Can Digitalization Improve Public Services? Evidence from Innovation in Energy Management*

Robyn Meeks†
Jacquelyn Pless‡
Zhenxuan Wang§

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Abstract

This paper examines how digitalization impacts public service provision through a study of the U.S. power sector. We exploit the staggered timing of electric utilities' investments in "smart" meters and find that electricity losses per unit sold decrease by 3.6%. This efficiency improvement is driven by a 5.9% reduction in total losses and 1.2% increase in sales. Additional results suggest this occurs through improvements in energy management. The effects are driven by government-owned utilities as opposed to privately-owned. Through a supplementary analysis of within-utility electricity reliability in Texas, we also find that digitalization decreased power outage duration but not frequency.

Keywords: digitalization; public services; energy management; electric utilities
JEL Codes: O30, L94, H11, Q40, H54, M15, L33

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† Sanford School of Public Policy, Duke University. Email: robyn.meeks@duke.edu.
‡ Corresponding author. MIT Sloan School of Management, 100 Main Street, Cambridge, MA, 02142. Email: jpless@mit.edu.
§ Nicholas School of the Environment and Sanford School of Public Policy, Duke University. Email: zhenxuan.wang@duke.edu.

1 Introduction

Economic activity—from business and industrial operations to healthcare and transportation—hinges on having a reliable supply of electricity. However, electricity grids in many countries are aging and increasingly susceptible to disruptions. Power outages in the United States alone cost between \$28 and \$169 billion annually (ASCE, 2021). Although severe weather is a common cause, other factors such as equipment failure and utility practices affect quality of service as well (EIA, 2021). The ability to manage the grid more efficiently will be especially important for ensuring grid resilience moving forward. In an effort to mitigate climate change, deployment of renewable energy sources with variable output and electrification of end-use products are accelerating. These shifting dynamics are intensifying demands on the system and introducing new challenges for utilities.

Digitalization is frequently discussed as being an important part of the solution, as "smart grid" technologies can, in theory, help monitor and optimize operations and improve system flexibility (Joskow, 2012). Advances in data storage, computation, and transmission are transforming most industries, and electricity is no exception. However, despite the hundreds of billions of dollars spent each year globally on modernizing electricity grids (IEA, 2023), whether digitalization delivers on its promises remains contentious.[1] The benefits depend on how utilities actually *use* the technology, but research remains thin.

In fact, little is known about the effects of digitalization on the provision of public services more generally. In the private sector context, information and communications technologies have been shown to enhance firm performance (Brynjolfsson and Hitt, 2003; Bartel, Ichniowski and Shaw, 2007; Brynjolfsson and Saunders, 2013; Goldfarb and Tucker, 2019). Organizations providing public services—like utilities, hospitals, and schools—operate under different conditions than those providing private goods or services though, so previous findings may not transfer. For example, they are often heavily-regulated and face different market forces (e.g., less competition), bureaucratic processes, and budgetary constraints. These

[1] Many utilities are not fully exploiting the technology's capabilities and therefore not accruing all of the potential benefits (Gold, Waters and York, 2020). Smart meters are also promoted as tools for empowering consumers to better-manage electricity use and reduce their bills, but access to data is often difficult, resulting in limited cost savings. For example, less than 3% of meters funded by the American Recovery and Reinvestment Act had real-time data features enabled a decade after installation (Utility Dive, 2022).

factors may influence whether they realize the potential benefits of digitalization because doing so may depend on complementary organizational capital, such as business processes, management practices, and skills (Brynjolfsson and Hitt, 2000; Bresnahan, Brynjolfsson and Hitt, 2002; Bloom, Sadun and Van Reenen, 2012; Brynjolfsson, Rock and Syverson, 2021).

In this paper, we provide evidence as to how digitalization impacts public service provision. Public services exhibit significant variation in quality and are notoriously difficult to study. To narrow this gap, we examine the effects of electric utilities' investments in advanced metering infrastructure (AMI) "smart meters" on utility performance and service quality across the U.S. from 2007 through 2017. Utilities historically relied on analog meters that were developed in the 1800s to track electricity consumption, requiring manual in-person readings and providing utilities with sparse, imprecise data. Deployment of AMI accelerated about 15 years ago, though, entailing substantial public and private expenditures, and the industry is now going through a "digital revolution." Approximately 119 million smart meters were installed in the U.S. as of 2022 (EIA, 2022).[2]

Smart meters provide real-time consumption and power quality data that can help utilities improve performance by reducing operational costs and enhancing billing accuracy, load management, and system monitoring. They also can improve reliability if utilities use the information on power outage location to restore power faster. There even is potential for reducing outage frequency. For example, as smart meters enable demand response programs that incentivize end-users to reduce consumption or shift energy use away from peak periods, outages due to excess demand may decrease.

Estimating the causal effects of digitalization on public service provision is empirically challenging for multiple reasons. First, technology adoption may be driven by endogenous organization-specific characteristics, such as how well-resourced or inherently innovative the utilities are, as well as local economic growth. To overcome this, we use the staggered timing of utilities' smart meter deployments and augment our difference-in-differences design with a two-stage least squares (2SLS) approach that removes pre-trends. It does so by exploiting covariates that are related to smart meter deployment only through unobserved confounds. The method is akin to Freyaldenhoven, Hansen and Shapiro (2019) and entails finding a proxy

[2] This is approximately 72% of total U.S. electric meters (EIA, 2022).

variable for confounders and instrumenting for it using leads of the treatment variable.

Furthermore, studying public services more generally is difficult due to challenges evaluating service quality for all customers and providers within an industry.[3] The U.S. electricity sector provides a unique setting in which utilities serve (just about) all electricity customers and they must report standardized operational and system information annually. We compiled data on these performance indicators as well as smart meter installations and utility characteristics (primarily from the U.S. Energy Information Administration). To study electricity reliability, we transcribed feeder line level (i.e., within-utility) power outage duration and frequency data for Texas from Public Utility Commission reports.

We start by examining the effects of smart meters on electricity losses and sales, two outcomes that capture multiple aspects of utility performance. Electricity losses—the difference between power supplied to the distribution system and that for which customers are billed—translate into costs for utilities. Although losing some power is unavoidable due to the physical properties of the system, high losses can reflect inefficiencies. For example, losses increase when the system is overloaded (i.e., demand exceeds a system's constraints). Given that line losses increase exponentially when the grid is constrained, better load management can reduce losses. Losses also increase when voltage fluctuates or equipment ages. This is a complex relationship, as power quality and reliability can both contribute to, and be exacerbated by, high losses.[4]

Sales refer to the amount of electricity for which customers are billed. Perhaps counterintuitively, both increases and decreases in sales could signal performance improvements. Sales could decrease if customers use smart meter data to reduce consumption (and thus their electricity bills).[5] Consumption changes also could help utilities' with load manage-

[3]For example, mortality is a frequently studied outcome to proxy for quality when studying healthcare. This clearly captures an important impact on customers and some aspects of quality, but it is mostly relevant for a select set of patients (e.g., patients that are very ill) and work to date mostly focuses on hospitals, which is just one type of healthcare service provider. Quality of service for other types of patients, services, and providers could include factors like the amount of time doctors spend with patients or diagnosis accuracy, which are much more difficult to measure consistently at scale.

[4]Power quality is lower when voltage is low (e.g., flickering or dimming of lights), and since voltage fluctuations can contribute to losses, high losses could reflect a poorer quality of power for end-users. Nontechnical factors like meter tampering can also contribute to losses.

[5]Customers also may value having more detailed information in general, reflecting an improvement in quality of services from the customer's perspective.

ment. At the same time, given consumption measurement was subject to human error with older technology, an increase in sales could reflect improved billing accuracy and processes. Furthermore, sales could increase if utilities use AMI to address bill non-payment and electricity theft, benefits that are commonly reported by utilities (U.S. DOE, 2016). Finally, sales may increase if a utility's customer base grows, which may occur if AMI attracts new customers given the additional products that it enables.[6]

We find that smart meter deployment improves utility performance in multiple ways. First, on average, losses per unit sold (henceforth "losses per sale") decrease by 3.6% relative to the pre-treatment mean. This efficiency improvement occurs through a 5.9% decrease in total losses as well as a 1.2% increase in total sales. Losses per sale decrease by 7.7% for utilities in the highest quartile of the pre-treatment losses per sale distribution. The decrease in total losses on average grows to approximately 7.6% after three years, which is consistent with utilities needing time to learn and to invest in organizational capital, such as new business processes and worker capabilities, for the performance benefits to materialize.

Next, we explore whether the sales increase is driven by sales per customer or number of customers. We find that both contribute. The former is consistent with more accurate billing and utilities leveraging the automated data to improve their operations and processes, while the latter suggests that utilities' customer bases grow. Our regressions directly control for some potential drivers of higher customer counts, such as population growth and new building construction. Dynamic pricing and other demand response programs increased after smart meter deployment, consistent with the potential explanation that smart meters may help attract new customers that value these products.

To further probe whether utilities make operational and energy management adjustments with AMI adoption, we examine the composition of the utility sector's local workforce. Integrating smart technologies and leveraging their capabilities to improve decision-making requires workers with different skills relative to those required with the traditional meters. Using the Occupational Employment and Wage Statistics data provided by the U.S. Bureau of Labor Statistics, we indeed find a reduction in meter readers. Utilities also appear to

[6] An increase in the customer base also could be due to local economic development as opposed to attracting new customers, but we control for this directly, as discussed later in the paper.

hire more "quants"—individuals like computer scientists who are equipped with the skills to analyze data and build energy system optimization models—which is consistent with utilities making organizational investments that can enhance the benefits of digitalization.

We use our data on power outages in Texas to examine whether reliability improves, which also can provide insight on whether utilities use smart meters to respond to outages faster or avoid them altogether. Following smart meter deployment, outage duration decreases by 5.5%, suggesting that utilities indeed use the technology to restore power faster. However, we find no reduction in outage frequency. This suggests that, although energy management improvements—such as enhanced system monitoring and load management—can enhance performance via reductions in losses and power outage duration, other solutions are needed to reduce the number of outages.

Taken together, our findings indicate that digitalization can enhance service quality and that energy management improvements are at play. This, in turn, implies that realizing the benefits of digitalization may depend on organizational capital (e.g., business processes, worker skills, etc.). To explore this further, we examine the heterogeneity in effects across utility ownership structure. Like many other public services, electricity providers can be either government- or privately-owned, resulting in different managerial incentives and constraints that may impact performance (e.g., profit-maximization versus social objectives) (Hart, Shleifer and Vishny, 1997; Shleifer, 1998; Duggan, 2000).[7] For example, since investor-owned utilities face pressures from shareholders to maximize short run profits, they may be less inclined to make costly and time-consuming investments that would improve service in the long run. Government-owned utilities may be more likely to make such investments because their customers are their constituents.

We find that the effects on losses and sales are driven entirely by government-owned utilities as opposed to those that are investor-owned or operate as cooperatives. Differences in other observable characteristics, like pre-treatment size and performance, do not account for the heterogeneity. These results are consistent with how organizational factors that generate incentives for improving energy management and quality of service may contribute to whether the benefits of digitalization materialize.

[7] Utilities' technology adoption decisions also may differ by ownership type (Rose and Joskow, 1990).

Summary of Contributions

This paper makes four main contributions. First, we provide new evidence on whether digitalization can improve electric utility performance and service quality. The infrastructure upon which economic activity relies is deteriorating in many countries. At the same time, utilities are facing new energy management challenges that impact reliability, as an increasing share of energy supply is coming from intermittent renewable resources and electrification of end-use products (e.g., vehicles) is rising, putting more pressure on the grid.

Although experts agree on the need for significant grid investment—and policymakers carved out $13 billion for grid modernization in the 2022 Infrastructure Investment and Jobs Act—the effects of smart meters on service provision have been under-studied.[8] A related but distinct literature examines whether interventions *facilitated* by smart meters, like providing information and introducing new pricing designs, impact *consumption* (Jessoe and Rapson, 2014; Ito, Ida and Tanaka, 2018; Burkhardt, Gillingham and Kopalle, forthcoming). To the best of our knowledge, we are the first to examine how utilities use these digital technologies and the effects on system performance and service quality. More generally, there is scant economics research on ways to improve reliability in developed countries (Borenstein, Bushnell and Mansur, 2023).[9]

Second, we contribute to the evolving literature on digitalization. Research examining how some digital technologies impact firm performance dates back to the 1990s and spans many fields of economics (see Draca, Sadun and Van Reenen (2009) and Goldfarb and Tucker (2019) for reviews). However, much less is known about the effects on public services, besides in healthcare (see Bronsoler, Doyle and Van Reenen (2022) for a review). Our study extends this literature to the electricity context while also allowing us to address two key challenges faced in the broader public services context as well. First, quality of services is notoriously difficult to measure (in both public and private settings). For example, mortality is a commonly-used indicator in health economics, which captures an outcome for consumers

[8]The American Recovery and Reinvestment Act of 2009 provided $4.5 billion for smart grid investments.

[9]There is a more extensive literature on reliability issues and electricity services in developing countries (Fisher-Vanden, Mansur and Wang, 2015; Trimble, Kojima, Arroyo and Mohammadzadeh, 2016; Allcott, Collard-Wexler and O'Connell, 2016; Zhang, 2018; Carranza and Meeks, 2021; Meeks, Omuraliev, Isaev and Wang, 2023), but the challenges (and therefore the solutions) are fundamentally different.

but not quality of service itself.[10] Our indicators relate to service provision and quality directly. Second, digitalization of healthcare studies tend to focus on a specific type of organization (e.g., hospitals) and therefore a select set of customers (e.g., inpatients). We study nearly all service providers across an entire industry within a country.

Third, our paper contributes to the relatively limited set of papers examining management of public services. Similar to the digital economics literature, the importance of management practices for *private* sector firm performance has been well-documented (Bloom and Van Reenen, 2007; Bloom, Brynjolfsson, Foster, Jarmin, Patnaik, Saporta-Eksten and Van Reenen, 2019; Gosnell, List and Metcalfe, 2020). There is very little on public service providers.[11] Bloom, Lemos, Sadun and Van Reenen (2020) and Bloom, Propper, Seiler and Van Reenen (2015a) study the role of location and competition for hospital performance and management, respectively, but not the effects of management on services. Bloom, Lemos, Sadun and Van Reenen (2015b) show that higher management quality in schools is correlated with better student outcomes, but data limitations prohibit a causal analysis.

Lastly, we contribute to the literature on privatization of public services. Understanding the implications of firm ownership is a long-standing issue in economics and private provision of *public* services is particularly controversial. However, research to date mostly focuses on how it affects financial outcomes.[12] We do not estimate the effects of privatization, but we add to this literature by documenting heterogeneity in the benefits of digitalization for service quality and provider performance across ownership types.

2 Background

In this section, we provide background information on electricity distribution systems in the U.S., indicators of the distribution companies' performance, and the ways in which

[10] People may die because of their conditions even if the quality of service is perfect. Some measures of service quality itself might include time spent with patients, diagnosis processes and accuracy, etc.

[11] A related nascent literature examines manag*ers* in the public sector (Janke, Propper and Sadun, 2019; Otero and Munoz, 2022; Fenizia, 2022), but individual attributes and organization-level practices are two separate channels through which management impacts performance (Metcalfe, Sollaci and Syverson, 2023).

[12] Recent exceptions study the impact on prison inmates (Mukherjee, 2021) and healthcare consumers (Bergman, Johansson, Lundberg and Spagnolo, 2016; Duggan, Gupta, Jackson and Templeton, 2023) but not on service quality directly.

digitalization could improve utilities' performance in the electricity sector.

2.1 Electricity Distribution in the U.S.

Electric grids are complex networks that deliver energy to consumers. They are comprised of power plants that generate electricity that is transferred to population centers through high-voltage transmission lines. Electricity is then delivered to end-use customers (residential, commercial, and industrial) through the local distribution system. The U.S. distribution system is expansive, serving 145 million end-users through 5.5 million miles of local distribution lines (EIA, 2016). In addition to the wires that transfer electricity to end-users, distribution systems also include substations and transformers that reduce ("step down") voltage to a level appropriate for end-users' equipment, and meters to monitor consumption.

The quality of service experienced by electricity utilities' customers is important for ensuring a well-functioning economy and high quality of life. Poor reliability (i.e., power outages) and power quality (i.e., voltage fluctuations) are costly for end-users. Even minor voltage fluctuations or brief outages can damage expensive machinery or shut down industrial processes. When service interruptions impact electronic medical equipment and devices or transportation systems, they can also be life-threatening.

Over the past decade, reliability declined in the U.S., with both outage frequency and duration increasing. The average customer experienced about seven hours of power interruptions in 2021, which is almost double the average outage time in 2013. Reliability also varies substantially across the country, with power interruptions ranging from 52 minutes in the District of Columbia to 80 hours in Louisiana (EIA, 2021). Many major outages are caused by extreme weather events, which include storms as well as extreme temperatures (both hot and cold), since such conditions lead to higher demand for air conditioning and heat. However, the grid is also aging—approximately 70% of transmission and distribution lines were constructed in the early- to mid-1900s and are now in the second half of their life expectancy (ASCE, 2021)—and increasingly vulnerable to disruptions due to equipment malfunction, poor utility practices, and overload (i.e., demand exceeding supply).

Many of these vulnerabilities could be addressed by upgrading technology to improve energy management. Until the early 2010s, most electricity meters—located at customers' premises to measure electricity consumption—were antiquated and unsophisticated (Munasinghe, 1981). The majority of U.S. end-users had conventional electro-mechanical meters that were developed in the late 1800s and predate other now obsolete technologies, such as the rotary phone (Smitherman, Nelson and Jr, 2010). The functionality of these older meters is extremely limited. For example, they require utilities to perform many tasks in person, such as reading meters to generate bills and manually disconnecting and reconnecting customers (e.g., when customers move or have not paid their bills). These limitations impose high operational costs, introduce human error, and provide no insight into when and where outages occur. This means service restoration requires significant time; end-users report outages to the utilities and field crews then deploy to locate the outage source. Lastly, conventional meters limit the potential for dynamic pricing and demand response programs, preventing opportunities for utilities to incentivize end-users to adjust consumption patterns.

2.2 Electric Utility Performance

Electricity distribution in the U.S. is managed by approximately 1,300 utilities that are responsible for selling and delivering reliable electricity to end-users.[13] Energy management by these utilities typically entails planning, controlling, storing, and distributing electricity with the objective of maximizing efficiency and minimizing the costs of operations and maintenance (e.g., distribution system upkeep and repairs, billing, emergency response, safety and regulatory compliance, and customer care). With 92% of the country's service interruptions occurring within the distribution system (ASCE, 2021), the performance of these utilities plays a pronounced role in the quality of service experienced by end-users. One key source of variation across utilities—which potentially affects performance—is their ownership structure. Utilities can be investor-owned (i.e., private), government-owned (i.e., owned by municipalities, the state, or the federal government), or cooperatives that are non-profits governed by their members (U.S. Department of Energy, 2015), and each of these comes with different incentives and constraints.

Utility performance can be measured in multiple ways and we start with two objective

[13] The U.S. has more than 3,200 electric utilities when also counting those responsible for generation and transmission. Some utility activities differ if they also control those components.

and quantifiable indicators that capture various aspects of their performance: electricity losses and sales. Electricity losses are a primary measure of the "efficiency and financial sustainability of the power sector" (Jiménez, Serebrisky and Mercado, 2014). They refer to and are measured as the difference between the electricity delivered to transmission and distribution systems and the amount for which customers are billed and pay. Electricity losses represent a decrease in utilities' revenue, as they pay for the electricity delivered to the system, even if it is not billed to end-users. Electricity losses are problematic for consumers as well, as they negatively affect reliability and power quality. And, in some cases, consumers bear the costs of losses if they are passed through to prices or other charges (Costa-Campi, Daví-Arderius and Trujillo-Baute, 2018).

Some degree of "technical" losses occur due to natural dissipation along distribution lines. These are unavoidable due to the physical properties of the system, such as conductor resistance. As a result, even in high income countries with efficient transmission and distribution systems, losses are between 6 and 8 percent of total electricity output (Jiménez et al., 2014). At the same time, line losses are exacerbated by other factors, such as increases in load and voltage fluctuations (Jiménez et al., 2014).[14] High losses, therefore, may reflect poor energy management or a history of insufficient maintenance and upgrades. Losses also can occur due to "non-technical" factors, like illegal cable hooking to bypass meters or incorrect electricity meter readings due to outdated and damaged technology or meter tampering.[15]

The second indicator of utility performance is electricity sales, which is the quantity of electricity billed to consumers. Greater sales could increase utility revenue, assuming there are no corresponding tariff decreases. Whether sales are measured on a per customer basis or in total can provide slightly different information about utility performance and its implications for consumers, which we discuss in the next sub-section. Overall, sales are important for utilities' fiscal sustainability and could also improve the quality of service experienced by customers if revenue is reinvested to improve grid resilience and energy management.

