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The impact of new technologies within and across industries is only felt through their widespread diffusion, yet studies of technology diffusion are scarce compared to other aspects of the innovation process. The electric power industry is one industry that is currently undergoing substantial change as a result of both technological and institutional innovations. In this dissertation I examine the economic rationale for the adoption of smart meters by electric power utilities and the relationship between smart meters and the evolving electric power industry. I contribute to empirical research on technology diffusion by studying the early diffusion of smart meters in the US electric power industry.

Using a panel dataset and econometric models, I analyze the determinants of both the interfirm and intrafirm diffusion of smart meters in the United States. The empirical findings suggest multiple drivers of smart meter diffusion. Policy and regulatory support have had a significant, positive impact on adoption but have not been the only relevant determinants. The findings also suggest that utility characteristics and some combination of learning, cost reductions, and technology standards have been important determinants affecting smart meter diffusion. I also explore the policy implications resulting from this analysis for enhancing the diffusion of smart meters. The costs and benefits of adopting smart meters have been more uncertain than initially thought, suggesting that some policy support for adoption was premature. The coordination of policies is also necessary to achieve the full benefits of using smart meters.

THE EARLY DIFFUSION OF SMART METERS IN THE US ELECTRIC POWER INDUSTRY

by

Derek Ryan Strong

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CHAPTER I
INTRODUCTION

This dissertation is an empirical study of the diffusion of a process innovation. Specifically, it studies the diffusion of smart electricity meters in the electric power industry of the United States. Smart meters refer to advanced electricity meters based on digital technology that are capable of recording electricity consumption data in hourly intervals or less and are also capable of two-way communication between the electric power utility and the consumer. Smart meters are considered a key technology for building smart electric power grids that use information and communication technology to efficiently and reliably match supply and demand in electricity markets. Smart meters enable time-varying pricing of electricity in retail markets and a more flexible demand side than has been the case historically. They also provide a basis for further innovation related to consumer engagement about electricity use.

The research herein adds to the body of knowledge on the diffusion of new technologies and has important public policy implications for innovation in the electric power industry. Furthermore, this research examines the adoption of technology in a heavily regulated industry, and therefore regulation plays a more important role here than in most diffusion studies. In this chapter I provide definitions and conceptual depictions of innovation and diffusion processes, basic information on smart metering technology, and specific research questions, all of which will aid in understanding the research as a whole.

1.1 The Innovation Process

Innovation can be defined generally as the implementation of a new idea. A new idea can take the form of a technology or institution, for example. The economics of innovation evolved from the economic study of science and technology. Science can be defined as the search for knowledge and technology can be defined as the application of scientific knowledge toward certain practical ends, typically in the form of tools (Audretsch et al. 2002, 156).

Technology also has both hardware and software dimensions. The hardware dimension refers to an artifact itself, or the physical aspects of a tool. The software dimension refers to an artifact's information base, or the ability to use a tool. Additionally, the knowledge embedded in technology has both a codified and tacit dimension. The context within which technology is developed and used, such as the organizational structure within firms, is another important dimension. These multiple characteristics of a technology affect the nature of its diffusion, making it less than straightforward (Rogers 2003, 12-14; Dosi and Nelson 2010, 91–93).

There are arguably three main stages in the process of technological change: invention, innovation, and diffusion. This trilogy, often attributed to Schumpeter (1939), highlights the difference between invention and innovation. Invention refers to the generation of new technology whereas innovation refers to the practical use of new technology. The mere creation of a new technology does not imply that it will be used. Entrepreneurship, then, plays a crucial role in bridging the invention and innovation stages. Diffusion refers to the spread of a new technology through an economy. Similarly, technology, if used, does not necessarily diffuse widely (Audretsch et al. 2002; Dosi and Nelson 2010, 91–93).

Conceptual models of the innovation process provide a useful means for summarizing the stages of the process and their interrelatedness. The early linear model of

innovation, often attributed to Bush ([1945] 1960), proposed that basic scientific knowledge led to applied scientific knowledge in the form of technology that then led to the commercialization and diffusion of that technology, captured in the Schumpeterian trilogy. Although the linear model helps frame discussion of the innovation process by identifying basic stages, it has been critiqued for having little empirical support for its sequential nature. Practical demands for or actual use of technology, for example, may necessitate or influence basic scientific research, and innovation may continue over time as a technology is improved during its diffusion. Nonlinear models of innovation modify the linear model by, for instance, adding feedback loops among the stages, indicating the systemic and interactive nature of the innovation process (Kline and Rosenberg 1986; Rogers 2003, 138; Godin 2006; Balconi, Brusoni, and Orsenigo 2010). Grupp (1998, 19) provides one such model where innovation does not necessarily proceed sequentially in time from basic research to technology development to diffusion and where these may occur in parallel, as depicted in Figure 1. This model highlights the interdependency and ambiguity of relationships of the stylized stages of the innovation process often found in the real world. The linear model persists in some form, however, because it offers a simple and useful heuristic for initially thinking about innovation and identifying key elements of the process (Balconi, Brusoni, and Orsenigo 2010).

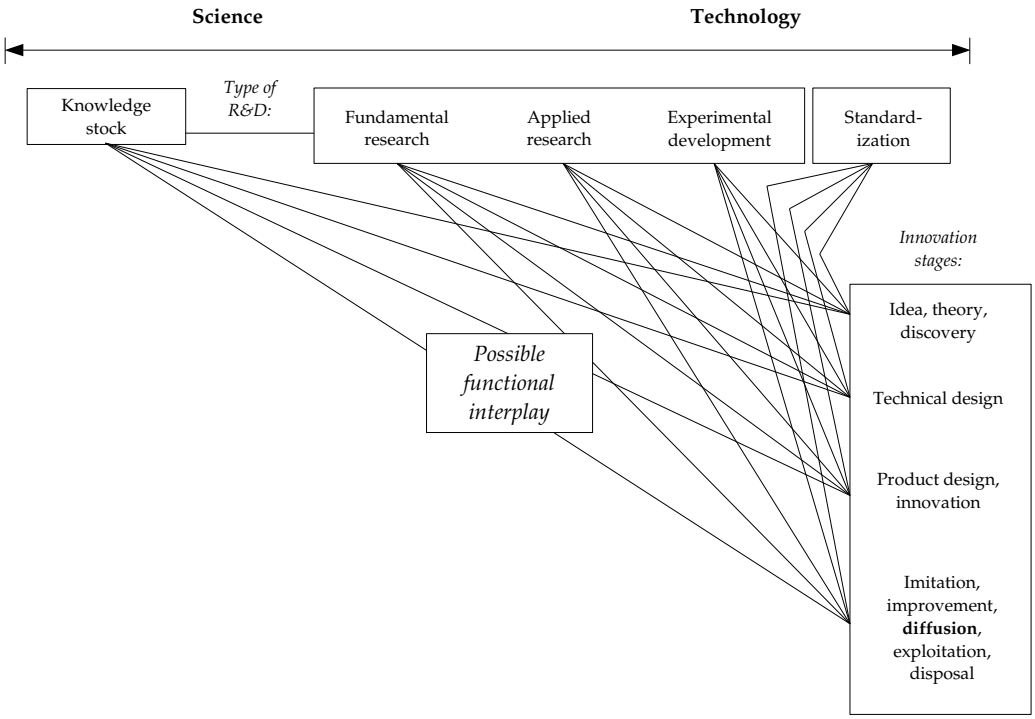


Figure 1. A Nonlinear Model of Innovation. Adapted from Grupp (1998, 19).

The diffusion stage of the innovation process is the focus of this dissertation but its study should not neglect the interactions that link it to the other stages. Decisions made early in an R&D process can impact the future path of diffusion (Grupp 1998, 20–21; Rogers 2003, 136–137; Ortt 2010). Diffusion may also be linked to R&D through supply-demand interactions (Stoneman 1987b, 80–97), and technologies may change and essentially be invented during their diffusion process (Bijker 1992). Such interactions may be termed "innofusion" and also highlight the potential importance of user innovation (Fleck 1988; Hippel 2010). The diffusion of technologies may also require R&D on the part of adopting firms in order for them to adapt technology to their needs, which can be termed "re-invention" (Rogers 2003, 180–188) or "creative adoption" (Antonelli 2006).

1.2 The Diffusion Process

Technological diffusion has several characteristics and is itself a process. Diffusion can be defined as the process by which an innovation is communicated through certain channels over time among the members of a social system (Rogers 2003, 5) or as the process by which an innovation spreads through an economy over time (Stoneman 2002, 3). Research on diffusion is multidisciplinary, including the fields of economics, marketing, management, sociology, anthropology, communication, and geography (Rogers 2003, 44–45). Each field may focus on different aspects of the diffusion process and use different methods of analysis, but they all study the same phenomenon and their respective research is relevant to other fields. Crossdisciplinary awareness has grown over time, but work remains to be done in advancing truly interdisciplinary research (Katz, Levin, and Hamilton 1963; Warner 1974; Ruttan 1996; Rogers 2003, 40). Although technological diffusion was well-studied during the early years of the economic study of innovation, research in this area has waned over time and focus has shifted to topics such as R&D and technology transfer from universities to industry. Many questions and avenues of research remain open, and the importance of technological diffusion for advancing productivity and economic growth and development suggest that it should be studied more than it currently is (Stoneman 2002, 303–306).

The multidisciplinary research on the diffusion of innovations has identified four fundamental elements of the diffusion process: the innovation, communication channels, time (and space), and the social system (Rogers 2003, 11). An innovation can be characterized by five attributes: relative advantage, compatibility, complexity, trialability, and observability (Rogers 2003, 15–16). There are also three types of adoption decisions: optional, collective, and authority (Rogers 2003, 28–30). The decision-making process of adopting an innovation has five sequential stages: knowledge, persuasion, decision, implementation, and confirmation (Rogers 2003, 169–170). All of these factors,

in addition to the promotional efforts of change agents, affect the rate of diffusion of an innovation (Rogers 2003, 221–223). The adoption of innovations can also be discontinued, either from failure to realize benefits or the adoption of superior innovations. For organizations like firms the decision-making process may be more complex (Gold 1980, 1981), involving agenda setting, matching, redefining and restructuring, clarifying, and routinizing (Rogers 2003, 421).

New technologies manifest themselves as product innovations or process innovations. The development and marketing of a new technology by a firm, for example, is a product innovation from that firm's perspective. If the new technology is a capital good, then from the perspective of a user firm this technology is a process innovation because it alters the production process of that firm. The diffusion of process technologies can be studied at different levels, including international, intranational, interindustry, intraindustry, interfirm, and intrafirm levels. Interindustry diffusion refers to the economy-wide spread of a technology whereas intraindustry diffusion refers to the spread within a specific industry. Interfirm diffusion refers to the adoption of technology across firms, or the extensive margin of use, whereas intrafirm diffusion refers to the intensity of use of technology within firms, or the intensive margin of use (Stoneman and Battisti 2010).

Important stylized facts about the diffusion of technology are that diffusion takes time and that rates of diffusion vary across technologies, industries, and countries (Stoneman 2002, 12–26). It is also the case that many technologies never diffuse. There are numerous other stylized facts as well (Kemp and Volpi 2008):

(1) Firms can adopt different technologies and the diffusion of one technology influences the diffusion of another, making diffusion difficult to predict.
(2) Diffusion involves the transfer of information.
(3) Diffusion is more than simply the transfer of information.

(4) Technologies that are economically attractive will have a faster rate of diffusion and a higher level of diffusion.
(5) Technologies that are economically attractive do not diffuse instantaneously.
(6) Technologies steadily improve during their diffusion.
(7) Expensive and complex technologies typically diffuse more slowly.
(8) The population of potential adopters changes over time.
(9) Diffusion typically follows an S-shaped curve.

This last fact refers to the measurement of a diffusion process at a macro level that often results in an S-shaped pattern of growth over time.

Diffusion metrics can be aggregated at the industry or national level or disaggregated at the firm level. In the interfirm case diffusion is often measured using the cumulative number of adopters, as depicted in Figure 2a. Mathematically this interfirm diffusion metric is given by

$$m_t = \sum a_t$$

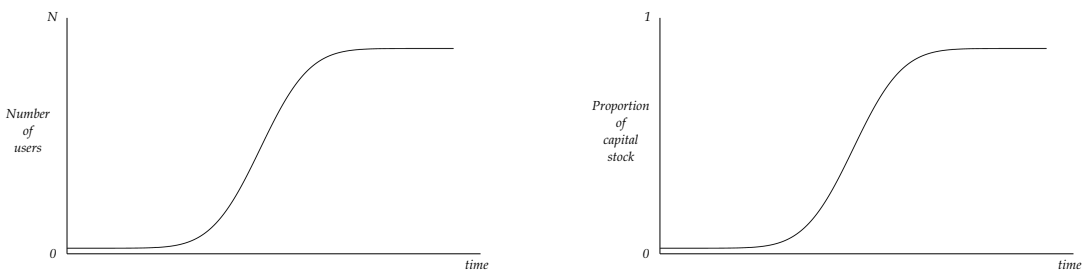
where m_t denotes the cumulative number of adopters a_t at time t. An alternative diffusion metric for the interfirm case is given by

$$M_t = \frac{m_t}{n_t}$$

where M_t denotes the proportion of adopters at time t determined by the number of current adopters m_t and total number of potential adopters n_t at time t (Karshenas and Stoneman 1995, 266).

The S-curve depicts four stages in a successful diffusion process or technological lifecycle: the introduction of an innovation, early growth in adoption, maturation and take-off, and saturation. An additional stage, not shown, can occur when a technology

becomes obsolete or is superseded by a new, superior innovation and subsequently declines. Viewing diffusion as a multistage process implies that the adoption environment and the determinants of diffusion can change over time such that diffusion must be analyzed in the appropriate context and with respect to other diffusion processes. Diffusion emerges at the macro level from the diversity and interaction of adoption decisions of individual firms at the micro level in a continually changing adoption environment (Grübler 1991).



a. Stylized S-curve for Interfirm Diffusion. **b.** Stylized S-curve for Intrafirm Diffusion.

Figure 2. Stylized Diffusion Patterns.

Intrafirm diffusion also typically follows an S-shaped pattern of growth as depicted in Figure 2b. Intrafirm diffusion is often measured by the proportion of the capital stock embodied in a new technology for a particular firm. Mathematically this intrafirm diffusion metric is given by

$$L_{it} = \frac{J_{it}}{K_{it}}$$

where L_{it} denotes the proportion of the capital stock embodied by a new technology for firm i at time t determined by the amount of new technology capital stock J_{it} and the

total capital stock K_{it} for firm i at time t. An alternative diffusion metric for the intrafirm case is given by

$$Z_{it} = \frac{X_{it}}{Y_{it}}$$

where Z_{it} denotes the proportion of output produced by a new technology for firm i at time t determined by the output produced by the new technology X_{it} and the total output produced Y_{it} for firm i at time t (Karshenas and Stoneman 1995, 266).

Furthermore, adopters may have different characteristics that place them in distinct adopter categories based on when they adopt, as depicted in Figure 3. Innovators, for example, may be more tolerant of uncertainty or possess a greater degree of innovativeness than other potential adopters and subsequently adopt earlier. The heterogeneity of adopter characteristics plays an important role in theories of technological diffusion.

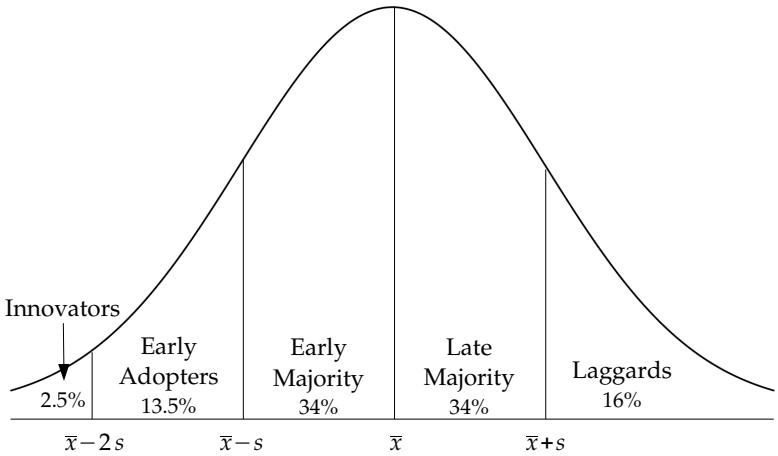


Figure 3. Stylized Categories of Adopters by Innovativeness. Adapted from Rogers (2003, 281), where $\bar{x}$ denotes mean adoption time and s denotes one standard deviation.

Existing research has highlighted a number of influential determinants in diffusion processes (Stoneman 2002, 52):

(1) Learning and the spread of information
(2) The cost of adopting new technology
(3) The performance of new technology
(4) Price expectations
(5) Technology expectations
(6) Firm characteristics and their distributions
(7) Discount factors and attitudes toward risk
(8) The extent of product differentiation
(9) The extent of first mover advantages
(10) The impact of other firms' adoption decisions
(11) The extent to which realized profits generate new investment

Diffusion theory attempts to explain why technological diffusion is not instantaneous.

1.3 Theoretical Perspectives on Technology Diffusion

Although this dissertation is primarily empirical, different theoretical perspectives may influence the interpretation of empirical data and the choice of empirical methods (Sarkar 1998, 155–158). At the same time, it is possible to use a general empirical model to assess the various theoretical factors in the adoption of technology (Karshenas and Stoneman 1993). The study of technology diffusion, like the study of innovation or the economy more broadly, can be approached from two distinct theoretical perspectives: neoclassical or evolutionary economics. Both schools of thought have developed within the economics of innovation over time as theoretical and empirical work has progressed. In particular, evolutionary thinking in innovation studies developed from the empirically observed importance of heterogeneity, bounded rationality, interaction, learning, and path dependency in innovation processes, aspects which are

usually not emphasized or easily accounted for in neoclassical thinking (Verspagen and Werker 2003; Antonelli 2009).

In general, neoclassical and evolutionary perspectives on the nature of economic reality are significantly different. These different viewpoints are essentially ontological, with the neoclassical approach presupposing a closed, mechanistic system and the evolutionary approach presupposing an open, processual system (Dopfer and Potts 2008, 1–14). The neoclassical perspective typically views the economy in static terms and emphasizes equilibrium states and exogenous change, using static tools to analyze the economy. Neoclassical modeling involves assumptions of unbounded rationality for economic agents where any uncertainity is reduced to risk. These models assume maximizing behavior where agents find optimal solutions. In contrast, the evolutionary perspective views the economy in dynamic and evolutionary terms and emphasizes the disequilibrium and endogenous nature of change and growth, using dynamic tools to analyze the economy. Evolutionary modeling involves assumptions of bounded rationality for economic agents in truly uncertain environments where the concepts of variety and selection play an important role. These models assume satisficing behavior where agents find adequate solutions (Nelson 1995; Grupp 1998, 51–52; Sarkar 1998; Nelson and Winter 2002; Dosi and Nelson 2010).

For the study of technology diffusion specifically, the neoclassical perspective views diffusion as a sequence of changing equilibrium states whereby one equilibrium level of technology adoption transitions to another equilibrium based on exogenous changes over time affecting the profitability considerations of firms. The evolutionary perspective views diffusion as a disequilibrium process whereby the technology, firms, and the adoption environment change continuously and endogenously over time leading to a self-propagating process through learning and selection pressures. Despite these differences, both approaches share in common an emphasis on the heterogeneity of firms with respect to their needs, capabilities, and other characteristics like size.

Additionally, the neoclassical approach may be more adequate in certain contexts, such as relatively certain adoption environments, and the evolutionary approach may be more appropriate in other contexts, such as relatively uncertain adoption environments (Sarkar 1998; Nelson, Peterhansl, and Sampat 2004; Dosi and Nelson 2010, 91–93; Stoneman and Battisti 2010).

1.4 Electricity and Smart Meters

Based on theories of the diffusion of new technologies, this dissertation assesses empirically the relative importance of various determinants in the diffusion of smart electricity meters in the United States. Electricity meters, in general, measure the consumption of electricity. Electricity is a form of energy, electrons in motion that carry electrical charge. It has two components: voltage and current. Voltage refers to the difference in electrical charge between two points, or the potential ability of electrons to do work. Current refers to the flow of electrical charge. Electricity is a secondary energy source generated from primary sources such as coal (nonrenewable) or wind (renewable). An important aspect of electricity is that supply and demand must be equal at every instant because storage is not economically viable with current technology (EIA 2017b).

Electricity has come to be viewed as a general purpose technology, used to power lighting, electric motors, and other applications. The use of electrical energy has spawned further innovation especially in the application of electric motors to various end uses. Electricity is now a basic input to most production processes and has arguably led to significant productivity improvements over other sources of energy, in industry as well as in the home. The efficiency of its use and the reliability of its supply is of great importance for modern economies (Rosenberg 1998; Bresnahan 2010).

Electricity meters have historically measured electrical energy, the total consumption of electricity (i.e., kilowatt-hours, or kWh). Some meters have also measured electric

power, the rate at which electricity is being consumed (i.e., kilowatts, or kW). Advanced meters available today possess the same functions as well as additional capabilities. They are able to measure and record consumption in real time. Smart meters refer to a specific type of advanced electricity meter based on digital technology that are capable of two-way communication between the electric power utility and the consumer. Smart meters are a product innovation from the meter manufacturer's perspective but they are a process innovation from the electric power utility's perspective. Furthermore, smart meters are one component of an advanced metering infrastructure that also includes communication networks and meter data management systems.

Smart meters are considered an enabling technology critical for the development of a smart electric power grid that efficiently and reliably matches supply and demand in electricity markets. These advanced meters provide capabilities for time-varying pricing of electricity, automated meter reading, and automated outage management among other uses. Smart meters can lead to more efficient use of electricity through real-time monitoring and analysis of consumption, especially through reductions in electricity use at times of peak demand when the power grid is most stressed. They can also aid in the integration of distributed generation and storage resources and electric vehicles onto the power grid through import-export measurement functions. Smart meters can have a positive environmental impact as a result of these capabilities. In addition to these benefits, smart meters also have costs. They are more expensive than other types of meters and they raise privacy, security, and health concerns (NETL 2008; EEI 2011).

Smart meters are currently halfway diffused in the United States as measured by the number of smart meters in use compared to the total number of meters, indicating that the diffusion process is ongoing (IEI 2016a; EIA 2017a). This should not, however, discourage a study of the diffusion of smart meters so far. Diffusion processes should be studied at successive stages in order to arrive at a fuller understanding of their determi-

nants. It is not guaranteed that smart meters will diffuse completely. This approach also provides a means to overcome the pro-innovation bias of much diffusion research that results from exclusively studying successful innovations ex post (Rogers 2003, 112–113). Therefore, this dissertation studies the *early* stage in the diffusion of smart meters.

1.5 Research Questions

There are three research questions addressed in this dissertation:

(1) What factors have influenced the interfirm diffusion of smart meters?
(2) What factors have influenced the intrafirm diffusion of smart meters?
(3) What are the policy implications for enhancing the diffusion of smart meters?

I will attempt to answer these questions in two main chapters, one analyzing the determinants of the interfirm and intrafirm diffusion of smart meters and the other assessing smart meter diffusion policies.

The analysis in this dissertation contributes to empirical research on technological diffusion by examining both the interfirm and intrafirm diffusion of a new technology in the context of a highly regulated industry. One contribution of this dissertation is its exclusive focus on diffusion, which is arguably understudied in the innovation literature compared to the invention and innovation stages. The insights provided can enhance innovation activities in the electric power industry. Studying the adoption of smart meters in particular is important because they can help transform retail markets by providing more opportunities for consumer engagement about electricity consumption and a more flexible demand side. They also support further technological and institutional innovation in the electric power industry.

Furthermore, public policy in the United States at both the state and federal levels has supported the adoption of smart meters by electric power utilities, principally for their role in fostering reductions in peak demand and overall consumption

with resulting benefits for consumers, the economy as a whole, the environment, and national security (Rose 2014). The research in this dissertation also contributes to the small empirical literature on diffusion policy. Additionally, the empirical analysis in this dissertation is based on a panel dataset created from data provided by the Energy Information Administration (EIA). The use of panel data in the empirical study of diffusion processes is rare, and the dataset itself is derived from publicly available data that facilitates reproducible research.[1]

The remainder of this dissertation proceeds with historical and institutional background on the US electric power industry and a description of smart metering technology (Chapter II), an overview of research on smart meters in the social sciences (Chapter III), an overview of models of technology diffusion (Chapter IV), and a discussion of hypothesized determinants of smart meter diffusion in the United States (Chapter V) that precede an empirical analysis of the early diffusion of smart meters in the United States (Chapter VI), an assessment of smart meter diffusion policies in the United States (Chapter VII), and a conclusion that summarizes key findings, provides an international comparison of smart meter diffusion, and suggests future areas of research (Chapter VIII).

1. All data analysis in this dissertation was performed with R (R Core Team 2017). Data and R code for importing, cleaning, and analyzing the data are available upon request.

CHAPTER II

SMART METERS AND THE US ELECTRIC POWER INDUSTRY

Understanding the historical and institutional context of the US electric power industry and the capabilities of smart metering technology is crucial for understanding the technology adoption decisions of electric power utilities and the evolving context within which smart meter diffusion occurs. In this chapter I provide historical and institutional background on the electric power industry in the United States and describe the technological evolution of electricity meters. I describe smart metering technology and present a comprehensive listing of their costs and benefits. Additionally, I suggest that electricity meters and the electric power industry have co-evolved over time, mutually influencing one another.

2.1 The Evolution of the US Electric Power Industry

The structure of the electric power industry in the United States has changed relatively little over time since the widespread adoption of state regulation by 1914, resulting in local or regional monopoly utility services for electricity supply. The most substantial changes have occurred in the past two decades, including the restructuring of electricity markets in a number of states during the 1990s that introduced elements of competition in the electricity supply chain. The California electricity crisis of 2000–2001, however, stopped restructuring from spreading further. The industry is undergoing substantial change in the present as a result of technological change, ecological pressures, and prior restructuring. Technological progress has occurred steadily in the industry over time. Perusing the history of the industry reveals that it has been, and continues to be, shaped by an interplay between technological and institutional innovations.

The origin of the electric power industry lies in the work of Thomas Edison during the late nineteenth century. Edison pioneered not only the technical aspects of electric lighting and electricity distribution but also the electric power utility as a business model. He was influenced heavily by the gas-lighting utility business model, his direct competitor at the time in lighting services. Edison's Pearl Street station in Manhattan came online in 1882 as the first central power station linked to a distribution system, analogous to the gas industry's distribution network. This was, in effect, the first utility. Electricity was originally used for lighting and only later were additional applications developed, primarily machines and appliances utilizing electric motors (Hughes 1983, 18–46; Neufeld 2016, 16–20).

During the early years of the industry competition was fierce and corruption was common. Private utilities negotiated contracts with municipalities and bribery and political favoritism often determined which utilities were awarded contracts. Some municipalities chose municipal ownership of electricity supply as a means to avoid this corruption. Municipal ownership also offered a more rapid development of electricity supply. Municipalities faced similar financial hurdles to privately owned utilities in the large amounts of upfront capital required, but they also had better access to capital markets. (Holland and Neufeld 2009; Neufeld 2016, 24–28).

The industry eventually came to desire monopoly status, under the influence of electric utility entrepreneur Samuel Insull. Insull was motivated by system expansion and achieving economies of scale to reduce the cost of electricity supply. By integrating distribution systems over wider geographical areas, Insull came to see state regulation as a means to achieve certainty and profitability of investments. The industry as a whole wanted to reduce inefficient and unprofitable competition stemming from the natural monopoly properties of electricity distribution. The threat of public power from municipally owned utilities was also an influence in accepting state regulation. As the industry moved in this direction it became subject to regulation at the state level. In 1905 New

York was the first state to establish a modern public utility commission and adopt regulation of the industry based on cost recovery through rates of return on capital investments. This rate-of-return regulation subsequently led to retail rates of electricity based on the average cost of supply. The economic rationale for regulation of the industry revolved around the natural monopoly characteristics of electricity supply. Regulation applied to a vertically integrated monopoly that implied the bundling of the electricity supply chain, integrating generation, transmission, distribution, and retailing under one firm in a given geographic area. This structure spread to most other states within two decades. Municipal and later co-operative utilities were not regulated in most cases because their ownership structures were viewed as having the best interest of consumers in mind. Vertical integration and state regulation of the industry persisted throughout most of the twentieth century, although not without significant policy changes along the way. The industry also sustained technological progress and reduced electricity prices over this time, primarily from efficiency gains and economies of scale in centralized generation (Hughes 1983, 201–226; Hirsh 1989, 13–86; Hirsh 1999, 11–31; Holland and Neufeld 2009; Neufeld 2016, 46–95).

Over the course of the first half of the twentieth century utility managers forged a consensus with politicians, regulators, financiers, electrical manufacturers, and consumers on the benefits of system expansion and interconnection with the oversight of state regulation. This grow-and-build strategy through technological momentum proved successful. There were regional differences, however, in the nature of growth with different regions pursuing distinct paths of growth dependent on unique supply, demand, and political factors (Hughes 1983, 140–174, 363–403, 404–460; Hirsh 1999, 33–54).

The Federal Water Power Act of 1920 created the Federal Power Commission and encouraged the development of hydroelectric generation projects. Importantly, it laid the foundation for the federal regulation of interstate wholesale electricity transmission via the commerce clause of the US Constitution. The Federal Water Power Act of 1930

and the Federal Power Act of 1935 boosted the regulatory power of the Federal Power Commission by making it an independent regulatory agency and giving it jurisdiction over all interstate wholesale transmission and power sales. The Commission was mandated to ensure reasonable and just electricity rates. These policies also allowed for the creation of federally owned utilities and the eventual support of rural electrification through the Tennessee Valley Authority and other agencies as well as the establishment of rural co-operative utilities (Holland and Neufeld 2009; Neufeld 2016, 158–160).

The stable structure of the industry began to erode during the 1970s from a number of factors. The 1973 oil crisis resulted in cultural changes and policy initiatives supporting energy efficiency and conservation, just as many utilities began switching from coal to oil as a primary fuel source for generating electricity. Additionally, the first nuclear power plants were built during this time period and were more expensive than expected because of cost overruns, delays, and safety regulations. Growth in demand for electricity was also lower than expected, leading to plant cancellations even after significant financial investment. Inflation in the overall economy also increased during this time period along with nominal interest rates, leading to higher borrowing costs. Technological stasis also occurred for conventional generation sources, reaching limits of thermal efficiency in converting pimary fuels to electrical energy. As a result of these factors, electricity prices began to rise rapidly throughout the country for the first time in the industry's history. Conventional methods of regulation came under attack for shielding utilities from the full consequences of their investment decisions through cost recovery mechanisms. These events together sowed the seeds of change. Additionally, during this time the Department of Energy Organization Act of 1977 created the Department of Energy (DOE) by consolidating energy-related federal agencies. It also transformed the Federal Power Commission into the Federal Energy Regulatory Commission (FERC), becoming an independent regulatory agency within the DOE (Hirsh 1989, 87–171; Hirsh 1999, 55–70; Holland and Neufeld 2009; DOE 2017a; FERC 2017).

The National Energy Act of 1978, which was composed of several different initiatives, implemented various policy changes such as emphasizing efficiency and streamlining the construction of new nuclear power plants. The most significant portion for the power industry was the Public Utility Regulatory Policies Act of 1978 (PURPA). This law required states to consider eliminating promotional rate structures such as declining block rates that decrease the price of electricity as more is consumed and to evaluate retail rates based on marginal costs. Though initially overlooked, PURPA also allowed third-party generation of electricity by independent power producers. Utilities were required by this law to purchase electricity from qualifying facilities that utilized cogeneration or renewable fuels, paying the avoided costs of what the utility would have had to incur to generate the electricity themselves. PURPA was enforced by FERC and allowed state experimentation with different regulatory models in the implementation of its provisions. PURPA would end up altering the electric power industry in the United States profoundly and can be considered the first step toward competition in wholesale electricity markets (Hirsh 1999, 73–100; Holland and Neufeld 2009).

The 1990s saw a move to liberalization of electricity markets, primarily because of concerns over high electricity prices but also as a means to encourage innovation. One of the indirect consequences of PURPA was the demonstration that large-scale power generation was no longer alone in offering low-cost electricity as a result of advances in cogeneration, gas turbine, and renewable energy technologies. PURPA led to the Energy Policy Act of 1992 that reinforced the policy shift toward wholesale competition. This law required utilities to wheel, or transmit and distribute, the electricity generated by exempt wholesale generators, a new kind of independent power producer, to wholesale customers even if the utility could have supplied these customers itself. It essentially mandated wholesale competition by separating generation from transmission. Furthermore, in 1996 FERC Order 888 declared the transmission system a common carrier, curbing the potential market power of existing utilities by allowing open access

to transmission networks. Together, these policies embedded competition in wholesale electricity markets and subsequently allowed wholesale prices to be largely determined by those markets (Hirsh 1999, 239–260; Holland and Neufeld 2009; FERC 2015b, 39).

Liberalization implied the unbundling of the electricity supply chain and the end of the utility consensus concerning the natural monoply characteristics of the industry and the benefits of regulation. It was recognized that generation and retailing could be unbundled from transmission and distribution. It was also recognized that the regulatory framework should persist for transmission and distribution networks that continue to be natural monopolies. Unbundling generation from transmission, however, created new problems in the coordination of generation activity to maintain the stability and reliability of the power grid. The nature of electric power grids, namely that supply must meet demand at every instant, requires these activities to be coordinated closely. Under vertical integration coordination is relatively easy because the monopoly distribution utility has complete information of and control over generation activity, but this is not true of independent generators in a competitive market. Unbundling gave rise to independent system operators and regional transmission organizations as new institutions to coordinate market activity and ensure reliability, safety, and low cost. Market power also became a concern (Hirsh 1999, 119–131, 261–271; Holland and Neufeld 2009; FERC 2015b, 39–40).

Two models of competition in electricity markets were developed during this period and currently exist in different states. One is the wholesale competition model where generating firms compete with one another to sell their electricity to distribution utilities that maintain retail monopolies in their respective service areas. The other is the customer choice model that typically couples wholesale competition with retail competition. This model represents a more substantial break from the past by allowing consumers to choose among electricity suppliers. Some states, however, may allow customer choice without having formal wholesale markets. Of those states that adopted the

customer choice model, only Texas has experienced active retail competition and to a lesser extent in the Northeast (Joskow 1997; Borenstein and Bushnell 2015).

