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

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Abstract

Electricity grids form the backbone of modern economies, but the utilities responsible for maintaining them face new energy management challenges associated with both aging infrastructure and climate change. Growing evidence suggests that digital technologies and data-driven decision-making may improve firm performance. However, existing work focuses on the private sector. Organizations providing public services have different incentives and constraints. In this paper, we narrow this gap through a study of the U.S. power sector. We construct a rich utility-level data set and estimate the effects of "smart" meters on electricity losses, a key indicator of system and utility performance. Implementing an augmented staggered difference-in-differences design, we find that electricity losses decrease by 4-7% following smart meter deployment, on average. Utilities' annual revenue increases by 1-2%. We show that the underlying mechanisms relate to changes in energy management. Consumption measurement and billing accuracy improve, as indicated by an increase in sales, giving utilities a clearer understanding of the system to enhance decision-making. Utilities invest in complementary organizational capital that is important for fully realizing the benefits of digitalization, such as hiring "quants." They also offer new products, like demand response programs, which attenuates the increase in sales but does not drive the reduction in losses. Power outage duration declines, suggesting that utilities use smart meters to improve reliability by restoring service faster after disruptions. Outage frequency remains unchanged.

Keywords: digitalization; smart grid; energy management; electric utilities; public services

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1 Introduction

Economic activity—from business and industrial operations to healthcare and transportation—hinges on having access to high-quality and reliable electricity. However, electricity grids in many countries are aging and increasingly susceptible to disruptions. Power outages in the United States now cost between \$28 and \$169 billion annually (ASCE, 2021). Although severe weather is often at play, poor power quality and reliability are also caused by other factors, like equipment failure and inadequate upgrading (EIA, 2021; Malik, 2024). Grid resilience thus depends crucially on the performance of electric utilities—the companies responsible for maintaining the system and delivering power to consumers. Improving grid management will be increasingly important 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 often considered an important part of the solution. "Smart grid" technologies that provide granular, real-time data and automation capabilities can now—at least in theory—help utilities optimize operations, monitor system performance, develop more accurate demand forecasts, and improve system flexibility (Joskow, 2012). 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 public services more generally. A flourishing literature is finding that digital technologies and data-driven decision-making can enhance firm performance in the private sector (Brynjolfsson and Hitt, 2003; Bartel, Ichniowski and Shaw, 2007; Brynjolfsson and Saunders, 2013; Brynjolfsson and McElheran, 2016; Goldfarb and Tucker, 2019; Brynjolfsson, Jin and McElheran, 2021b; Bar-Gill, Brynjolfsson and Hak, 2024). Previous findings may not transfer, however, as organizations providing public services—like utilities, hospitals, and schools—operate under different

[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 also can empower consumers to better-manage electricity use and reduce their bills, but 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).

conditions. For example, they often face different market forces (e.g., less competition), bureaucratic processes, and budgetary constraints, which can impact investments and innovative activity. Moreover, the benefits of complex information technologies (like smart grids) often depend on parallel investment in complementary organizational capital, such as new business processes and skills (Brynjolfsson and Hitt, 2000; Bresnahan, Brynjolfsson and Hitt, 2002; Bloom, Sadun and Van Reenen, 2012; Brynjolfsson, Rock and Syverson, 2021a).

In this paper, we provide evidence as to how digitalization impacts public service provision through a study of the U.S. electricity sector. We examine the effects of electric utilities' deployment of smart meters, important components of advanced metering infrastructure (AMI), 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 in-person readings and providing only sparse, imprecise data. Investments in 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 remotely transmit high-resolution data on consumption, power quality, outages, and more that can help utilities reduce operational costs and enhance billing accuracy, forecasting, asset and load management, and system monitoring. These are important aspects of energy management that impact utility performance, and in turn, quality of service. Smart meters also can improve reliability if utilities use the information provided on power outage location to restore service faster. Outage frequency may even decline.[3]

Estimating the causal effects of digitalization on public services is empirically challenging for multiple reasons. First, technology adoption may be driven by endogenous organization and market characteristics, such as providers' resources and local economic growth. To address endogeneity concerns, we augment a staggered difference-in-differences design with a two-stage least squares (2SLS) approach. Our method is akin to the one developed in Freyaldenhoven, Hansen and Shapiro (2019), which removes the potential effects of pre-trends

[2]This is approximately 72% of total U.S. electric meters (EIA, 2022). See Strong (2018) for details of smart meters early diffusion among U.S. electricity utilities.

[3]For example, if utilities are able to smooth demand throughout the day with the tools that are enabled by smart meters—such as demand response programs—outages related to excess demand may decrease.

by instrumenting a covariate that proxies for confounders with leads of the treatment.

Second, studying public services is particularly difficult due to challenges with measuring service quality, especially doing so systematically for all providers within an industry.[4] The U.S. electricity sector provides a unique setting to overcome this limitation. Utilities serve (just about) all electricity customers and are required to report standardized information annually to the U.S. Energy Information Administration (EIA). We combine numerous data sets from the EIA for the years 2007 through 2018—the time period over which AMI investments took off—that include detailed information on operations, services, and smart meter installations for all utilities in the U.S. We also transcribed within-utility feeder line level data on power outages in Texas from Public Utility Commission reports to study reliability.

We start by examining the effects of smart meters on electricity losses, a key indicator of utility performance. Each year, about 5-6% of electricity that is generated in the U.S. is lost during transmission and distribution, which translated into more than $6 billion in lost revenue for utilities in 2020 (Shadle, 2022). Losses are calculated as the difference between power supplied to the grid and that for which customers are billed, and the loss *rate* is the proportion of power that is lost. Although losing some power is unavoidable due to the physical properties of electrical systems, high losses usually reflect inefficiencies. For example, unbilled consumption can result from incorrect meter readings or electricity theft (e.g., meter tampering). Losses also increase as equipment ages, so they may reflect inadequate upgrading, increasing exponentially with voltage fluctuations when the system is overloaded (i.e., demand exceeds capacity). This is a complex relationship, as power quality and reliability can both contribute to, and be exacerbated by, high losses.[5]

We find strong evidence that smart meter deployment improved utility performance. On average, loss rates decreased by 3.8% relative to the pre-treatment mean. When omitting utilities in the bottom quartile of the pre-treatment loss rate distribution—initially high-performers that had little room to improve—we find a 5% decline. The improvements also grow over time. After three years, loss rates are 5.8% lower for utilities that deploy smart

[4]For example, healthcare studies frequently examine mortality as a proxy for quality, but deaths may occur even with high-quality care. Other measures could include the time doctors spend with patients or diagnosis accuracy. Furthermore, a lot of research focuses on hospitals, which is just one type of provider.

[5]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.

meters on average and 6.7% lower when omitting initially "high-performers." These results are consistent with how it can take time for the benefits of AMI to accrue, as improvements may scale with the proportion of meters replaced, and utilities may need to develop new business processes and skills necessary to operationalize the technology's functionalities.

Utilities also benefit from revenue gains. On average, revenue increased by 0.9% for utilities that deployed AMI relative to their pre-treatment mean and by 1.3% when restricting the sample to those that were lower performers at baseline. After three years, the increases grow to 1.7% and 2.2%, respectively, translating into \$2.4 to \$3.1 million in additional annual revenue per utility.

We probe the underlying channels of our results and find evidence of four mechanisms. First, consumption measurement and billing accuracy improve, as indicated by an increase in sales per customer.[6] Sales increase if utilities use AMI to address bill non-payment and electricity theft, benefits that utilities commonly report (U.S. DOE, 2016). Analog meters also may have been under-reporting actual usage given how they slow down as they age. Replacing many old meters with digital ones can significantly increase sales. Although these results imply higher electricity bills (all else equal), customers may value having a more accurate account of their energy usage, reflecting a higher quality of service. Enhanced accuracy also provides utilities with opportunities to improve important aspects of energy management—such as demand forecasting, load management and proactive maintenance—which in turn, can reduce technical losses.

Second, we find that the likelihood that utilities start offering new products like dynamic pricing and demand response programs increased, reflecting efforts to implement more sophisticated load management practices that could ultimately improve service quality and grid resilience. The increase in sales per customer that emerges with AMI deployment is also attenuated when utilities offer these products. At the same time, we do not find that introducing these products drives the loss reductions. This could be because the proportion of customers using the products during our sample period is low, though, so there could be potential for doing so with greater consumer uptake.

[6] Decreases in sales also could have signalled performance improvements. For example, sales could decrease if customers use information from their smart meters to reduce consumption (and thus their electricity bills), which could also help utilities' load management.

Third, to further investigate whether utilities make energy management adjustments, 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 for manually reading traditional meters. Using Occupational Employment and Wage Statistics data provided by the U.S. Bureau of Labor Statistics, we find a reduction in meter readers with AMI deployment along with an increases in the number of "quants" (e.g., computer scientists who are equipped with the skills required to analyze data and improve energy system modelling). These results are consistent with utilities making organizational investments that can enhance the benefits of digitalization.

Fourth, we examine whether reliability improves using our within-utility data on power outages in Texas. We find that outage duration decreased by 5.5% following AMI deployment on average, suggesting that utilities use smart meters to restore power faster when outages occur.[7] However, we find no change in outage frequency, suggesting that additional capabilities or other solutions may be needed to avoid outages altogether.

Taken together, our findings indicate that digitalization can enhance utility performance and service quality through energy management improvements. Complementary organizational capital is likely important for maximizing the benefits, which raises the question of which utilities invest in new business processes and skills. We explore this by examining whether there is heterogeneity across ownership type. Utilities can be either government- or privately-owned, resulting in different incentives and constraints (Hart, Shleifer and Vishny, 1997; Shleifer, 1998; Duggan, 2000), and utilities' technology adoption decisions may differ by ownership type (Rose and Joskow, 1990).[8] For example, investor-owned utilities face pressure to generate short-term returns for shareholders, which incentivizes efficiency but may come at the expense of longer-run investments that serve public interests (Flammer and Bansal, 2017). Government-owned utilities may have longer time horizons and be more likely to prioritize social objectives because their customers are their constituents. Consistent with this line of reasoning, we find that loss rate improvements are driven by government-owned utilities. Differences in other utility characteristics do not account for the heterogeneity.

[7] Smart meters notify utilities immediately when outages occur, allowing utilities to respond faster. More detailed data also helps utilities identify the cause and its location so they can solve the issue quicker.

[8] Privately-owned utilities include investor-owned utilities and cooperatives.

2 Related Literature and Contributions

This paper speaks to four main sets of literature. First, most specifically, we provide new evidence as to whether (and how) digitalization can improve electric utility performance and service quality. Ensuring access to high-quality and reliable electricity is first-order for fostering modern economic activity and quality of life. When the power goes out, schools shut down, traffic lights stop working, and life-sustaining medical equipment no longer functions. However, electricity infrastructure is deteriorating in many countries, and utilities are facing rising costs along with new energy management challenges. The share of energy supply coming from intermittent renewable resources—which must be balanced with demand in real time—and electrification of end-use products (e.g., vehicles) are increasing, putting more pressure on the grid and requiring new capabilities from utilities.

With these shifting market dynamics and the need to transition to a cleaner, more sustainable economy, understanding how to manage the grid efficiently is more crucial than ever. 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—large-scale empirical studies of how smart meters impact service provision and utility performance have been missing.[9] On the consumer side, Brandon, Clapp, List, Metcalfe and Price (2022) and List, Metcalfe and Price (2018) examine how smart technology impacts energy use in the U.S. and U.K., finding no significant effects. A related but distinct literature examines whether interventions *facilitated* by smart meters, like providing information and introducing new pricing designs, impact *consumption* (Wolak, 2011; Jessoe and Rapson, 2014; Ito, Ida and Tanaka, 2018; Bollinger and Hartman, 2020; Burkhardt, Gillingham and Kopalle, 2023; Blonz, Palmer, Wichman and Wietelman, forthcoming). To the best of our knowledge, we are the first to examine how utilities use these digital technologies to improve energy management and the impacts on system performance and service quality.

