J PROD INNOV MANAG 2011;28:169–186

Evaluating Government's Policies on Promoting Smart Metering Diffusion in Retail Electricity Markets via Agent-Based Simulation*

Tao Zhang and William J. Nuttall

In this paper, we develop an agent-based model of a market game in order to evaluate the effectiveness of the U.K. government's 2008–2010 policy on promoting smart metering in the U.K. retail electricity market. We break down the policy into four possible policy options. With the model, we study the impact of the four policy options on the dynamics of smart metering diffusion and suggest policy implications. The context of the paper is a practical application of agent-based simulation to the retail electricity market in the United Kingdom. The contributions of the paper are both in the areas of policymaking for the promotion of innovation diffusion in the electricity market and in methodological use of agent-based simulation for studying the impact of policies on the dynamics of innovation diffusion.

Introduction

One of the U.K. government's most prominent recommendations for the energy market is the adoption of smart metering technology, which, in addition to offering a broad range of benefits to energy consumers, can substantially cut CO_2 emissions. "Smart metering" is a catch-all term referring to a type of advanced and innovative metering technology which offers consumers information about energy consumption in more detail than traditional single phase electromechanical metering, and optionally interacts with energy suppliers via some communication network for monitoring and billing purposes (Ofgem, 2006a). As a novel technology in the U.K. energy market, smart metering is still in its infancy and its adoption will be a long and slow process. The characteristic of uncertainty in technology diffusion raises the strategic issue of what policies the government should introduce to boost the roll-out of smart meters in the U.K. energy market. Lessons from international experience (e.g., Italy, Sweden, and California) suggest that introducing smart metering in the context of monopoly provision can be a very successful strategy. However, the characteristics of competition and diversification of meter ownership in the U.K. metering market mean that the government faces a different context for policy. Therefore, in February 2006 the energy market regulatory agency in Britain (Ofgem) consulted different stakeholders and proposed six policy options. More recently (in May 2007), the U.K. government (the Department for Business, Enterprise and Regulatory Reform [BERR]) has announced its policies on promoting smart metering technology in its 2007 white paper on energy *Meeting the Energy Challenge*. However, how effective these policies are in terms of fostering the diffusion of smart metering and what other supplementary optimum strategy options can be used to strengthen the effectiveness of these policies in the U.K. energy market still remain questionable. This paper is motivated by a desire to develop a methodological framework for studying these two interrelated research questions.

Traditionally, from a methodological point of view the adoption of a new technology represents a particular form of collective behavior of users occurring in markets or economies. It mainly has been studied from the perspective of economics or static models, for example the "S-curve" model (Rogers, 1962), the Bass model of product growth (Bass, 1969), the adopter heterogeneity model (Hall and Khan, 2003), learning or epidemic model (Strang and Soule, 1998), and real options model (Dixit and Pindyck, 1994; Stoneman, 2001). These traditional models study the innovation diffusion at both macro and micro levels. At macro level, classic innovation diffusion models (e.g., the "S-curve" model and the Bass model of product growth) primarily focus on aggregate variables like market penetration and adverting effects,

Address correspondence to: Tao Zhang, Judge Business School, University of Cambridge, Trumpington Street, Cambridge CB2 1AG, United Kingdom. E-mail: T.Zhang@jbs.cam.ac.uk.
* The authors acknowledge the financial support of the ESRC Electricity Policy Research Group (EPRG), under the Towards a Sustainable Energy Economy (TSEC) Programme Work Package 3 (WP3). The authors also acknowledge the comments on this paper from one anonymous referee for the EPRG and four for JPIM.

while at the micro level classic innovation diffusion models (e.g., the adopter heterogeneity model, epidemic model, and real options model) primarily focus on the influence of the characteristics of individual adopters (i.e., consumers or firms) on their decision of adoption. Although these traditional models significantly contribute to our understanding of both macro-level innovation diffusion processes and micro-level factors that influence the adopters' decisions of adoption, it remains unclear how these micro-level factors lead to the dynamics of macro-level innovation diffusion. Additionally, empirical studies (e.g., Baker, 2001; Cutler and McClellan, 1996; Gray and Shadbegian, 1998; Mowery and Rosenberg, 1982) find that government policies and regulations have a profound effect on innovation diffusion. Although some recent studies (e.g., Hohnisch, Pittnauer, and Stauffer, 2008; Janssen and Jager, 2002, 2003; Watts and Dodds, 2007; Zhang and Zhang, 2007) have touched the field of studying the effects of micro-level consumer psychological factors (e.g., attitudes, preferences, satisfaction, and behavior) and social networks where consumers interact on the macro level innovation diffusion processes via dynamic simulation methods, how the impact of government policies and regulations on the dynamics of innovation diffusion can be modeled at microscopic level (i.e., the behavior and interactions of firms and adopters), and how we can manage the innovation diffusion processes under different policy/strategy scenarios receive inadequate study. In order to bridge the two research methodological gaps, this paper follows up our previous study (Zhang and Nuttall, 2007) and targets the aforementioned two interrelated research questions via agent-based simulation.

The agent-based model in this paper is a market game developed based on the real retail electricity market in Britain. This market game represents the interaction between electricity suppliers and the residential electricity consumers. Essentially, we investigate the effectiveness of BERR's 2008–2010 policies on promoting the diffusion of smart metering, and identify what supplementary optimum strategy options can be used to enhance the effectiveness of BERR's new policies in the market. The objective of the study is twofold. Firstly, we expect that the results of the study reported in this paper can potentially help stakeholders (especially government policymakers and energy suppliers) to take effective measures for boosting the roll-out of smart meters. Secondly, we aim to extend the application of agent-based computational simulation to analyzing and managing innovation diffusion processes in the energy market.

The structure of the paper is as follows. The second section describes the metering market in Britain. The third section describes Ofgem's six policy options and BERR's new policies on promoting smart metering in Britain. The fourth section presents our agent-based simulation model of smart metering technology adoption (the market game) in detail. The fifth section shows the four scenarios of policy options we simulated with the model. The sixth section focuses on the analysis of the simulation results and their policy implications. The seventh section discusses and concludes the study.

BIBLIOGRAPHICAL SKETCHES

Tao Zhang now is a research fellow in the Intelligent Modelling & Analysis Research Group, School of Computer Science, University of Nottingham. He was a Ph.D. candidate in the Electricity Policy Research Group, Judge Business School, University of Cambridge. His research interests are in the areas of complexity science and agent-based modelling for the energy market. Tao Zhang currently leads the agent-based simulation part in an EPSRC funded research project *Future Energy Decision Making for Cities—Can Complexity Science Rise to the Challenge*? He is an associate researcher of the ESRC Electricity Policy Research Group. Before he started his Ph.D. in Cambridge, he pursued his post-graduate studies in the U.K. universities of Exeter and Hertfordshire.

William J. Nuttall is a Senior Lecturer in Technology Policy at the University of Cambridge. While a Fulbright Post-Graduate Student in Physics at the Massachusetts Institute of Technology, he became interested in science and technology public policy. In early 2002 he moved to Cambridge University to be founding Course Director for a new Cambridge-MIT Institute (CMI) sponsored master's degree in Technology Policy. He holds a shared post between Judge Business School, where he is based, and Cambridge University Engineering Department. He is the author of the book *Nuclear Renaissance* (Taylor & Francis, 2005) and co-editor of the book *Future Electricity Technologies and Systems* (CUP, 2006). Dr Nuttall has a leading role in the ESRC Electricity Policy Research Group. He is a Fellow of Hughes Hall Cambridge.

The Retail Electricity Metering Market in Britain

It is a legal requirement that all but a few exempted electricity consumers must have an appropriate meter when they use electricity. As a result, currently there are around 22.5 million domestic electricity meters installed in England and Wales: 3 million prepayment meters, 3.3 million multi-tariff meters, and 16.2 million single-rate credit meters (Sauter, Watson, and Hughes, 2005). Each year, about 2.2 million meters are installed (out of which 1.2 million are at new sites and 1 million are replacements) (DGCG, 2003).

Metering services have two core components: one is the provision of an accurate meter of an appropriate type, the other one is data services (taking meter readings periodically and processing the data). Around 10% of domestic electricity meters are prepayment meters. These meters allow customers to prepay for their electricity use via various means of payment such as electronic tokens, keys, or payment cards.

Traditionally, the electricity Distribution Network Operators (DNOs) are the dominant meter operators for domestic meter points. They have a license obligation to provide metering services to all meter points, upon the request of the relevant electricity suppliers. DNOs own and manage the meter assets. They also charge electricity suppliers for metering services. The prices they charge electricity suppliers are regulated by Ofgem. In March 2001, Ofgem published its metering strategy, aiming to introduce competition in the metering market. Following this, full electricity metering competition entered into force in 2003. The purpose of introducing competition in electricity metering services was to encourage suppliers and metering service providers to lower prices, improve standards of service, and innovate. A key principle of the policy of introducing competition in the electricity metering services is to make electricity suppliers, not DNOs, primarily responsible for purchasing metering services—the so-called "supplier hub" principle (Ofgem, 2006b). Since then, some electricity suppliers have appointed third-party commercial metering service providers, rather then automatically continue to use existing providers, for providing electricity metering services to their domestic consumers. For example, Centrica has appointed United Utilities, OnStream, and Siemens for the provision of competitive electricity metering services to its domestic consumers (Ofgem, 2006b).