States have pursued different paths in restructuring their electricity markets. California, Pennsylvania, and New Hampshire were among the first states to implement restructuring in the mid-1990s, but the California electricity crisis of 2000–2001 gave pause to other states who were considering restructuring. The gains from restructuring have been regarded as modest, and some states even regretted the decision for a time. In states that chose not to restructure, traditional vertically integrated markets could still experience significant changes in some aspects of regulation, such as a move away from rate-of-return regulation toward performance-based regulation. Revenue decoupling, for instance, changes incentives for utilities such that increasing their profits is not depedent on selling more electricity. This approach to revenue regulation removes disincentives for investing in energy efficiency, although it may pose new problems. Currently, as depicted in Figure 4, the United States has a mix of traditionally regulated and liberalized electricity markets, varying by region and state. States indicated as having wholesale competition are those largely engaged in formal wholesale markets with independent system operators or regional transmission operators. This figure is a rough guide as wholesale markets may only exist in certain regions of a state and customer choice may only apply to commercial and industrial consumers or have other limitations. Additionally, some states without wholesale competition allow customer choice for industrial and commercial consumers. Despite the persistence of wholesale markets with fluctuating wholesale prices determined by marginal costs, time-varying retail prices reflecting such time-varying wholesale prices have not seen widespread adoption (Holland and Neufeld 2009; RAP 2000, 2011; EEI 2012; Borenstein and Bushnell 2015).

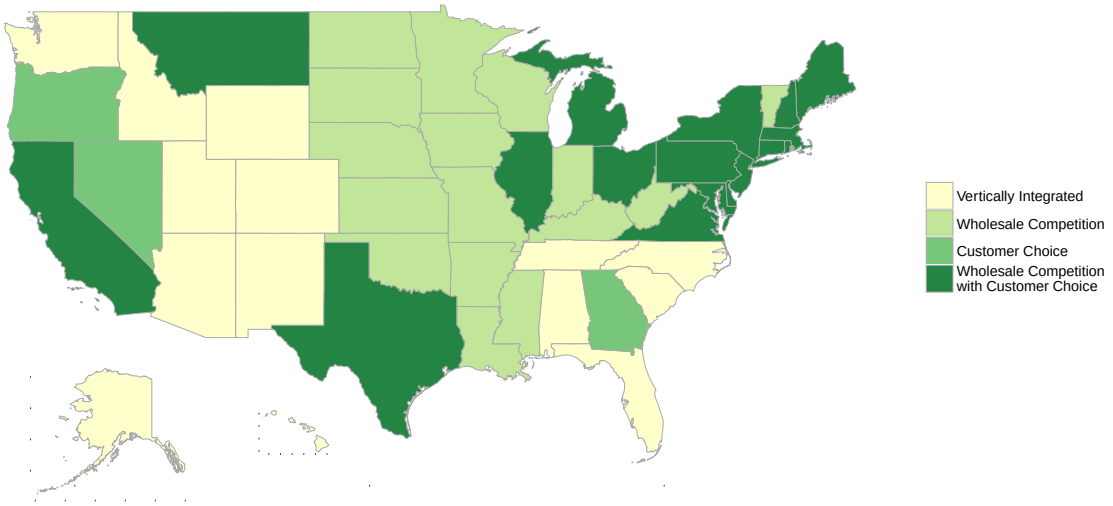


Figure 4. Status of Electricity Market Restructuring in 2017. Data from FERC (2015b), EMRF (2016), and ACCES (2017).

Further changes to the US electric power industry came in the Energy Policy Act of 2005. This law strengthened the power of FERC by repealing the Public Utility Holding Act of 1935, which effectively eliminated interstate holding companies that owned multiple utilities. This law also encouraged time-based pricing, demand response, net metering for distributed renewable generation (such as from solar photovoltaics), and incentives for energy efficiency. Although PURPA originally encouraged time-varying rates, the metering technology available at the time was apparently too costly for widespread use. But when cheaper technology became available in the 1990s time-varying prices still did not diffuse. Part of this hesitation may be explained by potential changes in the distribution of benefits among customer classes as a result of different rate structures. The law reinforced sections of PURPA by requiring state utility commissions to again consider time-based rates and the enabling metering technologies. Furthermore, the law charged FERC with assessing the status of demand response and advanced metering in the United States and required regulatory bodies in all states to authorize studies of advanced metering for potential deployment (EEI 2006a, 2006b;

FERC 2006, 2007, 2008, 2009a, 2011a, 2011b, 2012, 2013, 2014, 2015a, 2016; Joskow and Wolfram 2012).

Smart meters enable a greater variety of demand response options, which constitutes one of the most important benefits of this technology. Demand response can be defined as changes in electricity consumption in response to changes in electricity prices over time. Mechanisms for changing consumption include incentive-based programs, such as direct load control or interruptible rates, and price-based programs, such as time-of-use or real-time pricing. Times of high demand and stress on the electric power grid, the peak load problem, motivates demand response programs. The costs include the necessary metering infrastructure, other enabling technologies, and management of demand response programs. The benefits include bill savings, avoided infrastructure costs, improved reliability, and reductions in market power (FERC 2006; Albadi and El-Saadany 2008).

Creating a flexible demand side is part of a major recent development in the industry known as the smart grid. A smart grid combines information and communication technology with sensing and control technology applied to the power grid in order to increase the economic efficiency and physical reliability of electricity supply. The essence of the smart grid, synonomous with grid modernization, is the use of digital technologies allowing situational awareness through micro-level visibility of grid operations. In contrast, the use of analog technologies allows only a macro-level view of grid operations producing limited information and enabling only heuristic decision making. Smart grid technologies enable real-time monitoring and optimal decision making through automated control of the power grid. Sensors placed along the distribution grid, for example, can detect power outages and associated automation controls can reroute power in order to minimize the number of consumers affected. Another important aspect of the smart grid is the integration of intermittent and distributed generation and storage resources, often customer-owned, onto the grid. The smart grid enables a

more transactive grid with two-way flows of both information and electricity (NETL 2009; Joskow 2012).

The concept of a smart grid can be traced back to visions of a power grid with homeostatic control that balances supply and demand through dynamic pricing and automation technologies (Schweppe, Tabors, and Kirtley 1981). The use of information technology in enabling such a vision was predicted to increase the efficiency of energy use and supply resulting in improvements of energy and capital productivity. Additionally, it was predicted to aid the decoupling of energy use from economic growth and to potentially change the structure of utilities and the industry itself (Walker 1985, 1986). The smart grid can also be considered a technological paradigm that orients advances in electric power technology along certain technological trajectories (Dosi 1982). Technological and institutional change in the industry is difficult, however, as a result of technological momentum and regulatory, political, and cultural barriers, biasing some trajectories over others (Hirsh and Sovacool 2006). The outcomes of these recent technological and institutional developments are ongoing and yet to be fully seen.

The Energy Independence and Security Act of 2007 encouraged the development of the smart grid in the United States. Both this law and the preceding Energy Policy Act of 2005 supported advanced metering in the form of smart meters. In addition, this law tasked FERC with assessing the potential of and utilizing demand response resources, which it did with an assessment, plan, and implementation proposal (FERC 2009b, 2010, 2011c). In related efforts, the DOE together with the Environmental Protection Agency initiated a public-private collaboration to increase commitments to energy efficiency, resulting in a national action plan for energy efficiency (DOE/EPA 2006, 2008). Furthermore, the American Recovery and Reinvestment Act of 2009 (Recovery Act), passed in response to the Great Recession that began in 2007–2008, funded grid modernization programs administered by the DOE and originally authorized by the Energy Independence and Security Act of 2007. The Smart Grid Investment Grant

(SGIG) program subsidized deployment of smart grid technologies and the Smart Grid Demonstration Program (SGDP) subsidized R&D for smart grid technologies. Additional policies are needed to continue incentivizing investment in smart grids, with special care given to regional differences in power grid characteristics (NSTC 2011; Guo, Bond, and Narayanan 2015; DOE 2017b).

During the time since restructuring began, the environmental costs of generating electricity have gained prominence in public policy debates. Although local air and water pollution have always been a concern in the industry, attention has shifted to greenhouse gas emissions associated with the burning of fossil fuels and resultant global warming. Comprehensive climate change legislation, such as implementation of a carbon tax as a means to monetize the negative externalities, has not seen success at the federal level, and the recent Clean Power Plan is a regulatory approach from the executive branch to mitigate greenhouse gas emissions in the power industry. The rise of clean, renewable generation from solar and wind through policy support and declines in their costs of production has led to new technical and economic challenges as a result of their intermittent and distributed nature. In addition, energy storage and electric vehicles may also diffuse more widely in the future for similar reasons, posing additional challenges. Another benefit attributed to the smart grid is its ability to address such challenges and thus reduce the ecological footprint of the power industry. These issues will collectively shape the structure of and technological change in the industry going forward (EPRI 2008b; Hledik 2009; NETL 2011; Borenstein and Bushnell 2015).

The recent history of the US electric power industry highlights a theme of demand response as a means to address the peak load problem and engage customers in new markets. The desire to expand the participation of the demand side in electricity markets also includes pushes for retail electricity prices to reflect the dynamic prices determined in wholesale markets. Such time-varying rates are hoped to incentivize changes in consumption behavior, especially at times of peak demand. In 2011 FERC Or-

der 745 declared demand response to be equivalent to a generation source in wholesale markets, equating reductions in demand with avoided generation and valuing it as such. This represents an important change in market rules that has caused greater attention given to demand response resources. The bright line dividing federal and state regulation is also increasingly becoming blurred as a result. Technological change is required to make the demand side more flexible, and metering technology is especially crucial for enabling demand response programs (Rose 2014; Panfil 2015).

2.2 The Evolution of Electricity Meters

Technology and industrial structure often co-evolve (Hughes 1987; Nelson 1994). The evolution of the US electric power industry is tied to the evolution of electricity metering technology in a co-evolutionary process. Changes in the industry have led to changes in metering technology and changes in metering technology have led to—and are currently leading to—changes in the industry. The diffusion of certain metering technologies, then, is dependent in part on the overall form and context of the industry.

Electricity meters, in general, measure the consumption of electricity. Metering technology is integrally tied to the structure of retail electricity rates, and rate structures are ultimately limited by the capabilities of electricity meters. Retail rate structures can take different forms and are typically volumetric charges based on kilowatt-hours (kWh) of electricity consumed. They may also contain invariant components in the form of fixed charges. Rates often differ by customer class as well, which include residential, commercial, industrial, and sometimes others. Retail rates can be static or dynamic. Static rates are predetermined and may only change seasonally. In conventionally regulated markets static rates are determined through regulatory ratemaking processes whereas in markets with retail competition static rates are determined by retailers. Static rates include flat rates and time-of-use (TOU) rates. Flat rates are based on total consumption, irrespective of the time of day, in the form of a price per kWh consumed. Flat

rates can also be used in combination with a demand charge, a fee based on the maximum electric power demanded by a consumer at any instant. TOU rates refer to prices that vary over the course of a day but are predetermined and do not change in real time. A simple TOU rate structure combines a low rate for the off-peak period and a high rate for the on-peak period. The motivation behind TOU rates, and time-varying rates in general, is to incentivize customers to reduce consumption during periods of peak demand. A more complex rate structure may include rates for mid-peak shoulder periods as well. Demand charges can also be added to a TOU rate structure (Capehart and Storin 1983; Borenstein, Jaske, and Rosenfeld 2002; Lazar and Gonzalez 2015).

Dynamic rates are prices that change in real time. Unlike TOU rates they are not predetermined. Dynamic pricing is intended to reflect marginal system costs influenced by actual on-peak and off-peak times of demand. Real-time pricing (RTP) is the ultimate dynamic pricing with prices changing in real time (typically defined as each hour). Critical peak pricing (CPP) is a special type of dynamic pricing used to incentivize demand reduction during times of expected high demand, such as very hot days during the summer. CPP is typically determined a few days in advance and limited to a certain number of hours per year. CPP can be used in combination with any other type of rate structure (flat, TOU, or RTP). Dynamic rates can also be combined with demand charges. While more dynamic rates entail more risk, they also entail potentially more reward. The motivation for using time-varying prices is to increase the economic efficiency of electricity markets by aligning prices with marginal costs, curb potential market power in competitive markets, and increase economic equity by reducing cross-subsidies from those who consume more during off-peak times to those who consume more during on-peak times (Borenstein, Jaske, and Rosenfeld 2002; Lazar and Gonzalez 2015).

Early electric utilities charged their customers based on the number of lamps installed, independent of the actual consumption of electricity. For a short period this was reasonable because of the nature of users' needs at the time—primarily lighting in the

early evening. As the adoption of electric lighting and the uses for electricity expanded, however, it became clear that pricing of electricity should be based on consumption. This led to a demand for direct-reading electricity meters that measured total energy use (Bowers 1982, 193–201; Brown 1985; Bowers 1990, 373–377; Neufeld 2016, 34–41).

There was an intense debate within the early power industry over the most appropriate rates to charge consumers, even before economists turned their attention to the issue (Hausman and Neufeld 1984; Hausman and Neufeld 1989; Neufeld 2016, 34–41). Historically, residential and commercial rates have typically been flat whereas industrial rates have typically been more dynamic. Regardless, the pricing of electricity based on consumption requires a device to measure consumption, and a more complex rate structure requires a more sophisticated meter. Subsequently, the actual benefits of different rate structures are dependent upon, in part, the underlying costs of the enabling metering technology (Capehart and Storin 1983; Lazar and Gonzalez 2015).

The population of electricity meters is diverse, but only a few types of meters have been selected and widely used in the industry. In some cases, specific types of meters are used for very specific applications, such as special meters for use in high voltage applications. After moving to price electricity based on consumption rather than the number of lamps, Edison developed a meter based on an electrolytic cell. Other inventors and companies developed different kinds of meters during these early years, which were mostly analog, electromechanical devices. The industry desired practical instruments that were portable, quick and easy to read, and reliable. The Aron meter, the first electricity meter with direct reading of measurements, was based on pendulum clocks and wires that interacted with the electricity supply to measure consumption. Arthur Wright, a British pioneer in the power industry, invented the first recording meter in 1886 to monitor electric load, using paper pulled by clockwork and marked by a pointer connected to a meter (Bowers 1982, 193–201; Brown 1985; Bowers 1990, 373–377).

The Thomson meter, invented in 1882, was the first motor meter, where the total number of revolutions of a disc driven by an electric motor and restrained by an eddy current break measured electricity consumption. This meter was intended for direct current (DC) systems although it could be modified for alternating current (AC) systems. Induction motors were later developed that proved more convenient for use in meters on AC systems, after the "battle of the systems" resulted in the widespread adoption of alternating current. The Shallenberger meter, invented in 1898, incorporated an induction motor that drove a disc in a similar fashion. This meter design was subsequently improved upon and developed into the standard, analog watt-hour meter that became the working horse meter of the industry for decades. Measurements of total consumption are read manually via a row of dials (Bowers 1982, 200–201; Hughes 1983, 106–139; Brown 1985; Bowers 1990, 373–377; Neufeld 2016, 28–34).

During the debates surrounding rate structures in the early twentieth century, it was emphasized that there must be a practical way to implement time-varying rate structures. There were, in fact, analog meters available at this time that were capable of measuring electricity consumption during different time periods that could be used to levy simple TOU rates. This type of meter took the form of a basic Shallenberger meter with an additional register and a clock that would switch between the two registers based on predetermined time periods. A demand meter could also be attached to measure maximum power demand. More sophisticated designs were also available. Although meters capable of supporting TOU pricing were available during the early years of the industry, TOU rates were not adopted despite awareness of the peak load problem. Demand charges were adopted instead, not as a second-best approximation of peak-load pricing but arguably as a means to price discriminate and to compete with self-generation in industry. This pricing strategy also supported a growth strategy for the large, centralized vision of the industry. The reasoning behind the widespread adoption of demand charges, then, as well as the higher costs and inflexibility of more com-

plex meters, essentially explain the nondiffusion of these early TOU meters (Capehart and Storin 1983; Brown 1985; Neufeld 1987; Yakubovich, Granovetter, and McGuire 2005; Neufeld 2016, 34–41).

The electromechanical watt-hour meter has been used extensively in the residential class of consumers as well as the commercial and industrial classes, where it has often been paired with a demand meter. This type of meter was selected because of its relatively low purchase and maintenance costs, high reliability, and 25–30 year rated life. Electromechanical meters, still in use today although no longer commercially available, eventually gained competition from electronic meters as a result of advances in electronic and computing technology during the mid-twentieth century. The advent of solid-state technology, integrated circuits, and microprocessors led to the development of electronic meters utilizing digital signal processing. These meters originally performed the same functions as the standard analog electromechanical meter, measuring and providing a direct reading of total electricity consumption. Electronic meters were first used for large commercial and industrial customers who were subject to more complex rate structures than residential customers and required finer granular data on their electricity consumption. As the costs of electronic meters decreased their use spread to all customer classes (Capehart and Storin 1983; Brown 1985; EEI 2006a, 5–7; EEI 2011, 7–8).

The first generation of electronic meters still needed to be read manually via a digital display. The invention of automatic meter reading (AMR) in the 1970s, however, changed this. AMR meters combine an electronic meter with a communication module. This allows for the one-way communication of consumption data, either to a remote collector in a utility employee's vehicle or via a fixed network to a central location. Older electromechanical meters could also be retrofitted to AMR meters with a drop-in communication module at low cost. This technology helped automate the meter reading and billing process through telemetry. The communication system can either be a telephone

system, radio frequency (RF) system, low-frequency ripple system using power lines, or high-frequency power line carrier system, each of which have their advantages and disadvantages. AMR also enables tamper and outage detection. AMR can be considered one of the first steps toward a smart grid in that it combines information and communication technology with the power grid (Capehart and Storin 1983; FERC 2006, 20; EEI 2011, 7–12).

Electronic meters gradually evolved in the 1980s and 1990s from AMR into what have come to be known as smart meters. As microproccesor technology improved, electronic meters became capable of measuring and recording data on electricity consumption in separate time intervals (typically in 60-, 30- or 15-minute intervals). The microprocessor enabled easy programing of register schedules for use with time-varying rate programs. These meters also gained the ability to measure and record maximum power demand and could be programmed in a similar manner. In addition, they were capable of being programmed for complicated time-varying rates that could change over the course of a year based on a seven-day time clock and an annual calendar clock. They could also be connected to tape recorders for recording consumption data, but this proved too costly to implement widely. Memory storage was an initial limitation for the capabilities of electronic meters but subsequent improvements in memory storage technology overcame this barrier to increased functionality. These metering technologies have also influenced the development of digital display devices that allow active monitoring of consumption and direct and indirect load control systems, including automated energy management systems containing preprogrammed instructions based on preferences and prices that can manage a consumer's electricity load automatically through microcontrollers. Importantly, these electronic meters were upgraded to function with two-way communication (Capehart and Storin 1983; Sioshansi 1991; EEI 2011, 7–8).

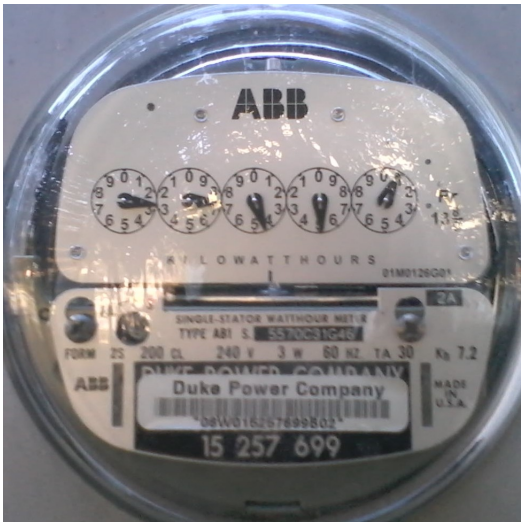


Figure 5. An Electromechanical Meter.

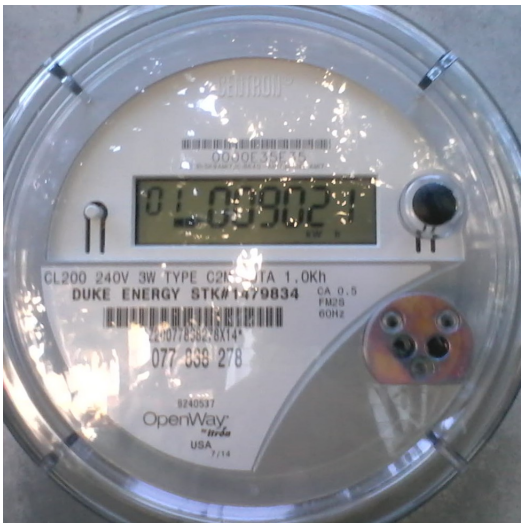


Figure 6. A Smart Meter.

A smart meter can be defined as a digital electricity meter capable of measuring and recording interval data combined with two-way communication capabilities. Smart meters are part of a smart meter system that has come to be known as advanced metering infrastructure (AMI). AMI is a system composed of smart meters, communication systems, and meter data management systems. The diffusion of smart meters

encompasses the diffusion of AMI, a set of complementary innovations. The presence of a two-way communication system via a fixed network implies that a utility can both send and receive messages to and from a customer's meter. The additional line of communication from the utility to the customer enables direct load control by utilities when combined with gateway networks and microcontrollers on machines and appliances. It also enables remote on-demand reads, remote meter programming, remote service switching, and remote switching of registers in a multiregister meter, which is useful for implementing time-based rates. In addition to electricity consumption smart meters can measure power demand and voltage. These measurements provide useful information to utilities for managing distribution grids Furthermore, the specific choice of the communication network architecture may depend on population density as well as a utility's vision for the smart grid because it can serve other functions apart from metering, such as distribution automation (NETL 2008; EEI 2011; MITEI 2011, 132–137).

Table 1 compares the capabilities of electromechanical, AMR, and smart meters. In sum, smart meters are a capital-embodied process innovation with distinct advantages over previous metering technologies. They are multi-function tools providing information-rich operational capabilities. Smart meters are also labor-saving and potentially capital-saving investments. Furthermore, the evolution of AMI from AMR and previous technologies exemplifies how technological change is combinatorial, incremental, and cumulative, often leading to greater complexity and capability over time (Rosenberg 1979; Arthur 2009).

Table 1. Capabilities of Metering Technologies.

Meter Type	Capabilities
Electromechanical	Manual reads
Automatic meter reading (AMR)	Automated reads, outage detection, tamper detection
Advanced metering infrastructure (AMI)	Interval data and time-varying rates, power quality data, import/export functions, remote on-demand reads, remote service switching, remote meter programming

Note: Additive capabilities from electromechanical to AMI.

From this description of the evolution of metering technology it is clear that both the needs of the power industry on the demand side and the technological opportunities offered by microprocessors on the supply side have shaped the direction of metering technology advancement. The barriers to implementing time-varying rates have not been technological but rather economic and behavioral. Uncertainties as to the actual response of consumers to time-varying prices, for example, have been an important barrier in addition to the costs of implementation and the regulatory approval process for investor-owned utilities. The economic rationale for smart meters depends on various factors. Smart meters have initially been more expensive than less advanced meters and there has been some uncertainty as to their rated life and their maintenance and reprogramming costs. If the relative advantage of smart meters does not provide sufficient benefits compared to costs, then their adoption and deployment may not be economical.

2.3 The Economic Rationale for Smart Meters

Smart meters offer many benefits over the electronic and electromechanical meters that preceded them, though they impose new costs as well. The costs and benefits of smart meters are diverse and they are distributed across multiple stakeholders.

2.3.1 Costs

Smart meters have four major elements of cost: expense, privacy, security, and health. Because of their capabilities smart meters incur a greater financial cost relative to less advanced meters, though their price has fallen over time. Furthermore, smart meters cannot realize their full benefits unless part of an AMI system, which requires the installation and associated costs of communication systems and meter data management systems. In some cases utilities can upgrade from AMR to AMI relatively easily, if a fixed network communication system was previously selected, by replacing AMR meters with smart meters and making incremental upgrades to the system. In other cases they have to build up the entire communication system. This issue will impact the total cost of deploying AMI such that the prior diffusion of AMR may impact the diffusion of AMI. Additionally, different deployment strategies, such as full, replacement, or targeted deployment, may incur different costs (Levy, Herter, and Wilson 2004; NETL 2008; EEI 2011).

Smart meters also impose potential costs to privacy, stemming from consumption data. Consumers may not be comfortable with utilities or other parties having access to detailed data on their electricity consumption. Such data can be used to identify the use of individual appliances and home or work patterns. The ownership of data is a point of issue. Related to privacy concerns, there are also security concerns with respect to unauthorized access to meters and their recorded data. Smart meters have physical ports to access data and are also networked with communication systems, both of which can potentially result in unauthorized access. Efforts have been made to protect data, however, such as increased endpoint security as well as data encryption. The National Institute for Standards and Technology (NIST) has established security guidelines and is collaborating with meter manufacturers and the industry as a whole to produce secure meters and networks. The Energy Independence and Security Act of 2007 empowered

NIST as the national coordinator for smart grid technology standards and cybersecurity guidelines. The North American Electric Reliability Corporation, whose mission is to ensure grid reliability, has also issued cybersecurity standards, and the American Recovery and Reinvestment Act of 2009 also increased cybersecurity measures through its smart grid programs (NETL 2008; EEI 2011; MITEI 2011, 197–234).

Smart meters that use wireless transmission for communication, leading to RF exposure, can potentially impose health costs. Scientific studies have shown, however, that RF exposure from smart meters is negligible. RF exposure is regulated by standards set by the Federal Communications Commission. Smart meters fall under a low power, unlicensed category, similar to wireless Internet routers. They also emit substantially less RF exposure than cell phones. Such devices have generally not been found to pose negative effects on human health. Nevertheless, all such devices undergo a testing and certification process with the Commission. Furthermore, smart meters, like all previous meters, are typically installed on the exterior of homes and businesses facing away from living and working spaces and in a partially shielded enclosure. Any exposure also occurs only when the RF device is in operation, which is usually no more than 15 minutes in total per day. Still, RF exposure from smart meters, if it occurs at all, has been shown to be well within legal limits (NETL 2008; EEI 2011).

Although most of these costs are uncertain and difficult to quantify, they may qualitatively impact the assessment of the optimal rate of smart meter diffusion. Their adoption may be premature if these issues have not been adequately addressed. The most certain and established costs of smart meters are the financial costs.

2.3.2 Benefits

The benefits of smart meters are multidimensional and intertwined with the benefits of smart grids. These benefits can be categorized based on the various stakeholders that they impact, including utilities, consumers, and society as a whole. The benefits can

also be divided between operational and nonoperational benefits with respect to utilities' needs and their management of the power grid. Framing the benefits of smart meters in terms of operational and nonoperational benefits is useful because it naturally leads to a discussion of smart meter diffusion policy from a market failure perspective in terms of private and social costs and benefits (Levy, Herter, and Wilson 2004).

Utilities benefit across the supply chain from the deployment of smart meters. For customer service and related field operations, smart meters reduce the cost of meter reading through the elimination of meter reading positions and associated expenses. They also help automate the billing process and reduce expenses in this area as a result, such as through reductions in billing errors. Smart meters can also reduce costs associated with service connections and disconnections through remote switching. Smart meters can reduce call center activity and associated costs through improved customer engagement and automated outage detection. Additionally, smart meters can detect meter tampering and electricity theft. Another byproduct of the data collected by smart meters is reduced costs for load research used in marketing and forecasting demand (NETL 2008; EEI 2011; MITEI 2011, 132–137).

For managing the power grid, advanced metering infrastructure enables utilities to engage in advanced distribution operations, advanced transmission operations, and advanced asset management, all of which are aspects of a smart grid and can lead to cost reductions. Power quality data collected by smart meters also aids utilities in improving the reliability of the distribution grid. As part of these smart grid operations, smart meter data benefits both transmission and distribution grids by improving transformer load management and capacitor bank switching. Smart meter data can also be used to develop new revenue streams through monetizing the flow of information and to improve efficiency of supply and demand, reliability of service, and grid system design and planning (NETL 2008; EEI 2011; MITEI 2011, 132–137).

Consumers of electricity benefit from smart meters through improved relationships with their utility resulting from access to finer consumption data that can be used for energy management purposes and engagement about energy use. Consumers also benefit from more accurate billing, a greater variety of rate options, improved reliability and outage restoration, and access to power quality data. Furthermore, smart meters can act as an interface between the power grid and the loads and distributed generation and storage resources of consumers. Smart meters are capable of net metering, for example, through measuring power inflow and outflow. Depending on public policy, this may incentivize consumers to also become producers of electricity (NETL 2008; EEI 2011; MITEI 2011, 132–137).

Additionally, smart meters enable consumers to participate in demand response programs and related markets. For residential consumers smart meters can be connected to home area networks that communicate information to household appliances. Consumers can program their preferences so that appliances such as washers and dryers only operate during certain time periods or depending on prices. Such activities can reduce consumers' bills. Consumers can also voluntarily allow utilities direct control over certain appliances typically in exchange for bill credits. Furthermore, insofar as smart meters reduce costs to the utility they also put downward pressure on electricity prices, from which consumers benefit. Some of these benefits, though, depend on policy and regulatory action and may not be available to all consumers (NETL 2008; EEI 2011; MITEI 2011, 132–137).

Society as a whole benefits from the use of smart meters principally through the demand response that they enable, by shifting consumption to off-peak times and lessening the peak load problem. Effective demand response can help avoid the cost of building excess capacity in peak generation and transmission and distribution networks. Blackouts can also be avoided through dynamic pricing and other demand response programs during periods of high demand, leading to significant financial savings through

avoidance of business productivity losses and breakdowns in other dependent systems like water distribution. Smart meters can also help integrate distributed energy resources like rooftop solar onto the grid that can benefit society through innovation and cleaner energy generation. Reductions in consumption during peak times and for overall energy use as well as increased generation from cleaner, distributed resources can also benefit society through improved environmental quality (NETL 2008; EEI 2011; MITEI 2011, 132–137).

Similar to the costs, some of the benefits of smart meters are more certain than others. Many of the benefits associated with the adoption of smart meters relate to consumption patterns and demand response. Yet it is uncertain how beneficial demand response programs can be because their effectiveness depends on how consumers actually respond to time-varying prices and other incentives. This cannot be predicted perfectly. Demand response is important because it opens up new markets and potential avenues of innovation in the electric power industry, another benefit of smart meters. Smart meters are a key technology in the development of smart grids that provide additional benefits beyond the meters themselves. Maximizing the value of AMI investments through multiple functions and nonmetering capabilities may be crucial to justifying the costs. Smart meters can serve as a technology platform on which to expand grid modernization and can do so at a relatively small marginal cost, such as through upgrading of communication networks for nonmetering purposes (Levy, Herter, and Wilson 2004; NETL 2008; EEI 2011; MITEI 2011, 132–137).

Table 2. Costs and Benefits of Smart Meters.

Private Costs	More expensive than other meter types
Social Costs	Privacy concerns from detailed data Security concerns from networked systems Health concerns from RF emissions
Private Benefits	Utility operations capabilities
Social Benefits	Economic efficiency through time-varying rates Energy management capabilities Integration of distributed generation and storage resources Reductions in environmental emissions

Table 2 summarizes the costs and benefits of smart meters. The costs and benefits are classified by private and social categories though some elements of the social costs and benefits may also apply to the private costs and benefits of utilities. For utilities, relative to society as a whole, the net benefits of smart meters may not be great enough to warrant their adoption or an adequate pace of adoption. Moreover, these costs and benefits vary across utilities. This creates a potential role for public policy in supporting the diffusion of smart meters, like that embodied in the Recovery Act smart grid programs. Although the financial expense of smart meters is an important determinant in the diffusion of smart meters, there are many other relevant factors illuminated by theoretical models of technology diffusion.

CHAPTER III

SOCIAL RESEARCH ON SMART METERS

The extant research on smart meters in the social sciences is broad. The majority of this social research, however, is related to the behavioral aspects of the consumption feedback that smart meters provide, often in combination with incentives given by time-varying rates. The realized benefits of smart meters from changes in consumption, as studied in the behavioral research, impact the diffusion of the technology through cost-benefit evaluations. Less research exists on the technological innovation aspects of smart meters, such as the determinants of their diffusion. Table 3 surveys and provides a classification of recent research related to smart meters. Though not exhaustive, this survey is representative of the distribution of research with respect to general research topics.

Table 3. Research on Smart Meters in the Social Sciences.

Author(s) (Year)	Research Topic	Results
Behavior		
Allcott (2011)	Smart meters and dynamic pricing	Hourly real-time pricing increases consumer surplus by $10 per household per year.
Buchanan, Russo, and Anderson (2014)	Smart meters and consumption feedback	Energy monitors facilitate learning about consumption behavior.
Buchanan, Russo, and Anderson (2015)	Smart meters and consumption feedback	The success of in-home displays on reducing overall consumption depends on user engagement.
Carroll, Lyons, and Denny (2014)	Smart meters and TOU pricing	TOU rates lead to significant reductions in both overall and peak demand.

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Author(s) (Year)	Research Topic	Results
Corbett (2013)	Smart meters and consumption feedback	Smart meters improve utilities' demand-side management efforts but also require organizational changes.
Darby (2006)	Literature review	Real-time direct feedback in combination with indirect feedback through accurate billing can lead to sustained reductions over time in overall demand.
Darby (2010a)	Literature review	Improved consumption feedback is necessary but not sufficient for reducing overall and peak demand.
Darby (2010b)	Smart meters and customer engagement	Significant reductions in overall demand require careful design of customer engagement.
Darby (2012)	Smart meters and energy poverty	Smart meters can help the energy poor by helping them manage their consumption.
Davis et al. (2013)	Smart meters and pilot studies	Significant bias exists in the experimental design of many studies regarding smart meters and their impact on consumption feedback.
Cosmo, Lyons, and Nolan (2014)	Smart meters and TOU pricing	Consumers significantly reduce peak demand after the introduction of TOU prices and information feedback.
Faruqui and Sergici (2010)	Literature review	Households respond to dynamic pricing by reducing peak demand but the magnitude of price response depends on multiple factors.

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Author(s) (Year)	Research Topic	Results
Faruqui, Sergici, and Akaba (2013)	Smart meters and dynamic pricing	Residential customers respond to dynamic pricing. Response to critical peak pricing is similar to response to critical peak rebates.
Faruqui, Sergici, and Akaba (2014)	Smart meters and dynamic pricing	Demand response to critical peak pricing is greater than response to critical peak rebates.
Gans, Alberini, and Longo (2013)	Smart meters and consumption feedback	Feedback reduces overall demand by 11-17% on average.
Gilbert and Zivin (2014)	Smart meters and consumption feedback	More frequent billing and reminders reduce overall household energy consumption by 0.6–1%, but there is significant heterogeneity in responses.
Guerreiro et al. (2015)	Sociopsychological factors influencing the use of smart meters	Subjective norms, perceived utility and risk, procedural justice, and time of use are important factors influencing the use of smart meters.
Hargreaves, Nye, and Burgess (2013)	Smart meters and consumption feedback	Over the longer term, energy monitors fall into the background and have limited potential for reducing overall consumption.
Hartway, Price, and Woo (1999)	Smart meters and TOU pricing	TOU pricing can be profitable to utilities.
Herter (2007)	Smart meters and critical peak pricing	High-use customers reduce peak demand more than low-use customers but low-use customers save more on electricity bills annually.