Research on the economics of electricity resiliency in developed countries also remains scant (Borenstein, Bushnell and Mansur, 2023).[10] The emerging literature includes two

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

[10]There is a more extensive literature on reliability 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; Berkouwer, Biscaye,

working papers examining technology adoption to study the value of reliability (Bollinger, Gillingham, Darghouth and Gonzalez-Lira, 2023; Brown and Muehlenbachs, 2023).

Second, more broadly, our paper contributes to the quickly-evolving literature studying how digitalization and data-driven decision-making impacts organization performance. Research related to the adoption of information and communications technologies dates back to at least the 1990s (see Draca, Sadun and Van Reenen (2009) and Goldfarb and Tucker (2019) for reviews). With managers having access to increasingly vast amounts of data, this literature continues to evolve, but the focus primarily has been on firms in the private sector (Brynjolfsson and Hitt, 2000; Bresnahan et al., 2002; Brynjolfsson and Hitt, 2003; Bartel et al., 2007; Bloom et al., 2012; Brynjolfsson and Saunders, 2013; Brynjolfsson and McElheran, 2016; Goldfarb and Tucker, 2019; Brynjolfsson et al., 2021a,b; Bar-Gill et al., 2024).

Whether digitalization improves public services has gone relatively under-studied despite their crucial role in maintaining well-functioning economies and high standards of living. Healthcare is one exception (see Bronsoler, Doyle and Van Reenen (2022) for a review), but this literature tends to face two key limitations that we are able to overcome by studying the electricity sector. First, quality of services is notoriously difficult to measure. Mortality is a commonly-used indicator, which captures an important outcome that may be correlated with quality of service but does not measure quality of service directly.[11] By studying electricity service providers, we are able to use precise, objective, and systematically reported indicators of performance and service quality. The second challenge is that data restrictions often lead researchers to studying a specific type of provider (e.g., hospitals as opposed to all physicians and specialists) and therefore a select set of customers (e.g., inpatients). With our data, we can study nearly all service providers across an entire industry within a country.

The third line of research to which our paper contributes relates to how management shapes organization performance. Similar to the digitalization literature—and perhaps even more so—most research in this space focuses on the private sector. In addition to early case studies and descriptive analyses of firms' management practices, an extensive empirical evidence base documenting the importance of management quality for firm performance

Mikdash, Puller and Wolfram, 2024), but the challenges (and therefore solutions) are fundamentally different.

[11] People may pass away 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.

has emerged with the availability of large-scale microdata (Bloom and Van Reenen, 2007; Bloom, Brynjolfsson, Foster, Jarmin, Patnaik, Saporta-Eksten and Van Reenen, 2019; Gosnell, List and Metcalfe, 2020). However, very little is known about management of public services. 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). 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 provide new insights on public versus private provision of 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 financial outcomes.[12] We do not estimate the effects of privatization, but we add to this literature by documenting heterogeneity in the effects across ownership type, which provides insight into the importance of managerial incentives for realizing the benefits of digitalization. That is, although privately-owned utilities have incentives and requirements to improve quality of service as well, they face short-term pressures to generate financial returns for shareholders. On the other hand, when organizations have longer time horizons and focus on social objectives, their investments may generate greater performance benefits.

3 Background on Power Sector and Research Setting

This section provides background on our research setting, including an overview of electricity distribution systems in the U.S., the role of utilities (i.e., service providers) and energy management, indicators of utility and system performance, and how digitalization could

[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.

theoretically improve performance and quality of service.

3.1 Electricity Distribution in the U.S.

Electric grids are complex networks that deliver power to consumers. They are comprised of high-voltage transmission lines that transfer electricity from power plants to population centers through high-voltage transmission lines (the "interstate highway" of the grid) and distribution systems that then deliver the power to end-users (residential, commercial, and industrial customers). Distribution systems include substations, transformers that reduce ("step down") voltage to the level required for end-use appliances and equipment, lower voltage power lines (the "last mile"), meters that monitor consumption located on end-users' premises, as well as customer services. The U.S. distribution system is expansive, serving 145 million end-users through 5.5 million miles of distribution lines (EIA, 2016).

Access to high-quality and reliable electricity is important for maintaining a well-functioning economy and quality of life, but the distribution system in the U.S. is aging quickly and increasingly susceptible to disruption. Approximately 70% of transmission and distribution (T&D) lines were constructed in the early- to mid-1900s and are now in the second half of their life expectancy (ASCE, 2021). Inadequately upgraded and poorly maintained infrastructure can come with serious consequences for power quality (e.g., voltage fluctuations) and reliability (i.e., outages). The distribution system is responsible for 92% of the country's power interruptions (ASCE, 2021), which are driven by a combination of aging infrastructure, severe weather, and various aspects of utility and energy management.[13]

Poor power quality can be disruptive and costly. Residential customers may experience low voltage and voltage fluctuations as dimming or flickering lights, but significant drops also can damage end-use products, which can be especially costly for commercial and industrial customers. Even minor voltage fluctuations can ruin expensive machinery and shut down production processes. Reliability in the U.S. also has been declining. The average customer experienced about 5.5 hours of power interruptions in 2022, up from a little over 3.5 hours in 2013, and it is far worse in some parts of the country (EIA, 2024). Outages sometimes are just inconvenient but also can be life-threatening, such as when they affect electronic

[13]We expand upon the role of utilities in Section 3.2 and measurements of performance in Section 3.3

medical devices and transportation systems.

3.2 Role of Utilities

Electricity distribution in the U.S. is managed by approximately 1,300 utilities that are responsible for maintaining the grid as well as selling and delivering electricity that can meet end-users' needs.[14] Utility performance and energy management, therefore, play a pivotal role in ensuring high-quality and reliable electricity service. Energy management entails optimizing assets and operations as well as planning, controlling, storing, and distributing electricity. Utilities also must remain fiscally sustainable by maximizing efficiency, generating revenue, and minimizing costs (e.g., distribution system upkeep and repairs, billing processes, emergency response, safety and regulatory compliance, and customer service).

Poor utility practices can lead to poor system performance and reliability. Although many outages in the U.S. are caused by extreme weather events, like storms that knock down power lines, about two hours of the power outage time per year experienced by the average U.S. customer over the last decade have been due to non-major events (i.e., causes besides extreme weather events) (EIA, 2024). Non-major event outages even accounted for most down time in some states.[15] For example, inadequate maintenance, upgrading, and vegetation management can make the system more susceptible to disruption. Supply and demand also must be balanced in real time. Weather events, therefore, can impact system performance not just by knocking down power lines but also through utilities' capacity to manage spikes in demand due to the use of air conditioning and heat, which can lead to overload (i.e., demand exceeding capacity) and equipment malfunction. Demand growth on the horizon due to data center build-out as well as the increasing proportion of electricity supply coming from intermittent renewable resources also introduces new energy management challenges for utilities.

[14] 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.

[15] For example, this was the case for West Virginia, Maine, and several other states in 2022 (EIA, 2024).

3.3 Electricity Losses as Key Performance Indicator

There are various ways to evaluate the performance of electricity distribution systems, which in turn, reflect utilities' performance with respect to delivering high-quality and reliable power as well as their financial standing. We primarily focus on one of the key performance indicators set out by the Institute of Electrical and Electronics Engineering (IEEE)'s standards: electricity losses.

From the point at which electricity is generated and supplied to the T&D system to when it is consumed, some proportion of it is lost at various stages; however, the extent of losses differs across settings. Electricity losses are, therefore, often considered an important indicator of the "efficiency and financial sustainability of the power sector" (Jiménez, Serebrisky and Mercado, 2014). Those occurring as electricity travels throughout transmission and distribution are referred to as line losses, calculated as the difference between the electricity supplied to the grid and the amount for which customers are billed. The loss rate—the percentage of electricity lost relative to total electricity supplied to the system—thus captures the overall efficiency of the system and performance of utilities responsible for managing it.

Transmission and distribution losses are frequently in the 6-8% range for high-income countries but can be as low as 2-3%, indicating that there is still room for improvement in many cases. For example, according to 2014 data from the World Bank, total transmission and distribution losses were 2% in Singapore, 3.4% in South Korea, and 3.9% in Germany.

Electricity losses are caused by both "technical" and "non-technical" factors. Technical losses occur naturally due to the physical properties of the system, such as conductor resistance, and mainly consist of power dissipation along distribution lines and transformers. Some degree of electricity losses are thus unavoidable. However, losses are higher when the system is poorly managed. For example, since losses increase as equipment ages, high losses could reflect a history of insufficient maintenance and upgrading. Losses are also exacerbated by factors like system overload (i.e., demand exceeding supply), which can occur if utilities do not adequately balance demand and supply or if demand unexpectedly spikes. Voltage fluctuations can exacerbate losses as well (Jiménez et al., 2014), which in turn, causes system instability or even collapse.[16]

[16]Furthermore, as energy losses transform into heat (they are resistance multiplied by the current squared),

"Non-technical" losses (NTLs), on the other hand, are caused by factors external to the system. They are caused by issues like illegal cable hooking—which allows people to bypass meters and consume electricity without paying for it—or incorrect electricity meter readings due to outdated and damaged technology, human error by utility workers, or meter tampering by customers. Although non-technical losses are more frequently associated with low and middle income countries—where they are indeed higher, on average—NTLs are also common in high-income countries like the U.S.

In addition to improving system efficiency for the sake of providing high-quality and reliable power to customers, reducing electricity losses is also increasingly important for utilities to remain financial viable. Electricity losses represent lost revenue, and utilities' financial standing plays a role in determining their capacity to make system investments and provide good service. Furthermore, utilities still must pay for electricity delivered to the system even if it is not billed to or paid for by end-users, and as utilities must purchase enough to meet actual demand plus losses, the amount purchased increases with expected losses. Consumers also may bear some of the costs, as they tend to be passed through to prices or other charges on electricity bills.

3.4 How Digitalization Can Improve Performance

Proposals to improve electricity system and utility performance frequently include modernizing the grid with digital technologies and enhanced energy management capabilities. Until the early 2010s, most electricity meters—the devices located on customers' premises to track electricity usage, primarily for billing purposes historically—were antiquated and unsophisticated (Munasinghe, 1981). The majority of customers still had conventional electromechanical 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. They require many tasks to be performed manually in person, such as reading meters to calculate the amount of power used during a billing period and manually disconnecting and reconnecting customers (e.g., when customers

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 and other equipment (FERC, 2020).

move or have not paid their bills). And when outages occur, utilities would rely on end-users to report them and field crews to locate and identify the outage source in person.

Recent advances in digital technologies and data generation, transmission, and storage are opening up new opportunities for utilities to improve their performance and the quality of service that they provide, though. Digitalization in the electricity context entails investing in advanced metering infrastructure (AMI)—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 data management systems (Gold et al., 2020). Smart meters provide high-frequency electricity data—usually at least at the hourly or 15-minute level—to utilities and end-users remotely. Investments in AMI initially progressed slowly in the U.S. but increased rapidly through the 2010s. The electricity sector's "digital revolution" extends well-beyond the U.S. as well.[17]

In the paragraphs that follow, we elaborate upon the potential functions of and benefits from AMI. Although these are frequently enumerated in technological and industry reports, there is little empirical evidence as to how these functionalities are employed—and the benefits accrued as a result—by utilities in practice.