Under the current regulatory framework, although domestic electricity consumers have the statutory right to make their own metering arrangements few have chosen to do so. Currently consumer demand for meter ownership and consumers making their own metering arrangements is virtually zero (Ofgem, 2001). Moreover, DNOs are still responsible for (own and manage) over 90% of domestic electricity meters. The vast majority of domestic electricity meters are simple single-phase electro-mechanical or electronic meters with either a single register or multiple registers (Sauter et al., 2005). Therefore, these meters can only be read manually on an annual or biannual basis. In order to prevent fraud, they are generally backstopped so as to prevent them from running backwards.

Ofgem's Six Policy Options and BERR's New Policies on Promoting Smart Meters

Ofgem's Six Policy Options

Currently, reducing greenhouse gas emissions, maintaining security of energy supply, and tackling fuel poverty are the three major challenges in the U.K. energy market. Smarter, more innovative electricity meters (smart metering) can potentially help tackle all the three issues (Ofgem, 2006b). Therefore, as an effective approach to energy efficiency, promoting smart metering is at the top of the government's energy agenda. Although competition has already been introduced in the electricity metering market, there is little evidence that electricity suppliers intend spontaneously to introduce smart meters to their domestic electricity consumers on a large scale in the next few years. In February 2006, Ofgem published a consultation document, *Domestic Metering Innovation*, which marks the launch of a significant initiative to work with the energy suppliers, the network operators, meter manufacturers, government, and other stakeholders to help identify and unlock the potential of smart meters. In this consultation document, Ofgem proposed six policy options for promoting smart meters based on the consideration of the regulatory arrangements, that is, should the introduction of smart meters be left to customers and energy suppliers to decide (i.e., through market competition), or mandated through some form of legislation and/or regulation by relevant authorities? The six policy options are summarized in Table 1.

U.K. Government New Policies on Promoting Smart Meters

Ofgem's efforts have not been lost on the U.K. government, which set promoting smart metering at the top of its energy agenda in order to comply with the EU Energy Services Directive, which states that "Member States shall ensure that, in so far as it is technically possible, financially reasonable and proportionate in relation to the potential energy savings, final customers for electricity, natural gas . . . are provided with competitively priced individual meters that accurately reflect the final customer's actual energy consumption and that provide information on actual time of use" (Vasey, 2007). In May 2007, BERR published a White Paper on Energy *Meeting the Energy Challenge*, which explicitly demonstrated the govern-

Table 1. Ofgem's Six Smart Metering Policy Options

Policy Option	Remarks
Address barriers to innovation	This option emphasizes the effect of competition, leaving the final decision on whether to install smart meters to consumers, suppliers, and the market.
Enable the customer to contract for a smart meter	This is a more radical policy option emphasizing the role of the consumer in promoting smart metering. It puts the consumer, rather than the supplier, at the center of the decision of what sort of smart meter they want to have. As consumers have the most to gain from smart metering, they might be best placed to choose whether to buy a smart meter. This policy option enables consumers to either own the meter, or contract directly with a meter provider for the meter or contract through the supplier with a meter operator.
Impose an obligation on suppliers	This policy option highlights the role of the regulator and the government in promoting smart metering, based on the lessons learnt from international experience such as Sweden (Ofgem, 2006b). Under this policy option, an obligation could be placed on all energy suppliers to install meters with a minimum specification. This could be done via either amending suppliers' licenses to impose this requirement by Ofgem or legislating directly by the government.
Rebundle metering services into networks	This policy option involves rebundling metering services into DNOs. Under this policy option, the DNOs would be re-positioned as monopoly providers for metering services. International experience in Italy shows that rebundling could allow for a massive roll-out of smart meters to all domestic consumers (Ofgem, 2006b).
Await international evidence	This policy option assumes that currently there is not enough evidence on consumer response to justify investing in smart meters. Policymakers (Ofgem and the government) should actively monitor the development of smart metering in countries where smart meters have been adopted to look at how consumers are responding. The international evidence could then be used to reappraise the case of smart metering in Britain.
Instigate a trial	This policy option assumes that international evidence may not be suitable to appraise the case of smart metering in Britain, because consumer response to smart metering varies according to the specific consumer characteristics, climate and culture of the country concerned. Thus, a policy option that Ofgem can make is to facilitate and support a large-scale trial of smart meters in Britain to gather firm evidence of the consumer response. However, any trial would need to run for a minimum of one year, and it would also take time to analyze the results of the trial, so the conclusions arising from the trial may not be available for another two years.

ment's ambition in promoting smart metering in the United Kingdom (excluding Northern Ireland). In this paper, BERR announced its new policies on promoting smart meters in retail electricity market, that is, an expected 10-year plan to roll out smart meters incorporating real-time visual display (RTVD) devices to all households. As an additional interim measure and a first step to true smart metering, between 2008 and 2010 RTVDs will be available free of charge to any household that requests one.

Modeling Government Policies on Promoting Smart Metering in Domestic Electricity Markets

Description of the Model

Since BERR has announced its policies on promoting smart metering in Britain, how effective these policies are and what other supplementary optimum strategies can be adopted to maximize the speed and the degree with which smart meters diffuse throughout the electricity market still remain questionable. Under BERR's new policies, while Ofgem is in favor of "meter competition approach" to roll out smart meters, some other stakeholders (e.g., Energywatch), based on an analysis of limited evidence from the U.K. metering market, argue that rebundling metering services to monopoly DNOs would be a more cost-effective approach (Asher, 2007). As the current regulatory framework (meter competition and diversified meter ownership) in the U.K. electricity metering market produces little quantitative evidence for economists and policymakers to assess the effectiveness of their smart metering policies via econometric models, a new research method for coping with this issue is helpful. We present research based on an agent-based computational simulation method. The model is an agent-based model developed based on social psychological theory. It targets the two aforementioned interrelated research questions, as an extension of our previous research (Zhang and Nuttall, 2007).

The model is a market game involving two parties: residential electricity consumers and electricity suppliers. Each party is represented by a type of agent. Thus the model has two types of agent: residential electricity consumer agents and electricity supplier agents. Similar to the real players in the real electricity market, these agents interact in a designed virtual environment in a computer. We make the agents in our model autonomous and interdependent, that is, each agent makes its own decisions, and it influences and is influenced by other agents. We formalize and code the policy options, carry out experiments in the virtual environment and then observe its system level emergent phenomena, of the diffusion of real-time visual displays. The simulation results can be seen as inferences of the diffusion of real-time visual displays in the real retail electricity market. Through a phenomenological comparison of different scenarios of policy options in the experiments and by analyzing the simulation parameters, we can assess the effectiveness of different policy options and identify the supplementary optimum strategies to support BERR's smart metering policies.

Behavior of Residential Electricity Consumer Agents

As residential electricity consumer agents represent residential electricity consumers (households), they are smart agents with human intelligent behavior in terms of decision making in choosing both energy suppliers and smart meters. In the real electricity market, the information about smart metering and electricity suppliers starts from electricity suppliers via mass media (e.g., TV, newspaper, and the Internet), and travels through the consumers' social network via word of mouth; a residential electricity consumer gains information about electricity suppliers and metering technologies from both his/her social network (e.g., neighbors, friends, or colleagues) and energy suppliers (through advertising such as TV, the Internet, and news reports), processes the information and then makes decisions. This decision-making process involves psychological (e.g., consumers' attitude, intention, and behavior), sociological (e.g., consumer interactions and influences conveyed by these interactions), and environmental (e.g., information from mass media) factors. Thus, developing high fidelity residential electricity consumer agents in this particular case requires a consideration of psychological, sociological, and environmental factors.

There are several well-established social psychological theories to explain consumers' acceptance of new technologies, among which we have identified five influential ones, namely technology acceptance model (TAM) (Davis, 1989), the theory of planned behavior (TPB) (Ajzen, 1985), the model of goal-directed behavior (MGB) (Perugini and Bagozzi, 2001), social cognitive theory (SCT) (Bandura, 1986), and the motivational model (MM) (Vallerand, 1997), whose core constructs are in psychology and sociology. Although these models are different in terms of the choices of constructs, a critical common point among them is the role of intention as a predictor of behavior, which has been empirically validated by many studies (e.g., Ajzen, 1991; Davis, 1989; Mathieson, 1991). Considering the requirements for developing high fidelity residential electricity consumer agents, we compare the suitability of the five social psychological theories from the perspectives of psychology, sociology, environment, and formulation and coding, as shown in Table 2. The comparison shows that TPB emphasizes the roles of psychological, sociological, and environmental factors in the decision-making process, and is also relatively easy to formulate and code, which makes it particularly suited to modeling consumer behavior in agent-based simulation. Thus we choose TPB to formalize the behavior of residential electricity consumer agents in this particular case.

The TPB model, as shown in Figure 1, suggests that the actual behavior of a person is determined by the person's intention (I) to perform the behavior. This intention is predicted by three factors: the person's attitude towards the behavior (A), the subjective norm (SN, i.e., the pressure the person perceives from his/her social network), and the perceived behavior control (PBC, i.e., the person's perception about his/her ability to perform the behavior). The person's background factors' contributions to the three predictive factors of intention are calibrated by the person's relevant personality parameters, which are described as "beliefs" in the TPB model.

Based on the TPB model, we summarize the characteristic features of consumers' decision making as follows: (i) intention is the immediate antecedent of an actual behavior (choose an option); (ii) a persuasive message will (both positively or negatively) influence a consumer's intention to choose an option only if it affects either his/her attitude towards the option or his/her perceived social pressure to choose the option from important referent individuals or groups such as the person's spouse, family, friends, or colleagues; (iii) when facing a range of options, a consumer is most likely to choose the one for which he/she has the largest intention, given that the consumer perceives he/she has the ability to choose the option.

