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"Power to the People: Does Ownership Type Influence Electricity Service?"

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Since the 1990s, American states have deregulated electricity markets. However, there has been little effort to privatize municipal utilities. Rather, after storm related power outages, the press has relayed calls for municipalizing investor owned utilities, and claimed that profit-making utilities do not have enough of an incentive to prepare for storms. Most storm preparedness discussions have focused on regularly cutting tree branches near power lines and burying power lines underground. We provide empirical evidence that municipal utilities spend more on maintenance of their distribution network (e.g., cutting trees), but bury a smaller percent of their lines underground, compared to investor owned utilities. In order to find the overall effect of ownership type on outages, we examine a stratified random sample of 241 investor owned, 96 cooperative, and 94 municipal utilities in the United States between 1999 and 2012. We find that storms disrupt electricity sales for municipal utilities; specifically, storm damages that equal 1% of personal income lead to a 1.85% decrease in residential electricity sales by municipal utilities. However, storms do not significantly affect residential electricity sales by investor owned utilities. These results are consistent with international experience with privatization. Specifically, countries that have privatized distribution have not seen an increase in disruptions to electricity service. JEL codes: L33, L94, D7.

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1 Introduction

In the 1990s, many governments brought market forces to the electric generating industry. Some countries also privatized electric distribution. For instance, in 1990, all the electric distribution companies in England and Wales were privatized. Similarly, in Australia, all distribution companies in the states of Victoria and South Australia were privatized in 1995 and 2001. In contrast, in the United States the share of residential customers served by government utilities remains unchanged (it went form 15% in 1990 to 14% in 2011). Further, municipal utilities continue to receive a variety of subsidies: federal income tax exemption, federal income tax exemption on debt issued by utilities, and lower prices for federal hydropower. Finally, the press has reported calls to municipalize investor owned utilities, rather than calls to privatize municipal utilities [Singer, 2012, Cardwell, 2013, Bruun, 2009, Janoski, 2012].

One of the main arguments for municipalization is the alleged poor performance of investor owned utilities after major storms.[1] For instance, following Hurricane Irene, many customers of investor owned Connecticut Light and Power were without electricity for 11 days, while customers of municipal utilities in Connecticut experienced only brief power outages [Singer, 2012]. Similarly, in Massachusetts, municipal utilities in some of the hardest-hit areas were able to restore power in one or two days, while investor owned utilities, like NStar, took a week [Cardwell, 2013].[2] The press has argued that these extended outages are due to investor owned utilities skimping on maintenance to pay higher dividends. For instance, prior to Hurricane Irene, Connecticut Light and Power spent $78 per customer on maintenance, while the Norwich Connecticut municipal utility spent $132 [Cox, 2011].[3] However, we are not aware of any empirical analysis that confirms that investor owned utilities spend less on storm preparedness or are more likely to suffer power outages

[1] The other goals for advocates of municipalization are lowering electricity rates and using more renewable energy.

[2] In addition, when northern New York was ravaged by an ice storm in 1998, customers of municipally owned Massena Electric had power back after two days, while customers of neighboring communities served by investor owned National Grid were in the dark for three weeks [Bruun, 2009]. Also, customers of Butler Power & Light, a municipally owned utility in New Jersey, had better electricity service after superstorm Sandy in 2012 than customers of neighboring towns, which were served by the investor owned Jersey Central Power & Light [Janoski, 2012]. In 2003, residents of White Park, Florida municipalized their electrical service in response to frequent power outages [Sigo, 2003]. The city of South Daytona, Florida, attempted to municipalize electrical service in order to insure more frequent tree trimming around lines and quicker responses by repair crews after major storms. However, in 2013, the voter of South Daytona rejected the municipalization measure [Weiss, 2013].

[3] Similarly, NStar had 3.08 linemen per 10,000 residents, while Massachusetts municipal utilities averaged 3.8 per 100,000 residents [Van Voorhis, 2012].

following storms. Here, we seek to fill this gap by examining whether the mode of ownership of an electric utility affects these quality of service measures.

First, we examine storm preparedness expenditures in a sample of 179 investor owned, 801 cooperative, and 1,437 municipal electric utilities in the United States for the years 1995–2002. Most discussion on storm preparedness has focused on maintaining electrical distribution lines (e.g., regularly cutting tree branches near power lines) and burying power lines underground. We find that, per line mile, municipal utilities spend more on maintaining their distribution network than investor owned utilities. However, the higher expenditures by municipal utilities could indicate their greater inefficiency, rather than their greater storm preparedness. For instance, a variety of studies have found increasing returns to electric distribution up to at least 20,000 customers [Salvanes and Tjøtta, 1994, Yatchew, 2000, Growitsch et al., 2009]. Many municipal utilities cannot take advantage of these economies of scale because a variety of institutional factors lead them to be too small.[4] Specifically, in our sample, 9% of municipal utilities have more than 20,000 residential customers, versus 82% of investor owned utilities.[5] Further, we find that municipal utilities have a smaller fraction of their distribution network underground. Thus, we cannot conclude that municipal utilities are better prepared for storms by solely examining maintenance expenditures.

Second, we examine the effect of ownership type on storm related outages, where we proxy outages by the percent difference between this month's electricity sales, and electricity sales in the same month of the prior year. For our proxy for outages, we have a stratified random sample of 241 investor owned, 96 cooperative, and 94 municipal utilities in the United States between 1999 and 2012. We find that storms that lead to damages (destruction of private and public property) that equal 1% of personal income lead to a 1.85% decrease in residential electricity sales by municipal utilities, but have no statistically significant effect on sales by investor owned utilities.

Our results suggests that privatizing municipal utilities would result in savings in federal subsi-

[4]An example of an institutional factor that ensures that municipal utilities remain small is the federal law which prohibits the use of tax-exempt municipal bonds to finance the purchase of electric power generating facilities from private utilities [Jones, 1989]. Another example is the Federal Energy Regulatory Commission order 888. Under this order investor owned utilities have to be compensated for "stranded costs," the losses in revenues to the utility that occur from municipalization [Doane and Spulber, 1997].

[5]There are many other reasons to expect municipal utilities to operate inefficiently. For instance, we expect managers of municipal utilities to have lower personal incentives to keep costs downs [Hart et al., 1997] and to have to respond to short term electoral pressures [Levitt, 1997, Vlaicu and Whalley, 2013].

dies and maintenance expenditures, while preserving the quality of service following storms. These conclusions are consistent with prior international experiences. There were fewer outages following the privatization of electric distribution in Argentina [Gonzalez-Eiras and Rossi, 2007] and in the state of Victoria, Australia [Hartley, 1999], while the privatization of electric distribution in Italy did not lead to an increase in power outages [Fumagalli et al., 2007]. However, we are not aware of any work that examines the effect of ownership type on storm preparedness in the United States.[6]

Section 2 provides our empirical framework and discusses potential threats to identification. Section 3 describes the data and provides summary statistics by ownership type. Section 4 presents the results. Section 5 concludes.

2 Empirical framework

In this paper we estimate two regressions. The first regression examines the effect of a utility's ownership type on spending on its distribution network. The second regression examines the effect of a utility's ownership type on storm related changes in power usage.

2.1 Effect of ownership on spending on the distribution network

In the first regression, the unit of observation is a utility u. The effect of a utility's ownership type on spending on its distribution network is measured in the following cross-sectional regressions:

$$\ln e_u = \alpha^{1e} + \alpha^{2e}_{s(u)} + \alpha^{3e}_{o(u)} + \beta^e X_u,$$
$$p_u = \alpha^{1p} + \alpha^{2p}_{s(u)} + \alpha^{3p}_{o(u)} + \beta^p X_u,$$

[6]U.S. studies have found that, compared to municipal electric utilities, investor owned utilities charge higher prices [Peltzman, 1971, Kwoka, 2002], but adopt new technologies earlier [Rose and Joskow, 1990]. There is also work examining the effect of regulation of investor owned utilities on outages. For instance, Hausman [2014] finds that deregulation leads to fewer unplanned power outages at nuclear power plants. Ter-Martirosyan and Kwoka [2010] find that regulatory provisions that provide incentives for low costs increase the length of power outages, while regulatory provisions that provide incentives for quality reduce the length of power outages. Lim and Yurukoglu [2014] find that there are fewer outages in states where a higher proportion of public utility commissioners are Republican.

where e_u are utility u's distribution operations and maintenance expenditures, per distribution line mile, and p_u is the percent of distribution lines underground. The variable $o(u)$ denotes the mode of ownership of utility u: Investor owned, Municipal, or Cooperative. The variable $s(u)$ is the state where the utility has most of its residential customers. Finally, X_u is a vector of controls.