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Author(s) (Year)	Research Topic	Results
Herter and Wayland (2010)	Smart meters and critical peak pricing	Larger users reduce peak demand the most. There is no significant difference in peak demand reductions with a higher critical peak price compared to a baseline critical peak price.
Herter, McAuliffe, and Rosenfeld (2007)	Smart meters and critical peak pricing	Customers with automated load control technologies reduce peak demand more than those without such technologies.
Herter, Wood, and Blozis (2013)	Smart meters and dynamic pricing	Customers with dynamic pricing reduce peak load more than those in load control programs.
Ivanov et al. (2013)	Smart meters and peak demand	Households with in-home displays and smart thermostats reduce peak demand by 15% compared to those without such technologies.
Jessoe and Rapson (2014)	Smart meters and consumption feedback	Consumption feedback facilitates learning, leading to reductions in overall and peak demand.
Kendel and Lazaric (2015)	Smart meters and consumption feedback	Smart meters should be combined with other measures like smart rates in order to have greater impacts on reducing overall and peak demand.
Léautier (2014)	Smart meters and dynamic pricing	Savings from real time pricing is negligible for most residential consumers, casting doubt on the value of deploying smart meters to this class of customers.

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Author(s) (Year)	Research Topic	Results
Matsukawa (2016)	Smart meters and dynamic pricing	Critical peak pricing combined with in-home displays lead to greater reductions in peak demand.
McKerracher and Torriti (2013)	Smart meters and consumption feedback	Overall energy savings from real-time feedback with in-home displays are less than previously found with larger and more representative samples.
Olmos et al. (2011)	Smart meters and dynamic pricing	Indirect feedback, critical peak pricing, and simple TOU pricing together lead to the greatest reductions in overall and peak demand.
Simshauser and Downer (2012)	Smart meters and dynamic pricing	Dynamic pricing improves load factors by 9 percentage points.
Torriti (2012)	Smart meters and TOU pricing	TOU pricing leads to higher average overall consumption as well as load shifting in mornings but not in evenings.
Torriti (2014)	Smart meters and consumption feedback	Smart meters reduce overall demand by 29.8% and by 5.2% more compared to load controllers.
Torriti (2016)	Literature review	Energy savings from smart meters with consumption feedback has declined in studies over time, owing to larger and more representative sample sizes.
Tsuda et al. (2017)	Literature review	The effectiveness of demand response instruments depends on the characteristics of consumers, location, and climate.

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Author(s) (Year)	Research Topic	Results
Wolak (2011)	Smart meters and dynamic pricing	The transaction costs of responding to real-time pricing are negligible for residential consumers.
Zhang, Siebers, and Aickelin (2016)	User learning	As consumers become more experienced with smart meters they save more energy, but consumer interest must be maintained over time.
Technology		
Erlinghagen, Lichtensteiger, and Markard (2015)	Smart meter communication standards	Many standards exist but are not necessarily interoperable, posing difficulties.
Gerpott and Paukert (2013)	Consumer valuation of smart meters	Consumer trust in data privacy and intention to change behavior are strongly related to willingness to pay.
Katz (2014)	Smart meters and demand response	Smart meters provide necessary information but other policies are needed to ensure demand response.
Kaufmann, Künzel, and Loock (2013)	Consumer valuation of smart meters	Most consumers perceive a positive value from smart meters and are willing to pay for them.
Kavousian, Rajagopal, and Fischer (2013)	Smart meter data	Weather, location, and floor area are the most important factors in residential consumption of electricity.
Krishnamurti et al. (2012)	Consumer valuation of smart meters	Consumers confuse smart meters with in-home displays and other related technologies and expect savings to be immediate.

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Author(s) (Year)	Research Topic	Results
Kurth (2013)	Smart meters and market design	Smart meters act as the interface between the grid and the market. Technological standards are crucial to achieving the most effective deployment by avoiding obsolescence and enabling interoperability.
Leiva, Palacios, and Aguado (2016)	Smart meters and energy policy	Smart meter standards are needed to facilitate energy management applications and electric vehicle charging.
Marvin, Chappells, and Guy (1999)	Environmental innovation	Different smart meter technical development pathways can be identified and inserting environmental concerns into any one is only partially a technical problem.
McKenna, Richardson, and Thomson (2012)	Smart meter data	Privacy issues can delay the deployment of smart meters if not adequately addressed.
McHenry (2013)	Smart meters and governance	Maximizing smart meter benefits requires collaboration and planning across multiple stakeholders.
Pepermans (2014)	Consumer valuation of smart meters	Consumer preferences are heterogeneous with respect to cost savings and privacy. Dynamic pricing receives low value.
Urban (2016)	Smart meter data privacy	Privacy and security threats from smart meter data can impose significant social costs if not addressed before widespread smart meter use.

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Author(s) (Year)	Research Topic	Results
Diffusion		
Chou and Yutami (2014)	Consumer adoption of smart meters	Perceived usefulness, ease of use, and low risk are associated with an increased propensity to adopt smart meters.
Dedrick et al. (2015)	Adoption of smart grid technologies	Adoption of smart grid technologies, like smart meters, requires organizational and regulatory changes.
Inderberg (2015)	Smart meter diffusion policy	Smart meter diffusion in Norway was led by national regulators. Consumer interest groups had little influence in the process.
Jennings (2013)	Smart meter diffusion policy	Effective deployment strategies target the correct group of customers based on the purposes for smart meter use.
Schiavo et al. (2013)	Smart grid policy and regulation	Regulation must change to foster innovation in electric power systems and related experience is key.
Pupillo and Serre (2013)	Smart meter diffusion policy	Government must play an active role to guarantee the diffusion of smart meters.
Rixen and Weigand (2013)	Smart meter diffusion simulation	The rate of diffusion is affected by learning and the level of diffusion is affected by cost-benefit thresholds.
Rixen and Weigand (2014)	Smart meter diffusion simulation	The best policy instrument for encouraging adoption of smart meters depends on specific objectives.

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Author(s) (Year)	Research Topic	Results
Spodniak (2011)	Smart meter diffusion	Central East European countries lag the rest of Europe in smart meter adoption. The lack of standards has slowed adoption.
Spodniak, Jantunen, and Viljainen (2014)	Smart meter diffusion	The role of the state in smart meter diffusion decreases after the market has developed.
Wunderlich (2013)	Consumer adoption of smart meters	Consumer attitudes and perceived locus of causality and control are important variables influencing adoption.
Zhang (2010)	Smart meter diffusion policy	Government initiatives and regulatory policies have played a major role in the diffusion of smart meters around the world.
Zhang and Nuttall (2011)	Smart meter diffusion simulation	Agent-based models of smart meter diffusion can inform policy options.
Zhou and Matisoff (2016)	Smart meter diffusion policy	Public policies supporting smart meters are more important for their diffusion than social interest groups or selection regimes.
Evaluation		
Faruqui, Harris, and Hledik (2010)	Cost-benefit analysis of smart meters	The additional benefits of smart meters from dynamic pricing, beyond their operational benefits, are necessary to achieve positive net benefits from adoption.
Cook et al. (2012)	Cost-benefit analysis of smart meters	Smart meters have substantial positive net benefits.

As the table shows, the majority of research can be classified as behavioral research related to consumption feedback and time-varying electricity prices, primarily for consumers in the residential customer class. These studies typically analyze smart meters combined with in-home displays that provide direct consumption feedback in real time. The literature reviews for studies of smart meters and their impact on consumption are especially useful for assessing the general findings of the behavioral research. In particular, Torriti (2016, 61–82) performs a systematic review of behavioral studies and finds that the estimated reductions in overall and peak demand from using smart meters with consumption feedback has declined in studies over time. The author argues that this finding primarily derives from improved sample design in more recent studies resulting in larger and more representative sample sizes. Earlier studies often faced a self-selection bias where motivated and energy-conscious consumers were more likely to participate in behavioral studies. The finding of a smaller demand reduction effect is important because these energy savings influence cost-benefit evaluations of smart meter adoption.

Behavioral studies have also been conducted by the industry itself as well as government agencies. Research on the impact of time-varying rates on consumer behavior stretches back to the 1970s and 1980s, such as the Electric Utility Rate Design Study carried out by the Electric Power Research Institute. EPRI (2009) summarizes the literature on residential consumption feedback and proposes a theoretical economic framework and research collaboration strategy to address further research questions. Ehrhardt-Martinez, Donnelly, and Laitner (2010) perform a systematic review of residential consumption feedback programs and find that some types of feedback are more effective than others. The authors also note that studies are needed with larger sample sizes extended over longer time periods to assess the persistence of energy savings. Foster and Mazur-Stommen (2012) review results from recent industry studies of real-time consumption feedback and find significant heterogeneity among consumers with respect to

demand reductions. Additionally, Darby et al. (2015) summarize the UK experience with smart meter deployments and identify best practices for consumer engagement. The Recovery Act SGIG program also funded behavioral studies for some subsidized smart meter deployments in order to produce more rigorous experimental designs testing the impact of different time-varying rate designs on peak demand reduction. Descriptions of these projects are summarized by Cappers, Todd, and Goldman (2013) and analysis of results can be found in DOE (2016b).

Apart from consumer behavior, other research topics have concerned such issues as smart meter data privacy and technology standards. Additionally, although there are numerous cost-benefit studies by utilities as part of their smart meter business cases, there are relatively few in academic outlets. The social research not explicitly concerned with the technological innovation aspects of smart meters is indirectly related to studies of smart meter diffusion through the expected impacts of the diffusion of this technology. The most relevant prior research for analyzing the diffusion of smart meters is relatively small, and I will discuss these studies in greater detail later when describing my empirical analysis.

CHAPTER IV
MODELS OF TECHNOLOGY DIFFUSION

Technology diffusion can be modelled theoretically and empirically as well as with simulations. In this chapter I provide a brief overview of theoretical models of technology diffusion and link them to empirical research. Surveys of diffusion models and empirical findings in the economics literature, from which I draw, can be found in Stoneman (1983, 1987b, 2002), Thirtle and Ruttan (1987), Metcalfe (1988), Grübler (1990, 11–69), Dosi (1991), Lissoni and Metcalfe (1994), Karshenas and Stoneman (1995), Sarkar (1998), Baptista (1999), Geroski (2000), Hoppe (2002), Hall (2005), and Stoneman and Battisti (2010). Studies of the diffusion of innovations span multiple disciplines, and I focus here on models of diffusion found in the economics literature. The models I describe focus specifically on the adoption of technologies by firms. I neglect models analyzing consumer adoption of technology as well as models analyzing the impact of technology diffusion on economic growth and development, though there is some overlap.

4.1 Theoretical Models of Technology Diffusion

Theoretical models of technology diffusion can be categorized into four types: epidemic, probit, game theory, and evolutionary models. Each type of model attempts to explain why the diffusion of technology does not occur instantaneously, as observed widely in empirical data. These models primarily concern interfirm diffusion but they can typically be extended to cover intrafirm diffusion as well. Each model contributes unique insights on the diffusion process that may be suited to particular settings. Nelson, Peterhansl, and Sampat (2004), for example, argue that diffusion is a complex and

varied process such that a plurality of theoretical perspectives is beneficial. The major differences among the theories lie in whether the diffusion process is conceptualized as a disequilibrium or an equilibrium process, whether it is driven by endogenous or exogenous forces, and whether adoption decisions are modeled using bounded or unbounded rationality.

4.1.1 Epidemic Models

The first theoretical models of technology diffusion relied on an analogy with medical epidemics, stemming from the characteristic S-curve observed in empirical data. This type of model, later termed an epidemic model, revolves around information, expectations, risk and uncertainty, and learning. In essence, the model is based on imperfect information about a technology on the part of potential users.

A simple epidemic model presupposes a homogeneous population of potential users that does not change over time. Interaction among innovators and the rest of the population spreads (or infects) others with information about the technology, leading others to adopt. As more potential users adopt, the probability of adopting for nonusers increases, reaching a maximum rate and then decreasing because of an unchanging population size. Information regarding the technology grows over time with associated reductions in uncertainty surrounding the technology. When combined with competitive pressures this information encourages more and more potential users to adopt. Such a process can be represented mathematically by a logistic equation that traces an S-curve over time, although other sigmoid or ogive functions can also be used. Such S-curves can be symmetric, as in a logistic or normal specification, but are often observed empirically to be asymmetric, as in a Gompertz specification. The mathematical formulations of epidemic models are especially useful for forecasting and simulation purposes, although such uses do not necessarily have an explicit theoretical underpinning related to a learning process. They are also useful for describing and comparing diffusion phe-

nomena at a macro level without resorting to any theoretical framework at the micro level.

Epidemic models represent diffusion as an endogenous, disequilibrium process involving the transition from one long-run equilibrium of technology use to another. Griliches (1957) and Mansfield (1961, 1968) are early, pioneering studies of diffusion based on epidemic models. Epidemic models can also be applied to intrafirm diffusion where the emphasis is placed on intrafirm learning (Mansfield 1963a, 1968).

One point of concern is the different types of information that can be transmitted. Awareness of a technology, one type of information, does not automatically lead to adoption. An evaluation process must take place first. Firms decide to adopt technologies based on their expected benefits, which are often uncertain. In this sense learning is integrally tied to reducing uncertainty about the benefits of a technology and also highlights the potential difference between information and knowledge. Information about a technology can concern its hardware or software aspects and their related codified or tacit knowledge dimensions. Awareness often highlights information about the hardware aspects in addition to codified knowledge, but persuasion typically requires tacit knowledge of the software aspects. The benefits of a technology may only be revealed through learning by using or through knowledge spillovers from existing users.

Information, furthermore, can be received from both external and internal influences (Lekvall and Wahlbin 1973). External sources include media and advertising from suppliers. Internal sources include peers. The interactive element in peer-to-peer learning reveals the potential importance of social and economic networks in the diffusion of new technologies. Learning is also costly, which can have significant impacts on the diffusion process. The complexity of a technology, in part, determines its own diffusion. Epidemic models predict a faster rate of diffusion for simpler technologies with clearly defined and perceived benefits.

Epidemic models have been critiqued on a number of grounds. Some critiques include the static, homogeneous population of potential users, unchanging technology, passive information processing on the part of potential users, and general lack of standard economic content concerning decision making. The exact nature of the interpersonal exchange of information in the model and the potential for other sources of information such as knowledge spillovers from rival firms is also a point of issue.

A fundamental critique of epidemic models is the lack of heterogeneity among potential adopters, although early users of the model were certainly aware of the importance of firm heterogeneity in their empirical applications. The degree of homophily in the population, for example, can impact the effectiveness of communication and persuasion among potential users. The ability of users to learn is another important factor affecting adoption decisions, as well as their degree of risk aversion. Despite these critiques, more sophisticated epidemic models can and have been developed to address these issues (Geroski 2000). Antonelli (1989) provides a neo-epidemic perspective on diffusion—similar to evolutionary approaches discussed later—by integrating bounded rationality assumptions into a micro-level framework that gives rise to a collective learning process. Many of the extensions of epidemic models can be found in the marketing literature, influenced by the seminal Bass model (Bass 1969). These are surveyed in Mahajan and Peterson (1985), Mahajan, Muller, and Bass (1990), and Meade and Islam (2006).

4.1.2 Probit Models

The desire for choice-based or decision-theoretic models and an emphasis on the heterogeneity of firm characteristics led to the development of technology adoption models based on conventional microeconomic reasoning. These models were later termed probit models from their empirical applications. They assume a heterogeneous population of unboundedly rational, profit-maximizing firms where the costs and ben-

efits from adoption may differ across firms as a result of differences in firm characteristics such as size, previous investments, or organizational factors. Firms compare benefits to costs and adopt if a threshold where benefits exceed costs is met. Simple models assume perfect information while extensions incorporate imperfect information. David (1969) and Davies (1979) are early examples of probit models.

A characteristic S-shaped diffusion path can be obtained in probit models from the changing costs and benefits over time specific to each firm, resulting in a distribution of adoption times. An increase in the number of adopters of a technology can occur either from a decrease in the costs or an increase in the benefits of adopting. Subsequently, the rate of diffusion is determined by the rate of change in costs and benefits. The costs and benefits themselves change exogenously either from changes in the adoption environment or changes in firm characteristics, and these changes can occur simultaneously affecting diffusion through multiple processes (Cabe 1991).

Probit models represent diffusion as an exogenous, equilibrium process. The equilibrium level of adopters reached in each time period is determined by costs and benefits in such a way that the diffusion process is represented by a sequence of changing equilibrium states over time. In contrast to epidemic models, probit models do not necessarily result in a saturation point where all potential users of a technology ultimately adopt. Some firms may find it unprofitable to adopt at any time or the costs and benefits of adopting change such that further diffusion ceases after a certain time period. In addition, probit models have been extended to the intrafirm dimension by Battisti (2000) and Battisti and Stoneman (2005), where the intensity of use of a technology within a firm is also determined within a profit-maximizing framework.

Critiques of probit models have been made in a few areas. The basic assumptions of this type of model do not include the possibility of interaction or strategic behavior among firms. Probit models also do not account for potential endogenous relationships in the diffusion process. Moreover, the models rely on strong assumptions

about firm behavior, including rationality and perfect foresight. Some models, though, assume myopic expectations within a profit-maximizing framework. Probit models incorporating learning and the formation of expectations by firms have been developed as well.

4.1.3 Game Theory Models

Sharing the assumptions of firm behavior found in probit models, game theory models analyze the impact of strategic interaction on technology adoption decisions. Reinganum (1981b) and Reinganum (1981a) develop the first game theory models applied to technology diffusion, from which other work is derived. In these models a stylized S-curve can be generated from strategic behavior related to the timing of adoption. First-mover advantages play a role here. The stock of adopters in any given time period may also impact the benefits of adopting for nonadopters. Further work in game theory models has involved issues of pre-emption and rent equalization in adoption timing (Fudenberg and Tirole 1985) as well as intrafirm diffusion (Stoneman 2013).

Game theory models show that even if homogeneous firms and perfect information are assumed diffusion occurs over time as a result of the interdependence of adoption decisions. In contrast, a probit model with the same assumptions but with a lack of interaction results in instantaneous diffusion. Additionally, the endogenous evolution of market structure stemming from the diffusion of a new technology is a possibility in these models. Critiques of game theory models are similar to critiques of probit models with respect to the strong assumptions about firm behavior.

4.1.4 Evolutionary Models

Critiques of the neoclassical unbounded rationality assumption led to the development of evolutionary models of technology diffusion. These models are distinct from the previously described models, but they share certain characteristics from each

of them. They are based on an evolutionary outlook on economics that is different from neoclassical conceptions. At the core of the evolutionary perspective are boundedly rational firms operating in irreducibly uncertain environments.

Evolutionary models view diffusion as a multistage process through which technology, firms, and the adoption environment change and co-evolve over time endogenously, such that the process is cumulative and adaptive and integrates variation, selection, and innovation (Grübler 1991, 1996; Silverberg 1991; Metcalfe 1988, 2005a). This view is consistent with nonlinear models of innovation in which invention, innovation, and diffusion can operate in parallel and with feedback. Changing environmental conditions can lead to different selection pressures over time amidst a variety of technological options. Competitive pressures may cause unfit firms to lose market share or exit an industry from not adopting profitable technologies. Time is viewed in historical terms as irreversible, and path dependence in technology adoption decisions is possible such that firm-specific capabilities and strategies built over time or decisions in the early stages of the diffusion process can significantly influence the path of diffusion. The presence of dynamic increasing returns to adoption is also important. These cumulative effects determine the path of diffusion, hence the evolutionary nature of the models. A characteristic S-curve can be obtained from learning and related reductions in uncertainty as well as imitation of successful adopting firms. Silverberg, Dosi, and Orsenigo (1988) is an early example of an evolutionary model of innovation and diffusion.

Evolutionary models share with epidemic models the notion that diffusion can be self-propagating but they incorporate active search and learning processes on the part of firms instead of the passive acquisition of information. They share with probit models an emphasis on the heterogeneity of firms and with game theory models the possibility of strategic interaction and endogenous changes in firm size and market structure, but they do so within a disequilibrium framework and with assumptions of bounded rationality. A disequilibrium perspective is rooted in the idea of circular and

cumulative causation where economic phenomena are viewed as adaptive processes not necessarily tied to an ultimate end of equilibrium. Bounded rationality is the notion that cognition is a scarce resource and that the costs of making decisions lead to nonoptimizing behaviors and strategies in uncertain environments (Conlisk 1996; Lee 2011; Mallard 2012; Todd and Gigerenzer 2012). Furthermore, bounded rationality can be connected to a disequilibrium perspective by viewing nonoptimizing behavior as procedural rationality in which decisions are refined and adapted over time in a learning process.

Much of evolutionary theorizing in the economics of innovation can be captured by replicator equations, originally developed to explain the evolution of populations in biology (Andersen 2004). The evolutionary approach models diffusion as the evolving population of technologies and their relative importance as a result of variety generation and selection mechanisms (Metcalfe 2005a). In this way evolutionary models view innovation and diffusion as interconnected processes. Other evolutionary models may be based on Pólya urns or on evolutionary game theory (Dosi and Kaniovski 1994). A general critique of evolutionary models is that they may overcomplicate representations of the diffusion process, providing little marginal value over simpler neoclassical approaches. They also include elements that are not easily quantified and thus cannot be formally modeled with mathematics (Grupp 1998, 75–76).

4.1.5 Comparing Theoretical Models

The differing theoretical models of diffusion are not necessarily mutually exclusive, even among evolutionary and nonevolutionary models. Nonevolutionary models can be interpreted as special cases of evolutionary models when firms possess perfect information and history does not affect current outcomes. In this way evolutionary models are robust to misspecification of assumptions concerning rationality and history. It is important to note that the different models simply emphasize one aspect of

the diffusion process, usually at the expense of the other potential determinants. Even these formal models do not necessarily capture all the potential determinants affecting the diffusion of a technology. The development of technology standards, for example, may play a key role in diffusion, and institutional factors like regulation are also important. Such factors may be integrated into some models of diffusion indirectly through changes in the adoption environment, but they may be endogenous and are typically difficult to quantify (Grupp 1998, 51–52; Sarkar 1998).

The variety and complexity of diffusion processes precludes the construction of a general model of diffusion (Gold, Peirce, and Rosegger 1970; Nelson, Peterhansl, and Sampat 2004). This complexity, however, does not preclude a general list of potential determinants that may impact a diffusion process, from which relevant factors may inform the use of appropriate models. Nelson, Peterhansl, and Sampat (2004) provide a typology of diffusion processes that is useful in this regard, based on the presence or absence of dynamic increasing returns and sharp, persuasive feedback. Probit models are arguably more appropriate when the benefits of a technology are clear or when increasing returns are absent. Evolutionary models are arguably more appropriate when there is substantial uncertainty regarding the benefits of a technology or when increasing returns are present, as in path-dependent processes. Table 4 summarizes and compares the theoretical models described above. The major differences exist between equilibrium and disequilibrium frameworks.

Table 4. Comparison of Technology Diffusion Theories.

Model	Framework	Characteristics
Epidemic	Disequilibrium	Endogenous reductions in uncertainty from learning through the spread of information
Probit	Equilibrium	Heterogeneous, profit-maximizing firms responding to exogenous changes in technology and adoption environment
Game Theory	Equilibrium	Strategic behavior in the timing of adoption
Evolutionary	Disequilibrium	Heterogeneous, satisficing firms adapting to endogenous changes in technology and adoption environment

Other models of technology diffusion not covered above or constrained to one theoretical perspective focus on specific applied issues. Diffusion occurs over both time and space so that geography may be a causal factor in the diffusion of new technologies (Hägerstrand (1953) 1967; Brown 1981). Substitution models depict the diffusion process as the displacement of an older technology for a newer technology, which is not always explicitly considered in diffusion models (Fisher and Pry 1971; Sharif and Kabir 1976). Other areas of research include the impact of regulation on adoption decisions (Capron 1971; Sweeney 1981), the adoption of complementary innovations (Antonelli 1993; Stoneman and Kwon 1994; Colombo and Mosconi 1995; Stoneman and Toivanen 1997; Battisti, Colombo, and Rabbiosi 2015), and network externalities and path dependence (David 1985; Farrell and Saloner 1985, 1986; Katz and Shapiro 1985, 1986; Arthur 1989). Furthermore, some research has modeled interaction between supply and demand in shaping technology choices (Metcalfe 1981; Stoneman and Ireland 1983; Stoneman 1987b, 80–97; Antonelli 1989). There may also be interaction between interfirm and intrafirm diffusion processes that has not been sufficiently covered in theoretical models. Suggestions and pathways for future research in the economics of technological diffusion can be found in Stoneman (2002, 303–306) and Stoneman and Battisti (2010).

4.2 Empirical Models of Technology Diffusion

Different theoretical perspectives on the determinants of the diffusion of technology inform the choice of empirical methods for analyzing real-world diffusion phenomena. Empirical work in the study of diffusion has involved case study, historical, and econometric methods. All of these methods can be complementary to one another and if used together can provide a fuller understanding of the diffusion process than any one method alone. Case study methods refer to in-depth analysis of the adoption decisions of a firm or small set of firms. Historical methods refer to the analysis of primary sources and other historical evidence to reconstruct diffusion processes and their determinants. Econometric methods refer to the use of regression analysis to assess the determinants of diffusion processes. Econometric analysis can be distinguished by the use of aggregate or disaggregate models (Karshenas and Stoneman 1995). Aggregate models assess the overall diffusion path by focusing on the number of adopters of a technology or proportion of output produced by a technology. They are typically used to compare diffusion patterns across technologies, industries, or countries. Disaggregate models focus on the decision-making processes of firms and typically concern the timing of adoption decisions.

Numerous approaches to disaggregate econometric analysis of diffusion phenomena have been used, but duration models are generally regarded as the best approach because of their explicit modeling of the timing of adoption. Regression models applied to technology adoption include binary and multinomial choice models, count data models, panel data models, duration models, or combinations of these. The availability of data has been a major limitation in empirical studies. This is especially the case for the intrafirm dimension. In particular, lack of data on the timing of adoption decisions leads to the use of econometric models other than duration models. Panel data covering a sufficient amount of time is ideal, tracking adoption and intensity of use

within firms along with relevant covariates. Such data are rare (Karshenas and Stoneman 1995; Stoneman 2002, 95–105).

In the existing empirical literature Griliches (1957) and Mansfield (1961, 1963a, 1968) are early examples that transformed the logistic equation from epidemic models into econometric models of interfirm and intrafirm diffusion. Many studies have utilized similar methods. Nabseth and Ray (1974) is another early example employing case study methods with some econometric analysis (where the data allowed) inspired by the preceding works. The relevance of duration models for diffusion were later recognized. Karshenas and Stoneman (1993) developed a flexible duration model that can incorporate a variety of potential determinants of a diffusion process arising from multiple theoretical perspectives. The authors categorize the potential determinants as epidemic effects (from epidemic models), rank effects (from probit models), and order and stock effects (from game theory models). They do not, however, explicitly address evolutionary perspectives. Their general framework has been used frequently in empirical research, primarily for studies of interfirm diffusion. The analysis of intrafirm diffusion may also be accommodated by duration models by specifying an extensive level of adoption and analyzing the time from a basic level of adoption until an extensive level of adoption. Foster and Wild (1999) and Foster (2004) examine econometric analysis from an evolutionary perspective with discussions of application to innovation diffusion based on an augmented logistic diffusion model.

The joint analysis of interfirm and intrafirm diffusion is another issue in the literature. Multistate duration models have been proposed by Karshenas and Stoneman (1995) as a way to model interfirm and intrafirm diffusion jointly, but they require substantial amounts of data. Multistate models have yet to be implemented in the literature, however, most likely owing to a lack of data. Sequence analysis is an extension of multistate models also appropriate for the study of diffusion. Multinomial choice models or

bivariate probit models can also be used by differentiating between basic adopters and extensive adopters.

The selection of an appropriate empirical model is determined by a number of factors. Data availability is a fundamental determinant. Research questions are another, such as a focus on the level versus the rate of diffusion. Theory must also play a guiding role in model selection. A thorough understanding of the technology under study and its historical, social, and economic contexts is imperative. In general, duration models are best equipped to explain the dynamics of technology diffusion because of their ability to use panel data and their explicit focus on the timing of adoption decisions. They model diffusion as a dynamic process and can be used with any theoretical perspective. Evolutionary perspectives, however, may require alternative approaches, though there is little empirical literature taking an explicitly evolutionary view that uses econometric methods. The relative complexity of evolutionary theories of diffusion highlights the potential limitations of econometric analysis when nonlinear, endogenous, and path dependent relationships are important characteristics of the diffusion phenomena under study. Qualitative variables such as institutions, social norms, and historical events are not always easily measured or amenable to econometric analysis. Evolutionary approaches more often use detailed historical and case study methods as alternatives or complements to econometric methods. In this way, evolutionary perspectives align with general critiques of econometrics that this research method cannot answer all questions and often neglects other sources of data and vernacular economic knowledge. Instead, this approach promotes pluralistic applied research methods with differential strengths and weaknesses that collectively advance knowledge of a subject through triangulation (Sarkar 1998; Swann 2006; Starr 2014).

4.3 Simulation Models of Technology Diffusion

Computer simulations offer a third mode of investigating diffusion phenomena. This is important given the general paucity of adequate data on diffusion processes. Simulation models are computer programs informed by theory and calibrated with reference to empirical data. Simulations can take the form of system dynamics models or agent-based models. System dynamics models are based on difference or differential equations, as found in epidemic models, whereas agent-based models are based on algorithms representing agent behavior, conducive to decision-theoretic models. These techniques originated from the study of complex systems, which are characterized by pervasive heterogeneity among agents, uncertainty and bounded rationality, interdependence and feedback, nonlinearity, emergence, and adaptation. Agent-based models are particularly useful for evolutionary perspectives in economics, where the economy is viewed as a complex adaptive system (Lane 1993a, 1993b; Watts and Gilbert 2014).

In agent-based models heterogeneous agents are embedded in social and economic networks and interact with one another over time. These models are typically calibrated to accord with specific economic and historical contexts surrounding the diffusion of a technology. In this regard, agent-based models can overcome some of the limitations of both mathematical and econometric models. They can more easily explore interactive behavior and nonlinear and endogenous processes. One important advantage of these models is overcoming the limitations of theoretical representative agent models that assume homogeneous agents in order to be analytically tractable. Nelson and Winter (1982) is an early example in the economics literature using computer simulations informed by evolutionary theory and concerning the search processes of firms with respect to technology generation and adoption. Silverberg, Dosi, and Orsenigo (1988) develop an evolutionary model of technology diffusion and use computer simulations to investigate their theory. More recently, Watts and Gilbert (2014) provide a

broad overview of agent-based models applied to innovation phenomena, with a focus on diffusion.

CHAPTER V
DETERMINANTS OF EARLY SMART METER DIFFUSION IN THE UNITED STATES

Theoretical models of technology diffusion elucidate the potential determinants of the early diffusion of smart meters in the United States. These relevant determinants can then be considered in empirical analysis. In this chapter I describe the relevant determinants and classify them into supply-side, demand-side, and environmental categories. I also provide expected effects of the determinants on smart meter diffusion.

5.1 Determinants of Technology Diffusion

The determinants of the diffusion of new technologies among firms can be grouped into three general categories: supply, demand, and environment (DePietro, Wiarda, and Fleischer 1990; Wejnert 2002). The significance and impact of any given determinant may differ across the interfirm and intrafirm dimensions. Supply-side factors include the nature of the technology, improvements in performance, technology standards, related infrastructure, entrepreneurship and marketing, production capacity, market structure, and cost structure (Rosenberg 1972; Brown 1981; Gold 1981; Stoneman and Ireland 1983; Miller and Garnsey 2000; Stoneman 2002, 78–92). Demand-side factors include user learning, both across and within firms, and heterogeneous firm characteristics, such as size, financial resources, absorptive capacity, and managerial strategy (Gold 1981; Stoneman 2002, 29–54). Environmental factors concern the adoption environment and include public policies, regulation, geography, or other dimensions (Gold 1981; Dosi 1991; Lissoni and Metcalfe 1994). There may also be interaction among all three general types of determinants.

Uncertainty, a fundamental aspect of economic activity, cuts across and influences all three categories. On the supply side, technology standards are one means to reduce uncertainty with respect to product quality, upgradability, and interoperability. On the demand side, potential adopters of a technology may be uncertain as to the actual capabilities or benefits of a technology and there may be heterogeneous expectations, hence the potential importance of learning in the diffusion process. Additionally, they may be uncertain about the potential technical improvements or changes in price of the technology over time, impacting their profitability considerations and timing of adoption. Environmental factors like public policy may also create or reduce uncertainty by shaping the adoption environment (Rosenberg 1972, 1976; Ireland and Stoneman 1986; Stoneman 2002, 55–66).

The majority of diffusion research, both theoretical and empirical, has focused on demand-side factors related to firm characteristics to the neglect of supply-side and environmental factors. Furthermore, the interfirm and intrafirm diffusion processes may have distinct determinants or they may be interdependent. Most research has examined these two processes separately, but recent empirical research has analyzed the two components jointly (Battisti and Stoneman 2003; Åstebro 2004; Hollenstein 2004; Battisti and Stoneman 2005; Battisti et al. 2007; Hollenstein and Woerter 2008; Battisti, Canepa, and Stoneman 2009; Arvanitis and Ley 2013). The selection environment within which adoption occurs as well as the relative importance of determinants may also change over time, which has not been studied extensively. Collectively, these issues can complicate empirical analysis considerably by requiring a greater theoretical sophistication and substantial amounts of data.

The relevant determinants in the early diffusion of smart meters include all three of the supply-side, demand-side, and environmental factors. Following Karshenas and Stoneman (1993), these determinants are motivated from the major currents in diffusion theory, including learning effects emphasized in epidemic and evolutionary models,

firm-specific effects emphasized in probit and evolutionary models, and environmental effects emphasized in evolutionary models and to a lesser extent in probit models.

5.2 Supply-Side Factors

Although the characteristics of adopters are the usual focus of diffusion research, the supply side may play an equally important role. Relevant supply-side factors affecting the diffusion of smart meters include price, competition among meter manufacturers, changes in product quality over time, and technology standards.

