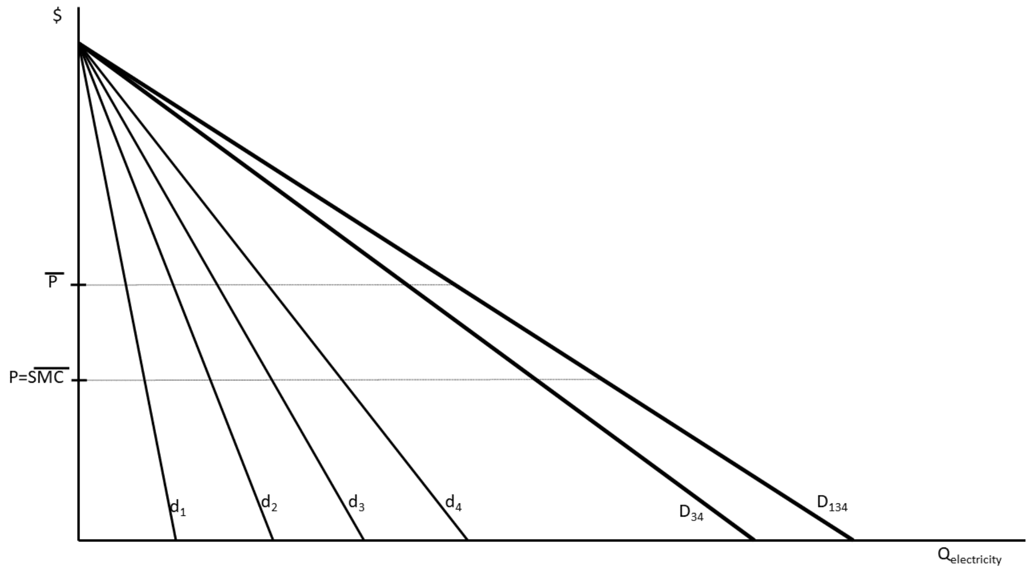


Figure A6: Illustration of Consumer Choices of Electrical Devices and Their Usage

if the additional consumer surplus from use is at least as large as the cost of the investment implies that long-run demand can be used to analyze the cost of adopting a device. For example, if this consumer chooses not to adopt device 1 when $P = \overline{P}$, but does choose to adopt it when $P = \overline{SMC}$, then for device 1

$$\sum_{h \in H} CS_{P=\overline{P}} < Cost\ of\ \ Adoption < \sum_{h \in H} CS_{P=\overline{SMC}}$$

where the appropriately discounted consumer surpluses are summed over all hours in which the device will be used. Adopting device 1 would then change this consumer's short run demand function in the illustrated hour from D_{34} to D_{134}.[27] Applying this approach to a continuum of devices, the marginal consumer surplus associated with the long-run response to changes in the average electricity price traces out the cost of incremental investments.

Though figure A6 illustrates the analysis with linear demand curves, we implement the calculations using modified constant-elasticity demand. Linear demand has the unfortunate property that an elasticity at $\overline{P}$ that is in the range of common empirical estimates yields implausibly low choke off prices and potentially understates price responsiveness at extremely low prices. On the other hand,

[27]Similarly, the fact that this consumer does not adopt device 2 at a price of $P = \overline{SMC}$ implies that the sum of discounted future consumer surpluses for device 2 at $P = \overline{SMC}$ does not exceed its cost of adoption.

constant-elasticity demand yields implausibly high, or infinite, quantities as price goes to zero or below, and unbounded willingness to pay for small quantities. In an attempt to model a more realistic demand setting, we take demand to be constant elasticity up to a price of \$2/kWh, about 20 times the average retail price, and then horizontal at \$2/kWh down to zero quantity. We also modify the function at low prices, imposing a quantity cut off at twice the quantity demanded when $P = \$0.05/kWh$ for each hour, which is about half the sample average retail price. In every hour, the demand function is determined by the assumed elasticity and the observed point $(\overline{P}, \overline{Q})$, through which both the short-run and the long-run demand curves are assumed to run.