2.2 Effect of ownership on storm related changes in power usage

In the second regression, the unit of observation is a utility u, operating in state s, year y, and month t. Again, the variable $o(u)$ denotes the mode of ownership of utility u: Investor owned, Municipal, or Cooperative. In order to estimate the effect of ownership type on storm-related changes in power usage, we use the following panel regression:

$$\Delta \ln q_{usyt} = \alpha_y^1 + \alpha_s^2 + \alpha_{o(u)}^3 + \sum_{m=h}^{k} \beta_{o(u)}^m \, \Delta \text{Damages}_{usyt-m} + \gamma_s \, \Delta \ln d_{usyt}. \tag{1}$$

The dependent variables, q_{usyt}, are residential electricity sales. The symbol Δ denotes the difference between the current month's value of q and the prior year's value of q; i.e., $\Delta \ln q_{usyt} = \ln q_{usyt} - \ln q_{usy-1t}$. There are two reasons for estimating the regression in long differences. First, the dependent variables are potentially seasonal. Thus, by eliminating seasonality, we reduce the errors in the dependent variables. Second, in many states, large storms tend to occur during months when electricity consumption is the highest. Thus, seasonal effects are potential sources of endogeneity.

In the more general version of our regression, we allow damages to have a contemporaneous ($m = 0$), lagged ($m > 0$), and lead effects ($m < 0$). Specifically, our main explanatory variable, Damages_{usyt-m}, is the sum of storm damages (destruction of private and public property) during year y, month $t - m$, over all the counties served by utility u in state s. Damages are measured as a percent of yearly personal income over the same counties. Thus, the variable "Damages" equals one if damages are 1% of personal income. Our primary coefficient of interest, $\beta_{o(u)}^m$, is the interaction of mode of ownership and storm damages that occurred m months prior. For instance, if $\beta_{\text{Municipal}}^1 = -2$, then, damages equalling one percent of personal income lead to a two-percent reduction in residential electricity sales by municipal utilities, one month after the storm.

The scalars α^1_y, α^2_s and $\alpha^3_{o(u)}$ denote year, state, and mode of ownership fixed effects. The variable d_{usyt} denotes the sum of heating degree days and cooling degree days, two variables commonly used to predict electricity consumption. We allow the impact of degree days on the dependent variable, γ_s, to vary by state.

We provide a graphical illustration of our findings by estimating Equation 1 with current damages, one lead, and one lag i.e., with $h = 1$ and $k = 1$. To simplify the tables, we estimate the effect of the sum of current and prior month's storm damages. In other words, we set $h = 0$, $k = 1$, $\beta^0_{o(u)} = \beta^1_{o(u)} = \beta_{o(u)}$, and estimate

$$\Delta \ln q_{usyt} = \alpha^1_y + \alpha^2_s + \alpha^3_{o(u)} + \beta_{o(u)} \sum_{m=0}^{1} \Delta \text{Damages}_{usyt-m} + \gamma_s \Delta \ln d_{usyt}. \tag{2}$$

2.3 Potential threats to identification

For the regressions with expenditures, we may be concerned that municipal utilities are more likely to face storms that are potentially damaging to electrical service. This positive correlation would arise if municipal utilities cover areas that cannot be served profitably by investor owned utilities, because of frequent storm damages to utilities. Thus, we would hypothesize that municipal utilities may have to spend more on maintenance of their distribution network because they have be more prepared for future storms or for an incoming storm. Institutional factors make it unlikely that ownership type is strongly correlated with current storm damages, because changes in ownership type are difficult, and ownership type of many utilities dates back to the 1940s.[7] While storm damages may have influenced ownership type in the 1940s, we expect technological and population changes to have altered the susceptibility of electrical systems to suffer storm related outages.[8] Thus, it is conceivable that current ownership type is more strongly correlated with county char-

[7] An example of an institutional factor that makes changes in ownership type difficult is the Connecticut law which sets the following requirements for creating a municipal utility: a two-thirds vote of the municipality's legislative body, approval of its chief executive, and approval of the voters at a referendum [McCarthy and Hansen, 2012]. Another institutional factor is public employee labor unions opposition of privatization of municipal utilities, presumably for fear of loss of employment and pensions [Beecher et al., 1995, Lopez-de-Silanes et al., 1997].

[8] Furthermore, politics was a big factor in determining their original ownership type. For instance, many municipal utilities were established around the turn of the nineteenth century as a means of combatting corruption in cities [Schap, 1986, Glaeser, 2004], while electric cooperatives are the product of the New Deal.

acteristics that made storms damaging 70 years ago, than with county characteristics that make storms damaging nowadays. Nonetheless, we check the robustness of our results by including variables for damages to private and public property in two different periods: 1994 through 2002 and 2003 through 2012.

For the regression with power usage, we discuss four possible threats to identification. The first is the concern that municipal utilities are less likely to face damaging storms. If this was the case, we may expect municipal utilities to be less prepared for storms, and hence to experience greater disruptions when faced with a major storm. We attempt to mitigate this problem by excluding from our sample utilities located in areas that suffered high levels of storm related damages in earlier years. We also rerun the regression excluding the observations of one state, one state at the time.

A second potential threat to identification arises from the concern that our measure of damages does not capture damages to electric utilities. The reason for this is that our measure of damages includes destruction to all personal and public property, and destruction of property belonging to electric utilities is likely to be a small fraction of the total. Further, a variety of factors influence the size of this fraction. For instance, in rural areas, electrical circuits are long and more exposed to a variety of factors that can lead to outages [Kaufmann et al., 2010]. Alternatively, the same wind speeds may result in different levels of monetary damages to private and public property, depending on whether the county is urban, rural, poor, or rich. We try to account for these possibilities by controlling for factors such as the nature of the storm, population density, income, and the value of houses.

A third potential threat to identification is the concern that the reduction in electricity sales after a storm results from a change in demand, rather than a change in supply.[9] For instance, if areas served by municipal utilities are more likely to have mass evacuations in anticipation of storms, then the reduction in the demand for electricity is greater for municipal than for investor owned utilities. We address this concern in two different ways. First, differences in demand may

[9] We expect changes in the demand of electricity because prior studies have shown that hurricanes have short term effects on the local economy. For instance, Belasen and Polachek [2009] find that Florida counties hit by hurricanes experience short terms increases in wages and decreases in employment, while Strobl [2011] finds that in response to hurricanes, coastal counties experiences short term decreases in personal income.

be due to differences in observable characteristics. Thus, these demand effects should be controlled for by including additional variables in the regression: damages caused by tropical storms, and the interaction of damages with income per capita, population density, and the value of houses. Second, we re-estimate Equation (2) with, as the dependent variables, retail sales and employment. If changes in electricity demand caused by a storm differ by utility ownership type, then we would also expect changes in employment and retail sales caused by a storm to differ by ownership type. Conversely, if we find small ownership type differences in the impact of storms on employment and retail sales, it is unlikely that our results are caused by ownership type differences in changes in the demand of electricity.

A fourth potential threat to identification is the concern that changes in power usage are a poor proxy for outages. In Section 3.2 we provide statistical evidence that power outages are correlated with changes in monthly sales. More importantly, measurement error in a dependent variable is only a source of bias if it is related to the explanatory variable. For instance, we might expect industrial power plants to have to make up for any losses in production during an outage. If this is the case, and if investor owned utilities sell a greater fraction of their power to industrial power plants, then measurement error is correlated with ownership type and our estimates are biased. We attempt to control for this potential threat to identification by separating residential from non-residential electricity sales. ‘

3 Data, samples and summary statistics

3.1 Expenditure data

We examine operations and maintenance expenditures on distribution networks, which is the wiring of electricity from electrical substations to customers (generally in lines below 35 kV).[10] For investor owned utilities and a few cooperatives, distribution expenditure data was obtained from FERC Form 1.[11] Operations expenditures include the cost of changing line transformer taps, load

[10] In contrast, transmission is the wiring of electricity from power plants or grid to electrical substations (generally in lines above 69 kV).

[11] https://www.ferc.gov/docs-filing/forms/form-1/data.asp.

tests of line transformers, and adjusting line testing equipment. Maintenance expenditures include the costs of straightening poles, trimming trees, and clearing brush.[12] For municipal utilities, expenditure data was obtained from U.S. Energy Information Administration, survey EIA-412, "Annual Electric Industry Financial Report." Giles and Hayes [1999] provided the length of the distribution system (overhead and underground) and additional distribution expenditure data.

3.2 Power usage data

There are three potential sources of outage data. The U.S. Department of Energy, Form OE-417 Electric Emergency and Disturbance Events, should list all significant power outages, and thus would seem to provide an ideal proxy for storm related outages. However, utilities are only required to report losses of electric service that affect more than 50,000 customers. Since, investor owned utilities are much larger than municipal utilities, this makes investor owned utilities much more likely to have to report a power outage. For instance, in 2011, only 2% of municipal utilities had more than 50,000 customers, versus 54% of investor owned utilities. Thus this data is a biased measure of which mode of ownership is more likely to experience power outages.