The cost of AMI has an impact on the profitability calculations of utilities. Cost reductions and improvements in technology performance over time can come about through a cumulative process of learning by doing on the part of manufacturers (Arrow 1962b; Nakićenović 2002; Thompson 2010). The price of smart meters has declined gradually over time since their introduction in the 1990s, likely the result of a general decline in the costs of electronic products. The decline, however, has only been slight, and the costs of communication systems and data management systems have remained relatively stable. Product quality has increased gradually at the same time, including an expanded capacity for upgradability. The cost of a smart meter may also depend on the exact functions desired, such as import/export metering or remote connect and disconnect. More functions generally incur a higher cost. The meters themselves represent roughly half the cost of an AMI system (FERC 2006; FERC 2010; EEI 2006a, 2006b; Haney, Jamasb, and Pollitt 2009; EPRI 2011).

The supply side of the meter market has historically been competitive, and product differentiation appears to be small. In the North American market, the major suppliers of smart meters currently include Itron, GE, and Sensus and have included Landis+Gyr, Elster, and Aclara in the past. There are also many smaller entities with lesser market shares. Globally there has been a trend toward consolidation among meter manufacturers over the past two decades. During this time, electronic meters have overtaken

the market share of electromechanical meters. The industry has largely come to view AMI as the standard metering technology for the future, and manufacturing firms have begun offering communication, data, analytics, and related services as a result. Manufacturing capacity on the part of these firms could potentially limit smart meter diffusion depending on the number of large orders from utilities that occur at the same time (ABS Energy Research 2005, 2006, 2007, 2009, 2010; Alejandro et al. 2014; Ulama 2015).

Technology standards can also play an important role in the diffusion of new technology by organizing a common technical language that reduces transaction costs and facilitates information diffusion (David 1987; Link and Tassey 1988; David and Greenstein 1990; Link and Kapur 1994; Metcalfe and Miles 1994; Tassey 2000, 2015; Blind 2004). Though they are a supply-side phenomenon, their development typically depends on user involvement. Standards can be categorized into two broad types, product and nonproduct standards, both of which are relevant to the diffusion of smart meters. Product standards refer to the functionality and design of the product, and nonproduct standards refer to other technical aspects on which the product is not based. Utilities may be reluctant to adopt smart meters, for example, if they are not certain that the product they purchase takes accurate measurements, if they fear vendor lock-in because of a lack of interoperability among smart grid technologies, or if they fear technological obsolescence in an evolving technology space. Standards are especially important if AMI is viewed as a technology platform and as foundational for the smart grid. Some standards already exist and others are currently being developed. Various organizations are involved with the standards setting process. Furthermore, there are standards for both smart meters and the broader smart grid, related to communication networks and the need for interoperability of devices connected to and interacting with the power grid. The lack of standards, especially surrounding interoperability, has likely delayed the diffusion of AMI (NETL 2008).

The American National Standards Institute (ANSI), a private nonprofit organization based in the United States, has coordinated the development of standards related to smart meters in collaboration with the National Electrical Manufacturers Association (NEMA). ANSI C12 is a set of standards related to electricity metering and are revised and updated over time as metering technology evolves. These standards concern performance criteria for electricity metering, including measurement accuracy, product design, data tables, and interfaces for communication networks. They represent a combination of product quality and interface standards. ANSI C12.1 and ANSI C12.20 cover measurement accuracy and were revised in 2008 and 2009, respectively, to bolster product quality. ANSI C12.19 defines how data collected by meters are structured and was last revised in 2012 from its 2008 version. ANSI C12.22 covers the interoperability of meters and their data with communication networks as well as the encryption of data. It was last revised in 2012 from its 2008 version. Another standard, NEMA SG-AMI 1-2009, was created in 2009 to enable firmware upgradability of smart meters, an important issue related to technological obsolesence (NEMA 2017).

The National Institute of Standards and Technology, an organization sponsored by the US federal government through the Department of Commerce, works with industry to develop standards across a broad range of scientific and technological fields with a focus on measurement. These standards are utilized by the previously described ANSI standards. NIST was also tasked by the Energy Independence and Security Act of 2007 to coordinate the development of technology standards and cybersecurity guidelines for the smart grid in the United States. It has engaged multiple stakeholders in the development process, including utilities, generators, product providers, consumers, and regulators (NIST 2014a, 2014b, 2017).

With respect to smart meters, NIST works on measurement accuracy, grid edge sensors, cybersecurity and data privacy, and the interoperability of meters with communication networks and data systems, including utility networks and behind-the-meter

home area networks associated with demand response activities. NIST played a leading role in encouraging early implementation of NEMA SG-AMI 1-2009. In 2009 NIST established the Smart Grid Interoperability Panel (SGIP) to aid the ongoing development of smart grid standards, originally as a public-private partnership. The SGIP has desired an accelerated timeline for the development of these standards and has utilized a priority action plan process to achieve this. The AMI-related standards compose one of nine priority areas. The organization eventually transformed into an industry-led nonprofit in 2013. NIST and SGIP have also been involved with developing technical standards for the Green Button Initiative, a program designed to facilitate access to electricity consumption data for consumers. NIST also works internationally with other organizations to develop smart grid standards, such as the International Electrotechnical Commission (IEC) whose IEC 61850 international standard is the basis for interoperability work (GSGF 2014; NIST 2014a, 2014b, 2017).

5.3 Demand-Side Factors

Relevant demand-side factors in the diffusion of smart meters include firm characteristics and learning processes. There are a number of heterogeneous utility characteristics influencing the decision to adopt smart meters. Expectations, relating to price, performance, or competing technologies, play a role in the timing of adoption. The expected profitability of adoption is calculated from the expected costs and benefits that may vary across utilities, region, and time. These costs and benefits are explicitly identified in utility business cases for deploying smart meters. The relative advantage of AMI over AMR, involving the additional functions beyond automation of the meter reading process, may be viewed differently across utilities. AMI is compatible with the previous adoption of AMR, owing to its direct evolution from AMR. AMI, however, constitutes a more complex investment than AMR because of its more sophisticated communication and data systems and potentially broader integration with other smart grid technologies.

As a result, it may be more difficult for utilities to trial the technology, though pilot programs and demonstration projects are not uncommon for larger utilities. The adoption of smart meters may also require organizational changes by utilities in order to realize the full benefits of their use.

Smart meters are a capital-embodied process innovation that require substantial investment. The cost of deploying AMI includes hardware and software costs as well as installation, project management, adjustment, integration, and maintenance costs. Deployment costs can also vary depending on the type of deployment pursued, including full, partial, targeted, or replacement deployment strategies. The benefits of deploying smart meters include automation of the meter reading and billing processes, improved operational management of the distribution grid, and improved customer service and engagement. Additional benefits may be discovered through learning by using. In making the decision to adopt smart meters, utilities weigh the expected costs against the expected benefits. Cost-benefit analyses likely differ across utilities, region, and time (NETL 2008; Haney, Jamasb, and Pollitt 2009; IEE 2011; EEI 2011; EPRI 2011).

Firm size is a widely analyzed variable in studies of innovation, and size can often represent more than one relevant factor (Cohen 2010). Diffusion research has typically found a positive association between firm size and the initial adoption of a technology and a negative association between firm size and intensity of use (Mansfield 1963a, 1963b, 1968; Rose and Joskow 1990; Fuentelsaz, Gomez, and Polo 2003; Arvanitis and Ley 2013). The inverse relationship between firm size and time to initial adoption may stem from the ability of larger firms to more easily handle the costs and risks associated with technology adoption. It may also be related to greater financial resources, more frequent capital turnover, closer relationships with equipment manufacturers, and greater R&D capacity (Mansfield 1963b, 1968; Canepa and Stoneman 2005). Larger firms may also find it more profitable than smaller firms to adopt technologies that have significant labor-saving benefits depending on factor market conditions, and this adop-

tion may enable further growth through economies of scale (David 1966). The absolute level of investment required and the speed of decision-making processes in larger firms may also slow down their intrafirm diffusion (Mansfield 1963a; Romeo 1975). Although larger firms may have more frequent capital turnover, their larger stock of capital can take longer to turnover completely as a result of vintage effects, which is the case for long-lasting electricity meters. Additionally, if larger firms tend to be earlier adopters, then they also generate the initial learning related to the actual benefits of adopting a technology that can spill over to other firms. Knowledge spillovers can also influence later adopters to adopt more intensively at a quicker pace. Utility size should have a positive effect on the rate of interfirm diffusion for smart meters and a negative effect on the rate of intrafirm diffusion.

For utilities, firm size overlaps to some extent with firm ownership. Investor-owned utilities (IOUs) are typically much larger relative to municipal utilities (munis) and co-operative utilities (co-ops). Utility ownership may impact adoption decisions differently than size through differing organizational influences and incentives as well as through regulation (Rose and Joskow 1990; Dedrick et al. 2015). Historically, munis and co-ops have arguably been more engaged with their customers and more open to investing in energy efficiency given their ownership structures. Insofar as smart meters further such goals, these ownership structures should exert a positive effect on their adoption. The general lack of regulatory burden for these utilities can also quicken the pace of adoption. Additionally, co-ops are primarily rural and cover large geographic areas, so the adoption of AMI should significantly reduce the costs of meter reads and service switching. At the same time, munis and co-ops may be more financially constrained relative to IOUs, posing a barrier to adoption. In addition, public electric utilities can also be integrated with public water and gas utilities that may share metering infrastructure, and a shared AMI infrastructure could be used for all these metering needs resulting in additional cost savings. Some IOUs, however, also own and operate

gas utilities and the same principle applies there. Municipal and co-operative ownership should also have a positive impact on intrafirm diffusion strictly because of their typically small size compared to IOUs.

Vintage effects may also impact adoption decisions (Mansfield 1963a, 1968; Antonelli 1993; Mulder, Groot, and Hofkes 2003; Das, Falaris, and Mulligan 2009). Vintage effects may exist for those utilities that have previously adopted AMR technology, such that the prior diffusion of AMR may impact the diffusion of AMI. Electronic meters typically have a useful life of 10–20 years, so the prior installation of an AMR system can increase the cost of adopting AMI through premature discontinuance of AMR. The operational efficiencies resulting from a deployment of AMR also exist for AMI and will have already been obtained if AMR has previously been deployed. Vintage effects can negatively impact both the rate of interfirm and intrafirm diffusion if older meters are replaced by newer smart meters over time. Additionally, most of the costs of adopting AMI are upfront while the benefits accrue over the product's lifecycle. The long-lived nature of AMI capital investments also likely leads to joint adoption and intensity decisions, helping to avoid sunk costs and the difficulty and cost of switching to other metering technologies after an AMI deployment. Smart meters can also become more valuable as more of them are deployed because of their role in grid operations and demand response programs.

The significance of a vintage effect, however, likely depends in part on the type of communication system previously installed for an AMR system (NETL 2008; EEI 2011). If a fixed communication system was previously selected, then the cost of upgrading to AMI should be less than if a mobile communication system was previously selected. Investment in the communication system would only incur relatively small incremental costs. Additionally, it may also be true that a utility that has previously adopted AMR may be more likely to adopt AMI as a result of the learning process with AMR technology. Such a utility may recognize the relative advantage of AMI over AMR

or assimilate the new technology into the organization more readily. Prior experience with demand-side management activities, like load response programs, may also positively impact smart meter adoption through a learning process. Technology adoption decisions can be positively affected by cumulative learning (Colombo and Mosconi 1995; Arvanitis and Hollenstein 2001). The net effect on AMI adoption of the prior adoption of AMR is ambiguous and depends on the timing and intensity of this prior adoption. The choice of AMR versus AMI can also reflect a utility's overall strategy and vision for grid modernization.

Adoption decisions are also affected by uncertainty. Because adoption decisions are also investment decisions, adoption is at least partially irreversible, resulting in sunk costs, and uncertainty can delay investment on the part of risk-averse firms (Pindyck 1991). One source of uncertainty is technological expectations (Rosenberg 1972, 1976; Balcer and Lippman 1984; Ireland and Stoneman 1986; Antonelli 1989; Weiss 1994). This uncertainty relates to issues of improving technology, technological obsolescence, and interoperability, addressed to an extent by the development of technology standards. These have all been concerns with smart meters (FERC 2008, 17–22). An additional source of uncertainty for IOUs is the ability to recover the costs of deploying smart meters under conventional regulation and the possibility of future deregulation.

Uncertainty is also tied to learning that occurs both within and across firms, leading to adaptive expectations over time. Learning involves becoming aware of a technology, its potential benefits, and how to adapt it to local conditions. Learning by using imparts knowledge to firms on the actual costs and benefits of adopting a technology and thereby reduces uncertainty, and this learning can be a social, interactive, and cumulative process that generates knowledge spillovers to nonusers and leads to incremental innovations even as the technology diffuses (Rosenberg 1982; Williams, Stewart, and Slack 2005). For utilities this also involves learning best practices in smart meter deployments to minimize costs and recognizing new benefits as they arise to maximize the

value of smart meters (EEI 2006a; EPRI 2010). Learning may be an important determinant in the diffusion of smart meters because some of their benefits, particularly those associated with demand response and consumer behavior, are uncertain. Pilot programs for smart meters, a form of trialing, likely play an important role in the learning process in this respect, reducing uncertainty for both utilities and regulators before committing to large-scale deployments.

Dynamic capabilities allow a firm to capitalize on learning to generate value in a changing environment (Teece 2010). The social and economic context within and around firms, including organizational structures and regulatory environments, also shapes innovative performance including that associated with learning (Lazonick 2005). The most salient capability influencing the adoption of technologies is absorptive capacity, referring to the ability of a firm to create value from externally sourced knowledge. The absorptive capacity of a firm impacts adoption decisions through a firm's ability to learn about technology and its potential benefits. The degree to which a firm can search for, process, and utilize knowledge external to itself impacts if and when it adopts a particular technology. Absorptive capacity may also be correlated with internal R&D activities (Cohen and Levinthal 1989; Cohen and Levinthal 1990; Rosenberg 1990). Research and development activities in the electric power industry are low relative to other industries. Most R&D is carried out by manufacturers and not utilities. Investor-owned utilities perform the most R&D, principally through the collaborative, industry-supported Electric Power Research Institute. This organization was formed in 1972 to address criticisms of the innovative capabilities of the industry (Hirsh 1989, 131–138, 159–171). Innovativeness is important in that it showcases the differing strategies that utilities have with respect to changing market conditions, regulation, and technology in the electric power industry.

Management strategy with respect to business models and technology choices is subjective but can also influence technology diffusion (Nabseth and Ray 1974; Met-

calfe and Boden 2003; Preece 1995; Tidd 2010b). Smart grid technology and the rise of distributed energy resources, including generation and storage, may require new business and regulatory models for utilities in order to maximize the full benefits of these technologies (Fox-Penner 2010; IEI 2015a, 2015b, 2016b; MITEI 2016; Shomali and Pinkse 2016). Utilities that adopt smart meters may also be likely to adopt other smart grid technologies. The adoption of information technologies may also require changes in the organizational structure and processes within firms, leading to productivity increases (Attewell 1992; Brynjolfsson and Hitt 2000). The adoption of AMI likely requires utilities to undergo some organizational changes and also acquire new skills and personnel related to information technology, data management, and analytics.

Distributed generation has diffused in large part because of net metering policies. State policies with respect to net metering vary in their design. The majority of states have enacted specific policies on net metering in order to reduce transaction costs, ensure reliability, and support other goals like reducing environmental emissions. By integrating import/export measurement functions into one meter, smart meters may reduce the costs of metering for these customers. Detailed data on the amount and timing of electricity generated through distributed generation can help utilities manage the grid more effectively. In states with visions of more competitive electricity markets, like California, Texas, and New York, distributed generation is expected and encouraged to grow. At the same time, smart meters also enable time-varying net metering rates, which may make distributed generation less profitable for some customers. Furthermore, distributed storage may follow a similar path to distributed generation if battery technology improves and associated costs are reduced. Overall, smart meters help enable both a more flexible supply side and a more flexible demand side. As a result, utilities with larger numbers of net metering customers should be more likely to adopt smart meters (Solar ABCs 2010; Römer et al. 2012; Borenstein and Bushnell 2015; Dedrick et al. 2015).

5.4 Environmental Factors

In addition to supply-side and demand-side factors, environmental factors can play a decisive role in the diffusion of new technologies. The institutional structure of the electric power industry is complex and polycentric. The methods of regulation and their interaction with technological change and market structure influence how firms pursue and adopt innovations (Hughes 1971; Sweeney 1981; Blind 2010). Public policy, including state and federal policies and regulations, prominently shapes the adoption environment of utilities with respect to smart meters (EIA 2011). Zhang and Nuttall (2011) and Rixen and Weigand (2014) study the impact of policy on the diffusion of smart meters via agent-based model simulations. They find that the impacts of different policies depend on objectives. In particular, they find that monetary grants boost both the speed and level of adoption, and they also find that liberalized markets are more conducive to adoption.

Regulation has been found to influence diffusion processes in various industries (Capron 1971; Oster and Quigley 1977; Hannan and McDowell 1984; Trajtenberg 1990; Battisti and Stoneman 1998; Stoneman and Battisti 1998, 2000; Acemoglu and Finkelstein 2008; Gruber and Koutroumpis 2013). Government initiatives supporting smart grids are major drivers in smart metering adoption around the world (Zhang 2010). In the United States, relevant federal policies include subsidies for smart meters and pressure from FERC to implement demand response programs, and relevant state policies include the structure of electricity markets, regulatory strategies and incentives, and technology mandates. This variation in state-level policy and regulation gives a spatial dimension to smart meter diffusion in the United States. Such policies are important because variation in selection environments can lead to variation in technology choice (Glynn 2002; Watson 2004). Additionally, the polycentric governance of electricity systems, divided between different levels of government, adds a layer of complexity that can adversely

impact technology diffusion if policies are not effectively coordinated (Goldthau 2014; Zhou and Matisoff 2016).

Federal policy has supported the adoption of smart metering and time-varying electricity rates despite the lack of legal jurisdiction, which rests with the authority of states to regulate the distribution and retail sale of electricity. In order to better coordinate policies at the federal and state levels, FERC and the National Association of Regulatory Utility Commissioners (NARUC) embarked on collaborative activities in 2006. Federal policy has provided incentives for smart meters but not mandates. The impetus for such support ultimately derives from energy efficiency and demand-side management goals that can be traced back primarily to the 1970s oil crisis. More specifically, the support for smart metering ultimately rests with the desire for demand response through time-varying rates. Three federal policies stand out overall in targeting smart meter adoption (Rose 2014).

One, the recognition of demand response as a viable and important resource in electricity markets has been a persistent, overriding policy objective. FERC has acted as a change agent in the diffusion of demand response, for which they have a keen interest in promoting enabling technologies like smart meters. Although FERC does not have jurisdiction over retail markets, retail markets can shape wholesale markets just as wholesale markets can shape retail markets. In particular, fluctuating prices in wholesale markets are typically not reflected in retail rates (Rose 2014).

Two, the Emergency Economic Stabilization Act of 2008, passed in response to the financial crisis of 2007–2008, included provisions that accelerated the tax depreciation for smart meters from 20 years to 10 years. This was an incentive for utilities to adopt smart meters as a means to further energy efficiency goals. These provisions also applied to other smart grid technologies (Rose 2014).

Three, the American Recovery and Reinvestment Act of 2009 modified and funded initiatives first approved in the Energy Independence and Security Act of 2007.

The DOE received and managed $4.5 billion over five years for smart grid initiatives. The two main programs funded were known as the Smart Grid Investment Grant program ($3.4 billion) and the Smart Grid Demonstration Program ($600 million). Other funded programs, for example, included workforce training and development ($100 million) and activities related to technology standards, interoperability, and cybersecurity ($12 million). The SGIG focused on deploying smart grid technologies. It provided matching grants to utilities who invested in AMI, subsidizing the costs of deployment by up to 50%. In total, the SGIG disbursed nearly $1 billion to 81 utilities leading to the installation of more than 16 million smart meters across the country (Rose 2014; DOE 2016a, 2016c, 2017b).

While policies at the federal level designed to enhance the diffusion of smart meters have primarily involved monetary incentives, policies at the state level have primarily involved regulatory mechanisms. Some aspects of state regulation may also indirectly influence the diffusion of smart meters. It is typically the case that only IOUs are subject to state regulation and not munis or co-ops. Although viewed as natural monopolies and regulated as such in one form or another, distribution utilities may face different incentives or pressures from the regulatory environment that influence their adoption decisions. These influences may come from regulatory action or state policies related to demand response and energy efficiency as well as the absence or presence of formal wholesale markets and customer choice for electricity supply. There is significant variation across the states with respect to these policies (EIA 2011; NGA 2016).

Common to all utilities in a given geographic region is the market structure. The metering stock is owned and operated by distribution utilities, which are regulated in some form regardless of a state's restructuring status. Initially, the process of restructuring electricty markets in the late 1990s created a disincentive to invest in advanced metering because of concerns over stranded assets. Some states even implemented competitive metering with the thought that this would facilitate the diffusion of advanced

meters. The initial experiences, however, resulted in the opposite effect. These states found that a competitive metering market was costly compared to a coordinated mass deployment of advanced meters, and competitive metering policies were thereafter abandoned. The very early diffusion of smart meters was primarily influenced by the high costs of adoption as well as the fear of stranded costs and uncertainty surrounding the ability to recover the costs of investment stemming from deregulation or the potential for future deregulation (EEI 2006a; NETL 2008).

The relationship between market structure and innovation has been studied extensively in the innovation literature, with the primary findings being that a moderate level of competition produces optimal innovation in most industries (Cohen 2010). In the electric power industry, research has found that the liberalization of electricity markets can promote innovation activity in energy-related products depending on institutional context and policy uncertainty (Markard and Truffer 2006; Sanyal and Cohen 2009; Jamasb and Pollitt 2008, 2011, 2015; Sterlacchini 2012; Sanyal and Ghosh 2013; Cambini, Caviggioli, and Scellato 2016).

In those areas where wholesale markets have existed, wholesale prices of electricity fluctuate over the course of a day reflecting the time-varying costs of generating electricity. Insofar as distribution utilities or retail suppliers must purchase electricity in these markets, they may wish to reflect these costs in time-varying retail prices. The desire for more efficient electricity markets was a primary driver behind restructuring policies. Smart meters are an enabling technology for time-varying pricing, so utilities in competitive areas may be more likely to adopt smart meters than those that are not. Of course, vertically integrated utilities in conventionally regulated states also face time-varying costs but their cost recovery mechanisms likely lead to less pressure to implement time-varying pricing. The nature of rate-of-return regulation may also influence technology adoption decisions through a capital-biased incentive.

State regulation is another major determinant of utilities' technology choices. Regulatory interest in advanced metering was boosted by the Energy Policy Act of 2005, which required all state regulatory commissions to consider advanced metering and time-varying rates. NARUC passed a resolution in February 2007 recommending that regulatory barriers be addressed with respect to the adoption of AMI. Recommendations included the development of AMI business cases, complementary policies and ratemaking strategies to support demand response, timely cost recovery of investments, and appropriate depreciation lives. In certain states AMI deployments have been delayed because of regulatory concerns over cost and consumer pushback related to privacy, safety, and health issues. Privacy and security concerns about smart meter data have also led to laws or regulatory rulings aimed at protecting consumer data, which could reduce uncertainty about data privacy and encourage smart meter adoption (EIA 2011; McKenna, Richardson, and Thomson 2012; Gerpott and Paukert 2013; Urban 2016).

There are multiple, and potentially complementary, dimensions of state regulation that may influence the adoption of smart meters by utilities. These dimensions include direct and indirect policies with regard to smart meter adoption. A number of states, either through legislation or regulatory rulings, have supported or mandated the deployment of AMI by IOUs (EIA 2011). The desire to expand demand response programs as well as pressure for improving billing practices can lead to policies supporting the adoption of smart meters (Praetorius et al. 2009, 115–150; Foster and Alschuler 2011). These mandates, however, have not necessarily emphasized the complementary adoption of time-varying rates, and some states even limit time-varying rates for residential customers (Lazar and Gonzalez 2015). Additionally, the nature of rate-of-return regulation may also incentivize capital-biased technology adoption decisions (Averch and Johnson 1962).

Another relevant regulatory variable is lost margin recovery, which removes disincentives for investments in energy efficiency. The two main types of lost margin recovery include lost revenue adjustments and decoupling. These mechanisms ensure that utilities do not lose profits from energy efficiency investments. Lost margin recovery itself, though, does not necessarily encourage such investments (Brennan 2010; RAP 2011; Sullivan, Wang, and Bennett 2011; Morgan 2013). Energy efficiency resource standards (EERS) incentivize such activity by establishing long-term, legally binding efficiency goals for utilities (or in some cases third-party efficiency program administrators). EERS currently exist in twenty-five states and mostly apply to IOUs though in some states other types of utilities are also subject to the standards. Of those states with EERS, most account for potential lost revenues by offering cost recovery through performance-based bonuses. Alternatively, third-party administrators or governmental agencies may be tasked with the efficiency goals, who do not possess an inherent disincentive to invest in energy efficiency. The combined presence of both lost margin recovery and EERS, occuring in over half of the states with EERS, should exhibit a stronger effect on energy efficiency incentives compared to the effect of either policy alone. The strength of such an effect, though, likely depends on the specific design of EERS, for which there is substantial variation across states (Brennan and Palmer 2013; Palmer et al. 2013; Steinberg and Zinaman 2014; ACEEE 2017a). These two policies may encourage the adoption of smart meters by utilities insofar as smart meters can lead to reductions in overall electricity demand through consumption feedback. Smart meters, however, are not necessary to identify areas for efficiency improvements and other investments may prove more profitable.

CHAPTER VI

EMPIRICAL ANALYSIS OF EARLY SMART METER DIFFUSION IN THE UNITED STATES

Smart meters currently compose about half of the electricity meter stock in use in the United States and they continue to diffuse. In this chapter I present an empirical analysis of the early diffusion of smart meters in the US electric power industry, considering jointly the determinants of both interfirm and intrafirm smart meter diffusion. I describe the patterns of diffusion and also use econometric models to assess the determinants of the diffusion process. Although smart meters have not fully diffused across the industry, the empirical analysis in this chapter remains informative and policy-relevant, focusing on the initial stages of the diffusion process.

Most of the theoretical and empirical research on technological diffusion is concerned with the interfirm dimension of diffusion, and when the intrafirm dimension is studied at all both dimensions are often analyzed separately. The lack of research on intrafirm diffusion is seemingly odd, given that the impact of process innovations like smart meters is only felt through their widespread diffusion across both the interfirm and intrafirm dimensions. This situation, however, likely results from a lack of data. Econometric analyses of technology diffusion have typically used cross-sectional data, which is not ideal because diffusion is an inherently dynamic process. My analysis will differ in this regard by using a panel dataset that tracks smart meter use by electric power utilities in the United States across both the interfirm and intrafirm dimensions over a period of eight years.

6.1 Data Sources

I use three datasets for the empirical analysis in this chapter. The principal dataset that I use comes from survey data collected by the US Energy Information Administration (EIA). The EIA began collecting data on the number of smart meters installed and operational by distribution utilities at the operating level in 2007 for its Annual Electric Power Industry Report, Form EIA-861. Participation in this survey is required of all entities that generate, distribute, or sell electricity in the United States. Within the dataset is information related to sales, revenue, generation, and energy efficiency among other topics. It effectively covers the population of utilities in the United States (EIA 2017a).[1]

Beginning in 2007, the survey requested from distribution utilities counts of AMR and AMI meters installed and operational by customer classes (residential, commercial, industrial, and transportation).[2] The survey also provides explicit definitions of the different types of meters when requesting counts of meter types in order to avoid confusion and differences in interpretation of advanced metering on the part of utilities. The survey defines standard meters as either electromechanical or electronic meters that measure aggregate kWh and where meters are read manually over monthly billing cycles for billing purposes only. It defines AMR meters as meters that collect data for billing purposes only and transmit these data one-way from the customer to the utility. It defines AMI as meters that measure and record data in intervals, at a maximum hourly, and subsequently provide this data to both the customer and the utility at least once daily. The survey also states that this data can be used for billing and other purposes and notes that these meters can range from hourly interval meters to real-time meters with two-way communication capabilities that can measure, record, and transmit

1. I only include data for utilities from the fifty states and the District of Columbia. I exclude the five utilities in US territories because of their unique policy and regulatory status.

2. Form EIA-826 also collects data on counts of AMR and AMI meters installed and operational on a monthly basis, providing a dataset with finer granularity, but this data first started being collected in 2011.

data in real time. Additionally, the survey instructs respondents to record AMI meters as AMR meters if they are only being used as AMR meters, although this note was removed from the survey form for 2013 and 2014 (EIA 2017a).

The survey, however, did not request counts of standard meters and counts of total meters installed and operational until 2013. The data concerning counts of total meters per utility are necessary for calculating proportions of meter types, which are necessary for tracking adoption levels within utilities. Data exist, however, on the total number of customers per utility, which I use to generate estimates of total meters for use in calculating proportions. In 2007 there were 639 observations recorded for counts of advanced meters while in 2014 there were 1,925 observations. This discrepancy exists, presumably, because of legitimate nonresponse, because those utilities who had no advanced meters simply skipped the associated questions for those survey years. I impute these missing responses as zeros (EIA 2017a).

Data concerning utility activities indicates there were 2,803 unique distribution utilities in the United States from 2007 to 2014 while only 1,991 utilities responded to the questions concerning counts of meters. These numbers, however, are not precise. The data tracking utility activities does not count IOUs that operate in more than one state as separate utilities. In contrast, the number of utilities responding to the meter questions is somewhat inflated because utilities that operate in more than one state report for each state. I leave IOU data at the operating level because of the importance of state regulation but add together state responses for munis and co-ops. Upon inspection it appears that those utilities who did not respond to the meter questions are small munis and co-ops. It is possible they simply did not respond to the meter questions because they had neither AMR nor AMI meters during the time period under study, but I exclude these utilities from the analysis (EIA 2017a).

The final analysis dataset that I use is primarily composed of data from the EIA survey. It allows me to both describe and analyze the temporal and spatial patterns of

smart meter diffusion in the United States by using utility-level data tracked over time. Additionally, the Recovery Act SGIG program provides data on the timing and count of smart meters installed as a result of this funding for the 81 utilities that were awarded grants for such purposes (DOE 2015). I also use various other sources to generate variables related to regulatory environments (EIA 2011; IEI 2014; FERC 2015b; EMRF 2016; ACCES 2017; ACEEE 2017a, 2017b). After a data cleaning process I arrived at a final analysis sample composed of 1,805 distribution utilities followed over eight years from 2007 to 2014.

6.2 Patterns of Diffusion

6.2.1 Aggregate Patterns

Figure 7 depicts the aggregate temporal pattern of smart meter diffusion in the United States with raw counts of smart meters. This pattern is also compared to the raw counts of AMR meters in order to assess how the meter population is changing over time. As shown, the smart meter diffusion path appears to correspond to the first half of an S-curve. Furthermore, the patterns shows that a possible substitution process from AMR to AMI is underway across the electric power industry.

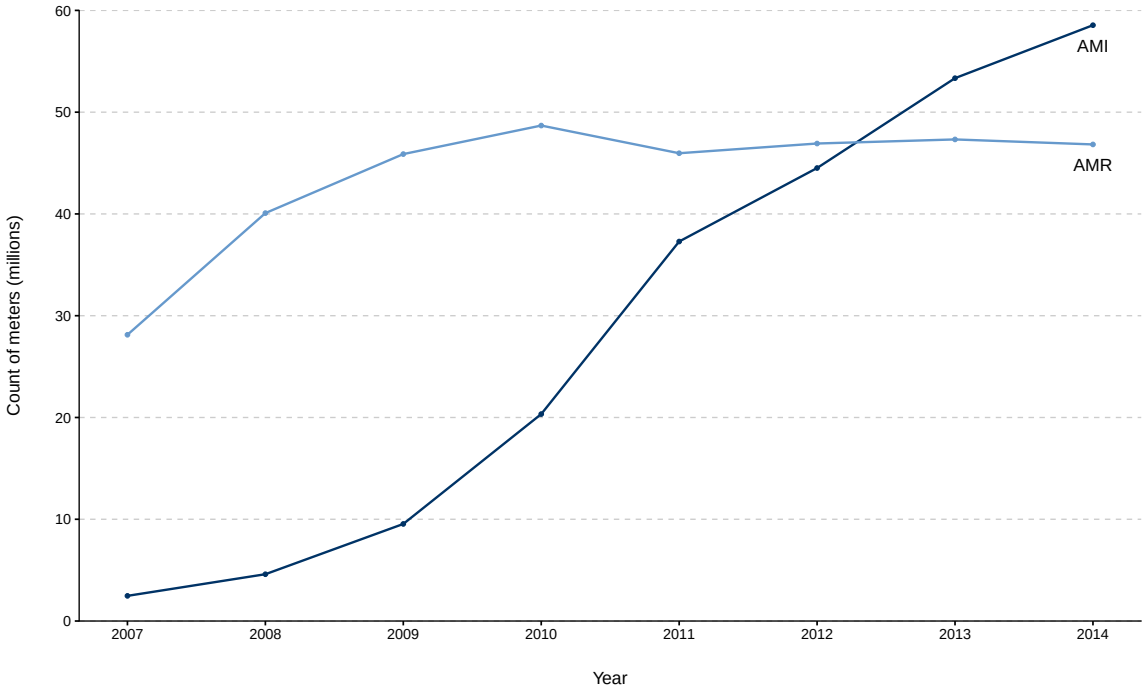


Figure 7. Temporal Pattern of Smart Meter/Advanced Metering Infrastructure (AMI) Diffusion Compared to Temporal Pattern of Automatic Meter Reading (AMR) Diffusion in the United States, 2007–2014. Data from EIA (2017a).

The SGIG subsidies, beginning in 2010, appear to have had a modest impact overall on the level of AMI deployments, though they certainly boosted the number of smart meters installed. In 2009 AMI totaled more than 9.5 million meters while in 2014 AMI totaled more than 58.5 million meters. The SGIG funded more than 16 million smart meters installed from 2010 to 2015, amounting to roughly one-third of the increase. Strong growth in AMI deployment was coincident with SGIG funding, perhaps signifying a crowding-in effect related to learning and knowledge spillovers as a result of the subsidies or to advancement of the smart grid as a whole.