DWL calculations are also potentially a function of how SMC changes with quantity. Following the discussion of externalities above, we have estimated the slope of SMC at the NERC region level. For each region, we regressed hourly average region SMC on hourly region quantity and month-of-sample dummies to capture variation in availability of wind, solar, and hydroelectric supply. The potential endogeneity of quantity is not a significant concern here, because virtually all customers face prices that are invariant to market conditions, as discussed earlier.[28] For eight of the nine regions, the estimated slope of the SMC(Q) function is positive and statistically significant, but economically extremely small, particularly compared to the slope of the demand function. For one region, the estimated slope is still positive, but even smaller and not statistically significant. For the utilities in our sample, a one standard-deviation increase in the quantity supplied is estimated to increase SMC by a quantity-weighted average of \$0.000006. For 99% of utilities, the change is less than \$0.0015, and for no utility is the change larger than \$0.005. Thus, for computational simplicity, we assume that SMC is constant over the range of the quantity changes considered.[29]

Table A4 presents the average DWL per normalized quantity for the U.S., the annual total DWL per customer, and the share of DWL attributable to the long-run mispricing $(\overline{P} \neq \overline{SMC})$ for combinations of short-run and long-run elasticities. The table suggests that the change in each type of deadweight loss is approximately linear in the elasticity, and that the basic finding that average DWL is small – compared to SMC or retail price – is robust to even fairly large elasticities.

[28]There is a second concern that high demand hours might be associated with larger or smaller production from wind and solar – likely larger for solar and smaller for wind – therefore shifting the SMC function. As discussed in appendix section 5 on external marginal costs, however, we did not find that accounting for supply from intermittent resources meaningfully changed the analysis of external marginal costs, so we did not make further adjustments to this regression.

[29]Incorporating non-constant SMC implies that there is no closed-formed solution for the intersection of SMC and the constant-elasticity demand functions, so requires an approximation to the intersection. When we solved for the intersection using a linear approximation of the constant-elasticity short-run demand functions around the value of SMC at $\overline{P}$, nearly all of the quantity changes in the DWL calculations were within 1% of the changes that result from assuming a constant SMC.

Table A4: Average Deadweight Loss Measures Under Alternative Elasticity Assumptions

			LR Elasticity					
			-0.1	-0.2	-0.3	-0.5	-0.7	-0.9
SR Elasticity	-0.1	DWL_{total} per kWh (¢)	0.131	0.207	0.283	0.435	0.587	0.738
		DWL_{total} per customer ($)	14.39	23.04	32.08	51.41	72.65	96.10
		DWL_{LR}/DWL_{total}	0.565	0.721	0.794	0.863	0.896	0.915
	-0.2	DWL_{total} per kWh (¢)	0.180	0.256	0.332	0.486	0.639	0.790
		DWL_{total} per customer ($)	19.78	28.56	37.74	57.41	79.06	103.00
		DWL_{LR}/DWL_{total}	0.412	0.582	0.675	0.773	0.823	0.853
	-0.3	DWL_{total} per kWh (¢)	0.226	0.303	0.379	0.534	0.688	0.840
		DWL_{total} per customer ($)	24.81	33.72	43.05	63.04	85.08	109.49
		DWL_{LR}/DWL_{total}	0.328	0.493	0.591	0.704	0.765	0.803
	-0.5	DWL_{total} per kWh (¢)	0.311	0.388	0.465	0.621	0.778	0.932
		DWL_{total} per customer ($)	34.06	343.22	52.81	73.42	96.19	121.48
		DWL_{LR}/DWL_{total}	0.239	0.384	0.482	0.604	0.676	0.724
	-0.7	DWL_{total} per kWh (¢)	0.387	0.465	0.544	0.702	0.860	1.017
		DWL_{total} per customer ($)	42.46	51.85	61.69	82.89	106.36	132.47
		DWL_{LR}/DWL_{total}	0.192	0.320	0.413	0.535	0.612	0.664
	-0.9	DWL_{total} per kWh (¢)	0.459	0.537	0.617	0.776	0.937	1.096
		DWL_{total} per customer ($)	50.28	59.89	69.98	91.73	115.87	142.79
		DWL_{LR}/DWL_{total}	0.162	0.277	0.364	0.484	0.562	0.616

Note: For each elasticity pair, the DWL_{total}, DWL_{LR}, number of customers, and normalized quantities are summed across the 6,215 utility-state-years, then the relevant sums are divided to obtain each statistic.

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