[14] Low voltage can cause system instability or collapse. High voltages can exceed equipment capabilities. Furthermore, as energy losses transform into heat (they are resistance multiplied by the current squared), they can subsequently lead to lines stretching and sagging such that they come into contact with surrounding objects and cause a fault, which also can permanently damage the line (FERC, 2020).

[15] Non-technical losses are typically higher in low and middle income countries than in high income countries, such as the U.S. (Jiménez et al., 2014).

2.3 Can Digitalization Improve Utility Performance?

In the electricity distribution context, digitalization entails investing in advanced metering infrastructure (AMI). This includes an integrated system comprised of "smart" meters installed at end user premises, a communication network (either wired or wireless) to transmit information between the meters and the distribution company, and meter data management systems (Gold et al., 2020). Although investments in AMI initially progressed slowly in the U.S., deployment increased rapidly in the 2010s.[16]

How can digitalization improve utility performance? There are two main mechanisms: benefits that emerge mechanically from the technological features alone and those resulting from capitalizing on AMI's functionalities to improve energy management.

2.3.1 Mechanical Effects from Technology Features

Investing in AMI may have immediate mechanical effects on utilities' performance given the technological features of smart meters relative to old or damaged meters. First, smart meters measure consumption accurately and usually in real time. On the other hand, analog meters were read manually, so consumption measurement was subject to human error (and estimated when workers could not access customers' premises). If the incumbent technology was consistently under-measuring consumption, billed sales per customer may increase following smart meter deployment (even if actual consumption does not change).[17]

Other features of the technology can also improve utility performance mechanically. For example, smart meters can shut down grid connections automatically if voltage spikes or dips outside of the range that engineers determine is safe. This can improve both utilities' financial performance and quality of service for consumers by protecting against voltage fluctuations (i.e., poor power quality), equipment damage, and the probability of costly future disruptions.

[16] This "digital revolution" of the electricity sector extends well-beyond the U.S. as well. For example, in 2013 alone, approximately $15 billion were invested in smart grids worldwide (IEA, 2015).

[17] How this affects customers is ambiguous. It could increase satisfaction if consumers value billing accuracy or if billing errors previously created distrust. However, they may dislike facing higher bills for the same quantity of electricity power previously consumed.

2.3.2 Energy Management

There are four main ways in which AMI can improve energy management which, in turn, can enhance utility performance. First, AMI's remote transmission of consumption data eliminates the need to send employees to manually read meters at consumers' premises. This can reduce labor and transportation billing-related costs and is often cited as a key motivation for utility investment in AMI.[18] Although this represents an operational efficiency gain either way, the net effect on labor costs depends on the extent to which the utility then hires workers with skills that can help them capitalize on the potential benefits of AMI. New employees may include computer scientists and software engineers who can analyze high frequency data and improve energy system optimization models, for example.

Second, remote data collection can improve billing accuracy, which is associated with reduced customer complaints and faster resolution of billing disputes (U.S. DOE, 2016). Remote data transmission circumvents the need to estimate consumption or interpolate bills when in-person meter readings are not possible. Further, it decreases human error in the billing process, as billing no longer relies on manual data entry (Nangia, Oguah and Gaba, 2016; Cooper and Shuster, 2021). Utilities can also make organizational and technological investments to integrate their data management systems with billing processes to streamline their business practices and operations, reflecting improvements in energy management.

Third, AMI allows utilities to offer consumers additional products, such as demand response programs and dynamic pricing options. These can enhance utility performance through behavioral changes made by either the utility or consumers. Smart meters provide utilities with granular data, two-way real-time communications, and the ability to control supply remotely, which allows them to analyze and forecast consumption more accurately and improve load management.[19] Furthermore, these products permit customers to learn about their electricity use patterns and to shift consumption away from high-priced periods,

[18] Prior to AMI, some utilities replaced conventional electro-mechanical meters with automatic meter reading (AMR) systems, which can broadcast consumption data within a very limited distance and permit remote disconnection (USAID, 2009). These provide some operational cost savings relative to electro-mechanical meters, as employees could collect consumption data by driving around neighborhoods; however, their capabilities fall short of AMI.

[19] These types programs could be implemented to some degree with intermediary technologies deployed prior to AMI, like AMR, but the granularity and real-time nature of AMI data allow for much more precision.

potentially reducing their electricity bills. For these reasons, smart meters could attract new customers, enhancing utilities' customer base (and thus sales and revenue).[20]

Lastly, deploying smart meters also may reduce outage duration and/or frequency, improving utility performance by reducing costs associated with restoration, enhancing revenue that otherwise would be lost, and improving quality of service experienced by end-users.[21] Smart meters often have a "last gasp" functionality that notifies utilities immediately of service disruptions and allows them to identify the precise location of outages (U.S. Department of Energy, 2014c). While the alert itself is mechanical in nature, improving performance by restoring service faster requires utilities to *use* the data to make decisions related to dispatching repair crews more quickly and to the correct locations.

The preceding three energy management changes and their resulting improvements —increasing billing accuracy, shifting load to off-peak times, and reducing the duration and frequency of service interruptions —could each directly and substantially affect losses and sales, the two key indicators of utility performance that we study. For example, improved billing accuracy may increase billed sales, as previously discussed. This enhances utilities' recovered revenue and, mechanically, translates into lower losses per sale. Moreover, shifting load from peak to off-peak times could reduce congestion, which in turn, reduces losses (Costa-Campi et al., 2018). Finally, utilities can use the real-time data to enhance forecasting capabilities, improve load management, and identify bottlenecks or other threats to the grid (Nangia et al., 2016; Gold et al., 2020), each of which can also lower losses.

3 Data and Sample Construction

We construct three data sets that are used throughout this paper. The first is at the utility level, linking information on U.S. electric utilities' performance, characteristics, and smart meter deployment, which we use for the majority of our analyses. We construct two additional data sets for exploring the mechanisms driving our results: feeder line-level data on

[20] This would be consistent with some evidence in the literature that investing in new technologies can help attract customers through quality differentiation (Lu, Rui and Seidmann, 2018).

[21] These potential improvements are frequently reported as a motivation for smart grid investments in various government reports and on utilities' websites (U.S. Department of Energy, 2014a,b; Duke Energy Progress, 2020; BC Hydro, 2016; Sprinz, 2018).

power outages for Texas and regional-level occupation data for the U.S. This section provides an overview of the data; additional details can be found in Appendix A.

3.1 Smart Meter Deployment and Utility Performance

To compile utility-level data on smart meter deployment and performance, we start with data from the U.S. Energy Information Administration (EIA)'s annual census of all electric utilities in the U.S. (Form EIA-861). It includes information on smart meter deployment, performance measures such as electricity losses and sales, operational data, dynamic pricing and demand response programs, and select utility characteristics. We collect data for the years 2007 (the first year in which AMI deployment data are available) through 2017 to construct several key variables of interest.

First, we create the variables for initial smart meter deployment (our main treatment variable) and deployment rates (the intensity of treatment). We use the number of electric meters that fall within each meter type (conventional or AMI) and use the first year in which the number of AMI meters is greater than zero as the year of initial smart meter deployment. We measure deployment rate as the ratio of total AMI meters to the total number of customers.

We also use these data to construct our utility performance measures, including total sales and sales per customer (both in megawatt hours), electricity losses per sale (which is the electricity lost per unit of electricity sold and therefore is measured as a %), revenue per customer (which reflects customers' average annual spending on electricity bills), and revenue per unit sold (which reflects the average annual electricity price). The EIA data reports electric operating revenue from different sources, including retail sales to end-users, delivery customers, sales for resale, transmission, and other electric activities. We take the sum of these to get total revenue. Furthermore, we use these data to identify whether utilities offer products like demand response programs and dynamic pricing, including the number of customers enrolled and the year in which such services were introduced (using the first year in which there are more than zero customers enrolled).

Lastly, we gather additional information on utilities' time-invariant characteristics like location and service territory from EIA-861, and ownership type and business scope from

S&P Global Market Intelligence.

3.2 Service Territory Population and Housing

We use two other key pieces of information throughout our main utility-level analyses—local population and new building construction—that we collected from other sources. We obtained county-level population data from the Survey of Epidemiology and End Results (SEER) and data on new building units from the U.S. Census' Building Permits Survey (BPS). Using the electric service territory information from EIA-861, we merge these county-level population and housing data with the EIA utility-level data, summing the population and housing measures for all counties that the utility serves.[22]

3.3 Baseline Sample Construction and Summary Statistics

After merging the data sets described above, we take a few additional steps to prepare the data for our empirical analyses that we detail in Appendix A. One important sample selection rule that we apply is omitting utilities that do not operate in the distribution segment of electricity delivery. We also limit the sample to include only utilities that either adopted AMI smart meters between the years 2010 through 2016 or did not adopt at all (but while keeping observations from 2007 through 2017). This allows us to include at least three years of pre-treatment data and one year of post-treatment data for all adopters. We also omit observations for which our key variables appear to be data entry errors (such as negative values for losses, sales, and customer counts).

Our final utility-level data set for the U.S. includes 14,241 observations across 1,303 utilities between 2007 and 2017.[23] Table 1 provides summary statistics. Column 1 provides the means and standard deviations of our main variables of interest for the full estimation sample. The average percentage of sales lost is about 5.7% and utilities serve about 57,000 customers on average. We also provide summary statistics separately for adopters

[22]Some counties are served by multiple utilities, so there is some double-counting of population and housing, but such measures are not available at the utility level. This should not bias our estimates, though.

[23]Because of the instrumental variable approach that we take, we actually gather data for the year 2018 as well, but 2018 is omitted when running the regressions because of using the lead policy variable as an excluded instrument (see Section 4).

in pre-treatment years (Column 2) and non-adopters (across all years) (Column 3) to explore whether they exhibit different characteristics. Those that eventually adopt AMI have slightly lower losses per sale in pre-treatment years relative to non-adopters but are much larger on average, as can be seen from how total sales and the number of customers served. We describe how we address this in our empirical approach in Section 4.

3.4 Additional Data

3.4.1 Regional Occupation Employment

When exploring the mechanisms through which AMI affects utility performance, we examine worker composition, since integrating smart meters and using the data that they generate reduces the need for meter readers while possibly requiring more software or data analysis-oriented workers. We assemble data on local occupation employment for each Metropolitan (MSA) and non-metropolitan (non-MSA) area from the Occupational Employment and Wage Statistics (OEWS) provided by the U.S. Bureau of Labor Statistics (BLS). These data provide annual information on total employment for each occupation category dating back to 1997. We extract the area-level employment information for the 2007-2018 period. Although these data do not differentiate occupations and employment by industry, all meter readers are associated with utilities, which we verified with state–industry level employment data (whereas other occupations could be in various sectors).[24] As a result, occupations such as meter readers may be associated with non-electric utilities (e.g., gas or water) as well.

3.4.2 Electricity Reliability in Texas

To explore whether utilities use smart meters to improve electricity reliability, we examine the impact of AMI deployment on power outage duration and frequency for the state of Texas.[25] We manually transcribed and compiled outage data at the feeder line level—the

[24]We collect data on employment estimates by state and industry from the U.S. BLS, which is derived from sample surveys. This data provides annual industry-specific estimates on the number of employment for each occupation category in each state after 2012. Using this data, we confirm that the occupation category associated with meter readers (i.e., 43-5041) only appears within utility industry (i.e., the corresponding two-digit NAICS code is 22).

[25]We study Texas because the U.S. outage data do not start until 2013 and, by that time, many utilities had already started to deploy AMI. In contrast, the Texas within-utility data starts in 2007.

power lines that carry electricity from substations to local or regional service areas—from the Public Utility Commission of Texas. Reliability is measured by two standard indices: System Average Interruption Duration Index (SAIDI) (the average duration of outages within a year) and System Average Interruption Frequency Index (SAIFI) (the average number of outages per year). This feeder line-level data set covers 7,294 feeder lines across 10 utilities operating in Texas between 2007 to 2016.

4 Empirical Strategy and Identification

4.1 Research Designs

Our primary goal is to identify the causal impact of smart meter deployment on utility performance. Estimating the effects using a simple OLS approach may be plagued by various endogeneity concerns. Utilities that choose to invest in AMI may differ systematically from those that do not—they may already be better-managed or more innovative, or alternatively, they may be experiencing an increase in electricity losses or diminished performance in other ways such that AMI could provide significant benefits. The likelihood or timing of adoption also may be correlated with local economic growth, consumer preferences, and other changing market characteristics, which may simultaneously impact our outcomes of interest.

To address these concerns, we use quasi-experimental variation in AMI meter installations by utilities over time, implementing event study and staggered difference-in-differences research designs augmented with a two-stage least squares (2SLS) approach similar to the one developed by Freyaldenhoven et al. (2019). This augmentation is designed to remove the effects of any pre-trends in the outcomes and provides the treatment effects net of the potential confound.

Event study. To start, we estimate an event study model to compare before and after differences in outcomes relative to initial deployment year as follows:

$$Y_{it} = \sum_{k \neq -1} \beta_k \mathbb{1}[t - \tau_i = k] + \alpha_i + \gamma_{st} + \delta \mathbf{X}'_{it} + \varepsilon_{it}. \tag{1}$$

where Y_{it} denotes the respective outcome measure of interest for utility i in year t. We are primarily interested in β_k, the coefficients on indicator variables representing the AMI deployment event years, whereby we use the first year when utility i deploys smart meters as the treatment year and k represents the gap between the current year t and initial deployment year τ_i. We exclude the dummy for $k = -1$ so that the pre- and post- treatment effects are relative to one year prior to the start of AMI deployment.

We include utility fixed effects (α_i) to control for time-invariant differences between utilities and state-year fixed effects (γ_{st}) to account for state-specific time-varying factors, such as market and policy conditions. We also control for some local observable time-varying characteristics in the matrix $\mathbf{X}_{it}$, which includes new building construction and population in counties within the utility's service region.[26] We cluster standard errors at the utility level.

Staggered difference-in-differences. To summarize the dynamic effects of AMI adoption, we also estimate the average effect within a pooled staggered difference-in-differences framework as follows:

$$Y_{it} = \beta_1 \text{AMI}_{it} + \alpha_i + \gamma_{st} + \delta' \mathbf{X}_{it} + \varepsilon_{it}, \tag{2}$$

where Y_{it} denotes the outcome of interest for utility i in year t, AMI_{it} is the main treatment indicator for smart meter adoption equal to one starting in the year the utility has deployed AMI and zero otherwise. We include the same set of fixed effects and controls as before and cluster standard errors at the utility level.

If we were to make no other adjustments to the event study and staggered difference-in-differences designs, identifying the causal effects of smart meter deployment would rest upon three key assumptions: 1) utility-level outcomes would have evolved along parallel trends absent treatment, 2) the average treatment effects do not vary by treatment timing, and 3) there are no spillover effects on untreated utilities (i.e., the stable unit treatment value assumption (SUTVA) holds). We now discuss the ways that we address concerns regarding potential violations of these assumptions.

[26] We use the inverse hyperbolic sine of new building construction because it contains zeros and use the log of population.

Identification and Extracting Pre-Trends.— The event study approach of Equation 1 allows us to explore the dynamic effects of smart meter deployment. We can examine whether there appear to be differences in outcomes for untreated and treated units in pre-treatment years (i.e., whether there are pre-trends), which has been the common practice for indirectly investigating whether the parallel trends assumption holds. However, recent studies note that such tests may be insufficient, as they may fail to detect pre-trends simply due to low statistical power (Freyaldenhoven et al., 2019; Roth, 2022; Roth, Sant'Anna, Bilinski and Poe, 2022). In a study of electric utilities, the concern is that even after including utility fixed effects, state-year fixed effects, and controls for some market trends in our baseline regressions, unobserved confounds may still exist.

In our specific setting, the main concern is that we cannot directly control for all local time-varying market and regional characteristics that may simultaneously impact the decision to deploy smart meters and the outcomes of interest. To address this, we follow the approach developed by Freyaldenhoven et al. (2019), which allows for causal identification of the treatment by removing the effects of pre-trends using an instrumental variables (IV) approach. The basic idea is to find a "proxy" variable for the unobserved confound and, instead of simply including the variable as a control, to instrument for it using leads of the treatment variable within a two-stage least-squares framework. The key assumption is that the "proxy" variable is affected by the unobserved confound (e.g., economic growth) but not by the treatment.[27]

The main task, therefore, is to find a variable that follows a pattern similar to that which is expected of the unobserved confound but is not driven by the utilities' smart meter investment decisions. We use the log of population as our proxy, as it is likely correlated with underlying forces associated with changing preferences (e.g., local economic growth) but is likely *not* directly determined by AMI deployment.[28] In addition, we continue to control for new construction build. We explore whether population is a suitable proxy and illustrate the

[27]As detailed in Freyaldenhoven et al. (2019), the approach removes the pre-trend effect such that estimated effects are net of the confound (i.e., the remaining dynamics of the outcome represent the causal effect). Freyaldenhoven et al. (2019) show that this approach outperforms alternative methods commonly applied in the literature to address potential pre-trends.

[28]As discussed earlier, we observe population at the county level, so we take the sum of the population in counties that fall within the utility's service territory.

approach's effectiveness in removing the estimated effect of the pre-trend when presenting our results in Section 5.

4.2 Other Identification Concerns

Potential Bias in Staggered Treatment Setting. A rapidly growing literature shows that staggered difference-in-differences models may produce biased estimates when treatment effects are heterogeneous across units and over time (Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021; Sun and Abraham, 2021).[29] For reasons similar to the potential endogeneity of AMI deployment timing, one may be concerned about such heterogeneous effects in our setting. That is, some utilities may be more innovative and thus adopt earlier, and more innovative utilities may more effectively improve quality of service by leveraging the technology's data and communications capabilities. Changing consumer preferences due to local population or economic growth also may induce utilities to adopt at different times, and if those utilities have more resources, the treatment effects may vary. Our 2SLS strategy addresses the primary concerns, but we also implement some of the other newly developed approaches as robustness checks in Section 5.4.

SUTVA. The final assumption is that there are no spillover effects on untreated units, as is always the case in difference-in-differences estimations. In our setting, the assumption is that a utility's deployment of smart meters does not affect other utilities' outcomes. This could be violated if, say, smart meters reduce line losses and this benefits nearby utilities that do not invest in AMI by reducing pressure on their system as well, as all distribution lines are ultimately connected to an interdependent grid and electricity flows across service territory boundaries. Spillovers are most likely to occur between utilities that share borders. As we describe later in Section 5.4.2, such spillovers should attenuate our results if anything. However, we probe this by carrying out various robustness checks in Section 5.4.2—such as dropping neighboring utilities from the sample—and the results are not affected.

[29] Estimates from models like the one depicted in Equation 2 are weighted averages of all possible 2×2 difference-in-differences between treated and untreated groups at different points in time and, therefore, may be biased if effects are heterogeneous across units or over time and result in negative weights.

5 Effects of Smart Meters on Losses and Sales

This section first presents our main results for the effects of smart meter deployment on electricity losses and sales. We then probe the identification assumptions.

5.1 Dynamic Effects

To begin, we estimate the dynamic effects of utilities' smart meter roll-outs on our primary measures of utility performance—electricity losses and sales. This allows us to visualize the main effects and to investigate whether the 2SLS approach seems to address endogeneity concerns. We plot the estimated coefficients β_k and their 95% confidence intervals in Figure 2, with the x-axis indicating the number of years relative to initial AMI deployment. Plots in the left column include estimates from a standard OLS approach (before extracting potentially confounding pre-trends). The plots in the right column are from the 2SLS estimator, whereby we use a one year lead of the AMI treatment variable as the excluded instrumental variable for the log of population.

Losses per sale do not appear to exhibit a strong pre-trend when estimating the effects using OLS (Panel A of Figure 2). However, as discussed earlier, this does not necessarily imply that no such pre-trend exists. Furthermore, total electricity losses (Panel C) do appear to exhibit an upward pre-trend and total sales decrease slightly at the same time. This is consistent with one of the potential sources of endogeneity discussed in Section 4. Factors like population growth could increase losses, as higher load could strain local infrastructure, and population growth may simultaneously impact utilities' decisions to invest. Consumer characteristics may be evolving such that demand for smart meters increases, for example.[30]

To explore whether population is a suitable "proxy" variable for the unobserved confounder—which we then instrument for using leads of the treatment variable as per our 2SLS approach—we examine the dynamics of population by estimating Equation 1 with (log) population as the dependent variable. We plot the coefficients in Appendix Figure B1. There

[30]We do not find the same pre-trend for total sales, but this is reasonable given how the relationship between population growth and sales is ambiguous. For example, urbanization may lead to population growth and more residential customers while large energy-intensive industrial firms may shut down. This may still increase losses given the different load profiles while having no effect on total sales.

indeed appears to be an upward sloping pre-trend similar to that observed for total electricity losses and, as expected, the trend for population continues past the treatment period. This suggests that population is likely a reasonable proxy, and as long as AMI deployment itself is not driving population growth (i.e., the second identification assumption of the method), our approach recovers the causal effect.