Additionally, Figure 8 depicts the state-level spatial patterns of smart meter diffusion in the United States with choropleth maps based on the proportion of AMI meters in use in each state. In contrast, Figure 9 depicts the state-level spatial patterns of AMR meter diffusion in the United States with choropleth maps based on the proportion of

AMR meters in use in each state. These spatial patterns are interesting insofar as they reflect differences in selection environments, most notably electricity market structures and regulation. There is no clear pattern, however, in this regard. Although California and Texas, two restructured states, have high proportions of smart meters in 2014, other states with conventional vertically integrated structures also have high proportions, including Alabama, Georgia, and Florida. This may suggest that regulation related to distribution utilities specifically, as opposed to market structure, is a more important driver of smart meter diffusion, even if policy rationales and instruments supporting the adoption smart meters vary across states. Additionally, the spatial patterns suggest that some utilities are choosing to adopt AMR over AMI.

6.2.2 Interfirm and Intrafirm Patterns

Figure 10 depicts the smart meter diffusion path in the United States with the cumulative proportion of basic and extensive adopters over time for the final analysis sample. As discussed later, I prefer to define basic adoption as a utility having a smart meter proportion greater than 5%, as a means to avoid capturing trialing and discontinuance, and extensive adoption as a utility having a smart meter proportion greater than 70%. This alternative measure of diffusion also shows the first half of an S-curve.

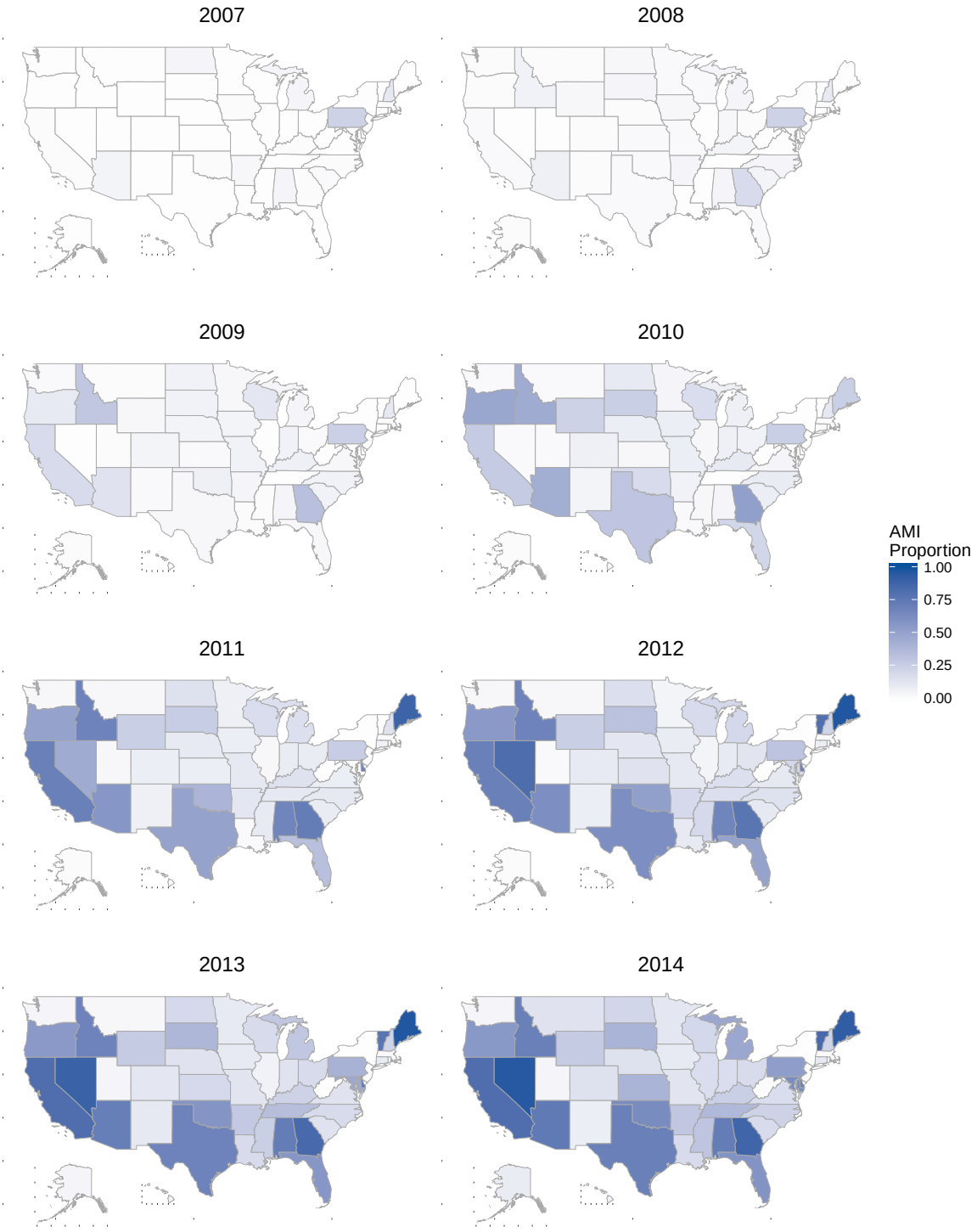


Figure 8. Spatial Pattern of Smart Meter/Advanced Metering Infrastructure (AMI) Diffusion in the United States by State, 2007–2014. Data from EIA (2017a).

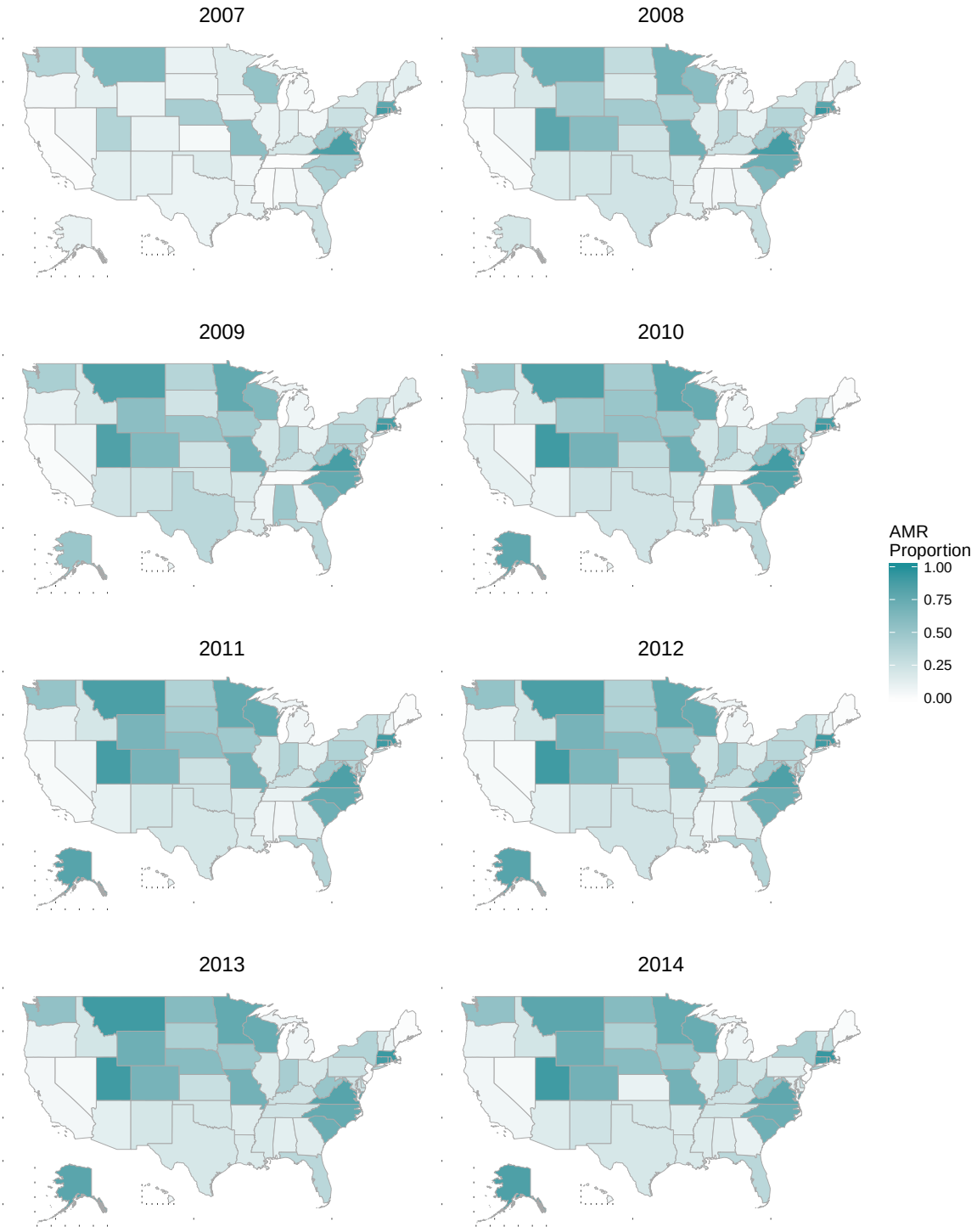


Figure 9. Spatial Pattern of Automatic Meter Reading (AMR) Diffusion in the United States by State, 2007–2014. Data from EIA (2017a).

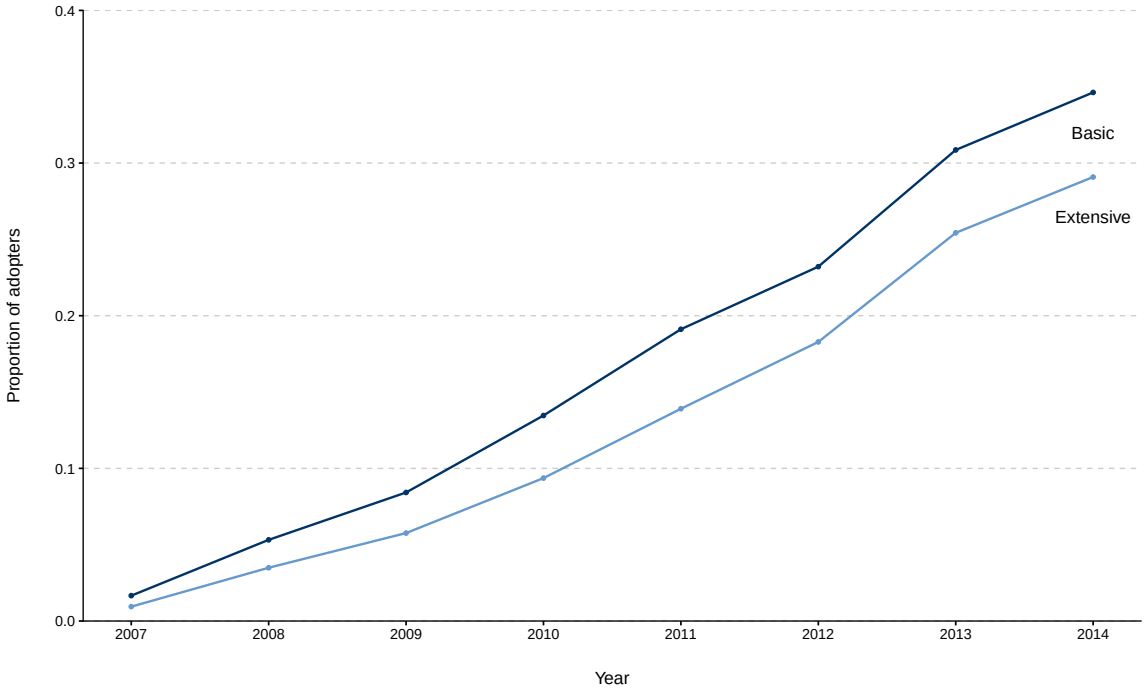


Figure 10. Cumulative Proportion of Basic and Extensive Adopters of Smart Meters.

The relative influence of interfirm and intrafirm diffusion in the overall diffusion of smart meters so far, in terms of the proportion of basic and extensive adopters, is about equal. The proportion of extensive adopters lags slightly behind basic adopters. In 2014, 35% of sample utilities have at least a basic level of adoption whereas 29% have an extensive level of adoption. This pattern may be somewhat misleading, however, given that IOUs have the largest metering stocks and by virtue of their size take longer to become extensive adopters. It is arguably easier and takes less time for smaller munis and co-ops to achieve an extensive level of adoption. As a result, the pattern does not adequately represent the contributions of the interfirm and intrafirm dimensions to the aggregate diffusion of smart meters in the industry in terms of raw counts of smart meters. The intrafirm component of IOUs dominates the general interfirm component simply because IOUs typically have much larger metering stocks than munis and co-ops, even though there are far fewer IOUs in number.

Figure 11 depicts the changing proportion of basic and extensive adopters over time within ownership types. I leave out the relatively small number of public utility districts and state and federal utilities for simplicity. By 2014, more than half of co-ops have adopted smart meters at a basic level whereas nearly one-third of IOUs have adopted at a basic level and nearly one-sixth of munis have adopted at a basic level. Even here, the proportion of extensive adopters lags slightly behind basic adopters for each ownership type. These patterns may suggest that the decisions to adopt and at what level to adopt are jointly determined and influenced by the same factors.

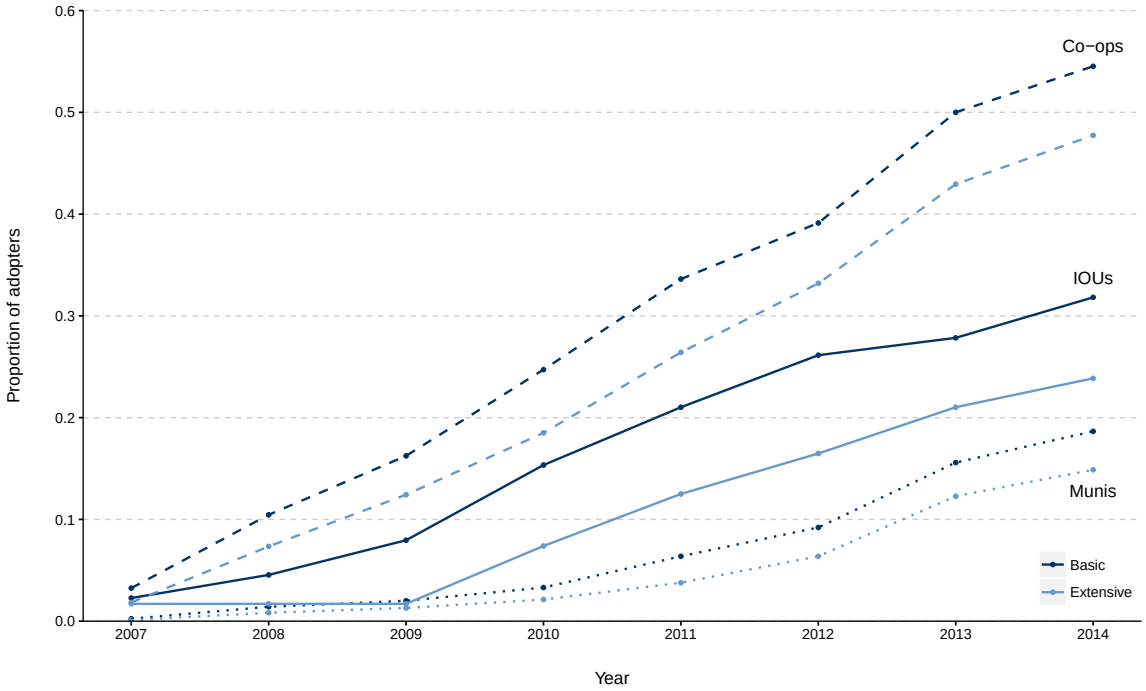


Figure 11. Cumulative Proportion of Basic and Extensive Adopters of Smart Meters by Ownership Type.

6.3 Duration Analysis of Smart Meter Adoption

A number of econometric models have been used to empirically assess the determinants of the diffusion of new technologies. Some models compete on theoretical

grounds, but the particular model chosen may also depend on the nature of the technology, context, stage in the diffusion process, and data limitations. The econometric models I use here, including duration and fractional response models, attempt to assess the factors at play in the decisions to adopt smart meters in the US electric power industry.

One econometric approach that explicitly models the timing of events—in this case technology adoption—and can also use panel data is duration analysis. A duration model that uses panel data is able to analyze the microdynamics of adoption decisions through which the aggregate diffusion path emerges. For these reasons and also its ability to handle censoring relatively easily, duration analysis has become popular in diffusion research. Duration analysis applied to technology adoption, the time it takes a firm to adopt a certain technology from when it is commercially available, was first used by Hannan and McDowell (1984) and is considered the ideal modeling strategy for interfirm diffusion and can also be used for intrafirm diffusion (Karshenas and Stoneman 1993, 1995; Baptista 1999; Fuentelsaz, Gomez, and Polo 2003). This particular method of analysis is used across many fields under different names, including event history analysis, survival analysis, and failure-time analysis. The basic ideas are common across fields but the specific models and techniques used are modified to suit the particular field in which they are applied (Heckman and Singer 1984b; Box-Steffensmeier and Jones 2004). Duration analysis is also useful for causal analysis, as opposed to merely correlational analysis, because it models the influence of past conditions on future outcomes (Blossfeld and Rohwer 1997).

In previous research on the diffusion of smart meters only one econometric model has been applied. Zhou and Matisoff (2016) use a linear panel analysis approach to model smart meter diffusion across the fifty United States using states as observational units. The authors use the same EIA dataset that I use but differ from my analysis by focusing exclusively on the impact of public policies across states and their interac-

tion with federal policies. This study is not concerned with utility characteristics or the timing of adoption but only with the level of diffusion. In addition, Dedrick et al. (2015) examine issues surrounding the adoption of smart grid technologies, including smart meters, but use qualitative interview data from only twelve utilities in the United States. Spodniak (2011) and Spodniak, Jantunen, and Viljainen (2014) examine smart meter diffusion in Central East Europe but use thematic and descriptive analysis. Zhang and Nuttall (2011) and Rixen and Weigand (2013, 2014) also examine aspects of smart meter diffusion but use agent-based model simulations instead of econometric analyses.

I use duration models to analyze the early diffusion of smart meters in the United States from 2007 to 2014. I include covariates reflecting the effects of learning, firm heterogeneity, and selection environments related to public policy and regulation on the rate of diffusion. Duration models are flexible in that they can incorporate determinants inspired by different theories of technology diffusion, including those focused on learning, firm characteristics, and adoption environments (Karshenas and Stoneman 1993). As such, this analysis is exploratory in nature, attempting to assess the drivers of smart meter diffusion in the United States. Duration models can also use either cross-sectional or panel data in either continuous or discrete time, such that data limitations play an important role in the specific duration model used.

6.3.1 Data Limitations and Modeling Considerations

Events typically take place in continuous time, although they can occur in discrete time if, for example, decisions are made routinely at certain times in firms. For the case of smart meters, the transition of a utility from a state of nonadoption to adoption takes place in continuous, historical time, yet the measurements of adoption from the EIA dataset are in discrete, yearly intervals. This kind of data is known as grouped duration data, a type of interval-censored data. Heckman and Singer (1984b) and Lancaster (1990) argue that duration analysis should use continuous-time methods for grouped

data if the underlying process occurs in continuous time and if the data allows. While this is certainly reasonable, data collection methods in the social sciences are often too coarse. The use of continuous-time models applied to grouped data with many event ties—simulatenous event occurrence—poses problems for estimation (Singer and Willett 2003; Allison 2014). It follows that the highly discrete nature of the EIA dataset with respect to the timing of adoption prevents the use of continuous-time models. Discrete-time duration models are preferable in these situations. Discrete-time models, though, have a few advantages; they can incorporate time-varying covariates more easily, treat the effect of time more flexibly, and be estimated more easily (Allison 1982, 2014; Sueyoshi 1995; Jenkins 1995; Singer and Willett 2003).

In any duration model it is necessary to define time and duration. The diffusion of technology concerns the time it takes for firms to adopt a technology (interfirm) as well as the time it takes to diffuse to a certain level of use within firms (intrafirm). Technically the process of diffusion begins at the moment of invention, but more practically it begins when the technology is first commercialized. Defining the time when diffusion starts, and thus the onset of risk of adoption, is crucial for duration analysis of technology adoption. For the case of smart meters, utilities technically became at risk of adopting smart meters when they were first commercialized, and thus measurements of the time it takes to adopt should start at this date. The first utility deployment of smart meters, however, occurred in the 1990s (FERC 2006). Defining the beginning of diffusion from this date would require substantially more data to model, but such data do not exist.[3]

Measurements of the timing of events are often censored in duration analysis. In the EIA dataset there are both left- and right-censored adoption times. Left-censoring occurs where we observe in the first year of data, 2007, that some utilities have already

3. Some data exists from the first FERC Demand Response and Advanced Metering Report (FERC 2006) but this survey uses a broader definition of advanced metering that may cover AMR meters. These data, therefore, are not comparable to the EIA data and in fact do not match well with the EIA data from 2007.

adopted smart meters but we do not necessarily know if this occurred in 2007 or in prior years. In a few cases, however, it is clear that a basic level of adoption occurred before 2007, although it is difficult to verify prior adoption from other sources in order to identify those observations that are in fact left-censored. Nonetheless, when comparing the total metering stock to the proportion of smart meters in 2007 for these utilities, only two utilities can be identified as certainly left-censored. The other utilities are small and not unlikely to have adopted in 2007, even at an extensive level.

I assume these utilities adopted in the first year of data such that their duration times are one year, even if for some utilities this is not true. This assumption is a practical measure in order to easily estimate the duration model. Listwise deletion of left-censored observations, an alternative strategy, may bias the estimation because the censoring is likely informative (missing not at random). Informative censoring means censoring and duration times are not independent. This follows from a theoretical emphasis on firm heterogeneity in that earlier adopters may be distinct in their characteristics (observed or unobserved) from later adopters. The disadvantage to making this assumption is that the model I use will potentially underestimate the effect of time, which is likely driven by cost considerations and uncertainty about the benefits of the technology. There are relatively few utilities in this position and the approximate ordering of adoption is still preserved. Additionally, right-censoring, which is relatively common compared to left-censoring, occurs in the last year of data, 2014, where we observe that many utilities have not yet adopted smart meters. The amount of right-censoring observed simply highlights that the diffusion process is ongoing. Accounting for right-censored observations in duration analysis is relatively easy.

Other issues with the EIA dataset also exist. Data limitations led me to use a sample of utilities less than the total in the dataset, based on the availability of relevant data for covariates as well as quality issues. After cleaning the data, I obtain a sample of 1,805 utilities to analyze out of the 1,991 total available. The primary data quality issue

relates to observing utilities with nonsensical switching from having all AMI meters to all AMR meters or from all AMR meters to all AMI meters and back again over sequential years. In addition, with the exception of IOUs, I combined utilities with operations in more than one state, with responses at the state-level, into a single set of observations for the primary state. Eight mergers and acquisitions also occured among utilities over this time period. I account for this by simply adding together the relevant survey responses as if they were one utility from the beginning (as is done in Fuentelsaz, Gomez, and Polo 2003).

Another important issue is that I cannot calculate precise proportions of smart meter use for utilities for most years of available data. In order to define adoption, the natural diffusion metric I employ is the proportion of a utility's metering stock that consists of smart meters. Many diffusion studies have simply defined adoption as a proportion greater than zero, but this can misleadingly pick up trialing of technology that should not be considered adoption. This is especially the case if the technology is discontinued after a trial period. Calculating proportions of smart meter use in this case would not be necessary and adoption could be defined as a count of smart meters greater than zero. Model results, however, may be sensitive to definitions of adoption. The EIA dataset does not contain counts of the total number of meters for each utility from 2007 to 2012 and the data for 2013 appears to be problematic, preventing me from calculating precise proportions for these years. Instead, I use data on the total number of customers to produce estimates for the total number of meters. Although the number of meters can be greater than the number of customers because some customers have more than one meter, using estimates of total meters based on counts of customers produces accurate if not precise estimates of proportions. I simply add a certain percentage of customers to the total customer count as a means to proxy the count of total meters for each utility. I use the 2014 data to compare total meters to total customers in order to determine the percentage increase on a utility-by-utility basis. I ultimately categorize

utilities as nonadopters and adopters based on a certain range of proportion of use, and I also perform sensitivity analysis around this issue so that a precise measurement is not vital to the duration analysis.

Another important modeling consideration is the joint analysis of interfirm and intrafirm diffusion. The decision to adopt and when and the decision on how intensively to adopt and when may not be independent. A few studies have modeled interfirm and intrafirm diffusion jointly using cross-sectional data (Battisti and Stoneman 2003; Åstebro 2004; Hollenstein 2004; Battisti and Stoneman 2005; Battisti et al. 2007; Hollenstein and Woerter 2008; Battisti, Canepa, and Stoneman 2009; Arvanitis and Ley 2013), but so far none have used panel data. Most of these studies have found that adoption and intensity decisions are independent and influenced by different factors and thus can be modeled separately, but this is likely not the case for the adoption of smart meters by utilities. Smart meter deployments are typically announced on a large scale, implying that adoption and intensity decisions are considered jointly. Perusing utility business cases for smart meters reveals that different scenarios are considered in cost-benefit analyses, such as full deployment or partial deployment. A joint decision process should not be surprising in this case given that smart meters are long-lived capital assets and can also exhibit positive network externalities because as more are deployed they become more valuable.

A multistate duration model integrates the analysis of these two dimensions into one model, thereby accounting for the potential interdependency of the two adoption decisions and their timing. Compared to a basic duration model, in a multistate model diffusion is modeled as a progressive, sequential process, defining multiple states of adoption based on certain ranges of proportions of use. Multistate models have been suggested by Karshenas and Stoneman (1995) but have yet to be implemented in the empirical literature on technology diffusion, primarily because they require substantial amounts of panel data. Data limitations also prevent me from pursuing a multistate

model. In the EIA dataset over half of the utilities who ultimately adopt are observed to transition directly from a state of nonadoption in one year to a state of complete adoption in the next. These utilities are overwhelmingly small munis and co-ops. A multi-state model requires a smoother transition that the coarseness of the dataset does not allow.

Because of these issues with the data, I cannot adequately assess the intrafirm component of smart meter diffusion within a duration framework. Based on these descriptions of adopters, however, and the fact that utilities typically announce a high level of adoption when deciding to deploy smart meters, the rate of intrafirm diffusion appears to be driven primarily by utility size. Vintage effects may also play a role here as well. For the interfirm dimension I simply model the time until adoption at a basic level using a discrete-time duration model, which for over half the utilities that adopt is the same time it takes to reach an extensive level of use. For the intrafirm dimension I model the level of adoption using a fractional response model.

6.3.2 Discrete-Time Duration Model

Duration analysis of technology adoption is a natural approach to analyzing interfirm diffusion, which models the time (i.e., the duration) until initial adoption of a technology (i.e., the event or transition). Previous diffusion research has used various types of duration models that estimate the conditional probabilities of adopting a technology. A general continuous-time model was developed by Karshenas and Stoneman (1993), based on the popular Cox proportional hazards model. This model suits empirical analysis of technology diffusion because it can incorporate a variety of theoretical perspectives, including learning and firm-specific effects. The general philosophy, however, that multiple theories can and should be tested in the same empirical model can be extended to other duration models. I follow this approach within a discrete-time duration model for analyzing smart meter diffusion in the United States. General discussions

of discrete-time methods in the context of duration modeling in social science research can be found in Allison (1982, 2014), Yamaguchi (1991), Box-Steffensmeier and Jones (2004), Singer and Willett (1993, 2003), and Tutz and Schmid (2016).

Let duration be denoted by the discrete random variable T such that $T \geq 0$. Then let t represent a discrete time period and a specific realization of T such that $t = 1, 2, ..., q$. A discrete-time approximation for an underlying continuous-time process groups the occurrence of events in the intervals $[0, 1)$ for $t = 1$, $[1, 2)$ for $t = 2$ and so on and where the origin of defined duration time, $t = 0$, precedes the first observed event occurrence. Let the probability mass function of T be given by

$$f(t) = Pr(T = t)$$

where $0 \leq f(t) \leq 1$ and $\sum_{t=1}^{q} f(t) = 1$, representing the probability of adopting at time t. The cumulative distribution function, then, is given by $F(t) = Pr(T \leq t) = \sum_{s \leq t} f(t)$ where s denotes possible time periods. Let the survival function be given by

$$S(t) = Pr(T \geq t) = \sum_{s \geq t}^{q} f(t) = 1 - \sum_{s < t} f(t) = 1 - F(t-1)$$

representing the probability of not adopting until time t or after. Let the hazard function be given by

$$h(t) = \frac{f(t)}{S(t)} = \frac{f(t)}{1 - F(t-1)}$$

representing the ratio of the probability of adopting at time t to the probability of surviving until time t or after. The hazard function can be re-expressed as a conditional probability such that

$$h(t) = Pr(T = t \mid T \geq t)$$

where $0 \leq h(t) \leq 1$, representing the probability of adopting at time t given that adoption has not already occurred.

Let the hazard rate for utility i where $i = 1, 2, ..., n$ at time t be given by

$$h_{it} = Pr(T = t_i \mid T \geq t, \boldsymbol{x}_{it})$$

where $0 \leq h_{it} \leq 1$ and $\boldsymbol{x}_{it}$ denotes a vector of covariates. This equation represents the discrete-time hazard function, the probability that a utility adopts at time t given that it has not already adopted and given relevant covariates that may change over time.

Adoption can be defined in various ways, depending on the technology under study and the specific diffusion metric used. Most diffusion studies define a basic level of adoption simply as the proportion of the capital stock embodied in the new technology or the output produced with the new technology being greater than zero. While this may be reasonable in some cases, I prefer to define adoption more stringently as a proportion of the metering capital stock greater than 5% in order to avoid capturing potential trialing and discontinuance (such as through pilot programs). I also perform sensitivity analyses by defining adoption alternatively as a proportion greater than zero and as a proportion greater than 10%.

Let the timing of adoption be represented by a binary variable, a_{it}, indicating whether adoption has occurred in the time interval $[t-1, t)$ such that

$$a_{it} = \begin{cases} 1, & \text{if } p_{it} \geq 0.05, a_{i,t-1} = 0 \\ 0, & \text{otherwise} \end{cases}$$

for $t = 1, 2, ..., t_i$ and where p_{it} denotes the proportion of smart meters installed and operational for utility i at time t. This implies that the number of observations that a utility contributes to the analysis dataset includes the years of nonadoption up to and including the first year of adoption, because no further information is needed once adoption occurs. Furthermore, utilities with right-censored observations, in which $a_{it} = 0$ for all years, contribute the full information they provide despite never adopting. The original panel dataset, then, shrinks to a utility-year dataset containing only the relevant years of data on a utility-by-utility basis. This data structure also easily accounts for time-varying covariates.

Subsequently, the hazard rate can be re-expressed as

$$h_{it} = Pr(a_{it} = 1 \mid a_{i,t-1} = 0, \boldsymbol{x}_{it})$$

and defined as a function of covariates and time such that

$$h_{it} = g^{-1}(\boldsymbol{x}_{it}, t)$$

where $g(\cdot)$ is a link function that bounds the hazard rate between 0 and 1. The duration model can then be interpreted within a binary response modeling framework and estimated using maximum likelihood methods with pooled data. Allison (1982) shows that the multiple observations that a single observational unit contributes to the analysis dataset can be treated as independently observed in a pooled model if events are non-repeatable. This is an assumption, stemming from the conditional nature of the hazard rate, that the repeat observations contributed by an observational unit are independent conditional on having survived to each time period and conditional on the associated covariate values in each time period. I relax this assumption, however, by using clustered standard errors to correct for any autocorrelation (Cameron and Miller 2015).

The logistic function is a popular link function, owing to its relative ease of estimation and interpretation. This leads to a pooled logit model estimated by maximum likelihood methods. Duration dependence can be accounted for by simply including a time variable, in the form of a linear trend, a polynomial of some degree, splines, or more flexibly as a set of indicator variables. A discrete-time logistic duration model can be specified as

$$h_{it} = \frac{exp(\boldsymbol{x}'_{it}\boldsymbol{\beta} + \boldsymbol{d}'_t\boldsymbol{\alpha})}{1 + exp(\boldsymbol{x}'_{it}\boldsymbol{\beta} + \boldsymbol{d}'_t\boldsymbol{\alpha})}$$

or more appropriately its inverse, $g(h_{it})$, as

$$ln\left(\frac{h_{it}}{1 - h_{it}}\right) = \boldsymbol{x}'_{it}\boldsymbol{\beta} + \boldsymbol{d}'_t\boldsymbol{\alpha}$$

where $\boldsymbol{x}_{it}$ denotes a vector of covariates including a constant with a vector of coefficients $\boldsymbol{\beta}$ and $\boldsymbol{d}_t$ denotes a vector of time variables with a vector of coefficients denoted by $\boldsymbol{\alpha}$ representing duration dependence. The exact specification of the time variables ultimately depends on theoretical considerations. For smart meter adoption, I prefer the most flexible form and use a set of indicator variables.

A logit model for discrete duration data was first proposed by Cox (1972). The logit model, however, is not directly connected with the Cox proportional hazards model but was intended as an approximation to the parameter estimates obtained in a Cox model if the grouped intervals were sufficiently narrow. The logit model is also not connected to any other continuous-time model. Subsequent work by Kalbfleisch and Prentice (1973) and Prentice and Gloeckler (1978) found that the complementary log-log link is the actual discrete-time analog of the Cox model and is also more appropriate when grouped intervals are not narrow.

An important difference in the selected link function concerns implicit assumptions of proportionality. A logit model results in a proportional odds assumption whereas a complementary log-log model results in a proportional hazards assumption. Proportionality refers to a constant relative difference between two firms' odds or hazard rates, respectively, in a given time period. A model specification with interactions between time and one or more covariates would constitute a nonproportional model. Such interactions imply that the effects of a covariate are not constant over time. I test this assumption of proportionality but find that it is inconsequential.

In the general context of binary response models, the complementary log-log link is most appropriate for datasets with very few event occurrences. Logit and complementary log-log specifications give very similar results when the probability of an event is low. The differences in the estimates between the two specifications are often negligible (Jenkins 1995; Singer and Willett 2003; Allison 2014). I perform sensitivity analysis with respect to the link function and find that the results are robust across logit, probit, and complementary log-log specifications. I focus on the logit model because of its relative ease of estimation and interpretation.