We can however use the OE-412 data to provide evidence of the importance of storm related outages. Specifically, we examine the 2003–2012 OE-417 events, excluding outages that affected fewer than 500 customers and where we could not identify the affected utilities. We group the source of outage into hurricane, winter weather, other weather, and non-weather related (breaker failures, fires, earthquakes, electrical system separation, generation inadequacy, load shedding, transmission equipment failure, and vandalism). For each type of outage, we use the average values for the number of customers affected and the duration. We compute the percent of customers affected as (# of customers affected)/(total # of residential customers), where the number of residential customers served by a utility is from the EIA-861 data (which is discussed below). The summary statistics reported in Table 1 show that weather related outages comprise 37% of outages, but tend to affect more customers and be of longer duration.

Another source of outage data comes from state utility commissions. This data was used to

[12]See Code of Federal Regulation, Part 101, Uniform System of Accounts Prescribed for Public Utilities and Licensees Subject to the Provisions of the Federal Power Act.

study the reliability of investor owned utilities' service by Ter-Martirosyan and Kwoka [2010] and Lim and Yurukoglu [2014]. However, state utility commissions do not usually collect outage data on municipal utilities and cooperatives, and thus we cannot use this source of data to examine the impact of mode of ownership on outages.

Instead, we proxy outages by changes in monthly electricity sales for a stratified sample of utilities surveyed by the U.S. Energy Information Administration.[13] This survey, the Monthly Electric Utility Sales and Revenue Report with State Distributions (EIA-826), provides residential sales (in megawatts), non-residential sales (in megawatts), and the number of residential customers. We also include 204 additional observation from the Florida Public Service Commission, Statistics of the Florida Electric Utility Industry (various years).

Our proxy for outages is the percent difference between this month's residential electricity sales and residential electricity sales the same month of the prior year.[14] For instance, we discussed in the introduction how customers of NStar suffered power outages after Irene hit Massachusetts on August 27, 2011. Our data reports that NStar sold 527,532 megawatts to residential customers on August 2011, compared to 557,290 in August 2010 and 548,929 in August 2012. Thus, the power outage was associated with a $(557{,}290 - 527{,}532)/557{,}290 = 5\%$ decrease in electricity sales.

There are two advantages with our proxy for power outages. First, the proper functioning of the electric grid requires balancing flows of electricity generated and sold.[15] Thus, we expect reported electricity sales to be highly accurate.[16] Second, electricity sales are available for all modes of ownership.

The OE-417 data provides some support for our proxy for outages, since reports of outages are correlated with changes in electricity sales. Specifically, in the 46 observations when utilities reported weather related outages that affected at least 10% of monthly residential customers hours,

[13] The random sampling procedures ensures coverage of all states and the District of Columbia, and over-samples larger utilities.

[14] Or more precisely the difference between the log of this month's residential electricity sales and the log of the previous year's electricity sales.

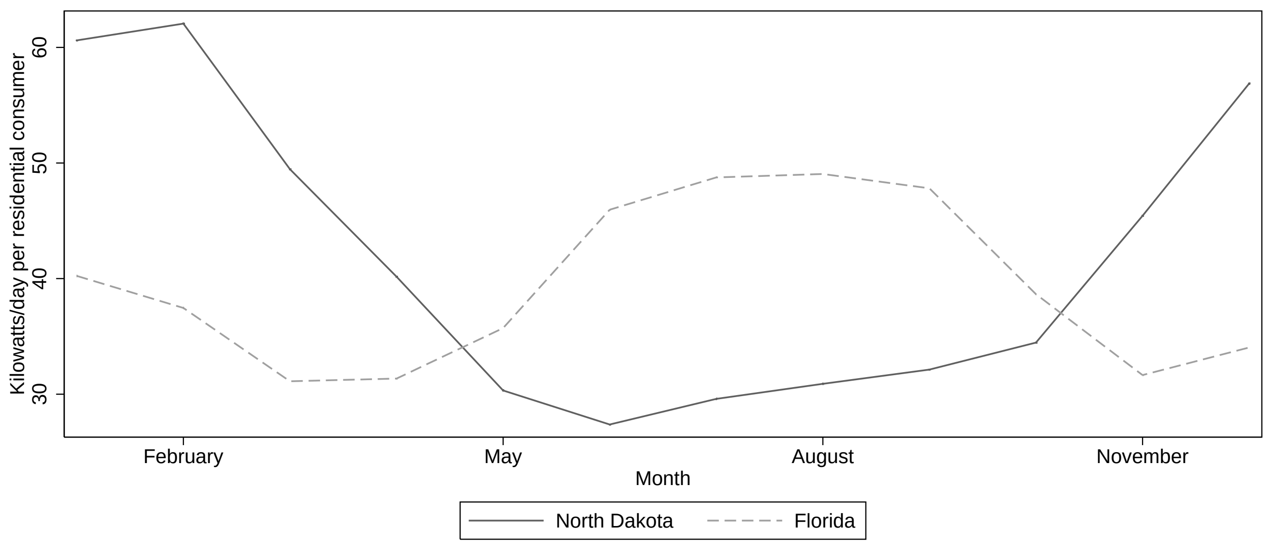
[15] One way to see this, is to look at the U.S. Electric Information Agency, Electric Power Annual 2012, Department of Energy, 2013. Table 1.3 provides total energy generated, lost, and exported from a survey of power plant operators (EIA-923), while Table 2.2 provides total sales from a survey of the power industry (EIA-861). By comparing the two tables we can verify that Sales = Generation − Losses − Exports.

[16] As discussed in Section 5.2, there is still error in our proxy because, for confidentiality reasons, the U.S. Electric Information Agency does not release sales of electricity purchased from power marketers, by utility and month.

monthly residential electricity sales decreased by 1.62%. In the 789 months when a utility had outages that affected less than 10% of monthly residential customer hours, residential electricity sales increased by 0.56%.[17] In the 46,822 months when a utility did not report any outages, residential electricity sales increased by 1.82%.

As discussed in Section 2, it is important that our analysis be in long differences in order to account for seasonality of residential electricity consumption, and the fact that seasonality varies by state. This is illustrated in Figure 1, which graphs average monthly residential sales for Florida and North Dakota for the years 1990 through 2012. In Florida, electricity consumption peeks during

Figure 1: Average residential consumption, by month and state, 1990-2012



the summer when air conditioning is used most intensively, while in North Dakota, electricity consumption peeks in the winter when heating is used most intensively.

[17] There are two reasons for why the number of observations with outages reported in this section is different from the one reported in Table 1. First, outages included in Table 1 can affect multiple utilities. In this case, in order to relate outages to changes in monthly electricity sales, we allocated outages to each utility in proportion to the number of residential customers. Second, in this section we only included outages for which we had monthly electricity sales.

3.3 Storm events data

Information on storm events was obtained from the National Oceanic and Atmospheric Administration, National Climatic Date Center, Storm Event Database.[18] We only examine storms from 1996 on since for prior years the database only includes tornado, thunderstorm wind and hail events.[19]

Damages refer to the destruction of private property (structures, objects, vegetation), public infrastructure, and public facilities [National Weather Service, 2007]. National weather officers obtain this information from insurance companies, emergency managers, the U.S. Geological Survey, the U.S. Army Corps of Engineers, power utility companies, newspaper articles, and other sources [National Weather Service, 2007]. The Storm Event Database includes 393,862 hurricanes, tornados, thunderstorms, floods, lightning and winter weather events. Table 2 lists summary statistics for these storm events. The two types of events with the highest per capita damages are tornadoes with F-scale higher than two, and hurricanes ($259 and $590 per capita property damages).

One potential problem with the storm data comes from the arbitrariness in labeling events. For instance, Downton et al. [2005] point out that the National Oceanic and Atmospheric Administration does not report the $520 million in flood damages in Massachusetts for February 1978 (where the "$520 million" amount is from a U.S. Army Corps of Engineers's report). In fact the National Oceanic and Atmospheric Administration did report this event, but reported it as a blizzard (with damages between $50 and $500 million).[20] In our main specifications, we resolve the arbitrariness of the labeling storm events by aggregating damages across all types of storm.

Again, we can use the OE-417 data to provides some support for our proxy for damages. In the 59 observations when utilities reported weather related outages that affected at least 10% of monthly residential customers hours, the area covered by the utility suffered monthly damages

[18]The database was downloaded at `ftp://ftp.ncdc.noaa.gov/pub/data/swdi/stormevents/csvfiles/` on July 17, 2014.

[19]Another potential source of data is the Spatial Hazards Events and Losses Database for the United States (SHELDUS). The authors of this database collected storm damages prior to 1996 from the National Oceanic and Atmospheric Administration's *Storm Data and Unusual Weather Phenomena with Late Reports and Corrections*. However, in those earlier years the publication used storm damage categories; for instance one category represents damages between $500 Million and $5 Billion. Thus, property damages before 1996 are not easily comparable to property damages in later years.

[20]National Oceanic and Atmospheric Administration, *Storm Data and Unusual Weather Phenomena with Late Reports and Corrections*, February 1978.

equal to 0.77% of personal income. In the 1,035 observations when a utility reported outages that affected less than 10% of monthly residential customer hours, the area suffered monthly damages equal to 0.37% of personal income.[21] In the 376,138 observations when a utility did not report any outages, the area suffered monthly damages equal to 0.02%.

