Dissertation

The Effect of Information on Household Water and Energy Use

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Abstract

The Effect of Information on Household Water and Energy Use

Water and Energy Utilities are faced with growing demand at a time when supply expansion is increasingly costly, inconsistent and taxing on the environment. Given that supply expansion is limited, to meet future needs utilities need demand-side management policies to result in more reliable and consistent consumer responsiveness. Currently, most households do not have access to the level or type of information needed to respond to price signals in a reliable and effective way. Advanced information technology solutions exist and are being increasingly adopted, but we need to know more about how the informational setting affects decision-making, consumption levels and price responsiveness. This research analyzes the effect of information on household water and energy consumption, which is a decision-making environment characterized by uncertainty and imperfect information. This study also analyzes additional complexities stemming from infrequent billing, non-linear pricing structures, and combined utility bills, each of which may dampen price signals.

I first develop a theoretical model of decision-making under uncertainty. I use this model to illustrate the effect of more frequent information, which eliminates uncertainty about past decisions, on remaining decisions within the billing period. The model emphasizes the role of risk preferences and the realization of the uncertain quantity. On average, risk averse consumers will increase consumption when uncertainty is reduced; risk seeking consumers will do the opposite. Introduction of a non-linear rate structure induces behavior that makes individuals appear as if they are risk averse or risk seeking, despite their actual risk

preferences. This model highlights the importance of modeling multiple decisions within a billing period and accounting for a spectrum of risk preferences.

In Chapter 3, I create a computerized laboratory experiment designed to generate data used to test some of the hypotheses formulated in the theoretical model presented in Chapter 2. Results from the experiment show that, on average, individuals consume more when provided with more frequent information that resolves uncertainty about past decisions made within a single billing period. This result is driven by the fact that the majority of participants are risk averse or risk neutral. Risk seeking participants instead reduce use when facing less uncertainty. Also as predicted by the theoretical model in Chapter 2, combining behavior driven by risk preferences with the presence of an increasing block rate structure results in behavior that looks like consumers are targeting the block boundary. This experiment shows that providing more information may not lead to reduced use without other incentives, goal-setting, or mechanisms designed to help individuals process the information.

In Chapter 4, I empirically analyze a ten-year household-level panel data set of monthly utility bills. A single utility provides electricity, natural gas and water services to its customers and therefore bills through a single utility bill. I first show that price responsiveness varies by the number and combination of services subscribed to by a given household. Second, through a price salience model I show that households are more responsive to the price of water when the water portion of the total bill is greater. When multiple services are contained on a single bill, the salience of any individual price signal is dampened. This study confirms that households are inelastic though not unresponsive to water prices. In order to make pricing policies more effective, utilities need to acknowledge that households may be responding to total utility costs (i.e., may respond to a high utility bill by reducing electricity use despite the true driver of the high bill) and will need to find ways to make quantity and price information more salient to their customers.

Chapter 5 concludes this dissertation by summarizing the contributions of the research and possible extensions for future work. By improving the informational environment surrounding household water and energy use, there will be great capacity for households to use water and energy more efficiently and ultimately make choices that reduce residential water/energy consumption and yield benefits for customers, utilities, and the environment.

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I thank my parents for being two living examples of the power of education, both as earners of advanced degrees and as educators. Their encouragement cultivated my curiosity, independence, and determination. I dedicate this dissertation to them in acknowledgement of their selfless actions that ushered me along this path and made me the person I am today. I also thank my brother for his quiet, unwavering support.

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While this dissertation embodies a seemingly epic journey, I hope it will simply stand amidst the first milestones of a life spent contributing to economics, education, and the natural environment.

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CHAPTER 1

Introduction

Utilities are faced with growing demand at a time when supply expansion is increasingly costly, inconsistent, and taxing on the environment. In order to better manage this growing gap, utilities need demand-side management programs to result in more reliable and consistent consumer responsiveness. Currently, a major barrier to predictable demand response is that most households do not have access to the type or frequency of information needed to conserve or shift from peak to off-peak periods. It is difficult to get consumers to respond to incentives if they do not receive clear signals about their use or about the prices they face. Advanced information solutions exist, but to make the best use of these technologies we need a better understanding of how people respond to receiving more information.

Most households do not know how much water or energy they consume (Jordan, 2011). Two national surveys by Attari et al. (2010) and Attari (2014) reveal that households underestimate energy and water use of various common household activities by a factor of 2.8 and 2, respectively. These surveys also show that most consumers do not know the most effective way to reduce consumption; most participants state that reducing use of existing technologies (e.g., turning off lights or taking shorter showers) is more effective than efficiency improvements (e.g., installing better insulation or a low-flow toilet). The decision-making setting contributes to this lack of understanding: households make multiple consumption choices before ever seeing a bill. When the monthly bill arrives, it is nearly impossible to make precise use of the quantity or price information. Since most households cannot track their use throughout the month and only receive dated price signals, they are not able to efficiently or cost-effectively reduce their consumption. Households need to be provided with regular and coherent information in order to understand the relationship between their actions, consumption and eventually their bill (List and Price, 2013).[1] While this is a common issue across both water and energy utilities, each are driven by different motivating factors and face different obstacles in realizing quantifiable demand responsiveness.

Energy utilities are mainly interested in reducing what is known as "peak" demand, which refers to both the smoothing out of demand over the course of day, and to avoiding the few hours of highest demand in a year (coincident peak demand), which occur on particularly cold or hot days. There are environmental benefits from reducing peak demand: utilities can reduce fuel consumption and greenhouse gas emissions by scaling back use of peaking power plants which are the 'dirtier,' more expensive power plants. Of the total energy consumed in the United States, the Environmental Protection Agency (EPA) estimates that approximately 39% is used to generate electricity (EPA, 2014). The U. S. Energy Information Administration (EIA) estimates that approximately 90% of residential greenhouse gas emissions are driven by natural gas and electricity consumption for heating, cooling, lighting, cooking and more (EIA, 2011). In addition to reducing combustion of fossil fuels and air pollution, lower energy demand will result in "reduced land and water use requirements for power plants and rights-of-way for power lines" (DOE, 2012b).

Reducing peak demand also results in greater economic efficiency as the marginal cost of generating energy during peak demand can be up to ten times higher than non-peak generation (Orcutt, 2010). Utilities can also avoid or at least defer the need for additional power plant capacity, transmission facilities and delivery infrastructure. For example, 20% participation in a demand response pricing program in Oklahoma is allowing the utility to

[1] List and Price (2013) argue that salience (and norms) matter most in managing the key problems utilities face. Making consumption and its cost salient via improved feedback and information results in increased price sensitivity and effectiveness of pecuniary-based policies.

offset its need for a new natural-gas peaking plant (DOE, 2012b). High demand during peak periods can contribute to outages, which disrupt economic activity for customers and the utility alike. Koomey and Brown (2002) identify three main reasons why peak times are likely to lead to outages: First, the very nature of energy generation is that it must be generated and delivered in tandem with when it is being demanded, i.e., it cannot effectively be stored. Second, generation capacity is fixed in the short term and takes many years and millions of dollars to build additional capacity. Finally – and most relevant to the research in this dissertation – there is a lack of responsiveness to real-time costs. This is due, in part, to the lack of metering technology to actually convey and charge customers real-time prices, but also because "even when metering technologies are capable of monitoring such price signals, sometimes the bills are delivered on a monthly basis, thus sidestepping the most powerful potential effect of real-time prices, the immediate behavioral feedback" (Koomey and Brown, 2002). Pricing and behavioral programs can be more cost-effective means of reducing peak demand and energy consumption overall. "We don't need more costly power plents to fix the psoblem. Better information and decision-making during times of peak demand could significantly reduce generation costs and the risk of power outages" (Orcutt, 2010).

The United States Federal Government has acknowledged the above issues and taken steps to encourage the energy industry. The Energy Independence and Security Act of 2007 outlines that the United States needs to modernize the electricity grid in order to better control our energy use; this goal includes advancement of 'smart grid' technology and providing consumers with better information and tools to understand and address their energy use.[2] This Act acknowledges that 'for the United States to realize its full demand response potential, customers must have access to, and a better understanding of, information about

[2]See the website www.smartgrid.gov to learn more.

real-time or near-real-time prices" (Congress, 2007). Given that households have very little information and limited tools to easily manage their use, the American Recovery and Reinvestment Act of 2009 created the Smart Grid Investment Grant (SGIG) programs, managed by the Department of Energy. A major objective of this part of the Recovery and Reinvestment Act of 2009 is to "empower customers with information so they can better manage their electricity consumption and costs" (DOE, 2012a).

As a result of SGIG initiatives, 65 million 'smart' meters will be installed by 2015, and over $4 billion will be spent on advanced metering infrastructure (AMI). AMI systems allow greater access to and use of real-time information; these systems create the potential for a two-way stream of communication between utilities and customers.[3] Utilities employ this technology to detect leaks, outages and inefficiencies, understand time-of-day consumption patterns, and improve demand forecasts, all of which can lead to a better understanding of consumer behavior and responsiveness to policies. A secondary use, which often lags these initial benefits of smart meters, is communication of data back to households. Households can access real time, or near-real time, streams of information on use, prices and total cost through an in-home display or a web portal. We still need to know "to what extent can AMI, coupled with time-based rate programs and enabling technologies such as in- home displays or programmable communicating thermostats, reduce peak and overall demand for electricity" (DOE, 2012a).

Water utilities, on the other hand, are motivated to encourage more efficient indoor water use and to reduce their version of 'peak' demand, which refers to the periods of greatest outdoor water use during summer months. By reducing peak outdoor watering

[3]See the 2009 survey "Smart Metering for Utilities", an Oracle White Paper for a thorough introduction for the use of smart meters in utilities (Oracle, 2009).

demand, it reduces or defers expansion of costly storage and treatment capacity. Summer use is typically two to four times greater than winter (indoor) use, therefore utilities need to have storage and treatment capacity for demands multiple times larger than average daily demand. With increasingly variable precipitation patterns, utilities are searching for ways to lower outdoor water demand; for example, cities like Los Angeles and Las Vegas are paying residents to replace water-intensive lawns with drought resistant landscaping (Lovett, 2013). The Intergovernmental Panel on Climate Change (IPCC) documented as a result of climate change, many regions of the United States and around the world are likely to experience increased variability in water supplies and increasingly severe spells of heat waves and/or drought conditions (IPCC, 2014). An EPA report highlights that between between 2007 and 2012 nearly every region in the United States has experienced water shortages, even in the absence of drought conditions (Ferraro and Price, 2013; Peace et al., 2013). Even where any population increases appear to be offset by efficiency improvements - supply variability will be enough to introduce vulnerability. “It is clear that climate change stands to increase national water demands and diminish national water supplies” (Averyt et al., 2013). What exacerbates this issue is that many of the areas that are already water stressed, like the Western and Southwestern regions of the U.S., are also the areas exhibiting the largest population migration and growth.

Climate change is affecting water utilities in other ways, too. In a report by the Center for Climate and Energy Solutions on the effect of climate change on water and wastewater utilities estimate a total cost of between “$448 billion and $944 billion for infrastructure and operations and maintenance to adapt to climate change impacts through 2050” (AMWA, 2009). This does not include cost of future regulatory controls; costs of complying with new regulation, especially in terms of water and wastewater treatment, is a major driver of rate increases. See Walton (2012) for an overview of the cost-related challenges (e.g. population growth, aging infrastructure, regulation, climate change, etc.) utilities will face in the near future or already face today.

A 2012 report by the American Water Works Association estimates that investment needs in major water infrastructure across the United States between 2011 and 2035 are over $1 trillion, with 75% of those costs stemming from needs in the Southern and Western regions, which are also those facing the greatest water supply challenges (AWWA, 2012). Of this $1 trillion, 54% is for replacement and the remainder to account for demand growth and population migration (AWWA, 2012). The AWWA report also concludes that regardless of the finance mechanism, these infrastructure costs *will* result in increased household water rates and bills. As it is, based on the sample from the AWWA Water and Wastewater Rate Surveys the average monthly cost of an average household level of consumption of water (1500 cubic feet) increased 68% between 2000 and 2010 (Rahill-Marier et al., 2013). With increasing costs and rates, the age of cheap water is coming to an end. As water supplies are become less reliable and other infrastructure costs are set to increase drastically, achieving predictable demand responsiveness is crucial. For both short and long-term revenue and cost planning, utilities will need to better understand how employing demand response programs will affect consumption and price responsiveness.

The value of quantifiable demand responsiveness is the avoided cost of supply; the effect of a demand response program, however, is currently hard to measure. Existing evidence as to the effect of demand response programs yield mixed results. These issues often stem from poor experimental design, little efforts to measure determinants of program participation or customer responses, or because the design or incentives of the program has been changed, making it hard to track impacts over time (Kassakian and Schmalensee, 2011).[4] Also, the initial SGIG reports warn that much of AMI-related technology is very new. Even where 'smart' meters have been installed, only a few studies on its effects on consumption and price responsiveness have been or are being completed. There is still a lot to learn about how changing information content, frequency of information and advanced technologies can be employed and how consumers interact with the technology; "more experience is needed with them by power companies, customers, and vendors before their appropriate roles in demand-side programs can be fully assessed" (DOE, 2012a). Despite the push on utilities to install AMI, it will still be a while before utilities take advantage of the opportunities to communicate data back to households and equip their customers with tools to more effectively understand and manage their use. This study furthers the understanding of how changing the informational environment may affect consumption patterns and price responsiveness.

1.1. Overview

This dissertation consists of three essays that each address issues related to information used by consumers in making decisions about water and energy use. The decision-making setting is characterized by uncertainty and imperfect information.[5]

In this setting I investigate three deviations from a well-functioning market:

(1) Uncertainty

[4] For example, when a utility allows customers to "opt-in" to a demand response program, this creates selection bias in the data. It will be hard to separate out the true effect of the program given that the people who opted to participate are likely different from those who did not actively seek to opt into the program.

[5] Other real-world applications like cell phone use, labor supply, credit card spending, health care choices, etc. can also fit into the class of issues discussed in this dissertation.

(2) Non-linear rate structures

(3) Combined bills

I investigate how timing of information can reduce uncertainty and affect consumption choices, how the effect of the timing of information changes under different price structures and how a combined bill for multiple services muffles the the price signal of any individual service.

In this setting a consumer makes multiple consumption decisions over a period prior to full realization of the cost by receiving a bill. While the benefits accrue immediately, the consumer only becomes aware of the cost after all consumption decisions have been made and they are presented an end-of-period bill. This facet contributes to the fact that consumers make consumption choices under uncertainty. The quantity is uncertain for at least three reasons: a) most households lack the means to track use throughout the billing period, b) water and energy are inputs to various household activities where the exact relationship is difficult to know (e.g., how many gallons of water does it take to keep a lawn green) and 3) quantity information and price signals are intermittent, unclear and confusing. Bills are difficult to understand, typically delivered only once a month, and water and energy are priced in obscure units like cubic feet and kWh. Over the course of a billing period, consumers face what I define as two separate types of quantity uncertainty: 'backward uncertainty,' since it is difficult or inconvenient to know total consumption up to any given point in the period, and 'forward uncertainty,' because the household is unlikely to know how much they will consume throughout the remainder of the period. As a result, when making decisions within a bill period, consumers are unaware of how much they have consumed to that point and how much they are likely to consume in total throughout the period.

Backward uncertainty can be mitigated by improving the timing of information through more frequent feedback than typically occurs in these settings.

The second complication in this class of decision-making settings is that consumers often face non-linear or penalty pricing plans where total consumption in a bill period beyond a threshold level results in a higher price or an additional fee. Due to quantity uncertainty, the consumer is unlikely to know where they are in reference to the threshold level at any point during the billing period. The main non-linear pricing structure focused on throughout this dissertation is the increasing block rate structure (IBR).[6] With an IBR, the per-unit price increases as consumption increases. The first block (amount or tier) of consumption is charged at one marginal price, all use beyond the first block boundary is charged at the second block marginal rate, and so on and so forth.

Finally, consumers may face charges for multiple goods or services on one bill. Even when the cost of the period of consumption decisions is realized, this price signal may be muddled by the costs of the other services. Consumers may be responding to total cost or to prices of other services. Even attentive customers find it unclear as to the most efficient or cost-effective way to affect their cost by altering behavior. This type of billing could render demand-management policies less effective. Overall, it may not be correct to model consumer price responsiveness in terms of the marginal price as in traditional economic theory if there is potential that the consumer is unclear or unaware of the relationship between quantity consumed and the marginal price.

Research investigating these decision-making environments is important because the information technology exists to 'unmuddle' prices signals and eliminate backward quantity uncertainty. As noted above, AMI technology is increasingly being implemented. This type

[6] These are alternatively referred to as tiered rate structures.

of technology changes the manner and frequency of the information stream available to consumers. However, there is still great uncertainty as to how this change in information delivery will impact consumption and responsiveness to changes in prices or other demand-management policies.

In Chapter 2, I develop an expected utility model of consumer behavior under quantity uncertainty. An individual makes a series of consumption choices within a billing period, each choice requiring an uncertain amount of inputs.[7] In a completely uncertain environment, the consumer never knows the input requirement of any individual choice and only learns total input use at the end of a billing period after all decisions have been made. I then show the effect on optimal choices of removing backward uncertainty by revealing previous input use up to the current decision within the period. The model is first presented in the context of a constant marginal price structure, then a two-tier increasing block rate structure. In the second case, quantity uncertainty causes marginal price uncertainty, which results in different behavior across different levels of quantity uncertainty than when the marginal price is known and constant. For example, an individual who is risk neutral but faces a positive probability of consuming in the second block (thus facing a higher marginal price) may appear to act risk averse. Overall, the theoretical model suggests that consumer behavior depends on 1) the level of uncertainty, which is dictated by the frequency of information provided within a period, 2) the content of the information (i.e., the value of the input requirement), 3) the individual's risk preferences, and 4) the rate structure.

Chapter 3 details an economic laboratory experiment designed to test the effect of removing backward uncertainty under linear and non-linear price structures, which is what

[7]For example, consider a household that sets the thermostat at a certain temperature. They will not know how many kWh of electricity this choice requires. With a smart meter in-home display, the household would better understand this relationship and be able track cost and energy use throughout a billing period.

is explored theoretically in Chapter 2. Like the theoretical model, the experimental setting is simplified to an individual making consumption choices under quantity uncertainty due to imperfect information. In the computerized laboratory experiment, participants make a series of decisions facing either complete uncertainty or only forward uncertainty if the individual receives feedback on her use resulting from previous decisions within the period. The feedback effect is tested under three rate structure treatments: a constant marginal price structure and two versions of a two-tier increasing block rate structure. Results show that providing quantity information that reduces uncertainty increases consumption levels, on average. This suggests that advanced metering technology, without goal-setting or other mechanisms in place, may not have the desired effect of inducing peak-demand shifting or conservation.

Chapter 4 contains an empirical analysis of how combined energy and water utility bills affect water consumption patterns and price responsiveness. As noted above, when multiple services are billed through a single monthly bill, the price signal of any single service is likely to be less salient to the consumer. Even when the cost of a billing period's consumption is realized, a given service's price signal may be muddled by the costs of the other services. This analysis is made possible by a novel data set that includes billing and consumption information for water, electricity and natural gas for a large number of households across nearly a decade. A single utility provides all three services and also bills for all three services through a single monthly bill. I create a model that tests the salience of the water price signal, given that water is billed along with electricity and natural gas within a single bill. I allow the responsiveness of price to vary by the weight of the water portion of the bill relative to the total utility bill. I find that household water demand is price-inelastic, but households pay relatively more attention to water prices when their water use contributes to a greater portion of their total utility spending. However, for this population, during the months when water expenditures are increasing and price responsiveness is increasing, total utility bills tend to decrease overall. As a result, these two observations provide additional evidence supporting the notion that household demand for water is generally price-inelastic, but not unresponsive, with respect to water prices.

Finally, Chapter 5 concludes with a discussion highlighting the contributions of this research and the implications for the changing informational setting surrounding water and energy use. Simply assuming that 'more information is better' may lead to more consumption as well as less happy and less attentive customers. Information needs to be easy to access and understand. Along with well designed information streams, consumers need the correct tools to take the next step once they understand their consumption and the price and non-price incentives in place.