6.4 Fractional Response Analysis of Smart Meter Adoption

To more adequately address the intrafirm component of smart meter diffusion, I also use a fractional response model where a utility's proportion of smart meter use is modeled directly as the response variable. A fractional response model is preferable to a linear model because it bounds the response between 0 and 1. Let p_{it}, where $0 \leq p_{it} \leq 1$, represent the proportion of smart meters installed and operational for utility i at time t. Furthermore, let p_{it} be defined as a function of covariates and time such that

$$p_{it} = g^{-1}(\boldsymbol{x}_{it}, t)$$

where $g(\cdot)$ is a link function that bounds the response between 0 and 1. Similar to binary response models, a link function is necessary to bound the response between 0 and 1. I focus again on a logit model for simplicity. A fractional response logit model can be specified as

$$p_{it} = \frac{exp(\boldsymbol{x}'_{it}\boldsymbol{\beta} + \boldsymbol{d}'_t\boldsymbol{\alpha})}{1 + exp(\boldsymbol{x}'_{it}\boldsymbol{\beta} + \boldsymbol{d}'_t\boldsymbol{\alpha})}$$

or more appropriately its inverse, $g(p_{it})$, as

$$ln\left(\frac{p_{it}}{1 - p_{it}}\right) = \boldsymbol{x}'_{it}\boldsymbol{\beta} + \boldsymbol{d}'_t\boldsymbol{\alpha}$$

where $\boldsymbol{x}_{it}$ denotes a vector of covariates including a constant with a vector of coefficients $\boldsymbol{\beta}$ and $\boldsymbol{d}_t$ denotes a vector of time variables with a vector of coefficients denoted by $\boldsymbol{\alpha}$. Different estimation techniques have been proposed for fractional response models, such as nonlinear least squares, but quasi-maximum likelihood methods have been shown to perform the best in most situations (Papke and Wooldridge 1996; Ramalho, Ramalho, and Murteira 2011).

In contrast to the duration model, in the fractional response model I use the entire panel dataset. Fractional response models, however, are a relatively new econometric method, and panel versions are still being developed. Additionally, different estimation techniques are required for different distributions of the response variable, which include both zeros and ones in my case (Ramalho, Ramalho, and Murteira 2011). Therefore, I estimate simpler pooled versions of fractional response models and use clustered standard errors by utility to correct for any autocorrelation (Cameron and Miller 2015). These estimates are still consistent, if not efficient. I also estimate both one-part and two-part models. One-part models consist of a fractional response model on the full

dataset regardless of the response values. Two-part models consist of a binary response model in the first part, differentiating between responses with zeros and those with positive values, and a fractional response model in the second part that includes only those observations with positive values. I also use a similar set of covariates to those in the duration models and represent time as a set of indicator variables.

6.5 Model Variables and Summary Statistics

Descriptions of model variables and expected effects of covariates are presented in Table 5, based on the hypothesized determinants discussed in the previous chapter. Summary statistics for model variables for the pooled sample are presented in Table 6. Sample characteristics by type of utility are presented in Table 7. Though IOUs represent a small proportion of utilities by number, they supply the majority of the American population with electricity by customer base.

Table 5. Descriptions of Model Variables.

Variable	Description	Expected Effect
Response		
AMI meter prop. (p_{it})	estimated proportion of AMI meters	
Adoption 1 ($p_{it} > 0$)	= 1 if estimated proportion of AMI meters > 0, = 0 otherwise	
Adoption 2 ($p_{it} \geq 0.05$)	= 1 if estimated proportion of AMI meters ≥ 0.05, = 0 otherwise	
Adoption 3 ($p_{it} \geq 0.10$)	= 1 if estimated proportion of AMI meters ≥ 0.10, = 0 otherwise	
Covariates		
Total customers (log)	continuous, log of total customers	+/-
Investor-owned utility	binary, = 1 if investor-owned utility, = 0 otherwise	+
Co-operative utility	binary, = 1 if co-operative utility, = 0 otherwise	+/-
AMR meter prop.	continuous, estimated proportion of AMR meters	+/-
Demand-side mgmt.	binary, = 1 if engaged in demand-side management activities (lagged one year), = 0 otherwise	+
Net metering	binary, = 1 if net metering customers > 0, = 0 otherwise	+
State AMI support	binary, = 1 if subject to state support for adoption of AMI, = 0 otherwise	+
Wholesale comp.	binary, = 1 if operating in formal wholesale markets, = 0 otherwise	+
Customer choice	binary, = 1 if operating in state with customer choice, = 0 otherwise	+
Lost margin recovery	binary, = 1 if subject to lost margin recovery, = 0 otherwise	+/-
Energy eff. stds.	binary, = 1 if subject to energy efficiency resource standards, = 0 otherwise	+/-
2008	binary, = 1 if year is 2008, = 0 otherwise	+
2009	binary, = 1 if year is 2009, = 0 otherwise	+
2010	binary, = 1 if year is 2010, = 0 otherwise	+
2011	binary, = 1 if year is 2011, = 0 otherwise	+
2012	binary, = 1 if year is 2012, = 0 otherwise	+
2013	binary, = 1 if year is 2013, = 0 otherwise	+
2014	binary, = 1 if year is 2014, = 0 otherwise	+

Table 6. Summary Statistics for Model Variables.

Variable	Mean	Std. Dev.	Min.	Max.
Response				
AMI meter prop. (p_{it})	0.30	0.44	0	1
Adoption 1 ($p_{it} > 0$)	0.41	0.49	0	1
Adoption 2 ($p_{it} \geq 0.05$)	0.35	0.48	0	1
Adoption 3 ($p_{it} \geq 0.10$)	0.34	0.47	0	1
Covariates				
Total customers (log)	9.31	1.75	2.08	15.49
Investor-owned utility	0.10	0.30	0	1
Co-operative utility	0.39	0.49	0	1
AMR meter prop.	49.64	46.11	0	100
Demand-side mgmt.	0.19	0.39	0	1
Net metering	0.50	0.50	0	1
State AMI support	0.02	0.15	0	1
Wholesale comp.	0.40	0.49	0	1
Customer choice	0.31	0.46	0	1
Lost margin recovery	0.05	0.21	0	1
Energy eff. stds.	0.24	0.43	0	1
2008	0.13	0.33	0	1
2009	0.13	0.33	0	1
2010	0.13	0.33	0	1
2011	0.13	0.33	0	1
2012	0.13	0.33	0	1
2013	0.13	0.33	0	1
2014	0.13	0.33	0	1

Notes: Pooled sample 2007–2014. n = 14,440 utility-years.

Table 7. Sample Characteristics by Type of Utility.

Utility Type	Number	Num. Prop.	Total Customers	Cust. Prop.
IOU	176	0.10	106,649,869	0.74
Co-op	708	0.39	17,790,309	0.12
Muni	847	0.47	13,685,438	0.10
PUD	64	0.04	3,736,686	0.03
State	7	0.00	1,336,782	0.01
Federal	3	0.00	39,731	0.00
Total	1,805	1.00	143,238,815	1.00

Notes: 2014 data. IOU = investor-owned utility. PUD = public utility district.

Utility size is proxied by the total number of customers. I log transform this variable because of the vast size differences among utilities. Utility ownership is captured by two indicator variables for IOUs and co-ops, with publicly owned utilities primarily composed of munis left as the reference group. The adoption of AMR meters is measured by the estimated AMR proportion of a utility's metering stock, expressed on a 0–100 scale. I estimate this proportion in the same way I estimate AMI proportions discussed previously. Demand-side management activities are captured by an indicator variable if a utility reported having customers in incentive-based demand response programs, including direct load control, interruptible rates, demand bidding/buyback, emergency demand response, capacity market programs, and ancillary service market programs. I lag this variable to ensure that it does not reflect demand response programs implemented during or after smart meter adoption. The impact of distributed generation resources through net metering programs is captured by an indicator variable for having net metering customers or not. I use an indicator variable instead of a continuous variable for total net metering customers in order to make interpretation easier. Alternative estimates suggest that the total number of customers is not as important as having net metering customers.

I also include a set of indicator variables reflecting different adoption environments. The impact of state support for smart meter adoption is captured by an indicator variable for those states that have actively supported smart meter deployments, such as through mandates or guaranteed recovery of investment costs.[4] This variable applies only to IOUs and for the effective years. Electricity market structures are captured by a set of indicator variables for utilities operating in the various formal wholesale markets, with utilities operating in conventionally regulated markets as the reference group.[5] Alternative estimates suggest that including multiple indicator variables for specific markets capturing any relevant differences in the markets are not important. Additionally, I include an indicator variable for states that have implemented customer choice for all customer classes.[6] I include two more indicator variables related to energy efficiency. States with lost margin recovery mechanisms, including lost revenue adjustments and decoupling, are captured by an indicator variable that applies to the relevant IOUs for the effective years.[7] Another indicator variable captures those states with energy efficiency resource standards that applies to the relevant utilities for the effective years.[8] I also considered an interaction term between these two variables to capture a possible synergistic effect resulting from removing disincentives to invest in energy efficiency while also providing incentives to invest in energy efficiency. Alternative estimates showed that this interaction variable was not significant and likelihood ratio tests concerning its inclusion were not rejected, so I exclude it for simplicity. Zhou and Matisoff (2016) also assess other variables hypothesized to affect smart meter diffu-

4. States with active support for smart meter adoption during the period under study include AZ, CA, CT, IL, ME, MA, PA, TX, and VT.

5. Formal wholesale markets include the CAISO, ERCOT, PJM, NYISO, SPP, MISO, and ISONE markets.

6. States with customer choice for all customer classes during the period under study include CT, DE, IL, ME, MD, MA, MI, NH, NJ, NY, OH, PA, RI, and TX along with DC.

7. States with lost margin recovery mechanisms for IOUs during the period under study include AL, AZ, AR, CA, CO, CT, HI, ID, IN, KS, KY, LA, ME, MD, MA, MI, MS, MO, MT, NV, NM, NY, NC, OH, OK, OR, RI, SC, SD, VT, WA, and WY along with DC.

8. States with energy efficiency resource standards during the period under study include AZ, AR, CA, CO, CT, HI, IL, IN, IA, ME, MD, MA, MI, MN, NV, NM, NY, NC, OH, OR, PA, RI, TX, VT, WA, and WI.

sion in the United States, like demographic characteristics and data privacy and security policies, but they do not find any evidence of their importance. I exclude these variables from my models for simplicity.

The remaining determinants are collectively captured by a set of indicator variables representing time with 2007 left as the reference year, including the impact of the SGIG subsidies, effects of learning, reductions in cost and improvements in performance of smart meters, and the development of technology standards. Subsequently, the time variables reflect calendar time dependence, a trend of variables changing over time, and not necessarily duration dependence (Colombo and Mosconi 1995), though the two are equivalent in this case because no new distribution utilities were created during the period under study if mergers are ignored. It is not ideal, of course, for the time variable to capture all these effects because I cannot adequately assess the impact of each effect separately, but multicollinearity issues prevent me from including additional variables. Learning effects are typically captured with a time variable or some other estimate of duration dependence (Karshenas and Stoneman 1993; Fuentelsaz, Gomez, and Polo (2003); Battisti and Stoneman 2005). Alternatively, a variable representing the cumulative stock of adopters can be used (Colombo and Mosconi 1995; Battisti, Canepa, and Stoneman 2009), but in this case the variable is highly collinear with time. Any measure of adoption costs, such as the average price of a smart meter, depicting the slight downward trend that has occurred would also be highly collinear with time. Using a set of indicator variables, however, allows some flexibility in teasing out some of these effects.

Similar multicollinearity issues have been common in previous empirical studies of diffusion. Fuentelsaz, Gomez, and Polo (2003) use time as a variable reflecting learning effects but note that it could capture other influences that change over time like changes in the technology or price. Colombo and Mosconi (1995) use time as a variable reflecting price and performance trends as well as growth of exogenous information about a technology. The difficulty of including system-level variables that vary over

time but are fixed across observational units is one of the drawbacks of discrete-time duration models.

These collinear variables, though, are interrelated theoretically, reflecting different sources of uncertainty that impact the expected profitability of adopting smart meters. Learning reflects reductions in uncertainty over time about the actual costs and benefits of adoption. Utilities may be uncertain about changes in the costs of adoption over time, such as changes in the price of smart meters. Furthermore, utilities may be uncertain about the performance, reliability, and interoperability of smart meters as well as future improvements in the technology, which should be reduced over time through the development of technology standards. These variable should exert a positive influence on adoption if these interrelated uncertainties are being reduced over time, such that time should be positively correlated with adoption.

With respect to the SGIG subsidies, although it is possible to identify the grant recipients, using an indicator variable for such purposes in the duration model is not possible because it results in quasi-complete separation. All recipients of the subsidies adopt smart meters but there are still utilities who did not receive the SGIG subsidies that do adopt smart meters. This quasi-complete separation means maximum likelihood estimates do not exist if such a variable is included in a binary response model (Albert and Anderson 1984). By including a set of indicator variables for time, however, it is possible to assess the effect of time before and after the SGIG subsidies became available. This allows at least some means to assess the impact of the SGIG program.

Additionally, a potentially important variable related to learning that is not captured in the covariates because of lack of data is absorptive capacity. Some measure of R&D activity, such as R&D expenditures or number of R&D employees, has typically been used as a proxy in previous diffusion research (Karshenas and Stoneman 1993; Colombo and Mosconi 1995; Battisti and Stoneman 2005) because absorptive capacity is likely correlated with internal R&D activities (Cohen and Levinthal 1989; Cohen and

Levinthal 1990; Rosenberg 1990). These data are not collected in the EIA dataset. The ownership variables, to an extent, may capture the effect of absorptive capacity because IOUs perform more R&D than other types of utilities and are more likely to be members of the Electric Power Research Institute, the industry-supported collaborative R&D organization. Of course, there is likely variation even within IOUs. In addition, a publicly available list of members of this organization does not exist for the period under study that could be used to create an indicator variable indicating membership.

It is possible that unobserved heterogeneity, in the form of utilities' abilities to learn, may be present in the model described. Some utilities, for example, may adopt smart meters earlier than others because of their superior ability to assess the costs and benefits of adoption. A selection effect would then ensue that decreases the baseline hazard rates over time, because utilities that are more susceptible to adopting do so first thus leaving in the population at risk of adoption those utilities that are not as susceptible. Neglecting sources of unobserved heterogeneity is known to bias estimates of baseline hazard rates, the time variables in this case, toward negative duration dependence, but it does not affect the estimates for the included covariates (Heckman and Singer 1984a, 1984b; Vaupel and Yashin 1985; Nicoletti and Rondinelli 2010). It is possible to account for unobserved heterogeneity by adding a firm-specific random effect term to the duration model. Heckman and Singer (1984a, 1984b) show that assumptions about the distribution of the unobserved heterogeneity term can produce sensitive results in continuous-time models and develop an alternative nonparametric estimation method. Land, Nagin, and McCall (2001) extend this analysis to discrete-time models, but the estimation method becomes considerably more complicated. I find positive positive duration dependence in model estimates that suggests unobserved heterogeneity can safely be ignored, though the effect of time could still be underestimated.

6.6 Empirical Findings

6.6.1 Life Table Estimates

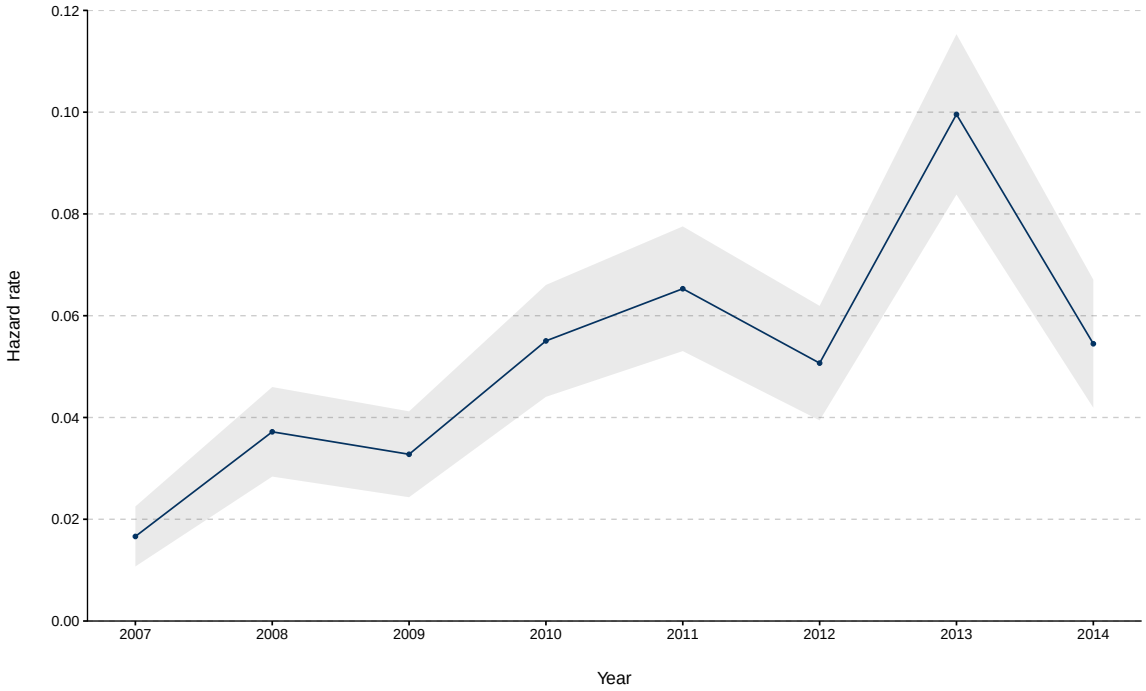
Before presenting the results of the regression analyses, life table estimates for time until smart meter adoption, defined as an AMI proportion ≥ 0.05, are presented in Table 8. These estimates are the discrete-time analog of the popular, nonparametric Kaplan-Meier estimates of hazard and survival rates for continuous-time data (Efron 1988). Life tables describe the distribution of event occurrences and how associated hazard and survival rates depend on time alone, essentially assuming a homogeneous sample. Decomposed by ownership types, 56 IOUs, 386 co-ops, and 158 munis adopted smart meters by the end of 2014. Graphical representations of the hazard and survival functions are depicted in Figure 12.

Table 8. Life Table Estimates of Hazard and Survival Rates for Smart Meter Adoption.

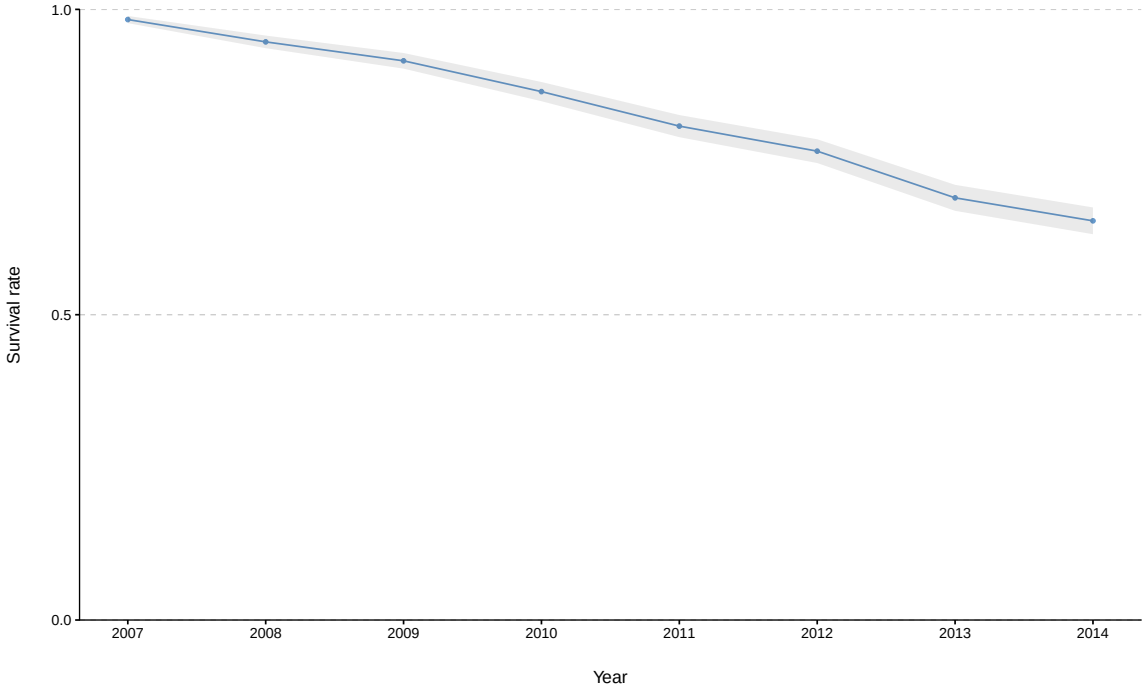
Year	$n_{adopters_t}$	$n_{riskset_t}$	$\hat{h}_t$	$se(\hat{h}_t)$	$\hat{S}_t$	$se(\hat{S}_t)$
2007	30	1805	0.017	0.0030	0.98	0.0030
2008	66	1775	0.037	0.0045	0.95	0.0053
2009	56	1709	0.033	0.0043	0.92	0.0065
2010	91	1653	0.055	0.0056	0.87	0.0080
2011	102	1562	0.065	0.0063	0.81	0.0093
2012	74	1460	0.051	0.0057	0.77	0.0099
2013	138	1386	0.100	0.0080	0.69	0.0109
2014	68	1248	0.054	0.0064	0.65	0.0112

Hazard and survival rates provide an alternative to diffusion curves for describing diffusion processes and provide more information than simply the level and speed of processes (Trajtenberg and Yitzhaki 1989). They should be interpreted jointly. While hazard rates indicate how likely it is to have an event in a given time period, they do not indicate how many events actually occur. Survival rates provide an estimate of the magnitude effect of the hazard rate. The specific estimates for each time period are

less important than the general trend of the values over time. The general trend for the hazard function is a steady increase over time, though there is a significant reversal in 2014. The magnitudes of the hazards are also quite low. The general trend for the survival function is a steady rate of adoption over time and also indicates that the median survival lifetime is beyond eight years. These trends, of course, could change as the diffusion process proceeds.



a. Hazard Function.



b. Survival Function.

Figure 12. Life Table Estimates of Hazard and Survival Functions for Smart Meter Adoption. 95% confidence intervals shaded in gray.

6.6.2 *Duration Model Estimates*

The estimates for discrete-time duration models with differing definitions of adoption are presented in Table 9. As a whole they suggest multiple determinants of smart meter diffusion in the United States including supply-side, demand-side, and environmental factors. Covariates with significant effects that are mostly robust across models include utility size, utility ownership, adoption of AMR, net metering, state support for smart meter adoption, and time.

Table 9. Estimation Results for Discrete-Time Duration Models.

	Model 1		Model 2		Model 3	
	AMI prop. > 0		AMI prop. ≥ 0.05		AMI prop. ≥ 0.10	
Variable	β	mfx	β	mfx	β	mfx
Constant	-6.471^{***}		-6.216^{***}		-6.093^{***}	
	(0.352)		(0.429)		(0.436)	
Total customers (log)	0.291^{***}	0.016^{***}	0.144^{***}	0.006^{***}	0.123^{**}	0.005^{**}
	(0.036)	(0.002)	(0.043)	(0.002)	(0.043)	(0.002)
Investor-owned utility	-0.177	-0.009	-0.749^{*}	-0.025^{**}	-0.626	-0.021^{*}
	(0.272)	(0.013)	(0.339)	(0.009)	(0.344)	(0.010)
Co-operative utility	1.186^{***}	0.071^{***}	1.689^{***}	0.081^{***}	1.782^{***}	0.084^{***}
	(0.098)	(0.007)	(0.117)	(0.007)	(0.119)	(0.007)
AMR meter prop.	-0.022^{***}	-0.001^{***}	-0.034^{***}	-0.001^{***}	-0.036^{***}	-0.001^{***}
	(0.001)	(0.0001)	(0.002)	(0.0001)	(0.002)	(0.0001)
Demand-side mgmt.	-0.787^{*}	-0.033^{**}	-0.129	-0.005	0.144	0.006
	(0.384)	(0.012)	(0.395)	(0.015)	(0.359)	(0.015)
Net metering	0.530^{***}	0.030^{***}	0.641^{***}	0.028^{***}	0.607^{***}	0.025^{***}
	(0.102)	(0.006)	(0.121)	(0.006)	(0.124)	(0.006)
State AMI support	0.516	0.033	1.193^{**}	0.070^{*}	1.234^{**}	0.070^{*}
	(0.304)	(0.023)	(0.402)	(0.032)	(0.409)	(0.032)
Wholesale comp.	0.219^{*}	0.012^{*}	0.137	0.006	0.135	0.005
	(0.104)	(0.006)	(0.125)	(0.005)	(0.128)	(0.005)
Customer choice	-0.185	-0.010	0.009	0.0003	-0.046	-0.002
	(0.117)	(0.006)	(0.135)	(0.005)	(0.138)	(0.005)

continued...

...continued

Variable	Model 1 AMI prop. > 0 β	mfx	Model 2 AMI prop. ≥ 0.05 β	mfx	Model 3 AMI prop. ≥ 0.10 β	mfx
Lost margin recovery	-0.060	-0.003	0.482	0.022	0.394	0.017
	(0.271)	(0.014)	(0.333)	(0.018)	(0.333)	(0.016)
Energy eff. stds.	-0.151	-0.008	-0.300^{*}	-0.011^{*}	-0.357^{*}	-0.013^{*}
	(0.118)	(0.006)	(0.148)	(0.005)	(0.151)	(0.005)
2008	0.520^{**}	0.032^{**}	1.052^{***}	0.056^{***}	0.919^{***}	0.045^{**}
	(0.168)	(0.012)	(0.225)	(0.015)	(0.234)	(0.014)
2009	0.430^{*}	0.026^{*}	1.134^{***}	0.062^{***}	1.254^{***}	0.067^{***}
	(0.183)	(0.013)	(0.232)	(0.016)	(0.232)	(0.016)
2010	0.982^{***}	0.069^{***}	1.795^{***}	0.114^{***}	1.793^{***}	0.109^{***}
	(0.171)	(0.015)	(0.221)	(0.020)	(0.225)	(0.019)
2011	1.314^{***}	0.102^{***}	2.123^{***}	0.147^{***}	2.194^{***}	0.147^{***}
	(0.170)	(0.017)	(0.220)	(0.022)	(0.223)	(0.022)
2012	1.051^{***}	0.077^{***}	2.020^{***}	0.140^{***}	2.072^{***}	0.139^{***}
	(0.186)	(0.017)	(0.232)	(0.023)	(0.234)	(0.023)
2013	2.096^{***}	0.200^{***}	3.083^{***}	0.268^{***}	3.125^{***}	0.262^{***}
	(0.177)	(0.023)	(0.224)	(0.028)	(0.228)	(0.028)
2014	1.843^{***}	0.169^{***}	2.594^{***}	0.209^{***}	2.689^{***}	0.211^{***}
	(0.208)	(0.026)	(0.254)	(0.030)	(0.255)	(0.030)
Num. obs.	12,023		12,588		12,662	
Log-Likelihood	$-2,412.648$		$-1,894.583$		$-1,830.561$	
Deviance	4,825.296		3,789.166		3,661.122	
Pseudo R^2	0.199		0.279		0.293	
Likelihood Ratio	950.011^{***}		$1,206.298^{***}$		$1,252.988^{***}$	

Notes: Pooled logit models. Averages of individual marginal effects. Clustered standard errors in parentheses. Significance levels: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Utility size is positively associated with adoption and the effect is statistically and economically significant. In contrast, the effect of ownership types is divergent. Relative to publicly owned utilities, IOUs are less likely to adopt and co-ops are more likely to adopt. The significance and magnitude of this effect, however, is greater for co-ops. This most likely owes to the rural nature of co-operative service territories where

automation of the meter reading process and remote service switching via two-way communcation is especially beneficial as a result of the large distances among customers. Additionally, this result could also derive from the customer-oriented perspective of co-op management. It is somewhat surprising that IOUs are less likely to adopt than publicly owned utilities given the greater amounts of R&D performed by IOUs. The effect could perhaps result from the regulatory burden of seeking approval for smart meter investments that munis do not face (Dedrick et al. 2015). Additionally, having net metering customers has a modest, positive effect on adopting smart meters.

The estimates for adoption of AMR should be interpreted with some caution because of the inability to properly capture the exact nature of AMR adoption. The effect across models is very small but suggests that a vintage effect dominates any learning effect from prior adoption, thus slowing the diffusion of smart meters. This is not to say that a learning effect is absent; rather, the vintage effect simply appears to be more substantial. Because of the opposing influences the small effect should not necessarily be interpreted as a vintage effect with no practical significance. Vintage effects likely have greater importance in practice than this estimate suggests. Alternatively, some utilities have decided to adopt AMR instead of AMI during the period under study, which can be observed in the data. This raises the issue of potential endogeneity of this variable and the resulting simultaneity bias if the decision to adopt AMR or AMI is considered jointly. The issue of choice among competing technologies, vintage effects, and endogeneity does not appear to have been addressed in the extant empirical research on diffusion, and simultaneity would be difficult to address with a discrete-time duration model using panel data.

State support for smart meter adoption has a positive effect on adoption, although it is not significant in Model 1. This suggests that active state support has been important for smart meter adoption, either enabling or constraining adoption by IOUs. The impact of the different electricity market structures across the United States is not

significant. Neither wholesale competition nor customer choice has a significant effect on adoption compared to conventionally regulated states. This finding suggests that time-varying, market-determined wholesale prices do not seem to exert a strong pressure on utilities to adopt smart meters in order to charge time-varying retail prices. In some cases, though, regulators may actually be limiting the availability of time-varying rates for retail customers. These combined findings suggest that the regulatory process is more important than market structure in the decision to adopt smart meters. Nonetheless, the two variables may be linked in that regulatory support for smart meters may also stem from a broader policy goal of liberalizing electricity markets, such as in states like California and Texas.

The impact of energy efficiency is also not significant. Lost margin recovery mechanisms do not exert a significant effect and the impact of energy efficiency resource standards is only weakly significant and not robust across specifications, suggesting that energy efficiency is not a significant driver of smart meter adoption. The estimates for energy efficiency resource standards are even negative, although the magnitudes are modest. It could be that competing investments have taken priority to achieve energy efficiency targets.

The effect of time on adoption is highly significant with an upward trend reflecting an increasing hazard of adoption over time. Figure 13 graphs the estimated marginal effects for the year indicator variables from Model 2, leaving 2007 as the reference year. The same marginal effects for the Models 1 and 3 display a similar trend though the magnitudes are slightly different. After the Recovery Act was signed into law there is a noticeable upward trend in the hazard after 2009 compared to 2009 and 2008. This finding suggests that smart meters may be too cost-prohibitive for many utilities to adopt, even if it may be socially desirable to do so. It may also be the case that utilities who received funding adopted earlier than they might otherwise have because of the availability of subsidies, thus increasing the rate of diffusion. Furthermore, there

is another noticeable upward trend after 2012 when a technology standard related to interoperability was developed. Some utilities have explicitly stated they have waited to adopt until certain technology standards have been finalized, such as the interoperability standard.

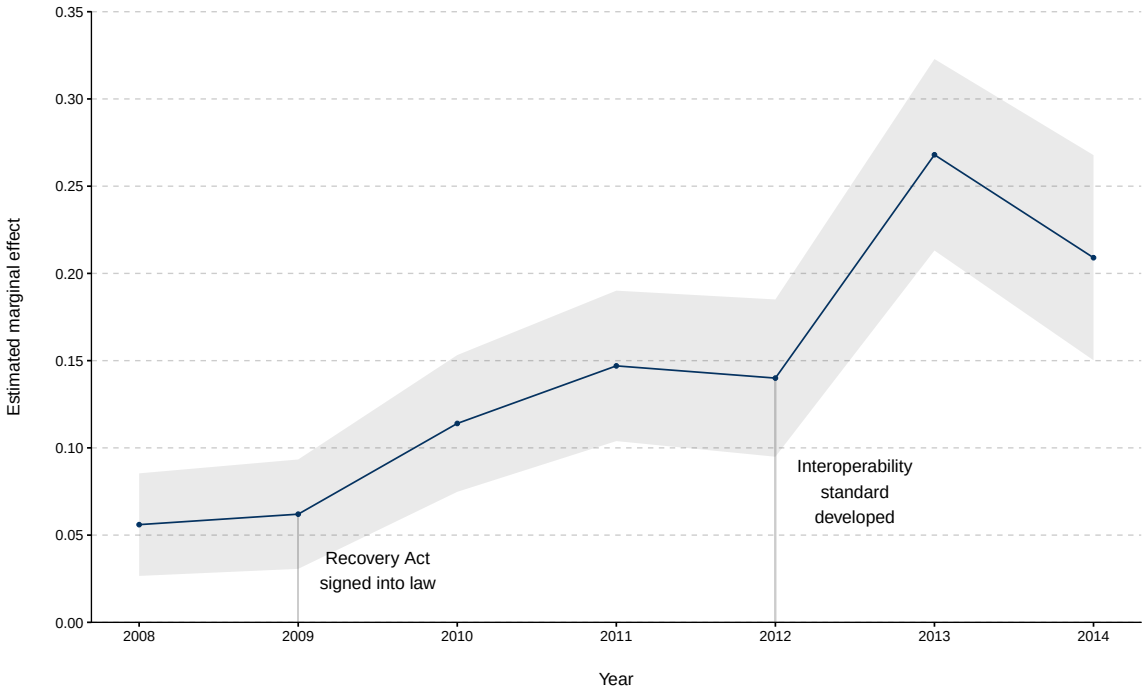


Figure 13. Estimated Marginal Effects for Year Indicator Variables from Model 2. 95% confidence intervals shaded in gray. 2007 left as reference year.

These noticeable effects seem to suggest that both the SGIG subsidies and technology standards have been important determinants for smart meter adoption. It is also likely, however, that cost reductions and learning have contributed to this general upward trend. Anecdotal evidence suggests that utilities have been learning the actual costs and benefits of adopting over time, both from using the technology and through knowledge spillovers (EPRI 2010). Although there is no way to completely disentangle these effects from one another, the use of year indicator variables in the duration model provides at least some means to do so but the estimates should be interpreted

with some caution. Additional evidence is needed to give greater weight to any one of these effects.

6.6.3 *Fractional Response Model Estimates*

The estimates for fractional response models are presented in Table 10. I exclude the demand-side management covariate in order to avoid any potential endogeneity because smart adoption can enhance these activities. The results of the fractional response models are similar to the duration model estimates. Covariates with significant effects that are mostly robust across models include utility size, utility ownership, adoption of AMR, net metering, state support for smart meter adoption, and time.

Table 10. Estimation Results for Fractional Response Models.