3.4 Other data

We obtain mode of ownership, the percent of electricity that is self generated, and the list of counties covered by each utility from a yearly survey conducted by the U.S. Energy Information Administration (EIA-861 – Annual Electric Power Industry Report).

Yearly personal income and mid-year population estimates for each county are obtained from the U.S. Department of Commerce, Bureau of Economic Analysis. We lag these numbers by one; thus, for 2012, we use the population for 2011. The average value of a detached house is from the 2000 Census.

Heating degree days and cooling degree days measure how far temperature are from 65. They were obtain from NOAA National Climatic Data Center for each weather station/month.[22] We use the ZIP code of each weather station to aggregate the weather station data at the county level, using as weights the ratio of all county addresses that are located in a particular ZIP code.[23] Moreover, the county weather data is aggregated at the utility level, using county population as weights. Finally, heating and cooling degrees are computed by adding together heating degrees and cooling degrees.

Data on retail sales is obtained from a variety of sources listed in Table A1 in the Appendix; for most states we use taxable sales as a proxy for retail sales. Employment statistics are from the

[21]Note that the number of observations with outages reported in this section is larger than the one reported in Table 1, because some outages included in the table affected multiple utilities.

[22]`http://www.ncdc.noaa.gov/cdo-web/search`. Specifically, for each weather station and day, the National Oceanic and Atmospheric Administration collects the minimum and maximum temperature. Then,

$$\text{Heating degrees for a particular day} = \max\left\{0, 65 - \frac{\min + \max}{2}\right\}$$
$$\text{Cooling degrees for a particular day} = \max\left\{0, \frac{\min + \max}{2} - 65\right\}.$$

Heating degree and cooling degree days for each station/month are computed by averaging heating degree and cooling degree for all the days of the month.

[23]`http://www.huduser.org/portal/datasets/usps_crosswalk.html`.

Bureau of Labor Statistics, Local Area Unemployment Statistics (LAUS).[24] We obtained information on which electric utilities are supervised by the state regulatory agency in 1990 from Rodgers and Bauer [1991].

3.5 Aggregation of county level data

All county level variables used in this study are aggregated at the level of the utility using the information for the counties served by each utility. However, the aggregation is done a bit differently in the expenditure sample vs. the power usage sample.

In the expenditure sample, since our data is a cross section, we use the information for the counties that are served by a utility in the year 2000. For instance, to compute the population in the area served by a utility, we add the populations of all the counties served by the utility in the year 2000. When computing damages for the years 1994 through 2002, we add up damages for all hurricanes, tornados, thunderstorms, lightning, and winter weather conditions events (ice storm, wintry mix, ...), over all years 1994 through 2002, and over all the counties served by the utility in the year 2000. Since we want to measure whether a utility serves an area which is prone to storm damages, we examine past storm damages in the area, regardless of whether that utility covered that area in the past.

In the outage sample, since our data set is a panel, we use the information for the counties that are served by a utility for each particular year. For instance, to compute damages in December 2006, we add up damages for all storm events in December 2006, in counties served by the particular utility in 2006. Since our regression is in first differences, our measure of damages for December 2006 is the difference between damages in December 2006 and damages in December 2005. Thus, to insure comparability in damages, we eliminate from the sample observations in years where a utility changed the area it covered.

[24] `ftp://ftp.bls.gov/pub/time.series/la/`.

3.6 Samples

Our expenditures sample consists of 179 investor owned, 801 cooperative, and 1,437 municipal utilities. These are the utilities for which we could obtain the length of distribution lines. Expenditure data is quite noisy and we were not able to obtain it for all years. In order to minimize the error, we averaged real distribution expenditures over the years 1995–2002. Nonetheless, the number of utilities for which we have distribution expenditures is substantially smaller and consists of 149 investor owned, 447 cooperatives, and 599 municipal utilities.

Starting in 1999, the EIA-861 survey provides the list of counties covered by each utility. For this reason, in the power usage sample, we restrict ourselves to the years 1999 through 2012. We exclude the only federal utility from our study (the U.S. Bureau of Indian Affairs' Mission Power), and lump together utilities owned by municipalities, states, and political subdivisions. Further, we exclude from our sample utilities that cover areas that had unusually high storm damages during the years 1994 through 1998, although our main findings still hold if we do not exclude these utilities.

Thus, our sample consists of utilities classified as investor owned, cooperative, and municipal. There are 260 investor owned, 119 cooperatives, and 97 municipal utilities.[25] If a utility changes ownership type over our sample, it is considered a different utility. In the power usage sample, we define utilities as firms operating in a single state. Thus, a utility that operates in three different states is counted as three different utilities. The unit of observation is a utility-year-month. Since our sample is from 1999 to 2012, each utility has at most $14 \times 12 = 168$ observations. The sample size is however reduced by the fact that we have a stratified sample and thus not all utilities are observed in all years. We end up with 31,659 observations from investor owned, 13,282 from cooperatives, and 13,474 from municipal utilities.

In the regressions, the sample is further reduced to account for a variety of sources of measurement error. Specifically, we lose the first year of observations for each utility since we estimate the regressions in long differences to account for seasonal effects. Another source of measurement error are changes in the counties served by a utility. We eliminate this measurement error by excluding

[25]We end up with a higher percentage of investor owned utilities in the power usage sample because the stratified sample over-samples larger utilities.

the years when a utility just changed county coverage.

An additional source of measurement error comes from sales of electricity purchased from power marketers. For confidentiality reasons, monthly electricity sales released to the public, do not include sales of electricity purchased from power marketers, and do not include the number of customers served with electricity purchased from power marketers. Thus, an increase in the use of electricity from power marketers leads to a decrease in reported monthly electricity sales. We reduce this measurement error in two ways. First, we note that an increase in sales of electricity purchased from power marketers decreases both residential electricity sales and the number of residential customers. Thus, we reduce the measurement error by examining residential electricity sales per customer. Second, we note that the EIA-861 data provides yearly electricity sales purchased from power marketers. Thus we reduce the error in reported monthly electricity sales by excluding all utilities-state-years in which the percent of customers that receive electricity purchased from power marketers changed by more than 10%, compared to the previous year.

3.7 Summary statistics

Table 3 provides summary statistics for our expenditure sample by ownership type. We note that investor owned utilities are by far the largest utility type, and municipal utilities the smallest. A few studies have estimated returns to scale in distribution of electricity. Using electric distribution data for Norway and Canada, Salvanes and Tjøtta [1994] and Yatchew [2000] find economies to scale for up to 20,000 customers, while using electric distribution data for seven European countries, Growitsch et al. [2009] find economies of scale throughout the sample. In our expenditure sample, 82% of investor owned utilities have more than 20,000 residential customers, while only 13% of municipal utilities have more than 20,000 residential customers. Thus, the referenced literature suggests that investor owned utilities operate at a more efficient scale than municipal utilities.

We also see that municipal utilities spend the most on operations and maintenance of their distribution network, while investor owned utilities bury the highest percentage of their distribution lines underground. Storm damages are normalized by dividing real damages (destruction of private and public property) by the year 2000 real personal income in the counties covered by the utility.

The average normalized damages for the years 1994 through 2002 was highest for cooperatives and lowest for investor owned utilities, while in 2003–2012, it was highest for investor owned utilities and lowest for municipal utilities. Thus, there appears to be quite a bit of variability in terms of which utilities suffer storm damages.

Table 4 provides summary statistics for our power usage sample by ownership type. Investor owned utilities tend to be the largest utilities while cooperative tend to be the smallest, regardless of whether we measure the size of a utility by residential electricity sales, non-residential electricity sales, the number of residential customers, or the total population in the counties served by the utility. For instance, the average investor owned utility has 410,181 residential customers, while the average cooperative has 35,772 residential customers. Further, we see that investor owned utilities self generate a much higher percentage of the electricity they sell, compared to municipal utilities (43% vs. 25%). We can also see that cooperatives cover areas with much lower density than municipal and investor owned utilities; namely 94 inhabitants per square mile vs. 406 and 380.

Nonetheless, municipal, investor owned, and cooperative utilities cover similar areas in terms of income per capita, residential electricity consumption per customer, and housing values. Income per capita is $35,307–$36,778, while the average residential customer purchases 41–42 kW of electricity per day. The average value of a detached house is similar in areas covered by municipal and investor owned utilities ($136,177 vs. $129,538), but lower in areas covered by cooperatives ($115,834). Despite the similar incomes, retail sales vary by mode of ownership; retail sales are $28 per capita and day in areas served by an investor owned utility vs. $36 in areas served by a cooperative. These differences may be due to our proxy for retail sales, which for most states is taxable sales. Thus, ownership type differences in taxable sales may be due to differences among states in which goods are taxed. Further, municipal, investor owned, and cooperative utilities cover areas with different weather patterns. Cooperative utilities see more extreme weather (18.3 degrees away from 65 vs. 16.3 for investor owned utilities). We constructed the sample of utilities in a way that insures that they had similar storm damages in the years 1996 through 1998. However, over our sample period (1999 through 2012), investor owned utilities covered areas with the highest storm damages, while municipal utilities covered areas with the lowest damages.