Mechanical Benefits. Some features of AMI technology can improve performance mechanically (i.e., with just deploying meters without additional action) and practically immediately. For example, smart meters often have the functionality to shut down grid connections automatically if voltage spikes or dips outside of the range that is safe and appropriate for end-use products and equipment. This can help prevent unplanned outages, and in turn, protect equipment from being damaged and reduce the probability of future disruptions.

Automated Billing and O&M Costs. Deploying smart meters can induce almost immediate cost savings and customer service benefits related to remote collection of consumption data and automating billing processes. With conventional meters, utilities incur significant labor and transportation costs associated with deploying workers to gather electricity use data onsite for billing purposes. Remote provision of consumption information and automated billing processes can, therefore, substantially reduce billing costs.[18] These operational

[17]In 2013 alone, approximately $15 billion were invested in smart grids worldwide (IEA, 2015).

[18]Indeed, this is one of the most frequently cited motivations for utility investment in AMI (U.S. Depart-

efficiency gains can be substantial and improve the customer experience, although the net effect on labor costs depends on the extent to which the utility also hires workers with other skills when shifting to AMI (e.g., computer scientists and software engineers who can analyze high-frequency data and improve dispatch models).

Reducing Technical and Non-Technical Line Losses. Utilities have additional opportunities to reduce technical and non-technical electricity losses when they deploy AMI. With respect to NTLs, rolling out smart meters can lead to utility workers identifying meter tampering and other forms of energy theft when replacing meters. Remote data transmission from smart meters also can reduce NTLs associated with incorrect meter readings, as it circumvents the need for estimating consumption or interpolating bills when in-person meter readings are not possible, decreasing human error in the billing process (Nangia, Oguah and Gaba, 2016; Cooper and Shuster, 2021). These improvements can also lead to reductions in customer complaints and faster resolution of billing disputes (U.S. DOE, 2016). At the same time, if the incumbent technology consistently under-measured actual consumption, bills may increase following smart meter deployment even if actual consumption does not change. Utilities' financial standing may therefore improve through enhanced revenue recovery, but the effects on customer satisfaction are ambiguous.[19]

When fully leveraging the high-frequency nature of the data generated, smart meters also can help utilities reduce technical line losses, especially if they also invest in complementary AMI technologies that provide information on power flows and quality as well as developing or acquiring the skills required for analyzing such data. The combination of more precise data with advanced analytics can allow utilities to improve energy planning and supply-demand balancing, such as by improving their demand forecasts, as well as identify consistent bottlenecks or places where the grid is consistently constrained (Nangia et al., 2016; Gold et al., 2020). These types of insights can help inform asset optimization and investment

ment of Energy, 2016). 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 and they still involve higher labor and transportation costs.

[19]It could increase satisfaction if consumers value billing accuracy or if billing errors previously created distrust. However, customers may dislike facing higher bills for the same quantity of electricity power previously consumed if old meters systematically under-measured true consumption.

decision-making, and in turn, lower electricity losses. Utilities also can use other AMI components in conjunction with smart meters to enhance voltage monitoring capabilities, which can reduce line losses and improve power factors (U.S. Department of Energy, 2016).

Smart meters also provide opportunities for utilities to offer new products, such as demand response programs and dynamic pricing schemes, which may enhance customer satisfaction while also providing opportunities for improving service and reducing losses as well.[20] Demand response programs provide utilities with greater control over supply and demand. More granular data and two-way real-time communications through smart meters can enhance their ability optimize power flows throughout the day and reduce demand during peak periods (Costa-Campi, Daví-Arderius and Trujillo-Baute, 2018). Dynamic pricing schemes that set prices higher during peak demand periods also provide opportunities for achieving similar outcomes depending on consumer response (i.e., if customers shift energy use away from peak periods). Such products also empower customers to lower their electricity bills, which may enhance customer satisfaction.

Reliability Benefits. Lastly, utilities can use smart meters to reduce power outage duration and/or frequency, improving the reliability of service for end-users as well as the financial performance of utilities. Voltage quality data can help utilities identify potential weak points in the system or recurring bottlenecks, which can lead to reduced outages if utilities address these issues with energy planning adjustments or system upgrades. Utilities also can use smart meters to respond to outages faster when they do occur, reducing the amount of time it takes to restore power. For instance, AMI meters are often equipped with "last gasp" alarms that inform utilities immediately of service disruptions, which also then provides more precise location information to identify the outage's original source (U.S. Department of Energy, 2014c). While the alerts are mechanical through the technology's features, the degree to which such features reduce power outage duration and the associated costs hinges upon utilities dispatching repair crews appropriately.[21]

[20] These types programs could be implemented to some degree with intermediary technologies deployed prior to AMI, like automated meter reading (AMR), but the data granularity and frequency allow for much more precision.

[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).

4 Data and Sample Construction

We construct and use three data sets 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 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.

4.1 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 the electricity loss rate (which is the percentage of total disposition that is lost through transmission and distribution), total sales and sales per customer (both in megawatt hours), 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.

4.2 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]

4.3 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).

[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.

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 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 5.

4.4 Additional Data

4.4.1 Regional Occupation Employment

When exploring mechanisms through which AMI affects utility performance, we examine worker composition. 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). We extract the area-level employment information for the 2007-2018 period. Although these data do not differentiate occupations from industries, all meter readers are associated with the utility sector, 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.

[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 5).

[24]We verified this with state-industry level employment data. We collected data on employment estimates by state and industry from the U.S. BLS derived from sample surveys, which 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).

4.4.2 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 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.

5 Empirical Strategy and Identification

5.1 Research Design

Our primary goal is to identify the causal impact of smart meter deployment on utility performance with a focus on the electricity loss rate. Estimating the effects using OLS may be plagued by various sources of endogeneity. 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 a systematically more significant decline in performance that motivates them to invest in AMI. The likelihood of deployment also may be correlated with local economic growth or other market characteristics that simultaneously impact electricity losses.

To address these concerns, we exploit quasi-experimental variation in utilities' AMI smart meter deployments and augment a staggered difference-in-differences model with a two-stage least squares (2SLS) approach that directly addresses a key source of endogeneity. To summarize, our enhancement is in the spirit of the methodology developed by Freyaldenhoven et al. (2019), who show how instrumenting a "proxy" variable that is correlated with a potential confounder—but not driven by the treatment—with the lead of the policy treat-

[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.

ment can identify the causal effect of the treatment. The method provides estimates of the treatment effect net of the pre-trend effects.[26]

Foundation of Model. Before discussing the 2SLS empirical strategy that we use throughout our analyses, we start by describing the foundation of our model that we build upon—event studies and staggered difference-in-differences. Using the first year that a utility deploys AMI smart meters as the treatment year, we start with an event study model that compares before and after differences in outcomes relative to the 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 local observable time-varying characteristics in the matrix $\mathbf{X}_{it}$ (new building construction and population in counties within the utility's service region).[27] We cluster standard errors at the utility level.

To summarize the dynamic effects of AMI adoption, we 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

[26]See Freyaldenhoven et al. (2019) for details on identification and we provide evidence of the pre-trend removal in our results section.

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

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, identifying the causal effects would rest upon three main 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 potential violations of these assumptions.

2SLS Augmentation.— 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 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 performance. To address this, we follow the approach developed by Freyaldenhoven et al. (2019), which allows for causal identification of the treatment by removing the potential effects of pre-trends using a 2SLS approach. One must find a "proxy" variable for the unobserved confounder, and instead of simply including the variable as a control, instrument for it using leads of the treatment variable. The key assumption is that the "proxy" is affected by the unobserved confounder (e.g., economic growth) but not driven by the treatment.[28]

[28] 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.

The main task, therefore, is to find a variable that follows a pattern similar to that which we expect the unobserved confounder to exhibit but which is not driven by AMI deployment. We propose and use population as our proxy, as it is plausibly correlated with economic growth and the related endogeneity concerns, but importantly, it is highly unlikely that AMI deployment is a key driver of population growth.

To empirically explore whether population may be a suitable proxy, we estimate Equation 1 with (log) population as the dependent variable and plot the coefficients in Appendix Figure B1.[29] Indeed, population increases over our sample period for utilities that deploy AMI relative to non-AMI utilities, suggesting that population is a reasonable proxy. As long as AMI deployment is not driving population growth, instrumenting for population with the treatment variable lead allows us to recover the causal effect of AMI.

5.2 Addressing Other Potential Identification Concerns

Treatment Timing. Staggered difference-in-differences models may produce biased estimates if treatment effects are heterogeneous across units and over time (Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021; Sun and Abraham, 2021).[30] For reasons similar to the potential endogeneity of AMI deployment timing, one may be concerned about such heterogeneity in our setting. 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. Local 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 directly addresses these concerns, but to be sure they do not bias our results, we also implement some of the other newly developed approaches as robustness checks in Section 6.3.

SUTVA. As is the case for any difference-in-differences research design, one key assumption behind our approach is that there are no spillover effects on untreated units. In our setting,

[29] 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.

[30] 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.

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 for a treated utility and this benefits neighboring 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. Such spillovers should attenuate our results if anything, but nonetheless, we probe this by carrying out various robustness checks in Section 6.3.2.

6 Main Results: Effects of AMI on Electricity Losses

This section presents both our main results from estimating the impacts of smart meter deployment on electricity losses as well as robustness checks probing the identification assumptions of our research design.

6.1 Dynamic Effects

To begin, we estimate the dynamic effects of utilities' smart meter roll-outs on our primary measure of utility performance—the electricity loss rate—employing the 2SLS estimator that extracts pre-trends by instrumenting our "proxy" variable (population) with a one-year lead of the treatment variable as the excluded instrument. Doing so illustrates our main findings for performance improvement while also allowing us to investigate whether our 2SLS approach addresses the endogeneity concerns discussed in Section 5.

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. Immediately following AMI deployment, the loss rate starts to decline. The decrease is small at first but continues to steadily drop over time, leveling off after about 3 years post-treatment. Increasing improvements over time are consistent with the benefits of technology adoption—particularly digital technologies with complex capabilities—needing time to materialize. Utilities may need to invest in complementary technologies and organizational capital, like new processes and acquiring workers with different skills, to fully reap the rewards, similar to other contexts (e.g., Brynjolfsson and Hitt, 2000; Bresnahan et al., 2002; Brynjolfsson et al., 2021a; Bronsoler et al., 2022).[31] The benefits of AMI also may scale with deployment intensity. We explore the magnitude of the effects over time further in the next sub-section.

Furthermore, we estimate the effects separately for the bottom quartile of the pre-treatment loss rate distribution and those above the bottom quartile, since the potential to reduce losses likely differs depending on baseline rates.[32] The estimates are plotted in Appendix Figure B2. For utilities above the bottom quartile (i.e., those with higher loss rates), the results are very similar to our main findings (Panel A), and reassuringly, we find no change in the loss rate for those that were already performing well (i.e., those in the bottom quartile of the pre-treatment loss rate distribution (Panel B).

Finally, the dynamics illustrated in Figure 2 also provide confidence in our 2SLS research design when comparing them to results from a standard OLS estimation. When taking our 2SLS approach, the differences in the loss rate through pre-treatment years are much more stable than they are when using OLS, suggesting that instrumenting our proxy variable with the treatment lead successfully removes some influence of confounders (see Appendix Figure B3 for a comparison). Although the OLS estimates exhibit only a slight pre-trend in the loss rate before making the 2SLS adjustment (Panel A), this appears to be extracted once doing so (Panel B). Moreover, there could be pre-trends in electricity losses that are dampened by opposing changes in total disposition (e.g., sales) once constructing the loss rate. We therefore examine the effects on (log) total losses as well, which indeed exhibit a slightly more pronounced pre-trend (Panel C of Appendix Figure B3) that disappears once we implement our 2SLS approach (Panel D).