	One-Part Model		Two-Part Model			
			Part One		Part Two	
Variable	β	mfx	β	mfx	β	mfx
Constant	-5.971^{***}		-6.990^{***}		1.779^{*}	
	(0.528)		(0.457)		(0.697)	
Total customers (log)	0.033	0.002	0.325^{***}	0.034^{***}	-0.274^{***}	-0.032^{***}
	(0.052)	(0.003)	(0.047)	(0.005)	(0.061)	(0.007)
Investor-owned utility	-0.283	-0.018	-0.140	-0.015	0.166	0.019
	(0.424)	(0.026)	(0.341)	(0.036)	(0.415)	(0.048)
Co-operative utility	2.220^{***}	0.138^{***}	1.366^{***}	0.143^{***}	1.782^{***}	0.206^{***}
	(0.143)	(0.007)	(0.123)	(0.011)	(0.176)	(0.020)
AMR meter prop.	-0.068^{***}	-0.004^{***}	-0.029^{***}	-0.003^{***}	-0.061^{***}	-0.007^{***}
	(0.003)	(0.000)	(0.002)	(0.000)	(0.002)	(0.000)
Net metering	0.937^{***}	0.058^{***}	0.877^{***}	0.092^{***}	0.165	0.019
	(0.131)	(0.008)	(0.104)	(0.011)	(0.163)	(0.019)
State AMI support	1.338^{**}	0.083^{**}	0.535	0.056	0.890^{*}	0.103^{*}
	(0.435)	(0.027)	(0.376)	(0.039)	(0.394)	(0.045)
Wholesale comp.	0.019	0.001	0.114	0.012	-0.328^{*}	-0.038^{*}
	(0.138)	(0.009)	(0.120)	(0.012)	(0.158)	(0.018)

continued...

...continued

	One-Part Model		Two-Part Model			
			Part One		Part Two	
Variable	β	mfx	β	mfx	β	mfx
Customer choice	0.093	0.006	−0.106	−0.011	0.199	0.023
	(0.166)	(0.010)	(0.146)	(0.015)	(0.201)	(0.023)
Lost margin recovery	0.290	0.018	0.234	0.024	0.255	0.029
	(0.365)	(0.023)	(0.317)	(0.033)	(0.365)	(0.042)
Energy eff. stds.	-0.383^{*}	-0.024^{*}	−0.187	−0.020	−0.207	−0.024
	(0.168)	(0.010)	(0.139)	(0.015)	(0.190)	(0.022)
2008	1.514^{***}	0.094^{***}	1.021^{***}	0.107^{***}	0.404	0.047
	(0.174)	(0.011)	(0.115)	(0.012)	(0.264)	(0.031)
2009	2.211^{***}	0.137^{***}	1.532^{***}	0.160^{***}	0.807^{**}	0.093^{**}
	(0.194)	(0.012)	(0.128)	(0.013)	(0.284)	(0.033)
2010	2.848^{***}	0.176^{***}	2.067^{***}	0.216^{***}	1.092^{***}	0.126^{***}
	(0.206)	(0.013)	(0.135)	(0.013)	(0.308)	(0.035)
2011	3.467^{***}	0.215^{***}	2.561^{***}	0.267^{***}	1.367^{***}	0.158^{***}
	(0.213)	(0.013)	(0.145)	(0.014)	(0.312)	(0.036)
2012	3.955^{***}	0.245^{***}	2.881^{***}	0.301^{***}	1.817^{***}	0.210^{***}
	(0.218)	(0.013)	(0.151)	(0.014)	(0.316)	(0.036)
2013	4.729^{***}	0.293^{***}	3.469^{***}	0.362^{***}	1.973^{***}	0.228^{***}
	(0.225)	(0.013)	(0.160)	(0.014)	(0.322)	(0.037)
2014	5.079^{***}	0.315^{***}	3.755^{***}	0.392^{***}	2.159^{***}	0.249^{***}
	(0.227)	(0.013)	(0.165)	(0.014)	(0.324)	(0.037)
Num. obs.	14,440		14,440		3,112	
GGOFF (LM)	3.834		89.923^{***}		40.103^{***}	
P test for one-part vs. two-part model (LM): 0.029						

Notes: Pooled logit models. Averages of individual marginal effects. Clustered standard errors in parentheses. Significance levels: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

The one-part model appears to fit the data better than the two-part model based on the insignificant P test statistic. Additionally, the logit specification for the one-part model appears appropriate based on the insignificant generalized goodness-of-functional form (GGOFF) test statistic. In contrast, for both the binary and fractional response parts of the two-part model the logit specification appears to not be appropri-

ate. Alternative specifications using different link functions, however, do not generate different results for the GGOFF test and the estimates for the parameters and marginal effects are similar.

The advantage of the two-part model is that it essentially distinguishes between the interfirm and intrafirm dimensions of adoption and models them jointly. The binary response part is similar to the discrete-time duration model in modeling interfirm diffusion, except it is estimated with the full panel dataset. The fractional response part only includes observations with positive values and therefore models the intrafirm dimension. The most noticeable difference in the estimates between part one and part two of the two-part model is for utility size, which is positively associated with adopting but negatively associated with the level of adoption. The estimates for the year indicator variables also reflect a general upward trend for both the one-part and two-part models.

6.7 Discussion

Duration analysis and fractional response analysis of smart meter adoption in the United States suggest that policy and regulatory support have positively influenced adoption and thus the rate and level of smart meter diffusion. This is consistent with the findings of Zhou and Matisoff (2016), but I also find that utility characteristics and some combination of learning, cost reductions, and technology standards are important. In the absence of public policy support for smart meter adoption, it is likely that the rate and level of smart meter diffusion would be lower than they currently are. The finding that learning and technology standards have likely been influential is important because policy has also supported these activities.

The diffusion of new technologies can be affected by a myriad of factors, including supply-side, demand-side, and environmental factors. The econometric evidence presented in this chapter suggests that factors from each category have influenced, with varying magnitudes, the adoption decisions of utilities with respect to smart meters.

The most significant variables for the time period under study, however, appear to be the policy and regulatory environment and some combination of learning, cost reductions, and technology standards. At the federal level, the monetary subsidies in the Recovery Act's SGIG program boosted both the level and rate of diffusion by reducing the costs of adoption. At the state level, policy and regulatory support for smart meters, either through technology mandates or the guaranteed cost recovery of AMI investments, has also had a significant impact on diffusion. The results also suggest that differences in electricity market structures have not impacted the diffusion of smart meters in a significant way; rather, regulation has been a more significant influence, either enabling or constraining smart meter adoption. There is also an association, however, between state policy and regulatory support for smart meters and liberalized electricity markets, such as in California, Texas, Illinois, and Massachusetts. This would suggest that an overriding policy goal of increasing competition, customer choice, and the flexibility of the demand side in electricity markets positively influences smart meter adoption through policy and regulation, but not necessarily through the structure of markets. Whether or not this policy support for smart meters has been warranted, or has been implemented in the best way or at the right time, is another issue.

CHAPTER VII

SMART METER DIFFUSION POLICIES IN THE UNITED STATES

The empirical findings from the previous chapter have public policy implications for enhancing the diffusion of smart meters in the United States. In this chapter I describe and assess existing smart meter diffusion policies in the United States and present additional empirical investigation of their impacts. Although the econometric analysis of the previous chapter investigates the effects of smart meter diffusion policies, it does not explore theories of diffusion policy and rationales for the specific diffusion policies enacted. The empirical analysis suggests a prominent role for policy in extending the diffusion of smart meters, which is consistent with previous research (Zhang 2010; Spodniak, Jantunen, and Viljainen 2014; Zhou and Matisoff 2016). Three aspects of diffusion policy, and public policy in general, frame the discussion in this chapter: rationale, instruments, and impact. These aspects concern the reasoning and motives for policy intervention, the methods of intervention, and the consequences of intervention (Stoneman 2002, 175–177).

7.1 Theories of Diffusion Policy

Theories of technological diffusion lead to theories of diffusion policy, aimed at identifying if and when public policy may be needed to alter a diffusion process and the appropriate methods for intervening in a diffusion process. Diffusion policy is typically oriented toward enhancing the diffusion of a particular technology, but it may also be oriented toward blocking diffusion. Diffusion policy is a type of technology policy and should be analyzed in the context of innovation policy more broadly. Two distinct approaches to diffusion policy exist: neoclassical theories concerned with correcting

market failures and evolutionary theories concerned with avoiding lock-in to inferior technology choices. More broadly, the two approaches align with market failure and system failure approaches to innovation policy. Although these two approaches are opposed in some ways, they may be viewed as complementary (Bach and Matt 2005; Lundvall and Borrás 2005; Metcalfe 2005b, 2007; Steinmueller 2010; Bleda and Río 2013; Pyka 2014; Fagerberg 2016).

The general rationale for innovation policy is the tendency toward underproduction of scientific and technological knowledge in markets as a result of the uncertainty of practical outcomes from innovation activities, the inability to fully appropriate the benefits from innovation activities, and the need to invest in prior knowledge to produce new knowledge from innovation activities (Nelson 1959; Arrow 1962a). In the market failure approach, public policy should then promote a socially optimal level of knowledge production determined by the positive externalities of knowledge. This approach is concerned more with the generation than the diffusion of knowledge and also treats knowledge as having public good characteristics. A policy of subsidizing basic scientific research, as opposed to applied technological research and development, is more strongly supported by the market failure approach. Because the market failure argument focuses on static, allocative efficiency, it may neglect dynamic, adaptive efficiency. Additionally, the market failure approach may prove to be an inadequate guide to practical policy making given the uncertainty and path dependence in innovation processes that prevents the identification of a socially optimal level of knowledge production (Smith 2000; Bach and Matt 2005; Chaminade and Edquist 2006, 2010; Bleda and Río 2013; Fagerberg 2016).

Perceived inadequacies with the market failure approach to innovation policy, which focuses on individual firm incentives, led to an innovation systems approach that recognizes the importance of the connections and interactions among different elements in an innovation system that function together to generate and diffuse innovations (Free-

man 1987; Lundvall 1992; Nelson 1993). These elements include firms, research universities, public laboratories, and other nonmarket institutions that collectively advance technology. The networks connecting the various elements of an innovation system facilitate the combining of disparate ideas, diffusion of knowledge, and learning and adaptation in an open, dynamic environment (Cohendet and Meyer-Krahmer 2005; Powell and Grodal 2005; Powell and Giannella 2010; Özman 2015). The systems perspective can be applied at a national, regional, or sectoral level and is also careful to emphasize historical and institutional specificities that affect economic performance (Edquist 2005; Metcalfe 2005b, 2007; Soete, Verspagen, and Weel 2010). For economic policy in general, a systems view orients policy toward creating a supportive institutional environment for an evolving economic system and thereby transcends the dualistic policy frames of intervention versus nonintervention (Colander and Kupers 2014).

The ultimate goal of investing in innovation activities is to turn technological knowledge into economic value. The innovation systems approach can also be distinguished from the market failure approach based on the analysis of knowledge. Knowledge is equated to information in the market failure approach whereas knowledge is distinguished from information in the systems approach. At a general level, knowledge can be decomposed into codified and tacit dimensions that differentiate between knowledge that is easly communicated and that which is not (Leppälä 2015).

The market failure rationale for innovation policy treats knowledge as a public good, but this may not necessarily be the case. This results from the treatment of knowledge as information in neoclassical models, such that all knowledge is generic, codified, easily transferred at low cost, and context independent. Subsequently, knowledge is viewed as nonrival and nonexclusive and thus creates positive externalities leading to a market failure in the allocation of resources to knowledge production. While basic scientific knowledge may fit this description of a public good, technological knowledge often does not as a result of its specificity, tacitness, difficulty to acquire, and context depen-

dence. If knowledge is differentiated in these and other ways and dispersed throughout the economy within heterogeneous people, firms, and other organizations, then knowledge has both public and private characteristics and learning and search processes become more important for understanding innovation processes and formulating policy (Smith 2000; Metcalfe 2005b, 2007; Chaminade and Edquist 2006, 2010; Lundvall and Lorenz 2012).

Imperfect knowledge is linked to true uncertainty and bounded rationality in decision making that in turn motivates learning and active search for knowledge. Knowledge is generated and diffused on social and economic networks that help shape knowledge management practices and learning processes, serving as both a cause and a consequence of economic performance (Cohendet and Meyer-Krahmer 2005; Powell and Grodal 2005; Powell and Giannella 2010; Özman 2015). Viewing knowledge as multidimensional may impact diffusion and policy making through learning processes. Institutions play an important role in reducing uncertainty and facilitating network connections. The main policy recommendation in the systems approach is to enrich innovation networks through which knowledge is generated and diffused. For the diffusion of technologies, enriching innovation networks can facilitate the diffusion of knowledge about technologies in both its codified and tacit dimensions. The diffusion of this technological knowledge through both centralized and peer-to-peer channels can then influence adoption decisions.

The systems perspective affects the theory and practice of innovation policy by expanding the relevant set of policy rationales and instruments, including those related to education and labor (Edquist 2005; Lundvall and Borrás 2005; Soete, Verspagen, and Weel 2010; Steinmueller 2010; Fagerberg 2016). In contrast to the market failure approach, the systems approach to innovation policy is concerned more with institutional and system failures and also recognizes the potential for government failure. The systems approach is concerned with missing actors, institutions, and associated con-

nections. Network connectivity also evolves to create new business opportunities and institutions based on the search processes for solutions to social and economic problems, so supporting network infrastructure and mobility should be a goal of innovation policy (Ricard 2015). Although endorsed by many countries, the innovation systems approach has also been difficult to translate from theory into practice because of its sometimes unclear concepts and complex depictions of innovation processes that do not readily generate policy instruments (Smith 2000; Mytelka and Smith 2002; Woolthuis, Lankhuizen, and Gilsing 2005; Chaminade and Edquist 2006, 2010; Bleda and Río 2013).

Diffusion policy has arguably been understudied in the literature on innovation policy, even though the impact of technological innovations can only be felt through their widespread use (Stoneman 2002, 305–306). In practice, diffusion policy is typically oriented toward increasing the rate of diffusion with the presumption that faster is better, although theory demonstrates that this is not always the case. Conventional diffusion policy theory is framed in terms of market failure as a rationale with either information provision or adoption subsidies as instruments (Stoneman and David 1986; Stoneman 1987a; Stoneman and Diederen 1994; Caiazza 2015). The market failure argument for diffusion policy rests on the comparison between the private and social costs and benefits of technology adoption. Diffusion policy may be warranted if the socially optimal level of technology adoption is not reached in an economy or not reached fast enough in the absence of policy intervention. This theory can be used to derive a welfare-optimal diffusion path, but the appropriate policy instrument and timing depends on the context, such as the state of technological expectations or market structure (Ireland and Stoneman 1986; Stoneman and David 1986; Stoneman 1987b, 67–79; Stoneman and Diederen 1994). In contrast to the market failure approach, the systems approach to diffusion policy as informed by evolutionary thinking focuses on avoiding inefficiencies as opposed to incentivizing efficiencies. The goal for policy from this perspective is to avoid lock-in to an inferior technology and to ensure variety in technology

choice (Metcalfe 1994a, 1994b, 1995a, 1995b; David 2005, 2007; Pyka 2014). Either approach is concerned with overcoming barriers to diffusion and achieving certain social goals (Edler 2010; Caiazza 2015).

Different theoretical perspectives on diffusion can lead to different rationales and instruments for diffusion policy. Epidemic models of diffusion view information and learning as the key determinants in diffusion processes and thus produce a relatively limited set of policy rationales and instruments concerning the provision of information. Probit models of diffusion focus on the effects of firm heterogeneity and thus produce a wider array of policy rationales and instruments related to firm characteristics. Game theory models also point to the relevance of strategic interaction, and evolutionary models emphasize both firm heterogeneity and learning in a continually changing environment.

Nonlinear models of the innovation process suggest that technology policy should not focus on diffusion in isolation. Interdependencies between diffusion and the other stylized stages of the innovation process suggest that technology policies for invention, commercialization, and diffusion cannot always be separated and should be considered in tandem and designed to work together synergistically. While integrating the supply of and demand for innovations in theoretical models enables welfare comparisons of diffusion paths, it also complicates policy design. Good policy for R&D may be bad policy for diffusion, and vice versa. Additionally, policy makers do not necessarily have the requisite knowledge to determine the welfare-optimal diffusion path (Stoneman 1987a, 1987b; David 1986; Stoneman and Diederen 1994; Metcalfe 1994a, 1994b, 1995a, 1995b; Hahn and Yu 1999; Geroski 2000; Williams, Stewart, and Slack 2005, 211–247; Caiazza 2015).

The most common diffusion policy instruments include information provision and adoption subsidies, but other instruments include demonstration projects, support of technology standards development, and public procurement. A policy mix with mul-

tiple instruments may also be needed to ensure widespread diffusion. Furthermore, the boundaries of diffusion policy may not always be clear. Environmental regulation, for example, may incentivize the diffusion of certain technologies over others. Additionally, education policy affects human capital development that can in turn determine what technologies are used or not used based on the available skillsets and capabilities in an economy. (David 1986; Stoneman and Diederen 1994; Caiazza 2015).

The use of information provision to stimulate the adoption of new technologies is premised on the belief that firms may not be aware of new technologies or may not understand the full costs and benefits of adopting new technologies. The provision of information aims to reduce this uncertainty through learning and thereby encourage adoption. Differentiating between information and knowledge, however, implies that simply providing information to firms may not be enough to encourage adoption. If there is a considerable tacit dimension to knowledge about using a certain technology, then the transfer of knowledge becomes more difficult and costly. Information provision may then have to be combined with subsidies to generate knowledge through learning by using. Building absorptive capacity for technology adoption is another policy instrument to consider when both learning and firm heterogeneity are taken to be important determinants in diffusion processes. Absorptive capacity also links generation and diffusion in innovation systems (Wegloop 1995; Goodwin and Johnston 1999). Subsequently, an information provision policy can be transformed into a more general learning policy, either passively providing information or actively generating knowledge in uncertain environments.

Adoption subsidies aim to reduce the costs of adopting new technologies through financial incentives and enhance their diffusion as a result. Even if some firms may adopt without such incentives, given firm heterogeneity, subsidies may be needed to induce further adoption along both the interfirm and intrafirm dimensions. Subsidies may also be needed to encourage early adoption and generate learning which can then

feedback to suppliers to improve technologies that can then lead to mass market adoption. The heterogeneity of firms, however, may make it difficult to design an optimal subsidy (Stoneman and Diederen 1994).

Apart from these more common and direct instruments, the support of technology standards development can be considered an important indirect instrument for diffusion policy. Different types of standards may impact the diffusion of technologies in different ways. Quality standards, for example, reduce uncertainty as to the performance and reliability of a technology. Product standardization can generate economies of scale in production and thus reduce unit costs. Additionally, interface standards can alleviate the fear of vendor lock-in. The development of standards can reduce uncertainty and lower costs and thus positively influence technology adoption (David 1987; David and Greenstein 1990; Tassey 2000, 2015; Blind 2004).

Uncertainty plays an important role in formulating and assessing diffusion policies. Expectations of the costs and benefits of technology adoption may play an important role in the formation and impact of diffusion policies (Ireland and Stoneman 1986). This is true for both neoclassical and evolutionary approaches to diffusion policy, but they differ qualitatively in how expectations of firms are conceived and modeled. Neoclassical models assume unbounded rationality whereas evolutionary models assume bounded rationality. The distinction is one of decision making under risk versus uncertainty. From the perspective of ecological rationality, decision making should be connected to the decision-making environment that is defined in part by the presence and degree of uncertainty (Lee 2011; Todd and Gigerenzer 2012). Neoclassical views are more appropriate under conditions of little or no uncertainty whereas evolutionary views are more appropriate under conditions of true uncertainty.

In neoclassical thought there is, strictly speaking, no uncertainty at all. Any uncertainty is reduced to risk, where all the possible outcomes of a decision are known along with their associated probabilities of occurring. When modeling behavior, risk is

accounted for by attaching probability weights to all possible outcomes in an optimization framework. Risk can be distinguished from uncertainty where risk is equated to known probabilities of known outcomes and uncertainty is equated to unknown probabilities and unknown outcomes (Keynes 1921; Knight 1921). Uncertainty can also be viewed in a nondualistic framework as composed of varying degrees of uncertainty (Dow 2015, 2016). Uncertainty may also be termed true, fundamental, radical, or irreducible uncertainty to distinguish it from risk, and it results from imperfect knowledge of the world because of continual, endogenous change in an open system. Decision making in truly uncertain environments is characterized not by optimizing but by satisficing and heuristics (Lee 2011; Todd and Gigerenzer 2012).

The distinction between risk and uncertainty is important for thinking about diffusion processes and for policy making aimed at altering diffusion processes. Uncertainty, in contrast to risk, implies limits to knowledge and motivates simpler strategies for decision making. Uncertainty also implies that policy makers are boundedly rational and learn with firms together as a diffusion process proceeds. Policy making, therefore, is necessarily adaptive and interacts and co-evolves with technology as well as the development of innovation theory (Metcalfe 1995a, 1995b; Mytelka and Smith 2002; Witt 2003). Uncertainty undermines, to some extent, the market failure rationale for diffusion policy because it presupposes that policy makers can identify a socially optimal diffusion path. It can be difficult, if not impossible, to ascertain an optimal diffusion path in an uncertain environment. Welfare comparisons of different diffusion paths can also be difficult if relevant factors change over time like preferences and the technology itself, especially if those changes are endogenous (Stoneman 1987a, 1987b).

Because evolutionary perspectives take more seriously the distinction between risk and uncertainty, evolutionary diffusion policy is concerned less with selecting and enhancing the diffusion of a particular technology and more with preventing inferior technologies from becoming locked-in through a path dependent process. From an evo-

lutionary perspective, uncertainty is inherent in innovation systems and not a market failure itself. It prevents the identification of a socially optimal diffusion path, limiting the purview of policy makers. Diffusion policy from an evolutionary perspective seeks to reduce uncertainty and to ensure a variety of technology is available to be selected through minimizing switching costs and encouraging experimentation. Strengthening network ties so that diffusion of knowledge and learning can occur more widely is another policy goal. Additionally, evolutionary policy aims to balance incentives for both the generation and diffusion of technology (Metcalfe 1994a, 1994b, 1995a, 1995b; David 2005, 2007; Pyka 2014).

7.2 Rationales and Instruments for Smart Meter Diffusion Policies

The rationales and instruments for smart meter diffusion policies can be discussed within the theoretical frameworks of diffusion policy. The complex distribution of the costs and benefits of smart meters among different stakeholders, in part resulting from the complex regulatory and governance structure of the electric power industry itself, gives rise to many reasons for supporting their diffusion through policy. In particular, the benefits of smart meters from demand response are primarily social benefits because reducing peak demand improves reliability of electric power grids and can save infrastructure costs in the long run. Smart meters can also reduce greenhouse gas emissions through energy efficiency and the integration of renewable energy sources. Along with barriers to adoption, these isues provide a rationale for public policy support for smart meter adoption (Zhang 2010; Brown and Zhou 2013; McHenry 2013; Pupillo and Serre 2013; Katz 2014).

From a market failure perspective, a policy rationale for aiding the diffusion of smart meters can be made only under certain circumstances. The benefits of smart meters, especially those from enabling time-varying rates, must be compared to the costs. Only if the social benefits of a higher level of smart meter adoption than occurs in a mar-

ket exceed the costs of installation can policy support be justified. There is no general case for subsidizing smart meter diffusion (Doucet and Kleit 2002; Brennan 2004; Römer et al. 2012). In most cases, the private benefits for utilities from operational efficiencies are not sufficient to justify smart meter deployments. It is often the case that the benefits obtained from demand response programs are needed to justify such deployment. Theoretical and empirical studies demonstrate both short-term and long-term benefits from changes in consumption patterns induced by time-varying pricing. These benefits result from improved allocative efficiency and asset utilization as well as reductions in environmental emissions. The level of benefits, however, depend on demand elasticities and market contexts such as rules, load profiles, and mix of generation sources (Borenstein, Jaske, and Rosenfeld 2002; Borenstein 2005a, 2005b; Borenstein and Holland 2005; Joskow and Tirole 2006; Holland and Mansur 2006, 2008; Ata, Duran, and İşlegen 2016).

The rationales for smart meter diffusion policies in the United States revolve around a number of complementary objectives including reducing peak demand, empowering consumers with consumption data, encouraging energy efficiency, reducing environmental emissions, and fostering innovation. These policies are typically part of a broader push for smart grids and should be assessed with this in mind because of the complementarity of smart grid technologies and policies. Government support of energy technologies like smart meters can overcome barriers to adoption such as lack of information or financial constraints. Given these rationales, policy makers and regulators have used various instruments to incentivize adoption of smart meters. These include both adoption subsidies and cost recovery mechanisms and to some extent information provision. Additionally, smart meter technology standards were developed with the aid of policy. Specific diffusion policies include the Recovery Act smart grid programs at the federal level subsidizing smart meters and associated learning and standards development as well as active support at the state level through regulatory mechanisms (GAO 2004; NSTC 2011; Weyant 2011; Aldy 2013; Rose 2014; CEA 2016).

Federal policies supporting the diffusion of smart meters have been motivated primarily to enhance demand response and energy efficiency but also a means to create more dynamic retail markets linked with wholesale markets and to spur innovation. Policy instruments have included a mix of adoption subsidies and information provision as well as public procurement and support for standards development. The Recovery Act invested an unprecedented $90 billion in clean energy projects as part of a broader effort to stabilize the US economy during the Great Recession and to invest in infrastructure that supports sustainable long-term growth. Apart from the recession, the clean energy investments in the Recovery Act were motivated by market failures in energy markets related to environmental impacts, energy security, incentives for innovation, information provision, and financial constraints (Aldy 2013; Rose 2014; CEA 2016; DOE 2017b).

The clean energy projects in the Recovery Act focused on technology deployment and embodied the largest form of federal support for the adoption of smart meters through the Smart Grid Investment Grant program. The SGIG program subsidized the cost of adopting smart meters by those utilities who applied for and were awarded monetary grants. The SGIG program clearly emobides the diffusion policy of adoption subsidies meant to lower the cost of adopting smart meters to incentivize utilities to adopt. Additionally, a mix of ten investor-owned, municipal, and co-operative utilities also received funding and assistance to carry out consumer behavior studies related to time-varying electricity prices as part of their smart meter deployments. The SGIG program, then, also embodies the diffusion policy of information provision by generating knowledge about the actual costs and benefits of adopting. Furthermore, the broader Recovery Act smart grid program also supported the development of smart meter technology standards and funded workforce training and development related to smart grid technologies, activities that have also aided the diffusion of smart meters (Aldy 2013; Rose 2014; CEA 2016; DOE 2017b).

State policies, either from legislation or regulatory action, supporting smart meter adoption do not necessarily fit into a market failure argument for diffusion policy. Given the high levels of regulation in electricity markets, regulation does not simply correct market failures but actively shapes electricity markets in different ways depending on the exact nature of regulation. The rationale for economic regulation, however, derives from market failure arguments related to both the natural monopoly characteristics of electricity distribution and services affected by the public interest, so the rationale for supporting smart meters and smart grids ultimately results from a duty to protect the public interest in one or more ways. Therefore, state policies supporting smart meters are carried out through regulatory instruments.

State policies concerning smart meters have typically been prompted by the previously described federal efforts at grid modernization. The Energy Policy Act of 2005 requested states to consider implementing time-varying pricing and deploying enabling technology like smart meters as a means to reduce costs. In addition, state policies have typically been motivated by similar rationales to the federal policies, including increasing energy efficiency and reducing peak demand to constrain system costs, reducing operational costs and therefore electricity prices, reducing environmental externalities, and empowering consumers through consumption data and rate choice. The policies are typically part of wider smart grid policies that also encourage distributed generation and net metering. Related policies that protect consumer data have also been implemented (EIA 2011; Urban 2016).

The support for smart meters by states exists on a continuum from passive to active support. For example, some states simply order utilities to provide smart meters if requested by a customer, but do not order mass deployments. Only a small number of states can be considered to have an active program of support for deploying smart meters. In Arizona, California, Connecticut, Illinois, Maine, Massachusetts, Pennsylvania, Texas, and Vermont, there have been concerted efforts to invest in smart meters as part

of a wider push for smart grids with a more active state role in transforming electricity markets. Additionally, these requirements typically specify metering functionality but not specific hardware. The diffusion of smart meters in these states has been aided by regulatory instruments such as guaranteed cost recovery of smart meter investments (EIA 2011).

7.3 Impacts of Smart Meter Diffusion Policies

More than 16 million smart meters were installed for 81 utilities across the country as a result of the SGIG subsidies. Of the 16 million meters from the SGIG grant, more than 14.5 million smart meters were deployed to residential consumers, more than 1.6 million meters were deployed to commercial consumers, and the remainder were deployed to industrial consumers. Figure 14 shows that after the Recovery Act smart grid programs were implemented the rate and level of smart meter diffusion increased substantially. Of the 81 utilities awarded grants, only one had previously installed smart meters, 200 in total. The SGIG grants extended both the interfirm and intrafirm dimensions of smart meter diffusion, amounting to rougly one-third of the overall increase in smart meter use during the time period of the program. Figure 14 also depicts illustrative counterfactuals. The first alternative diffusion path depicted can be considered as one possible counterfactual, constructed by simply subtracting the 16 million smart meters contributed by the SGIG. This alternative path, however, does not take into account the learning generated from SGIG smart meter deployments and the knowledge spillovers that could have encouraged other utilities to adopt smart meters. The second alternative path depicts a diffusion path that accounts for the possible lack of learning (DOE 2015, 2016a, 2016c, 2017b).

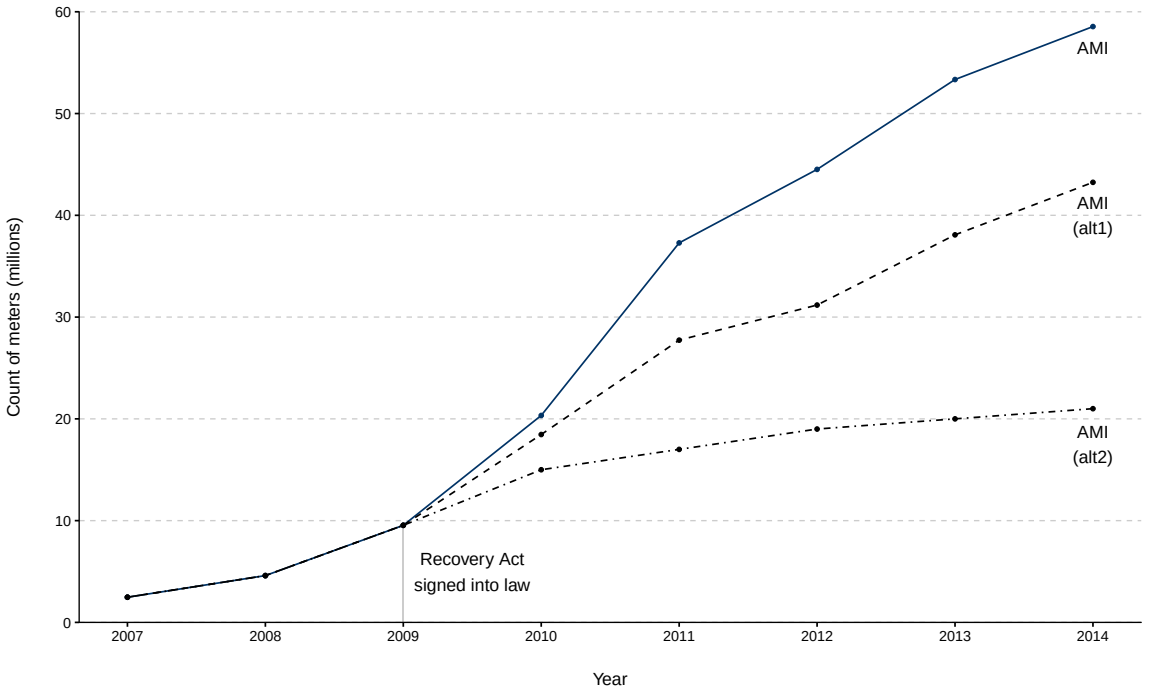


Figure 14. Temporal Pattern of Smart Meter/Advanced Metering Infrastructure (AMI) Diffusion in the United States with Illustrative Counterfactual Trends in the Absence of Recovery Act SGIG Funding, 2007–2014. Observed data from EIA (2017a). First counterfactual based on data from DOE (2015) subtracted from observed data from EIA (2017a). Second counterfactual not based on data.

The use of smart meters from the SGIG grants produced many benefits based on their capabilities. All the meters were capable of interval reads, more than 10.8 million of the meters were capable of remote connect and disconnect, more than 12.6 million were capable of outage reporting, and more than 14.5 million were capable of tamper detection. As a result of these and other capabilities, smart meters led to improved restoration times and reduced numbers of customers affected in outage events, improved operational efficiencies resulting in cost savings, improved customer service and satisfaction, improved energy efficiency, reductions in peak demand, and reductions in environmental emissions. The SGIG grants also deployed various customer devices, including 10,468 in-home displays, 2,174 energy management systems, 408,188 direct load control devices, 259,836 programmable controllable thermostats, and 292 smart appliances.

These devices are coupled with smart meters to manage energy use. The deployment of smart meters also led more than 417,000 customers to enroll in some form of time-varying rate program, although this number is small compared to the total number of smart meters deployed (DOE 2015, 2016a, 2016c).

At the state level, the active support of smart meter adoption has led to high proportions of smart meter use in those states. Figure 15 depicts the level of smart meter use by state in 2014. Those states that have actively supported smart meter adoption have seen, unsurprisingly, high proportions of smart meter deployment, such as Arizona, California, Maine, Pennsylvania, Texas, and Vermont. At the same time, other states without active support have also seen high proportions, such as Alabama, Florida, Georgia, Idaho, and Nevada. Some of these high proportions have resulted from SGIG funding. The majority of states without active support, however, do not have high proportions.