Once implementing the 2SLS estimator, the pre-trends in total losses and total sales indeed disappear, and the event study plots now suggest that AMI improves utility performance (see the right hand column of Figure 2). Losses per sale decrease (Panel B), and although the effect is initially small, losses per sale continue to decline in the years following deployment, leveling off after about 3 years. The efficiency improvement appears to be driven by both a decrease in total losses (Panel D) as well as an increase in total sales (Panel F). Total losses decline steadily and substantially until leveling off around a 10-20% reduction after 3 years. Likewise, total electricity sales start to increase immediately and reach approximately 3-4% after 5 years. A common policy objective for AMI is to empower consumers to lower their electricity bills by *reducing* consumption, so it is worth noting that our findings of increased sales do not necessarily mean an increase in consumption. Rather, it could be that sales increase because of either improved consumption measurement and billing accuracy or a growing customer base. We explore this further in Section 6.

Beyond reflecting performance improvements, these results also suggest that utility-side behavior may be at play. Increasing effects over time post-deployment is consistent with how the performance benefits of new technologies—particularly digital technologies with complex capabilities—often do not materialize until after a period of complementary investments in organizational capital, like new skills and processes (Brynjolfsson and Hitt, 2000; Bresnahan et al., 2002; Brynjolfsson et al., 2021; Bronsoler et al., 2022).[31] The benefits of AMI also may scale with deployment intensity. We explore this further in the next sub-section.

5.2 Average Effects

Estimating the average effects following Equation 2 and using our 2SLS approach, we find that losses per sale decrease by 0.002 percentage points (Column 1 in Panel A of Table

[31] Cutler (2011), among others, also makes this point when studying IT adoption in healthcare settings.

2). This represents a 3.6% reduction relative to AMI adopters' pre-treatment mean. The efficiency improvement is driven by both a 5.9% decrease in total losses and 1.2% increase in total sales (Columns 2 and 3 of Panel A). For comparison, we also provide the results from the staggered difference-in-difference model using only OLS (see Appendix Table B1). These coefficients can be interpreted as "unadjusted"—they include both the true causal effect as well as the confounder effects. Without our methodological augmentation, the results would have suggested that there are no statistically significant effects on any of the three outcomes.

The benefits of smart meter adoption also may scale with *intensity* of treatment (i.e., the proportion of customers with smart meters), so our estimates of the average effects may understate the true improvements. We estimate the effects of deployment intensity and find that losses per sale decrease by 5.4% relative to the pre-treatment mean (Column 1 of Panel B in Table 2) when going from no smart meters to 100% deployment.[32] The increase in the effect is driven by the sales component, as the effect on total losses decreases slightly and the effect on total sales doubles to 2.5% (Columns 2 and 3 of Panel B).

Figure 2 also suggests that the effects of AMI increase over time. This can occur for a few reasons. It may take time for utilities to develop the necessary skills to effectively leverage smart meter capabilities, for example, or to invest in complementary AMI technologies (like data management systems). Therefore, our estimates may be attenuated by the relatively small effects on performance in the early years of deployment. To explore this, we omit the year of initial deployment and the two years thereafter such that the estimates reflect the benefits three years post-deployment forward.[33] Although the effects on losses per sale and total sales are the same as the full deployment case (Columns 1 and 3 of Panel C in Table 2), the magnitude of the effect on total losses is much larger: losses decrease by 7.6% (Column 2 of Panel C). We investigate the underlying mechanisms in Section 6.

[32]The excluded instrument in this case is a one year lead for the proportion of customers with AMI as opposed to the AMI treatment indicator.

[33]All years of data are still included for utilities that never adopt AMI.

5.3 Heterogeneity by Pre-Treatment Losses

As discussed in Section 2, even in well-maintained distribution systems, some low level of line losses are expected given the natural dissipation that occurs. There may be very little room to improve for some utilities. Our estimates of the average effect across all utilities, therefore, may understate the potential benefits of digitalization for utilities that are performing poorly.

We estimate the AMI deployment effects separately for utilities that were in the highest quartile of the losses per sale among AMI adopters in pre-treatment years and those that were in the lowest quartile.[34] Results are presented in Table 3. As expected, the effects for utilities previously experiencing the highest losses per sale (Panel A) are much larger than what we found on average. Losses per sale decrease by 7.7% for these utilities relative to their mean pre-treatment losses per sale of 9.1%. Total losses decrease by 7.9% and total sales increase by 3%. In contrast, there is no effect on losses or sales for those utilities that were already high-performers (Panel B).

5.4 Robustness Checks

5.4.1 Treatment Effect Heterogeneity Across Adoption Time Periods

Recent literature points to several reasons to be cautious when interpreting estimates from staggered difference-in-difference research designs. One strand addresses the parallel trends assumption and how the standard tests examining treated and control groups in pre-treatment years may not detect statistically significant differences simply because of low statistical power (Roth, 2022). We address this by extracting the effects of pre-trends directly following the proposed 2SLS method of Freyaldenhoven et al. (2019), which we apply throughout all of our main analyses.

Another potential concern relates to treatment effect heterogeneity across time periods in which treatment occurs. In the multi-period staggered treatment context, coefficients from standard TWFE models are convex weighted averages that include early-treated units as part of the control group for later-treated units, and if treatment effects differ based on treatment timing, such estimates do not identify an average treatment effect (e.g., see

[34]Non-adopters in each sub-sample are those with losses per sale under or over the same cutoffs.

Borusyak, Jaravel and Spiess (2021), de Chaisemartin and D'Haultfoeuille (2020), Goodman-Bacon (2021), Callaway and Sant'Anna (2021), Sun and Abraham (2021)).

To probe this concern, we implement Callaway and Sant'Anna (2021)'s "doubly robust" DiD method using stabilized inverse probability weighting. The approach essentially allows group-time average treatment effects on the treated to be nonparametrically point-identified and aggregated, whereby a "group" is defined based on the time period when units (i.e., utilities) are first treated. The results are presented in Appendix Table B2. We first only include never-treated units in the control group (Panel A) and then add not-yet-treated units to the control group (Panels B). The estimates are similar to our baseline findings in both cases, with losses per sale decreasing by 0.002 percentage points and total losses decreasing by about 4%. With this approach, the effect on total sales is no longer statistically significant (and the coefficient decreases); however, we consider the 2SLS approach more reliable given it removes the effects of pre-trends, addressing the main identification concern in our setting.

Furthermore, we estimate the same model but include only utilities in the highest quartile of pre-treatment losses—those for which the effects should be most substantial—as we did in Section 5.3. Reassuringly, the magnitudes of the effects on losses per sale and total losses are nearly identical to when using the 2SLS approach for the same set of utilities (and are statistically significant at the 1% level) (Columns 1 and 2 of Appendix Table B3). Losses per sale decrease by 0.007 percentage points and total losses decrease by a little more than 8%. The effect on total sales is again not statistically significant, but the magnitude of the effect is higher than when estimating the average effect (1.2-1.4%). Overall, these findings are consistent with smart meter deployment improving utility performance.

5.4.2 SUTVA

A final key assumption underlying difference-in-differences research designs is that there are no spillover effects from the treatment on untreated utilities (i.e., the stable unit treatment value assumption (SUTVA) holds). This might be a concern because many utilities' distribution lines are ultimately all connected to the same grid, so electrons can flow across utility borders. In our context, spillovers would likely attenuate the estimates, since declining losses in one region might also improve system performance (i.e., reduce losses) in neighboring regions. Nonetheless, we explore the possibility of SUTVA violations in two ways. First, we control for whether a neighboring utility deployed smart meters and find that the results do not change (see Columns 1-3 of Appendix Table B4).[35] We next estimate the effects of AMI on the amount of power received/imported from other utilities and the amount of power exported/delivered to other utilities. If the adoption of AMI in one utility's service area negatively affects the grid in others' service areas, we might expect changes in exported and imported power. We find no statistically significant effects on either (see Columns 4 and 5 of Appendix Table B4).

6 Innovation in Energy Management

Our results thus far suggest that smart meter deployment can improve electricity service provider performance as measured by reductions in losses and increases in sales. In this section, we shift to developing a better understanding of the underlying mechanisms through which these improvements are achieved.

6.1 Billing Accuracy and Competitiveness

One potential benefit of smart meters is that utilities can use them to improve billing processes in ways that could reduce some labor and transportation costs while also increasing billing accuracy. Smart meters provide consumption data remotely (and usually in real time), whereas conventional meters must be read manually by utility workers. Although we do not directly observe labor costs, we can explore whether utilities appear to make such improvements in a few ways. To do so, we first decompose the effect of AMI meters on total electricity sales (in this sub-section). Then, in a later sub-section, we examine the local workforce composition and provide additional insights into potential billing process changes.

Our finding that total sales increase could result from an increase in either sales per customer or the total number of customers (or both). These reflect different mechanisms underlying the performance improvements. If sales per customer increase, then total sales

[35] Since we do not observe the exact utility border locations in our data, we define utilities as neighbors if they serve customers in the same county.

may increase due to more accurate electricity consumption measurement and billing (conditional on end-users not actually increasing consumption). These increases could result from the technology's mechanical effects and enhanced billing accuracy.

Total electricity sales also may increase due to a growing customer base. To ensure that the increase in number of customers could simply reflect local economic growth within the utility's service area, all of our regressions control directly for the number of new buildings. Additionally, our instrumental variable approach helps address ways in which local economic growth might impact outcomes. Any increase in the number of customers, while holding new construction and population constant, therefore, is likely associated with a customer base that is growing for other reasons. For example, smart meters may force previously informal customers to shift to formal connections or simply an increase in metering of individual entities at locations previously sharing one meter (e.g., buildings with multiple apartments). Alternatively, smart meters may attract customers that are particularly interested in gaining information on their energy use, using the products that AMI enables (like demand response programs), or improving the accuracy of their electricity bills. This would make utilities with AMI more competitive. Since using AMI to gain customers requires effective customer engagement, including investments in communications and marketing, this also would suggest that utilities are taking additional actions to realize the potential benefits of AMI.

We estimate the effects of AMI deployment on both sales per customer and the number of customers. The event study plots are in Figure 3. In Panel A, we find a small but immediate increase in sales per customer that continues to increase slightly over time, but then levels off after approximately one year. The immediacy of the effect is consistent with the smart meters measuring consumption more accurately and/or utilities making billing process adjustments relatively quickly, which is reasonable since this is one of the more basic uses of smart meter data. On the other hand, the increase in the number of customers emerges much more gradually, which is consistent with utilities needing time to invest in new communications and marketing efforts to attract new customers.

The coefficient estimates from pooling the data are in Appendix Table B5. In Panel A, the main effects on both outcomes using the full baseline sample are not statistically significant but have the expected positive signs. However, when examining treatment intensity, going from zero smart meters to full deployment (Panel B) increases sales per customer by approximately 2.1%. The magnitude of this effect could reasonably be explained by an improvement in consumption measurement accuracy. The number of customers still does not increase with treatment intensity, but this is consistent with how it takes time to attract new customers. As expected, once omitting the year of initial deployment and the two years that follow (Panel C), we find a 1.1% increase in the number of customers (which is statistically significant at the 10% level). At the same time, there is no statistically significant effect on sales per customer at this point; this could be due to statistical power, although the point estimate also decreases slightly.[36]

6.2 Introducing Dynamic Pricing and Demand Response Programs

Smart meters provide utilities with opportunities to introduce or improve dynamic pricing and other demand response programs, and doing so signals improved performance.[37] These additional products could attract new customers. Furthermore, as these programs aim to incentivize end-users to reduce consumption or shift the timing of energy use away from high-demand periods, they could reduce losses and improve grid resilience.[38]

To investigate whether utilities introduce these types of programs after AMI deployment, we estimate the AMI effects on availability of these products. We do so using indicator variables equal to one when the number of customers using dynamic pricing and demand response programs becomes positive and zero otherwise. The results are presented in Columns 1 and 2 of Table 4. On average, the likelihood of introducing these services indeed increases by 3.9% and 3.3% for dynamic pricing and demand response programs, respectively (Panel A). The effects increase slightly to 4.7% and 4.9% when utilities go from no deployment to full deployment (Panel A of Appendix Table B6). When dropping the first two years post-deployment, the likelihood of using these programs increases to 7% and 6.5% (Panel B

[36]We cannot say definitively why this effect may diminish over time. One potential explanation is that consumers do eventually adjust, such as by making energy efficiency investments.

[37]Some forms of dynamic pricing, such as seasonal pricing, can be implemented without smart meters, while others could be more useful for intra-day load balancing, like tariff structures that apply different rates throughout the day. Similarly, demand response programs can be defined broadly and some forms could have been used without smart meters as well.

[38]Line losses increase exponentially when the grid is overloaded given the relationship between consumption and current.

of Appendix Table B6).

Next, to test whether offering these programs may be one driver of utility competitiveness, we estimate the effect of AMI interacted with the indicators for dynamic pricing and demand response programs (see Columns 3 and 4 of Table 4). Indeed, the provision of these products drives the increase in utilities' customer base.

Depending on consumer responsiveness, these products also may contribute to lower electricity losses if consumption changes alleviate constraints on the grid during high-demand periods. We do not observe the timing of consumption to test this directly. To explore it indirectly, we estimate the interaction effects of AMI deployment and the use of dynamic pricing or demand response programs on sales per customer and losses per sale (Columns 5-7 in Table 4). There are two key takeaways. First, both products offset the increases in sales per customer, suggesting some degree of consumer responsiveness (Columns 5 and 6 of Table 4). However, the effects are relatively small, and they do not seem to account for any of the reductions in losses per sale (Columns 7 and 8).[39] This is consistent with other recent work studying a large-scale deployment of smart thermostats, whereby there is no significant effect on energy use (Brandon, Clapp, List, Metcalfe and Price, 2022). Our findings suggest that, although reductions in sales from the use of these programs can provide some system benefits (e.g., reduce the need for additional capacity investments), they are not substantial enough to improve electricity losses on their own.

6.3 Organizational Capital

If utilities use the AMI to directly transmit consumption data to their billing systems, then we should observe a decrease in the number of utility meter readers employed by utilities. Furthermore, fully realizing the benefits of AMI—beyond just a reduction in labor costs—may also require additional investments in complementary technologies, communications networks, and human capital. This is because integrating the new technology and analyzing the data that it provides in order to improve load management and voltage optimization requires advanced data analysis and forecasting skills.

We do not observe the number or type of workers at the utility level to test this directly.

[39] The same is true for total losses but the results are omitted from the table for space purposes.

To explore workforce composition as a proxy for organizational change, though, we gather annual metropolitan service area (MSA) by occupation data to examine whether there is a reduction in local employment of utility meter readers and/or an increase in data and software engineering-oriented workers.[40]

We first provide graphical evidence on the relationship between the composition of workers in the local labor market and AMI adoption. In each panel of Figure 5, the horizontal axes represent the proportion of customers that are AMI within an MSA. The vertical axes are the residuals of the logarithm of employment after absorbing the MSA fixed effects, population, and building units. We classify the occupations into three categories—meter readers, quantitative and computation jobs, and others—and show the binned-scatter plot for each of the category. Panels A and B of Figure 5 provide compelling evidence that AMI deployment is associated with a decline in meter readers and an increase in quantitative and computation jobs. In contrast, there is no clear pattern between AMI adoption and other jobs (Panel C), which is reassuring.

To quantify the effects, we estimate the following triple-difference model:

$$Y_{ijt} = \beta \mathrm{AMI}_{it} \times \mathrm{RelatedOCC}_j + \alpha_{ij} + \delta_{it} + \varepsilon_{ijt}. \tag{3}$$

The outcome variable is the logarithm of the number of employment in MSA i for occupation j in year t. AMI_{it} is a binary indicator for whether any utility operating in MSA i has deployed AMI in year t. $\mathrm{RelatedOCC}_j$ is a binary indicator for AMI-related occupation, which is defined as either meter readers (denoted by "Billing") or quantitative and computation jobs (denoted by "Quant"). We control for macroeconomic shocks, such as population growth and regional economic policies, which may affect the number of workers differently across locations with MSA-year fixed effects and for time-invariant differences in the labor force across MSAs with MSA-occupation fixed effects. The coefficient of interest, β, captures how the number of employment for meter readers or quantitative and computation jobs within an MSA area is changing relative to other unrelated occupations.

[40] The MSA-level data does not specify industry, but as the meter reader occupation category covers only the utilities sector (electricity, gas, and water), we can be fairly confident that changes in this occupation category are strongly correlated with changes in electricity utilities specifically.

Table 5 presents the estimation results. In Column 1, we find that the number of meter readers decreases by 18.6% relative to other occupations. We also drop observations associated with quantitative and computation jobs in Column 2, because if there is a simultaneous increase in these types of workers due to AMI adoption, they would make a poor control group. We still find an 18.2% decrease in meter readers. We carry out the same exercise to estimate the effect for quantitative and computation jobs, and indeed find that they increase by 7.4% relative to other occupations, as shown in Column 3. When omitting meter readers from this estimation to address potential SUTVA violations, we again find a 6.8% increase in quantitative and computation jobs.

We also limit the sample to include only MSAs that either deployed AMI between the years 2008 and 2016 or do not deploy at all.[41] Panel A of Table B7 reports the estimates, which are similar to those in Table 5. In Panel B, we further exclude the MSAs that already deployed smart meters by 2008 and the estimated effects are similar. For quantitative and computation jobs, the coefficient estimates are smaller and become less statistically significant, but this is likely due to sample size limitations.

Taken together, these findings suggest that, on average, utilities invest in organizational innovation with the adoption of smart meters. This is consistent with management innovation being an underlying driver of the service provision improvements.

6.4 Reliability: Power Outage Frequency and Duration

Although lower electricity losses signal that the system is more stable and less vulnerable to technical issues and disturbances, losses are not a direct measure of reliability as experienced by end-users. We therefore examine the effects on power outage duration and frequency directly by compiling feeder-line level data on power outage frequency and duration for utilities in Texas.[42] Examining power outages also provides insight into whether and how utilities make management and operational adjustments with AMI. That is, while smart meters notify utilities automatically and immediately of when and where power outages

[41] In our utility-level analysis, we limit the sample of utilities with AMI to those that deployed between 2010 and 2016, but we do not impose such a restriction here because most (291 out of 434) MSAs have at least one utility with AMI by then, so we would lose more than 80% of the sample.

[42] Within-utility variation allows us to control for utility-level trends.

occur, utilities must engage with the information transmitted by the smart meters and respond accordingly to reduce outage duration. Furthermore, smart meters may even provide utilities with opportunities to avoid outages altogether if load management improvements alleviate constraints that otherwise would have led to a disturbance.

We estimate the following model:

$$Y_{ijt} = \beta_1 \text{AMI}_{jt} + \alpha_i + \gamma_t + \delta' \mathbf{X}_{jt} + \varepsilon_{ijt}, \tag{4}$$

where Y_{ijt} denotes the reliability outcome for feeder line i of utility j in year t and the indicator AMI_{jt} is utility-level AMI deployment treatment variable defined as before. We include feeder line-level fixed effects (α_i) to control for time-invariant line-specific factors that may impact reliability as well as year fixed effects (γ_t) to account for changing conditions over time that are common across all feeder lines in Texas. The matrix $\mathbf{X}_{jt}$ includes the same controls as in our baseline analyses as well as utility-year linear trends in some cases, as having within-utility variation allows us to control for how utilities and their customers may be changing differently over time.

The results are presented in Table 6 and are consistent with utilities indeed using the smart meters to respond to outages.[43] Outage duration (i.e., the number of minutes of sustained interruptions experienced by a utility's average customer) decreases by 5.4-5.8% following AMI deployment (Columns 1 and 2). On the other hand, we find no effect on outage frequency, suggesting that further action beyond the energy management improvements associated with reductions in losses—such as improved system monitoring and load management—are required for avoiding outages in this setting.

6.5 Financial Benefits and Investment Payback

Our findings suggest that AMI could bolster utilities' fiscal sustainability but we have not yet discussed the economic significance of the effects. We cannot calculate all financial performance benefits directly, as we do not observe some of the parameters required for examining outcomes like labor costs associated with meter reading or power outage restoration. We

[43] We use the inverse hyperbolic sine for the outcomes here because of the presence of zeros.

can, however, examine utilities' revenue and the implications of reduced losses for costs.

First, increases in sales from improved billing accuracy suggest that utilities benefit from enhanced revenue recovery, but utilities also may pass through cost savings to consumers by reducing prices. We therefore start by estimating the effects of AMI deployment on total revenue. The results are presented in Columns 1 and 2 of Table 7. When considering the average effect for the full sample (Column 1, Panel A), we find that the increase in revenue appears to be relatively small (0.9%).