6.2 Average Effects

We now turn to estimating the average effect of AMI deployment over the post-treatment period following Equation 2 and implementing our 2SLS approach. We find that the loss rate decreases by 0.002 percentage points on average (Column 1 of Table 2), representing a 3.8% reduction relative to AMI adopters' pre-treatment mean loss rate. These estimates

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

[32] For utilities that deploy AMI at some point throughout our sample period, the cutoff for the bottom quartile of pre-treatment loss rates is 3.8%.

likely understate the potential utility performance improvements, though, as the sample includes utilities that already achieve a low level of line losses and thus have very little room to improve. When omitting utilities in the bottom quartile of the pre-treatment loss rate distribution, we find that the loss rate declines by 0.003 percentage points on average, reflecting a 5.8% improvement relative to the pre-treatment mean (Column 2 of Table 2). On the contrary, loss rates do not change for utilities that were already performing well, as expected (see Column 1 of Appendix Table B1).

Intuitively, the dynamic effects plotted in Figure 2 also indicate that efficiency improvements increase over time. Benefits may scale with intensity of treatment (i.e., the proportion of customers with smart meters), for example, and roll-outs may occur over a couple of years. It also can take time for utilities to develop or acquire the skills to fully leverage smart meter capabilities, or for them to invest in complementary AMI features (like data management systems) that are important for realizing the benefits of digitalization.

To account for this, we omit the year of initial deployment and the two years that follow such that we capture the efficiency improvements achieved three years post-deployment and thereafter.[33] When doing so, we find that the loss rate declines by 0.003 percentage points, reflecting 5.8% efficiency gain relative to the pre-treatment mean loss rate for utilities that deploy AMI (see Column 3 of Table 2). When omitting utilities in the bottom quartile of the pre-treatment loss rate distribution, this increases to a 0.004 percentage point decline, which translates into a 6.7% efficiency gain relative to the pre-treatment mean of AMI utilities in the sample. Once again, we find no change in loss rates for utilities that were already performing well when omitting the deployment year and two years thereafter (see Column 2 of Appendix Table B1).

Lastly, to demonstrate the importance of implementing the 2SLS approach, we compare these results to what we would have found had we used OLS (see Appendix Table B2). When doing so, the estimates can be interpreted as "unadjusted"—they include both the true causal effect as well as the confounder effects. We generally still find negative and statistically significant effects on the loss rate when doing so but the magnitudes are smaller. When using the full sample using OLS, we find a 1.9% decline relative to the sample mean

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

compared to the 3.8% effect we find when implementing the 2SLS approach (Column 1 of Appendix Table B2).

6.3 Additional Identification and Robustness Checks

Recent research points to several reasons to be cautious when using OLS to estimate staggered difference-in-difference models. The 2SLS approach that we apply throughout the paper addressing endogeneity associated with smart meter deployment and adoption aims to directly tackle some of those concerns. For example, one main strand of the literature argues that standard tests for the parallel trends assumption (i.e., examining differences in pre-treatment years) may not detect statistically significant differences simply because of low statistical power (Roth, 2022). Our approach addresses this by extracting potential effects of pre-trends in the spirit of the method developed in Freyaldenhoven et al. (2019). In this sub-section, we address two other potential concerns: treatment effect heterogeneity across time periods and spillovers to untreated units.

6.3.1 Adoption Timing

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

To deal with this, we implement Callaway and Sant'Anna (2021)'s "doubly robust" DiD method using stabilized inverse probability weighting. The approach 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 B3. We first only include never-treated units in the control group (Columns 1-2) and then also include not-yet-treated units (Columns 3-4). The point estimates are identical to our main findings in both cases, remaining statistically significant at the 5% level when including all utilities in the sample and becoming statistically stronger (to the 1% level) when omitting initially "high-performers."

6.3.2 SUTVA

Another key assumption underlying all difference-in-differences research designs is that there are no spillover effects on untreated utilities (i.e., the stable unit treatment value assumption (SUTVA) holds). This might be a concern because utilities' distribution lines are ultimately all connected to the same grid. In our context, spillovers would likely attenuate the estimates if anything, 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 Column 1 of Appendix Table B4).[34] Second, we estimate the effects of AMI on the amount of power received/imported from other utilities and 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 2 and 3 of Appendix Table B4).

6.4 Implications for Financial Performance and Pricing

Reductions in losses can bolster utilities' financial performance in various ways. Although we cannot examine all potential benefits with our data—for example, we do not have information on operational and labor costs that may decline if utilities shift away from manual meter readings—we can observe the implications of AMI for revenue and pricing. Reductions in losses imply enhanced revenue recovery, so we expect to see an increase in total revenue, all else equal. The effects on pricing could go in either direction, as utilities may pass through the benefits to consumers in the form of lower prices, or they may increase prices to recover costs associated with AMI investments.

Table 3 provides the estimated effects on total revenue (Columns 1-2) and average prices

[34] 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.

(Columns 3-4), which we construct as total revenue divided by total sales. When including the full sample, the results suggest that total revenue increases by about 0.9% in the post-deployment period on average (Column 1, Panel A) and by about 1.7% after three years (Column 1, Panel B). Relative to the pre-treatment mean total revenue for utilities that deploy AMI ($139.8 million), these translate into revenue increases of $1.3 million per year on average and $2.4 million per year after three years. Once omitting utilities that were already high performers before deploying AMI, we find that revenue increases by 1.3% on average (Column 2, Panel A) and 2.2% after three years (Column 2, Panel B). Relative to the pre-treatment mean revenue for these utilities ($142.2 million), these figures translate into revenue gains of $1.8 million on average and $3.1 million after three years.

If utilities achieve these improvements by passing through costs to consumers, we would expect to find an increase in prices. However, we find no change in average prices (Columns 3 and 4). This suggests that revenue increases due to enhanced performance. We explore the underlying mechanisms through which this occurs next.

7 Mechanisms

We now shift to developing a better understanding of the channels through which utility performance improves. We provide four sets of results that are consistent with utilities using AMI to enhance different aspects of energy management, which in turn, can boost system performance and service quality: improving consumption measurement and billing accuracy; introducing new products, like dynamic pricing and demand response programs; investing in complementary human and organizational capital, such as workers with "quant" skills; and responding to power outages faster.

7.1 Improving Consumption Measurement and Billing Accuracy

One of the ways in which AMI can reduce losses and enhance performance is through improved consumption measurement and billing accuracy. With analog technology, meter readings and data entry are subject to human error. Digital meters are also more accurate. Electromechanical meters degrade and slow down as they age, leading to electricity usage readings that are lower than actual consumption (EPRI, 2008). Replacing many old meters could, therefore, lead to a substantial increase in sales. Although this means higher electricity bills—a common customer complaint—customers also may value more accurate billing. Utilities' also can re-invest the recovered revenue to further improve infrastructure. Moreover, having a more accurate picture of the system can help utilities reduce technical losses as described in Section 3.4. Lastly, smart meters can also increase sales by enhancing utilities' ability to identify electricity theft (e.g., meter tampering or illegal connections), which is a significant source of NTLs in the U.S. (EPRI, 2008; U.S. DOE, 2016).

With these factors in mind, we explore whether AMI appears to reduce losses through improved billing accuracy by examining electricity sales. Figure 3 illustrates that (logged) sales per customer indeed start to increase immediately following AMI deployment, and the magnitude of the change continues to grow for about three years. The immediacy of the effect is consistent with new meters increasing the accuracy of consumption measurement and billing, including reducing electricity theft. The continued increase for a few years is consistent with the utility requiring time to achieve full deployment.

7.2 Introducing New Products

Smart meters allow utilities to introduce or improve dynamic pricing and other demand response programs, which can incentivize customers to shift demand away from peak periods when the grid is constrained.[35] As described in Section 3, even small reductions in demand during these peak times can reduce technical losses. Offering such programs also can improve customer satisfaction if they have flexibility in the timing of their consumption and value the opportunity to lower their electricity bills.

To investigate whether such products play a role in improving performance, we first examine whether the likelihood that utilities offer them increases following AMI deployment. We construct indicator variables equal to one when the number of customers using dynamic pricing or demand response programs first becomes positive and zero otherwise as our dependent variables. The results are presented in Columns 1 and 2 of Table 4. On average,

[35] Some forms of such programs could be implemented without smart meters, such as seasonal pricing, but more granular real-time information on electricity usage allows for intra-day load smoothing.

the likelihood of introducing these services indeed increases by 3.9% and 3.3% for dynamic pricing and demand response programs, respectively.

Next, we explore whether consumers appear to have changed their electricity use behavior with the introduction of such products, and if so, whether this contributes to the decline in losses. We do not observe the timing of consumption to test this directly, unfortunately. However, we examine whether the introduction of these products impacts total sales per customer to test whether there are any changes in gross consumption. We interact the AMI treatment with our indicator variables for whether the utility has started to offer dynamic pricing or demand response programs and estimate the interaction effects on sales per customer (Columns 3-4 of Table 4). We then do the same with loss rates as the dependent variable to see whether the introduction of these programs enhances the effect of AMI on losses (Columns 5-6 of Table 4).

There are two key takeaways. First, both products offset the increases in sales per customer that emerge following AMI deployment, suggesting some degree of consumer responsiveness. However, these offsets do not seem to account for the loss rate improvements, suggesting that other factors drive loss reductions in our setting. This is not to say that dynamic pricing and demand response programs—and the demand smoothing that can be achieved either on the consumer or utility side—could never contribute to performance improvements, though. Consumers' uptake of these products was still quite low during our study period, so a more meaningful effect could potentially be achieved with broader use and could be explored in future work.

7.3 Investing in Complementary 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 meter readers employed by utilities. Furthermore, fully realizing the benefits of AMI likely requires additional investments in complementary organizational innovation and human capital, similar to the case of when firms adopt information and communication technologies.[36] Integrating AMI technology

[36]The broader literature studying information technology adoption finds that successful implementation and realization of the benefits requires complementary investments, and notably, organizational innovation

into existing processes and practices, and analyzing the data that it generates to improve performance, requires advanced data analysis and software skills.

We do not observe the number or type of workers at the utility level to test this directly. 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.[37]

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:

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

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. 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

(Brynjolfsson and Hitt, 2000; Caroli and Van Reenen, 2001; Bresnahan et al., 2002; Brynjolfsson et al., 2021a).

[37] 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.

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.

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.[38] Panel A of Table B5 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.

7.4 Responding to Power Outages Faster

Finally, we explore whether utilities may use smart meters to improve reliability (i.e., power outage duration and frequency). As discussed in Section 3.4, smart meters are often equipped with last gasp alarms that automatically notify utilities when outages occur. Utilities must

[38] 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.

actually respond accordingly, though, to restore power and for outage duration to decline. We interpret such behavior as an improvement in energy management. Furthermore, utilities also may be able to avoid some outages, such as those caused by equipment failure, if they use AMI to identify bottlenecks and investment needs.

Using our feeder-line level for utilities in Texas, we estimate the effects of AMI deployment on reliability with 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 primary 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.[39] 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. This suggests that further action beyond improved monitoring and identifying weak points may be important for avoiding outages, such as making additional investments in the grid. Future work could explore this by examining whether investments made post-AMI deployment help reduce outage frequency.

8 Implications of Utility Ownership

Our findings suggest that investing in AMI can provide efficiency and quality of service benefits, and that energy management plays an important role. This raises the question of what determines which utilities have the incentives and capabilities to make longer-run

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

management and organizational investments to realize those benefits in the first place.