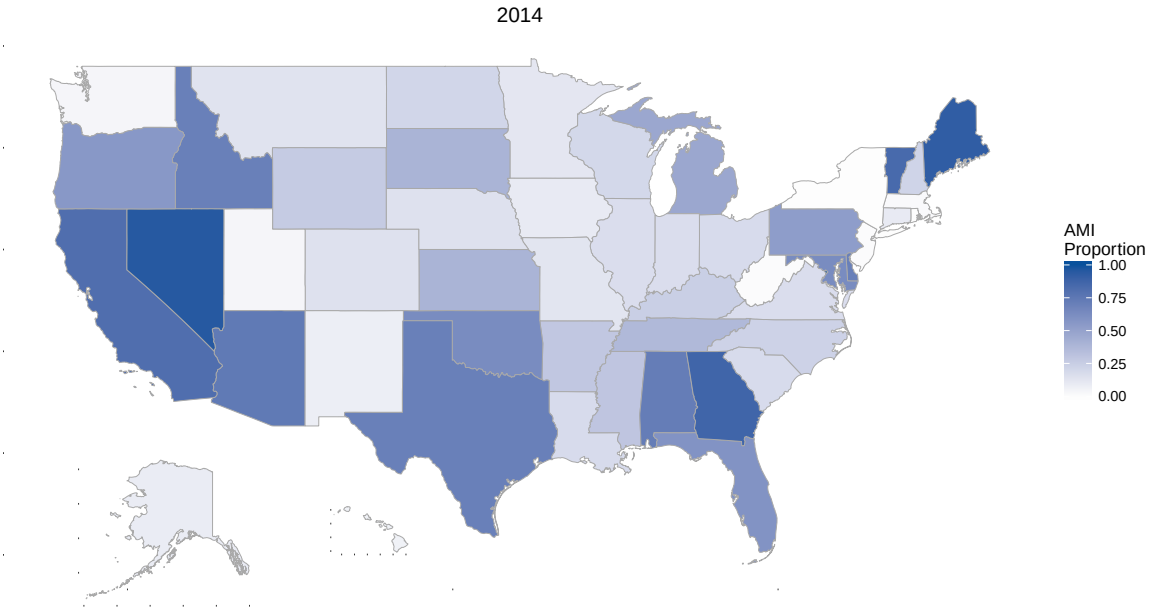


Figure 15. Spatial Pattern of Smart Meter/Advanced Metering Infrastructure (AMI) Diffusion in the United States in 2014. Data from EIA (2017a).

Other trends related to smart meter diffusion should be examined to give some context in assessing the impact of diffusion policies. These trends relate to how smart meters are actually being used and leveraged to create additional value. Figure 16 shows the aggregate pattern of smart meter diffusion decomposed by customer class. The growth in smart meter use is primarily a result of its extension to residential consumers. Table 11 presents data from Form EIA-861 on certain aspects of how smart meters are being used. Data on the total number of smart meters with home area network (HAN) gateways, total number of customers with daily digital access (DDA) to consumption data, and total number of customers with direct load control (DLC) capabilities were first collected in 2013. These data indicate that the meters are capable of these functions, but it does not imply that they are actually being used as such.

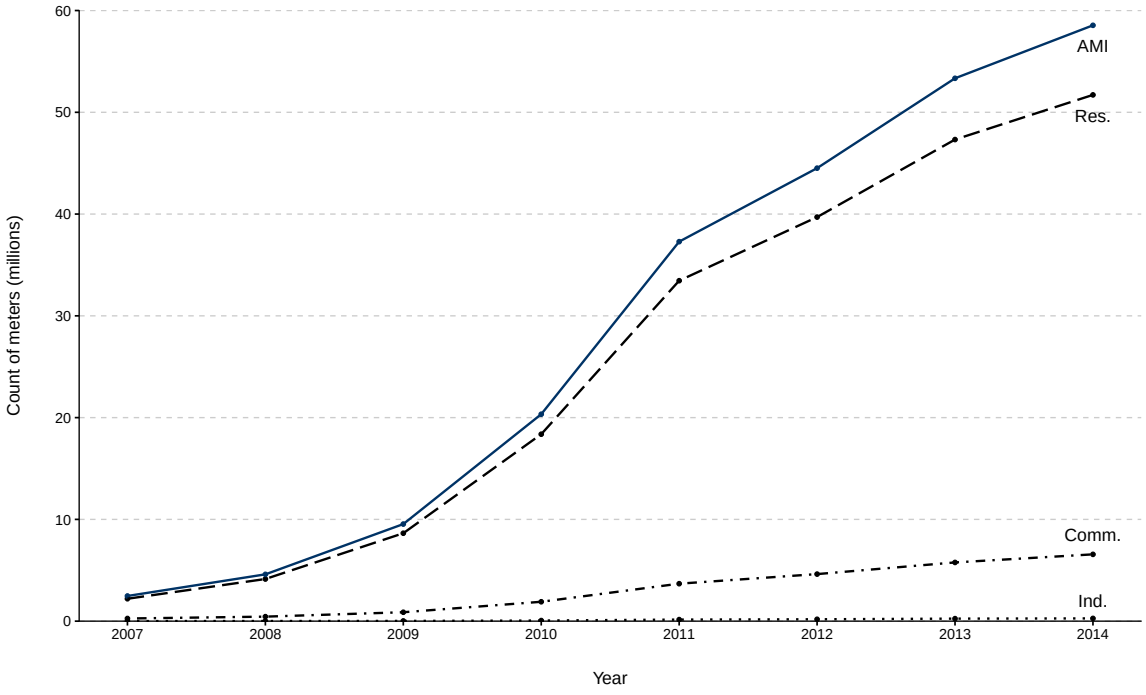


Figure 16. Temporal Pattern of Smart Meter/Advanced Metering Infrastructure (AMI) Diffusion in the United States by Customer Class, 2007–2014. Data from EIA (2017a).

Table 11. Characteristics of Smart Meter Use.

Year	Number of Meters	Number of Meters with HAN	Number of Customers with DDA	Number of Customers with DLC
2013	53,341,422	1,305,013	30,620,539	3,424,994
2014	58,545,938	2,006,859	35,686,536	3,757,183

Notes: Data from EIA (2017a). HAN = home area network. DDA = daily digital access. DLC = direct load control.

Figure 17 shows the aggregate pattern of customers enrolled in demand response and dynamic pricing programs. More than 9 million customers were enrolled in demand response programs and more than 6.3 million customers were enrolled in dynamic pricing programs in 2014, far below the number of smart meters deployed. Table 12 also shows the number of utilities offering dynamic pricing programs decomposed by type of pricing. Other impacts of smart meter use related to their social benefits would be interesting to know, such as improvements in energy efficiency or reductions in peak demand, but such data in the aggregate are not readily available. Smart meters are also being used, of course, for operational purposes such as meter reading and outage management and new uses for them are being discovered (DOE 2016a; IEI 2016a).

Table 12. Number of Utilities Offering Dynamic Pricing Programs.

Year	TOU	RTP	VPP	CPP	CPR
2013	414	86	16	58	22
2014	490	77	18	67	26

Notes: Data from EIA (2017a). TOU = time of use. RTP = real time pricing. VPP = variable peak pricing. CPP = critical peak pricing. CPR = critical peak rebates.

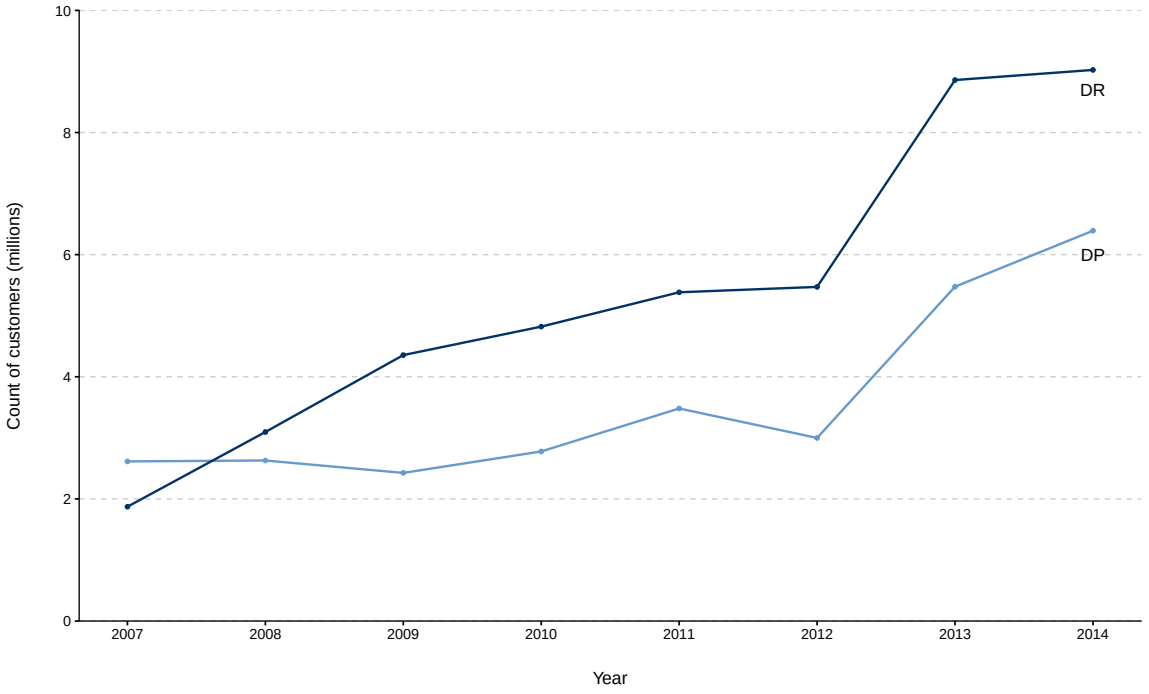


Figure 17. Temporal Pattern of Utility Customers in Demand Response (DR) and Dynamic Pricing (DP) Programs in the United States, 2007–2014. Data from EIA (2017a).

7.4 Assessing Smart Meter Diffusion Policies

Smart meter diffusion policies should be assessed in the context of the energy innovation system and energy and environmental policy in the United States. Systems of innovation differ substantially at the sectoral level, and even sectors exhibiting high levels of innovation have systems that are organized differently (Malerba 2005). The energy innovation system is international in scope and consists of a diverse set of actors, networks, and institutions engaged in interdependent and uncertain innovation activities. Relative to other sectors, rates of innovation are slower in energy systems as a result of the intensiveness and longevity of the capital stock, the need for experimenting and learning, and the low level of technology clustering and spillovers (Gallagher, Holdren, and Sagar 2006; Gallagher et al. 2012). Energy policy is intertwined with environmental policy because of the environmental externalities resulting from the production and con-

sumption of energy. Energy innovation policy is relevant for the policy mix because of the role of technological change in both creating and resolving environmental externalities (Jaffe, Newell, and Stavins 2005; Praetorius et al. 2009, 9–43; Popp, Newell, and Jaffe 2010).

Although a systematic comparison of neoclassical and evolutionary approaches to diffusion policy specifically, as opposed to innovation policy more broadly, has not yet been attempted, I assess smart meter diffusion policies while keeping both theoretical perspectives in mind. The assessment criteria concerns the strength of the policy rationale, the appropriate use of policy instruments, and the impact of the policy with respect to its stated objectives. Clearly, the SGIG subsidies and active state support for smart meters have increased both the rate and level of smart meter diffusion, but it is less clear if such policies have been warranted or implemented in the best way. It is debatable whether the push for smart meters has been an appropriate policy goal or, alternatively, if the push has been premature.

The most effective smart meter diffusion policies to pursue depend on specific policy objectives, market contexts, and timing (Zhang 2010; Zhang and Nuttall 2011; Rixen and Weigand 2014). The main goal of all the smart meter diffusion policies in the United States has been to enhance the flexibility of the demand side in electricity markets at times of peak demand through demand response and dynamic pricing programs. These policies have emphasized large-scale smart meter deployments so that smart meters are used for residential customers in addition to commercial and industrial customers. Pilot projects, however, have typically preceded mass deployments. Such a strategy emphasizes a mix of policy instruments where learning is subsidized first to ascertain the costs and benefits of adoption and then, if found beneficial, financial incentives of some kind are enacted to facilitate mass deployment. Smart meter adoption may be beneficial for some utilities but not for others, depending on local con-

ditions, consumer preferences, and ability of consumers to shift load from on-peak to off-peak times.

The SGIG program subsidized both adoption costs and learning through matching funds. To be considered for funds a utility was required to submit an application involving the rationale for adoption, connections to smart grid functions, expected uses, expected costs and benefits of deployment, a detailed deployment plan, a plan for assessing technology performance, and a plan for further expansion. Grant recipients were competitively selected based on the merit of the applications. Recipients were also required to report on activities, progress, and lessons learned throughout deployment timelines. This knowledge was then aggregated across utilities through case studies and reporting as a mean to diffuse knowledge to the industry as a whole (DOE 2016a, 2016c, 2017b).

The nature of the SGIG program, through the application process and the matching funds, was arguably well designed in that it led to a self-selection process for utilities that expected smart meters to be profitable investments and integrated into larger smart grid projects. Because the application required detailed plans, the grant process ensured that only utilities with thoughtful plans would receive subsidies. Additionally, because the grants were matching funds, it ensured a certain level of commitment to using smart meters by leveraging utility funds. The SGIG to some extent also recognized that utilities are different in their characteristics by specifying a generic subsidy of 50% of program costs as opposed to a set level of funds. The design of the program accounts for the heterogeneity of utility characteristics by considering the diverse needs, abilities, costs and capital vintages, and regulatory environments of utilities, emphasized in probit and evolutionary theories of diffusion. Those utilities that desired to use smart meters could apply and potentially receive funding if selected, but those that did not want to use smart meters were not forced to use them. The requirements, however, could operate on unobserved heterogeneity in that only utilities that had the capacity to

apply for funds and comply with the reporting requirements applied for and received funds. This could have perhaps biased the grants away from smaller utilities who did not have such capacity, but the program was likely targeted toward larger utilities anyway.

The SGIG program also invested in learning as a means to reduce uncertainty about technology performance and encourage continued investment in smart grid technologies after the program ended. The SGIG program also subsidized learning through the reporting of lessons learned in smart meter deployments and the consumer behavior studies that examined the effects of time-varying rates on consumption patterns. The results from the Sacramento Municipal Utility District study were positive enough to encourage implementation of default time-of-use rates for residential customers in the near future, which also influenced the same policy for the state of California as a whole. Additionally, although the SGIG deployed a relatively small number of customer devices, the behavioral studies showed more demand reduction with such devices. The SGDP also subsidized learning through smart grid demonstration projects involving smart meters. Through public-private partnerships with smart grid technology vendors, these smart grid programs also helped to mature the industry (DOE 2016b, 2016c).

Other aspects of the Recovery Act smart grid programs may be critiqued. It may be considered odd, for example, to simultaneously subsidize large deployments of smart meters while funding research into their effects on consumer behavior, because these effects can be important factors in cost-benefit evaluations. In addition, although the Recovery Act also provided support for the development of technological standards and cybersecurity guidelines related to smart meters, it may also be considered odd to simultaneously subsidize large deployments of smart meters before these important standards and guidelines are in place. At the same time, SGIG grant recipients were required to address interoperability, security, and privacy concerns in their smart meter deployment plans, and the two-way communication function of smart meters allows

software updates as new standards and security protocols are developed. These critiques point to a possible tension between the Recovery Act's goals of macroeconomic stability in the short-run through "shovel-ready" projects and investment in infrastructure for long-run growth and technology that is not yet mature (MITEI 2011, 197–234; Aldy 2013; CEA 2016; DOE 2016b, 2016c).

In critiquing smart meter diffusion policies, the main issues with the market failure approach is the identification of the socially optimal diffusion path for smart meters. There has been uncertainty associated with the actual costs and benefits of adoption, including both the private costs and benefits for utilities and the social costs and benefits for electricity consumers and society as a whole. The costs are mostly up front and many of the benefits are long-term but not guaranteed, such as those from demand response. Although some uncertainty has been reduced over time as smart meters have been deployed in large numbers across the country, uncertainty persists and has led to diverging opinions about how beneficial smart meters actually are. The benefits ultimately depend on how smart meters are used, such as for demand response programs and integration with other smart grid technologies. The social benefits and the privacy and security costs are difficult to quantify, in part because of these uncertainties. These complexities prompt a need for regulatory oversight and governance throughout smart meter deployments (EPRI 2008a; Neenan and Hemphill 2008; NETL 2008; Haney, Jamasb, and Pollitt 2009; McHenry 2013; Leiva, Palacios, and Aguado 2016).

There has been pushback from consumer advocates and even some utilities questioning the cost-benefit evaluations. Some of this pushback from residential consumers has related to the perceived negative health effects of wireless transmission of consumption data from smart meters, and this has led to fee-based opt-out programs in some states for consumers who do not want smart meters installed on their homes. Additionally, the lifespan of smart meters is expected to be 10–15 years with potential for obsolescence as the technology changes and improves, which could impose additional costs.

The more forceful arguments against smart meters, however, relate to a general lack of consumer interest in smart meters and time-varying rate programs. Because subscriptions to time-varying rate programs have not diffused nearly as widely as have smart meters, many of the benefits associated with demand response that have been used to justify deployments have not yet been realized in most cases. These benefits are often necessary to return positive net benefits (EEI 2006b, 2006a; Neenan and Hemphill 2008; Haney, Jamasb, and Pollitt 2009; Faruqui, Harris, and Hledik 2010; IEE 2011; MITEI 2011, 132–137; Cook et al. 2012).

After the large deployments of smart meters in Texas, in 2013 only 0.8% of customers with smart meters had accessed the Smart Meters Texas web portal to view their consumption data and only 0.2% of customers had connected their smart meters to some kind of automation device like a smart thermostat. This apparent lack of interest may result from lack of funds and emphasis on customer education and engagement concerning smart meters. Ease of access to smart meter data and market design may also be important factors (SPEER 2014). Other states found that large-scale deployments of smart meters were not cost-effective. Such analysis and critiques have even found their way into the popular press regionally (Galbraith 2012; Starkman 2013; Turkel 2015; Finnerty 2016) and nationally (Smith 2009; Wald 2009, 2014; Vergano 2011; Chediak 2012; Guerrini 2014; Mooney 2015). To some extent, this uncertainty also likely reflects that the benefits from demand response vary in different contexts, as a result of climate and load profiles or the generation mix, for example. Dynamic pricing may not necessarily have environmental improvements, and flatenning peak demand may increase dependence on fossil-fueled baseload generation (Holland and Mansur 2008; Ata, Duran, and İşlegen 2016). Policy support, then, may be suitable in some areas but not others.

The benefits of smart meters from demand response seem to be more uncertain than initially thought, resting on the uncertain behavior of consumers. A major part of the uncertainty in demand response benefits surrounds the debate as to whether or not

residential consumers have sizable enough loads to reduce during peak demand, respond to dynamic pricing, or are interested enough in such programs. Because the benefits from demand response are typically necessary to make smart meters cost-effective, the behavioral research on consumer response to smart meter consumption feedback and time-varying pricing is important to consider. While much of the behavioral research finds that consumers do respond to dynamic pricing by shifting consumption, this research has often suffered experimental design problems such as small samples and self-selection bias (Davis et al. 2013). The level of peak demand and overall energy reductions has declined in studies over time as a result of better design (Torriti 2016, 61–82).

The consumer behavior studies that were part of certain SGIG smart meter deployments were an attempt to provide a more rigorous design through randomized and controlled trials to assess demand reductions. All studies relied on opt-in programs and two also compared results to opt-out programs. The key findings from these studies were that opt-out programs maintained higher enrollments but lower peak demand reductions than opt-in programs, automated control technologies led to more peak demand reductions than in their absence and were cost-effective, consumers were largely not interested in in-home displays, and demand reductions depended on the on-peak to off-peak price ratios. Additionally, continual engagement was found to be necessary to maintain customer interest in the long-term (DOE 2016b). These findings are consistent with other research, which also highlight the limitations and unintended consequences of consumption feedback (Hargreaves, Nye, and Burgess 2013; Buchanan, Russo, and Anderson 2014, 2015).

These findings collectively suggest that the benefits attributed to smart meters from demand response may be lower and the costs higher than anticipated, potentially calling into question the cost-effectiveness of deploying smart meters to most or all residential consumers if the operational benefits to utilities are not sufficient. This is es-

pecially true if the majority of the benefits from demand response come from a minority of customers. Emphasizing residential customers is important because, as depicted in Figure 16, the growth of smart meter use results from expanding their use to residential customers. This imposes substantial costs compared to only industrial and commercial customers. There are also concerns about the ability of some consumers to respond to dynamic pricing, raising the issue of fairness. It is likely true, however, that even customers who do not particpate in dynamic pricing programs can benefit from the positive externalities generated by those customers who do participate, reducing peak demand and therefore the associated avoided costs. These concerns can be overcome with proper design of dynamic pricing programs and customer engagement, taking into account the complex distribution of costs and benefits (Borenstein, Jaske, and Rosenfeld 2002; GAO 2004; Alexander 2010; Brand 2010; Faruqui 2010; Felder 2010; Hanser 2010; Hogan 2010; Levinson 2010; Faruqui and Palmer 2011; Léautier 2014).

The lack of residential consumer interest in demand response and dynamic pricing programs could also be a failure to effectively engage customers or coordinate policies. This has arguably been the experience in Texas (SPEER 2014) and elsewhere (Murray and Hawley 2016). Customer engagement can ensure that smart meter deployments and demand response programs are both fair and effective and targeted to those who are willing and able to participate (Honebein, Cammarano, and Donnelly 2009; Alexander 2010; Brand 2010; Honebein 2010). The deployment of smart meters has largely not been matched with the adoption of time-varying rates, despite a long history of interest and countless pilot projects in the industry. This is starting to improve, however, as California and Massachussets are set to adopt time-of-use rates for residential customers as the default rate in the near future. Additionally, complementary policies related to customer choice and the adoption of data privacy and sharing programs like the Green Button Initiative are also relevant (SPEER 2014; Lazar and Gonzalez 2015).

Another interesting issue is the potential for leveraging existing AMR meters for dynamic pricing. One SGDP pilot project investigated the possibilities and found that it was technically possible to use AMR meters for such purposes at a substantially lower cost compared to AMI meters. They were found to not always be reliable, but improvements in technology have overcome the issues encountered. The communication system and meter data management system components of AMI were found likely to be needed to effectively enable dynamic pricing on a wide scale. The communication system may also be used for other smart grid purposes, which AMR could not provide. Additionally, the project found loss of interest in dynamic pricing programs over time. Therefore, AMR-enabled demand response programs would only be useful for interested customers who could be expected to reduce their on-peak consumption (Navigant Consulting 2014).

On the cost side, there are also uncertainties related to smart meter standards, data privacy, and cybersecurity. Some utilities adopted smart meters prior to the development of key standards, like interoperability, and therefore incurred either reduced benefits from limited capabilities or increased costs to replace meters. Smart meter data can reveal detailed information on household activities, raising concerns of surveillance and targeted home invasion. Because the data is typically transmitted wirelessly to a utility, the data can potentially be intercepted by an unauthorized third party. Data can also be intercepted through unauthorized physical access to the meter. There has also been ambiguity as to who owns smart meter data, posing legal issues. In addition, unauthorized access to smart meter software can allow a third party to manipulate data records and send false information to grid operators. Although there has been policy action around these issues, privacy and security measures have not kept up with the pace of smart meter deployments and the smart grid as a whole (CRS 2011, 2012; GAO 2011; Makovich 2011; Urban 2016).

Policy that supports a technology too soon is one of the concerns of evolutionary perspectives on technology diffusion. Such support may lock-in technology choices to an inferior technology. For smart meters, the idea of avoiding evolutionary inefficiencies is not immediately applicable because smart meters are capable of performing the same functions as the prior AMR meters. These competing metering technologies are not distinct in that sense. There is not necessarily a possibility of industry-wide lock-in, but individual utilities can be locked-in for a time because smart meters are long-lasting capital investments. The issue here, then, is unnecessary costs, including the opportunity cost of investment funds, if smart meters are not as beneficial as hoped.

The issues raised here suggest that the push for smart meters has been too fast. In the push for smart grids, too much attention appears to have been given to the benefits and not enough to the costs, and many of the proclaimed benefits have not yet materialized. Consumers appear not to be interested enough in demand response programs and will not necessarily benefit from smart grid technologies in the short-run, and there may be cheaper technical alternatives to smart meters for those who are. Additionally, cybersecurity and privacy concerns have not been adequately addressed. The deployment of smart meters and smart grid technologies has arguably been too fast at the level seen because of still evolving technology. Some states like Pennsylvania and Connecticut, however, in pushing for smart meters have been flexible in deployment timelines by requiring a certain level of deployment within 10–15 years that takes account of learning as well as vintage effects. The smart grid should be a more gradual evolution of the electric power industry where concern is taken to understand the implications of smart grid technology, and consequently public policy should be more cautious (Brennan 2004; Levinson 2010; Makovich 2011; Blumsack and Fernandez 2012; McHenry 2013). Additionally, these issues highlight that the market failure approach to diffusion policy is difficult to implement in practice when technology diffusion is a result of supply and demand interactions and when the technology is changing over time.

They also highlight the need for diffusion theory and the theory of diffusion policy to consider complementary technology use.

If the push for smart meters has been too fast because of uncertain costs and benefits, then this suggests that smart meter diffusion policies should have put more emphasis on learning before committing to large deployments with the aid of adoption subsidies. Diffusion policies oriented toward learning about the costs and benefits of smart grid technologies should lead to more rigorous and better designed pilot projects, helping to reduce uncertainty. From a systems perspective, policy could also support the absorptive capacity of utilities related to technology adoption and encourage learning networks for knowledge diffusion. The absence of absorptive capacity and learning networks can be barriers to knowledge, thus impeding the effective adoption of technology (Kelley and Brooks 1991; Attewell 1992; Williams, Stewart, and Slack 2005). Policy aimed at absorptive capacity could provide support to the legacy Electric Power Research Institute or to alternative institutions, accounting for the diversity of utility characteristics, needs, and market environments.

Because R&D is also linked to learning on both the supply and demand sides of new technology, an integrated policy design that connects and balances generation and diffusion is also needed in the electric power industry as grid modernization proceeds (Sagar and Zwaan 2006; Weiss and Bonvillian 2009; Sivaram 2017). R&D and learning-by-doing on the supply side improve the supply of new technology, and R&D and learning-by-using on the demand side improve the demand for new technology. Discussions of research, development, demonstration, and deployment (RDD&D), however, are not uncommon in the energy industry, reflecting at least some understanding of the connections between traditional R&D and diffusion. In the electric power industry specifically, utilities perform relatively little R&D compared to equipment suppliers and other industries. The liberalization of electricity markets has also reduced R&D activities by utilities. Policy is needed to reverse this trend in order to solve the challenges of grid

modernization, climate change, and other policy goals while taking into account the nature and variety of market structures and regulation (Jamasb and Pollitt 2008, 2011, 2015; Sanyal and Cohen 2009; Sanyal and Ghosh 2013). The nature of regulation may also need to change to accomodate new technologies (Kiesling 2009; Praetorius et al. 2009; Costello 2012; Costello 2016a, 2016b; Römer et al. 2012; Schiavo et al. 2013; Katz 2014; MITEI 2016; Shomali and Pinkse 2016). Further research and data collection is needed to analyze the actors, institutions, and networks in the innovation system of the electric power industry, and the energy sector more broadly, in order to inform policy making in this area (Sagar and Holdren 2002; Gallagher, Holdren, and Sagar 2006; Gallagher et al. 2012).

CHAPTER VIII
CONCLUSION

The analysis in this dissertation concerns the early diffusion of smart electricity meters in the United States. Public policy and regulation have supported the adoption of smart meters by utilities in the United States, principally as a means to foster demand response in electricity markets. Using a panel dataset and econometric models, I analyzed the determinants of the early diffusion of smart meters in the US electric power industry. These models were informed by theories of technological diffusion as well as the history and institutional context of the electric power industry. In addition, I assessed smart meter diffusion policies in the United States as informed by theories of diffusion policy.

8.1 Key Findings

The key findings of the empirical analysis in this dissertation include the importance of policy and regulation, utility characteristics like size, ownership, and capital vintages, as well as some combination of learning, cost reductions, and technology standards as determinants in the diffusion of smart meters. These findings were consistent across the interfirm and intrafirm dimensions of adoption, implying that decisions to adopt and at what level to adopt have been considered jointly by utilities and determined by the same set of factors. In the absence of public policy support for smart meter adoption, it is likely that the rate and level of smart meter diffusion would be lower than has occurred. This finding is consistent with previous research (Zhou and Matisoff 2016), but I also find that utility characteristics and some combination of learning, cost reductions, and technology standards are important determinants.

Public policy support for smart meter diffusion, at both the state and federal levels, is primarily based on the desire to enhance demand response activities in electricity markets and to deploy an initial technological foundation for smart grids. Whether or not policy support for smart meters has been warranted, or has been implemented in the best way or at the right time, is another issue to consider. Although there is a rationale for smart meter diffusion policies, based on the social benefits from demand response, they are not generalizable. Some utilities or regions may benefit more from smart meters than others. The timing of diffusion policies is especially important to consider. A reasonable argument can be made that some smart meter diffusion policies, in the form of state policy or regulatory support as well as the Recovery Act SGIG subsidies, were premature. The costs and benefits of smart meter adoption have been more uncertain than initially thought, and a substantial level of smart meter adoption occurred before the development of important technology standards related to cybersecurity and interoperability.

The analysis covered in this dissertation concerned the time period 2007–2014. In 2015 and 2016 there were reported slowdowns in smart meter deployments, based on utility deployment announcements, that have been attributed to the end of the Recovery Act funds. The diffusion of smart meters appears to be growing again, however, as major utility deployments begin in states like New York and Massachusetts that have not yet adopted at extensive levels. It is predicted that smart meters will grow to 90 million meters in 2020, roughly 70% of the electricity metering stock in the United States (IEI 2016a).

8.2 International Comparisons

The diffusion of smart meters varies across countries. The United States has not adopted smart meters as quickly as other developed countries. Some of the major users of smart meters globally include Italy, Sweden, Finland, the United Kingdom, Germany,

Ontario (Canada), and Victoria (Australia). Italy was an early adopter of smart meters and ran into technical problems as a result, increasing the cost of adoption. In contrast, Germany chose to focus on renewable generation of electricity instead and is now beginning to deploy smart meters, in part because of lessons learned about the constraints on the power grid from intermittent generation sources for which smart meters can help. The United Kingdom, Canada, and Australia have also seen pushback against government-led smart meter deployments similar to that experienced in the United States. Public policy has aided the diffusion of smart meters in many of these countries, although different instruments have been used to varying success (Haney, Jamasb, and Pollitt 2009; Zhang 2010; Brown and Zhou 2013). In Europe, after a push from the European Commission in 2009 to deploy smart meters, mass deployments were found to be cost-effective in the majority of European Union member countries and large scale deployments then commenced. It is predicted that more than 200 million meters will be deployed in Europe by 2020, roughly 72% of the electricity metering stock in Europe (EC 2014).

8.3 Future Research

Future research related to the topic of this dissertation could cover a number of areas. The econometric evidence presented here could be complemented with evidence from case studies, in-depth interviews, and mixed-method studies in order to gain a better understanding of the decision-making processes within utilities with respect to metering technology adoption and technology choice more generally (Metcalfe and Boden 2003; Preece 1995; Tidd 2010b; Dedrick et al. 2015). Qualitative research would be especially informative for how the interaction between investor-owned utilities and the regulatory process influences technology adoption decisions. Understanding the specific reasons why smart meters are being adopted or not adopted, beyond a vague profitability explanation, would give new insight into the subjective aspects of utility

management, changing utility business models, and utility strategy, particularly with respect to grid modernization. Detailed knowledge of how and why technology choices are made within utilities can also aid the construction and implementation of diffusion policies. Moreover, the specific ways in which smart meters are actually being used, as well as the variation in this use among utilities, would also be useful in assessing the actual benefits of smart meters and their impact on productivity (EPRI 2013). Additional evidence from such research would help triangulate the relative impacts of learning, cost reductions, and technology standards on the diffusion of smart meters that could not be separated in the econometric methods of this dissertation. Other research could examine the complementary adoption of smart grid technologies. Because the adoption of technologies is in part creative, requires adaptation, and is influenced by firm strategy (Attewell 1992; Antonelli 2006), adoption decisions can often be complementary and path dependent as a result of the cumulative nature of the knowledge base within firms (Colombo and Mosconi 1995; Arvanitis and Hollenstein 2001).

In general, regulation can impact innovation activities and therefore regulation can also be an instrument of innovation policy (Blind 2010). State policy and regulation was found to be an important determinant in smart meter diffusion, so the interaction between the regulatory process and technological change in the electric power industry should receive more attention in research. Technological change is important because it enables new value creation opportunities and associated markets. Because smart meters and other smart grid technologies reduce the transaction costs associated with buying and selling electricity in real time, dynamic retail markets can emerge that are more closely integrated with wholesale markets. Smart grid technologies and dynamic retail markets combined with advancement in distributed generation and storage technologies could even lead to decentralized coordination of electricity markets. Radical technological change in the industry, however, is hampered by customer, utility, and regulatory inertia, resulting in a status quo bias. Investments in smart grid technologies that re-

duce capital and operational costs require a different set of regulatory instruments to incentivize adoption, especially when the costs are upfront and the benefits are realized in the long term. The industry itself has also recongized that the regulatory model is in need of change. The conventional cost-of-service regulatory model as informed by a static view of markets from neoclassical economics could be complemented by an alternative regulatory model informed by a more dynamic view of markets from evolutionary economics. An evolutionary perspective would aim to reorient regulation toward a more adaptive mindset in a constantly changing technology space. Additionally, the coordination of policies at different levels of government and across related issues is important to consider (Munson and Kaarsberg 1998; Hirsh and Sovacool 2006; Kiesling 2009; Praetorius et al. 2009; MITEI 2011, 2016; NSTC 2011; Römer et al. 2012; Brown and Zhou 2013; Schiavo et al. 2013; McHenry 2013; Katz 2014; Marques, Bento, and Costa 2014; Guo, Bond, and Narayanan 2015; Zhou and Matisoff 2016).

Future research could also include analysis of the nature of innovation in the electric power industry, both from a technological and institutional perspective. Smart grids can be considered a technological paradigm in which the industry focuses its innovative efforts to solve problems, but there are competing visions, or technological trajectories, of where and how smart grid technology should be developed (Dosi 1982). The concepts of the supergrid and transactive energy can be considered two such trajectories on opposing extremes. States differ in their specific goals and visions for shaping electricity markets and comparative institutional analyses would be helpful in understanding directions of technological change. The shaping of electricity markets can be interpreted within the conceptual framework of public sector entrepreneurship (Leyden and Link 2015), and future research should investigate the implications of this for technological change in the electric power industry. More research could address the relationships among market structure and regulation and innovative capacity. Additionally, studies of the quantity and quality of R&D in the industry as well as the energy

innovation system as a whole would also be informative. Such analyses could help understand barriers to innovation, predict the direction of technical change, and reveal the institutions and policies that influence paths of innovation toward certain desired ends (Gallagher, Holdren, and Sagar 2006; Kiesling 2009; Praetorius et al. 2009; Gallagher et al. 2012).

The future of the electric grid in the United States is in flux and will likely change in different regions and at different times. Information and communication technologies, like smart meters, are at the heart of this change by enabling new capabilities and thereby new markets. They will continue to play a pivotal role in shaping the rate and direction of technical change in the electric power industry.

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