When limiting the sample of adopting utilities to those in the top quartile of the pre-treatment losses per sale distribution—utilities that have the most room for improvement and that we previously found to benefit the most from AMI in Table 3—revenue increases by 4.1% on average (Column 2 of Panel A). This represents an increase of $4.7 million per year relative to the $115.5 million average pre-treatment annual revenue for AMI adopting utilities in this sample. The effect increases to 6.5% when omitting the first three years of deployment to capture the potential effects once time passes (Column 2, Panel C), which leads to $7.5 million more revenue.

When estimating the effects of going from having no smart meters to full deployment for the entire sample, we find that total revenue increases by 1.9% on average (Column 1, Panel B) and by 5.5% for utilities in the top quartile of pre-treatment losses per sale (Column 2 of Panel B). These represent increases of $2.66 million and $6.35 million per year, respectively, relative to the pre-treatment averages for AMI adopting utilities in their respective sample.[44]

To put these revenue figures into context relative to the cost of investing in smart meters, let's assume that the total cost of installing a smart meter is $200 per meter including both hardware and labor, which is likely on the high end and thus a conservative figure to use for calculating the payback period.[45] Utilities adopting AMI had 62,440 customers on average in pre-treatment years in the full sample and 62,934 in the "high" pre-treatment losses sub-sample such that full deployment for the average utility would cost about $12.49 and $12.59 million, respectively. When considering the effect on revenue when going from no

[44] Average revenue in pre-treatment years for AMI adopting utilities is $139.8 million for the full sample and $115.5 million for utilities in the "high" pre-treatment losses category.

[45] Cost estimates in 2015 were $200 (Greenough, 2015), and hardware costs have come down over time. Recent increases in cost of labor may offset some of the hardware cost reductions, though.

deployment to full deployment and no discounting (Panel B of Table 7), investing in AMI smart meters pays off in about 4.7 years on average for the full sample and 1.98 years for utilities with "high" pre-treatment losses. Note that these (relatively quick) payback periods can be considered upper bounds since they only rely upon estimates of increased recovered revenue as opposed to any cost reductions.

Second, reductions in electricity losses represent reductions in costs. We found that total losses decrease by 5.9% on average for the full sample and 7.9% for utilities with high pre-treatment losses. Considering that the average prices of electricity are \$97.1 and \$108.2 per MWh in these samples, respectively, the average cost savings resulting from reductions in losses of \$0.477 million on average for all AMI adopting utilities and \$12.87 million for those with high pre-treatment losses. Unsurprisingly, while there are particularly attractive financial benefits for utilities with respect to recovered revenue even if utilities previously were performing quite well, utilities with high pre-treatment losses have just as much to gain from reducing losses (even before considering how the effect may increase over time).

We also find no change in prices (calculated as total revenue per unit sold (\$/MWh), on average (Columns 3 and 4 of Table 7). This is consistent with revenue increasing from changes in sales (due to improved billing accuracy and a growing customer base), as opposed to prices, and it suggests that utilities are not passing through the financial benefits. At the same time, we do find that average prices increase by 3% in the longer run when omitting the first three years post-deployment (Column 4, Panel C of Table 7). This represents a 0.3 cents per kWh increase relative to the pre-treatment mean price of 9.7 cents per kWh. The aggregate effect on customers' bills is relatively small. When considering the price increase, pre-treatment mean sales per customer, and the 1.3% increase in sales per customer in the long run (the estimate in Column 1, Panel C of Appendix Table B5), the average increase in electricity bills is \$35 per year (or \$2.9 per month).[46]

[46] Initial annual bills are calculated using pre-treatment average sales per customer and prices. To calculate post-AMI bills, we use pre-treatment sales per customer multiplied by 1.013 (to account for the 1.3% increase in sales per customer) and pre-treatment prices multiplied by 1.03 (to account for the 3% increase in prices.)

7 Implications of Utility Ownership

Although the utility sector historically has been slow to change and lagged behind other sectors when it comes to innovation, our findings suggest that the reductions in losses and increases in sales following AMI deployment are driven by improvements in energy management. This, in turn, raises the question of what determines a utility's incentive and capacity to make the necessary investments in organizational capital to benefit from digitalization.

One potential explanation is utility ownership. On the one hand, economists have long-argued that private firms aiming to maximize profits tend to be more productive and innovative than those in the public sphere (Shleifer, 1998; Hart et al., 1997) and that privatization can enhance the growth and efficiency of previously government-owned firms (Ehrlich, Gallais-Hamonno, Liu and Lutter, 1994). At the same time, investor-owned utilities face pressures from shareholders to earn profits (typically on a quarterly basis). This may dissuade them from making the additional costly and time-consuming investments beyond just technology adoption itself—like upgrading old equipment or overhauling business practices and processes—that improve quality of service but may take several years to pay off. On the other hand, government-owned utilities do not face such pressures. If anything, they may be even more inclined to focus on investments that provide substantial social benefits, as they are usually elected officials and their customers are their constituents.

In this section, we explore whether ownership structure shapes the benefits that materialize from AMI. Given that utilities also differ on other observable dimensions across ownership types, such as size (see Appendix Table B9), we end this section with evidence that the heterogeneity we find is not driven by other observable differences.

7.1 Heterogeneity in Effects by Utility Ownership

We estimate the effects of smart meter deployment on our main performance indicators separately by ownership type and a clear picture emerges. In the event study plots in Figure 4, the effects on losses per sale, total losses, and total sales are all driven by government-owned utilities. Losses per sale and total losses start declining quickly (Panels A and B)—and drastically relative to the average main effects in Figure 2—while total sales increase (Panel

C). In contrast, there are no effects on any of these outcomes for IOUs or cooperatives.[47]

The effects on losses for government-owned utilities are also economically large (see Appendix Table B10). For example, when considering the intensity of treatment results (Panel B), we find that going from no deployment to full deployment reduces losses per sale by 12.2% relative to the pre-treatment mean for utilities that deploy AMI and total losses decrease by 15.1%. Total sales increase by 2.1%, similar to what we find in our main estimates. The effects on losses per sale and total losses are not statistically significant when dropping the first two years post-adoption (Panel C), which is likely due to statistical power, but the magnitudes of the coefficients are similar to (or slightly stronger than) the baseline estimates in Panel A, and the effect on total sales increases to 3.4% (while remaining statistically significant at the 10% level).

Taken together, these results suggest that ownership structure may play an important role in shaping utilities' incentives to use AMI to improve performance. They also indicate that our main results may actually understate the potential benefits of smart meters, as they are attenuated by the inclusion of two sets of utilities (cooperatives and IOUs) for which we do not document any meaningful effects.

7.2 Alternative Explanations of Ownership Heterogeneity

One interpretation of these results is that ownership structure may impact the incentive and capacity to invest in the organizational capital required to realize the benefits of AMI. Although all utilities have incentives to reduce electricity losses, enhance revenue recovery, and improve reliability, privately-owned utilities may instead distribute the recovered revenue to shareholders rather than making additional investments to improve performance in the long run. At the same time, other characteristics that differ systematically between government-owned and privately-owned utilities may contribute to heterogeneity in outcomes, like pre-treatment losses and utility size. We explore those here and find no evidence that they drive the heterogeneity in outcomes.

[47] The coefficients for IOUs and cooperatives generally remain flat (hovering around zero). In the case of total losses for IOUs, there is a slight increase, if anything, that appears to just be the continuance of the trend in the pre-treatment years, which is consistent with smart meter adoption having no effect.

Pre-treatment losses. As shown in Section 5, the effects of AMI on utility performance were driven by utilities with high pre-treatment electricity losses (i.e., utilities that had the most to gain). If government-owned utilities systematically have higher losses per sale prior to AMI adoption relative to IOUs and cooperatives, poor initial performance may explain some of the differences in outcomes across ownership type.

This does not seem to be the case. Average pre-treatment losses per sale were lower for government-owned utilities (5.3%) relative to both IOUs (7.2%) and cooperatives (6.5%). Furthermore, we estimate the effects separately for government-owned and non-government-owned utilities when only including utilities with "high" pre-treatment losses and find that the effects are still driven entirely by government-owned utilities (see Table 8).[48] We define "high" pre-treatment losses per sale in this case as utilities with losses per sale in the top quartile of the government-owned pre-treatment sample distribution (6.5%).[49]

Utility size. Another factor could be utility size, as the time it takes to fully deploy smart meters scales with the number of customers, and the effects on performance increase with treatment intensity and time. IOUs are much larger than government-owned utilities, with the median number of customers in pre-treatment years for utilities in our sample being 366,485 for IOUs and only 5,939 for government-owned utilities. Cooperatives are closer to government-owned utilities in terms of number of customers but still larger (13,935 in pre-treatment years).

We explore this by examining heterogeneity in outcomes by utility size and ownership groups. We group cooperatives and IOUs together as "privately-owned" for statistical power purposes (and also because we find no effects on either group). Although not many government-owned utilities are large enough to be comparable with privately-owned utilities, there is a sufficient sub-sample of privately-owned utilities that are small enough to be comparable with government-owned utilities. If the overall effects on privately-owned utilities are only attenuated because of utility size, then we should find that performance improves

[48] We combine cooperatives and IOUs in this exercise due to the small sample size of IOUs.

[49] We use the government-owned distribution's top quartile cutoff for defining "high" in both samples so that the cutoff point is the same. The 75th percentile of the pre-treatment losses per sale distribution for non-government-owned utilities is 8%, and while we do not present these results in the table, there are no effects when using this cutoff either.

for these *small* privately-owned utilities.

To test this, we omit utilities with more than 43,177 customers in their pre-treatment years on average, which is the cutoff for dropping the top 5% of the government-owned utility size distribution. It also represents much smaller privately-owned utilities relative to their own size distribution.[50] The event study plots are provided in Appendix Figure B4. Results for government-owned utilities are in the left column and those for non-government-owned are in the right column. Despite the utilities being similar sizes (and small) in each sample, the effects of AMI on losses per sale, total losses, and total sales are still only among government-owned utilities. We conduct the same exercise when including utilities that are even smaller—those with fewer than 27,520 customers on average in their pre-treatment years (i.e., the cutoff for the top 10% of the government-owned utility size distribution) and find the same patterns (see Appendix Figure B5).

Adoption timing. A final potential driver of heterogeneous effects across ownership structure is adoption timing. The estimated effects may be larger for utilities that adopted earlier in our sample simply because we observe them for more years post-treatment, as some effects increase as utilities learn to leverage the capabilities (shown earlier). Alternatively, since technologies tend to advance over time, the effects for later adopters may be higher if later versions of AMI provide additional features that can further improve performance. Although our empirical strategy addresses the endogeneity of adoption timing overall, differences in effects across ownership type may still arise if adoption timing also varies across ownership type.

Notably, we omitted the earliest adopters of all ownership types throughout the entire paper so far by excluding utilities that adopted prior to 2010. This helps alleviate potential concerns associated with very early adopters differing from late adopters. Furthermore, though, the adoption timing is similar across ownership type. The median year of adoption is 2014 for government-owned utilities and 2013 for privately-owned utilities.

[50] This approach of using the government-owned utility distribution to determine the cutoff for both subsamples allows us to estimate the effects for comparably-sized utilities, as trimming based on the distribution for non-government-owned utilities would result in still estimating the effects only for very large utilities.

8 Conclusion

Digitalization is increasingly promoted as a solution for improving firm performance. Yet the potential for enhancing public service provider performance has been unclear to date. This paper examines the impact of digitalization on utility performance and quality of service in the U.S. electricity sector, which provides a unique setting in which adoption of digital technologies is relatively widespread and objective performance and service quality measures are reported consistently. We found that, on average, electricity losses per sale decrease by 3.6%. The effects are much larger for utilities with high pre-treatment losses. Findings from additional analyses suggest that energy management improvements—such as automated billing processes and enhanced system monitoring capabilities—are at play.

These effects are driven entirely by government-owned utilities rather than investor-owned utilities or cooperatives. Differences in other observable characteristics do not account for the heterogeneity. Therefore it is likely that the diverging managerial incentives across ownership types account for this heterogeneity.

The impacts of AMI on electricity reliability are mixed. Power outage duration decreased, signalling that utilities use the information from AMI to identify and respond to interruptions more quickly. Yet, the frequency of outages does not change as a result of AMI deployment. This suggests that improvements in energy management that come with AMI are insufficient to prevent outages from occurring.

The findings in this paper are important and timely for policy. Electricity infrastructure in the U.S. and many other countries is aging, making the grid increasing vulnerable to extreme weather events. At the same time, extreme weather events are occurring with increasing frequency due to climate change. Governments globally are allocating large amounts of public expenditures to modernizing infrastructure in hopes of adapting and preparing for climate change, but research on whether these investments deliver on their promise is scant. Taken together, our findings suggest that digitalization can be a tool for improving public services, but the benefits may hinge upon organizational capital and incentives.

References

Allcott, Hunt, Allan Collard-Wexler, and Stephen D. O'Connell, "How Do Electricity Shortages Affect Industry? Evidence from India," *American Economic Review*, 2016, *106* (3), 587–624.

ASCE, "A Comprehensive Assessment of America's Infrastructure: 2021 Report Card for America's Infrastructure," *American Society of Civil Engineers*, 2021.

Bartel, Ann, Casey Ichniowski, and Kathryn Shaw, "How Does Information Technology Affect Productivity? Plant-Level Comparisons of Product Innovation, Process Improvement, and Worker Skills," *The Quarterly Journal of Economics*, 2007, *122* (4), 1721–1758.

BC Hydro, "BC Hydro Power Smart Fact Sheet," 2016. https://www.bchydro.com/news/press_centre/news_releases/2016/smi-fact-sheet.html.

Bergman, M.A., P. Johansson, S. Lundberg, and G. Spagnolo, "Privatization and Quality: Evidence from Elderly Care in Sweden," *Journal of Health Economics*, 2016, *49*, 109–119.

Bloom, N., R. Sadun, and J. Van Reenen, "Americans Do IT Better: US Multinationals and the Productivity Miracle," *American Economic Review*, 2012, *102* (1), 167–201.

Bloom, Nicholas and John Van Reenen, "Measuring and Explaining Management Practices across Firms and Countries," *The Quarterly Journal of Economics*, 2007, *122* (4), 1351–1408.

_ , Carol Propper, Stephan Seiler, and John Van Reenen, "The Impact of Competition on Management Quality: Evidence from Public Hospitals," *The Review of Economic Studies*, 2015, *0*, 1–33.

_ , Erik Brynjolfsson, Lucia Foster, Ron Jarmin, Megha Patnaik, Itay Saporta-Eksten, and John Van Reenen, "What Drives Differences in Management Practices?," *American Economic Review*, 2019, *109* (5), 1648–1683.

_ , Renata Lemos, Rafaella Sadun, and John Van Reenen, "Healthy Business? Managerial Education and Management in Health Care," *The Review of Economics and Statistics*, 2020, *102* (3), 506–517.

_ , _ , Raffaella Sadun, and John Van Reenen, "Does Management Matter in Schools?," *Economic Journal*, 2015, *125* (5), 647–674.

Borenstein, S., J. Bushnell, and E. Mansur, "The Economics of Electricity Reliability," *Journal of Economic Perspectives*, 2023, *37* (4), 181–206.

Borusyak, Kirill, Xavier Jaravel, and Jann Spiess, "Revisiting Event Study Designs: Robust and Efficient Estimation," *arXiv:2108.12419 [econ]*, 2021.

Brandon, A., C. Clapp, J. List, R. Metcalfe, and M. Price, "The Human Perils of Scaling Smart Technologies: Evidence from Field Experiments," *Working Paper*, 2022.

Bresnahan, T., E. Brynjolfsson, and L. Hitt, "Information Technology, Workplace Organization, and the Demand for Skilled Labor: Firm-Level Evidence," *The Quarterly Journal of Economics*, 2002, *117* (1), 339–376.

Bronsoler, A., J. Doyle, and J. Van Reenen, "The Impact of Health Information and Communication Technology on Clinical Quality, Productivity, and Workers," *Annual Review of Economics*, 2022, *14*, 23–46.

Brynjolfsson, E. and A. Saunders, *Wired for Innovation: How Information Technology is Reshaping the Economy*, MIT Press, 2013.

_ **and LM. Hitt**, "Beyond Computation: Information Technology, Organizational Transformation and Business Performance," *Journal of Economic Perspectives*, 2000, *14* (4), 23–48.

_ **and M. Hitt**, "Computing Productivity: Firm-Level Evidence," *Review of Economics and Statistics*, 2003, *85* (4), 793–808.

_ **, D. Rock, and C. Syverson**, "The Productivity J-Curve: How Intangibles Complement General Purpose Technologies," *American Economic Journal: Macroeconomics*, 2021, *13* (1), 333–72.

Burkhardt, J., K. Gillingham, and P. Kopalle, "Field Experimental Evidence on the Effect of Pricing on Residential Electricity Conservation," *Management Science*, forthcoming.

Callaway, Brantly and Pedro HC Sant'Anna, "Difference-in-differences with multiple time periods," *Journal of Econometrics*, 2021, *225* (2), 200–230.

Carranza, Eliana and Robyn Meeks, "Energy Efficiency and Electricity Reliability," *The Review of Economics and Statistics*, July 2021, *103* (3), 461–475.

Cooper, Adam and Mike Shuster, "Electric Company Smart Meter Deployments: Foundation for a Smart Grid (2021 Update)," Technical Report April 2021.

Costa-Campi, Maria Teresa, Daniel Daví-Arderius, and Elisa Trujillo-Baute, "The economic impact of electricity losses," *Energy Economics*, September 2018, *75*, 309–322.

Cutler, D., "Where Are the Health Care Entrepreneurs? The Failure of Organizational Innovation in Health Care," *Innovation Policy and the Economy*, 2011, *11* (1), 1–28.

de Chaisemartin, C. and X. D'Haultfoeuille, "Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects," *American Economic Review*, 2020, *110* (9), 2964–2996.

Draca, M., R. Sadun, and J. Van Reenen, "Productivity and ICTs: A Review of the Evidence," *The Oxford Handbook of Information and Communication Technologies*, 2009.

Duggan, Mark, "Hospital ownership and public medical spending," *The Quarterly Journal of Economics*, 2000, *115* (4), 1343–1373.

_ **, Atul Gupta, Emilie Jackson, and Zachary Templeton**, "The Impact of Privatization: Evidence from the Hospital Sector," *NBER Working Paper 30824*, 2023.

Duke Energy Progress, "Smart Grid Frequently Asked Questions," 2020. https://www.duke-energy.com/our-company/about-us/smart-grid/smart-meter.

Ehrlich, Isaac, Georges Gallais-Hamonno, Zhiqiang Liu, and Randall Lutter, "Productivity Growth and Firm Ownership: An Analytical and Empirical Investigation," *Journal of Political Economy*, 1994, *102* (5), 1006–1038.

EIA, "Today in Energy," Nov 2021. https://www.eia.gov/todayinenergy/detail.php?id=50316.

_ , "U.S. EIA Frequently Asked Questions," Nov 2022. https://www.eia.gov/tools/faqs/faq.php?id=108&t=1.

EIA, U.S., "U.S. electric system is made up of interconnections and balancing authorities," 2016.

Fenizia, Alessandra, "Managers and Productivity in the Public Sector," *Econometrica*, 2022, *90* (3), 1063–1084.

FERC, "Federal Energy Regulatory Commission Reliability Primer: An Overview of the Federal Energy Regulatory Commission's Role in Overseeing the Reliable Operation of the Nation's Bulk Power System," 2020. Available at: https://www.ferc.gov/sites/default/files/2020-04/reliability-primer$_1$.*pdf*, *AccessedOctober*2023.

Fisher-Vanden, Karen, Erin T. Mansur, and Qiong Juliana Wang, "Electricity Shortages and Firm Productivity: Evidence from China's Industrial Firms," *Journal of Development Economics*, 2015, *114*, 172–188.

Freyaldenhoven, S., C. Hansen, and J. Shapiro, "Pre-Event Trends in the Panel Event-Study Design," *American Economic Review*, 2019, *109* (9), 3307–3338.

Gold, Rachel, Corri Waters, and Dan York, "Leveraging Advanced Metering Infrastructure To Save Energy," *American Council for an Energy-Efficient Economy (ACEEE)*, January 2020, *Report U2001.*

Goldfarb, Avi and Catherine Tucker, "Digital Economics," *Journal of Economic Literature*, 2019, *57* (1), 3–43.

Goodman-Bacon, Andrew, "Difference-in-differences with variation in treatment timing," *Journal of Econometrics*, 2021, *225* (2), 254–277.

Gosnell, G., J. List, and R. Metcalfe, "The Impact of Management Practices on Employee Productivity: A Field Experiment with Airline Captains," *Journal of Political Economy*, 2020, *128* (4).