CHAPTER 2

A Theory of Consumer Decision-making under Uncertainty

2.1. Introduction

In this chapter I develop a theoretical model of individual decision-making under uncertainty; the decision setting is designed to incorporate the key aspects of household water and energy consumption as described in the introductory chapter: The individual consumer makes multiple consumption decisions about a good over a period of time prior to full realization of the cost. While the benefits accrue immediately, the consumer only becomes aware of the cost after all consumption decisions have been made when they are presented with an end-of-period bill that reflects the cost of *total* consumption over the period. Consumption of the good requires an unknown quantity of inputs. For example, consider a household that sets its thermostat at a certain temperature. The household will not know how many kWh of electricity this choice requires; this uncertainty will be due in part to weather variation and in part to the inability of the household to track consumption or attribute electricity consumption specifically to temperature settings. This consumer faces two types of quantity uncertainty: forward and backward. Forward uncertainty refers to a lack of knowledge of future consumption, based on the inherent uncertainty of future needs and conditions. Backward uncertainty occurs because it is often impossible or inconvenient to keep track of previous consumption within the period. As a result, when making decisions within a bill period, the consumer is unaware of how much they have consumed up to that point and how much they are likely to consume, in total, throughout the period. As such, in the case of setting the thermostat, the household will not know how many kilowatt-hours of electricity this choice has consumed at any given point in the bill period, and the household will not know how much more electricity will be consumed by the end of the billing period. Backward uncertainty can be mitigated by improving the timing of information through more frequent feedback than typically occurs in these settings. This chapter develops a model of how removing backward uncertainty affects total consumption and intra-period consumption choices across two common pricing structures.

In a completely uncertain environment, the consumer never knows the input requirement of any individual choice and only learns total input use at the end of a billing period after all decisions have been made. If the individual instead only faces forward quantity uncertainty, then she has information about the input requirements of each individual choice after that specific choice has been made. At any decision point in the billing period, she will know how much she has consumed up to that point, but will still be uncertain of how much she will consume in the remainder of the period. In the model, I illustrate the effect on optimal choices of removing backward uncertainty by revealing previous input use up to the current decision within the period. The effect of uncertainty depends on the risk preferences of the consumer and the nature of the price structure they face. I model the effect for three types of risk preferences: risk averse, risk neutral and risk seeking. The model is first presented in the context of a constant marginal price structure (CMP), then a two-tier increasing block rate structure (IBR). In the second case, quantity uncertainty causes the consumer to be uncertain as to which marginal price they face, and removing backward uncertainty will have a different effect on the behavior. Overall, optimal behavior is found to depend on the level of quantity uncertainty (i.e., the frequency of feedback and the true realization of the uncertain input requirements), risk preferences, and the rate structure. I develop a number of testable predictions from the theoretical framework, which I investigate using data generated from a computerized laboratory experiment discussed in Chapter 3.

Modeling decision-making under uncertainty is not a new endeavor. This model differs from those in the existing literature in a few notable ways. First, I model multiple, sequential choices within a billing period. Existing models do not capture this aspect of the decision-making environment; instead they essentially model the billing period as the unit of decision-making, even in models of sequential decision-making under uncertainty (Sandmo, 1974; Ito, 2014). Without incorporating this aspect, we cannot separate out the effect of backward uncertainty. In household water and energy use, *many* choices are made within the billing period. When the household only receives an end-of-period bill, they make all of the period's decisions before any uncertainty is realized. Even when the uncertainty is realized, the multiple-choice nature of the environment keeps the individual from knowing the true values of individual input requirement.

Second, I allow for a spectrum of risk preferences. Other models, typically via their choice of functional form, assume the individual is risk averse or risk neutral (Ito, 2014). Without allowing for many types of risk preferences, we would not be able to illustrate the variety of possible sets of choices made with and without uncertainty, especially when facing a non-linear rate structure. While this theoretical model is designed to illustrate how more frequent feedback may influence household water and energy use, the findings here can also be applied to any other setting where multiple decisions are made facing uncertainty and are made prior to realization of cost.

The next section provides background and a discussion of related decision-making models. I first introduce utility theory and expected utility theory. Then, I briefly survey some other models that provided guidance on construction of the model and how levels of risk and information might be expected to influence the individuals decisions. I then discuss the IBR structure, which presents some challenging mathematical and conceptual complications.

2.2. Literature Review

Utility theory (UT) is the traditional approach to consumer choice theory. It assumes a rational decision-maker whose preferences are complete and transitive. An assumption embedded in UT that the consumers preference relationships are continuous, which allows the preferences to be represented through a utility function. Uncertainty is one of the main characteristics of the economic settings of interest in this dissertation. As compared to a certain decision-making environment, uncertain outcomes lead to different consumption decisions; changes in the level uncertainty will affect consumption decisions. Expected utility theory is the extension of UT that describes behavior where the individual makes choices under uncertain outcomes.

2.2.1. Expected Utility Theory

The expected utility model combines decision theory with probability theory and is used to explain decision-making under uncertainty. Expected utility is equal to the sum of each outcomes utility multiplied by its associated probability:$E[U] = \sum_i (U_i p_i)$, where $i = 1...n$ refer to the possible outcomes, so U_i and p_i refer to the utility and probability of that outcome.

It is assumed that an individual will make the choice that maximizes her expected utility, given her preferences. This is known as an axiomatic approach, where the researcher assumes certain conditions about the decision-makers preference structure, then uses the model to examine how the individual makes choices in the setting of interest. EUT is analytically convenient and provides normative results, which can serve as a guide in decision-making. In Chapter 3, I use the EUT models developed in this chapter to predict behavior in a laboratory experiment involving uncertainty.

Individuals with different risk preferences will respond differently to uncertainty; I use Jensens Inequality to show this. For example, Jensens Inequality shows that if an individual is risk averse, it is equivalent to the assuming the utility function is convex; the expected utility of a choice is less than the utility of the expected outcome of that choice. When uncertainty is present, a risk averse individual will underconsume relative to the risk neutral individual, who will under-consume relative to the risk seeking individual. For a thorough introduction to the concept of risk see Rothschild and Stiglitz (1970, 1971); they discuss the effect of risk on expectations and on economic decisions under uncertainty. Studies in this area typically assume one type of risk preference: often risk averse or risk neutral individual. I avoid this constraining assumption, leaving it to empirical research to confirm the type(s) of risk preferences of the individuals in the particular sample. I use risk preferences to illustrate how removal of backward uncertainty could possibly influence a variety of decision-makers.

Much of the theoretical literature on decision-making focuses on one of the following contexts: (i) capital investment models, where the firm makes capital or labor investment choices under demand or price uncertainty (e.g. Nickell (1977)), (ii) labor-leisure models where the individual makes choices under income or employment uncertainty (Burdett and Mortensen, 1978), or (iii) consumption-savings models where the individual makes consumption, savings and borrowing choices under a variety of economic uncertainties (Epstein, 1980; Hahm and Steigerwald, 1999). A common environmental application is climate change, where the government must choose a policy given uncertainty on how will emissions today impact humans in the future (Arrow and Fisher, 1974). The type of uncertainty involved in the bulk of the literature is typically a form of price or cost uncertainty.

The nature of my problem of interest does not exactly stem from any of these uncertainties, therefore requires a different treatment. There is no inherent uncertainty in the price of the input or in how much income the individual has over the course of the period of decisions. The nature of the uncertainty is input requirement uncertainty a quantity uncertainty. While this quantity uncertainty causes input cost uncertainty, modeling the setting only as cost uncertainty would not allow complete analysis of the effect of providing information on quantity use. Quantity uncertainty is not modeled often since it is not common for an individual to not know this information.

Production theory models have provided the most insight, as the individual in my settings can be thought of producing something that provides a known utility but requires an unknown amount of inputs. Leland (1972) provides a model of production under demand uncertainty, using Jensens Inequality to reach the same results as I do in relation to how risk preferences will affect output choices: The principle of increasing uncertainty implies the risk averse firm will produce less than it would under certainty If follows that optimal output of the risk preferring firm will be larger under un-certainty than under certainty. Risk neutrality implies uncertainty will not affect the firm's output. Coes (1977) provide proof of how increasing demand uncertainty will reduce the optimal level of output if absolute risk aversion is non-increasing. Therefore, if demand uncertainty is reduced, the optimal output level will be relatively higher.

Strong and Goemans (forthcoming) also use this literature and provides a quantity uncertainty model that will serve as the foundation for the model in this paper. Their application is to household water use and the effect of a device which communicates real-time water consumption information to the households. They model quantity uncertainty, but also incorporate consumer perceptions about the quantity they consume. They find that the effect of providing more information (reducing quantity uncertainty) will depend on risk preferences, but also how these risk preferences interact with household bias and the rate structure. Strong and Goemans model consumption for the entire billing period as the choice variable. As such, one notable way that I extend this model is to allow for multiple decisions within a billing period, which is used to show the effect of backward uncertainty.

2.2.2. Modeling Sequential Decisions

Most models with a chronological component are two or three period models that aim to theoretically show optimal rational behavior under uncertainty over time. See Sandmo (1974) for an early review of two-period consumption models under uncertainty and my list above for the common contexts of these models. They focus on how increasing uncertainty (like Rothschild and Stiglitz (1970, 1971) concept of increasing risk), along with the other parameters of the model affects the optimal level of investment, labor, consumption or emissions. Most discuss the relationship between the first-period decision and flexibility in available options in later periods. The literature also focused on how the optimal choices change if the uncertainty is expected to be resolved or reduced over time, as discussed above. They show that if the individual is expecting to gain information in the future about the uncertain variable she will make more conservative choices today to preserve some flexibility in taking advantage of the information later.

For example, in the theoretical literature on optimal capital investment or portfolio investment under uncertainty, Jones and Ostroy (1984) show that investment will be lower earlier if there are expectations to gain information in the future. Demers (1991) shows similar implications, though in this literature the investment decisions often contain a degree of irreversibility in that earlier choices may lock in or constrain the individual to a smaller set of options in the future. Individuals may be more even more cautious when mistakes are costly; this implies that we may see individuals being more conservative when prices or costs are higher (Demers, 1991). The expectation of more information in the future implies more risk now (Epstein and Zin, 1989). Similarly, Sandmo (1970) shows this too in consumption-savings models: increased uncertainty about future income decreases consumption today, which means increased savings today. These results are more applicable to decisions regarding consumers initial decisions about health care plans or cell phones plans, while my analysis focuses on the within-billing period decisions made after this choice. Still the role of expecting to have feedback is important: it suggests that our individuals may be more conservative in their consumption earlier on in the billing period if they expect to be able to learn more about how their choices impact their net utility. More recently, Baker (2006) finds that when the payoff function is separable in the random variable, that and increase in informativeness may have a similar effect on first period decision-making as when there is an increase in uncertainty. All of these studies indicate that risk attitude does not affect the qualitative effects of information.

Overall, these models could be employed to model the aggregate consumption decision, but it is the intra-period decisions under different levels of uncertainty that is of interest and, to my knowledge, has not been modeled yet. Antle (1983) highlights the importance of modeling the intra-period decisions in a farming context. Because farm managers can be expected to utilize all available information in decision making, they will feed back information from earlier production stages to later input choices. Only modeling the final consumption totals will not be able to show the impact of removing backward uncertainty. Two individuals, one with and one without backward uncertainty, could theoretically have the same total consumption in a period, but the intra-period decisions will be different: the consumer without feedback will choose the same quantity each time, whereas the other consumer will alter her choices in reaction to the feedback and the information it provides.

A final note on the literature of sequential decision-making is the use of discounting over time. This is typically appropriate for a temporal model, but I argue it is not necessary in my model because a month is the common time frame of a billing period in my settings; a month is not a sufficient enough amount of time for discounting to significantly affect decisions.

2.2.3. Incorporating Non-linear Price Structures

The EUT model is typically constructed with reference to a linear budget constraint, but this is often not the case for my class of economic problems. For example, water, electricity, cell phone minutes and data use, and labor supply are all decisions made while facing a non-linear price structure. Non-linear budget constraints create mathematical and conceptual complexities in the EUT framework.

Ignoring uncertainty for a moment, a non-linear price structure complicates the modeling of consumer decisions because the individual now faces a non-linear budget constraint. For the IBR case, this is called a piece-wise or a kinked budget set. Typically, a utility maximizing consumer chooses the quantity where the utility indifference curve is tangent to the linear budget constraint. This is a unique, global maximum. However, an IBR creates a piece-wise convex budget constraint where the tangency point may occur within a block or at a kink point. Deriving the demand functions from the utility theory is no longer straightforward. Also, the traditional comparative statics embodied in price and income effects may be zero instead of negative and positive, respectively (Moffitt, 1986).

Theoretically, the non-linearity issue is addressed by first determining quantity demanded conditional on the choice of block or the kink point. This conditional demand is described using the indirect utility function. Then, given each of these indirect utilities, the consumer chooses whichever level of consumption within the optimal block yields the highest utility. Utility maximization will only occur at a kink point if the utility maxima along the kinks neighboring blocks occur in the infeasible range of both block segments. Moffitt (1986, 1990) provides the early work on the modeling of non-linear kinked budget constraints. Hanemann (1984) and Hewitt and Hanemann (1995) also provide similar theoretical models for non-linear budget constraints with applications to water demand. Olmstead et al. (2007) mathematically show the difference in price elasticities under and IBR versus a CMP structure. Price elasticity of demand under increasing block prices is more complex because it involves a secondary income effect that results from infra-marginal price changes. They also reaffirm the interest in these issues since non-linear prices dominate in markets for many goods and services other than water, including electricity, local and wireless telephone services, and labor supply under progressive income taxation.

Econometrically, when inputs are priced according to an IBR structure, marginal price and total input use are co-determined. Using a traditional demand estimation technique will have a significant endogeneity problem, leading to biased and inconsistent estimators and results. Burtless and Hausman (1978) first mobilized a solution in the context of estimating elasticities under non-linear prices (taxes) when estimating labor supply (number of hours worked and net marginal wage are jointly determined). The problem has been described as the consumer first making a discrete choice then making a continuous choice. In addition to the labor supply/income tax case above, examples include whether to buy or rent a home, then how large of a home to live in; what vehicle to buy, then how much to use it. The idea is that the two choices ought to be modeled together since the discrete and the continuous choice partly depend on the other. The developments in utility theory under non-linear prices and the empirical struggles lead to the currently still dominant econometric counterpart: the discrete-continuous choice model. The discrete/continuous choice (DCC) is an econometric model Hanemann (1984) provides the first unified DCC model derived from utility theoretic underpinnings. His paper first models the choice of which block to consume in, then how much water to consumer within that block. However, this model is used for empirical estimate to address the issue of jointly determined marginal price and quantity consumed. This model, while it address the non-linear rate structure, does not include uncertainty. It assumes that households are fully informed, which as described in Chapter 1, is likely not the case.

2.2.4. Alternatives to EUT with non-linear prices

Decision-making under uncertainty with non-linear rate structures (with multiple possible marginal prices) has motivated a literature surrounding what price signal consumers are actually aware of and respond to. The evidence provided by empirical literature suggests that there is a degree of uncertainty surrounding prices in addition to the quantity uncertainty discussed above. Some studies suggest that consumers may respond to an average price rather than the correct marginal price in cases of complicated price structures (Shin, 1985). Borenstein (2009) models consumers as setting behavioral rules prior to the start of the period, optimizing given a distribution of exogenous demand shocks. Bushnell and Mansur (2005) show that customers are more responsive to price signals from the previous bill than to current conditions. Behavioral economists, borrowing from psychology, argue that there is a limit to rationality and cognitive ability. Individuals are more likely to use heuristics or be myopic in making their decisions in complex situations rather than behave like the rational 'homo-economicus.' Liebman and Zeckhauser (2004) coined the term "schmeduling" as a descriptor of an individual who is inaccurately perceiving the price schedule, and further define two varieties: ironing and spotlighting. Ironing is in line with consumers focusing on average prices, whereas spotlighting is in line with the myopia literature. For the sake of focusing on the role of quantity uncertainty, I assume that the consumer knows the rate structure and the price parameters perfectly. I address some of these behavioral issues in the empirical study found in Chapter 4 of this dissertation.

2.2.5. Summary

No existing model in the literature is wholly appropriate to model this decision-making environment. Recall that in order to capture the issues of interest, a model needs the following features: quantity uncertainty, intra-period level sequential decisions, and ability to incorporate non-linear price structures. In the existing literature, most uncertainty is modeled as a type of price uncertainty and/or focuses on how uncertainty affects irreversible decisions. Existing sequential decision models assume a longer time frame and therefore use a discount rate. Plus most of these studies set up the framework such that first-period decisions are made with complete certainty in first-period information, but only with uncertainty in future periods. Most also assume a risk averse representative agent. Finally, models that do look at consumption under non-linear prices may not incorporate uncertainty and typically only consider one-shot consumption choices instead of sequential decisions.

The next section begins the theoretical model, which is an extension of the model found in Strong and Goemans (forthcoming). I start with the case where the individual faces a constant marginal price structure.

2.3. Theoretical Model

2.3.1. Case 1: Constant Marginal Price

Consider a model where an individual makes consumption choices about two goods, x and z, over a period of time. Utility from x and z are additively separable where $u(x)$ and $v(z)$ denote the sub-utility functions. Also assume that $u(x), v(z)$ are both continuous and twice differentiable. The period consists of S sub-periods, and the consumer makes S sequential consumption choices about how much x to consume where x_s denotes the quantity chosen at sub-period time s. Total consumption, x, in a period is the sum of all sub-period choices such that $x = \sum_{s=1}^{S} x_s$. It is assumed that all remaining income in a period is spent on z, the composite numeraire good.

Consumption of x_s requires the use of an input w_s. The number of inputs required for consumption depends on a random input requirement $r_s \sim (\bar{r}, \sigma)$ such that $x_s r_s = w_s$.[8] Define $f(w_s|x_s, r_s)$ as the probability density function such that $E[w_s] = x_s E[r_s] = x_s \bar{r}$, and $w_s \sim (x_s \bar{r}, x_s^2 \sigma)$. The total cost of consumption, $C(x)$, is determined by the total amount of inputs used throughout the period. Let p be the marginal price of w and I denote income for the period.[9] Assuming the individual exhausts all of her income in a period, the budget constraint holds with equality: $I = p \sum_{s=1}^{S} w_s + z$, where the price of z is normalized to one.

The consumer knows, with certainty, the utility gained from consuming x as well as the marginal price of w, but the input requirement r_s is not known to the individual prior to making the consumption choice x_s; as such, w_s and the resulting cost of consumption is not known prior to choosing x_s either. In a given period, the individual faces one of two settings: (1) both backward and forward uncertainty (complete uncertainty), or (2) only forward uncertainty. Under complete uncertainty, the individual only receives an end-of-period bill containing the total cost after all consumption choices have been made. As a result, the individual never knows the individual realizations of the input requirements $r_1, r_2 ... r_S$, and only learns her total input use w after all quantity choices have been made. In Setting (2), the consumer receives feedback on the previous decision's input requirement r_{s-1}, and an up-to-date input use total $\sum_1^{s-1} w_s$ *after* each choice within the period (i.e., before making choice x_s), in addition to the end-of-period bill containing w. Providing this information eliminates

[8] Let $g(r_1, r_2 ... r_S)$ be the pdf, where the probabilities are the same but independent across random input requirements. Assume this pdf is symmetric around some mean. Also, note that only positive values of w_s make sense, and as such $\int_{-\infty}^{0} f(w_s|x_s, r_s) dw_s = 0$

[9] Assume all prices are exogenously set. For utility services, this assumption is reasonable. First, most utilities' costs are fixed costs. They determine revenue needs and expected total demand, then work backwards to set variable (dependent on quantity) pricing structures that will result in the required revenue. Many utilities are also restricted to act as a non-profit entity. It is therefore reasonable to assume that an individual utility customer does not have any influence on prices.

backward uncertainty since the individual knows how previous consumption choices within the period have impacted her remaining income and, in turn, the potential utility to be gained from consumption of the composite good z.