We formalize residential electricity consumer agents' behavior based on the TPB model. We assume that, in the virtual environment, two kinds of interactions can influence an ordinary residential electricity consumer agent i to choose option α (whether

Table 2. Comparison of the Suitability of Social Psychological Theories for Consumer Agent Design

Model	Psychological Factors	Sociological Factors	Environmental Factors	Formulation and Coding
TAM	Four psychological factors (Perceived usefulness [U], Perceived ease of use [EOU], Attitude [A], and Behavioral intention [BI]) are defined.	Not included in TAM.	External variables are mentioned, but not clearly defined.	Relatively easy, as there are only four main psychological predictors in the model, and the relationships are already formalized.
TPB	Three psychological factors (Attitude [A], Perceived behavioral control [PBC], and Intention [I]) are defined.	The influence on intention from the social network, subjective norm (SN), is defined.	Environmental background factors are included in the model.	Relatively easy, as the predictive variables and their relationships have already been defined and formalized.
MGB	Eight psychological factors (Attitude, Positive anticipated emotion, Negative anticipated emotion, Perceived behavioral control, Desire, Frequency of past behavior, Recency of past behavior, and Intention) are defined.	The influence on intention from the social network, subjective norm (SN), is defined.	Environmental background factors are mentioned but not clearly defined in the model.	Difficult, as too many variables are defined in the model. The relationship between different variables is not clearly formalized.
SCT	Specific psychological variables are not clearly defined in the general SCT model. Instead, some are defined based on the context of the studied behavior. For example, self-efficacy, affect, and anxiety were defined in a study of consumer's acceptance of computers (Compeau, Higgins, and Huff, 1999).	The general SCT model emphasizes the role of human agency in the Triadic Reciprocality but does not clearly define the interactions between human agencies.	The general SCT model emphasizes the important effects of environmental factors on behavior, but does not define any specific environmental factors.	Difficult, as specific predictive variables are not defined.
MM	Three levels of psychological mediators (Autonomy, Competence, and Relatedness) and psychological predictors (intrinsic and extrinsic motivation) are defined.	Three levels of social factors (i.e., human factors) are mentioned, but not defined specifically.	Three levels of environmental factors (i.e., the nonhuman factors included in the social factors) are mentioned, but not defined specifically.	Difficult, as the model has three levels of generality, and the relationships between the predictive variables are not clearly defined.

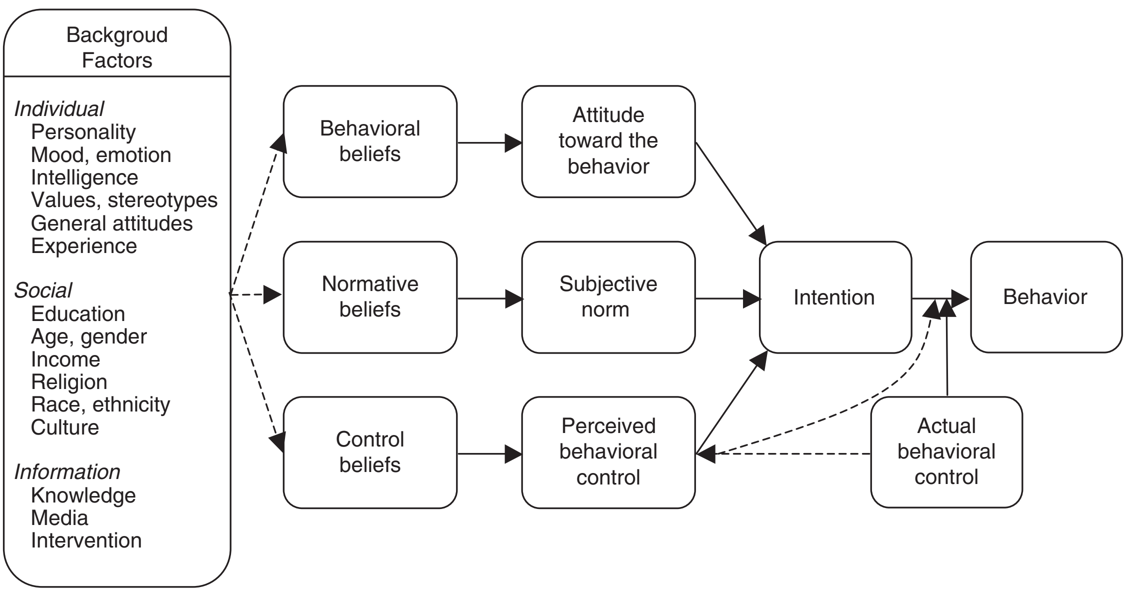

Figure 1. The TPB Model
Source: Ajzen and Fishbein, 2005, p. 194.

choosing a smart meter or not with a particular electricity supplier agent). One kind, in the form of price information of electricity and benefits of smart metering, is the interaction between residential electricity consumer agent i and electricity supplier agents. The other kind, in the form of word-of-mouth effects and personal influences, is the interaction between residential electricity consumer agent i and other residential electricity consumer agents. Based on the TPB model, the interaction between residential electricity agent i and a particular electricity supplier agent such as information about electricity prices P_E^α sent to residential electricity consumer agent i from the electricity supplier agent can influence residential electricity consumer agent i's attitude towards choosing option α, but its influential power is calibrated by residential electricity consumer agent i's personality trait "price sensitivity." Therefore, residential electricity consumer agent i's attitude towards choosing option α can be formulated as follows:

$$A_i^\alpha = W_{iP} * P_E^\alpha, \tag{1}$$

where A_i^α = residential electricity consumer agent i's attitude towards choosing option α, and W_{iP} = residential electricity consumer agent i's personality trait "price sensitivity."

P_E^α varies uniformly between 80 and 100, reflecting the reality that there is no big difference between the electricity prices of different electricity companies. W_{iP} varies uniformly between -1 and 0. If W_{iP} is near 0 it means residential electricity consumer agent i is not sensitive to price, and consequently price can hardly reduce its intention to choose option α. If W_{iP} is near -1, it means residential electricity consumer agent i is very sensitive to price, and consequently high price can significantly reduce its intention to choose option α.

The interaction between residential electricity consumer agent i and other residential electricity consumer agents, such as a positive/negative persuasive message or personal influence about option α from an important referent residential electricity consumer agent j, can influence residential electricity consumer agent i's subjective norm towards choosing option α, but its influential power is calibrated by residential electricity consumer agent i's motivation to comply with residential electricity consumer agent j. Therefore, residential electricity consumer agent i's subjective norm towards choosing option α can be formulated as follows:

$$SN_i^\alpha = \sum_{j=1}^{n} (W_{ij} * Inf_{ji}^\alpha), \tag{2}$$

where SN_i^α = residential electricity consumer agent i's subjective norm toward choosing option α, Inf_{ji}^α = influence from residential electricity consumer agent j to residential electricity consumer agent i about choosing option α, W_{ij} = residential electricity consumer agent i's motivation to comply with residential electricity consumer agent j, and n = the number of other residential electricity consumer agents interacting with residential electricity consumer agent i.

Inf_{ji}^α varies uniformly between -100 to 100. When Inf_{ji}^α is near -100 it means residential electricity consumer agent i receives a very negative influence from residential electricity agent j, which consequently reduces residential electricity consumer agent i's intention to choose option α significantly; when Inf_{ji}^α is near 100 it means residential electricity consumer agent i receives a very positive influence from residential electricity agent j, which consequently contributes to residential electricity agent i's intention to choose option α significantly. W_{ij} varies uniformly between 0 and 1. When W_{ij} is near 0 it means residential electricity consumer agent i is insensitive to advice from residential electricity agent j, while when W_{ij} is near 1 it means residential electricity consumer agent i can easily be affected by residential electricity agent j.

A range of environmental factors (such as smart metering infrastructure, service availability in a particular area, or unexpected events) can influence residential electricity consumer agent i's perception of his/her ability (the perceived behavioral control) to choose option α. Therefore, these factors can be regarded as control beliefs in the TPB. Analogously, the influential power of a control belief about option α, C_{ki}^α, is calibrated by residential electricity consumer agent i's related perceived power of the control factor, PC_{ik}. Residential electricity consumer agent i's perceived behavioral control towards choosing option α can be formulated as follows:

$$PBC_i^\alpha = \sum_{k=1}^{m} (PC_{ik} * C_{ki}^\alpha), \tag{3}$$

where PBC_i^α = residential electricity consumer agent i's perceived behavioral control towards choosing option α, and m = the number of control factors.

C_{ki}^α varies uniformly between 0 to 100. When C_{ki}^α is near 0 it means the environmental factor has modest effects on residential electricity consumer agent i's intention to choose option α, while when C_{ki}^α is near 100 it means the environmental factor has strong effects on residential electricity consumer agent i's intention to choose option α. PC_{ik} varies uniformly between 0 and 1. When PC_{ik} is near 0 it means residential electricity consumer agent i cannot easily be affected by a particular environmental factor, while when PC_{ik} is near 1 it means residential electricity consumer agent i can easily be affected by a particular environmental factor.

Combining residential electricity consumer agent i's attitude (equation 1), subjective norm (equation 2), and perceived behavioral control (equation 3) towards choosing option α, residential electricity consumer agent i's intention to choose option α can be expressed as follows:

$$I_i^\alpha = \sum_{j=1}^{n} (W_{ij} * Inf_{ji}^\alpha) + \sum_{k=1}^{m} (PC_{ik} * C_{ki}^\alpha) + W_{iP} * P_E^\alpha, \tag{4}$$

where I_i^α = residential electricity consumer agent i's intention to choose option α.