One potential factor could be ownership. An extensive literature in economics discusses and documents differences in performance across publicly-owned versus privately-owned organizations.[40] Utilities in the U.S. can be government-owned (i.e., operated by municipalities, the state, or the federal government), investor-owned (IOUs), or cooperatives (i.e., non-profits operated by their members). For the purposes of our analyses, we group IOUs and cooperatives together as "privately-owned utilities" (POUs). Profit-maximization objectives may incentivize POUs to invest in innovative activities and technology adoption that improve efficiency, but such investments may focus more so on short-run cost savings given pressure from shareholders to generate returns quickly. On the other hand, government-owned utilities may tolerate longer time horizons, which may be important for fully realizing the benefits of digitalization given the importance of developing new processes and skills. They also may focus more on social objectives given how they are usually run by elected officials and their customers are their constituents.

We estimate the effects of smart meter deployment on loss rates for government-owned versus privately-owned utilities and a clear picture emerges: the efficiency gains are driven by government-owned utilities. Figure 4 plots the estimated coefficients separately for each group. Losses start declining quickly for government-owned utilities (Panels A)—and more substantially relative to the average effects in Figure 2. In contrast, there is no change in the loss rate for privately-owned utilities (Panel B).[41]

The results indicate that the reductions in electricity losses are driven by government-owned utilities. If government-owned utilities do prioritize longer-run benefits and tolerate longer time horizons for earning positive returns on their investments, then these results are consistent with complementary organizational change and management improvements being important for AMI to reduce losses.

One may be concerned that differences in other utility characteristics drive the heterogeneous results described above. For example, given the effects of AMI are largest for utilities with the worst baseline performance, pre-treatment performance may be at play

[40]See Shleifer (1998) and Hart et al. (1997) for seminal examples.

[41]We also plot the effects separately for IOUs and cooperatives in Appendix Figure B4 and find no decline in either case.

if government-owned utilities had higher loss rates. We find that was not the case. The average pre-treatment loss rate was lower for government-owned utilities (0.048) relative to IOUs (0.054) and cooperatives (0.058).

We also probe the extent to which utility size plays a role, since IOUs tend to be much larger than government-owned utilities and the time required to fully deploy smart meters may scale with the number of customers.[42] To investigate this, we construct sub-samples of utilities that are a comparable size across ownership types by omitting those in the top 5% of the size distribution in untreated years.[43] We again find that the effects are driven by government-owned utilities with no change in loss rates for privately-owned utilities that are equally small (see Appendix Figure B5.)

9 Conclusion

Digitalization is often found to enhance various aspects of firm performance, such as reducing costs and enhancing productivity. However, whether this applies to the public services context has been unclear to date. Results from existing work studying private sector firms may not transfer given how organizations providing public services often operate under different market conditions and face different incentives and constraints. Studying digitalization in the public services context can be difficult due to relatively low uptake in many industries, though, and understanding how to improve public services more generally can be difficult due to challenges with measuring quality of service.

We overcome these challenges by examining 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 now widespread and objective performance and service quality measures are reported consistently. We found that, on average, the electricity loss rate decreased by 3.8%. The effects are much larger for utilities with high pre-treatment losses and once at least three years have passed since initial deployment. Findings from

[42]The average number of customers for government-owned utilities is 17,885 in comparison to 599,187 for IOUs and 23,874 for cooperatives.

[43]The cutoff is 115,248 customers. There are not enough large government-owned utilities to limit the sample only to large utilities for comparison.

additional analyses suggest that various aspects of energy management—such as improved billing accuracy and enhanced system monitoring—are likely at play.

The impacts of AMI on electricity reliability are mixed but consistent with anecdotes from utilities when reporting on the benefits incurred from AMI during the time period that we study. Power outage duration decreased, signalling that utilities use the information from AMI to identify and respond to interruptions more quickly. The frequency of outages does not change, though.

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 susceptible to disruption. At the same time, extreme weather events are occurring with increasing frequency due to climate change and utilities are facing new energy management challenges with the integration of intermittent renewable electricity as well as expected load growth that is on the horizon. Governments globally are allocating large amounts of public expenditures to modernizing infrastructure in hopes of adapting and preparing for this transition, 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 electricity service quality and utility performance, but the magnitude of the benefits may hinge upon investing in complementary organizational capital.

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Main Text Tables

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

	Full Sample (1)	AMI Adopters Pre-Adoption Years (2)	Non-Adopters All Years (3)	Difference of Means (4)
Loss Rate (%)	0.052	0.052	0.054	0.002
	(0.026)	(0.024)	(0.028)	(0.001)
Total Losses (000s MWh)	65.77	83.22	37.73	-45.5
	(275.46)	(340.94)	(132.40)	(4.68)
Total Sales (000s MWh)	1160	1436	686	-749.5
	(4284)	(5098)	(2522)	(74.0)
Total Revenue (million $)	119.5	139.8	68.1	-71.7
	(498.2)	(569.2)	(240.4)	(7.94)
Number of Customers (000s)	57.01	62.44	33.70	-28.7
	(258.05)	(271.18)	(127.50)	(3.88)
Sales per Customer (MWh)	31.00	27.01	36.39	9.38
	(140.51)	(17.15)	(206.42)	(3.18)
Rev. per Customer (000s $)	2.88	2.43	3.33	0.896
	(11.94)	(1.12)	(17.57)	(0.270)
Average Prices ($/kWh)	0.102	0.097	0.102	0.005
	(0.034)	(0.028)	(0.039)	(0.001)
Observations	14,252	4,241	6,546	14,252
Number of Utilities	1,304	704	600	1,304

Notes: Table provides summary statistics of key variables used in the utility-level analysis. Column 1 includes the full sample, Column 2 includes pre-treatment years for utilities that deploy AMI between 2010 and 2016, and Column 3 includes all years for utilities that do not deploy AMI through our sample period. The differences of the means in Column 4. Standard errors are in parentheses. Data are from the Energy Information Administration for the years 2007 through 2017.

Table 2: Effect of Smart Meter Deployment on Electricity Loss Rate

Dependent Variable:	Loss Rate (1)	Loss Rate (2)	Loss Rate (3)	Loss Rate (4)
PostAMI	-0.002** (0.001)	-0.003** (0.001)	-0.003** (0.001)	-0.004** (0.002)
Observations	14,252	10,769	12,266	9,268
Estimate as % Change	3.8%	5.0%	5.8%	6.7%
Mean Pre-Treat DV	0.052	0.060	0.052	0.060
Sample Restrictions:				
Omit Initially High Performers		x		x
Include 3+ Years Post-Adoption Only			x	x
Utility FEs	x	x	x	x
State-Year FEs	x	x	x	x
Local Market Controls	x	x	x	x

Notes: Table presents our main results for the average change in loss rate following smart meter roll-outs. In all regressions, we estimate the model of Equation 2 following our 2SLS approach, using a one-year lead of the AMI treatment variable as the excluded instrument for log(population) and the year prior to initial AMI adoption ("-1") as the omitted year. Local market controls include population and new building construction within counties that the utility serves. Coefficients on the instrumental variable in the first stages are between 0.007 and 0.01 and statistically significant at the 10% level. Mean values of dependent variable are calculated using pre-treatment observations for AMI adopters. Standard errors are clustered at the utility level. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table 3: Financial Implications - Revenue and Prices

Dep. Var. (log):	Total Revenue		Average Prices	
	(1)	(2)	(3)	(4)
Panel A: Full Sample				
PostAMI	0.009*	0.013**	-0.003	-0.002
	(0.005)	(0.006)	(0.004)	(0.005)
Observations	14,252	10,769	14,252	10,769
Panel B: 3+ Years Post-Adoption				
PostAMI	0.017*	0.022*	-0.006	-0.005
	(0.010)	(0.012)	(0.007)	(0.009)
Observations	12,266	9,268	12,266	9,268
Mean Pre-Treat DV	$139.8M	$142.2M	$0.097/kWh	$0.102/kWh
Omit Initially High Performers		x		x
Utility FEs	x	x	x	x
State-Year FEs	x	x	x	x
Local Market Controls	x	x	x	x

Notes: Table presents estimates of the effects of smart meter roll-outs on (logged) total revenue (Columns 1-2) and average prices (Columns 3-4). In all regressions, we estimate the model of Equation 2 following our 2SLS approach, using a one-year lead of the AMI treatment variable as the excluded instrument for log(population) and the year prior to initial AMI adoption ("-1") as the omitted year. The full sample is used in Panel A, and in Panel B, we omit the initial year of deployment and the two years that follow. Local market controls include population and new building construction within counties that the utility serves. Mean values of dependent variable are calculated using pre-treatment observations for AMI adopters. Standard errors are clustered at the utility level. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table 4: Provision of Complementary Products

Dependent Variable:	Dyn. Pricing (1)	Dem. Resp. (2)	Sales/ Cust. (3)	Sales/ Cust. (4)	Loss Rate (5)	Loss Rate (6)
PostAMI	0.039**	0.033**	0.020**	0.020***	-0.002**	-0.002*
	(0.017)	(0.015)	(0.009)	(0.007)	(0.001)	(0.001)
AMI x DP			-0.034*		0.001	
			(0.018)		(0.001)	
DP			0.012		-0.001	
			(0.016)		(0.002)	
AMI x DR				-0.053***		-0.000
				(0.019)		(0.001)
DR				0.024*		-0.001
				(0.013)		(0.001)
Observations	14,252	14,252	14,252	14,252	14,252	14,252
Mean Dep. Var.	0.208	0.112	3.18	3.18	0.052	0.052
Utility FEs	x	x	x	x	x	x
State-Year FEs	x	x	x	x	x	x
Local Mkt. Controls	x	x	x	x	x	x

Notes: Table presents results related to products that could enhance the benefits of AMI (dynamic pricing and demand response programs). In Columns 1-2, dependent variables are indicators for whether utilities offer dynamic pricing or demand response programs, respectively. In Columns 3-4, the dependent variable is (logged) sales per customer, and in Columns 5-6, it is the loss rate. In all regressions, we estimate the model of Equation 2 following our 2SLS approach, using a one-year lead of the AMI treatment variable as the excluded instrument for log(population) and the year prior to initial AMI adoption ("-1") as the omitted year. Mean values of dependent variable are calculated using pre-treatment observations for AMI adopters. Standard errors are clustered at the utility level. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table 5: Investing in Complementary Organizational Capital

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

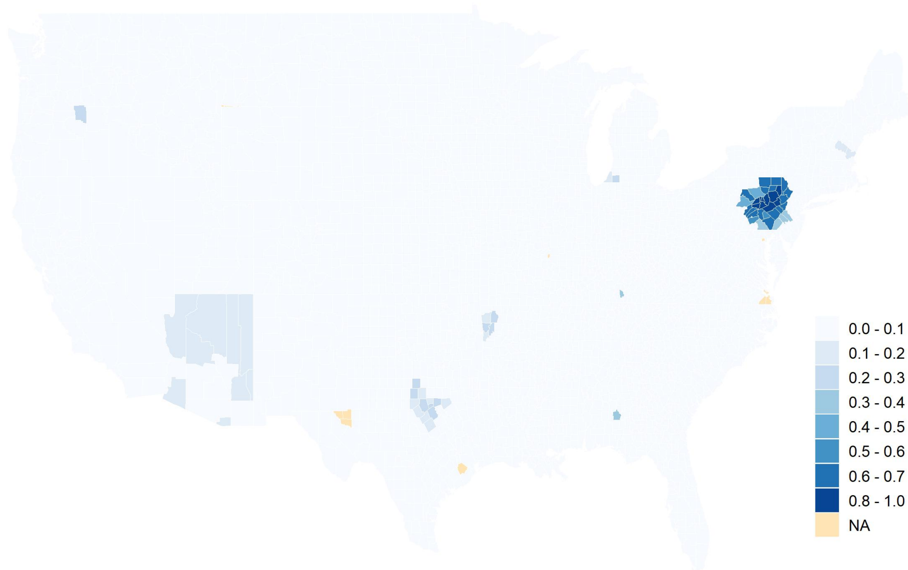
Notes: Table provides results from estimating effects of AMI on the number of employees in meter reader (Columns 1-2) and quantitative data analysis-oriented (Columns 3-4) occupations. Dependent variable is log(employment) and data are at the MSA-occupation-year level. Standard errors are clustered by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