4 Results

4.1 Expenditure sample

In Table 5 we regress the logarithm of operations and maintenance distribution expenses (per mile of distribution line) on indicator variables for ownership type, with cooperative ownership as the excluded category. We see that municipal utilities spend $1.961-1.055 \approx 91\%$ more per mile than investor owned utilities. Some of the differences in cost may be due to the fact that municipal utilities serve more densely populated areas, where maintaining the distribution network is inherently more expensive. For this reason, we rerun the regression with additional controls for the log of the number of customers per line mile, the log of the percent of electrical customers that are residential, and the log of county wages in the sector of trade, transportation and utilities. As expected, distribution expenditures are higher for utilities with more customers per distribution line mile. Nonetheless, even with these controls, we find that municipal utility spend $0.036-(-0.426) \approx 46\%$ more per mile than investor owned utilities.

The higher distribution expenses may be due to the fact that municipal utilities faced more storms in our sample period. Specifically, in 1994–2002, areas covered by municipal utilities in the expenditure sample had twice the storm damage as areas covered by investor owned utilities (see Table 3). However, in a utility's income statement, storm damages are classified as "extraordinary expenses," and thus are not included in our measure of operations and maintenance expenses. Nonetheless, it is possible that municipal utilities spend more on distribution maintenance because they are in areas that have greater storm activity. We provide two reasons for why this explanation is not sufficient to explain the higher maintenance expenditures by municipal utilities. First, in 2003–2012, damages in areas covered by investor owned utilities were 83% higher than damages in areas covered by municipal utilities (see Table 3). Thus, while it is clear that storm damages are highly volatile, municipal utilities in the expenditure sample do not appear to be located in areas with greater propensities to suffer storm damages. Second, we rerun the regression with storm damages in 1994–2002 and 2003–2012 as additional control variables. Even with these controls, we find that municipal utilities spend $0.001-(-0.442) = 44\%$ more per mile on distribution than investor owned utilities.

We run the same type of regressions with the percent of distribution lines underground as the dependent variable. We find that investor owned utilities have 8% points more distribution lines underground (thus almost twice the percent of distribution lines underground as municipal utilities). Further, utilities in more densely populated areas have a higher percentage of their distribution lines underground. In summary, our results support newspaper accounts that claim that municipal utilities spend more on maintenance of distribution lines, compared to investor owned utilities. However, our results also indicate that municipal utilities are not necessarily better prepared for storms, since they have a smaller percent of their distribution lines underground.

4.2 Power usage sample

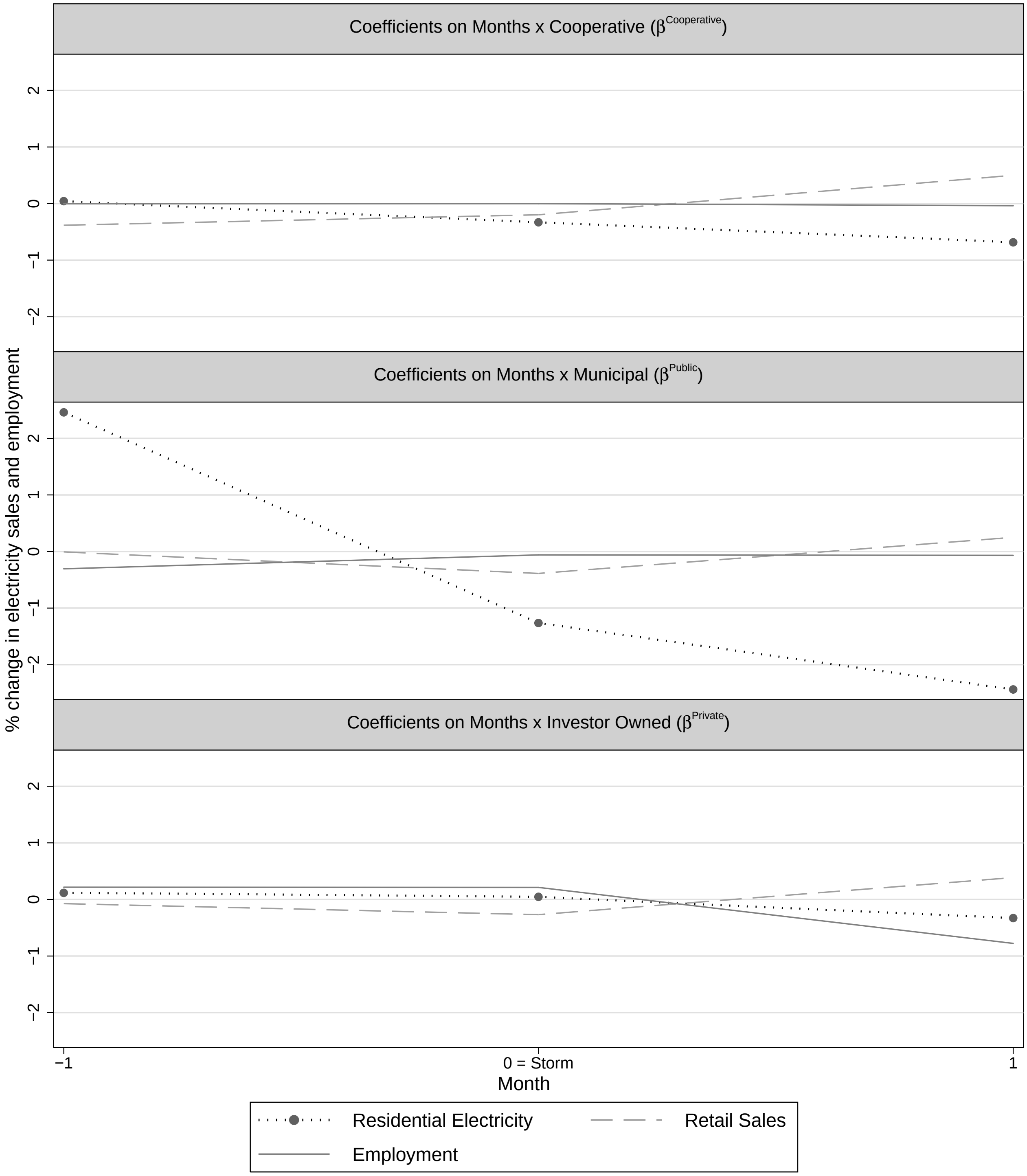
In order to estimate the overall effect of storm preparedness on quality of service, we examine changes in electricity sales that follow major storms. First, we provide graphical evidence of our main result. We estimate three separate regressions of the following form:

$$\Delta \ln q_{usyt} = \alpha_y^1 + \alpha_s^2 + \alpha_{o(u)}^3 + \sum_{m=-1}^{1} \beta_{o(u)}^m \, \Delta\text{Damages}_{usyt-m} + \gamma_s \Delta \ln d_{usyt}, \tag{3}$$

with as the dependent variable, q_{usyt}, residential electricity sales per customer, retail sales, and employment. Thus, we include the current value of damages as well as a lag and a lead. These variables are interacted with the mode of ownership of the utility. For instance, when the dependent variable is residential electricity sales, the coefficients $\beta^{-1}_{\text{Municipal}}, \beta^{0}_{\text{Municipal}}, \beta^{1}_{\text{Municipal}}$, describe the percent change in electricity sales by a municipal utility that occur the month before the storm, the month of the storm, and the month after. These coefficients are plotted in the middle panel of Figure 2.

We can see that residential electricity sales for municipal utilities decline by 1.2%–2.4% in the month of the storm and the following month. For investor owned utilities, electricity sales decline

Figure 2: Percent change in residential electricity sales, employment, and retail sales from one month before to one month after a major storm



Coefficient estimates for month dummies ($\beta^m_{\text{Cooperative}}, \beta^m_{\text{Municipal}}, \beta^m_{\text{Investor Owned}}$) from three separate regressions: $\Delta \ln q_{usyt} = \alpha^1_y + \alpha^2_s + \alpha^3_{o(u)} + \sum_{m=-1}^{1} \beta^m_{o(u)}\, \Delta\text{Damages}_{usyt-m} + \gamma_s \Delta \ln d_{usyt}$. An observation, $usyt$, is a utility-state-year-month. The dependent variables, q_{usyt}, are residential electricity sales per customer, employment, and retail sales. Storm damages are summed across all counties served by utility u. The mode of ownership of utility u is $o(u)$: cooperative, municipal or investor owned. Thus, $\beta^m_{\text{Municipal}} = -2$ indicates that storm damages of 1% if personal income reduces the dependent variable by 2%, m months after the storm. The regressions include the interaction of degree days and state, and year fixed effects.

by 0.3% the month after the storm. Finally, electricity sales for cooperatives decrease by 0.3–0.6% the month of the storm and the following month. Employment declines are small in magnitude for cooperatives and municipal utilities (0.0001%–0.07%), but larger for investor owned utilities (0.3% the month after the storm). Finally, retail sales only decline significantly after a storm in areas covered by cooperatives.