When facing a number of options, the one for which a given residential electricity consumer agent i has the greatest intention is his/her preferred one, that is, his/her final decision on which energy supplier to use and whether to choose a smart meter or not. The decision making can be formulated as follows:

$$D_i = \max\{\mathrm{I}^1, \mathrm{I}^2, \mathrm{I}^3, \ldots \mathrm{I}^\alpha\}, \tag{5}$$

where D_i = residential electricity consumer agent i's final decision.

Behavior of Electricity Supplier Agents

Electricity supplier agents are business organizations which compete in the electricity market under the economic regulations set by relevant authorities. Market reports based on empirical investigations (Ofgem, 2001) suggest that currently the competition between electricity suppliers in the U.K. electricity market is based primarily on price comparison. Hence in our model of market game, the behavior of an electricity supplier agent includes: (i) disseminating its electricity price information to residential electricity consumer agents in the virtual environment; and (ii) adjusting electricity price each three months, based on the variation of its overall market share. The behavior can be formulated as follows:

$$P_{E_{(t)}}^\alpha = \begin{cases} P_{E_{(t-1)}}^\alpha & \text{if } t \bmod 3 \neq 0 \\ d * P_{E_{(t-1)}}^\alpha & \text{if } t \bmod 3 = 0 \end{cases}$$

where t = time steps in the simulation, and d = a parameter for adjusting the electricity price.

The value of parameter d is set based on the price variation in the real electricity market. In the simulation, we set the parameter d ranging between 1 and 1.3, based on the fact that between January 2008 and May 2009 the retail price index of electricity in the United Kingdom varied between 160.9 and 208.9 (see Figure 6).

The Environment Design

The environment in our model is a virtual system where agents behave and interact in a computer. The virtual system in our model of market game is a square lattice of 62500 cells ($250^* 250$) with periodic boundary conditions. Cells can be either blank or occupied by residential electricity consumer agents, as shown in Figure 2. The population density in the environment can be controlled by a relevant parameter.

Realistically, people interact not only with their local neighbors, but also with those who live remotely from them (De Bruyn and Lilien, 2008; Dodds, Muhamad, and Watts, 2003). Based on related literature in social network theory (Barabasi and Albert, 1999; Milgram, 1967; Scott, 2000; Watts and Strogatz, 1998), we consider two types of interactions between a residential electricity consumer agent with other residential electricity consumer agents: regular interactions and random interactions, as shown in Figure 3. This design enables the social networks in the environment to have the characteristic features of both "small-world" and scale-free effects.

The Simulation: Virtualizing Government's Smart Metering Policies

Scenarios of Policy Options

BERR's new policies for promoting smart metering state that, as a first step to smart metering, between 2008 and 2010 any household requesting an RTVD can get one free of charge. The key issue raised by this policy is: who pays for this device? Based on this issue, we further break down the policy into three dimensions: (i) the government subsidizes; (ii) electricity suppliers pay for RTVDs; (iii) DNOs pay for RTVDs. Under the three strategies, the next issue is how best to roll out RTVDs. If the government subsidizes RTVDs, these devices can be rolled out in either the context of monopoly (by DNOs) or the context of competition (by electricity suppliers); if electricity

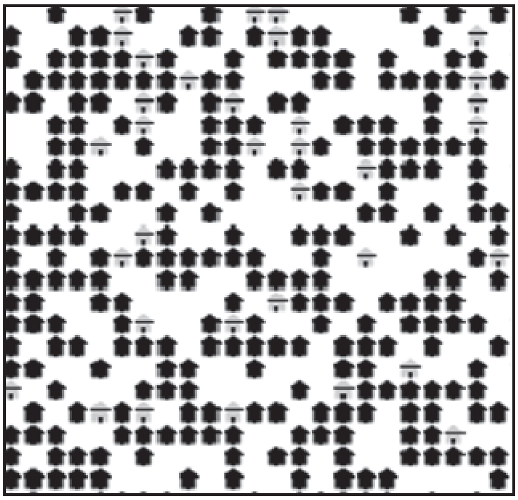

Figure 2. The Environment

Note: In the virtual community, residential electricity consumer agents are randomly populated in the cells (black or gray houses), and the white areas are unpopulated cells (nonresidential areas). Each populated cell has just one residential electricity consumer agent, and the number of total residential electricity consumer agents is controlled by the parameter called ''population density'' which ranges from 0 to 1. In the simulation, the value of population density is 0.4. The black houses are the residential electricity consumer agents with conventional meters, while gray houses are the residential electricity consumer agents with innovative meters (real-time visual display devices). In order to eliminate edge effects, the square lattice has periodic boundary conditions (for further details about periodic boundary conditions, see Janssen and Jager [1999] and Hegselmann and Flache [1998]).

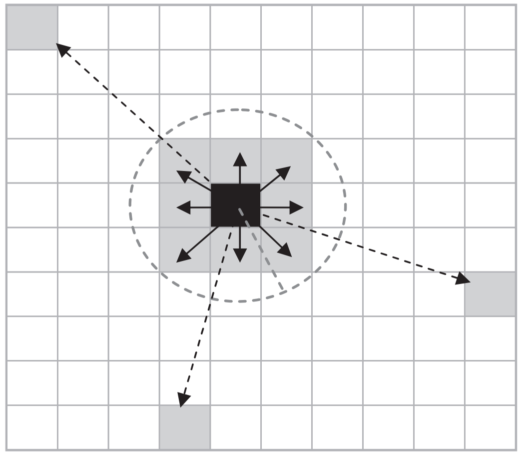

Figure 3. A Residential Electricity Consumer Agent's Regular and Random Interactions with Other Residential Electricity Consumer Agents

Note: In the virtual environment, for example, the black residential electricity consumer agent on the one hand can regularly receive influences from and exert influences on its neighboring residential electricity consumer agents through regular interactions (solid arrows) with them, and the number of regular interactions is controlled by a parameter called ''radius,'' which varies between 0 and 10. If the value of ''radius'' is large (i.e., a long-dashed radius), the black residential electricity consumer agent will have a large number of regular interactions. On the other hand, the black residential electricity consumer agent can randomly receive influences from and exert influence on other residential agents who are remote from it through random interactions with them (dashed arrows) and the number of random interactions it has is controlled by a parameter called ''random interaction,'' which varies uniformly between 0 and 10.

suppliers pay for RTVDs and are responsible for rolling them out, they will be rolled out in the context of competition; if DNOs pay for RTVDs and are responsible for rolling them out, they will be rolled out in the context of monopoly. Therefore, our model of market game will simulate the scenarios of these policy options, as shown in Figure 4.

Simulation Process

We develop six electricity supplier agents representing six major competitors in the U.K. electricity market with the initial market share of each electricity supplier agent the same as its counterpart's market share in the real U.K. electricity market (Figure 5).

Several empirical studies have theorized the patterns of innovation diffusion (e.g., Amendola and Gaffard, 1988; Davies, 1979; Rogers, 1962; Veneris, 1990). Moreover, as suggested in a U.K. electricity market report (Ofgem, 2007), two distinctive characteristics of the domestic retail electricity market in Britain are static market shares of the major electricity retail competitors and dynamic consumer switching between electricity suppliers. Therefore, we choose three indicators to examine in the model: (i) the impact of different policy options on the dynamics/patterns of RTVD diffusion; (ii) the evolution of electricity supplier agents' market shares; and (iii) residential electricity consumer agents' switching between electricity supplier agents.

We simulate the four scenarios of policy options shown in Figure 4. We design each time step in the model as one month. In all four scenarios, a residential electricity consumer agent cannot switch electricity supplier agent within two time steps (complying with the 28-day rule in the real electricity market; Ofgem, 2001). We design a personality parameter ''enthusiasm'' (ETH_i) to signify the degree to which a residential electricity consumer agent is interested in having a RTVD. The parameter ETH_i determines a residential electricity consumer's initial intrinsic attitude towards smart metering. Each residential electricity consumer agent has been assigned a parameter

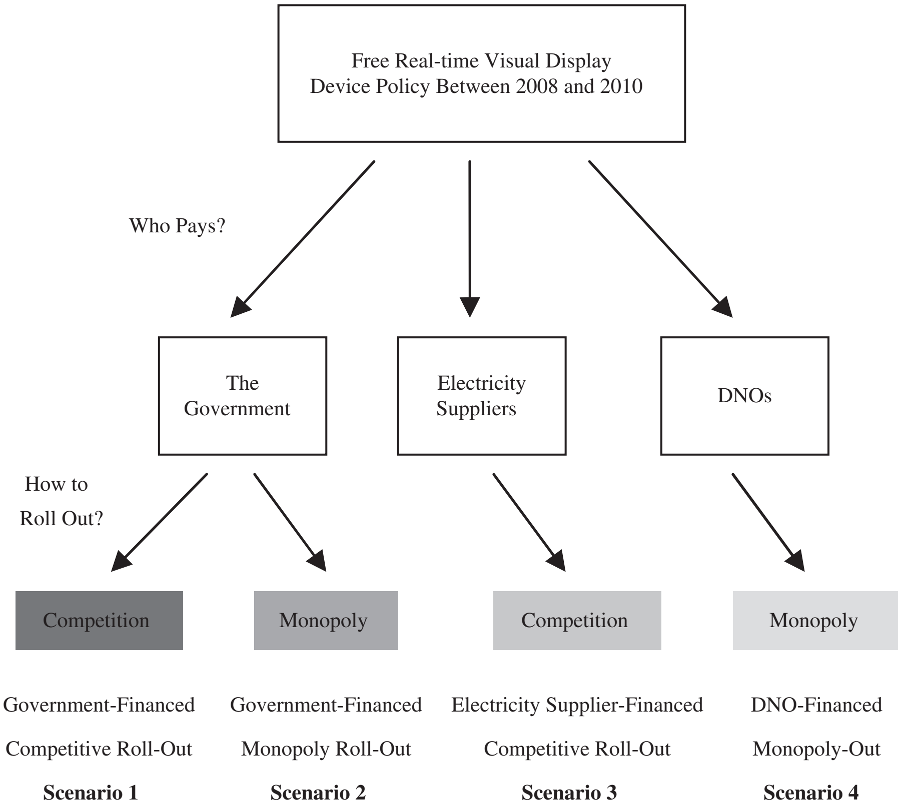

Figure 4. Scenarios of Smart Metering Policy Options in the Simulation

ETH_i varying uniformly between 0 and 1. The greater the value of a residential electricity consumer agent's "enthusiasm," the more interested the agent is in smart metering. In order to assess the effectiveness of different policy options, the four scenarios are under the same initial setting shown in Table 3. A summary of the personality parameters of residential electricity consumer agent i and external stimuli triggering its intention to choose option α is given in Table 4.