Table 6: Impact of Smart Meters on Power Outages in Texas

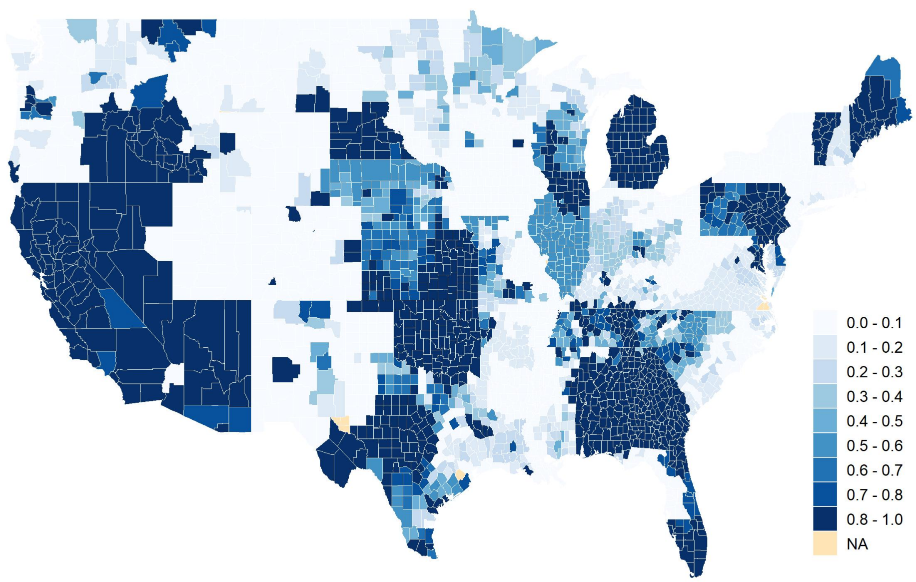
Dependent Variable (ihs):	Outage Duration (SAIDI)		Outage Frequency (SAIFI)	
	(1)	(2)	(3)	(4)
PostAMI	-0.054*	-0.058*	-0.000	-0.013
	(0.028)	(0.031)	(0.013)	(0.015)
Observations	61,233	61,233	61,233	61,233
Mean Pre-Treat DV	91.32	91.32	0.950	0.950
Feeder FEs	x	x	x	x
Year FEs	x	x	x	x
Local Market Controls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

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)

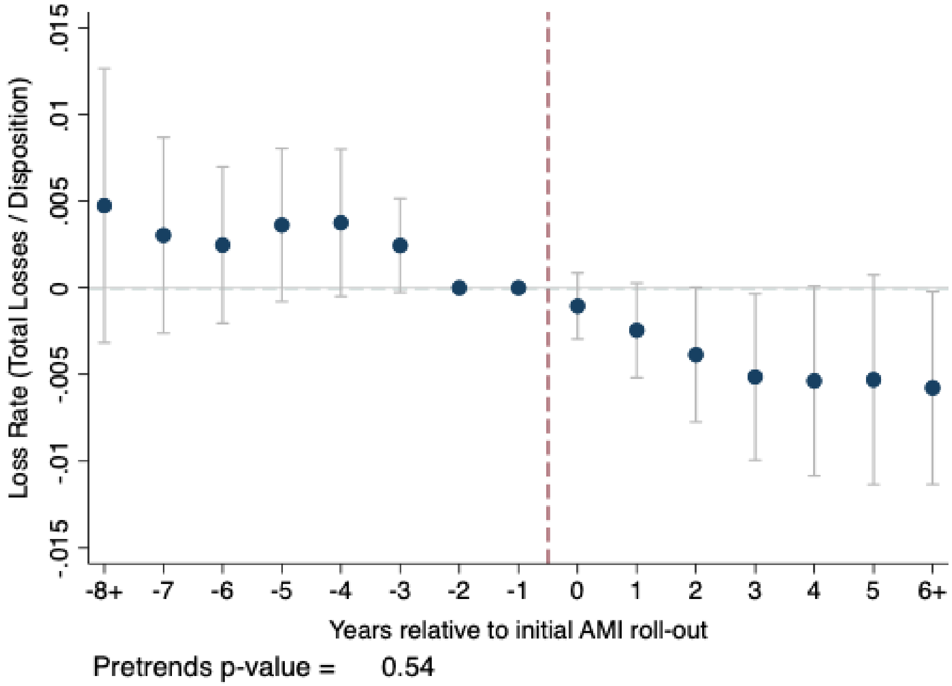


Figure 2: Effect of Smart Meter Deployment on Electricity Loss Rate

Notes: Figure illustrates main results for the effect of AMI deployment on electricity loss rates. Plot provides coefficients β_j and their 95 percent confidence intervals from estimating Equation 1 with our 2SLS estimator, using a one year lead of the AMI treatment variable as the excluded instrument for log(population) and omitting the year prior to initial AMI adoption ("-1"). Utility and state-year fixed effects as well as local market controls are included. Standard errors are clustered at the utility level.

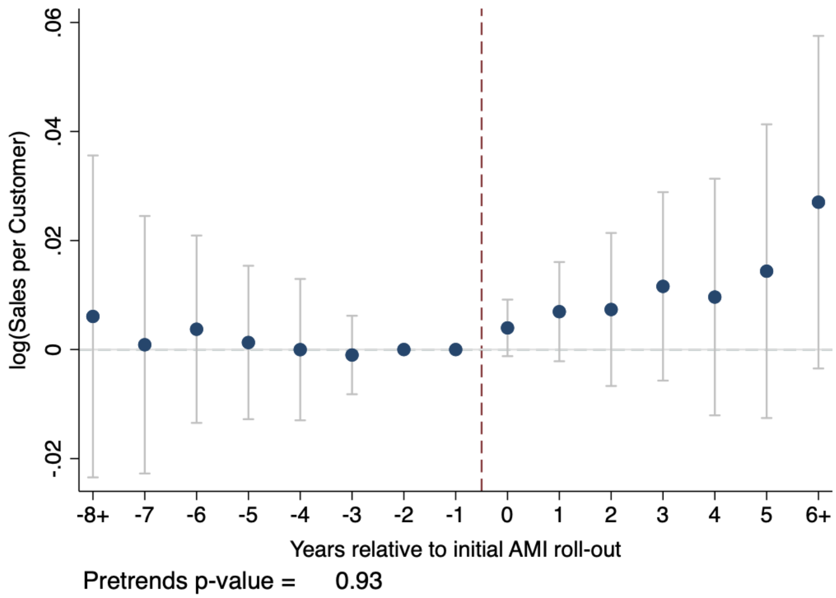
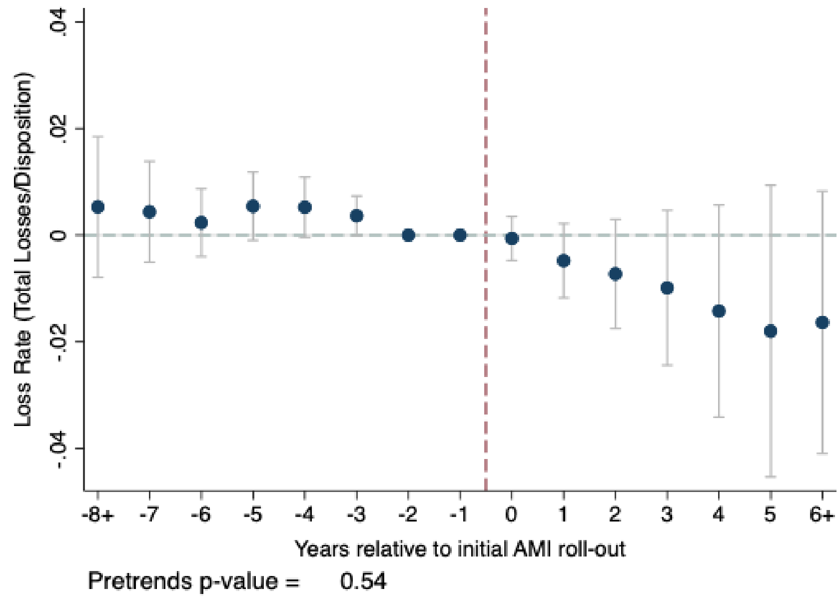
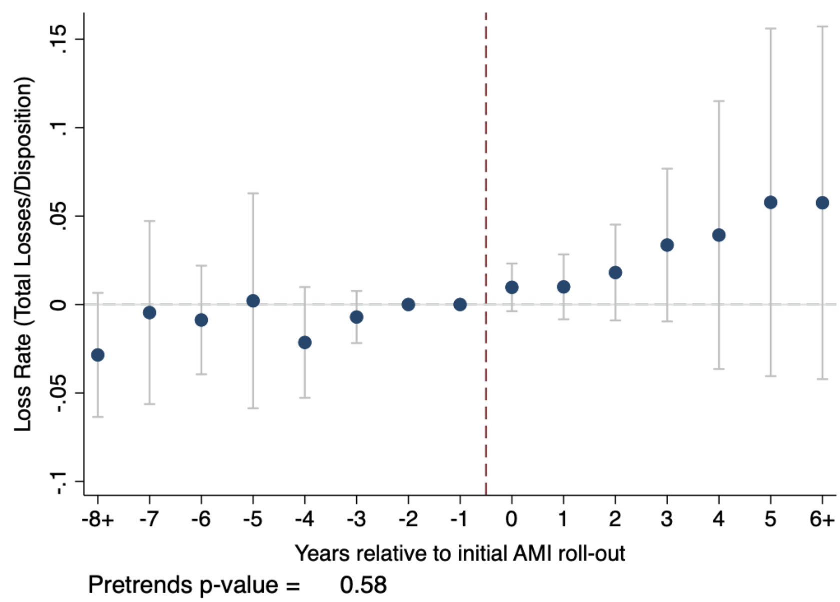


Figure 3: Effect of Smart Meter Deployment on Sales per Customer

Notes: Figure illustrates effect of AMI deployment on (logged) sales per customer. Plot provides coefficients β_j and their 95 percent confidence intervals from estimating Equation 1 with our 2SLS estimator, using a one year lead of the AMI treatment variable as the excluded instrument for log(population) and omitting the year prior to initial AMI adoption ("-1"). Utility and state-year fixed effects as well as local market controls are included. Standard errors are clustered at the utility level.