To illustrate the effect of removing backward uncertainty, consider a single billing period consisting of two sub-periods ($S = 2$). The consumer's optimization problem under complete uncertainty is to maximize expected utility subject to a budget constraint:

$$\text{(1)} \qquad \underset{\{x_1, x_2, z\}}{\text{Max}} \; E\left[u(x_1, x_2) + v(z)\right] \quad s.t. \quad I = p\sum_{s=1}^{S} w_s + z$$

Let x_1^{cu} and x_2^{cu} denote the optimal choices under complete uncertainty; the first-order conditions shown in Equations 2a and 2b identify that the individual optimizes by equating the marginal utility of consumption with the expected marginal cost. The marginal cost of consumption is essentially the marginal impact to residual income to be spent on z, seen most easily when using the budget constraint to substitute for z.

$$\text{(2a)} \qquad u_{x_1}(x_1^{cu}, x_2^{cu}) = pr_1 \int_0^{\infty}\int_0^{\infty} v_z(I - p\sum_{s=1}^{2} x_s r_s) f(w_1) f(w_2) dw_1 dw_2$$

$$\text{(2b)} \qquad u_{x_2}(x_1^{cu}, x_2^{cu}) = pr_2 \int_0^{\infty}\int_0^{\infty} v_z(I - p\sum_{s=1}^{2} x_s r_s) f(w_1) f(w_2) dw_1 dw_2$$

If the individual gets feedback on the resulting input use w_1 from the first consumption decision x_1, then this removes backward uncertainty. For now, assume, that the individual learns that the realized value of the input requirement $\tilde{r}_1$ is $\overline{r}$. Without backward uncertainty, Equation 2b is modified to reflect that the optimal x_2^{fu} choice is made facing forward uncertainty only as shown in Equation 3.[10]

$$u_{x_2}(x_1^{cu}, x_2^{fu}) = pr_2 \int_0^\infty v_z(I - p(x_1^{cu}\tilde{r}_1 + x_2 r_2))f(r_2)dr_2 \tag{3}$$

The difference between the second sub-period choice under complete uncertainty versus only forward uncertainty will depend on the individual's risk preferences. Mathematically, risk preferences are reflected by the curvature of the utility function. If the individual is risk averse in numeraire (z) consumption, then the utility function $v(z)$ is concave. Risk neutrality implies linear utility in the numeraire good and a constant second derivative. Risk seeking implies a convex numeraire utility function. Proposition 1 summarizes the predictions for behavior, given risk preferences.

Proposition 1: If the individual is risk averse and $\tilde{r}_1 = \overline{r}$, then $x_2^{fu} \geq x_2^{cu}$. If the consumer is risk neutral, then $x_2^{fu} = x_2^{cu}$. Finally, if the consumer is risk seeking, then $x_2^{fu} \leq x_2^{cu}$. [11]

[10]Note that this framework, as is, suggests that the first sub-period choice will be identical regardless of whether or not the individual will have access to feedback throughout the period. The literature on precautionary savings argues that simply knowing that feedback will be available effectively reduces uncertainty (see Gollier and Brunak, 2001). As such, with less uncertainty, there is less need for "precautionary savings" and first sub-period output choice will, all else equal, be larger. This is only for individuals who are risk averse and the third derivative of the utility function is positive. There is some evidence of this in the week-to-week results in Section 3.4.3, but a specific investigation is left for future research.

[11]If $\tilde{r}_1 = \overline{r}$, and we assume strict concavity/convexity, $x_2^{fu} > x_2^{cu}$ for the risk averse individual and $x_2^{fu} < x_2^{cu}$ for the risk seeking individual.

Proof of Proposition 1: Recall Equations 2b, and 3 that identified the optimal sub-period 2 choices: x_2^{cu} and x_2^{fu}:

$$u_{x_2}(x_1^{cu}, x_2^{cu}) = pr_2 \int_0^{\infty}\int_0^{\infty} v_z(I - p\sum_{s=1}^{2} x_s r_s) f(r_1) f(r_2) dr_1 dr_2$$

$$u_{x_2}(x_1^{cu}, x_2^{fu}) = pr_2 \int_0^{\infty} v_z(I - p(x_1^{cu}\tilde{r}_1 + x_2 r_2)) f(r_2) dr_2$$

If the realized value $\tilde{r}_1 = \overline{r}$, then, by Jensen's Inequality the following are true:

For a risk averse individual:

$$\int_0^{\infty} v_{x_2}(I - p(x_1^{cu}\overline{r} + x_2 r_2)) f(r_2) dr_2 \geq \int_0^{\infty}\int_0^{\infty} v_{x_2}(I - p\sum_{s=1}^{2} x_s r_s) f(r_1) f(r_2) dr_1 dr_2$$

$$u_{x_2}(x_1^{cu}, x_2^{cu}) \geq u_{x_2}(x_1^{cu}, x_2^{fu})$$

$$x_2^{cu} \leq x_2^{fu}$$

For a risk neutral individual:

$$\int_0^{\infty} v_{x_2}(I - p(x_1^{cu}\overline{r} + x_2 r_2)) f(r_2) dr_2 = \int_0^{\infty}\int_0^{\infty} v_{x_2}(I - p\sum_{s=1}^{2} x_s r_s) f(r_1) f(r_2) dr_1 dr_2$$

$$u_{x_2}(x_1^{cu}, x_2^{cu}) = u_{x_2}(x_1^{cu}, x_2^{fu})$$

$$x_2^{cu} = x_2^{fu}$$

For a risk seeking individual:

$$\int_0^\infty v_{x_2}(I - p(x_1^{cu}\overline{r} + x_2 r_2)) f(r_2) dr_2 \leq \int_0^\infty \int_0^\infty v_{x_2}(I - p\sum_{s=1}^{2} x_s r_s) f(r_1) f(r_2) dr_1 dr_2$$

$$u_{x_2}(x_1^{cu}, x_2^{cu}) \leq u_{x_2}(x_1^{cu}, x_2^{fu})$$

$$x_2^{cu} \geq x_2^{fu}$$

□

The true value of r_1 will not always be $\overline{r}$. While Proposition 1 illustrates the base effect of removing backward uncertainty through feedback, this effect will be exacerbated, muted or indeterminate, depending on the true value of r_1 communicated through the feedback. As an example, consider a risk averse individual. Without feedback, she will be conservative in her x_2 choice and under-consume relative to a more certain world. The base effect of removing backward uncertainty will reduce some uncertainty in her optimization problem, and will result in a relatively larger x_2 choice (i.e., $x_2^{fu} \geq x_2^{cu}$). If she learns that the true value of r_1 is less than $\overline{r}$, then this will induce an even larger increase in consumption in the second sub-period. However, if she learns that the true value of r_1 is greater than $\overline{r}$, then the overall effect on her optimal x_2 choice is indeterminate: The reduction in uncertainty is predicted to increase consumption, but the knowledge that her x_1 choice used more inputs than expected is predicted to reduce her consumption. The overall effect would require more specific information about her utility function. Table 2.1 summarizes the effect of providing feedback (removing backward uncertainty) on the optimal x_2 choice for each type of risk preferences and each possible realization of r_1.[12]

[12]These results are different from the previous literature of 1-period models, like Strong and Goemans (forthcoming). Here, by looking at sequential decisions within a billing period, I explicitly model the fact that risk preferences *and* the value of the information matters. For example, a risk averse individual who

TABLE 2.1. Constant Marginal Price Theoretical Results

Optimal x_2 Choices: Complete Uncertainty vs. Forward Uncertainty

	Realized Value $\tilde{r}_1$		
Risk Preference	$r_1 < \overline{r}$	$r_1 = \overline{r}$	$r_1 > \overline{r}$
Risk Averse	$x_2^{fu} > x_2^{cu}$	$x_2^{fu} \geq x_2^{cu}$	$x_2^{fu} \lesseqgtr x_2^{cu}$
Risk Neutral	$x_2^{fu} \geq x_2^{cu}$	$x_2^{fu} = x_2^{cu}$	$x_2^{fu} \leq x_2^{cu}$
Risk Seeking	$x_2^{fu} \lesseqgtr x_2^{cu}$	$x_2^{fu} \leq x_2^{cu}$	$x_2^{fu} < x_2^{cu}$

These lead to a number of testable hypotheses about behavior with and without backward uncertainty. For example, programs that increase the frequency of delivery of quantity information to their customers will tend to increase use if the targeted population is risk averse.

2.3.2. Case 2: Increasing Block Rate

Now consider the case where the individual faces a non-linear input price structure, specifically a two-tier increasing block rate structure. Let p_1 be the marginal price for all inputs used up to the block boundary B, and p_2 be the marginal price for all input units used beyond B, where $p_1 < p_2$.[13] The individual maximizes expected utility subject to a piece-wise budget constraint:

learns that input requirements were less than expected could appear to behave the same as a risk seeking individual who learns that input requirements are greater than expected. In a 1-period framework these two observations would look identical, but in the theoretical framework presented here, the risk preference effect is disentangled from the effect of the nature of the information (realized value of uncertain values).

[13]Note that when $p_1 = p_2$, it is a degenerate block rate structure which is simply the CMP case. In many instances there is also a fixed cost that is independent of quantity consumed. For example: a connection fee or a flat cost-of-service charge. The focus of this model is to show how the consumer responds to feedback in terms of quantity, thus only the terms that are a function of quantity are of interest here. Adding a constant term to the budget constraint merely shifts the budget set upward and will not impact the results.

(4)

$$\underset{\{x_1,x_2,z\}}{\text{Max}}\ E\left[u(x_1,x_2)+v(z)\right] \quad \text{subject to} \quad \begin{cases} I = p_1 \sum_s^S w_s + z & \text{if } \sum_s^2 w_s \leq B \\ I = p_1 B + p_2(\sum_s^S w_s - B) + z & \text{if } \sum_s^2 w_s > B \end{cases}$$

If the individual consumes $w = B$, she faces the unit price p_1 and this point on the budget line is called the kink point. The maximization problem is similar to the CMP case, but now contains three terms reflecting two marginal prices: one for input use up to block boundary B, and one for any inputs used beyond B. The individual faces the possibility that her total input demand may be less than or greater than the block boundary, and therefore that the marginal price may be p_1 or p_2. Note, when substituting for z, z is replaced with the appropriate piece of the piece-wise budget constraint.

(5)

$$\underset{\{x_1,x_2,z\}}{\text{Max}}\ u(x_1,x_2) + \int_0^{B-w_1}\int_0^{B} v(I - p_1\sum_s^S w_s)f(w_1)f(w_2)dw_1dw_2 + \int_{B-w_1}^{\infty}\int_{B}^{\infty} v(I - p_1B + p_2(\sum_s^S w_s - B))f(w_1)f(w_2)dw_1dw_2$$

The first-order equations (Equations 6) identify the optimal x_1^{cu} and x_2^{cu} choices where marginal utility is equal to the expected marginal cost, which is that impact on remaining income to be spent on z at the end of the period. The right-hand side consists of two terms, where the first term reflects the probability of the consumption falling within the first block as well as the resulting marginal utility. The second term reflects the same information for the second block.

$$u_{x_1}(x_1^{cu}, x_2^{cu}) = p_1 r_1 \int_0^{B-w_1} \int_0^{B} v_z(I - p_1 \sum_s^S w_s) f(w_1) f(w_2) dw_1 dw_2$$

(6a)

$$+ p_2 r_1 \int_{B-w_1}^{\infty} \int_B^{\infty} v_z(I - p_1 B + p_2(\sum_s^S w_s - B)) f(w_1) f(w_2) dw_1 dw_2$$

$$u_{x_2}(x_1^{cu}, x_2^{cu}) = p_1 r_2 \int_0^{B-w_1} \int_0^{B} v_z(I - p_1 \sum_s^S w_s) f(w_1) f(w_2) dw_1 dw_2$$

(6b)

$$+ p_2 r_2 \int_{B-w_1}^{\infty} \int_B^{\infty} v_z(I - p_1 B + p_2(\sum_s^S w_s - B)) f(w_1) f(w_2) dw_1 dw_2$$

As in the CMP case, learning the true value of r_1 removes backward uncertainty and reduces the uncertainty faced in making the x_2 choice. Similarly to the CMP case, first assume that the individual learns that r_1 does indeed equal $\overline{r}$. The first-order condition with respect to x_2 is now made facing forward uncertainty only, where x_2^{fu} is the optimal choice in this case. Equation 7 is Equation 6b modified to reflect the removal of uncertainty surrounding the impact of the first quantity choice x_1^{cu}.

$$u_{x_2}(x_1^{cu}, x_2^{fu}) = p_1 r_2 \int_0^{B-w_1} v_z(I - p_1(x_1^{cu}\overline{r} + x_2 r_2) f(w_2) dw_2$$

(7)

$$+ p_2 r_2 \int_{B-w_1}^{\infty} v_z(I - p_1 B + p_2((x_1^{cu}\overline{r} + x_2 r_2) - B) f(w_2) dw_2$$

The difference between the second sub-period choice with complete uncertainty (x_2^{cu}) and only forward uncertainty (x_2^{fu}) will depend not only on the individual's risk preferences, but also if she expects her total input use W to be less than or greater than the block boundary B.

Compared to facing a CMP rate structure, quantity uncertainty under an IBR structure will lead to uncertainty surrounding the marginal price. The individual expecting to be in the first block will face some positive probability of input demand actually exceeding the block boundary and facing the higher marginal price. This possibility induces behavior similar to risk aversion for those expecting to be in block 1, as the expected cost of over-consuming is greater than the expected cost of under-consuming. The individual expecting total input use to fall in the second block instead faces a positive probability that her total input use is actually less than B and that she will not face the higher marginal price at all. This case induces behavior similar to risk seeking, and here the expected cost of under-consuming is greater than the expected cost of over-consuming. I refer to these as 'induced' risk behaviors, because they are not true preferences, but the block rate may make an individual appear to behave as if they are risk averse or seeking. The induced risk behavior is independent of the individual's true risk preferences over z consumption.

Proposition 2: If $r_1 = \overline{r}$, the individual is risk neutral, and expects $W \leq B$, then $x_2^{fu} \geq x_2^{cu}$. If the same individual instead expects $W > B$, then $x_2^{fu} \leq x_2^{cu}$. [14]

Proof of Proposition 2: Note that $p = p_1$ and $p_1 < p_2$, and recall that for a risk neutral individual, the first derivative of the sub-utility function is a constant $v_z(z) = \overline{v}_z$. Then, the first-order equations 6b, and 7, which identify the optimal sub-period 2 choices under

[14] If $\tilde{r}_1 = \overline{r}$, and we assume strict concavity/convexity, $x_2^{fu} > x_2^{cu}$ for the individual expecting $W \leq B$ and $x_2^{fu} < x_2^{cu}$ for the individual expecting $W > B$.

complete uncertainty and only forward uncertainty, x_2^{cu} and x_2^{fu}, for the individual facing an IBR can be rewritten as:

$$u_{x_2}(x_1^{cu}, x_2^{cu}) = p_1 r_2 \overline{v}_z \int_0^B \int_0^{B-w_1} f(w_1)f(w_2)dw_1dw_2 + p_2 r_2 \overline{v}_z \int_B^\infty \int_{B-w_1}^\infty f(w_1)f(w_2)dw_1dw_2$$

$$u_{x_2}(x_1^{cu}, x_2^{fu}) = p_1 r_2 \overline{v}_z \int_0^{B-w_1} f(w_2)dw_2 + p_2 r_2 \overline{v}_z \int_B^\infty f(w_2)dw_2$$

If the individual expects $W \leq B$, then she expects that $x_1^{cu}\overline{r} < B$.

In the Complete Uncertainty case, $w > B$ if $w_1 > B$, $w_2 > B$, or if both $w_1, w_2 < B$ but $w_1 + w_2 > B$. Formally, the probability that $w = w_1 + w_2 > B$ is as follows:

$$Prob(w_1 + w_2 > B|cu) = \int_B^\infty f(w_1)dw_1 + \int_B^\infty f(w_2)dw_2 + \int_{B-w_1}^\infty f(w_2)dw_2 \int_0^B f(w_1)dw_1$$

However, in the applicable Forward Uncertainty only case, $w > B$ only if $w_2 > B$ or if $w_2 < B$ but is large enough such that $w_1 + w_2 > B$.[15] Formally:

$$Prob(w_1 + w_2 > B|fu) = \int_B^\infty f(w_2)dw_2 + \int_{B-x_1^{cu}\overline{r}}^\infty f(w_2)dw_2$$

Comparing these two probabilities, it is clear that:

$$Prob(w_1 + w_2 > B|cu) > Prob(w_1 + w_2 > B|fu)$$

[15]I say applicable because if the individual learns that $w_1 > B$ then this portion of the proposition no longer applies to this individual. This proposition only applies if the realized value w_1 is indeed less than B.

Necessarily,

$$Prob(w_1 + w_2 \leq B|cu) < Prob(w_1 + w_2 \leq B|fu)$$

Since $p_1 < p_2$,

$$p_1 r_2 \overline{v}_z \int_0^B \int_0^{B-w_1} f(w_1) f(w_2) dw_1 dw_2 + p_2 r_2 \overline{v}_z \int_B^\infty \int_{B-w_1}^\infty f(w_1) f(w_2) dw_1 dw_2$$

is greater than

$$p_1 r_2 \overline{v}_z \int_0^{B-w_1} f(w_2) dw_2 + p_2 r_2 \overline{v}_z \int_B^\infty f(w_2) dw_2$$

Therefore:

$$u_{x_2}(x_1^{cu}, x_2^{cu}) > u_{x_2}(x_1^{cu}, x_2^{fu})$$

$$x_2^{cu} \leq x_2^{fu}$$

And the individual appears to be risk averse.

If the individual expects $W > B$

In the Complete Uncertainty case, $w \leq B$ only if $w_1 + w_2 \leq B$. Formally, the probability that $w = w_1 + w_2 \leq B$ is as follows:

$$Prob(w_1 + w_2 \leq B|cu) = \int_{B-w_1}^B \int_0^B f(w_1) f(w_2) dw_1 dw_2$$

Under the Forward Uncertainty only case, $w_1 + w_2 \leq B$ only if $w_2 \leq B - w_1$. Formally:

$$Prob(w_1 + w_2 \leq B|fu) = \int_{B-w_1}^{B} f(w_2)dw_2$$

Comparing these two probabilities it is clear that:

$$Prob(w_1 + w_2 \leq B|cu) > Prob(w_1 + w_2 \leq B|fu)$$

Necessarily,

$$Prob(w_1 + w_2 > B|cu) < Prob(w_1 + w_2 > B|fu)$$

Since $p_1 < p_2$,

$$p_1 r_2 \overline{v}_z \int_0^B \int_0^{B-w_1} f(w_1)f(w_2)dw_1dw_2 + p_2 r_2 \overline{v}_z \int_B^{\infty} \int_{B-w_1}^{\infty} f(w_1)f(w_2)dw_1dw_2$$

is less than

$$p_1 r_2 \overline{v}_z \int_0^{B-w_1} f(w_2)dw_2 + p_2 r_2 \overline{v}_z \int_B^{\infty} f(w_2)dw_2$$

Therefore:

$$u_{x_2}(x_1^{cu}, x_2^{cu}) < u_{x_2}(x_1^{cu}, x_2^{fu})$$

$$u_{x_2}(x_1^{cu}, x_2^{fu}) \geq u_{x_2}(x_1^{cu}, x_2^{cu})$$

$$x_2^{fu} \leq x_2^{cu}$$

And the individual appears to be risk seeking. $\square$

However, the true value of r_1 may not be $\overline{r}$ and the effect of reducing uncertainty on behavior will be dampened or exacerbated, depending on the true value. For example, consider a risk neutral individual. If she expects to $W \leq B$, and learns that $r_1 < \overline{r}$ then $x_2^{fu} > x_2^{cu}$, but if she learns that $r_1 > \overline{r}$, the overall impact of the information is ambiguous: $x_2^{fu} \lesseqgtr x_2^{cu}$. Reducing uncertainty increases consumption, but the true value of r_1 reduces consumption. As such, the resulting x_2^{fu} depends on the relative strengths of these two forces. Table 2.2 organizes all possible combinations of risk preferences and learned values of r_1 for an individual expecting to total input consumption W to be in block 1 and block 2, respectively.