Scenario 1 (Government-financed competitive roll-out) simulates the strategy that the government wholly subsidizes RTVDs and electricity suppliers are primarily responsible for administering the roll-out of these devices. The simulation in this scenario is based on the following principles: (i) the electricity supplier agents are competing to gain market share; (ii) as they do not have to bear the cost of RTVDs, they disseminate the information of the free RTVD policy throughout the whole virtual environment; (iii) meter competition enables electricity supplier agents to deliver RTVDs of different types/functions to residential electricity consumer agents, and thus residential electricity consumer agents have many options of RTVD.

Scenario 2 (Government-financed monopoly roll-out) simulates the strategy that the government subsidizes RTVDs, and DNOs are responsible for administering the roll-out of these devices. The simulation in Scenario 2 is based on the following principles: (i) the electricity supplier agents are competing to gain market share; (ii) as they do not have to bear the cost

Group	Dec-02	Jun-03	Dec-03	Jun-04	Dec-04	Jun-05	Mar-06	Mar-07	ES Agent
BGT	22%	23%	24%	24%	23%	22%	22%	22%	A
Powergen	22%	22%	21%	21%	21%	21%	20%	19%	B
SSE	13%	14%	14%	15%	15%	16%	16%	18%	C
npower	16%	16%	15%	15%	15%	15%	15%	16%	D
EDF Energy	15%	15%	14%	14%	13%	13%	13%	14%	E
ScottishPower	10%	10%	11%	12%	13%	13%	13%	12%	F

Figure 5. ES Agents in the Model of Market Game
Source: National market share in electricity (Ofgem, 2007).

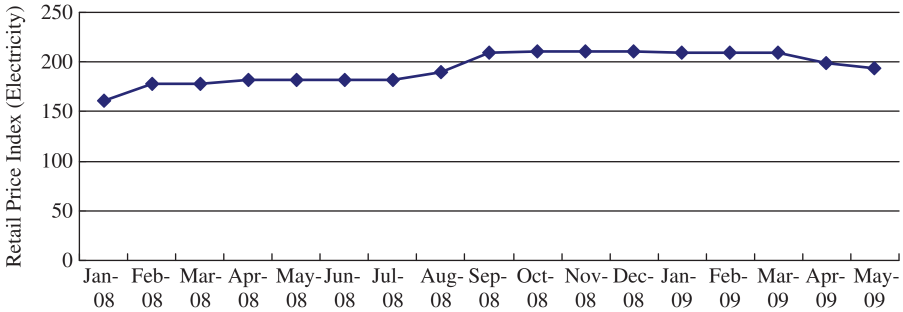

Figure 6. Electricity Retail Price Index (RPI) in the United Kingdom (January 2008–May 2009)
Source: Office for National Statistics.

of RTVDs, they disseminate the information of free RTVD policy throughout the whole virtual environment; (iii) there is a DNO of monopolistic power in the virtual environment; (iv) electricity supplier agents instruct the DNO to deploy RTVDs to residential electricity consumer agents upon the requests from residential electricity consumer agents; (v) the DNO only delivers one selected type of RTVD to residential electricity consumer agents, thus residential electricity consumer agents only have one option for a RTVD.

Scenario 3 (Electricity supplier-financed competitive roll-out) simulates the strategy that electricity suppliers pay for RTVDs and they are also responsible for deploying these devices. The simulation in Scenario 3 is based on the following principles: (i) the electricity supplier agents are competing to gain market share; (ii) as they have to absorb the cost of RTVDs, they are not keen to disseminate the information of the free RTVD policy to residential electricity consumer agents; (iii) meter competition enables electricity supplier agents to deliver RTVDs of different types/functions to residential electricity consumer agents, and thus residential electricity consumer agents have many options of RTVD.

This organizational behavior has already been witnessed in the U.K. wireless telecommunication market. In the wireless telecommunication market mobile phone customers can retain their existing mobile numbers when switching between network operators, the so-called Mobile Number Portability (MNP) policy. Although this policy was introduced to the wireless telecommunication market by the Office of Communications (Ofcom) in 1999, to date only a small number of customers know about it because network operators are not keen to publicize the policy. The

Table 3. The Initial Parameter Settings in the Four Scenarios of Simulation

Parameter	Value/Distribution	Remarks
Number of electricity supplier agents	6	There are six electricity supplier agents in the virtual market.
Population density	0.40	40% of the cells in the virtual community are populated, i.e., there are 25000 ($62500^{*}0.4 = 25000$) residential electricity consumer agents in the virtual community.
Market-share-A	0.22	Initially electricity supplier agent A has 22% market share.
Market-share-B	0.19	Initially electricity supplier agent B has 19% market share.
Market-share-C	0.17	Initially electricity supplier agent C has 17% market share.
Market-share-D	0.16	Initially electricity supplier agent D has 16% market share.
Market-share-E	0.14	Initially electricity supplier agent E has 14% market share.
Market-share-F	0.12	Initially electricity supplier agent F has 12% market share.
Random interaction	Uniformly distributed between 0 and 10	The number of each residential electricity consumer's random interactions.
Radius	Uniformly distributed between 0 and 10	Each residential electricity consumer agent regularly interacts with a random number of other residential electricity consumer agents within a 10-unit radius.
d	Varying between 1 and 1.3	Every three months, electricity supplier agents adjusted their electricity prices based on the electricity retail price index in the real U.K. electricity market between January 2008 and May 2009.

Table 4. The Scales and Distributions of Parameters in the Simulation

Parameter			Scale	Distribution	Remarks
Agent *i*'s personality parameters		W_{iP}	− 1 to 0	Random uniform distribution	Residential electricity consumer agent *i*'s personality trait "price sensitivity"
		W_{ij}	0 to 1	Random uniform distribution	Residential electricity consumer agent *i*'s motivation to comply with residential electricity consumer agent *j*
		PC_{ik}	0 to 1	Random uniform distribution	Residential electricity consumer agent *i*'s related perceived power of a control factor
		ETH_i	0 to 1	Random uniform distribution	Residential electricity consumer agent *i*'s interest (the "enthusiasm") in having a smart meter
External stimuli	Interactions between residential electricity consumer agent *i* and electricity consumer agents	P_E^{α}	80 to 100	Determined by the computer based on market share	Electricity price information that residential electricity agent *i* receives from a particular electricity supplier agent
	Interactions between residential electricity consumer agent *i* and other residential electricity consumer agents	Inf_{ji}^{α}	− 100 to 100	Random uniform distribution	Influence (both positive and negative) from residential electricity consumer agent *j* to residential electricity consumer agent *i* about choosing option α
	Environmental factors and random events	C_{ki}^{α}	0 to 100	Random uniform distribution	The influential power of a control belief about option α

reason for their unwillingness to publicize the MNP policy is that if a customer switches from one network to another network and keeps his/her existing mobile number, the recipient network operator will have to pay a charge to the donating network operator for the routing of a parted call. This is the so-called Donor Conveyance Charge (DCC) in the wireless telecommunication market. We posit that those consumers most interested in, and enthusiastic about, mobile telephones will be those most likely to know of the MNP policy. For further information, see Ofcom (2001).

Scenario 4 (DNO-financed monopoly roll-out) simulates the strategy that DNOs pay for RTVDs and are also responsible for deploying these devices. The simulation in Scenario 4 is based on the following principles: (i) the electricity supplier agents are competing to gain market share; (ii) as they do not have to absorb the cost of RTVDs, they disseminate the information of the free RTVD policy throughout the whole virtual environment; (iii) there is a DNO of monopolistic power in the virtual environment; (iv) electricity supplier agents instruct the DNO to deploy RTVDs to residential electricity consumer agents upon the requests from residential electricity consumer agents; (v) in order to minimize the cost of deployment, the DNO only delivers RTVDs of minimum specifications (the cheapest type of RTVD) to residential electricity consumer agents, thus residential electricity consumer agents only have one low specification option for RTVDs.

Simulation Results

The model was programmed with NetLogo 4.0.4. (The NetLogo version of the model is available at: http://www.openabm.org/model-archive/zhang_nuttall_jpim.) As the United Kingdom's free RTVD policy lasts for two years, in the simulation we focus on the first 24 months. We focus on the three aforementioned indicators. Through the four simulation scenarios we observe three interesting emergent phenomena, which may give us phenomenological information for assessing the effectiveness of BERR's new policies on promoting smart metering in the real U.K. electricity market.