Greenough, J., "The Smart Meter Report: Forecasts, regional breakdowns, costs, and savings for a top IoT device," 2015. Business Insider, April 9, 2015. Available at: https://www.businessinsider.com/the-smart-meter-report-a-look-at-how-the-smart-meter-market-is-evolving-2015-3: :text=The

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

IEA, "Energy Technology Perspectives 2015: Mobilising Innovation to Accelerate Climate Action," Technical Report 2015.

_ , *Electricity Grids and Secure Energy Transitions: Enhancing the Foundations of Resilient, Sustainable and Affordable Power Systems*, OECD, October 2023.

Ito, Koichiro, Takanori Ida, and Makoto Tanaka, "Moral Suasion and Economic Incentives: Field Experimental Evidence from Energy Demand," *American Economic Journal: Economic Policy*, 2018, *10* (1), 240–267.

Janke, K., C. Propper, and R. Sadun, "The Impact of CEOs in the Public Sector: Evidence from the English NHS," *Working Paper 25853*, 2019.

Jessoe, Katrina and David Rapson, "Knowledge Is (Less) Power: Experimental Evidence from Residential Energy Use," *American Economic Review*, 2014, *104* (4), 1417–1438.

Jiménez, Raúl, Tomás Serebrisky, and Jorge Mercado, *Power Lost: Sizing Electricity Losses in Transmission and Distribution Systems in Latin America and the Caribbean*, Inter-American Development Bank, November 2014.

Joskow, Paul L, "Creating a Smarter U.S. Electricity Grid," *Journal of Economic Perspectives*, February 2012, *26* (1), 29–48.

Lu, S., H. Rui, and A. Seidmann, "Does Technology Substitute for Nurses? Staffing Decisions in Nursing Homes," *Management Science*, 2018, *64* (4), 1842–59.

Meeks, Robyn C., Arstan Omuraliev, Ruslan Isaev, and Zhenxuan Wang, "Impacts of electricity quality improvements: Experimental evidence on infrastructure investments," *Journal of Environmental Economics and Management*, 2023, *120*, 102838.

Metcalfe, Robert D., Alexandre B. Sollaci, and Chad Syverson, "Managers and Productivity in Retail," *Working Paper*, 2023.

Mukherjee, A., "Impacts of Private Prison Contracting on Inmate Time Served and Recidivism," *American Economic Journal: Economic Policy*, 2021, *13* (2), 408–438.

Munasinghe, Mohan, "Electricity Pricing; a Comprehensive Framework," *IEEE Transactions on Power Apparatus and Systems*, August 1981, *PAS-100* (8), 3959–3968.

Nangia, Varun, Samuel Oguah, and Kwawu Gaba, *Can Utilities Realize the Benefits of Advanced Metering Infrastructure?: Lessons from the World Bank's Portfolio*, World Bank, Washington, DC, July 2016.

Otero, Cristobal and Pablo Munoz, "Managers and Public Hospital Performance," *Working Paper*, 2022.

Rose, N. and P. Joskow, "The Diffusion of New Technologies: Evidence from the Electric Utility Industry," *RAND Journal of Economics*, 1990, *21* (3).

Roth, J., P.H. Sant'Anna, A. Bilinski, and J. Poe, "What's Trending in Difference-in-Differences? A Synthesis of the Recent Econometrics Literature," *conditionally accepted, Journal of Econometrics*, 2022.

Roth, Jonathan, "Pretest with Caution: Event-Study Estimates after Testing for Parallel Trends," *American Economic Review: Insights*, 2022, *4* (3), 305–322.

Shleifer, Andrei, "State versus Private Ownership," *Journal of Economic Perspectives*, 1998, *12* (4), 133–150.

Smitherman, Barry T, Donna L Nelson, and Kenneth W Anderson Jr, "Public Utility Commission of Texas Report to the 82nd Texas Legislature: A Report on Advanced Metering as Required by House Bill 2129," Technical Report 2010.

Sprinz, James, "Global trends in smart metering," *Smart Energy International*, December 2018.

Sun, Liyang and Sarah Abraham, "Estimating dynamic treatment effects in event studies with heterogeneous treatment effects," *Journal of Econometrics*, 2021, *225* (2), 175–199.

Trimble, Chris, Masami Kojima, Ines Perez Arroyo, and Farah Mohammadzadeh, "Financial Viability of Electricity Sectors in Sub-Saharan Africa: Quasi-Fiscal Deficits and Hidden Costs," Technical Report, The World Bank 2016.

U.S. Department of Energy, "Fault Location, Isolation, and Service Restoration Technologies Reduce outage Impact and Duration," Technical Report 2014.

_ , "Municipal Utilities' Investment in Smart Grid Technologies Improves Services and Lowers Costs," *Smart Grid Investment Grant Program (SGIG) Reports on Technology Applications and Results*, 2014.

_ , "Smart Grid Investments Improve Grid reliability, Resilience and Storm Responses," Technical Report 2014.

_ , "United States Electricity Industry Primer," Primer DOE/OE-0017, Office of Electricity Delivery and Energy Reliability 2015.

U.S. DOE, "Advanced Metering Infrastructure and Customer Systems: Results from the SGIG Program," 2016.

USAID, "Optimal Feeder Level Connection: Training and Field Support Toolkit," Technical Report, USAID 2009.

Utility Dive, "97% of smart meters fail to provide promised customer benefits. Can $3B in new funding change that?," 2022. Utility Dive, Available at: https://www.utilitydive.com/news/97-of-smart-meters-fail-to-provide-promised-customer-benefits-can-3b-in/632662/, Accessed December 2023.

Zhang, Fan, "In the Dark: How Much Do Power Sector Distortions Cost South Asia?," Technical Report, The World Bank 2018.

Main Text Tables

Table 1: Summary Statistics of Key Variables (Baseline Estimation Sample)

	Full Sample (1)	AMI Adopters Pre-Adoption Years (2)	Non-Adopters All Years (3)	Difference of Means (4)
Losses per Sale (%)	0.057	0.056	0.060	0.004
	(0.031)	(0.028)	(0.034)	(0.001)
Total Losses (000s MWh)	65.81	83.22	37.77	45.4
	(275.57)	(340.94)	(132.51)	(4.68)
Total Sales (000s MWh)	1160	1436	687	749
	(4285)	(5098)	(2524)	(74.02)
Total Revenue (million $)	119.6	139.8	68.2	71.6
	(498.4)	(569.2)	(240.6)	(7.95)
Number of Customers (000s)	57.05	62.44	33.75	28.69
	(258.14)	(271.18)	(127.60)	(3.88)
Sales per Customer (MWh)	31.00	27.01	36.41	-9.40
	(140.57)	(17.15)	(206.59)	(3.18)
Rev. per Customer (000s $)	2.88	2.43	3.33	-0.90
	(11.95)	(1.12)	(17.58)	(0.270)
Average Prices ($/kWh)	0.102	0.097	0.102	-0.005
	(0.034)	(0.028)	(0.040)	(0.001)
Observations	14,241	4,241	6,535	10,776
Number of Utilities	1,303	704	599	1,303

Notes: Table provides summary statistics of key variables used in the U.S.-level analysis for the full baseline regression sample (Column 1), AMI adopters in their pre-adoption years (Column 2), and non-adopters (Column 3). The differences of the means for adopters in pre-adoption years and non-adopters are in Column 4. Standard errors are in parentheses. Data are from the Energy Information Administration for the years 2007 through 2017. The sub-sample of AMI adopting utilities includes those that adopted between 2010 through 2016.

Table 2: Effect of Smart Meter Roll-outs on Electricity Losses and Sales

Dependent Variable:	Losses per Sale (1)	log(Total Losses) (2)	log(Total Sales) (3)
Panel A: Average Effects Over Full Sample Period			
PostAMI	-0.002**	-0.059**	0.012**
	(0.001)	(0.026)	(0.005)
Observations	14,241	14,241	14,241
Effect as % Change	-3.6%	-5.9%	1.2%
Panel B: Intensity of Treatment Effects			
Prop. AMI	-0.003***	-0.049**	0.025***
	(0.001)	(0.020)	(0.006)
Observations	14,241	14,241	14,241
Effect as % Change	-5.4%	-4.9%	2.5%
Panel C: Average Effects 3+ Years Post-Treatment			
PostAMI	-0.003**	-0.076*	0.024**
	(0.002)	(0.044)	(0.010)
Observations	12,255	12,255	12,255
Effect as % Change	-5.4%	-7.6%	2.4%
Mean of DV (Pre-Treatment)	0.056	83.22	1,436
Utility FEs	x	x	x
State-Year FEs	x	x	x
Local Market Controls	x	x	x

Notes: Table presents the main results for the effects of smart meter roll-outs on electricity losses per sale (Column 1), (log) total losses (Column 2), and (log) total sales (Column 3). Panel A presents our baseline main findings when using the full sample and estimating the 2SLS difference-in-differences model of Equation 2. In Panel B, we estimate the treatment intensity effects (the proportion of meters that are AMI meters). In Panel C, we estimate the average effect using the baseline sample but omit the year of adoption and the two years that follow for AMI adopters. Local market controls include (log) population and the inverse hyperbolic sine of new construction building within counties that the utility serves. For all regressions, we implement the 2SLS estimator using one lead of the AMI treatment variable to instrument for the covariate log(population). The coefficient on the treatment lead in the first stage is 0.007 and statistically significant at the 10% level in Panels A and B and 0.008 without statistical significance in Panel C. The mean values of dependent variables are provided in levels (000s MWh) and are calculated using only observations for AMI adopters in pre-treatment years. Standard errors are clustered at the utility level. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table 3: Heterogeneity in Main Effects by Pre-Treatment Losses per Sale

Dep. Var.:	Losses/Sale (1)	log(Total Losses) (2)	log(Total Sales) (3)
Panel A: Top Quartile of Pre-Treatment Losses per Sale			
PostAMI	-0.007***	-0.079***	0.030**
	(0.002)	(0.025)	(0.012)
Observations	3,234	3,234	3,234
Mean of DV (Pre-Treatment)	0.091	118,978	1,273
Panel B: Bottom Quartile of Pre-Treatment Losses per Sale			
PostAMI	0.001	-0.025	0.003
	(0.002)	(0.097)	(0.013)
Observations	2,531	2,531	2,531
Mean of DV (Pre-Treatment)	0.029	40.01	1,313
Utility FEs	x	x	x
State-Year FEs	x	x	x
Local Market Controls	x	x	x

Notes: Table presents estimates for the AMI treatment effect on losses per sale (Column 1), (logged) total losses (Column 2), and (logged) total sales (Column 3) when splitting the sample based on pre-treatment losses per sale (i.e., using observations for pre-AMI years for AMI adopters and all observations for non-adopters). Panel A includes those in the top quartile (losses per sale exceeding 7.3%) and Panel B includes those in the bottom quartile (losses per sale below 3.8%). Standard errors are clustered by utility. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table 4: New Product Offerings and Utility Competitiveness

Dependent Variable:	Dyn. Pricing (1)	Dem. Resp. (2)	# Cust. (3)	# Cust. (4)	Sales/ Cust. (5)	Sales/ Cust. (6)	Loss/ Sale (7)	Loss/ Sale (8)
PostAMI	0.039**	0.033**	-0.003	-0.000	0.020**	0.020***	-0.003**	-0.002*
	(0.017)	(0.015)	(0.003)	(0.002)	(0.009)	(0.007)	(0.001)	(0.001)
PostAMI x DP			0.018**		-0.034*		0.001	
			(0.008)		(0.018)		(0.002)	
DP			-0.000		0.013		-0.001	
			(0.007)		(0.016)		(0.002)	
PostAMI x DR				0.018**		-0.053***		-0.000
				(0.009)		(0.019)		(0.001)
DR				0.002		0.024*		-0.001
				(0.006)		(0.013)		(0.001)
Observations	14,241	14,241	14,241	14,241	14,241	14,241	14,241	14,241
Mean DV (Pre-Treat)	0.208	0.112	62,442	62,442	3.184	3.184	0.056	0.056
Utility FEs	x	x	x	x	x	x	x	x
State-Year FEs	x	x	x	x	x	x	x	x
Local Mkt. Controls	x	x	x	x	x	x	x	x

Notes: Table presents various sets of results related to utilities' provision of new products (dynamic pricing and demand response programs) that smart meters can enable and/or improve. The dependent variables are indicators for whether utilities offer dynamic pricing or demand response programs in Columns 1-2, (logged) number of customers in Columns 3-4, (logged) sales per customer in Columns 5-6, and losses per sale in Columns 7-8. Columns 1-2 present the main AMI treatment effects. In Columns 3-8, we interact the AMI treatment with the dynamic pricing and demand response program indicators. Standard errors are clustered at the utility level. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table 5: Reorganization of Workforce Composition

Dep. Var. (log):	Number of Employees			
	(1)	(2)	(3)	(4)
PostAMI × Meter Readers	-0.186***	-0.182***		
	(0.041)	(0.041)		
PostAMI × Quant Workers			0.074***	0.068***
			(0.019)	(0.019)
Observations	100,340	95,642	100,340	97,500
MSA-Occupation FEs	x	x	x	x
MSA-Year FEs	x	x	x	x
Drop Quant Workers		x		
Drop Meter Readers				x

Notes: Table provides results from estimating effects of AMI on the number of employees in meter reader (Columns 1-2) and quantitative data analysis-oriented (Columns 3-4) occupations. Dependent variable is the logarithm of employment by MSA-occupation-year. Standard errors are clustered by MSA area. Asterisks denote *$p<0.10$, **$p<0.05$, ***$p<0.01$.

Table 6: Effect of Smart Meter Roll-outs on Power Outages in Texas

Dependent Variable (ihs):	Outage Duration (SAIDI)		Outage Frequency (SAIFI)	
	(1)	(2)	(3)	(4)
PostAMI	-0.054*	-0.058*	-0.000	-0.013
	(0.028)	(0.031)	(0.013)	(0.015)
Observations	61,233	61,233	61,233	61,233
Mean of DV (Pre-Treatment)	91.32	91.32	0.950	0.950
Feeder FEs	x	x	x	x
Year FEs	x	x	x	x
Local Market Controls	x	x	x	x
Utility-Year Trends		x		x

Notes: Effects of AMI deployment on electricity reliability in Texas using within-utility feeder line-level data and estimating the baseline model following our 2SLS approach. Dependent variable is the inverse hyperbolic sine of SAIDI (power outage duration in minutes) in Columns 1-2 and SAIFI (outage frequency) in Columns 3-4. Observations are weighted by number of customers per feeder line. Additional local market controls include new building construction and (log) population with the lead AMI treatment variable as the excluded instrumental variable. The coefficient of the treatment lead in the first stage is 0.008 and is statistically significant at the 1% level. Standard errors are clustered at the feeder line level. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table 7: Financial Implications of Smart Meter Deployment

Dep. Var. (log):	Total Revenue		Average Prices	
Sample:	Full Sample	High Losses	Full Sample	High Losses
	(1)	(2)	(3)	(4)
Panel A: Average Effects Over Full Sample Period				
PostAMI	0.009*	0.041***	-0.003	0.011
	(0.005)	(0.012)	(0.004)	(0.007)
Observations	14,241	3,234	14,241	3,234
Panel B: Intensity of Treatment Effects				
Prop. AMI	0.019***	0.055***	-0.006	0.007
	(0.006)	(0.014)	(0.004)	(0.008)
Observations	14,241	3,234	14,241	3,234
Panel C: Average Effects 3+ Years Post-Treatment				
PostAMI	0.017*	0.065***	-0.006	0.030**
	(0.010)	(0.024)	(0.007)	(0.014)
Observations	12,255	2,769	12,255	2,769
Utility FEs	x	x	x	x
State-Year FEs	x	x	x	x
Local Market Controls	x	x	x	x

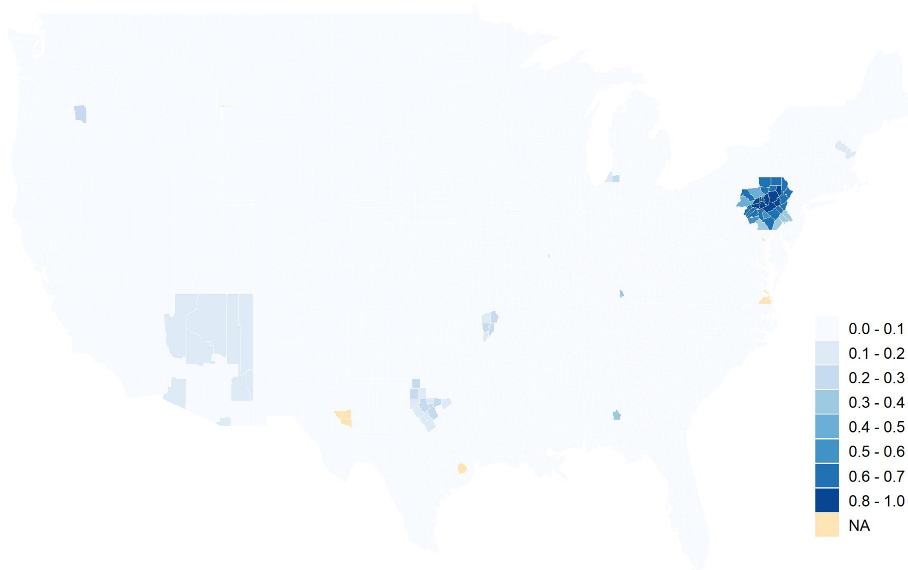
Notes: Table presents results for the effects of smart meter roll-outs on total revenue (Column 1), revenue per customer (i.e., bills) (Column 2), and average prices (revenue per sale) (Column 3). Panel A estimates the average effect for the full baseline sample, Panel B estimates the intensity of treatment effect (the proportion of customers with AMI meters), and Panel C estimates the average effect but omits the year of adoption and two years that follow such that the estimates capture the effects on outcomes 3+ years post-treatment. Local market controls include (log) population and the inverse hyperbolic sine of new construction building within counties that the utility serves. For all regressions, we implement the 2SLS estimator using one lead of the AMI treatment variable to instrument for the covariate log(population). The coefficient on the treatment lead in the first stage is 0.007 and statistically significant at the 10% level. Standard errors are clustered at the utility level. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table 8: Heterogeneous Effects of AMI Deployment by Ownership for Utilities with High Pre-Treatment Losses per Sale

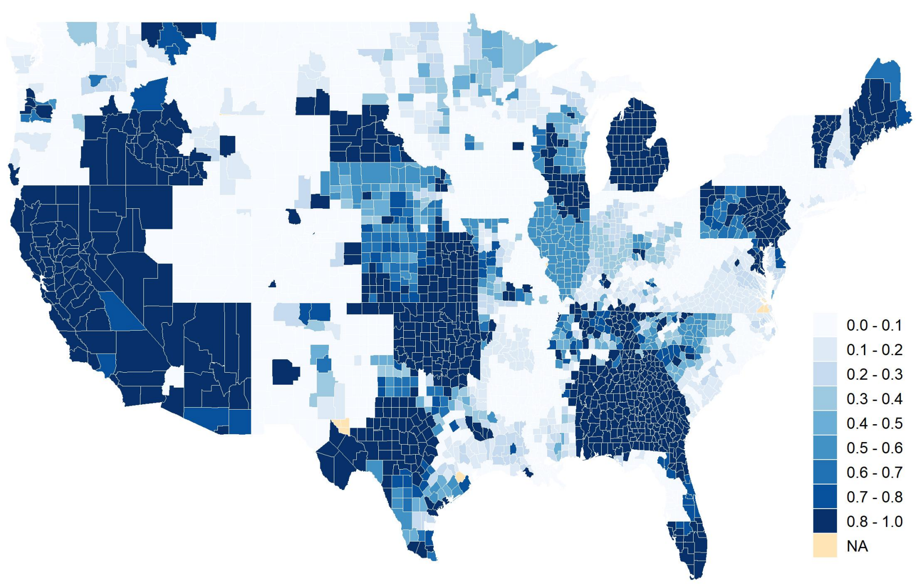
Dependent Variable:	Loss/Sale	log(Total Losses)	log(Total Sales)
	(1)	(2)	(3)
Panel A: Government-Owned Utilities			
PostAMI	-0.010**	-0.126**	0.040**
	(0.005)	(0.057)	(0.017)
Mean DV (Pre-Treatment)	0.085	18.37	242.6
Observations	1,650	1,650	1,650
Panel B: Non-Government-Owned Utilities			
PostAMI	-0.004	-0.024	-0.003
	(0.005)	(0.196)	(0.056)
Mean DV (Pre-Treatment)	0.084	150.4	1,771
Observations	2,829	2,829	2,829
Utility FEs	x	x	x
State-Year FEs	x	x	x
Local Mkt. Controls	x	x	x

Notes: Table presents estimates for the AMI treatment effect separately for government-owned (Panel A) and non-government-owned (Panel B) utilities when limiting the sample to only include the top quartile of the government-owned pre-treatment losses per sale distribution (i.e., utilities with average pre-treatment losses per sale equal to or higher than 6.5%). Dependent variables are losses per sale (Column 1), (log) total losses (Column 2), and (log) total sales (Column 3). Means of pre-treatment dependent variables are in levels (with total losses and sales being in 000s). Local market controls include (log) population and the inverse hyperbolic sine of new construction building within counties that the utility serves. For all regressions, we implement the 2SLS estimator using one lead of the AMI treatment variable to instrument for log(population). Standard errors are clustered at the utility level. Asterisks denote *$p<0.10$, **$p<0.05$, ***$p<0.01$.