Table 2.2. Increasing Block Rate Theoretical Results

Optimal x_2 Choices: Complete Uncertainty vs. Forward Uncertainty

Individual expects $W \leq B$

	Value of r_1		
Risk Preference	$r_1 < \overline{r}$	$r_1 = \overline{r}$	$r_1 > \overline{r}$
Risk Averse	$x_2^{fu} > x_2^{cu}$	$x_2^{fu} > x_2^{cu}$	$x_2^{fu} \geq x_2^{cu}$
Risk Neutral	$x_2^{fu} > x_2^{cu}$	$x_2^{fu} \geq x_2^{cu}$	$x_2^{fu} \lesseqgtr x_2^{cu}$
Risk Seeking	$x_2^{fu} \geq x_2^{cu}$	$x_2^{fu} \lesseqgtr x_2^{cu}$	$x_2^{fu} \leq x_2^{cu}$

Individual expects $W > B$

	Value of r_1		
Risk Preference	$r_1 < \overline{r}$	$r_1 = \overline{r}$	$r_1 > \overline{r}$
Risk Averse	$x_2^{fu} \geq x_2^{cu}$	$x_2^{fu} \lesseqgtr x_2^{cu}$	$x_2^{fu} \leq x_2^{cu}$
Risk Neutral	$x_2^{fu} \lesseqgtr x_2^{cu}$	$x_2^{fu} \leq x_2^{cu}$	$x_2^{fu} < x_2^{cu}$
Risk Seeking	$x_2^{fu} \leq x_2^{cu}$	$x_2^{fu} < x_2^{cu}$	$x_2^{fu} < x_2^{cu}$

2.3.3. CMP vs. IBR

It is difficult to assess all of the differences between consumption decisions made when facing a CMP versus an IBR structure without assuming specific parameters or functional forms. Nevertheless, there are a few observations that can be made within this general theoretical framework. Set the marginal price of the first block to be equal to the price under a CMP structure: $p_1 = p$. Let $x_1^{cu,CMP}$ and $x_2^{cu,CMP}$ denote the optimal sub-period choices under complete uncertainty, within the CMP rate structure. Depending on risk preferences, and on where expected input use is relative to the block boundary, optimal consumption facing an IBR will differ from that of the individual facing the CMP.

Proposition 3: If $w^{cu,CMP} \leq B$ and the individual is risk neutral, then $x_s^{cu,CMP} \geq x_s^{cu,IBR}$, $\forall s \in S$. If the individual is risk averse, then $x_s^{cu,CMP} > x_s^{cu,IBR}$, $\forall s \in S$, where this $x_s^{cu,IBR}$ is less than the optimal $x_s^{cu,IBR}$ choice for the risk neutral individual. If the individual is risk seeking, then the relationship between $x_s^{cu,CMP}$ and $x_s^{cu,IBR}$ is indeterminable.

These results follow from Proposition 2 and Jensen's Inequality. These results are important because under complete uncertainty, an IBR will result in greater overall 'conservation' than what occurs when consumers face a CMP due to changes in the marginal price and an income effect. **Proof of Proposition 3**: Note that $p = p_1$ and $p_1 < p_2$, and recall that for a risk neutral individual, the first derivative of the sub-utility function is a constant $v_{x_s}(z) = \overline{v}_{x_s}$ $\forall s \in S$. As such the CMP first order conditions from Equation 2 can be re-written as:

$$u_{x_1}(x_1^{cu}, x_2^{cu}) = pr_1\overline{v}_z \int_0^{\infty}\int_0^{\infty} f(w_1)f(w_2)dw_1dw_2$$

$$u_{x_2}(x_1^{cu}, x_2^{cu}) = pr_2\overline{v}_z \int_0^{\infty}\int_0^{\infty} f(w_1)f(w_2)dw_1dw_2$$

And the IBR first-order conditions from Equation 6:

$$u_{x_1}(x_1^{cu}, x_2^{cu}) = p_1r_1\overline{v}_z \int_0^{B-w_1}\int_0^{B} f(w_1)f(w_2)dw_1dw_2 + p_2r_1\overline{v}_z \int_{B-w_1}^{\infty}\int_{B}^{\infty} f(w_1)f(w_2)dw_1dw_2$$

$$u_{x_2}(x_1^{cu}, x_2^{cu}) = p_1r_2\overline{v}_z \int_0^{B-w_1}\int_0^{B} f(w_1)f(w_2)dw_1dw_2 + p_2r_2\overline{v}_z \int_{B-w_1}^{\infty}\int_{B}^{\infty} f(w_1)f(w_2)dw_1dw_2$$

For the risk neutral individual whose $x^{cu,CMP} \leq B$, since $p = p_1$ and $p_1 < p_2$:

$$pr_1\overline{v}_z \int_0^{\infty}\int_0^{\infty} f(w_1)f(w_2)dw_1dw_2 < p_1r_1\overline{v}_z \int_0^{B}\int_0^{B-w_1} f(w_1)f(w_2)dw_1dw_2 + p_2r_1\overline{v}_z \int_{B}^{\infty}\int_{B-w_1}^{\infty} f(w_1)f(w_2)dw_1dw_2$$

$$u_{x_s}(x_1^{cu,CMP}, x_2^{cu,CMP}) < u_{x_s}(x_1^{cu,IBR}, x_2^{cu,IBR})$$

$$x_s^{cu,CMP} > x_2^{cu,IBR}$$

For the risk averse individual whose $x^{cu,CMP} \leq B$, Proposition 1 showed that, all else equal, the level of x for a risk averse individual facing complete uncertainty will be less than what a risk neutral individual facing CMP would choose under complete uncertainty. Given the above proof for the risk neutral person:

$$x_s^{cu,CMP,rn} > x_2^{cu,IBR,rn} > x_2^{cu,IBR,ra}$$

where 'rn' denotes risk neutral, and 'ra' denotes risk averse. $\square$

For the individual whose expected total input use under the CMP structure is above the block boundary, optimal consumption will decrease, but the magnitude of the difference between $x_1^{cu,CMP}$ and $x_1^{cu,IBR}$ will depend on risk preferences and the differential between the IBR marginal prices. For example, imagine an individual whose input demand under CMP would be greater than the block boundary of the IBR. The higher marginal price of the second block will necessarily reduce consumption, relative to the CMP optimal consumption. However, the optimal consumption under IBR may fall to the kink point or remain in block 2, depending on the parameters of her preferences and the rate structures. Comparing optimal behavior with and without backward uncertainty across the two rate structures gets increasingly complicated as decisions now further depends on the realization of the random input requirements. As such, these specifics are not included in this paper.

Overall, the theoretical model suggests that consumer behavior depends on 1) the level of uncertainty, which is dictated by the frequency of information provided within a period, 2) the content of the information (i.e., the value of the input requirement), 3) the individual's risk preferences and 4) the rate structure. This model highlights the role that backward uncertainty plays when multiple decisions are made within a single billing period. Also, allowing for a spectrum of risk preferences opens up the possibility for heterogeneity in the responses to reduced quantity uncertainty. The predictions outlined in the propositions lead to a number of testable questions, which are empirically examined through an experiment described in the next chapter.

CHAPTER 3

An Experimental Analysis of the Effect of Information on Consumption under Uncertainty

There are several commonplace instances where consumption choices are made under some kind of uncertainty. Water and energy consumption are two commonplace instances where the consumption choices are made under some kind of uncertainty. As described in Chapter 1, this is because quantity and price information is often only (if ever) learned ex-post consumption on an end-of-period bill. It has been found that the traditional [household energy] billing system is inadequate for effective consumer decision-making: the average monthly bill lacks "the detail which would make sense of the bill and allow for effective experiments in reducing it: Consider groceries in a hypothetical store totally without price markings, billed via a monthly statement like 'US$527 for 2362 food units in April'. How could grocery shoppers economize under such a billing regime?" (Kempton and Layne, 1994). While there has been a focus on the effect of price uncertainty in making water/energy use decisions, this experiment advances understanding of the role of uncertainty stemming from consumers having imperfect information about the *quantity* they are consuming.

Households make many water and energy consumption decisions throughout a billing period. The quantity is uncertain for at least three reasons: 1) most households lack the means to track use throughout the billing period, 2) water and energy are inputs to various household activities where the exact relationship is difficult to know (e.g., how many gallons of water does it take to keep a lawn green), and 3) quantity information and price signals are intermittent, unclear and confusing. Bills are difficult to understand, typically delivered only once a month, and water and energy are priced in obscure units like cubic feet and kWh. Over the course of a billing period, consumers face what I define as two separate types of quantity uncertainty: 'backward uncertainty', since it is difficult or inconvenient to know total consumption up to any given point in the period, and 'forward uncertainty', because the household is unlikely to know how much they will consume throughout the remainder of the period.[16] [17] This paper explores the effect of backward uncertainty on consumer behavior.

What further complicates this decision-making environment is that households often face non-linear pricing structures. Among U.S. energy and water utilities the most common non-linear pricing structure is the increasing block rate (IBR) structure where the per unit price increases by 'blocks' as total consumption increases. Typically the motivation of an IBR is to provide a basic amount to everyone at an affordable price, encourage conservation/efficiency, and maintain stable and sufficient revenue for expensive capital infrastructure and maintenance projects.[18] When facing a non-linear rate structure, quantity uncertainty induces marginal price uncertainty, as it is difficult to know where consumption stands relative to pricing thresholds.

[16]This paper is motivated by household water and energy use. However, the theory and the experiment are context-free so the results can apply to more than water or energy use. The decision-making environment presented here can apply to healthcare, cell phone use, credit cards, 'smart' parking meters and labor supply, to name a few.

[17]These definitions are somewhat related to what some literature has termed 'rational ignorance' or 'rational irrationality' (Ameriks et al., 2004). See Nataraj and Hanemann (2011) for further background on this issue. In Davis (2011): "Recent research has highlighted the many ways in which energy use is particularly prone to what traditional economics would deem "irrational" behavior. Electricity and heat are effectively invisible, their prices are delineated in abstract and unfamiliar units, and monthly billing ensures a temporal distance between usage and payment". Similarly, Jordan (1999) provides a good overview of how water is different from most goods, with emphasis on the how the billing system makes the 'rational' consumer assumptions unlikely to exist.

[18]This is still true for water utilities, though electricity utilities are increasingly turning to time-of-use pricing, or criticial-peak pricing structures to address the unique load issues of energy demand and supply.

Backward uncertainty can be reduced or eliminated by improving the timing of information through more frequent feedback than typically occurs for household water and energy use. The development in information technology known as advanced metering information (AMI) systems is allowing greater access to and use of real-time information; these systems create the potential for a two-way stream of communication between utilities and customers.[19] Utilities employ this technology to detect leaks, outages and inefficiencies, understand time-of-day consumption patterns, and improve demand forecasts, all of which can lead to a better understanding of consumer behavior and responsiveness to policies. A secondary use, which often lags these initial benefits of smart meters, is communication of data back to households. Households can access real time, or near-real time, streams of information on use, prices and total cost through an in-home display or a web portal. Customers need to be provided with regular and coherent information in order to understand the relationship between their actions, water/energy use and eventually their bill (List and Price, 2013).[20]

As advanced metering technology is increasingly deployed, utilities hope that more frequent information will encourage conservation and enhance effectiveness of existing demand-side management (DSM) policies. However, evidence to date on their effectiveness has been mixed. In this complicated environment, effective use of technology like smart meters will require a better understanding of the following: 1) How removing backward uncertainty through feedback affects total consumption and induces intra-period adjustments, 2) how feedback affects price responsiveness, and 3) how the rate structure impacts the effect of

[19]See the 2009 survey: "Smart Metering for Utilities", an Oracle White Paper for a thorough introduction for the use of smart meters in utilities Oracle (2009).

[20]List and Price (2013) argue that salience (and norms) matter most in managing the key problems utilities face. Making consumption and its cost salient via improved feedback and information results in increased price sensitivity and effectiveness of pecuniary-based policies.

feedback. Utility managers need to be aware of and consider the possible consequences when designing interfaces and information.

In this chapter, I use the theoretical predictions developed in Chapter 2 in an expected utility model of consumer behavior under quantity uncertainty. Like the theoretical model presented in Chapter 2, the experimental setting is simplified to an individual making consumption choices under input quantity uncertainty due to imperfect information. In the computerized laboratory experiment, participants are incentivized to maximize profit: a sequence of decisions are made facing either complete uncertainty about input requirements or only forward uncertainty if the individual receives feedback on her input use resulting from previous decisions within the period. The feedback effect is tested under three rate structure treatments: a constant marginal price structure and two versions of a two-tier increasing block rate structure.

Results confirm that participants understood the experiment by responding to prices and baseline incentives in a manner consistent with standard economic theory. Next, analysis shows that more frequent feedback increased average consumption, increased variance in weekly output levels and lowered price responsiveness – independent of rate structure. Results from the IBR sessions suggest that the effect of prices and the block boundary depend on the distribution of user preferences relative to the block boundary. Participants with preferences consistent with expected use below (above) boundary increased (decreased) use. This result is consistent with the theory that researchers should observe 'bunching' at the kink points (block boundaries) of a non-linear price schedule if individuals understand the rate schedule and act rationally (Ito, 2014). This idea will be further discussed in reviewing the related literature.

There exists heterogeneity in the decision-making of participants, which can partially be explained by differences in risk preferences and gender. Using estimates of risk preferences elicited through a Holt and Laury (2002) lottery, I find that risk averse and risk neutral participants are positively responsive to feedback and more price responsive than risk seeking participants.[21] I also find evidence of rate structure induced risk behavior in the IBR sessions (i.e., risk neutral participants acting like they are risk averse due to the positive probability of facing a higher marginal price). This behavior sometimes makes participants appear to target the block boundary, however, the risk preferences explanation fits the data better.[22] Finally, female participants are more responsive to feedback than their male counterparts, a result which is interestingly independent of the other experiment treatments and risk preferences.

This line of inquiry is important because utilities are faced with growing demand at a time when supply expansion is increasingly costly, inconsistent and taxing on the environment. "Concerns abound in the United States where a recent government survey suggests that at least 36 states are anticipating some form of water shortage by 2013" (Ferraro and Price, 2013). In addition to anticipated gaps, current infrastructure is old and failing: "By the year 2030, studies show the average water utility will have to spend 3.5 times more on pipe replacement than it spends today" (Black and Veatch, 2013). Supply expansion is limited, and to meet future needs, utilities need demand-side management (DSM) policies to result in more reliable and consistent consumer responsiveness.[23] The United States government sees

[21]The expected utility model developed in the conceptual framework section predicts much of the risk-preference related behavior seen in the experiment.

[22]The notion of the boundary as a goal is actually in line with how IBRs are often designed. Utilities price a quantity of 'acceptable' use at the lowest block price, and use above that quantity is priced at a higher marginal rate. Conservation is thus encouraged for activities above and beyond what is considered a necessary amount of use. They are, in theory, designed with equity goals in mind.

[23]In addition to efficiency goals, electricity DSM programs typically focuses on shifting demand from peak to off-peak hours of the day, whereas water programs aim to reduce peak summertime outdoor water use

the smart grid as a means to modernize the U.S. electricity transmission and distribution system, which involves the "integration of 'smart' appliances and consumer devices" as well as "provision to consumers of timely information and control options" (Congress, 2007).[24] The Energy Independence and Security Act of 2007 notes that "for the United States to realize its full [energy] demand response potential, customers must have access to, and a better understanding of, information about real-time or near-real-time prices" (Congress, 2007). Currently, most households do not have access to the level or type of information needed to achieve these goals.

Despite this push, few utilities have yet to take advantage of the utility-to-household smart meter communication opportunities and even where this data exists, program implementation often confounds clear analysis and privacy laws make it difficult to study household level data. Beyond these barriers to accessing 'real world' data, it is difficult and costly to apply different treatments (like different bill design, bill frequency or prices) to properly randomized subsets of customers. The experiment presented here makes it possible to test economic theories prior to incurring the risk and expense of a real-world application or field test and does not disrupt real-world activities.[25] I am not aware of any previous studies that have considered the effect of resolving backward uncertainty in a controlled experimental setting or the impact of information under alternative pricing schemes. This work complements a growing literature on price and quantity salience, as well as household water and energy use.

[24] Though much of the attention is on smart grid development in the energy sector, there is growth on the water side, too. See the summarizing article John (2012). Historically, water utilities tend to lag, but eventually follow, the direction of electric utilities.

[25] See Mäki (2005), Samuelson (2005) and Smith (1989) for an examination of the relationship between economic theory and experiments.

The remainder of the chapter is organized as follows: Section 3.1 reviews the related literature, Section 3.2 contains an overview of the experiment participants, experiment design and the empirical model, and Section 3.4 discusses the results. Finally, Section 3.9 presents some concluding thoughts.

3.1. Literature Review

3.1.1. Feedback and Information

There is evidence that households have limited information about their water and energy use. Jordan (2011) shows how, even with their water bill in front of them, it might be difficult for a household to identify how much water they have consumed. A study by Attari et al. (2010) shows that the average individual underestimates household energy use by a factor of 2.8 and is typically unaware of the most cost-effective ways to conserve energy (most choose reduced use over improving efficiency). This reflects a lack of knowledge surrounding water/energy use requirements of appliances. In a survey on energy feedback preferences, Roberts et al. (2004) found that consumers "would, given the right feedback, examine reasons for change in consumption and may be stimulated to take action". Informative billing initiatives in Norway showed how customers appreciated improved accuracy and extra information (historic and comparative feedback, a guide to which end-uses were the highest consuming), began to read their bills more frequently and with more understanding, and began to alter their behavior (Wilhite, 1997; Whilhite et al., 1999).[26]

Historically, frameworks like the information deficit model suggest that simply giving people more information will improve knowledge and influence behavior, but a wealth of

[26]Karlan et al. (2010) find that reminders increased savings and that reminders will be more effective when they increase the salience of a specific expenditure. Chetty et al. (2009) show using sales tax on groceries that tax salience influences behavior: the more salient the tax, the lower the resulting consumption level.

research shows that this is not always the case (Miller, 2001). From the field of psychology, Lam et al. (2011) provide a review of the effect of feedback and show in their own experiment that "frequent feedback can overwhelm an individual's cognitive resource capacity, thus reducing task effort and producing an inverted-U relationship with learning and performance over time". Lurie and Swaminathan (2009) find in an inventory management game that more frequent feedback in a 'noisy' decision-making environment leads to "excessive focus on and more systematic processing of more recent data as well as a failure to adequately compare information across multiple time periods." This literature suggests, in complicated decision-making environments, feedback itself may not induce effective, efficient or beneficial adjustments to decisions.

Experiments in the psychology literature focuses on the effect of feedback or information on performance, finding that despite the tendency to think that more information is always better, there is actually a limit to an individual's ability to effectively use the additional feedback to better their decision-making. Diehl and Sterman (1995) find that subjects' performance did improve somewhat as the time delay between action and result shortened, but in a complex environment, subjects' performance worsened with increased feedback indicating that individuals have a difficult time navigating complex settings. Kluger and DeNisi (1998) perform a meta-analysis of the literature on feedback interventions (FI) to date and find that FIs reduce performance in more than one-third of the cases. Atkins et al. (2002) also find that subjects performed poorly in complex dynamic decision-making tasks. In reviewing subject comments on decision rationales they find that "participants were aware of complexity factors but were unable to cope with them effectively". Other study results that investigate the effect of feedback on use decisions are mixed: two separate investment experiments found that if participants expect to receive more frequent feedback or updated information it lead to more conservative investment choices and lower investment quantities overall to preserve flexibility (Gneezy and Potters, 1997; Bellemare et al., 2005) [27]

Studies using energy and water field observations also yield mixed results on the impacts of additional information both on the ability of consumers to improve decision-making and on overall consumption. The first thrust of interest dates to the late 70's and early 80's where a series of studies found that some information programs reduced electricity consumption, while others found it increased consumption.[28] These studies do generally agree that feedback is more effective (either in reducing overall use or shifting to off-peak periods) the more frequently it is provided to the households (Fischer, 2008), though there are some studies which show no change in behavior or even an increase in electricity use (Bittle et al., 1979). Problems with the early studies include small sample size and failure to follow up on long-term impacts.

The more recent swath of studies yield varied results, too. In the energy use studies, some find solid evidence of conservation while others find no significant changes or even increases in use. In a meta-analysis of studies focused on interventions in household energy use,

[27] These observations are not limited to the psychology literature, the rational inattention (which models attention as a scarce resource) and bounded rationality literatures in the field of economics is growing and often cited in research on household water and energy use. See Wiederholt (2010) for an introduction to rational inattention and Kahneman (2003) for a resource on bounded rationality.