Indicator 1: Dynamics/Patterns of Real-Time Visual Display Diffusion

First, an "S-curve" pattern of technology adoption (Rogers, 1962) has been reproduced in our model of market game. We have run the model many times and plot the data in Figure 7. It shows that the trends of

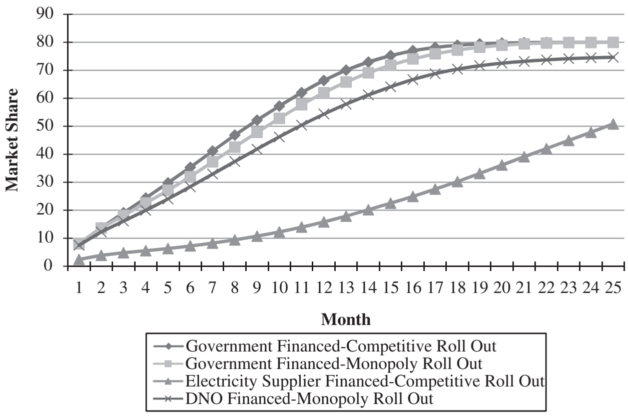

Figure 7. The Trends of Real-Time Visual Display Diffusion Source: Enel, Italy.

RTVD adoption in the four scenarios all have a common pattern of "S-curve," which complies with our empirical observation from the Telegestore Project of promoting smart meters carried out by Enel in Italy, where a single type of smart meters was deployed by a monopoly electricity supplier (ENEL) without government subsidy (like the DNO-financed monopoly roll-out scenario in our simulation experiments; see Figure 8). Figure 7 can also help us evaluate the effectiveness of the four strategies. From Figure 7 we can see that the adoption of RTVDs happens most quickly in Scenario 1 (government-financed competitive roll-out), followed by the adoptions in Scenario 2 (government-financed monopoly roll-out), Scenario 4 (DNO-financed monopoly roll-out) and Scenario 3 (electricity supplier-financed competitive roll-out). Thus policy implications from this are: (i) under the free-to-consumer RTVD policy, the government subsidizing the roll-out of RTVDs is a more effective approach than that electricity suppliers and DNOs bear the cost of these devices; (ii) if the government subsidizes the rollout of RTVDs, imposing an obligation on electricity suppliers so as to force them to roll out these devices through competition is a

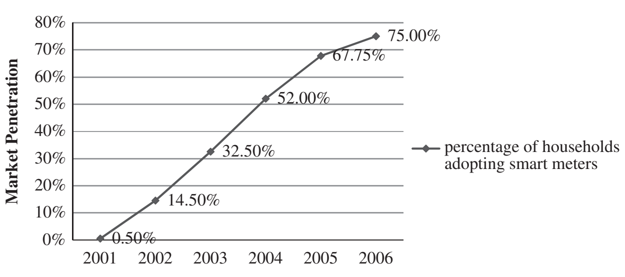

Figure 8. The Pattern of Smart Metering Technology Adoption in the Telegestore Project

more effective way than rolling out smart meters in the context of monopoly through rebundling metering services to DNOs; (iii) if the government is unable to subsidize the roll-out of RTVDs and the cost of these devices has to be borne by electricity suppliers or DNOs, rolling out these devices in the context of monopoly through rebundling metering services to DNOs is a more effective way than rolling out these devices in the context of competition through imposing an obligation on electricity suppliers.

Indicator 2: Evolution of Electricity Supplier Agents' Market Shares

Second, a stable state of market shares appears as an emergent phenomenon in the simulation. In the model, although one electricity supplier agent initially can take a large market share based on its market power, other competitors will soon fight back, and finally a relatively stable state of market shares will appear after a certain period of simulation (Figures 9–12). This stable state of electricity supplier agents' market shares in the virtual liberalized market is in line with our empirical observation from the real U.K. domestic retail electricity market (Figure 13).

Indicator 3: Residential Electricity Consumer Agents' Switching between Electricity Supplier Agents

Third, our simulation shows a dynamically unstable state of consumer switching after the introduction of RTVDs. In the early stage a large number of residential electricity consumer agents switch electricity supplier agent seeking a preferred RTVD; later, although a stable state of market shares appears, as a result of competition every month there are still a considerable number of residential electricity consumer agents switching electricity supplier agents, as shown in Figure 14. This emergent phenomenon complies with our empirical observations of consumer switching from the real U.K. domestic retail electricity market (see Figure 15).

Discussion

The Current State of U.K. Smart Metering

The model provides phenomenological insights that can help predict trends in the diffusion of smart metering in the U.K. in response to government smart metering

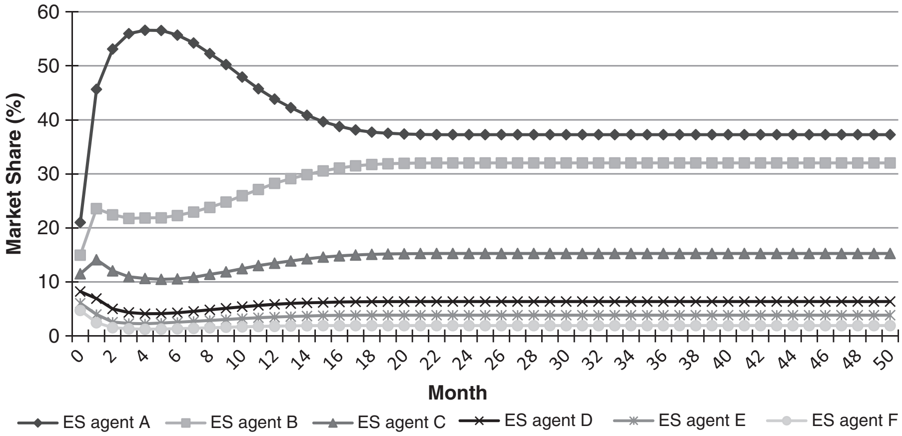

Figure 9. Evolution of Electricity Supplier Agent's Market Shares in Scenario 1 (Government-Financed Competitive Roll-Out)

policies. What we observed from the real U.K. electricity market is that the U.K. government is pursuing an approach that has the least effectiveness: electricity supplier-financed competitive roll-out. BERR announced the free RTVD policy in May 2007, but did not use any incentive to subsidize the roll-out of the devices. Consequently electricity suppliers have to undertake the costs of rolling out RTVDs if consumers request the devices. In order to minimize the cost, electricity suppliers have tended to avoid using any mass media to disseminate the free RTVD policy. (We note a recent [October 2009] exception to this from British Gas [Centrica], with its Energy Smart Monitor publicity campaign.) This has resulted in a state that only a very small number of consumers who really care about smart metering (the enthusiastic residential electricity consumer agents in our model) know the policy. Although we do not have the statistical data with regard to how many RTVDs have been deployed by electricity suppliers in the United Kingdom, from our observation we estimate that the number is quite small. This empirical observation is in line with the simulation results from the model. In this sense, the model somewhat demonstrates the predictive power of agent-based models in dealing with complex social systems, though making predictions about complex systems in a very critical issue.

General Applicability of the Model

The model we presented in this paper is potentially a useful tool for analyzing policies and strategies for promoting technology diffusion, and managing technology diffusion processes in the electricity market or similar network industries (e.g., gas, water, and telecommunication) in which governments have kept strong regulations. On the consumer side, consumers' decision of technology adoption has been based on a well-established social psychological theory (the TPB), which catches the effects of psychological, sociological, and environmental factors in the decision-making process. By changing the consumer agent personality parameter setting—for example,

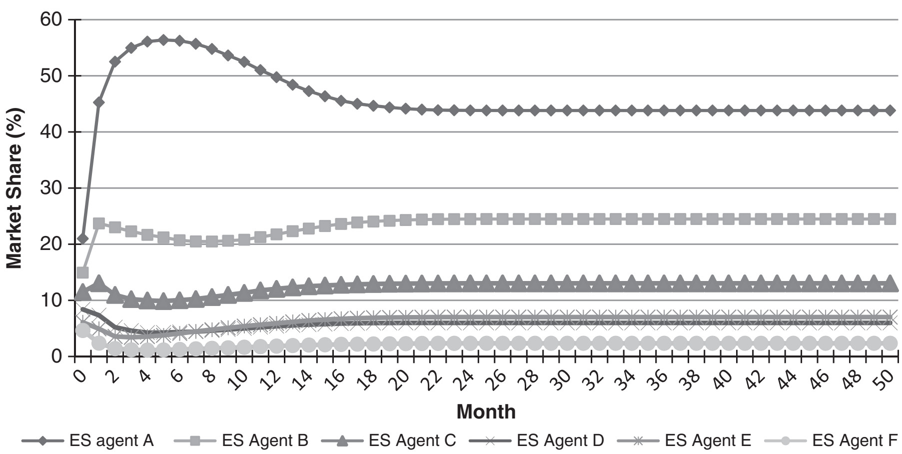

Figure 10. Evolution of Electricity Supplier Agents' Market Shares in Scenario 2 (Government-Financed Monopoly Roll-Out)

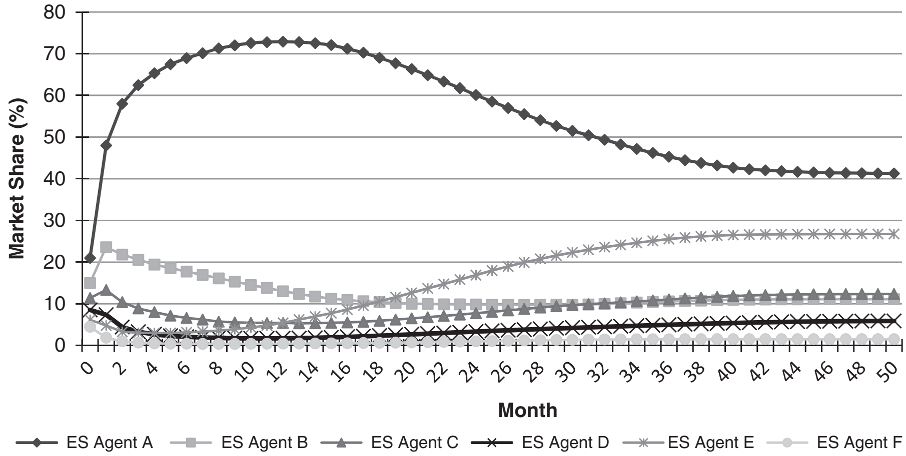

Figure 11. Evolution of Electricity Supplier Agents' Market Shares in Scenario 3 (Electricity Supplier-Financed Competitive Roll-Out)

the values and distributions of W_{iP}, W_{ij}, PC_{ik}, ETH_i—we can study the adoption of a technology in consumer groups of different attributes. By changing the values and distributions of "random interaction" and "radius," we can study how different social network structures influence the processes of technology diffusion. On the firm side, as their economic behaviors (competition, cooperation, and R&D) are influenced by government policies/regulations, by changing the values/distributions of current parameters in the model (i.e., P_E^{α} and d) or adding new parameters into the model we can study how different government policies/regulations affect the dynamics of innovation diffusion.