Thus, a major storm is most likely to reduces electricity sales in areas covered by municipal utilities. Further, this reduction appears to be due to a change in the supply of electricity, rather than a change in demand. Specifically, reductions in employment and retail sales are small in magnitude and tend to occur in areas with cooperatives and investor owned utilities, rather than in areas covered by municipal utilities.

Table 6 reports these results in regression format. The dependent variable for each regression is specified in Column 1, while the main explanatory variables are in Row 1. The first explanatory variable, "Damages," is the sum of storm damages the month of the storm and the following. The next five explanatory variables are damages interacted with ownership type, the nature of the storm, and county characteristics. To simplify the table we did not include a full lag structure. However, the regressions still include controls for year fixed effects and the interaction of state fixed effects and the log of heating and cooling degrees, while the standard errors are clustered at the state level. All coefficients are reported as percentages.

In the first row, the dependent variable is residential electricity consumption and the main explanatory variable is "Damages." Storm damages of 1% of personal income are associated with a 0.06% decrease in residential electricity consumption the month of the storm and the following month. When we interact damages with the mode of ownership, we find that storm damages of 1% of personal income reduce residential electricity sales for municipal utilities by 0.51% + 1.34% = 1.85%, but have no effect on residential electricity sales for investor owned utilities. Storm damages of 1% of personal income also reduce non-residential electricity sales for municipal utilities by 0.71%, but have no effect on non-residential sales for investor owned utilities.

Our results may be driven by decreases in electricity demand following a storm. Specifically, it is possible that demand decreases by a greater amount in areas served by municipal utilities, compared to areas served by investor owned utilities. We attempt to address this concern by examining the effect of storm damages on retail sales and employment. When we estimate Equation (3) with retail sales and employment as the dependent variables, we do not find a decrease in these variables following a storm in areas served by municipal utilities. This suggests that the decline in electricity sales in areas served by municipal utilities is not driven by ownership-type differences in changes in electricity demand.

We may also be concerned that these results are driven by ownership type differences in storm damages. We attempted to address the concern by excluding from our sample utilities in areas that had unusually high levels of damages between 1994 and 1998. To further address this concern, we control for damages caused by a tropical storm, and interact damages with income per capita, population density, and the average value of a house. Following a storm, we find greater decreases in residential electricity sales in more rural areas, but the other variables do not have statistically significant effects.[26] Further, the inclusion of these variables does not qualitatively change our results.

To provide additional evidence that our results are not driven by a correlation between the nature of the storms and the mode of ownership, we re-run the regressions excluding the observations of one state at the time. The magnitude of the coefficients is the largest if we exclude Tennessee, and the smallest if we exclude Utah from the sample. Nonetheless, all 51 regressions give qualitatively the same findings.

4.3 Further findings

We found greater decreases in electricity sales following major storms in areas served by municipal utilities. In this section, we examine whether these findings are driven by characteristics of municipal utilities other than their ownership type. In all the regression in this subsection, we include the interaction between population density and storm damages, since we found this variable to affect changes in electricity sales.

First, we saw in Table 4 that municipal utilities are smaller than investor owned utilities. It

[26]For space considerations, the regression with housing values in not included in Table 6.

is possible that larger utilities are better at dealing with storms; for instance, they may use crews from unaffected areas to restore electricity service in the affected areas. If this is the case, the bad performance of municipal utilities may be due to their size, rather than a lack of managerial incentives. For this reason, Table 7 examines the impact of storms on residential electricity sales with, as an additional term, the interaction of storm damages and the log of lagged yearly residential electricity sales. The inclusion of this additional variable does not qualitatively affect our results.

Second, utilities differ in whether they generate or buy the electricity they distribute. Specifically, investor owned utilities self generate a higher fraction of the power they sell, compared to municipal utilities. Thus the better storm performance by investor owned utilities could be explained by a greater control of their electricity supply. For this reason, we estimated the impact of storms on residential electricity sales with, as an additional term, the interaction of storm damages and the percent of electricity that is self generated. Again, this additional variable is statistically insignificant and its inclusion does not qualitatively affect our results.

Third, not all states regulate municipal utilities. Thus, the worse performance of municipal utilities may be due to lack of regulatory control. Alternatively, regulation may worsen storm preparedness and the performance of municipal utilities would be even worse if they were all regulated.[27] For this reason we estimate the impact of storms on residential electricity sales with, as an additional control, the interaction of storm damages and an indicator for whether the utility is subject to the state regulatory commission. Even with this additional variable, we find a greater decrease in electricity sales in areas covered by municipal utilities. Further, we find greater reductions in electricity sales following a storm in states that regulate municipal utilities.

The greater decrease in electricity sales from regulation may be due to demand rather than supply effects. For instance, electricity demand may decrease by a greater amount in states that regulate municipal utilities if these states are more likely to issue mandatory evacuations before a storm. For this reason we rerun the same regression with retail sales and employment as the dependent variables. We find that employment decreases less in states that regulate municipal utilities and find no difference in changes in retail sales across regulatory types. Thus, the effect of

[27]For instance, Connecticut Light and Power's lack of preparedness for Storm Irene and the October Nor'easter was blamed on the state regulatory agency for not authorizing enough funding for vegetation management [Davies Consulting, 2012].

regulation on electricity sales is most likely to be a supply effect; i.e., regulated municipal utilities are more likely to have outages following storms than non-regulated municipal utilities.

5 Conclusion

Alleged lack of storm preparation by investor owned utilities has led to popular support for an expansion of municipal electrical services following the 1998 ice storm in upstate New York, Hurricane Irene, and superstorm Sandy [Singer, 2012, Cardwell, 2013, Bruun, 2009, Janoski, 2012]. We examined spending on the distribution system for a sample of 179 investor owned, 801 cooperative, and 1,437 municipal utilities in the United States for the years 1998–2002. Compared to investor owned utilities, municipal utilities spend more on maintenance of distribution lines, but have a smaller fraction of distribution lines underground. Thus, there are several reasons for why we should not conclude that municipal utilities are better prepared for storms, solely by noticing that municipal utilities spend more on maintenance. First, investor owned utilities have a higher percentage of lines underground. Second, the higher distribution expenses may be evidence of wasteful spending by municipal utilities, rather than greater maintenance. Third, the higher distribution expenses by municipal utilities could be evidence that they are too small to benefit from economies of scale.

In order to examine empirically which utilities have the best performance in response to major storms, we examined a stratified random sample of 241 investor owned, 96 cooperative, and 94 municipal utilities in the United States during the years 1999 through 2012. We provided evidence that electricity sales decrease more when the utility is municipally owned. Thus, our evidence contradicts one of the justifications for calls to expand municipal electrical service; namely, the alleged better performance of municipal utilities during storms. Prior international evidence reached a similarly conclusion, namely that the privatization of the electrical distribution network does not lead to more power outages [Fumagalli et al., 2007, Gonzalez-Eiras and Rossi, 2007, Hartley, 1999].

Methodologically, we provided a novel proxy for to measure power outages; the difference between monthly electricity sales and the previous years' monthly electricity sales. To validate our measure we found it to be correlated to outages recorded on the U.S. Department of Energy form OE-417. We also compared changes in monthly electricity sales after a storm to changes in monthly employment and monthly retail sales. We do not find electricity sales to move conjointly with retail sales and employment. Thus, changes in electricity sales are more likely to represent changes in the supply of electricity than changes in the demand of electricity.

Table 1: Summary statistics for outages from OE-417

Outage type	#Events	Customers affected (%)	Duration (hours)
Hurricane	210	40	106
Winter weather	203	21	86
Other weather	222	22	83
Non-weather	1095	24	67

Sources: The number of customers affected, the duration of the outage, and the outage type are obtained from 2003–2012 U.S. Department of Energy, Office of Electricity Delivery and Energy Reliability, OE-417 Electric Emergency and Disturbance Events. We have excluded events that affected fewer than 500 customers and events where the affected utilities could not be identified. The number of residential customers served by a utility is from the EIA-861 data. The percent of customers affected is computed as 100 $\times$ (Customers affected)/(Residential customers). "Non-weather events" include breaker failures, fires, earthquakes, electrical system separation, generation inadequacy, load shedding, transmission equipment failure, and vandalism.

Table 2: Summary statistics for storm events

Event type	#Events	Population per event	Damages Total in $M	Damages Per cap in $
Tropical cyclones	5,372	178,309	163,877	171.08
Hurricanes	1,191	133,025	93,434	589.74
Tornadoes	20,104	118,978	23,104	9.66
Tornadoes with F-scale > 2	745	80,934	15,644	259.45
Winter weather	83,009	100,799	8,747	1.05
Floods	28,775	179,259	169,059	32.77
Thunderstorms	244,385	167,669	17,728	0.43
T-storm w/ wind > 80 mph	9,318	185,320	8,094	4.69
Lightning	11,026	341,437	773	0.21

Source: National Oceanic and Atmospheric Administration, National Climatic Date Center, Storm Event Database.