[28] For more specific examples of relevant research: Seligman and Darley (1977) found that immediate feedback resulted in reduced energy use, though the study only used 29 homes. Another early electricity study found that only monetary rebates reduced use, and feedback and information actually increased use (Winett et al., 1978). Battalio et al. (1979) and Sexton and Sexton (1987) both found that households enrolled in information or self-monitoring electricity programs, they revised their estimated costs downward and increased consumption. Gaskell and Pike (1983) conducted a study asking householders to read their meters daily. They also provided information on energy use to a subset of the study sample. Those who were *not* provided with the information, and only checked their meters, actually increased consumption of natural gas and electricity. Sexton et al. (1989) finds that an in-home display, which communicated time-of-day pricing, mostly shifted energy use to off-peak times and did not reduce consumption overall. Matsukawa (2004) considers the role of an electricity monitoring device in the presence of a constant price structure on electricity consumption and finds that, in general, households conserve in the presence of better information.

Abrahamse et al. (2005) find that information/feedback increases knowledge but may not induce any changes. The authors suggest that feedback combined with goal-setting or other information programs are more effective than these programs alone (Abrahamse et al., 2005). A report by Darby (2006) reviews 38 studies on feedback interventions finding that not all resulted in energy savings, but those that did averaged between 5-15%. She warns that it is important to recognize that "feedback is a necessary but not always a sufficient condition for savings and awareness [amongst consumers]" (Darby, 2006). A survey of in-home display pilot programs across twelve U.S. energy utilities finds that feedback improved energy efficiency and reduced consumption by 7% on average (Faruqui et al., 2010).[29] However, Allcott and Rogers (2012) shows that responsiveness to personalized energy-use feedback reports diminishes in between delivery of reports, a trend called "backsliding."

Fewer studies have been conducted on water use. Two residential studies show that better information/knowledge or frequent feedback actually *increases* water use: Carter and Milon (2005) find that households who are 'informed' - have knowledge about marginal and average price - consume relatively more water than those households who are less informed. Strong and Goemans (forthcoming) find that households who had more frequent consumption feedback through in-home display water smart meters consumed more than households who only received information through a monthly bill.

There is one notable study that links the lab and the 'real' world: Chermak et al. (2013), compare actual water use through historical billing with laboratory behavior and find no difference in price elasticties between the 'real' behavior and the lab behavior for the majority of the participants. This research suggests that experimental procedures, like the

[29]Even the currently hot research on social nudges and conservation behavior also note the importance of frequency for information programs to be effective (**?**Allcott and Mullainathan, 2010). Much of the current economic literature corroborates the findings in the field of psychology described earlier.

one presented here, may be used to generate reliable, realistic data that is comparable to 'real-world' data and can "provide valuable insight looking forward – to consumer response to price, situations or policies that do not exist yet" (Chermak et al., 2013).

3.1.2. Price Responsiveness and Rate Structure

Some studies focus on price knowledge and price responsiveness with the idea that more effective and more frequent feedback to consumers could improve price responsiveness, which would make DSM pricing policies more effective and possibly require less severe price increases to meet desired reductions. For example, some studies have found that feedback improves effectiveness of dynamic pricing policies like critical-peak pricing or time-of-use pricing (Faruqui et al., 2010; Darby, 2006; Jessoe and Rapson, 2014). However, in addition to evidence of households not knowing how much water or energy they consume, it is well documented that consumers often lack knowledge of the rate structure they face and the marginal price they face within a billing period because it is difficult and costly to track use or understand complicated rate structures (Foster and Beattie, 1981; Gaudin, 2006).[30] Note that this is different from the marginal price uncertainty I focus on; these studies focus on information improving knowledge of rate structures and prices whereas I assume households know the rate structure and prices. In field studies of non-linear pricing, it is difficult to separate the effect of learning about consumption from the effect of learning about prices and cost.

[30] Other surveys asking about price knowledge find that a small amount of people have any awareness of prices. Of their respective study sample populations, Carter and Milon (2005) found 6%, Brown et al. (1975) found 4.4%, and Stratus Consulting (1999) found 7% were aware of the correct prices. In a survey of information presented on monthly electricity bills, Gaudin (2006) shows that price elasticity increased by 30% or more when price information is given on the bill. Jessoe et al. (2013) show that factors other than current prices influence electricity consumption choices, and better understanding of consumer behavior might allow real-time feedback to enhance pricing policies.

This issue of what price knowledge consumers have has led to the question of finding out which price signal consumers *do* respond to, if any. In theory, when a population of consumers face an IBR structure, the non-linear nature leads to disproportionately more demand curves intersecting with the kink points (block boundaries), which is called 'bunching.' However, if consumers either do not fully know or understand their rate structure or consumption patterns, then we would not expect to observe this pattern in real-world data (Ito, 2014).[31] Kahn and Wolak (2013) find that providing education and information about an IBR structure leads consumers to respond to marginal prices, which results in an increase in bunching.[32] Strong and Goemans (forthcoming) also find that when households have an in-home display, more households water use is closer to block boundaries. When participants have more frequent feedback (do not face backward uncertainty), I too find evidence of increased bunching around the block boundary in the IBR sessions of my experiment.

Field data typically consists of consumers simultaneously facing the same price schedule, so there are few studies on behavior under different rate structures. Cavanagh et al. (2002) and Olmstead et al. (2007) show that households are more responsive to water prices under an IBR than a constant per-unit price and suggest that perhaps an IBR makes prices more salient to consumers. However, a recent pilot program in the Commonwealth Edison service area in Chicago does not find significant differences in consumption between flat rate schedules and a variety of non-linear and dynamic rate structures (Wakefield et al., 2011).

[31] The focus on bunching stems from studies on behavior under non-linear tax structures, like federal income taxes (de Bartolome, 1995; Saez, 2010; Chetty et al., 2010; Liebman and Zeckhauser, 2004). These studies also relate to research finding that consumers responding more to average price than marginal price (Shin, 1985; Ito, 2014)

[32] Kahn and Wolak (2013) show that teaching consumers to read their bill and understand the non-linear price structure results in improved responsiveness to marginal prices rather than average prices. Those customers who learn they face a marginal price lower than their average price increase consumption, while those who learn that they instead face a marginal price higher than their average price decrease consumption. See Kahn and Wolak (2013) for a concise description of what is required for an IBR to be effective.

3.2. Experiment Overview

The central experiment, which mirrors the theoretical model in Chapter 2, is designed to capture the household water/energy-use decision-making environment. Participants are incentivized to be profit-maximizing producers of a generic output, which require an uncertain, randomly chosen amount of inputs ranging from one to five, each equally probable. The uncertain input requirements were randomly drawn prior to the experiment, rather than being generated during the experiment. A participant never knows the series of input requirements beforehand, and the series is held constant across all sessions for more straightforward analysis.

Over the course of a session, a participant makes an output decision for each of four 'weeks' in each of twelve 'months' (forty-eight total choices). The participant knows his/her individual marginal revenue schedule and the input price structure, both of which remain constant for the entire session. The price parameters of the input price structure are also known but change across months. Table 3.1 outlines how parameters change during a session. An output decision is made without knowledge of that week's input requirement condition and therefore without complete knowledge of the marginal cost of producing an additional output.

Each participant is randomly assigned to be either a "Low" or "High" value producer, which was dictated by the marginal revenue (MR) schedule assignment: $Marginal\,Revenue_{Low} = 19 - 2Q$, $Marginal\,Revenue_{High} = 29 - 2Q$. These marginal revenue schedules were designed to investigate how low and high value users may respond to feedback in general, but especially in block rate structure treatments. These two groups of people can be thought to mimic low vs. high-income households, or households with indoor water use only vs. households with outdoor water use. The specific MR schedules are designed so that high value producers would be expected to noticeably produce more output and therefore demand more input units. Furthermore, under an increasing block rate structure, the high value producer would on average, be expected to have an input demand in the higher-priced block, whereas a low value producer's input demand is expected to fall in block one.[33],[34]

As shown in Table 3.1, in some months a participant only received monthly summaries of their choices, including total revenue, total input use and cost, and profit. In these months the participants are making decisions under complete uncertainty. In the other months, participants not only saw the monthly summaries, but also received weekly updates after they made a week's output choice and the input condition was realized; this information contained the previous week's input requirement and input use, as well as the cumulative input use to date. In these months, participants are making choices without backward uncertainty. In all sessions, the participants were exposed to each feedback treatment (six months of each treatment). All participants saw a feedback screen in between weekly output choices, but in the months without the feedback treatment, some of the information was

[33]In the IBR82 session, low-value producer input demand is always expected to be below the block boundary and high-value producer input demand is always expected to be above the block boundary. However in the IBR41 sessions, while all high-value producer input demand is always expected to be above the block boundary, there are some months where low-value producer input demand will also be expected to be greater than the block boundary.

[34]Not only does the theoretical model require consideration of different preferences, the literature also suggests heterogeneity in responsiveness across preference: (Reiss and White, 2005) found considerable heterogeneity in households' price and income elasticities. A 2005 report, the Impact Evaluation of the California Statewide Pricing Pilot, also found heterogeneity in price responsiveness of electricity use: high energy-using households are more responsive to prices than low energy-using homes Associates (2005). The different producer preference types can be thought of as one that reflects a high willingness to pay, which could indicate higher incomes or greater demand for non-essential uses of energy/water.

not available. This is done to control for the participants seeing different 'amounts' of information.

Table 3.1. Experiment Timeline

Timing of Prices and Feedback

Month	Price Level	Session A	Session B
1	Low		Weekly Feedback
2	Low	Weekly Feedback	
3	High	Weekly Feedback	
4	High		Weekly Feedback
5	Medium		Weekly Feedback
6	Medium	Weekly Feedback	
7	Low	Weekly Feedback	
8	Low		Weekly Feedback
9	High		Weekly Feedback
10	High	Weekly Feedback	
11	Medium	Weekly Feedback	
12	Medium		Weekly Feedback

Three different versions of the experiment were conducted, testing two types of rate structures: a constant marginal price, and two variations of a two-tier increasing block rate structure. The first IBR's block boundary is at 82 input units, while the other IBR's block boundary is at 41 input units. For each of these rate structures there was an 'A' and a 'B' session. Across A and B, the only difference is the ordering of the feedback treatment; see Table 3.1. With this design, behavior is observed both with and without feedback, facing identical parameters. In each rate structure, participants faced three price levels across the twelves months. Table 3.2 outlines each of these levels across each rate structure. Prices will be discussed in terms of levels throughout the remainder of the paper. Note the difference between the CMP and IBR price definitions, as later I will discuss how the effect of feedback varies by price level and rate structure, but it will not always be an apples-to-apples comparison. For example, when comparing responsiveness to feedback in high-priced months, in the CMP sessions this will mean the participant faced \$4 per input, while the IBR session participants faced \$2 per input up to the block boundary and \$5 per input for all inputs used beyond the block boundary.

Table 3.2. Definition of Price Levels (in lab dollars/input)

Rate Structure	Constant Marginal Price (CMP)	Increasing Block Rate (IBR)*	
Prices		Block 1	Block 2
Low Level	\$2	\$2	\$3
Medium Level	\$3	\$2	\$4
High Level	\$4	\$2	\$5

*Two IBR structures are tested: one with a block one boundary at 41 inputs, and one with a block boundary at 82 inputs. A CMP rate structure can be alternatively considered an increasing block rate structure with a boundary at zero.

There are five stages in a session procedure: (1) instructions, practice problems, and clarifying questions, (2) the central experiment, (3) a Holt-Laury lottery experiment to elicit risk preferences,[35] (4) a series of survey questions, and (5) payment to the participants.[36]

3.2.1. Experiment Participants

Participants were recruited in undergraduate economics courses at Colorado State University. In total, 119 students participated across six sessions.[37] Payment was based on performance in the main experiment and results of the Holt-Laury lottery. The experiment is conducted in terms of "lab dollars," which are converted to real U.S. dollars using separate

[35]The lottery was conducted as follows: After the participants completed the lottery experiment, only one of their 10 choices determined their additional earnings. We determined payoff by randomly selecting a number between 1 and 10, which determined which set of lotteries (containing an A lottery and a B lottery) were the "real" lotteries. Then a randomly selected number between 1 and 100 determined the outcome of these lotteries. Then the participant's earnings were increased by the payout amount, depending on which of the lottery options they had selected.

[36]The experiment was developed and executed using zTree (Zurich Toolbox for Readymade Economic Experiments), a user-friendly software program for experimental economics (Fischbacher, 2007).

[37]Several months after these initial six sessions, two more sessions were conducted using 21 local Water and Electric Utility employees. Both an A and B session of the IBR82 version were conducted. Much to the Utility practioners' surprise, no difference was found between the student participants and the Utility practitioners' decision-making.

conversion rates for high and low value producers to account for inherent difference in potential earnings depending on this random value assignment: for high-value producers: 150 lab dollars= 1US dollar; 50 lab dollars= 1US dollar for low-value producers. An experiment session lasted between 90 and 120 minutes with an average payout of $28.20.[38]

3.3. Data and Randomization

In setting up an experiment, a critical goal is to randomize the treatment assignments. Treatment assignment should be independent of the impact of the treatment on the outcomes, i.e., we assume conditional independence and no presence of selection bias or omitted variable bias.[39] The two main treatment variations are the weekly feedback assignment and the rate structure assignment. All participants received weekly feedback in half of the months and only the monthly feedback in the other half, so there is no need to worry about the randomization of the feedback treatment. The rate structure treatment assignment depended on which day the participants registered for the experiment. We conducted two sessions of the CMP structure, and four of the IBR structure (two with block boundary=82; two with block boundary=41). There are no statistically significant differences in average participant characteristics across sessions or rate structures. The producer type (High or Low) was assigned to the laboratory computers on an alternating basis; so the assignment of these

[38]Experiment payouts have been subject to criticism in experiments: It has been found to be better to have payout be a function of performance in the game instead of a flat pay out (Croson, 2005). As such, all decisions made in the main experiments and the lottery are made to be potentially payoff relevant in order to ensure incentive compatibility. Payment for the main experiment portion is based upon the participant's cumulative earnings across all twelve months, and payment for the lottery is described above. Croson (2005) also argues that the payout needs to be comparable with the opportunity cost of the participant's time. The average payout of $28.20 across all sessions is quite reasonable for undergraduate students.

[39]Participation in one group or another should not affect the distribution of potential outcomes, after controlling for the variation in outcomes induced by differences in participant characteristics. By randomizing across treatment groups, the difference in the average outcomes for the treated and the non-treated groups is the average treatment effect. This is easily controlled for in a laboratory experiment but is more difficult with field experiments where participants likely self-select into the different treatment groups, e.g. opting in to a utility pilot program. Also, we do not need instrumental variables or other econometric means to handle endogeneity because we can assume the treatment variable to exogenous.

preferences depended on where the participant sat down, which is highly unlikely to be correlated with their decision-making characteristics. They could have just as easily sat at the computer next to theirs and had the other producer preferences.

Table 3.3 provides brief information on variables used throughout the results section.

Table 3.3. Description of Variables

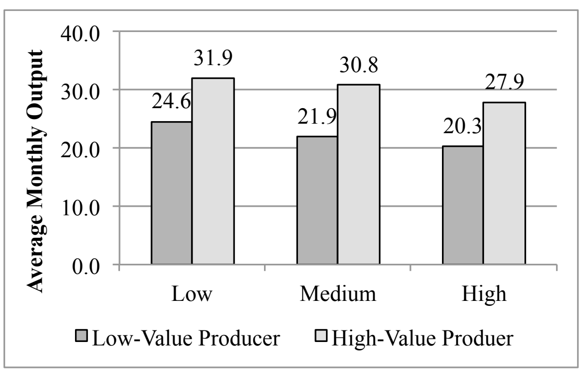
Variable	Type	Description	Variation
Month Input	Continuous	Total inputs used in the month	Individual & Month
Month Output	Continuous	Total output produced in the month	Individual & Month
Feedback	Dummy	=1 if a month with weekly input feedback	Individual & Month
Producer Type	Dummy	=1 if a high-value producer	Individual
Low Price Level	Dummy	=1 if a month with the low price level	Month
Med Price Level	Dummy	=1 if a month with the medium price level	Month
High Price Level	Dummy	=1 if a month with the high price level	Month
CMP	Dummy	=1 if CMP rate structure	Session
IBR82	Dummy	=1 if IBR structure with threshold at 82 inputs	Session
IBR41	Dummy	=1 if IBR structure with threshold at 41 inputs	Session
Avg Input Req	Continuous	Average weekly input requirements for the month	Month

3.4. Results

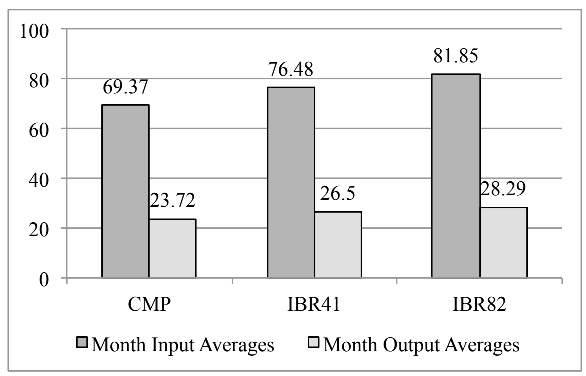
The results section is organized as follows: (1) an analysis of the internal validity of the experiment, (2) the effect of feedback on monthly totals, and weekly decisions, (3) the effect of feedback on price responsiveness, (4) the effect of the rate structure, and (5) discussion of behavior and heterogeneity.

3.4.1. Internal Validity: Did the participants understand the Experiment?

The participants responded to fundamental incentives as standard economic theory predicts. Figure 3.1a illustrates that participants assigned high-value preferences produced more output each month than the participants assigned with low-value preferences. The producer output difference was greatest during the constant marginal price sessions, with high-value producers producing an average of about 45% more output each month, though the expected utility model predictions suggest that high-value participants should produce about twice as much as low-value participants in CMP sessions. The increasing block rate structures induced smaller differences across producers: 36% and 27% for the IBR82 and IBR41 sessions, respectively. Figure 3.1a also shows that participants responded to higher prices by producing less output. Finally, Figure 3.1b shows that participants responded to rate structures as expected: On average, output was largest during the IBR82 sessions, and smallest during the CMP sessions. These results are due to the way price levels are set, as discussed in the experiment overview.



(A) Monthly Output levels by Producer Type and Price Levels



(B) Monthly Input and Output levels by Rate Structure

FIGURE 3.1. Internal Validity

3.4.2. Feedback Effect

Most of the following results are presented in terms of effects on input demand. While individuals make choices about output, the overall goal of this study is to evaluate the impact on input demand. A water utility, for example, is interested in and can more readily observe how water use changes rather than what the household does to change their water use. The analysis will focus on output when investigating how participants adjusted behavior from week to week.

3.4.2.1. *Month Level.* To isolate the effect of feedback on input use, I estimate the following random effects model where w_{jm} denotes total monthly input demand for participant j in month m. This will be the baseline model of analysis. Other portions of the results will deviate from this model by splitting the sample, including interaction terms and, in the week-to-week analysis, changing the dependent variable.

(8)

$$w_{jm} = \alpha_i + \beta_1 Feedback_{jm} + \beta_2 MedPrice_m + \beta_3 HighPrice_m + \beta_4 IBR82_j + \beta_5 IBR41_j$$
$$+\beta_6 ProducerType_j + \beta_7 AvgRequ_m + u_j + \varepsilon_{jm}$$

Table 3.4 contains the regression results from the model in Equation 8. Participants repsond to prices as expected: input demand decreases as input price increases. Feedback, on average, increases average input use by 2.92 (which is approximately 1 more output per month). Participants' average input demand is the largest under IBR82 and lowest under the CMP rate structure. High-value producers used about 22 more inputs per month than low-value producers, on average.[40] These results are consistent with standard economic theory.

[40]While in some scenarios and in some studies cited in the introduction information has been shown to reduce consumption, these findings are not at odds with those found here. The effect of information depends partially upon the *content* of the information. For example, in the caloric intake study, consumers were underestimating their consumption and therefore the feedback was negative and they reduced consumption (Bollinger et al., 2011), though in another study on calories postings, Loewenstein (2011) found that consumers increased caloric intake with improved information on caloric content.