Main Text Figures



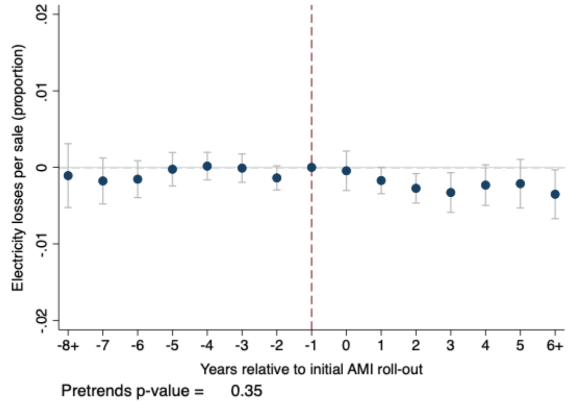
(a) 2007



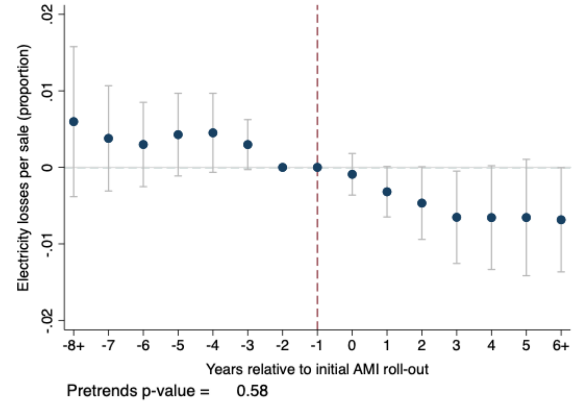
(b) 2018

Figure 1: AMI Meter Adoption in 2007 versus 2018

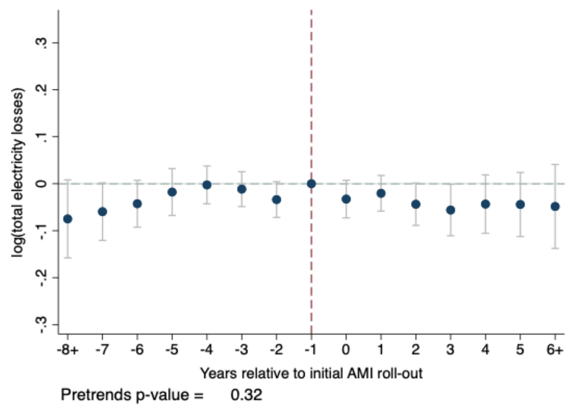
Notes: Maps show how AMI smart meter deployment increased from 2007 (Panel A) to 2018 (Panel B). Created by authors using data from the Energy Information Administration (Form EIA-861)



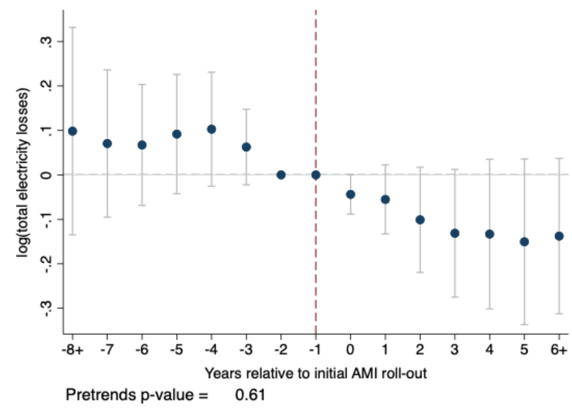
(a) Losses per Sale (Standard DiD)



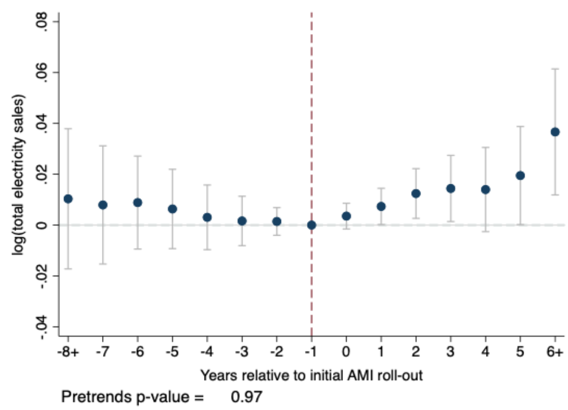
(b) Losses per Sale (2SLS)



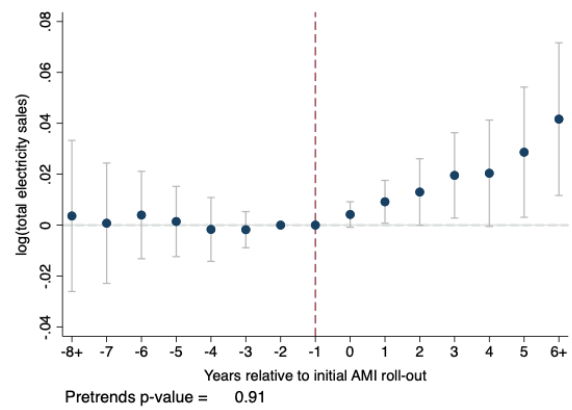
(c) log(Total Electricity Losses) (Standard DiD)



(d) log(Total Electricity Losses) (2SLS)



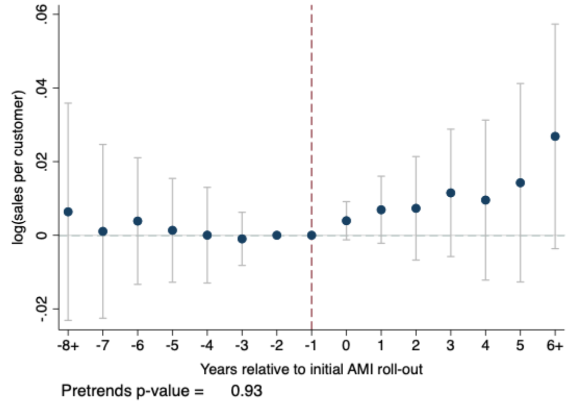
(e) log(Total Electricity Sales) (Standard DiD)



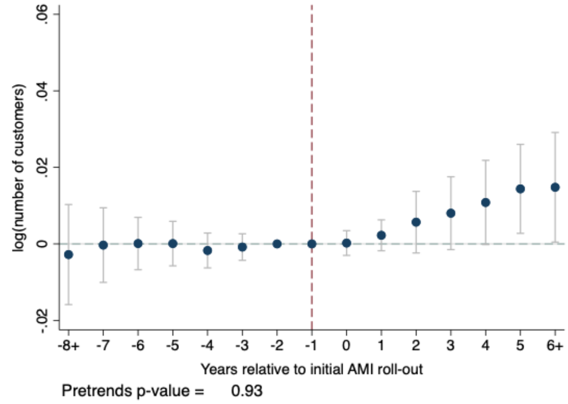
(f) log(Total Electricity Sales) (2SLS)

Figure 2: Effects of Smart Meter Roll-outs on Electricity Losses and Sales

Notes: Each figure plots estimates of coefficients β_j from Equation 1 and their 95 percent confidence intervals with the year prior to initial AMI adoption ("-1") as the omitted year. Plots on the left are from OLS estimations and plots on the right implement the 2SLS estimator using a one year lead of the AMI treatment variable as the excluded instrument for log(population). Baseline fixed effects and controls included. Standard errors are clustered at the utility level.



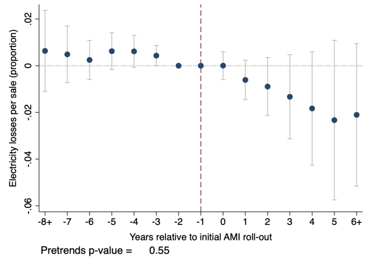
(a) log(Sales per Customer)



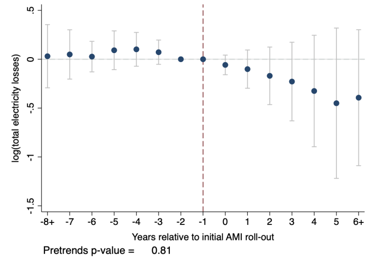
(b) log(Number of Customers)

Figure 3: Effect of Smart Meter Roll-outs on Sales per Customer and Number of Customers

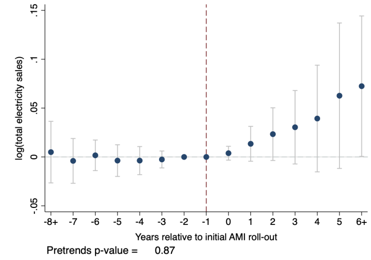
Notes: Each figure plots estimates of coefficients β_j from Equation 1 and their 95 percent confidence intervals with the year prior to initial AMI adoption ("-1") as the omitted year. Estimates are from implementing the 2SLS estimator using a one year lead of the AMI treatment variable as the excluded instrument for log(population). Baseline fixed effects and controls included. Standard errors are clustered at the utility level.



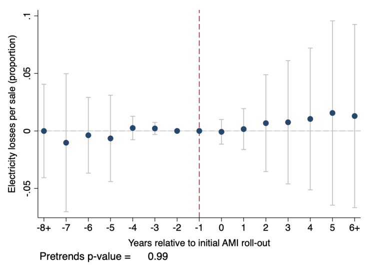
(a) Losses per Sale, Gov-Owned



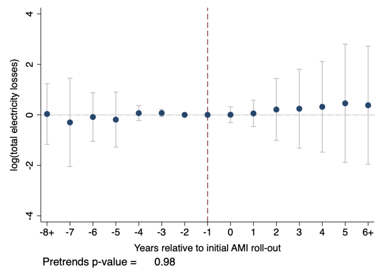
(b) log(Total Losses), Gov-Owned



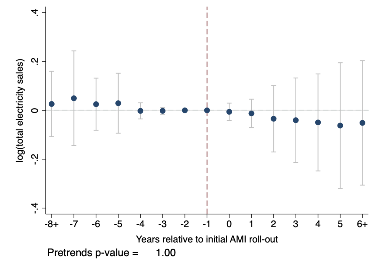
(c) log(Total Sales), Gov-Owned



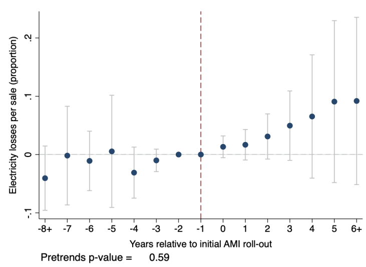
(d) Losses per Sale, Cooperatives



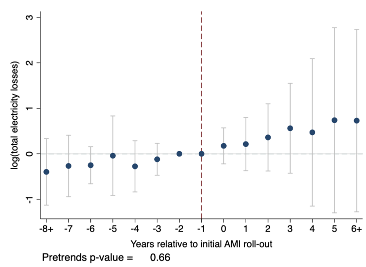
(e) log(Total Losses), Cooperatives



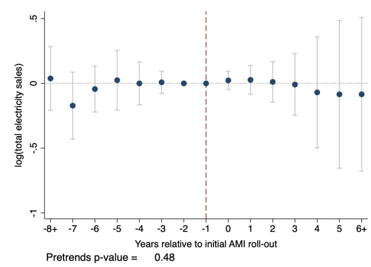
(f) log(Total Sales), Cooperatives



(g) Losses per Sale, IOUs



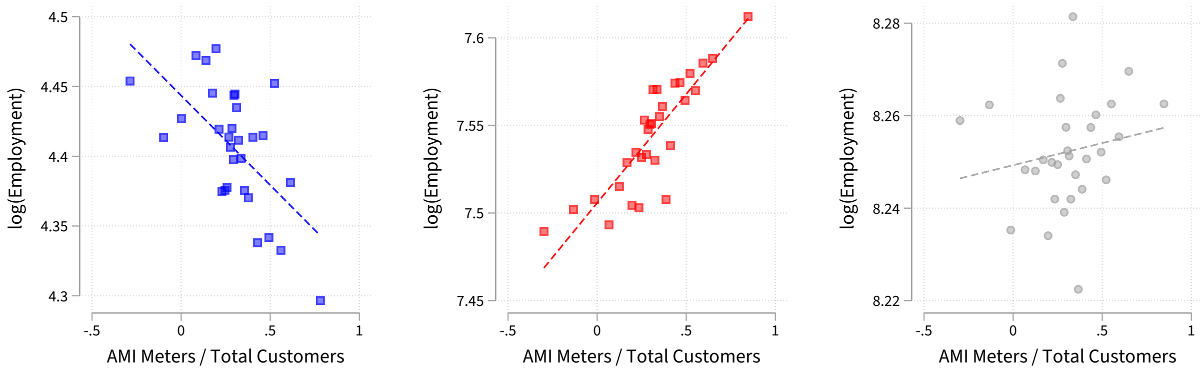
(h) log(Total Losses), IOUs



(i) log(Total Sales), IOUs

Figure 4: Heterogeneous Effects of Smart Meter Deployment on Main Outcomes by Utility Ownership Type

Notes: Figure provides estimates of AMI deployment on losses per sale, (log) total losses, and (log) total sales when splitting the sample by ownership type. Each plot provides estimates of coefficients β_j from Equation 1 using the 2SLS estimator approach and 95 percent confidence intervals with the year prior to initial AMI adoption ("-1") as the omitted year. Baseline fixed effects and controls included. Standard errors are clustered at the utility level.



(a) Meter Readers (b) Quantitative & Computation (c) Others

Figure 5: Meter Readers, Quant-Related Jobs, and Other Occupations as AMI Deployment Increases

Notes: Labor data are at the MSA-occupation level and aggregated into bins. The outcome variable on the vertical axis is the residual of log(Employment) after controlling for MSA fixed effects, population, and building units.

A Appendix: Data and Sample Construction (For Online Publication)

A1 Utility-Level Data

We assemble utility-level information on basic characteristics, operations, sales, and meter adoption for the period 2007–2018 from the Energy Information Administration (EIA) forms and S&P Global. We restrict our sample to the contiguous U.S. (not including Alaska, Hawaii, or other offshore territories).

Basic Characteristics. We use S&P Global, EIA Forms 860 and 861 to construct detailed data on utility-level basic characteristics, including location, county-level service territory, ISO, FERC region, regulation status, ownership type (i.e., cooperative, investor-owned, government agencies, etc.), and electric activities (i.e., generation, transmission, and distribution).

Advanced Metering. Advanced metering information is derived from Schedule 6 of EIA-861. Since 2007, the data reports the number of electric meters by state, customer category, and meter type, including automated meter reading (AMR) and advanced metering infrastructure (AMI). In addition to smart meter adoption, these data also include the number of customers with the following advanced technology features enabled by the AMI since 2013: (1) digital access to daily energy usage; (2) home area network (HAN) gateway that allows the meter to communicate with customer's devices; (3) direct load control (LC) that permits remote shutdown or cycle a customer's electrical equipment on short notice. We aggregate the data to the utility level and calculate the total number of AMR and AMI per utility in each year. For any missing values in the number of AMI for certain years, we impute them using the value from the nearest available year prior to the missing year.

Operations. Operational data comes from EIA-861. We collect utility-level total energy losses, which measure the amount of electricity lost from transmission and distribution. We drop the records with negative loss values as these are likely mistakes in EIA's data collection and reporting process. EIA-861 also reports detailed sales and revenue information, which is decomposed into different parts, including retail sales to ultimate customers (i.e., electricity sold to customers purchasing electricity for their own use and not for resale), sales for resale (i.e., electricity sold for resale purposes), delivery customers (i.e., unbundled customers who purchase electricity from a supplier other than the electric utility that distributes power to their premises), transmission of electricity, and other electric activities. For the retail sales to ultimate customers, EIA-861 has information on sales, revenues, and customer counts by four customer categories, including residential, commercial, industrial, and transportation.

Dynamic Pricing and Demand Response. EIA-861 contains the number of customers enrolled in demand response programs (e.g., energy savings or actual peak savings) or dynamic pricing programs (e.g., time-of-use pricing or real-time pricing) by utility, state, customer category, and balancing authority. The information on aggregate customer counts for all demand response or dynamic pricing programs is available after 2007, but Specific customer count on a single program is only available after 2013. We therefore calculate the total number of customers enrolled in any demand response programs or any dynamic pricing programs for each utility in a year. For any missing values in the number of enrolled customers, we impute them using the value from the nearest available year prior to the missing year. There are also data entry errors in the raw data where the number of enrolled customers is reported to be zero but the values in adjacent years are positive. For these cases, we replace the zeros with the non-zero values from the previous year.

Population and Building Construction. We supplement the utility data with measures on local population and building construction. The population data comes from the Survey of Epidemiology and End Results (SEER). It has annual population size for each county by age, race, and sex since 1969. For each year, we create two population measures based on this data: total population in a county and the size of the population older than 18. The second measure aims to capture the number of adults but excludes infants or teenagers who are unlikely to be homeowners. Data on new building units comes from the Building Permits Survey (BPS) administrated by the U.S. census. It provides annual statistics on the number and valuation of new privately owned residential housing units authorized by building permits for each county. From this data, we calculate the new and cumulative building units for the period 2007–2018. We merge these county-level population and housing data with electric utility data through their service territory information. Specifically, we sum up all the population or housing measures for the counties that a utility serves.

Sample Construction. We merge the above utility-level annual data sets based on EIA-assigned unique utility ID and year. The combined data set at this stage contains 27,009 observations of 2,657 electric utilities. We implement a few additional cleaning steps to construct the final data set. First, we exclude utilities that do not operate in the distribution segment of electricity delivery (23,750 observations of 2,089 utilities left). Second, we omit observations that likely represent data entry errors, such as negative losses or customer counts (21,368 observations of 1,917 utilities left). Third, for each utility, we calculate the ratio of year-specific disposition of electricity to its mean disposition and then drop the observations with such ratio larger than 2 (21,352 observations of 1,917 utilities left). These observations exhibit a sudden jump in total disposition of electricity and could be mistakes in data reporting. Fourth, we restrict to utilities that have at least 11 years of non-missing electricity losses data to maintain a high degree of panel balance (19,897 observations of 1,669 utilities left). Finally, we limit our sample to include only utilities that either adopted AMI smart meters between the years 2010 through 2016 or did not adopt at all. This allows us to include at least three years of pre-treatment data and one year of post-treatment data for all adopters. we also exclude extreme outliers in terms of losses per sale (with values falling into the top or bottom 1% of the pre-AMI-adoption sample year) or the number of total customers (with values less than 20). The final data set contains 15,568 observations of 1,305 utilities. We measure the intensity of AMI deployment using the ratio of AMI meters to the total number of customers. Since one customer might be associated with more than one meter, this ratio can sometimes larger than 1. For these cases, we reset the ratio to be 1. In the utility-level analysis, since we construct the instrument using the one-year forward of the policy variable, the data for 2018 (i.e., the last sample year) are omitted, and therefore the regression includes 14,241 observations across 1,303 utilities between 2007 and 2017.

A2 Feeder-Level Reliability in Texas

Feeder line data on service quality comes from the Public Utility Commission of Texas (PUCT), a state agency regulating electric, water, and telecommunication utilities. Each year, PUCT requires electric utilities to submit an annual service quality report in accordance with Substantive Rule §25.81. These reports contain detailed information on service quality and the total number of customers for each feeder line.

We focus on two international standards for measuring service reliability within an electricity distribution system: the System Average Interruption Duration Index (SAIDI) and System Average Interruption Frequency Index (SAIFI). These measures provide standardized methods of electricity service reliability such that services are comparable across utilities and over time.[51] Both of these address interruptions, which are defined as losses of power delivery to one or more customer. According to the IEEE Guide for Electric Power Distribution Reliability Indices, SAIFI is a measure as to how often the utility's average customer experienced a sustained interruption in service (more than 5 minutes) within a given year. SAIDI measures the number of minutes of sustained interruptions that the utility's average customer experiences, with interruption duration being the length of time between the start of service being interrupted and the time when service delivery is restored.