Limitations of the Model

As the theoretical base of our agent-based model, the Theory of Planned Behavior, is a complex social psychological model which has three blocks of components, it is important to acknowledge the limitations of our model. First, when applying the TPB model, we faced an issue of choosing residential electricity consumers' personality parameters. The TPB model suggests that a broad range of "beliefs" jointly determine a person's intention to perform a behavior. But in the model, we can only purposefully choose those highly related to the behavior of adopting an RTVD. To a certain degree, this decreases the fidelity of a residential electricity consumer agent. Other studies of using agent-based simulation to model innovation diffusion avoid this limitation by basing their consumer agent decision rules on other theories such as "contagion" (e.g., Valente, 1995), preference (e.g., Garcia, 2005), or utility/profit maximization (e.g., Guardiola et al., 2002).

A second limitation is the distributions of model parameters. In the process of constructing residential

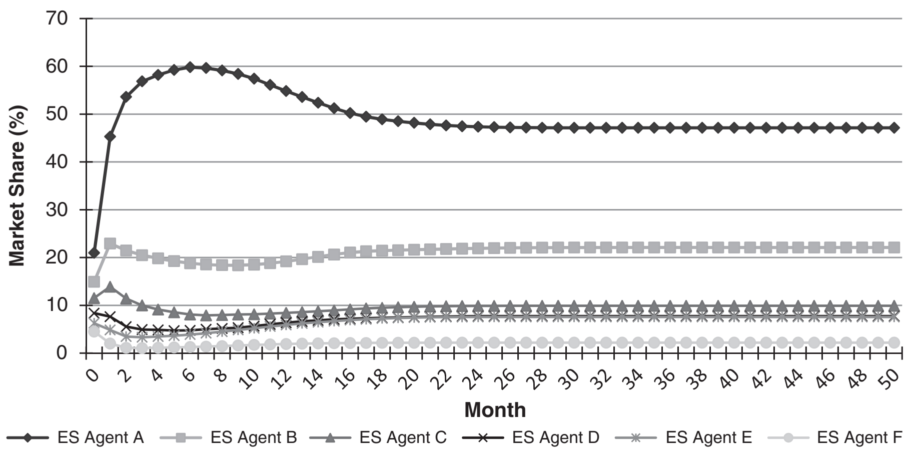

Figure 12. Evolution of Electricity Supplier Agents' Market Shares in Scenario 4 (DNO-Financed Monopoly Roll-Out)
Source: Ofgem, 2007.

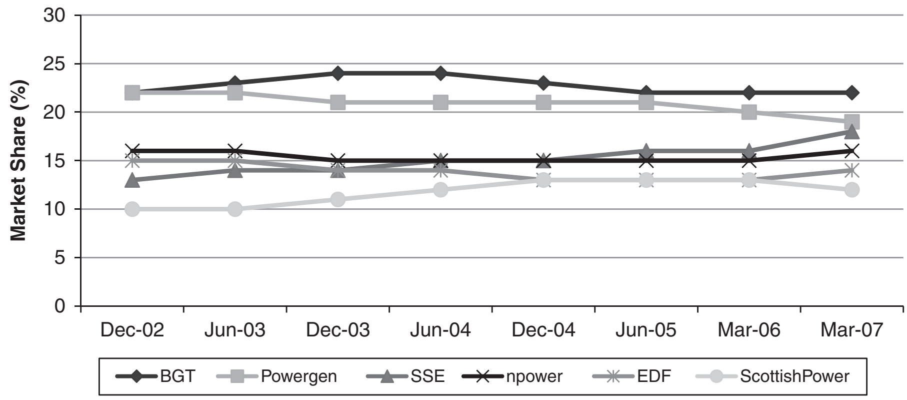

Figure 13. The Stable State of Competitors' Market Shares in the U.K. Electricity Market

electricity consumer agents, we face an issue of how to determine the values and distributions of a residential electricity consumer agent's personality parameters. In order to create heterogeneity of the residential electricity consumer agents, we assume the personality parameters are uniformly distributed and let computers determine all the values of a residential electricity consumer agent's personality parameters based on a random uniform distribution rule, as shown in Table 4. For instance, the personality parameter ETH_i determines a residential electricity consumer agent's level of interest in smart metering. Based on this assumption, in the model the numbers of residential electricity consumer agents at different levels of interest in having an RTVD are the same. This assumption has not yet been justified by any study.

A third limitation falls to the weights of the three blocks of components in the TPB model. In order to simplify the model and facilitate the simulation, we assume the three blocks of components in the TPB model—namely attitude, subjective norm, and perceived behavioral control—contribute to behavioral intention equally. However, in reality some adopters might be very interested in an innovative technology (high attitude) but have low social involvement in promoting the diffusion of the technology (low subjective norm), or they might be interested more in promoting the diffusion of the innovative technology (high subjective norm)

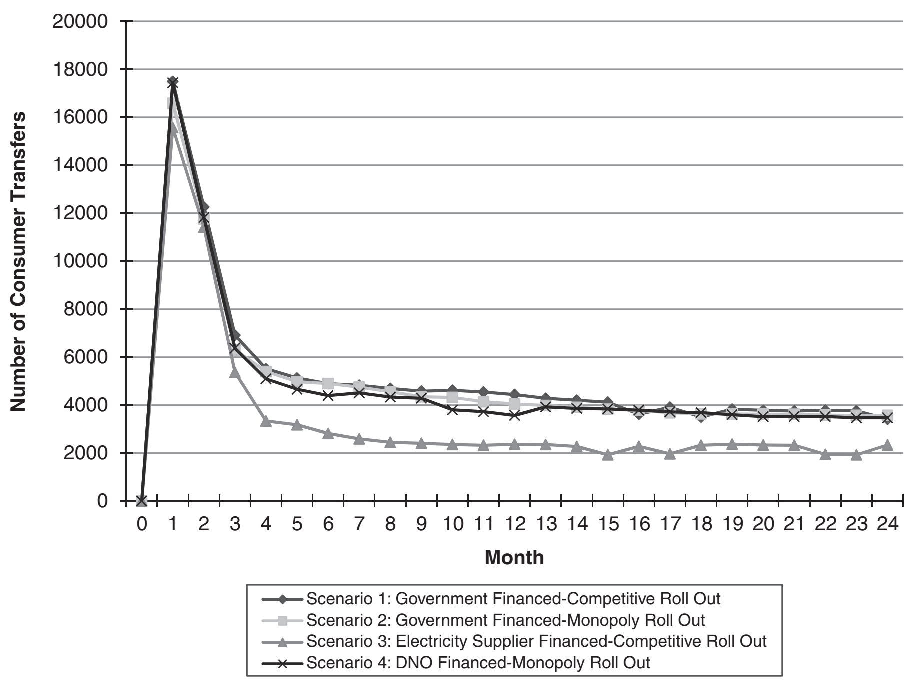

Figure 14. Monthly Residential Electricity Consumer Agent Transfer Flows
Source: Ofgem, 2007.

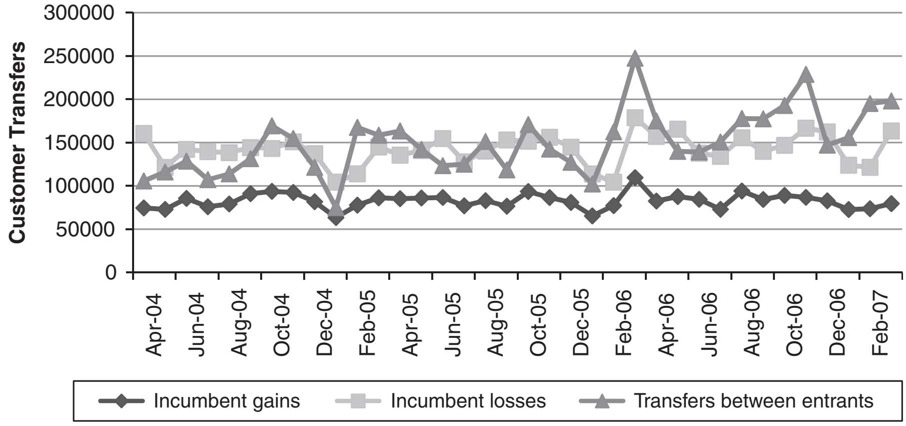

Figure 15. Monthly Transfer Flows in the Real U.K. Electricity Market

than in the technology itself (low attitude). In these special cases, the contributions of the three components to the behavioral intention should be weighted differently. The current model does not capture this point.