Table 3.4. Effect on Monthly Input Demand

Independent Variable	Coefficient
Feedback	2.972***
	(0.993)
Medium Price Level	-6.289***
	(1.404)
High Price Level	-12.208***
	(1.310)
IBR82	12.192***
	(3.913)
IBR41	6.816***
	(3.913)
Producer Type	22.529***
	(3.188)
Average Input Requirements	25.568***
	(0.863)
constant	-11.501***
	(4.198)
Overall R^2	0.4717

Standard errors are in parentheses. *, **, *** denotes p-values of 0.10, 0.05 and 0.01 respectively.
Low Price Level and CMP are the categories left out of the price and rate structure dummy variable structures, respectively.

3.4.3. Weekly Decisions

Analyzing week-to-week *output* choices rather than input demand will illustrate how the participants adjusted their output choice behavior for each of the feedback treatments. Feedback reduces uncertainty and provides additional information. Participants are therefore expected to be more likely to adjust weekly output choices when they have access to this information.

To illustrate, I first compute the standard deviation from the average weekly output level for each participant in each month and compare the distribution of all participants by feedback treatment. Figure 3.2 illustrates this, showing that the standard deviation from the mean weekly output level increases with feedback, i.e., the distribution shifts to the right. This result is statistically significant and is robust to producer value type and rate structure type.

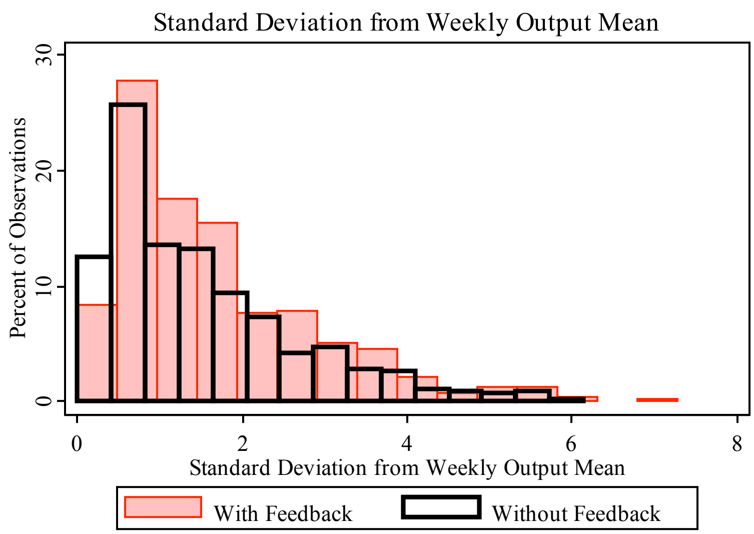


FIGURE 3.2. Distribution across All Sessions

Output choices in weeks without feedback are more correlated than the weekly output choices in months with the weekly feedback. With complete uncertainty, participants are only expected to make decisions based on their preference assignment, prices and expectations about the input requirement. High-value producers' output choices are slightly more correlated across weeks than the output choices of low-value producers, regardless of feedback treatment. Output choices in the CMP sessions are more correlated across weeks than in the IBR sessions. For the complete set of correlation coefficients, see Table A.2 in Appendix A.2.

The theoretical framework suggest that the effect of feedback is conditional on the actual information provided. The feedback effect is augmented by two pieces of information, (1) the previous week's input requirement condition relative to the average input requirement, and (2) the updated input use total. For example, if the feedback received *after* week 1 revealed that input requirement conditions were higher than expected, the individual may reduce their output choice in week 2. But, if the feedback revealed a lower-than-expected input requirement then the individual may instead increase her output choice in week 2. I segment the analysis into two sections, CMP observations and IBR observations, since theory predicts that the effect of feedback is influenced by the presence of a non-linear rate structure.

For each week, I run the following random effects model shown in Equation 9 where x_{js} denotes the output choice for participant j in week s. Even though the subscript s is used all independent variables actually vary at the individual or month level, with the exception of the Feedback interaction term. For CMP session participants, the updated input use total information should have less of an impact on decisions than in the IBR sessions since there are no pricing thresholds, and as such, we do not include this interaction term in the regression.[41] It was included on the weekly feedback screens in CMP sessions to avoid any bias in participants seeing different amounts of information across rate structure treatments.

$$\begin{aligned} x_{js} = \alpha_j + \beta_1 Feedback_{js} + \beta_2 Feedback \times [r_{s-1} - \overline{r}] + \beta_3 Feedback \times \sum_{1}^{s-1} w_{js} \\ + \beta_4 MedPrice_s + \beta_5 HighPrice_s + \beta_6 ProducerType + \varepsilon_{js} \end{aligned} \tag{9}$$

[41]Including the feedback interaction term with the updated input total results in insignificant coefficients for all feedback terms. This result isn't surprising because while the overall effect of feedback at the month level is significant, breaking it down by weekly output breaks down the effect into smaller and less significant effects. This is not the case for IBR sessions because the updated input total reduces marginal price uncertainty.

Table 3.5 presents the results, which suggest that feedback increases average weekly output levels, significantly in weeks 2 and 4, and the input requirement appears to not significantly influence weekly output choices.[42]

TABLE 3.5. Effect of Feedback on Weekly Output Choices: CMP sessions only

Dependent Var:	x_1	x_2	x_3	x_4
Feedback	0.184	0.378**	-0.169	0.442**
	(0.198)	(0.198)	(0.199)	(0.212)
Feedback$\times[r_{s-1} - \bar{r}]$	—	-0.015	0.133	0.036
		(0.116)	(0.103)	(0.123)

Standard errors are in parentheses. Results are from the random effects model (equation 9) which also controls for producer value type and price level.
*, **, *** denotes p-values of 0.10, 0.05 and 0.01 respectively.

In the IBR sessions, the updated input use total information *is* expected to affect weekly output choices since it allows participants to learn where input use is relative to the block boundary and marginal price threshold. Furthermore, this part of the feedback effect is likely to be different for individuals learning input use is above or below the pricing threshold. As such, for IBR sessions, the weekly output regression model in Equation 9 is split by updated input total (above or below block boundary). Table 3.6 presents these results.[43]

One issue in estimation of the effect of feedback, conditional on these pieces of information, is the fact that the updated input use total is a function of previous output decisions within the week. As noted earlier, week-to-week output decisions are correlated, making the updated input use total likely to be correlated with the error term. I use an instrumental

[42]For week 1, we can only test for the difference in expecting to have weekly feedback throughout the month.

[43]Again, for week 1, we can only test for the difference in expecting to have weekly feedback throughout the month. The participants know that they will be receiving weekly feedback throughout the coming 'month.' This knowledge appears to results in increased production in week 1, which is consistent with the precautionary savings literature. For week 2 estimation, a collinearity issue arises if both Feedback*$r_1 - \bar{r}$ and Feedback*w_1 are included as independent variables. As a result, only Feedback*$r_1 - \bar{r}$ is kept in the week 2 output regression.

variables estimation approach to address this issue. While input use totals are not random across weeks, the input requirement and whether or not the individual received weekly feedback are both random and not correlated with the error term.

Table 3.6. Effect of Feedback on Weekly Output Choices: IBR sessions only

Learn: $\sum_1^{s-1}(w_s) \leq B$				
Dependent Var:	x_1	x_2	x_3	x_4
Feedback	0.313**	0.222*	1.826***	4.134***
	(0.139)	(0.135)	(0.673)	(0.0138)
Feedback$\times[r_{s-1} - \bar{r}]$	—	-0.321***	-0.157	-0.016
		(0.075)	(0.138)	(0.151)
Feedback$\times \sum_1^{s-1}(w_s)$	—	—	-0.047***	0.0764***
			(0.018)	(0.0139)
Learn: $\sum_1^{s-1}(w_s) > B$				
Dependent Var:	x_1	$x_2^{\diamond}$	x_3	x_4
Feedback	—	-2.420**	-0.295	-1.599
		(0.949)	(0.461)	(2.984)
Feedback$\times[r_{s-1} - \bar{r}]$	—	-0.211	5.187***	-0.1222
		(0.723)	(0.242)	(0.232)
Feedback$\times \sum_1^{s-1}(w_s)$	—	—	0.008	0.0213
			(0.030)	(0.035)

$^{\diamond}$ Note that for the IBR82 sessions, no participants' input use total exceeds the block boundary until week 3. There are only 21 observations across the months in IBR41 sessions where a participant learns that input use is already over 41 after week 2.
Standard errors are in parentheses. Results are from the random effects model (equation 9) which also controls for producer value type and price levels. Sample is split by input total above or below block boundary.
*, **, *** denotes p-values of 0.10, 0.05 and 0.01 respectively.

If the individual learns that total input use is below the block boundary, feedback increases weekly output levels. This effect increases in magnitude across weeks. However, when the participant learns that their updated input total is above the block boundary, feedback decreases output production. The value of the previous week's input requirement relative to the average is generally negative, as expected, but typically not statistically significant. These results corroborate the bunching and risk preference results discussed in Section **??**.

3.5. Effect of Feedback on Price Responsiveness

Since feedback provides additional information to respond to, feedback will likely affect price responsiveness. To test this, I estimate Equation 8, but adjust the model to additionally include feeback-price level interaction terms. Table 3.7 shows the relative strengths of the effects of price and feedback on monthly input demand. The baseline average monthly input demand (28.35 units) is for low price level months without feedback. When facing the lowest price level, feedback has no significant effect on input demand. The overall effect of increasing the price above the low level is negative, i.e., input demand decreases. However, for both medium and high price levels, price responsiveness is muted for participants making decisions in months with weekly feedback. Prices drive input demand down, but feedback reduces uncertainty and drives input demand up.

Table 3.7. Relative Strength of Feedback and Price Effects

Baseline (No Feedback) Low Price D_{inputs}	28.340
Marginal Effects:	
Feedback*Low Price†	-0.151
	(1.718)
Medium Price Level†	-8.443***
	(1.857)
Feedback*Medium Price†	4.147**
	(1.718)
High Price Level†	-14.740***
	(1.785)
Feedback*High Price†	4.921***
	(1.718)

*, **, *** denotes p-values of 0.10, 0.05 and 0.01 respectively.
Estimates from a version of the random effects model 8 as seen in Table 3.4, but with price-feedback interaction terms.
† Relative to lowest price level months without feedback.

As outlined in the literature review, there are a number of studies that have found that feedback *increases* price responsiveness. I do not believe that those results are necessarily at odds with my findings. In this study, the effect of reducing quantity uncertainty (effect of feedback) is isolated as much as possible from the effect of removing price uncertainty. Given that most households do not know or understand the rate structure they face (Carter and Milon, 2005), it is likely that the field studies are capturing the co-mingled effect of a household learning about quantity *and* prices at the same time. In some cases, feedback has been provided in the midst of implementing a conservation pricing structure and/or other conservation messaging (e.g., drought conditions) concurrently. In this study, feedback is identified to have a positive effect on consumption for most participants. In other studies, this may still be the case but other incentives may be stronger and result in a net reduction in consumption.

3.6. Rate Structure Effects

The effect of feedback and price responsiveness varies by rate structure. To show this, I run the model in Equation 8 with the sample split by rate structure. The results presented in Table 3.8 show that effect of feedback is strongest under the constant marginal price rate structure, and the least impactful under the IBR with the largest first block width (82). Weekly feedback increases average input demand by approximately 4.4, 3.2 and 1.4 units for CMP, IBR41 and IBR82 sessions, respectively. Participants facing the IBR with block boundary of 41 input units are more responsive to feedback than those facing the IBR82 structure partially because there are fewer 'cheap' input units available to use before facing the higher marginal price, and therefore updated information on input use-to-date is more important. Reponsivesness to feedback may be strongest in the CMP sessions because, with the exception of the low price level months, participants do not have access to 'cheap' input units ($2/input). The CMP session participants may therefore 'value' the weekly feedback more than those in IBR sessions who, regardless of price level, will always be able to use some inputs at the lowest possible marginal price.

Table 3.8. Feedback and Price Effects across Rate Structures

Partial Effects on Monthly Input Demand

	CMP	IBR41	IBR82
Feedback Effect	4.412**	3.181**	1.375*
	(1.952)	(1.542)	(1.641)
Effect of Medium Price Level†	-6.422**	-10.245***	-2.187
	(1.952)	(2.180)	(-0.940)
Effect of High Price Level†	-14.236***	-14.620***	-7.822***
	(2.574)	(2.033)	(2.164)

*, **, *** denotes p-values of 0.10, 0.05 and 0.01 respectively.
Estimates from a version of the random effects model 8 as seen in Table 3.4, but with the sample split by rate structure.
† Relative to lowest price level.

This is corroborated by the fact that particpants are also less responsive to prices the further away the block boundary is, i.e., particpants in CMP and IBR41 sessions decrease input demand more in response to price change than those in the IBR82 sessions.[44] This result also makes sense because as the width of the first block decreases, more participants are impacted by the price change. Approximately 88% of observed monthly input demand totals are above the block boundary in the IBR41 sessions, whereas only 43% of observations are above the block boundary in the IBR82 sessions.[45] Most participants in the IBR41 sessions

[44]Recall that for CMP when the price changes, the price of all units change. For the IBR structures, only the price of the second block of units changes. When comparing price responsiveness, the two IBR structures can be directly compared for each price level. A CMP structure can be thought of as a IBR structure with a block boundary at zero units. However, given the design of the prices the comparison from the CMP to an IBR is less straightforward, as discussed in the experiment overview 3.2. For example, the medium price level for CMP is $3/input, but the block rate structures are priced at $2/input for the first block of units and $4/input for all units beyond the block boundary.

[45]The feedback effect appears small in the IBR82 sessions, but if we split the sample by input total above or below the block boundary as was done in the week-to-week analysis, results show that those below the block boundary respond positively to feedback and are less responsive to changes in block 2 prices. Participants

may be treating their rate structure more like a CMP structure since they, on average, expect to be in the second block and facing the higher marginal price.

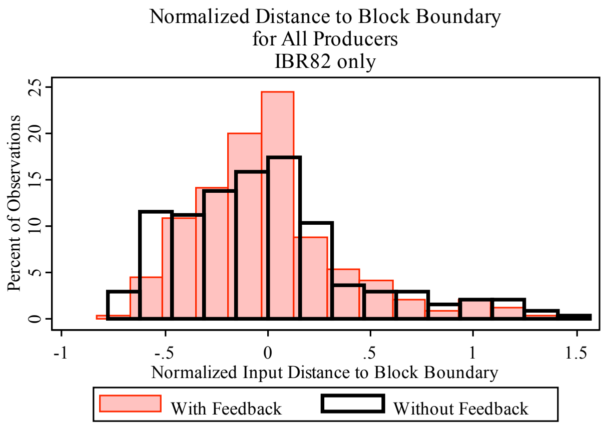
3.7. Behavioral Considerations

As some of the literature suggests, individuals may be responding to the 'wrong' information when provided with feedback in uncertain, complex decision-making environments (Lurie and Swaminathan, 2009; Diehl and Sterman, 1995; Atkins et al., 2002). The fact that participants are less price responsive when provided weekly feedback suggests that perhaps they are more responsive to the information about input use instead. In the IBR sessions, results of the week-by-week output analysis show that participants increase (decrease) input use if they learn that their current input total is below (above) the block boundary. Furthermore, written comments provided by participants after the experiment suggest that some focused excessively on the block boundary, and perceived the boundary as a 'goal' input level. Recall that Abrahamse et al. (2005) suggests that feedback may be more effective when paired with goal setting. In the absence of explicit goal setting, the participants may be assuming the block boundary is the goal for input demand. One possible explanation for this behavior is that participants in the IBR are 'targeting' the block boundary, and do so more obviously when they have feedback which informs where input use is relative to the boundary. To address this possibility, I generate a variable of input 'distance' to block boundary for observations in the IBR sessions.

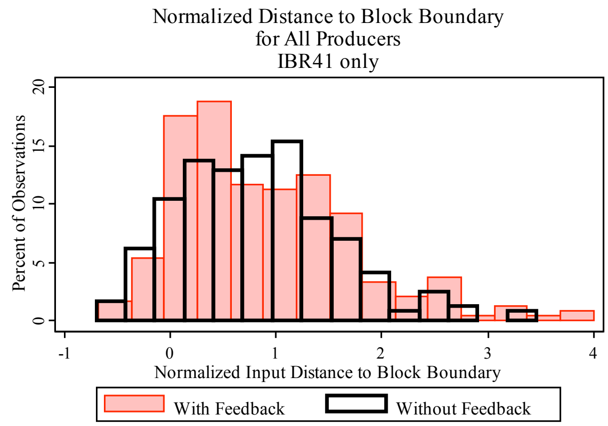
$$dist2block_{it} = \frac{MonthInputs_{it} - B_i}{B_i}$$

who are above the boundary in respond negatively to feedback and are significantly price responsive. As such, the combined effect is smaller and overall positive. However, this is not a perfect apples-to-apples comparison, since the effect of feedback is conditional on past behavior, which cannot be instrumented for as was done in the week-to-week analysis.

A value of zero would indicate that input demand for the month was equal to the block boundary (82 or 41). Values below (above) zero indicate input demand below (above) the block boundary.



(A) IBR82



(B) IBR41

FIGURE 3.3. Monthly Input Demand "Distance" to Block Boundary

Figure 3.3 shows that with feedback a great percentage of observations occur closer to the block boundary. With feedback, participants whose input use is below the block boundary increase consumption toward the block boundary, while those in the second block decrease consumption. This relative increase in observations around the block boundary is evidence of increased bunching, as discussed in the literature review (Section 3.1.2). The literature suggests that if a researcher observes a lack of bunching at a kink point, consumers may not know or understand the non-linear price schedule they face. Here, I suggest that without feedback there is less bunching because quantity is non-salient. Participants know the price schedule, but without feedback they are uncertain of if (or when) input demand is in the second block. With feedback, input quantity is more salient, distance to the second block (and the higher marginal prices) is more salient, and thus results in greater bunching at the kink points. However, for the IBR41 sessions, while some participants' input demand decreases toward the block boundary, there are a number who are above the block boundary and still increase input demand. If targeting were the correct explanation for behavior under an IBR structure, we would not expect this pattern.

The alternative, and more accurate, explanation for behavior seen in the experiment is risk preferences. As seen in the theoretical framework, the effect of feedback when facing a linear price structure hinges on risk preferences, e.g., a risk averse (seeking) individual is expected to increase (decrease) monthly output production and input use if provided feedback that reduces uncertainty (these findings are summarized in Tables 2.1). Figure 3.4 illustrates the percent change in monthly input demand with feedback, as compared to no weekly feedback, for CMP sessions. As predicted, risk seeking participants reduced input demand and risk averse participants increased input demand when provided complete weekly feedback. Risk neutral participants are predicted to have no difference in input demand, however we see an increase on average.[46]

Risk-related predictions will be muted or enhanced by the presence of a non-linear rate structure since, unlike the CMP structure, there is a positive probability of the consumer facing a higher marginal price. Furthermore, behavior induced by the non-linear rate structure depends on whether the individual expects total input use to fall above or below the block boundary. Figure 3.5 illustrates the effect of feedback conditional on risk class, with the IBR sample split by those whose input demand falls below or above the block boundary.[47]

[46]The theoretical framework shows that the effect of feedback will be influenced by the content of the feedback. On average the input requirements in the experiment are truly randomly drawn and therefore the input requirements are on average equal to 3. As such, when discussing changes in average monthly input demand there is no need to discuss input requirements specifically.

[47]Figure A.2, in the Appendix, instead splits the sample by producer-value type, which is a less precise proxy for expecting input demand to be below or above the block boundary.