In the PUCT reports, both SAIDI and SAIFI are calculated by taking the mean of outage duration and frequency over all customers served by a feeder line in a year. Specifically, for feeder line i in year t,

$$I_{it} = \frac{\sum_{c \in i} X_{cit}}{N_{it}}. \tag{5}$$

In the above equation, X_{cit} is the number (for SAIFI) or duration (for SAIDI) of outage events experienced by customer c served by feeder line i in year t, and N_{it} is the total number of customers. A lower SAIDI or SAIFI value means a higher level of service reliability.

Sample Construction. The raw feeder line data contains 104,610 observations of 11,470 feeder lines from 12 utilities during 2007-2020. We implement a few additional processing steps to construct the final data. First, we restrict the sample to 2007 – 2016. After 2016, there are mergers and acquisitions among these utilities, since which the identifiers of feeder lines owned by those utilities have completely changed. Consequently, we are not able to match those feeder lines with the pre-2016 data. We also exclude two utilities —Cap Rock and Sharyland —that experienced mergers or acquisitions before 2016. Second, we restrict to feeder lines that have at least 6 years of non-missing reliability data. Then, we match this feeder-line-level data with utility-level AMI deployment based on EIA-assigned utility ID and name. The final data set contains 68,529 observations of 7,294 feeder lines from 10 utilities in Texas.

[51] The measures are limited to an extent, as they capture interruptions but not other power quality measures, such as drops and surges in voltage.

A3 Regional Employment Data

We assemble a dataset on occupation-level employment in each Metropolitan (MSA) and nonmetropolitan (non-MSA) area using the information from the Occupational Employment and Wage Statistics (OEWS) provided by the U.S. Bureau of Labor Statistics (BLS). It provides annual information on the number of total employment for each occupation category in each area, dating back to 1997. This area-level data, however, does not provide industry decomposition, and hence the employment represents all industries in an area. We retrieve the area-level employment data for the 2007-2018 period and restrict to the contiguous U.S.

We define an occupation as bill-collection-related labor if it belongs to the following category (with the corresponding occupation code in parenthesis): Meter Readers, Utilities (43-5041). We then drop other occupations in the same 2-digit category as those bill-collection-related ones (i.e., 43 - Office and Administrative Support Occupations). This is to mitigate the concern on spillover effects or occupation substitutions between those bill collection jobs and other office- or administration-related jobs. Then, the six-digit-level occupation data is aggregated to the two-digit level. We define jobs related to quantitative and computation if they belong to the following 2-digit occupation category: Computer and Mathematical Occupations (15-0000).

Sample Construction. To match this area-level employment data with AMI information, we first create county-level AMI adoption by aggregating the utility-level advanced metering data based on each utility's service territory. Specifically, for each county and year, we sum up the number of AMI meters over all the utilities serving that county. Then, we aggregate the county-level data to the area-level using the MSA and non-MSA area definitions provided by BLS.[52] For the counties that are matched with more than one area, we evenly divide the number of AMI meters in those counties before doing the aggregation. The combined data set contains 140,760 observations of 22 two-digit occupation categories in 642 MSA or non-MSA areas. We made two additional steps for the data cleaning. First, we omit the observations with a positive average wage but zero number of employment, which are likely to be data reporting errors. Second, we exclude areas that never had any bill-collection-related labor throughout the sample period. The final data set contains 100,848 observations of 22 two-digit occupation categories in 434 areas.

[52]BLS provides a mapping between each county and the corresponding MSA or non-MSA area. The data is available here: https://www.bls.gov/oes/2020/may/msa_def.htm.

B Appendix: Additional Tables (For Online Publication)

Table B1: OLS Estimates of the Effect of Smart Meters on Electricity Losses and Electricity Sales

Dep. Var.:	Losses per Sale (1)	log(Total Losses) (2)	log(Total Sales) (3)
PostAMI	-0.001	-0.018	0.007
	(0.001)	(0.016)	(0.006)
Observations	15,544	15,544	15,544
Mean of DV (Pre-Treatment)	0.056	83.22	1,436
Utility FEs	x	x	x
State-Year FEs	x	x	x
Local Market Controls	x	x	x

Notes: Table presents the main results for the effects of smart meter roll-outs on electricity losses per sale (Column 1), (log) total losses (Column 2), and (log) total sales (Column 3) when using OLS to estimate Equation 2. The means of the dependent variables are in levels (000s MWh in Columns 2 and 3) and are calculated using only observations for AMI adopters in pre-treatment years. Additional controls include log(population) and the inverse hyperbolic sine of new building construction within counties that the utility serves. Standard errors are in parentheses and clustered at the utility level. Asterisks denote *$p<0.10$, **$p<0.05$, ***$p<0.01$.

Table B2: Implementing Doubly-Robust Stacked Diff-in-Diff Approach (Full Sample)

Dep. Var.:	Losses per Sale (1)	log(Total Losses) (2)	log(Total Sales) (3)
Panel A: Only Never Treated in Control			
PostAMI	-0.002*	-0.040*	0.006
	(0.001)	(0.022)	(0.006)
Panel B: Not Yet Treated Also in Control			
PostAMI	-0.002*	-0.039*	0.007
	(0.001)	(0.022)	(0.006)
Utility FEs	x	x	x
State-Year FEs	x	x	x
Controls	x	x	x

Notes: Regression results from implementing the"stacked" doubly robust DiD method of Sant'Anna and Zhao (2020) based on stabilized inverse probability weighting and OLS. Only utilities that are never treated are included in the control group in Panel A and utilities that are not yet treated are added to the control group in Panel B. Standard errors are clustered at the utility level. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table B3: Implementing Doubly-Robust Stacked Diff-in-Diff Approach (Utilities in Highest Quartile of Pre-Treatment Losses Only)

Dep. Var.:	Losses per Sale	log(Total Losses)	log(Total Sales)
	(1)	(2)	(3)
Panel A: Only Never Treated in Control			
PostAMI	-0.007***	-0.085**	0.014
	(0.003)	(0.034)	(0.015)
Panel B: Not Yet Treated Also in Control			
PostAMI	-0.007***	-0.083**	0.012
	(0.003)	(0.032)	(0.015)
Utility FEs	x	x	x
State-Year FEs	x	x	x
Controls	x	x	x

Notes: Regression results from implementing the"stacked" doubly robust DiD method of Sant'Anna and Zhao (2020) based on stabilized inverse probability weighting and OLS and when limiting the sample to only those in the top quartile of pre-treatment losses (using the distribution of pre-treatment losses for AMI adopters to determine the cutoff). Only utilities that are never treated are included in the control group in Panel A and utilities that are not yet treated are added to the control group in Panel B. Standard errors are clustered at the utility level. Asterisks denote **p* <0.10, ***p* <0.05, ****p* <0.01.

Table B4: Investigating Whether Spillovers Bias the Results

Dependent Variable:	Losses/Sale (1)	Losses (2)	Sales (3)	Imports (4)	Exports (5)
PostAMI	-0.002**	-0.059**	0.012**	-0.027	-0.079
	(0.001)	(0.027)	(0.005)	(0.066)	(0.067)
Neighbor Deployed AMI	-0.001	-0.015	0.009		
	(0.001)	(0.036)	(0.009)		
Observations	14,241	14,241	14,241	14,241	14,241
Mean Dep. Var.	0.057	9.523	12.529	0.423	0.409
Utility FEs	x	x	x	x	x
State-Year FEs	x	x	x	x	x
Local Market Controls	x	x	x	x	x

Notes: Table provides results from tests exploring whether SUTVA might be violated. The dependent variables in Columns 1 through 5 are losses per sale, (logged) total losses, (logged) total sales, (ihs) imported electricity from neighboring utilities, and (ihs) exported electricity to neighboring utilities. Neighboring utilities are defined as those serving the same county. All specifications are estimated using our baseline 2SLS procedure. Local market controls are (ihs) new construction build and (log) population, and a one-year treatment variable lead is used as the excluded instrument for (log) population. Standard errors are clustered at the utility level. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table B5: Effect of Smart Meters on Sales per Customer and Number of Customers

Dependent Variable (log):	Sales per Customer (1)	Number of Customers (2)
Panel A: Average Effects Over Full Sample Period		
PostAMI	0.008	0.004
	(0.006)	(0.003)
Observations	14,241	14,241
Panel B: Intensity of Treatment Effects		
Prop. AMI	0.021***	0.004
	(0.006)	(0.003)
Observations	14,241	14,241
Panel C: Average Effects 3+ Years Post-Treatment		
PostAMI	0.013	0.011*
	(0.010)	(0.006)
Observations	12,255	12,255
Utility FEs	x	x
State-Year FEs	x	x
Local Market Controls	x	x

Notes: Table presents estimated effects of smart meter roll-outs on (log) electricity sales per customer in Column 1 and (log) total number of customers in Column 2 when using the 2SLS estimator. Panel A provides estimates from when including the full baseline sample. Panel B provides estimates of the proportion of meters that are smart meters. Panel C provides findings from when excluding the year of adoption and two years that follow such that the estimates capture the effects on outcomes 3+ years post-treatment. Local market controls include (log) population and the inverse hyperbolic sine of new construction building within counties that the utility serves. For all regressions, we implement the 2SLS estimator using one lead of the AMI treatment variable to instrument for the covariate log(population). The coefficient on the treatment lead in the first stage is 0.007 and statistically significant at the 10% level in both Panels A and B. Standard errors are clustered at the utility level. Asterisks denote *$p<0.10$, **$p<0.05$, ***$p<0.01$.

Table B6: Additional Results for the Effects of Smart Meters on Utilities' Provision of Innovative Services

Dependent Variable:	Dynamic Pricing	Demand Response
	(1)	(2)
Panel A: Intensity of Treatment Effects		
Prop. AMI	0.047***	0.049***
	(0.016)	(0.016)
Observations	14,241	14,241
Panel B: Average Effects 3+ Years Post-Treatment		
PostAMI	0.070**	0.065**
	(0.031)	(0.032)
Observations	12,255	12,255
Mean of DV (Pre-Treatment)	0.208	0.112
Utility FEs	x	x
State-Year FEs	x	x
Local Market Controls	x	x

Notes: Table presents effects of smart meter adoption on utilities' provision of innovative services that aim to incentivize consumer behavior change. Dependent variables are indicators for whether utilities offer dynamic pricing (Column 1) and demand response (Column 2). The main effects prior to estimating the intensity of treatment and timing results are in Columns 1 and 2 of Table 4. Standard errors are clustered at the utility level. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table B7: Utility Reorganization of Workers – Restricted Sample

Dep. Var. (log):	Number of Employment			
	(1)	(2)	(3)	(4)
Panel A: Exclude MSAs that adopted AMI before 2008 or after 2017				
PostAMI × Billing	-0.186***	-0.182***		
	(0.041)	(0.041)		
PostAMI × Quant			0.070***	0.065***
			(0.019)	(0.019)
Observations	56,763	54,102	56,763	55,162
Panel B: Exclude MSAs that adopted AMI before 2009 or after 2017				
PostAMI × Billing	-0.189***	-0.187***		
	(0.058)	(0.058)		
PostAMI × Quant			0.043*	0.037
			(0.025)	(0.025)
Observations	32,951	31,410	32,951	31,986
MSA-Occupation FEs	x	x	x	x
MSA-Year FEs	x	x	x	x
Drop Quants		x		
Drop Meter Readers				x

Notes: Table provides results from estimating effects on the number of employment. Dependent variable is the logarithm of employment by MSA-occupation-year. Standard errors are clustered by MSA area. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table B8: Effect of Smart Meter Roll-outs on Power Outages in Texas (Intensity of Treatment Estimates)

Dependent Variable (ihs):	Outage Duration (SAIDI)		Outage Frequency (SAIFI)	
	(1)	(2)	(3)	(4)
Prop. AMI	-0.823***	-1.843***	-0.273***	-0.552**
	(0.200)	(0.587)	(0.085)	(0.241)
Observations	61,233	61,233	61,233	61,233
Mean of DV (Pre-Treatment)	91.32	91.32	0.950	0.950
Feeder FEs	x	x	x	x
Year FEs	x	x	x	x
Local Market Controls	x	x	x	x
Utility-Year Trends		x		x

Notes: Effects of smart meter roll-outs based on treatment intensity (i.e., proportion of customers with smart meters) on electricity reliability in Texas using the 2SLS approach. Dependent variable is the inverse hyperbolic sine of SAIDI (power outage duration in minutes) in Columns 1-2 and SAIFI (outage frequency) in Columns 3-4. Data are at the feeder line level. Observations are weighted by number of customers per feeder line. Additional local market controls include new building construction and (log) population with the lead AMI treatment intensity variable as the excluded instrumental variable. The coefficient of the treatment lead in the first stage is 0.036 and statistically significant at the 1% level. Standard errors are clustered at the feeder line level. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table B9: Summary Statistics of Key Variables by Utility Ownership Type

	All Utilities		**Adopters Pre-AMI**		**Non-Adopters**	
	Gov	Non-Gov	Gov	Non-Gov	Gov	Non-Gov
	(1)	(2)	(3)	(4)	(5)	(6)
Losses per Sale (%)	0.052	0.063	0.048	0.064	0.056	0.068
	(0.032)	(0.028)	(0.028)	(0.026)	(0.033)	(0.035)
Total Losses (000s MWh)	22.61	116.64	29.30	131.52	13.01	88.38
	(90.16)	(388.52)	(95.93)	(455.24)	(22.01)	(220.58)
Total Sales (000s MWh)	477	1964	635	2153	273	1533
	(1415)	(6035)	(1679)	(6757)	(473)	(4228)
Total Revenue (million $)	46.0	206.2	57.3	213.7	25.1	156.2
	(169.8)	(702.1)	(180.3)	(757.4)	(43.0)	(401.1)
Number of Customers (000s)	17.91	103.10	22.51	98.21	10.34	81.61
	(60.74)	(369.85)	(66.56)	(364.38)	(21.38)	(212.67)
Sales per Customer (MWh)	36.72	24.27	29.90	24.42	42.26	24.44
	(190.15)	(19.65)	(13.13)	(19.72)	(251.47)	(21.59)
Rev. per Customer (000s $)	3.32	2.37	2.63	2.26	3.79	2.39
	(16.19)	(1.35)	(0.94)	(1.23)	(21.42)	(1.52)
Average Prices ($/kWh)	0.097	0.109	0.093	0.101	0.096	0.112
	(0.028)	(0.040)	(0.022)	(0.032)	(0.031)	(0.051)
Observations	7,698	6,543	2,004	2,237	4,388	2,147
No. of Utilities	702	594	302	401	400	193

Notes: Table provides summary statistics of key variables used in the U.S.-level analysis for the full baseline regression sample split by ownership type (government-owned vs. non-government, which includes investor-owned utilities and cooperatives). Standard errors are in parentheses. Data are from the Energy Information Administration for the years 2007 through 2017. The sub-sample of AMI adopting utilities includes those that adopted between 2010 through 2016.

Table B10: Effect of Smart Meter Roll-outs on Electricity Losses and Sales for Government-Owned Utilities

Dependent Variable:	Losses per Sale (1)	log(Total Losses) (2)	log(Total Sales) (3)
Panel A: Average Effects Over Full Sample Period			
PostAMI	-0.003	-0.105	0.017
	(0.003)	(0.068)	(0.011)
Observations	7,653	7,653	7,653
Panel B: Intensity of Treatment Effects			
Prop. AMI	-0.006***	-0.151**	0.021*
	(0.002)	(0.059)	(0.011)
Observations	7,653	7,653	7,653
Panel C: Average Effects 3+ Years Post-Treatment			
PostAMI	-0.004	-0.146	0.034*
	(0.004)	(0.109)	(0.020)
Observations	6,815	6,815	6,815
Mean of DV (Pre-Treatment)	0.048	29.25	635.2
Utility FEs	x	x	x
State-Year FEs	x	x	x
Local Market Controls	x	x	x

Notes: Table presents estimated effects of smart meter roll-outs on electricity losses per customer in Column 1, (log) total losses, and (log) total sales when using the 2SLS estimator and restricting the sample to government-owned utilities only. The means of the dependent variables are in levels of MWh (and in Columns 2 and 3, they are in 000s). Panel A provides estimates from when including the full baseline sample, Panel B provides results from when estimating the effect of intensity of treatment (defined as the proportion of customers with AMI meters), and Panel C provides findings from when excluding the year of adoption and two years that follow such that the estimates capture the effects on outcomes 3+ years post-treatment. Local market controls include (log) population and the inverse hyperbolic sine of new construction building within counties that the utility serves. For all regressions, we implement the 2SLS estimator using one lead of the AMI treatment variable to instrument for the covariate log(population). Standard errors are clustered at the utility level. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table B11: Effect of Smart Meter Roll-outs by Utility Ownership and Incumbent Technology

Ownership:	**Government-Owned Utilities**						**Non-Government Utilities**					
Pre-AMI Tech.:	Previous Upgrades			No Previous Upgrades			Previous Upgrades			No Previous Upgrades		
Dep. Var.:	Loss/ Sale	log(Tot. Losses)	log(Tot. Sales)	Loss/ Sale	log(Tot. Losses)	log(Tot. Sales)	Loss/ Sale	log(Tot. Losses)	log(Tot. Sales)	Loss/ Sale	log(Tot. Losses)	log(Tot. Sales)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Average Effects Over Full Sample Period												
PostAMI	-0.007	-0.226**	0.034*	0.004	0.090	-0.007	-0.000	0.005	-0.013	-0.005	-0.118	-0.008
	(0.005)	(0.106)	(0.020)	(0.007)	(0.183)	(0.023)	(0.001)	(0.053)	(0.027)	(0.009)	(0.203)	(0.042)
Observations	4,648	4,648	4,648	2,874	2,874	2,874	4,777	4,777	4,777	1,645	1,645	1,645
Panel B: Intensity of Treatment Effects												
Prop. AMI	-0.009***	-0.320***	0.044**	0.003	0.137	0.004	0.001	-0.060	0.132	0.003	-0.113	-0.014
	(0.003)	(0.106)	(0.020)	(0.009)	(0.231)	(0.019)	(0.011)	(0.403)	(0.548)	(0.016)	(0.374)	(0.107)
Observations	4,648	4,648	4,648	2,874	2,874	2,874	4,777	4,777	4,777	1,645	1,645	1,645
Panel C: Average Effects 3+ Years Post-Treatment												
PostAMI	-0.014*	-0.387*	0.064*	0.006	0.148	-0.005	0.000	0.010	-0.035	0.120	2.156	0.151
	(0.008)	(0.206)	(0.037)	(0.012)	(0.297)	(0.036)	(0.004)	(0.162)	(0.103)	(3.815)	(69.687)	(4.689)
Observations	4,212	4,212	4,212	2,475	2,475	2,475	3,998	3,998	3,998	1,243	1,243	1,243

Notes: Table presents estimated effects of smart meter roll-outs on electricity losses per sale, (log) total losses, and (log) total sales. Estimates for government-owned utilities are in Columns 1-6 and non-government utilities in Columns 7-12. The sample is limited to utilities that had AMR meters prior to AMI deployment in Columns 1-3 and 7-9 and those that did not in Columns 4-6 and 10-12. Panel A estimates the average effect for the full baseline sample, Panel B estimates the intensity of treatment effect (the proportion of customers with AMI meters), and Panel C estimates the average effect but omits the year of adoption and two years that follow. All regressions include utility and state-year fixed effects and local market controls, which include (log) population and the inverse hyperbolic sine of new construction building within counties that the utility serves. For all regressions, we implement the 2SLS estimator using one lead of the AMI treatment variable to instrument for the covariate log(population). Standard errors are clustered at the utility level. Asterisks denote *$p<0.10$, **$p<0.05$, ***$p<0.01$.