Conclusions

The issue of what policies and strategies the government should make in terms of promoting smart metering in the United Kingdom is still an open research question, and thus a better understanding of the evolutionary process in technology diffusion has important implications for policymaking. An agent-based model of a market game is described in this paper. The model helps us understand the dynamics of smart metering technology diffusion under different policy options, and also provides us with some initial insights for evaluating the government's current smart metering policy and managing the diffusion of smart metering technology in the U.K. electricity market.

As an extension to our previous research (Zhang and Nuttall, 2007), the contribution of the model can be discussed methodologically and practically. On the methodological side, the model supports an argument for a direct integration of social psychological theories and agent-based computational simulation. Because the behavior of residential electricity consumer agents in the model is based on a well-established social psychological theory and the whole model is developed based on empirical observations (e.g., price competition in the U.K. electricity market), the simulation results from our model resemble real phenomena (e.g., the "S-curve" pattern of technology adoption, stable market shares of major competitors, and the dynamically unstable state of consumer switching), as widely observed. This also signifies the validity of the model. Moreover, empirical evidence from the current U.K. electricity market also somewhat shows the predictive power of agent-based simulation in dealing with complex social systems.

On the practical side, the model provides a framework for both studying the impact of government policies on the dynamics of innovation diffusion and managing innovation diffusion processes under different public policies. Several empirical studies (e.g., Baker, 2001; Cutler and McClellan, 1996; Gray and Shadbegian, 1998; Mowery and Rosenberg, 1982) find that policies and regulations generally can have powerful effects on innovation diffusion, often via the ability of a government or regulatory agency to "sponsor" innovation diffusion with network effects (Hall and Khan, 2003). However, these empirical studies are unable to reveal how government policies and regulations affect the dynamics of innovation diffusion at microscopic level. Our agent-based model presented in this paper bridges this gap by modeling at microscopic level how electricity companies' economic behavior in response to the government's smart metering policies and the interaction between electricity companies and residential electricity consumers lead to the dynamics of smart metering diffusion. Understanding this is an effective means for making useful smart metering policies and managing the processes of smart metering diffusion under different policy scenarios in the electricity market.

References

Ajzen, I. 1985. From intentions to actions: A theory of planned behavior. In: *Action control: From cognition to behavior*, ed. J. Kuhl, and J. Beckmann, 11–39. Heidelberg: Springer.

Ajzen, I. 1991. The theory of planned behaviour. *Organizational Behaviour and Human Decision Processes* 50: 179–211.

Ajzen, I., and M. Fishbein. 2005. The influence of attitudes on behavior. In *The handbook of attitudes*, ed. D. Albarraci, B. T. Johnson, and M. P. Zanna, 173–221. Mahwah, NJ: Erlbaum.

Amendola, M., and J.-L. Gaffard. 1988. *The innovative choice: An economic analysis of the dynamics of technology*. Oxford: Blackwell.

Asher, A. 2007. Utility metering: A smarter approach. *Utility Business* (December).

Baker, L. C. 2001. Managed care and technology adoption in health care: Evidence from magnetic resonance image. *Journal of Health Economics* 20 (3): 395–421.

Bandura, A. 1986. *Social foundations of thought and action: A social cognitive theory*. Englewood Cliffs, NJ: Prentice-Hall.

Barabasi, A.-L., and R. Albert. 1999. Emergence of scaling in random networks. *Science* 286 (5439): 509–12.

Bass, F. M. 1969. A new product growth for model consumer durables. *Management Science* 15 (5): 215–27.

Compeau, D. R., C. A. Higgins, and S. Huff. 1999. Social cognitive theory and individual reactions to computing technology: A longitudinal study. *MIS Quarterly* 23 (2): 145–58.

Cutler, D. M., and M. B. McClellan. 1996. *The determinants of technological change in heart attack treatment*. Working Paper 5751. Cambridge, MA: National Bureau of Economic Research.

Davies, S. 1979. *The diffusion of process innovations*. Cambridge: Cambridge University Press.

Davis, F. D. 1989. Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly* 13 (3): 319–40.

De Bruyn, A., and G. L. Lilien. 2008. A multi-stage model of word-of-mouth influence through viral marketing. *International Journal of Research in Marketing* 25: 151–63.

DGCG Technical Steering Group. 2003. Metering for micro-generation. P02a Work Stream 4. London: Distributed Generation Coordinating Group.

Dixit, A. K., and R. S. Pindyck. 1994. *Investment under uncertainty*. Princeton, NJ: Princeton University Press.

Dodds, P. S., R. Muhamad, and D. J. Watts. 2003. An experimental study of search in global social networks. *Science* 301 (5634): 827–29.

Garcia, R. 2005. Uses of agent-based modelling in innovation/new product development research. *Journal of Product Innovation Management* 22 (5): 380–98.

Gray, W. B., and R. J. Shadbegian. 1998. Environmental regulation, investment timing, and technology choice. *Journal of Industrial Economics* 46 (2): 235–56.

Guardiola, X., A. Diza-Guilera, C. J. Perez, A. Arenas, and M. Llas. 2002. Modeling diffusion of innovations in a social network. *Physical Review E* 66:026121. http://arXiv.org/arXiv:cond-mat/0204141v1.

Hall, B. H., and B. Khan. 2003. Adoption of new technology. Working paper, University of California, Berkeley.

Hegselmann, R., and A. Flache. 1998. Understanding complex social dynamics: A plea for cellular automata based modelling. *Journal of Artificial Societies and Social Simulation* 1 (3). http://www.soc.surrey.ac.uk/JASSS/1/3/1.html.

Hohnisch, M., S. Pittnauer, and D. Stauffer. 2008. A percolation-based model explaining delayed takeoff in new-product diffusion. *Industrial and Corporate Change* 17 (5): 1001–17.

Janssen, M. A., and W. Jager. 1999. An integrated approach to simulating behavioural processes: A case study of the lock-in of consumption patterns. *Journal of Artificial Societies and Social Simulation* 2 (2). http://www.soc.surrey.ac.uk/JASSS/2/2/2.html.

Janssen, M. A., and W. Jager. 2002. Simulating diffusion of green products: Co-evolution between firms and consumers. *Journal of Evolutionary Economics* 12 (3): 283–306.

Janssen, M. A., and W. Jager. 2003. Simulating market dynamics: Interactions between consumer psychology and social networks. *Artificial Life* 9 (4): 343–56.

Mathieson, K. 1991. Predicting user intentions: Comparing the technology acceptance model with the theory of planned behaviour. *Information Systems Research* 2 (3): 173–91.

Milgram, S. 1967. The small world problem. *Psychology Today* 1 (1): 60–7.

Mowery, D. C., and N. Rosenberg. 1982. Government policy and innovation in the commercial aircraft industry, 1925–75. In *Government and technical progress: A cross-industry analysis*, ed. R. R. Nelson, 163–77. New York: Pergamon Press.

Ofcom. 2001. *Mobile number portability determination requests explanatory document*. http://www.ofcom.org.uk/static/archive/Oftel/ind_info/numbering/mnpdetre.pdf.

Ofgem. 2001. *Smart metering working group report*. London: Ofgem.

Ofgem. 2006a. *What is a smart meter?* London: Ofgem.

Ofgem. 2006b. *Domestic metering innovation*. Consultation Document 20/06. London: Ofgem.

Ofgem. 2007. *Domestic retail market report*. London: Ofgem.

Perugini, M., and R. P. Bagozzi. 2001. The role of desires and anticipated emotions in goal-directed behaviour: Broadening and deepening the theory of planned behaviour. *British Journal of Social Psychology* 40 (1): 79–98.

Rogers, E. M. 1962. *Diffusion of innovation*. New York: Free Press.

Sauter, R., J. Watson, and L. Hughes. 2005. *Metering, communication and control technologies for micro-generation*. ESRC Sustainable Technologies Programme Working Paper Series 2005/1. Brighton, UK: University of Sussex.

Scott, J. P. 2000. *Social network analysis: A handbook*. London: Sage.

Stoneman, P. 2001. *Financial factors and inter firm diffusion of new technology: A real options model*. EIFC Working Paper No. 2001–08. Coventry, UK: University of Warwick.

Strang, D., and S. A. Soule. 1998. Diffusion in organizations and social movements: From hybrid corn to poison pills. *Annual Review of Sociology* 24: 265–90.

Valente, T. W. 1995. *Network of models of diffusion of innovation*. Cresskill, NJ: Hampton Press.

Vallerand, R. J. 1997. Toward a hierarchical model of intrinsic and extrinsic motivation. In *Advances in experimental social psychology*, ed. M. P. Zanna, 271–360. New York: Academic Press.

Vasey, G. M. 2007. SMART metering—Requires SMART technology. *Issue Alert* (European Edition). http://www.microgen.co.uk/microgen/uploads/UtilliPoint%20SMART%20Metering.pdf.

Veneris, Y. 1990. Modeling the transition from the industrial to the informational revolution. *Environment and Planning A* 22 (3): 399–416.

Watts, D. J., and P. S. Dodds. 2007. Influentials, networks, and public opinion formation. *Journal of Consumer Research* 34: 441–58.

Watts, D. J., and S. H. Strogatz. 1998. Collective dynamics of ''small-world'' networks. *Nature* 393: 440–2.

Zhang, T., and W. J. Nuttall. 2007. *An agent-based simulation of smart metering technology adoption*. EPRG Working Paper 0727. Cambridge: University of Cambridge.

Zhang, T., and D. Zhang. 2007. Agent-based simulation of consumer purchase decision-making and the decoy effect. *Journal of Business Research* 60 (8): 912–22.