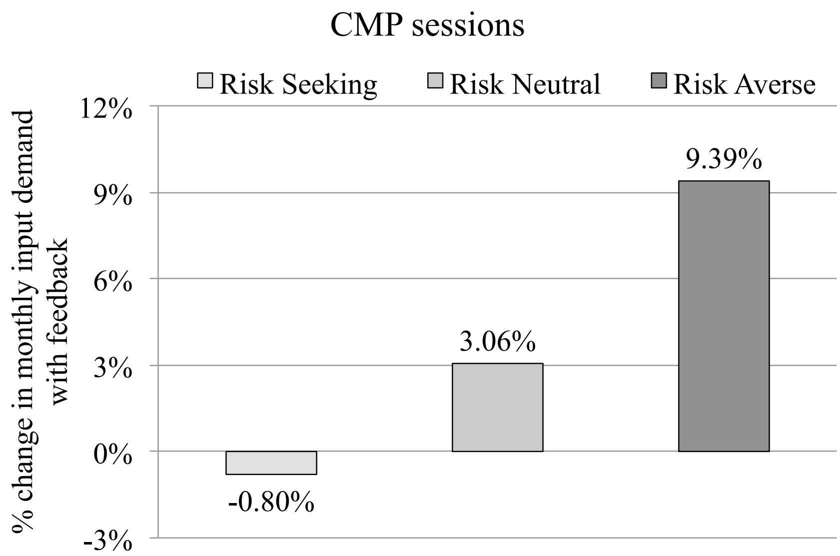


Figure 3.4. Effect of Feedback on Average Monthly Input Demand by Risk Class

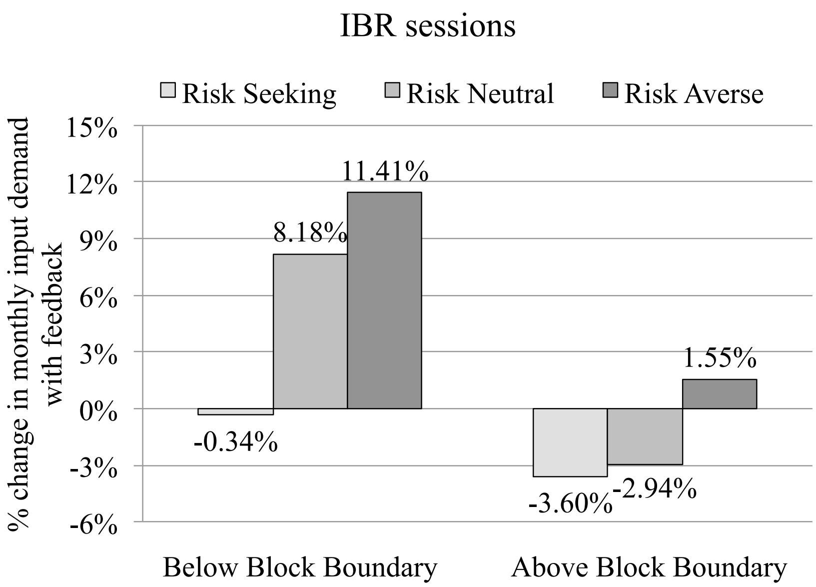


Figure 3.5. Effect of Feedback on Average Monthly Input Demand by Risk Class

As anticipated, risk neutral participants whose input demand is less than the block boundary increase average input demand when provided feedback, appearing to act as if they are risk averse. Risk averse participants below the block boundary increase average input demand by even more than the risk neutral participants when provided weekly feedback.

The risk seekers whose input demand falls below the block boundary slightly decrease input demand, suggesting that true risk preferences are stronger than the influence of the rate structure. The effect of feedback is also impacted by the rate structure for those whose input demand is in block 2: true risk neutral participants appear to be risk seeking by reducing monthly input demand when provided feedback, and true risk seekers reduce average monthly input demand by even more than the risk neutral participants. The risk averse individual still increases input demand when provided feedback, but by less than those below the block boundary illustrating the muting effect of the rate-structure. This again suggests that the influence of risk preferences are stronger than the influence of the rate structure.

The majority of participants are found to be risk averse or risk neutral in the Holt-Laury lottery, which explains why participants below the block boundary increase use, appearing to be 'target' the block boundary. For participants above the block boundary, feedback results in an increased input demand for those who are risk averse and a decrease for risk neutral and risk seeking individuals. As such, the predictions in the theoretical model match behavior in the experiment and dispel the possibility that consumers facing an IBR structure are targeting the block boundary.

3.8. Heterogeneity

3.8.1. Gender

Gender turns out to be a strong driver in differences across decision-making. To show this I run model in Equation 8 with the sample split by gender; results are presented in Table 3.9, the male participants were not systematically responsive to feedback as a group. Female participants, however, were significantly and positively responsive to feedback in terms of input demand. Table 3.9 is a condensed table; full regression results can be found in Table A.4 in the Appendix. Despite this result, female participants tend to earn less in profits over the course of the experiment. This suggests one of two things: (a) that females are more conservative in their production decisions to start with, so despite being responsive to feedback, they will necessarily earn less profit, or (b) female participants are ineffectively responding to feedback and reducing their earnings as a result. The gap between average earnings between months with and without weekly feedback, however, is larger for males than for females. Males also typically earned less in months with weekly feedback, suggesting that hypothesis (a) may be more accurate. We do find that even when controlling for producer value assignment, female participants consistently produced less output and used fewer inputs than their male counterparts.[48]

TABLE 3.9. Role of Gender

	Male	Female
Independent Variable	Monthly Input Demand	
Feedback	1.577	5.245***
	(1.230)	(1.504)
Medium Price Level	-4.684***	-8.920***
	(1.832)	(2.126)
High Price Level	-12.241***	-12.158***
	(1.709)	(1.983)

Standard errors are in parentheses.
*, **, *** denotes p-values of 0.10, 0.05 and 0.01 respectively.
Estimates from a version of the random effects model in Equation 8, but with the sample split by gender. Only the coefficients on feedback and price level dummy variables are included in this table.

Another possiblity for this difference stems from the evidence in the literature that females tend to be more risk averse and responsive than men. A meta-analysis of risk-taking tendencies found that women are more risk averse than men, a gap that decreases with age

[48]The result of gender differences in average output production and input use is statistically significant at the 1% level.

(Byrnes et al., 1999). Croson and Gneezy (2009) survey economic experiments and also find women to be more risk averse than men. However, gender is not strongly correlated with our risk preference measure and, on average, male participants are slightly more risk averse than the females. These facts do not support risk preferences as the reason for differences by gender in decision-making. As such, gender and risk preferences can be two unique ways of classifying consumers and explaining differences in decision-making.

3.9. Conclusion

This chapter explores the effect of quantity uncertainty on consumption and price responsiveness, in the presence of two common rate structures. The decision-making setting is designed to mimic household water and energy use, though this restriction is not necessary and the results can be applied to other similar decision-making settings. A theoretical framework containing an expected utility model generates predictions that are tested using data from a computerized laboratory experiment. The effect of removing backward uncertainty is found to depend on the realization of the uncertainty quantity, the rate structure and risk preferences.

While utility managers hope that providing households with more frequent feedback on consumption will encourage conservation and enhance existing pricing policies, this is not necessarily the case. Results suggest that more frequent feedback may induce individuals to consume more, not less. Demand will likely be more variable, and depending on the rate structure in place, individuals may be less responsive to prices, too. Participants become more responsive to feedback and prices when they are or expect to be impacted by price changes. These results leads to two considerations for rate structure design *with* the ability to frequently communicate with consumers: a constant marginal price may be more effective for encouraging price responsiveness, and price responsiveness under an increasing block rate greatly depends on the distribution of consumers.

Given that choices are made under some level of uncertainty, risk preferences play a key role: risk averse and risk neutral participants are positively responsive to feedback, while risk seeking participants tend to not respond to feedback but generally reduce consumption when backward uncertainty is removed. There is also evidence of rate structure induced risk preferences during the IBR sessions. Despite the common link between gender and risk preferences documented in the literature, this study finds no correlation, but does find that female participants clearly increase consumption in response to feedback and tend to make more conservative consumption decisions. Male participants, as a group, are less responsive to feedback. These results highlights the importance of understanding the consumer base and responsiveness: for example, who in a household pays the utility bills and influences water and energy consumption decisions?

This study contributes to the literature on decision-making under uncertainty and the literature on water/energy demand. First, this study provides a theoretical framework for the decision-making environment which incorporates two distinct types of quantity uncertainty (forward and backward), multiple decisions within a billing period and explicitly accounts for different categories of risk preferences. Second, the theory and the experimental results highlight important factors when considering rate structure and information design. Finally, the study provides an experimental baseline to compare to existing and future field studies. This paper contributes to a better understanding of consumer behavior under uncertainty, and serves as a basis for many additional research areas including the effect of different combinations of policy instruments and the effect of different presentations or frequencies of feedback.

CHAPTER 4

An Empirical Analysis on the effect of Combined Energy and Water Utility Bills

4.1. Introduction

In the American West, water supplies are increasingly variable during a time when population – and urban water demand – is expected to continue growing rapidly. As such, demand-side management (DSM) programs are becoming more important as utilities project less reliable water supplies. Price elasticity and the factors that influence water demand are of particular interest because price is increasingly used to reflect scarcity and encourage conservation (Faruqui et al., 2010). Furthermore, utilities are often constrained by zero-profit mandates yet have considerably high fixed costs. This means that utilities using volumetric pricing must be confident in the relationship between price and quantity demanded, since a change in either will affect revenue, which has serious implications for utilities' infrastructure projects and long-term planning (Olmstead et al., 2007). Water and energy utilities are increasingly pricing their services according to complex non-linear rate structures known as increasing block rate (IBR) structures.[49] There is uncertainty as to what degree consumers know about and understand these rate structures.

Household water/energy decision-making environments are significantly more complicated than the typical consumption decision. Liebman and Zeckhauser (2004) identify conditions that may prevent consumers from perfectly optimizing at the margin of household water/energy use: (1) Complex, non-linear rate structures that are updated or altered often,

[49]This is true for water utilities, though electric utilities are switching to time-of-use rate structures that better reflect the cost structure of electricity generation.

(2) a gap in time between the benefit of consumption and realization of the cost (payment), (3) combined or bundled goods/services, and (4) when the environment is not conducive to learning. These conditions partly stem from the fact that energy and water are actually inputs to other goods which makes it difficult for a customer to derive the cost of activities like air conditioning and clothes washing. Also, there are unclear and infrequent pricing signals and as a result, there is evidence that consumers may instead be responding to average prices or total bills rather than marginal prices. “Assuming that customers are perfectly informed and perfectly optimizing on the margin, is at odds with the way that nearly everyone actually thinks about their residential water and electricity consumption” (Borenstein, 2009).

This study provides new evidence surrounding Condition (3), specifically the question of how billing for multiple utility services through a combined bill influences price responsiveness to the price of water services. This analysis is made possible by a novel data set that includes billing and consumption information for water, electricity and natural gas for a large number of households across nearly ten years. A single utility provides all three services and also bills for all three services through a single monthly bill. Even when the cost of a billing period’s worth of consumption is realized, a given service’s price signal may be muddled by the costs of the other services. Consumers may be responding to total cost or to prices of other services. Even attentive customers might find the most efficient or cost-effective way to affect their cost by altering behavior unclear, and as such combined bills may render demand-management policies less effective. It may not be correct to model consumers price responsiveness in terms of the marginal price as in traditional economic theory if there is potential that the consumer is unclear or unaware of the relationship between quantity consumed and the marginal price.

In this study, I model the salience of the water price signal, given that water is billed along with electricity and natural gas within a single bill. I allow the responsiveness of price to vary by the weight of the water portion of the bill relative to the total utility bill. I find that responsiveness to water prices increases as the proportion of the total bill attributable to water services increases. Households pay more attention to water prices, when their water use contributes to a greater portion of their total utility spending. I also provide evidence that the number of services subscribed to, and therefore the number of price signals, also influences consumption patterns and price responsiveness. This study provides additional support of household water demand being generally inelastic, but not unresponsive, with respect to water prices. Given this unique data set I am able to provide evidence of how different combinations of bills, and the varying proportion of a bill attributable to water, affects water responsiveness.

This paper is organized as follows: First, I review the relevant literature. Next, I present the empirical models followed by a description of the data. Finally, I discuss the results and present some concluding remarks as well as some suggestions for future work in this area.

4.2. Literature Review

This study builds on work in the behavioral economics literature, including the bounded rationality literature, as well as the work in the salience literature, which covers how the availability and accessibility of information affects decision-making. I also discuss literature related to the effect of combined bills or purchases within the salience context. Much of the literature agrees that the typical household does not know the prices they face or how much they consume (Jordan, 2011; Carter and Milon, 2005). Households underestimate their water use by a factor of 2, on average (Attari, 2014). Attari (2014) also finds that most households perceive curtailing use as a more effective strategy to conserving water than efficiency improvements. This perception conflicts with expert recommendations on the most effective ways to reduce use. Similar findings for energy use are detailed in an earlier study Attari et al. (2010).

The bounded rationality literature explains that sometimes decision-makers use heuristics to transform a complex decision into an easier one.[50] This theory states that the use of average price as an approximation of actual marginal price is rational if the cognitive cost of responding to the marginal price is higher than the associated utility gain. Liebman and Zeckhauser (2004) termed this smoothing of a tiered rate structure as 'ironing'.[51] Ironing will occur "when there is a single payoff for all of the bundled choices within an accounting period" (Liebman and Zeckhauser, 2004). Average price is easy to calclate from information commonly provided on a utility bill.The gain from re-optimizing consumption with marginal price is likely to be quite small if consumers have already optimized with respect to average price since rate structures are complicated and most households do not have access to real time information on use, information that would be necessary to know the marginal price they face.[52] The case studies in Liebman and Zeckhauser (2004) show that a consumer may over-consume and be less price responsive under the conditions consistent with the complex decision-making environment surrounding household water/energy use.

[50]See Kahneman (2003), DellaVigna (2009) for an introduction to the bounded rationality literature.

[51]In addition to a theoretical treatment, Liebman and Zeckhauser (2004) illustrate ironing using the 1998 introduction of the Child Tax Credit.

[52]The rational inattention literature is somewhat related. It models attention as a scare resource. Individuals must decide how to allocate their attention and, in the context of this study, a household will have to choose what information surrounding their water and energy use to pay attention to and what to ignore. See Wiederholt (2010) for an introduction to rational inattention; see Ameriks et al. (2004) for a discussion of the 'absent-minded' consumer.

The salience literature focuses on how the accessibility and availability of information affects decision-making. Gaudin (2006) highlights that in markets with *ex post* billing, like municipal utilities, prices are less salient and “when prices are not transparent, elasticity estimates are potentially lower than their full information potential.” In her sample, including price Information on utility bills increased price responsiveness by 30% (Gaudin, 2006), and ”when prices are not transparent, elasticity estimates are potentially lower than their full information potential.” In a time-of-use pricing study, Jessoe et al. (2013) find that real-time information increased responsiveness to temporary price increases by three standard deviations.

Gilbert and Graff-Zivin (forthcoming) identify two key reasons that utility prices are likely not salient to consumers. First, rate structures are complicated and can confuse customers. Second, consumption decisions are made in real-time whereas the cost is only “experienced” monthly when the bill arrives. The infrequent access to quantity and price information makes it nearly impossible to respond to marginal prices at the point of consumption. And second, consumption decisions are spread out across appliances without price information for individual uses. Even if the marginal price of a unit of electricity were known with certainty, translating this price into the price of running the dishwasher or powering a flat screen television for an hour is not a trivial task (Gilbert and Graff-Zivin, ming, (forthcoming)).

There are several examples showing the effect of salience: Automatic bill payment is used by many households, often as a way to reduce the need to remember to pay the bill each month, and therefore to automatically reduce or eliminate any attention paid to utility bills. In a residential electricity study Sexton (forthcoming) finds that automatic bill pay reduces salience of electricity prices and increases electricity use by 5%, on average.[53] Gilbert and Graff-Zivin (forthcoming) find that households do reduce electricity consumption within a few days following receipt of their monthly electricity bill, but consumption increases over the course of the billing period as the salience of the most recent monthly bill diminishes.

The utility literature, with respect to non-linear rate structures, often gleans insights from the tax literature since many common tax structures are non-linear (e.g., income taxes). In a laboratory experiment using income tax tables, de Bartolome (1995) find that some participants clearly use their average tax rate rather than the marginal tax rate, a result which is at least partly due to the ease of the average rate calculation over the marginal rate calculation. In two separate field experiments, Chetty et al. (2009) find that the more salient the tax, the lower the resulting consumption level. The authors show this in the first experiment by illustrating that included sales tax in the posted price reduces consumption; in the second experiment they show that increases in excises taxes that are included in posted prices result in greater reductions in consumption than in sales taxes that are only added at the register (Chetty et al., 2009).

Water and energy prices are also likely to be less salient for many consumers since the weight of expenditures on utilities is low relative to overall household spending in a given month. Strong and Smith (2010): "Utilities are typically associated with a small fraction of a budget. Small price changes in any one of them are unlikely to induce large reallocation of income among all goods. This feature of demand can compound the difficulties in estimating household demand. The effects of small price changes may primarily induce reallocation of the expenditures on household utilities." Noting that many utility bills contain only a total

[53]Finkelstein (2009) finds that when drivers use electronic toll collection mechanisms, the toll become less salient and drivers become less sensitive, in terms of driving, to the toll price.

bill amount Jordan (2011) posits that households may respond to last month's bill, rather than their marginal price or even average price. "If consumers respond to more to the total amount of the bill rather than any one item, the use of water pricing along to provide conservation incentives may become less effective" (Jordan, 2011). This particular driver of the salience problem is not addressed in this study as it would require quite detailed household-level data on income and non-utility expenditures. For this study, however, I do identify and analyze a new reason that likely renders water and energy prices less salient to consumers where a single utility delivers all utility services: combined utility bills.

Literature on the effect of combined bills is quite limited. To my knowledge, the 'bill bundling' literature often consists of analysis of markets where multiple goods and services are bundled into one product, and the price of any individual good or service is less if purchased in a bundle than if the consumer were to purchase it a la carte (e.g., cable-internet-telephone bundles, season tickets, value meals, travel packeges, etc.). In this context, Soman and Gourville (2001) do a study of transaction decoupling and find that price bundling "often can and should decrease price sensitivity and increase purchase likelihood."

There are some similarities between the gap between benefits and costs that exist in the *ex post* billing world of water and energy utility services and credit cards. In an article on mental accounting, Thaler (1999) notes how when a given good or services is paid for via credit card, the payment will be bundled in with a number of other payments. When a bill contains multiple items, the effect of any individual purchase will lose salience. Because of this lack of association between the price paid for each product and the benefit associated with that product, the adverse impact of the payment is diminished (Soman and Gourville, 2001). Soman (2003) shows that the degree of payment transparency for a given payment mechanism is positively related to the "pain of paying" and negatively related to consumption levels. In another study on the effect of payment mechanisms, Prelec and Simester (2001) find that willingness-to-pay for sports tickets increased when customers were instructed to use credit cards (rather than cash). Similarly, when a monthly utility bill arrives, it is near impossible to parse out the cost of any given water or energy-using activity that contributed to the final bill.

4.3. Empirical Models

4.3.1. Baseline Model

I begin with a baseline model of water demand to provide evidence of differences in price responsiveness across bill types. I use average price rather than marginal price since the literature on this complex decision-making environment largely supports that this is the price signal households respond to, if any (Ito, 2014; Wichman, 2014; Kahn and Wolak, 2013). I use the lagged average price as the most recent price information will be from the previous bill (Arbués et al., 2003; Renwick and Archibald, 1998; Bushnell and Mansur, 2005; Wichman, 2014; Ito, 2014). Also, it can be argued that lagging the price variable address the fact that the average price and water use are co-determined when a household faces a non-linear rate structure. The log-log functional form is similar as models in Shin (1985); Nieswiadomy and Molina (1991); Taylor et al. (2004); Chetty et al. (2009), among others. The basic model is specified as follows, where subscript i denotes household i and subscript t denotes month t. X is a vector of exogenous control variables; see Table 4.1 for definitions.

$$ln(w_{i,t}) = \alpha + \beta_1 ln(AP_{i,t-1}) + \gamma(X)_{it} + \epsilon_{it} \tag{10}$$

I use this baseline model to first illustrate the difference in responsiveness to the water price signal when there are different numbers and combinations of services on a single utility bill.