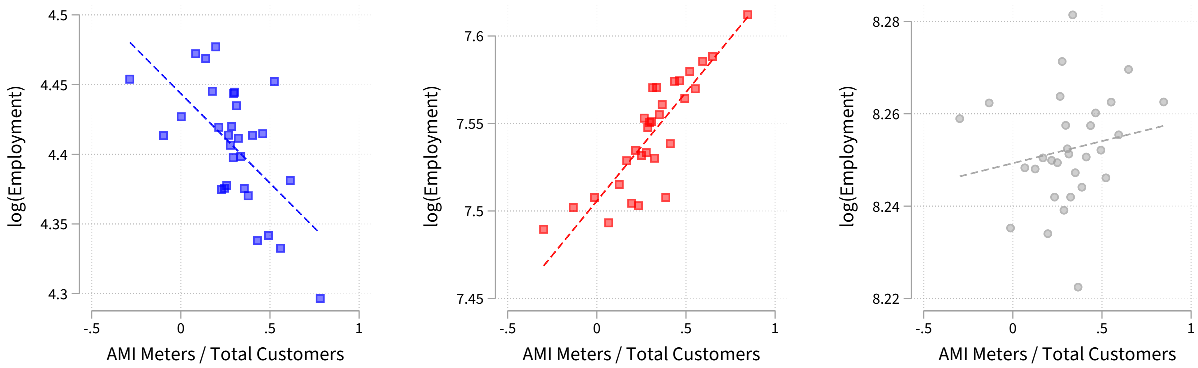
(a) Government-Owned Utilities



(b) Privately-Owned Utilities

Figure 4: Heterogeneity in Smart Meter Effects on Loss Rates by Utility Ownership

Notes: Figure illustrates effects of AMI deployment on loss rates separately for government-owned (Panel A) and privately-owned (Panel B) utilities (IOUs and cooperatives). Plots provide coefficients β_j and their 95 percent confidence intervals from estimating Equation 1 with our 2SLS estimator, using a one year lead of the AMI treatment variable as the excluded instrument for log(population) and omitting the year prior to initial AMI adoption ("-1"). Utility and state-year fixed effects as well as local market controls are included. Standard errors clustered by utility.



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

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

Notes: Figure plots relationship between the proportion of customers with AMI meters and number of employees in the utility sector that are meter readers (Panel A), quantitative and computation workers (Panel B), and other occupations (Panel C). Labor data are at the MSA-occupation level and are aggregated into bins. The outcome variable on the vertical axis is the residual of log(employment) after controlling for MSA fixed effects and local market characteristics (population and new 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 electricity 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. We then calculate the electricity loss rate as the share of total electricity losses relative to total electricity disposition. 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 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. 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 omit utilities that adopted AMI prior to 2010 and after 2016 such that the sample includes all utilities that never adopt and those that do adopt between 2010 and 2016. 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 with respect to loss rates and number of customers. We omit utilities with average pre-treatment loss rates in the top 1% or bottom 1% of the distribution of utilities' average loss rates when they have not adopted AMI as well as utilities with fewer than 20 customers. The final data set used throughout our primary analyses contains 14,252 observations of 1,304 utilities.

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.[44] 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.

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

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

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.[45] 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.

[45] 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: Falsification Test - No Effect on Loss Rate for Utilities with Initially Low Loss Rates in Pre-Treatment Period

Dependent Variable:	Loss Rate (1)	Loss Rate (2)
PostAMI	0.000 (0.003)	-0.000 (0.006)
Observations	3,417	2,907
Mean Dep. Var.	0.029	0.029
Utility FEs	x	x
State-Year FEs	x	x
Local Market Controls	x	x

Notes: Table presents coefficients from estimating effect of smart meter deployment on the loss rate when restricting the sample to only include utilities with low pre-treatment loss rates (i.e., initially high performers). Provides a falsification test, as no effect is expected. All specifications are estimated using our 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 B2: Effect of Smart Meters on Loss Rate Using OLS Instead of 2SLS

Dependent Variable:	Loss Rate (1)	Loss Rate (2)	Loss Rate (3)	Loss Rate (4)
PostAMI	-0.001*	-0.002***	-0.002	-0.003**
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	15,556	11,754	13,455	10,172
Mean Dep. Var.	0.052	0.059	0.052	0.059
Sample Restrictions:				
Omit Initially High Performers		x		x
Include 3+ Years Post-Adoption Only			x	x
Utility FEs	x	x	x	x
State-Year FEs	x	x	x	x
Local Market Controls	x	x	x	x

Notes: Table presents estimates from running the same regressions as in the main results table (Table 2) but using OLS rather than 2SLS for comparison. The dependent variable is the loss rate in all cases. Local market controls are (ihs) new construction build and (log) population. Standard errors are clustered at the utility level. Asterisks denote $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$.

Table B3: Doubly-Robust Stacked Diff-in-Diff Estimates

Dep. Var.:	Loss Rate (1)	Loss Rate (2)	Loss Rate (3)	Loss Rate (4)
PostAMI	-0.002** (0.001)	-0.003*** (0.001)	-0.002** (0.001)	-0.003*** (0.001)
Observations	14,259	10,786	14,259	10,786
Control Group	Never Treated	Never Treated	All	All
Sample	Full	Omit High Perf.	Full	Omit High Perf.
Utility FEs	x	x	x	x
State-Year FEs	x	x	x	x
Controls	x	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. In Columns 1 and 2, only utilities that are never treated are included in the control group and untreated observations are included in the control group in Columns 3 and 4. In Columns 2 and 4, we omit the bottom quartile of the pre-treatment loss rate distribution (i.e., high pre-treatment performers). The dependent variable is the loss rate in all cases. Local market controls are (ihs) new construction build and (log) population. Standard errors are clustered at the utility level. Asterisks denote *$p<0.10$, **$p<0.05$, ***$p<0.01$.

Table B4: SUTVA - Investigating Whether Spillovers Bias the Results

Dependent Variable:	Loss Rate	Imports	Exports
	(1)	(2)	(3)
PostAMI	-0.002**	-0.027	-0.079
	(0.001)	(0.066)	(0.067)
Post Neighbor Adopting	-0.000		
	(0.001)		
Observations	14,252	14,252	14,252
Mean Dep. Var.	0.052	0.422	0.409
Utility FEs	x	x	x
State-Year FEs	x	x	x
Local Market Controls	x	x	x

Notes: Table provides results from tests exploring whether SUTVA might be violated. The dependent variable in Column 1 is the loss rate. In Columns 2 and 3, it is (ihs) imported and exported electricity from neighboring utilities, respectively. 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: Robustness Checks for Reorganization of Workers Results

Dep. Var. (log):	Number of Employment			
	(1)	(2)	(3)	(4)
Panel A: Exclude MSAs with AMI Deployment 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 with AMI Deployment 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 when restricting the sample in different ways that align with the restrictions imposed in our main analyses using utility-level data. In Panel A, we exclude MSAs with any AMI deployment before 2008 or after 2017. In Panel B, we exclude MSAs with any AMI deployment before 2009 or after 2017. 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 B6: 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)
Loss Rate (%)	0.048	0.057	0.045	0.058	0.050	0.060
	(0.027)	(0.023)	(0.024)	(0.022)	(0.028)	(0.027)
Total Losses (000s MWh)	22.59	116.64	29.30	131.52	13.00	88.38
	(90.10)	(388.52)	(95.93)	(455.24)	(21.99)	(220.58)
Total Sales (000s MWh)	477	1964	635	2153	273	1533
	(1414)	(6035)	(1679)	(6757)	(472)	(4228)
Total Revenue (million)	45.9	206.2	57.3	213.7	25.1	156.2
	(169.7)	(702.1)	(180.3)	(757.4)	(42.9)	(401.1)
Number of Customers (000s)	17.88	103.10	22.51	98.21	10.32	81.61
	(60.70)	(369.85)	(66.56)	(364.38)	(21.35)	(212.67)
Sales per Customer (MWh)	36.71	24.27	29.90	24.42	42.23	24.44
	(190.01)	(19.65)	(13.13)	(19.72)	(251.15)	(21.59)
Rev. per Customer (000s)	3.31	2.37	2.63	2.26	3.79	2.39
	(16.18)	(1.35)	(0.94)	(1.23)	(21.39)	(1.52)
Average Prices ($/kWh)	0.097	0.109	0.093	0.101	0.097	0.112
	(0.028)	(0.040)	(0.022)	(0.032)	(0.031)	(0.051)
Observations	7,709	6,543	2,004	2,237	4,399	2,147
No. of Utilities	707	597	303	401	404	196

Notes: Table provides summary statistics of key variables by ownership type (government-owned vs. non-government-owned, 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.

C Appendix: Additional Figures (For Online Publication)

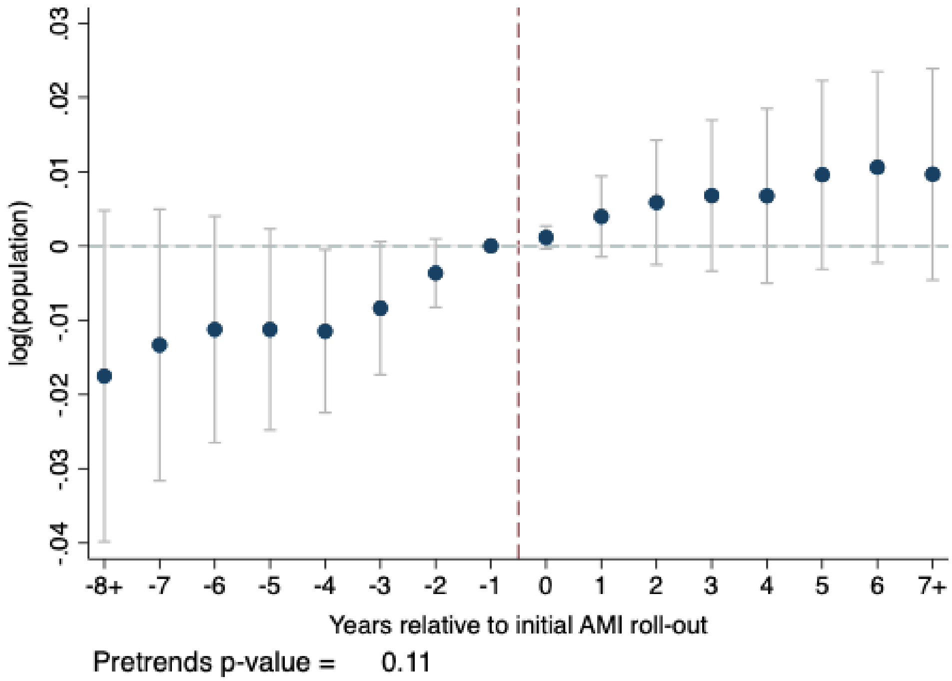
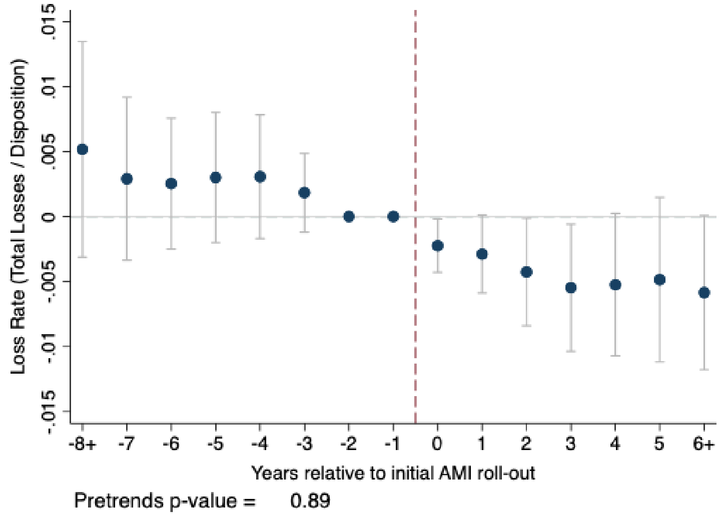
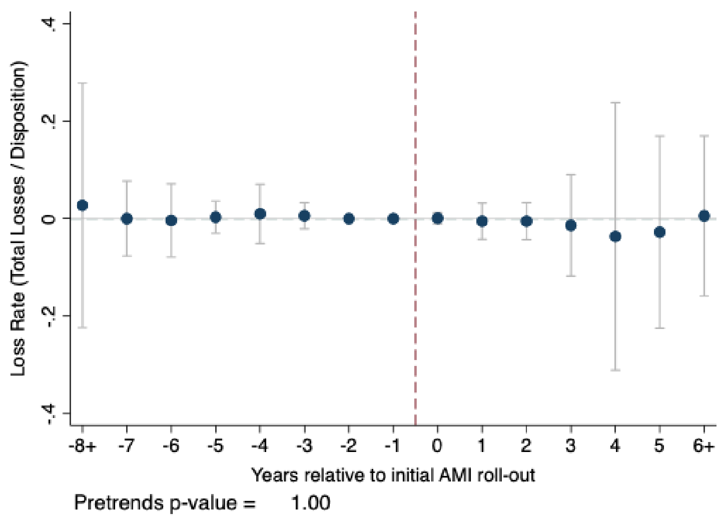


Figure B1: Dynamics of (Log) Population Around the First Year of Smart Meter Deployment

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.