Table 3: Mean values for expenditures sample

Utility ownership type	Municipal (n=1437)	Investor Owned (n=179)	Cooperative (n=801)
Distribution expend. per mile ($)	12,743	4,031	6,011
Distribution miles	312	16,240	2,495
Underground distribution lines (%)	13	20	10
More than 20,000 customers (%)	9	82	27
Customers per mile	62	38	9
Percent residential	83	86	87
Wage for trade, transportation, and utilities ($)	40,683	47,663	40,875
Yearly damage 1996–2002 (%)	0.165	0.082	0.234
Yearly damage 2003–2012 (%)	0.165	0.302	0.221

In order to form a single cross section, except when noted, for each utility, we compute the mean value of each variable for the years 1995–2002. "Distribution" is the wiring of electricity from electrical substations to customers (generally in lines below 35 kV). Expenditure consist of operations and meaintenance expenditures; i.e., changing line transformer taps, loads tests of line transformers, adjusting line testing equipment, straightening poles, trimming trees, and clearing brush. Sources: FERC Form 1, EIA-412, and Giles and Hayes [1999].

Table 4: Mean values for power usage sample

Utility ownership type	Municipal	Investor Owned	Cooperative
Residential sales (megawatts/day)	3,622	11,371	1,348
Percent self generated	25	43	5
Non-residential sales (megawatts/day)	5,783	18,709	1,449
Residential customers	116,119	410,495	35,772
Population in counties covered by utility	815,953	1,910,633	452,793
People/sq. mi. in counties covered by utility	406	380	94
Income per capita in counties covered by utility	36,254	36,788	35,307
Average house value in counties covered by utility	136,177	129,579	115,834
Residential sales (kW per capita/customer & day)	42	41	42
Retail sales (per capita, per day)	33	28	36
Monthly damages (% of personal income)	0.004	0.017	0.012
Monthly damages in 1996–1998 (% of personal income)	0.003	0.004	0.003
Heating and cooling degrees	16.3	17.5	18.3

The sources for the data are described in Section 3.

Table 5: Effects of ownership on electrical distribution spending

	Exp. per mi.	Exp. per mi.	Exp. per mi.	% Undgrd.	% Undgrd.	% Undgrd.
Investor	1.055***	-0.426***	-0.442***	10.326***	2.306	2.316
	(0.077)	(0.081)	(0.080)	(1.990)	(2.176)	(2.169)
Municipal	1.961***	0.036	0.001	2.815***	-5.530***	-5.476***
	(0.107)	(0.103)	(0.101)	(1.039)	(1.350)	(1.365)
Cust. per dist. mi.		0.927***	0.942***		4.062***	4.044***
		(0.039)	(0.037)		(0.419)	(0.424)
Percent resident.		-0.806***	-0.830***		-4.781	-4.738
		(0.116)	(0.120)		(5.622)	(5.584)
Wages		-0.034	-0.048		15.235***	15.358***
		(0.100)	(0.095)		(2.535)	(2.577)
Damage 1996–2002			6.945**			25.948
			(3.390)			(64.611)
Damage 2003–2012			-1.209			-46.893
			(2.595)			(41.966)
R^2	0.470	0.743	0.750	0.024	0.097	0.097
Observations	1195	1194	1191	2333	2330	2326

Notes – The unit of observation is the utility. Except when specified otherwise, all variables are averages over the years 1995–2002. The dependent variables are distribution and maintenance expenditures by mile of distribution lines and the percent of distribution lines that are underground. All variables are in logarithms except for ownership type and percent underground. A utility's ownership type is Investor owned, Municipal, or Cooperative (excluded category). The regressions include state fixed effects. Robust standard errors are clustered at the state level. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

Table 6: Effect of storms on electricity use, retail sales, and employment

Explanatory variable:	Damage	Damage × Municipal	Damage × Investor	Damage × Trop. Storm	Damage × Inc/Cap	Damage × Density	N
Dependent variable							
Mw residential	-0.07						49,767
	(0.07)						
Mw non-residential	-0.07						50,132
	(0.06)						
Retail sales	0.11						21,098
	(0.09)						
Employment	0.05***						50,546
	(0.01)						
Mw residential	-0.51**	-1.34***	0.50**				49,767
	(0.20)	(0.46)	(0.20)				
Mw non-residential	-0.33**	-0.38	0.29**				50,132
	(0.13)	(0.82)	(0.13)				
Retail sales	0.15***	-0.23	-0.10				21,098
	(0.04)	(0.28)	(0.27)				
Employment	-0.02	-0.05	0.08***				50,546
	(0.03)	(0.06)	(0.03)				
Mw residential	-0.67***	-1.18**	0.49**	0.18			49,767
	(0.23)	(0.45)	(0.20)	(0.17)			
Mw residential	-11.44	-1.32***	0.35		1.06		49,767
	(8.75)	(0.39)	(0.24)		(0.85)		
Mw residential	-0.88***	-1.33***	0.32*			0.08***	49,767
	(0.19)	(0.40)	(0.18)			(0.02)	

Each row summarizes the results of a separate regression where the unit of observation is the utility-state-year-month. All variables are in long differences; for instance, 'Mw residential' is the change in residential electric consumption per customer compared to the same month in the previous year. All variables, except 'Damages,' are in logs. 'Damages' are storm damages in the two prior months divided by personal income. The regressions also include the interaction of state and heating and cooling degree days, as well as year fixed effects. Robust standard errors are clustered at the state level. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

Table 7: Effects of storm damage on electricity use, retail sales, and employment with utility controls

Explanatory variable:	Damage	Damage ×					
		Municipal	Investor	Density	Size	% Self. Gen.	Regulated
Dependent variable							
Mw residential	-2.36	-1.31***	0.08	0.12*	0.09		
	(2.04)	(0.34)	(0.41)	(0.07)	(0.12)		
Mw non-residential	2.23	-0.42	0.60**	-0.01	-0.18**		
	(1.33)	(0.76)	(0.26)	(0.04)	(0.08)		
Retail sales	5.47	-0.37	0.90	0.36	-0.48		
	(4.65)	(0.81)	(1.05)	(0.52)	(0.43)		
Employment	1.23	-0.07	0.03	0.12***	-0.13*		
	(1.02)	(0.09)	(0.16)	(0.02)	(0.07)		
Mw residential	-0.64*	-1.28***	0.60*	0.03		-0.57	
	(0.35)	(0.47)	(0.34)	(0.06)		(0.50)	
Mw non-residential	0.00	-0.20	0.89	-0.07		-1.51	
	(0.57)	(0.63)	(0.62)	(0.12)		(1.19)	
Retail sales	0.30	0.18	0.43	-0.04		-1.02	
	(1.33)	(0.93)	(0.58)	(0.32)		(0.81)	
Employment	-0.12	0.16	0.50	0.02		-1.62*	
	(0.33)	(0.15)	(0.41)	(0.07)		(0.89)	
Mw residential	-0.60***	-1.17***	0.61***	0.07***			-0.54***
	(0.13)	(0.30)	(0.13)	(0.02)			(0.13)
Mw non-residential	-0.52***	-0.30	0.27*	0.07***			-0.23
	(0.14)	(0.85)	(0.15)	(0.02)			(0.20)
Retail sales	-0.07	0.04	-0.10	-0.02			0.31
	(1.27)	(0.90)	(0.25)	(0.34)			(0.40)
Employment	-0.97***	-0.11	-0.45***	0.17***			0.29***
	(0.11)	(0.11)	(0.09)	(0.02)			(0.06)

Each row summarizes the results of a separate regression, where the dependent variable is the log of residential electricity use and the unit of observation is the utility-state-year-month. All variables are in long differences. is the change in residential electric consumption per customer compared to the same month in the previous year. 'Damages' are storm damages in the two prior months divided by personal income. The regressions also include the interaction of state and heating and cooling degree days, as well as year fixed effects. "Size" is the log of previous year's residential electricity use, "Regulated" denotes whether the utility is regulated by the state commission, "% Self. Gen.' represents the percent of the electricity sold that is self generated. Robust standard errors are clustered at the state level. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

References

Janice A. Beecher, G. Richard Dreese, and John D. Stanford. Regulatory implicationsof water and wastewater utility privatization. The National Regulatory Research Institute, 95-09, July 1995.

Ariel R. Belasen and Solomon W. Polachek. How disasters affect local labor markets: The effects of hurricanes in Florida. *Journal of Human Resources*, 44(1):251–276, Winter 2009.

Matthew Bruun. Municipal utilities pondered after storm mess; irate customers looking for options. *Sunday Telegram (Massachusetts)*, A1, January 11, 2009.