C Appendix: Additional Figures (For Online Publication)

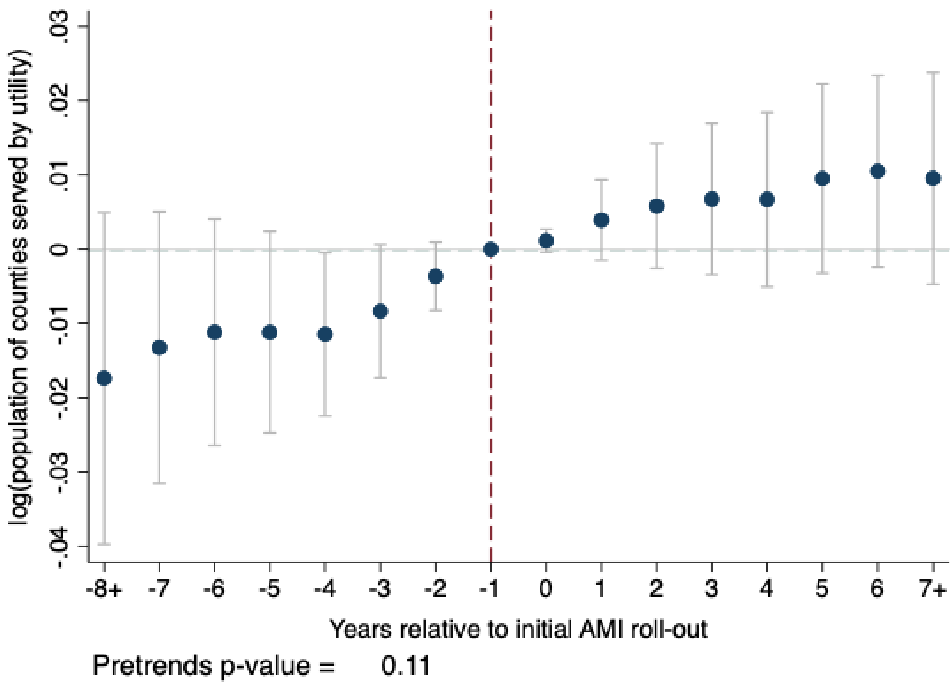
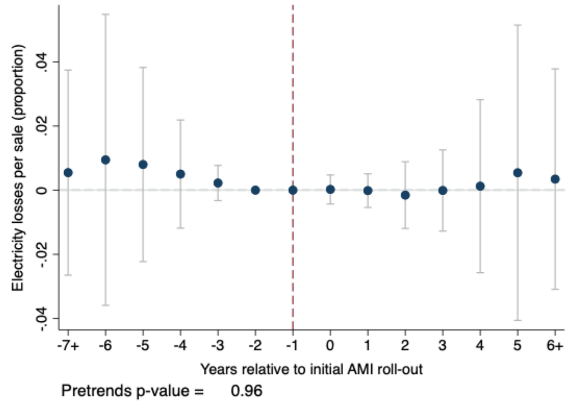
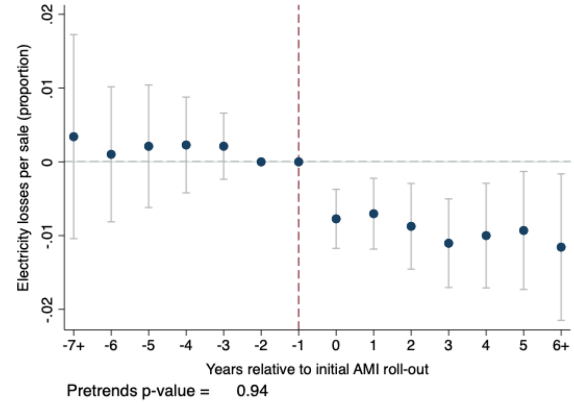


Figure B1: Dynamics of (Log) Population Around the First Year of Smart Meter Deployment

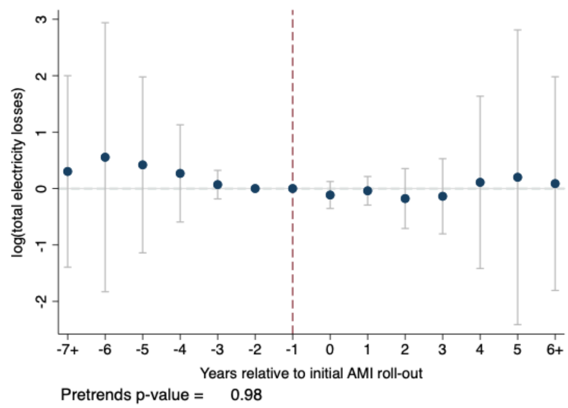
Notes: Figure plots estimates of coefficients β_j from Equation 1 using (log) population as the dependent variable with the year prior to initial AMI adoption ("-1") as the omitted year. Baseline fixed effects and controls included (besides population). Standard errors are clustered at the utility level.



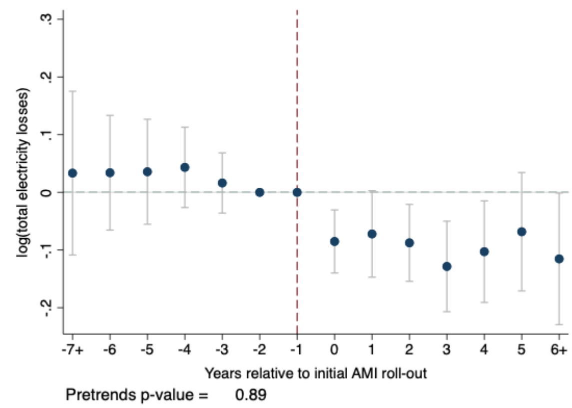
(a) Effects on Losses per Sale, Bottom Quartile



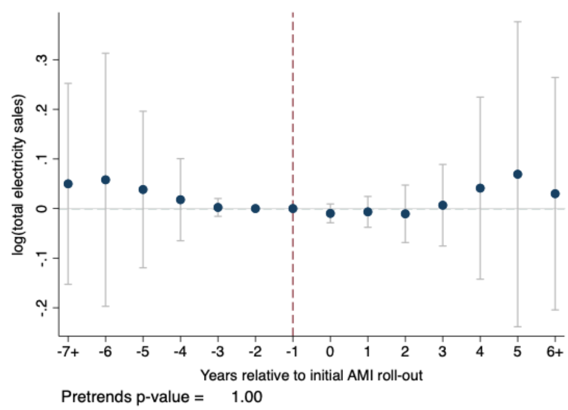
(b) Effects on Losses per Sale, Top Quartile



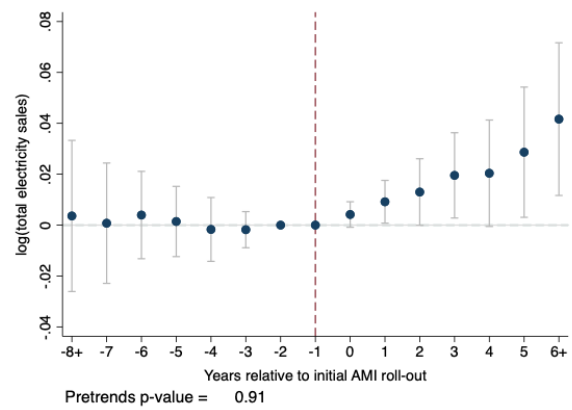
(c) log(Total Electricity Losses), Bottom Quartile



(d) log(Total Electricity Losses), Top Quartile



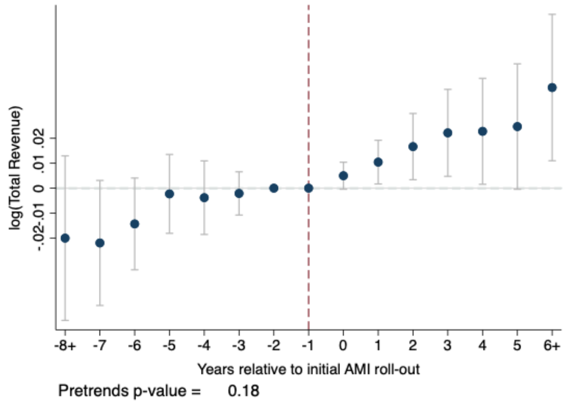
(e) log(Total Electricity Sales), Bottom Quartile



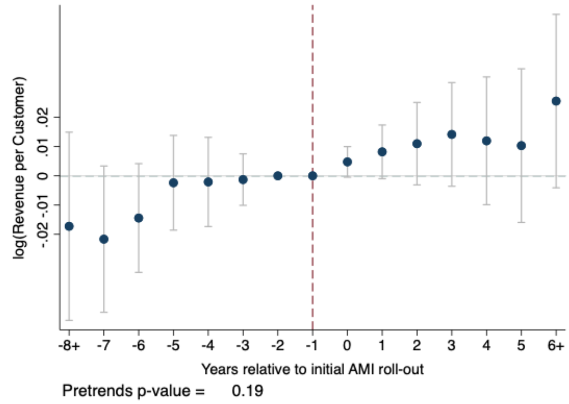
(f) log(Total Electricity Sales), Top Quartile

Figure B2: Heterogeneous Effects of Smart Meter Roll-Outs on Main Outcomes by Pre-Treatment Losses per Sale

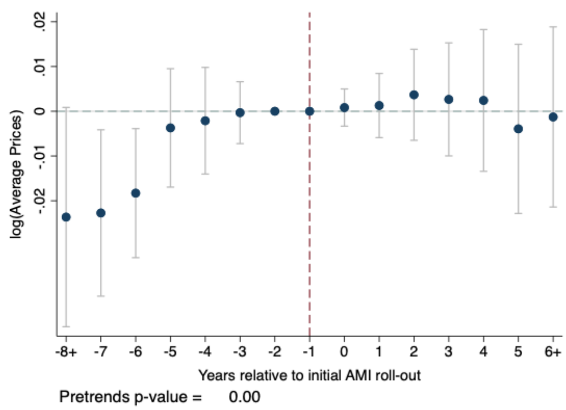
Notes: Each figure plots estimates of coefficients β_j from Equation 1 and their 95 percent confidence intervals with the year prior to initial AMI adoption ("-1") as the omitted year. Sample is limited to bottom quartile of losses per sale distribution in untreated years on the left side and top quartile on the right side. Estimates are from implementing the 2SLS estimator using a one year lead of the AMI treatment variable as the excluded instrument for log(population). Baseline fixed effects and controls included. Standard errors are clustered at the utility level.



(a) Total Revenue



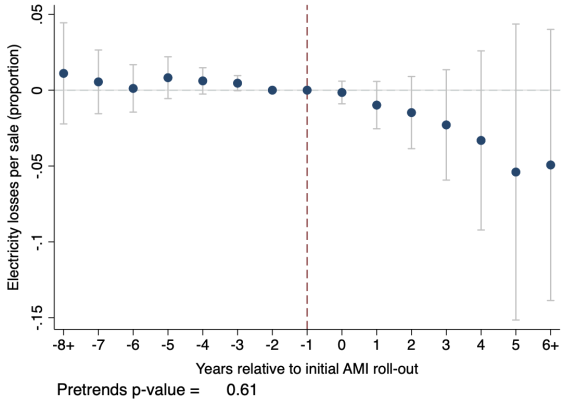
(b) Revenue per Customer



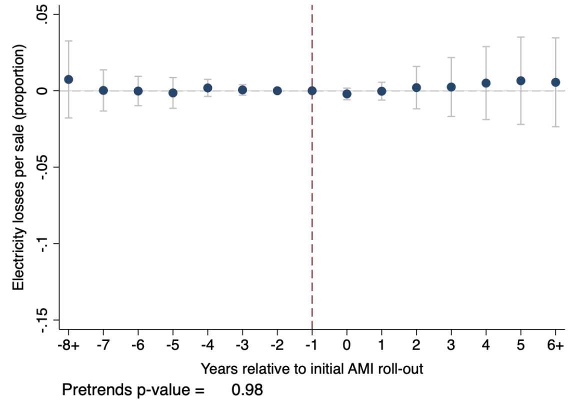
(c) Average Prices

Figure B3: Effects of Smart Meter Roll-outs on Revenue and Prices

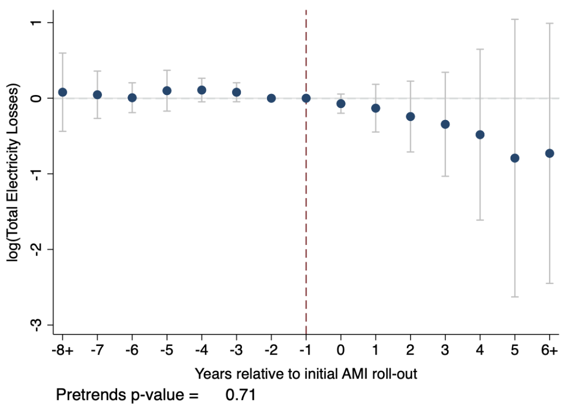
Notes: Figure provides estimated effects of AMI adoption on total revenue (Panel A), revenue per customer (Panel B), and average prices (Panel C) (all dependent variables are in logs). Each figure plots estimates of coefficients β_j from Equation 1 and their 95 percent confidence intervals with the year prior to initial AMI adoption ("-1") as the omitted year. Estimates are from implementing the 2SLS estimator using a one year lead of the AMI treatment variable as the excluded instrument for log(population). Baseline fixed effects and controls included. Standard errors are clustered at the utility level.



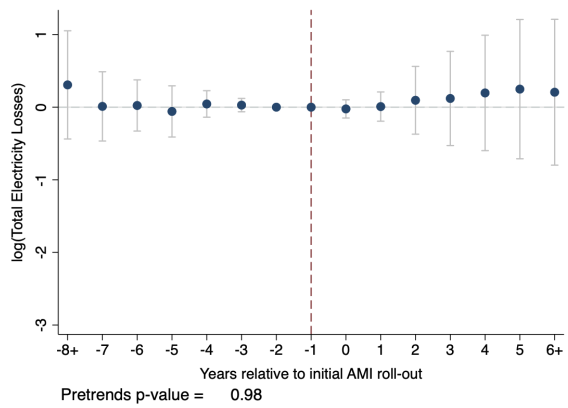
(a) Losses per Sale (Gov-Owned)



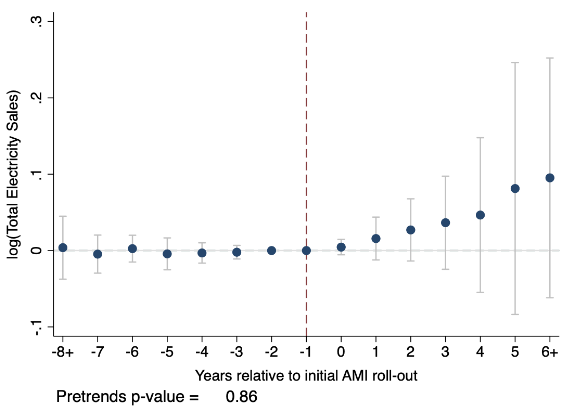
(b) Losses per Sale (Non-Gov)



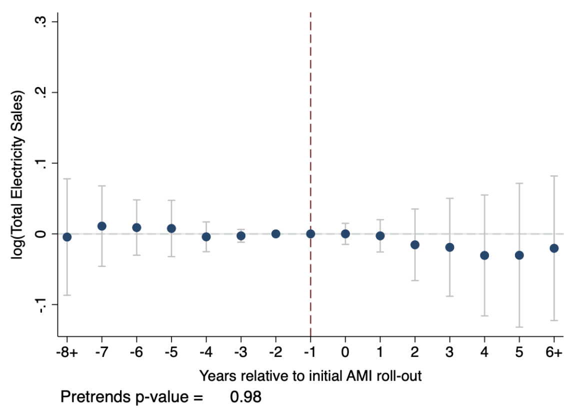
(c) log(Total Losses) (Gov-Owned)



(d) log(Total Losses) (Non-Gov)



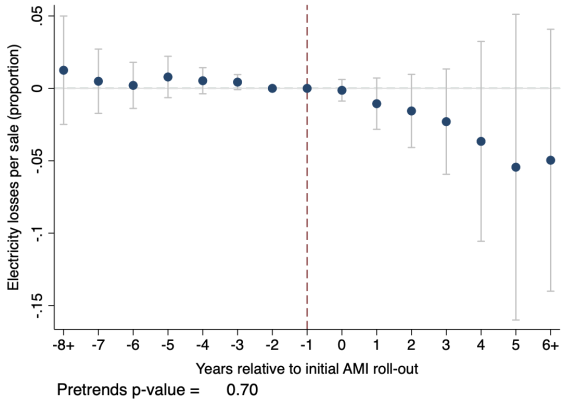
(e) log(Total Sales) (Gov-Owned)



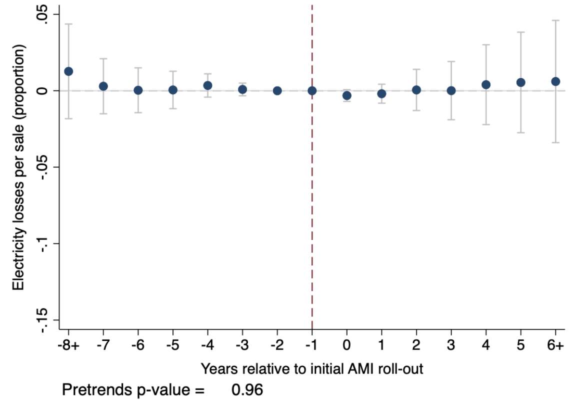
(f) log(Total Sales) (Non-Gov)

Figure B4: Effects of Smart Meter Roll-outs for "Smaller" Utilities by Ownership Type (Dropping Largest 5% According to Government-Owned Distribution)

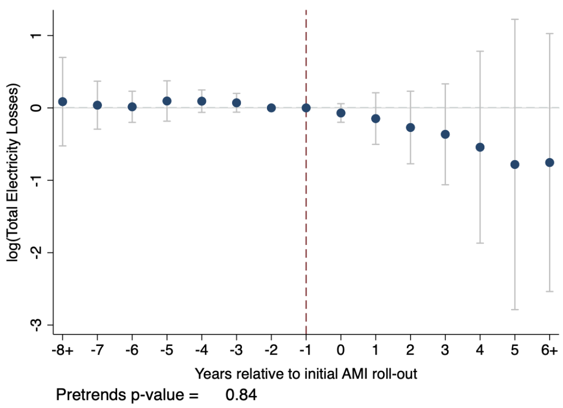
Notes: Each figure plots estimates of coefficients β_j from Equation 1 and their 95 percent confidence intervals with the year prior to initial AMI adoption ("-1") as the omitted year when implementing the 2SLS estimator using a one year lead of the AMI treatment variable as the excluded instrument for log(population). Subsamples omit the top 5% of the pre-treatment government-owned utility size by customer count (i.e., subsamples include utilities with fewer than 43,177 customers on average in pre-treatment years). Baseline fixed effects and controls included. Standard errors are clustered at the utility level.



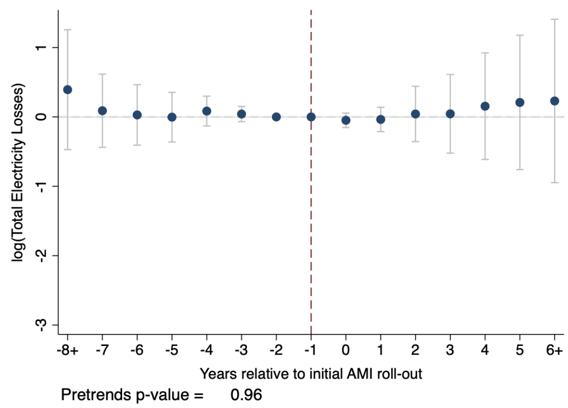
(a) Losses per Sale (Gov-Owned)



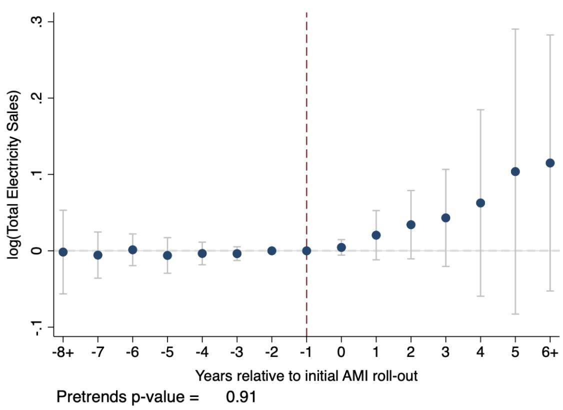
(b) Losses per Sale (Non-Gov)



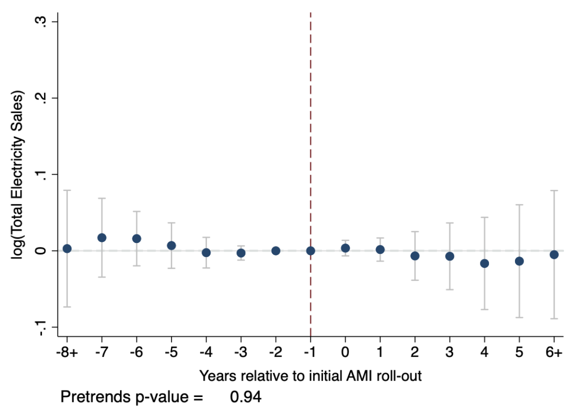
(c) log(Total Losses) (Gov-Owned)



(d) log(Total Losses) (Non-Gov)



(e) log(Total Sales) (Gov-Owned)



(f) log(Total Sales) (Non-Gov)

Figure B5: Effects of Smart Meter Roll-outs for "Smaller" Utilities by Ownership Type (Dropping Largest 10% According to Government-Owned Distribution)

Notes: Each figure plots estimates of coefficients β_j from Equation 1 and their 95 percent confidence intervals with the year prior to initial AMI adoption ("-1") as the omitted year when implementing the 2SLS estimator using a one year lead of the AMI treatment variable as the excluded instrument for log(population). Sub-samples omit the top 10% of the pre-treatment government-owned utility size by customer count (i.e., sub-samples include utilities with fewer than 27,520 customers on average in pre-treatment years). Baseline fixed effects and controls included. Standard errors are clustered at the utility level.