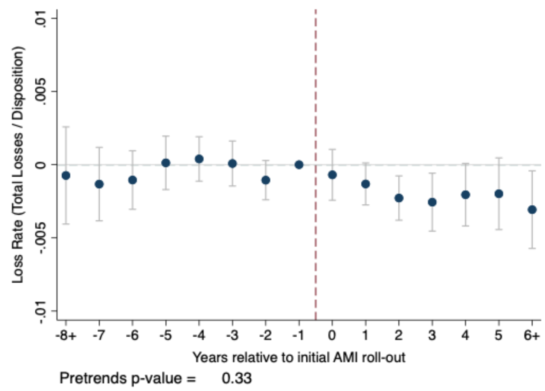
(a) High Pre-Treatment Loss Rate



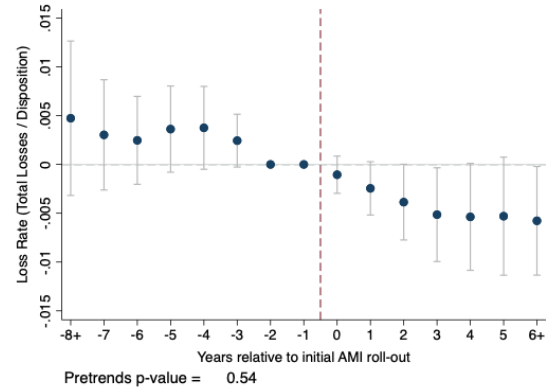
(b) Low Pre-Treatment Loss Rate

Figure B2: Heterogeneous Effects of Smart Meter Deployment on Loss Rate by Pre-Treatment Performance

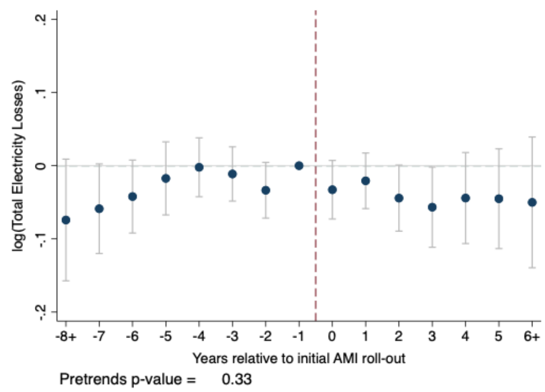
Notes: Figure illustrates heterogeneous effects of AMI deployment on loss rates by pre-treatment performance. Panel A includes utilities that were above the bottom quartile of the pre-treatment loss rate distribution (i.e., initially poor performers) and Panel B includes utilities that were in the bottom quartile (i.e., initially high performers). Plots provide coefficients β_j and their 95 percent confidence intervals from estimating Equation 1 with our 2SLS estimator, using a one year lead of the AMI treatment variable as the excluded instrument for log(population) and omitting the year prior to initial AMI adoption ("-1"). Baseline fixed effects and controls included. Standard errors are clustered at the utility level.



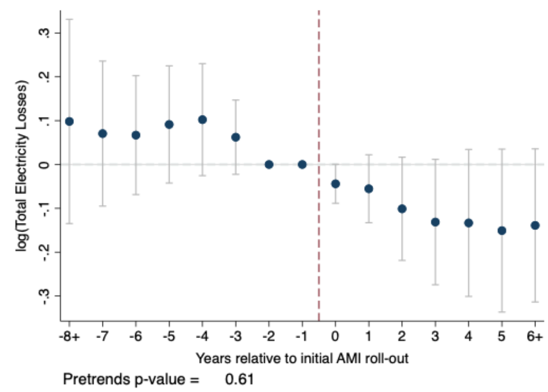
(a) Loss Rate, OLS



(b) Loss Rate, 2SLS (Main Results)



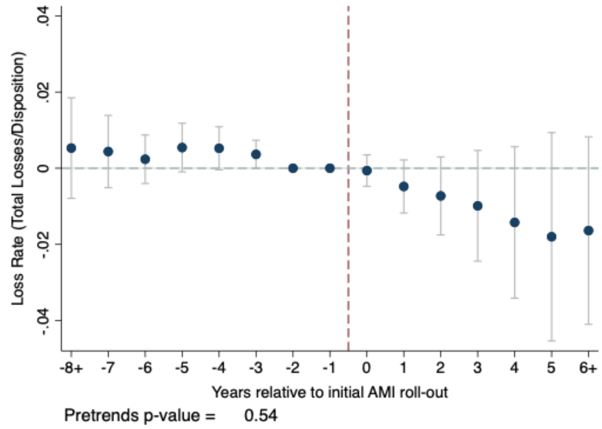
(c) Total Losses, OLS



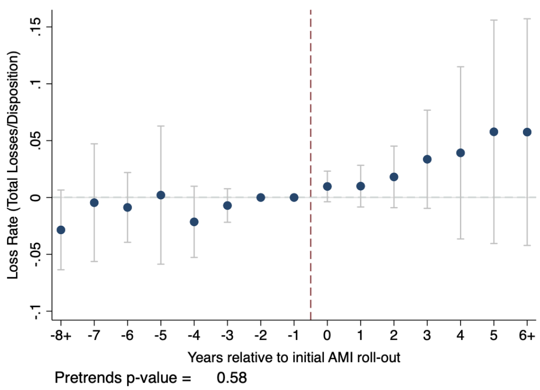
(d) Total Losses, 2SLS

Figure B3: Comparison of Results When Using OLS versus 2SLS Augmentation

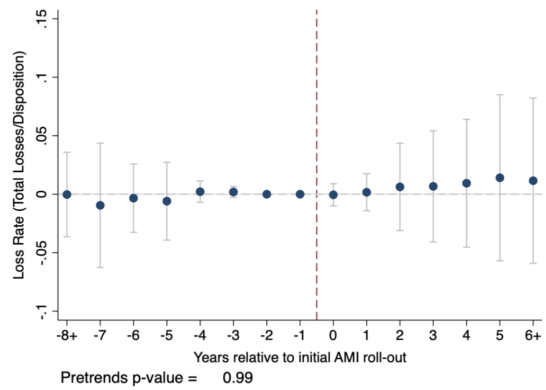
Notes: Figure illustrates the importance of implementing our 2SLS estimator to examine the effects of AMI deployment by comparing the effects on losses when just using OLS (Panels A and C) relative to when using the 2SLS approach (Panels B and D). Plots provide coefficients β_j and their 95 percent confidence intervals from estimating Equation 1, omitting the year prior to initial AMI adoption ("-1"). In Panels B and D, we use a one year lead of the AMI treatment variable as the excluded instrument for log(population). In Panel A, there is a slight pre-trend in loss rates, and since this could be dampened by an opposing pre-trend in total disposition, we also look at total losses and find a stronger pre-trend (Panel C). These pre-trends disappear when using the 2SLS approach. Utility fixed effects, state-year fixed effects, and local market controls are included. Standard errors are clustered at the utility level.



(a) Government-Owned Utilities



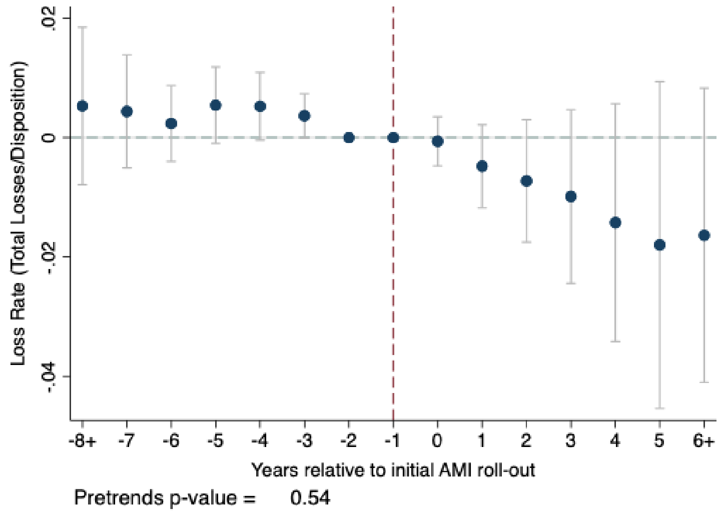
(b) Investor-Owned Utilities



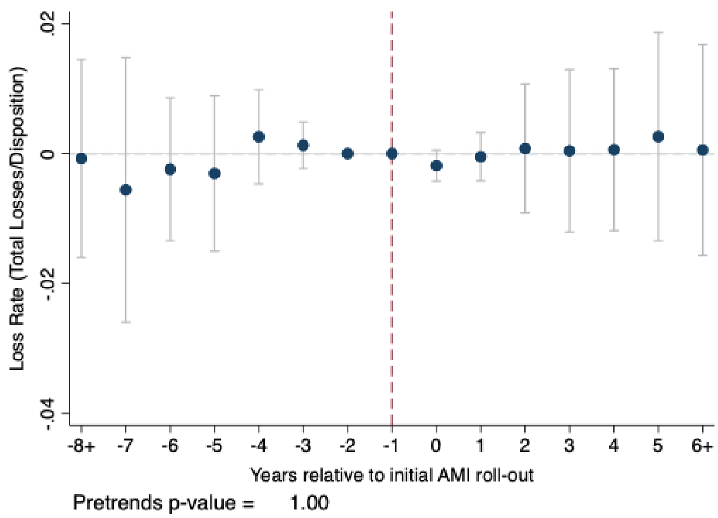
(c) Cooperatives

Figure B4: Heterogeneity in Smart Meter Effects on Loss Rates by Utility Ownership

Notes: Figure illustrates heterogeneous effects of AMI deployment on loss rates by utility ownership. Plots provide coefficients and their 95 percent confidence intervals from estimating Equation 1 separately for government-owned utilities (Panel A), investor-owned utilities (Panel B), and cooperatives (Panel C) using our 2SLS estimator approach and omitting the year prior to initial AMI adoption ("-1"). Utility fixed effects, state-year fixed effects, and local market controls are included. Standard errors are clustered by utility.



(a) Government-Owned



(b) Privately-Owned

Figure B5: Heterogeneous Effects of Smart Meter Deployment on Loss Rate by Ownership for "Smaller" Utilities

Notes: Figure plots heterogeneous effects of smart meter deployment on loss rates by utility ownership when omitting "large" privately-owned utilities, defining large as those with a pre-treatment average size exceeding the maximum pre-treatment average size of government-owned utilities. This provides a sample of comparably-sized utilities with 16% of IOUs omitted. Government-owned utilities are included in Panel A and privately-owned utilities (i.e., investor-owned and cooperatives) are in Panel B. Plots provide coefficients β_j and their 95 percent confidence intervals from estimating Equation 1 with our 2SLS estimator, using a one year lead of the AMI treatment variable as the excluded instrument for log(population) and omitting the year prior to initial AMI adoption ("-1"). Utility fixed effects, state-year fixed effects, and local market controls are included. Standard errors are clustered at the utility level.