Diane Cardwell. Power to the people. *New York Times*, B1, March 14, 2013.

Rob Cox. The troubling Connecticut power failure. *New York Times*, November 3, 2011.

Davies Consulting. Final report: Connecticut Light and Power's emergency preparedness and response to Storm Irene and the October Nor'easter. Prepared for: Northeast Utilities System, February 2012.

Michael J. Doane and Daniel F. Spulber. Municipalization: Opportunism and bypass in electric power. *Energy Law Journal*, 18(2):333–361, 1997.

Mary W. Downton, J. Zoe Barnard Miller, and Roger A. Pielke Jr. Reanalysis of U.S. national weather service flood loss database. *Natural Hazards Review*, 6(1):13–22, February 2005.

Elena Fumagalli, Paola Garrone, and Luca Grilli. Service quality in the electricity industry: The role of privatization and managerial behavior. *Energy Policy*, 35(12):6212–622, December 2007.

Ellen Flynn Giles and Ann T. Hayes, editors. *McGraw-Hill Energy Directory of Electric Power Producers and Distributors 2000.* 108th Editions of the Electrical World Directory. McGraw Hill, New York, NY, 1999.

Edward L. Glaeser. Public ownership in the American city. In Amy E. Schwartz, editor, *Urban Issues and Public Finance: Essays in Honor of Dick Netzer*, pages 130–162. Edward Elgar, Northampton, 2004.

Martin Gonzalez-Eiras and Martin A. Rossi. The impact of electricity sector privatization on public health. Working Paper, Inter-American Development Bank, 2007.

Christian Growitsch, Tooraj Jamasb, and Michael Pollitt. Quality of service, efficiency, and scale in network industries: An analysis of European electricity distribution. *Applied Economics*, 41 (20):2555–2570, 2009.

Oliver Hart, Andrei Shleifer, and Robert W. Vishny. The proper scope of government: Theory and an application to prisons. *Quarterly Journal of Economics*, 112(4):1127–1161, November 1997.

Peter Hartley. Reform of the electricity supply industry. *Economia Mexicana*, 8(1):45–90, 1999.

Catherine Hausman. Corporate incentives and nuclear safety. *American Economic Journal: Economic Policy*, 6:178–206, 2014.

Steve Janoski. 2 towns want to join Butler utility after company's fast storm repairs. *The Record (Berger County, NJ)*, L03, November 17, 2012.

L. R. Jones. Assessing the financial feasibility of municipal electric utility formation. *State & Local Government Review*, 21(1):38–46, Winter 1989.

Larry Kaufmann, Lullit Getachew, Matt Makos, and John Rich. System reliability regulation: A jurisdictional survey. Pacific Economics Group, 2010.

John E. Kwoka. Governance alternatives and pricing in the U.S. electric power industry. *Journal of Law, Economics and Organization*, 18(1):278–294, 2002.

Steven D. Levitt. Using electoral cycles in police hiring to estimate the effect of police on crime. *American Economic Review*, 87(3):270–290, 1997.

Claire S.H. Lim and Ali Yurukoglu. Dynamic natural monopoly regulation: Time inconsistency, asymmetric information, and political environments. Mimeo, April 2014.

Florencio Lopez-de-Silanes, Andrei Shleifer, and Robert W. Vishny. Privatization in the United States. *RAND Journal of Economics*, 28(3):447–471, 1997.

Kevin McCarthy and Lee R. Hansen. Forming a municipal electric utility. Office of Legislative Reserach, Research Report, State of Connecticut, January 2012.

National Weather Service. Storm date preparation. Instruction 10-1605, 2007.

Sam Peltzman. Pricing in public and private enterprises: Electric utilities in the United States. *Journal of Law and Economics*, 14(1):109–147, 1971.

Paul Rodgers and Karon Bauer. *1990 Annual Report on Utility and Carrier Regulation of the National Association of Regulatory Utility Commissioners*. National Association of Regulation Commissioners, Washington D.C., 1991.

Nancy L. Rose and Paul L. Joskow. The diffusion of new technologies: evidence from the electric utility industry. *RAND Journal of Economics*, 3(21):354–373, Autumn 1990.

Kjell G. Salvanes and S. Tjøtta. Productivity differences in multiple output industries: An empirical application to electricity distribution. *Journal of Productivity Analysis*, 5(1):23–43, April 1994.

David Schap. *Municipal ownership in the electric industry*. Praeger Publishers, New York, NY, 1986.

Shelly Sigo. Voters in Winter Park, Fla., approve $50m of bonds to buy electrical utility. *The Bond Buyer*, September 11, 2003.

Stephen Singer. Connecticut eyes utility system changes. *Berkshire Eagle*, November 22, 2012.

Eric Strobl. The economic growth impact of hurricanes: Evidence from U.S. coastal counties. *Review of Economics and Statistics*, 3(2):575–589, May 2011.

Anna Ter-Martirosyan and John Kwoka. Incentive regulation, service quality, and standards in U.S. electricity distribution. *Journal of Regulatory Economics*, 38(3):258–273, December 2010.

Scott Van Voorhis. Power outages: Who pays the bill? New England Center for Investigative Reporting, February 19, 2012.

Razvan Vlaicu and Alexander Whalley. Hierarchical accountability in government: Theory and evidence. Mimeo, University of Maryland, 2013.

Ray Weiss. South Daytona, FPL aiming to repair short-circuited relationship. *News-Journal* (Daytona Beach, Florida), June 16, 2013.

A. Yatchew. Scale economies in electricity distribution: A semiparametric analysis. *Journal of Applied Economics*, 15(2):187–210, March/April 2000.

Table A1: Date sources for retail sales

State	Years	Type	Source
CO	1999–2012	Taxable sales	State of Colorado, Department of Revenues, Statistical Studies and Reports, Colorado Retail Sales and Sales Tax Summaries, Monthly County Summaries
CT	2002–2012	Taxable sales	State of Connecticut, Department of Revenue Services, DRS Monthly Comparative Statement Reports. Data is only available at the state level and hence it is only used for utilities that covers the entire state.
DC	1999–2012	Taxable sales	District of Columbia, Cash Collection Report, Office of Revenue Analysis
FL	1999–2012	Taxable sales	State of Florida, Department of Revenue, Gross Sales by County
HI	1999–2012	Taxable sales	State of Hawaii, Department of Taxation, Monthly Tax Collection Reports, General Excise and Use Tax Collections
ID	2003–2012	Taxable sales	State of Idaho, State Tax Commission, Sales/Use Tax by County
IL	2004–2012	Taxable sales	State of Illinois, Department of Revenue, Monthly Disbursements
KS	2006–2012	Taxable sales	State of Kansas, Department of Revenue, Office of Policy and Research, State Sales Tax Collections by County
ME	2004–2012	Taxable sales	State of Maine, Office of Policy and Management, Maine Taxable Retail Sales
MD	2009–2012	Taxable sales	State of Maryland, Comptroller of Maryland, Sales and Use Tax County Tables
MS	2001–2012	Taxable sales	State of Mississippi, Department of Revenue, Diversions to Cities from Sales Tax Collections
NE	1999–2012	Net sales	State of Nebraska, Department of Revenue, Monthly Net Taxable Sales by County
NM	2003–2012	Taxable sales	State of New Mexico, Taxation and Revenue Department, Monthly Local Government Distribution Reports
NV	2004–2012	Taxable sales	State of Nevada, Department of Taxation, Monthly Taxable Sales Statistics
NC	2005–2012	Taxable sales	State of North Carolina, Department of Revenue, Monthly Sales and Use Tax Statistics
NC	1999–2005	Gross retail sales	State of North Carolina, Department of Revenue, Monthly Sales and Use Tax Statistics
OH	2000–2012	Taxable sales	State of Ohio, Department of Taxation, County and Regional Transit Authority Permissive Sales and Use Tax Collections and Tax Rates, by Month

State	Years	Type	Source
OK	1999–2012	Gross retail sales	University of Oklahoma, Center for Economic and Management Research, Oklahoma Resources Integration General Information Network System, Sales Subject to Sales Tax
SD	1999–2012	Taxable sales	State of South Dakota, Department of Revenue, Business Tax Division, South Dakota Sales and Use Tax Report
TN	1999–2012	Retail sales	State of Tennessee, Department of Revenue, Retail Sales
TX	1999–2012	Taxable sales	State of Texas, Comptroller of Public Accounts, Local Sales and Use Tax, Allocation Historical Summary
UT	2008–2012	Taxable sales	State of Utah, Tax Commission, Monthly Taxable Sales Report
VT	2000–2012	Taxable sales	State of Vermont, Department of Taxes, Statistics – Sales & Use Monthly Report
VA	1999–2012	Gross sales	University of Virginia, Center of Economic and Policy Studies, Local Option Sales and Use Tax Distribution
WI	2002–2012	Taxable sales	State of Wisconsin, Department of Revenue, County Sales Tax Distribution
WY	2005–2012	Taxable sales	State of Wyoming, Department of Revenue, Net Distribution by County