4.3.2. Salience Model

There are a variety of reasons why the price of water may not be salient to the households making consumption decisions. In this model, I estimate the extent to which the salience of water price signals may be dampened if water consumption does not contribute much to the total utility bill. I test how the responsiveness to the lagged average price of water varies with the proportion of the total utility bill that stems from water services. My hypothesis is that as the proportion of the bill attributable to water services increases, price responsiveness will also increase. The salience model is specified as follows, where subscript i again denotes household i and subscript t denotes month t. X is a vector of exogenous control variables; see Table 4.1 for definitions.

$$ln(w_{i,t}) = \alpha + \beta_1 ln(AP_{i,t-1}) + \beta_2 ln(AP_{i,t-1}) \times \left(\frac{Wbill_{i,t-1}}{Tbill_{i,t-1}}\right) + \gamma(X)_{it} + \epsilon_{it} \tag{11}$$

The coeffecient on the lagged average price (β_1) will be the "base" price elasticity, and the coefficient on the interaction term (β_2) will be the price elasticity "adjustment factor." To determine the overall price elasticity, add the base elasticity to the water bill to total bill ratio times the adjustment factor. I first run this model with household level fixed effects across each of the bill types. Second, since the majority of households have Tri-bills, I use this subset to model four different specifications of the salience model. In two specifications

I control for household heterogeneity with household-specific fixed effects; in the other two I control for this with more granular zip code dummy variables and the low-to-high outdoor water use categorical variable. I also illustrate the effect of instrumenting for prices, which as noted above may not be needed given that the price variables are lagged.

4.4. Data

A large Western municipal utility provided household-level, monthly consumption and billing data from January 2000 through June 2010. This particular utility is somewhat unique in that it provides water services, electricity services and natural gas services. Customers may subscribe to any combination of these services, and all services are billed through a single monthly bill. Since this analysis focuses on water use, customers in this subset of the population fall into one of three categories: 'tri-bill' if they receive all three services, 'dual-bill' if they receive water and either electricity or natural gas, and 'single-bill' if they only receive water.[54] In the Western U.S., all households use water and electricity, only some use natural gas, too. As such, households that have tri-bills (receive water, electricity and natural gas through the utility) or an electric-water dual-bills likely do not get any other water or energy services from other providers.[55] Those households that do not get water or electricity from this particular utility likely live in a particular area that falls in the service area of another electricity or water provider. Therefore, the monthly billing records of water-only or water-natural gas dual-bills are incomplete; we do not observe their use or their bills of any services supplied by other providers. There may be unobservable differences across

[54] Note that the 'single-bill' type does not mean that the household does not use electricity or natural gas, but rather that they do not receive these services from the Utility that provided the data.

[55] While this is likely true, there is a possibility that some electric-water dual-bill households get natural gas services from another provider.

households with different combinations of bills. The majority of customers, approximately 88% of all observations in the initial data set, subscribe to all three services.

There are some analysis limitations that are a function of the data. The data has been stripped of any identifying information, save for the zip code and a household identification number. As such, individual level household demographic or socio-economic information is not included. While I can control for household-variation through household fixed effects, I cannot individually identify the effect of variables like income, house size, lawn size, or a number of other variables that would help to explain water demand. Also, though there is significant variation in prices across time, I cannot test the effect of implementing the increasing block rate structure on price responsiveness or price salience, as it was introduced along with non-price policies and media attention of drought conditions. In general, a huge challenge to estimating relationship between price and quantity demanded is the non-experimental natural of utility pricing (Nataraj and Hanemann, 2011).

I limit the data to households with a minimum water consumption of 133 cubic feet (cf), and a maximum of 10,000 cf. This ensures observations where people are continuously living in the home during the billing period, and eliminates extreme outliers where perhaps a leak lead to such inadvertently high levels of consumption. Average winter water use is around 800 cf, and average summer water use is around 3000 cf. The service area of this utility experienced a significant drought starting in 2002 and extending through 2005. The utility initially implemented voluntary watering restrictions, but in 2003 turned to mandatory watering restrictions. As the drought intensity eventually lessened, the utility went back to voluntary restrictions starting at the end of 2005. In this case, mandatory restrictions on residential customers consist of limits on the time of day and the number of days a household can water outdoors in a given week. This utility enacted three levels of mandatory restrictions over time that reflect the varying intensity of drought conditions; watering was limited to either one, two or three days a week. I do not include yearly dummies or other dummies that might encompass all years within the drought period or all years post-drought. The reason for this is that the various restriction variables capture these time periods. Prior to the drought, there are no restrictions in place. Leading up to the drought, nearly all bill period days in the Summer of 2002 are under voluntary restrictions. During the drought, nearly all bill period days are under some type of mandatory restrictions. After the drought, nearly all bill period days are under voluntary restrictions. Table 4.1 contains definitions of all variables used in this study.

TABLE 4.1. Definition of Variables

Variable	Definition
w	water consumption in cubic feet [56]
AP	Average Price (including fixed costs) of Water [57]
#BPdays	Number of days in the billing period
BlockRate	Dummy; = 1 if increasing block rate structure in place
02Volun	% of days in BP under Summer 2002 voluntary restrictions
OneDayRestrict	% of days in BP under 1 day only watering mandatory restrictions
TwoDayRestrict	% of days in BP under 2 days only watering mandatory restrictions
ThreeDayRestrict	% of days in BP under 3 days only watering mandatory restrictions
0506Volun	% of days in BP under voluntary restrictions starting Summer 2005
Wbill	Water bill
Tbill	Total bill[58]
MaxTemp	Maximum temperature in °F
Precip	Inches of precipitation
Unemp	6-month moving average of the unemployment rate
LowtoHigh	Categorical variable (1-7) of low to high outdoor water users[59]

[56]Water consumption is measured in cubic feet (cf); for reference, 1 cubic foot of water is approximately 7.5 gallons of water.

[57]Average price for an observation is calculated as the total water bill divided by total water consumption.

[58]Total bill consists of all charges for the combination of utility services subscribed to; may include water, electricity and/or natural gas services

[59]A value of 1 indicates very low outdoor water use, whereas a value of 7 indicates that the household is among the highest outdoor water users. See Table B.1 in the Appendix for how these categories are defined.

Table 4.2 presents some summary statistics of the variables in the model. A billing period is typically about 30 days. The mean value for the block rate structure dummy indicates that 55% of the observations were during months when an IBR was in place. This area of the United States is quite arid as indicated by an average precipitation of just over one inch per month. The Table 4.2 also presents some specifics on water consumption, water bills and total bills by the combined bill type. Note that average water consumption, and therefore the average water bill, does not vary much across bill types. There is significant variation in the amount of total bills and therefore the proportion of the total bill driven by water services. On average, Tri-bills have the highest total utility bills and also the lowest ratio of water bill to total bill. Average utility bills are more similar for the dual-bill households, though electric-water dual bills tend to be slightly higher.

Table 4.2. Summary Statistics

Variable	Mean	Min	Max
#BP days	30	26	35
BlockRate	0.55	0	1
MaxTemp	63.4° F	33.6° F	92.5° F
Precip	1.14”	0”	8.19”
	Tri-Bills		
w (cf)	1291	134	10,000
Wbill	$32.17	$6.19	$766.40
Tbill	$155.58	$25.11	$1197.57
Wbill/Tbill	0.219	0.015	0.910
	Electric & Water Bills		
w (cf)	1290	134	9,572
Wbill	$33.97	$6.72	$360.36
Tbill	$110.28	$11.00	$635.95
Wbill/Tbill	0.311	0.037	0.915
	Natural Gas & Water Bills		
w (cf)	1,293	144	8,240
Wbill	$33.50	$7.04	$445.67
Tbill	$95.82	$18.21	$618.28
Wbill/Tbill	0.396	0.037	0.960
	Water Only Bills		
w (cf)	1076	133	9,463
Wbill	$28.78	$6.40	$462.06
Tbill	$28.78	$6.40	$462.06
Wbill/Tbill	1	1	1

4.4.1. Price Variation

Figure 4.1 provides an illustration of the variation in the volumetric water rates over the time span of the data set for a few levels of water consumption. In response to drought conditions and changes in state-level recommendations about rate structures, the first three-tier increasing block rate structure was put in place beginning in July 2002. From 2002 through 2005, the IBR was only in place from May to October, with a constant marginal price in place the rest of the months. Starting in May of 2006, the block rate structure is implemented place year-round. There are fixed fees as part of the water bill. These are constant charges assessed on a per-day basis, i.e., the only variation in the fixed cost portion of a bill stems from the number of days in the billing period. These fees range from 14 cents per day in 1999 up to almost 34 cents per day in 2010.

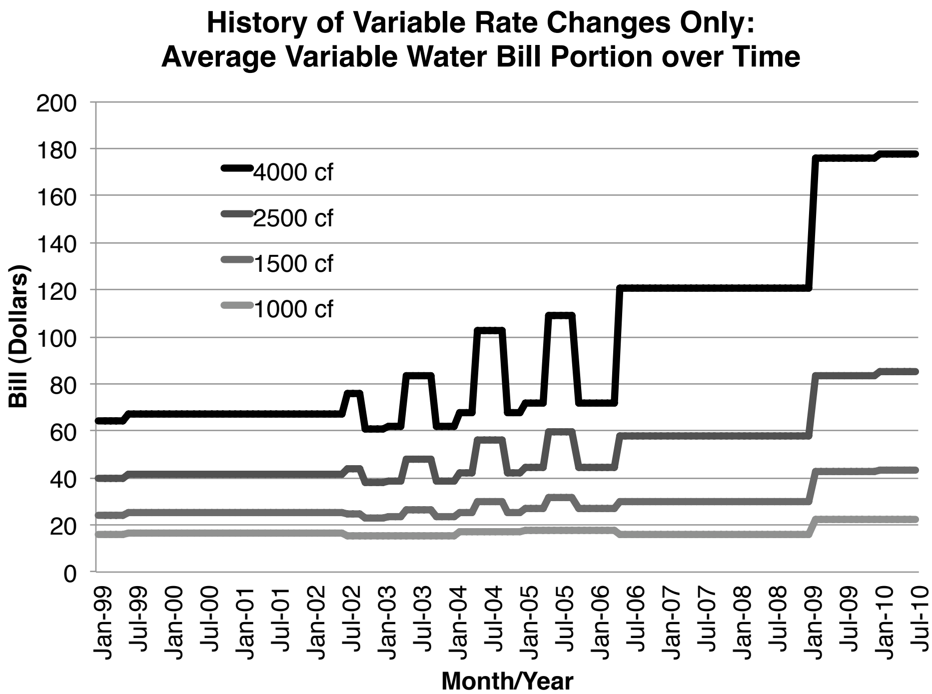


FIGURE 4.1. Rate Changes

Figure 4.2 illustrates how marginal price, average price, and average price without fixed costs varies across different levels of water consumption. The top graph is an example from the first series of block rate structures, when the IBR was in place only during summer months. The block 1 boundary is at 999 cf and the block 2 boundary is at 2999 cf. The second graph illustrates the year-round IBR that began in 2006; now the second block boundary is at 2499 cf. For consumption levels within the first block, average price is notably higher than marginal price. Average price without fixed costs is exactly equal to marginal price. For consumption beyond the first block boundary, average price is always less than the marginal price. Also, average price calculated with and without fixed costs are not significantly different, except for those consuming below 999 cubic feet (i.e., in Block 1).

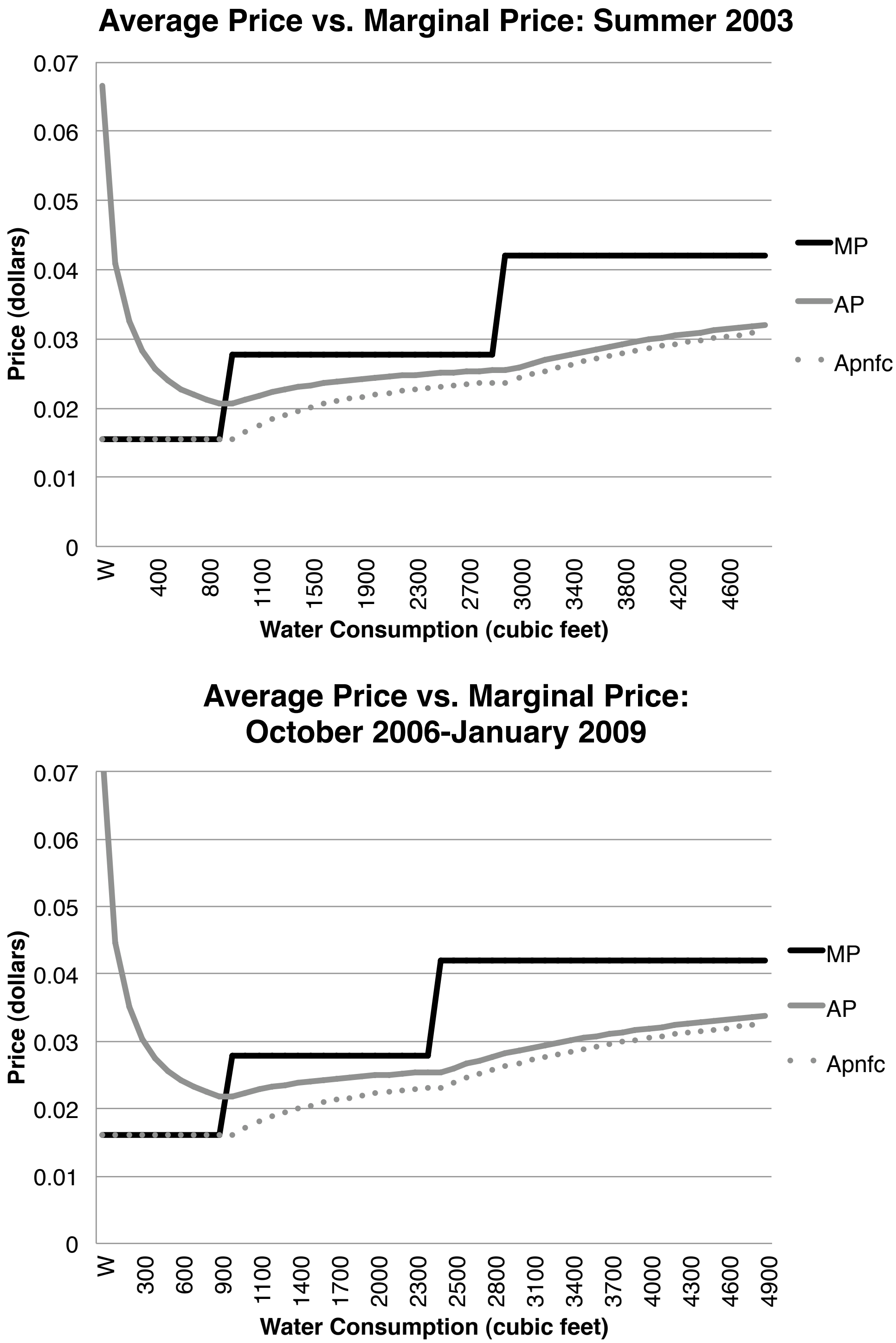


Figure 4.2. Price Comparisons

4.4.2. Bill Variation

The portion of the total utility bill attributable to water services varies noticeably throughout the year; see Figures 4.3 and 4.4 for the variation across Tri-Bill households. This water proportion clearly increases during the summer months. The electricity portion tends to stay the same year-round, with a slight increase in the summer months, likely due to air conditioning use. Natural gas use is quite low during the summer, and is largest during winter months as homes in this area heat with natural gas. The total bill itself varies quite a bit across months. For this particular part of the United States, bills are highest in the winter months and lowest in the 'shoulder' months, like May and September, when there is very little outdoor water use yet temperatures are such that neither heating or cooling is significantly necessary. These graphs illustrate why responsiveness to water prices is typically found to be greater in the summer months than the winter months, but still may not be elastic. While the proportion of the total bill attributable to water consumption increases, the total utility bill decreases, which may render lower price responsiveness to utilities in general.

Figures 4.5 and 4.6 provide the breakdowns for the electricity and water dual-bills. Notice that for these households, the bill has less of a summer-winter seasonality to it. Also, the electricity bill is on average greater than 50% in every month. Figures 4.7 and 4.8 provide the breakdowns for the natural gas and water dual-bills. These bills have a very clear seasonal pattern. The water bill portion typically is greater than half during the summer months, but is a quite small portion during the winter months.

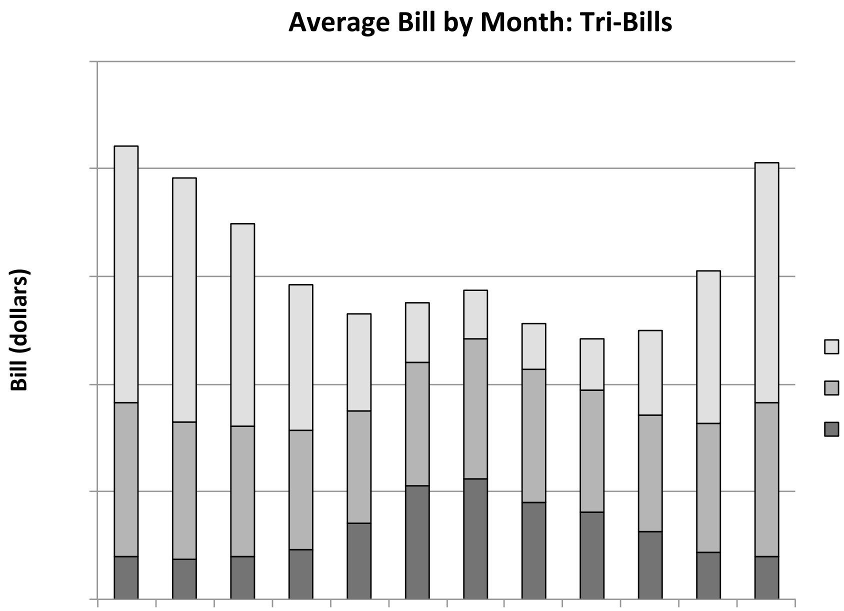


Figure 4.3. Tri-Bill Variation (A)

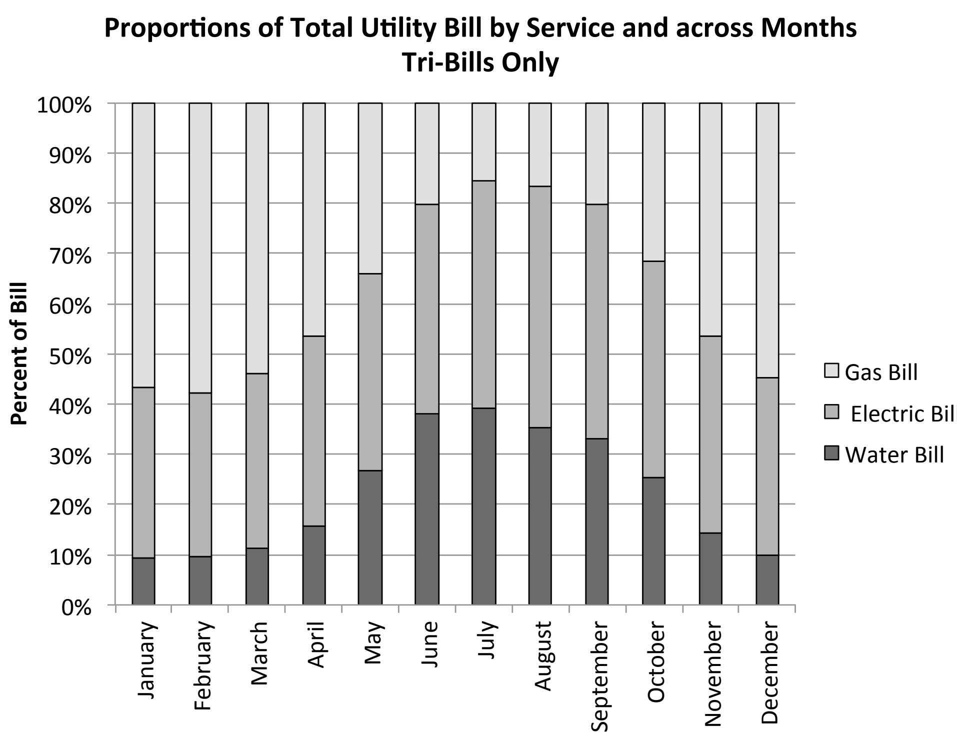


Figure 4.4. Tri-Bill Variation (B)

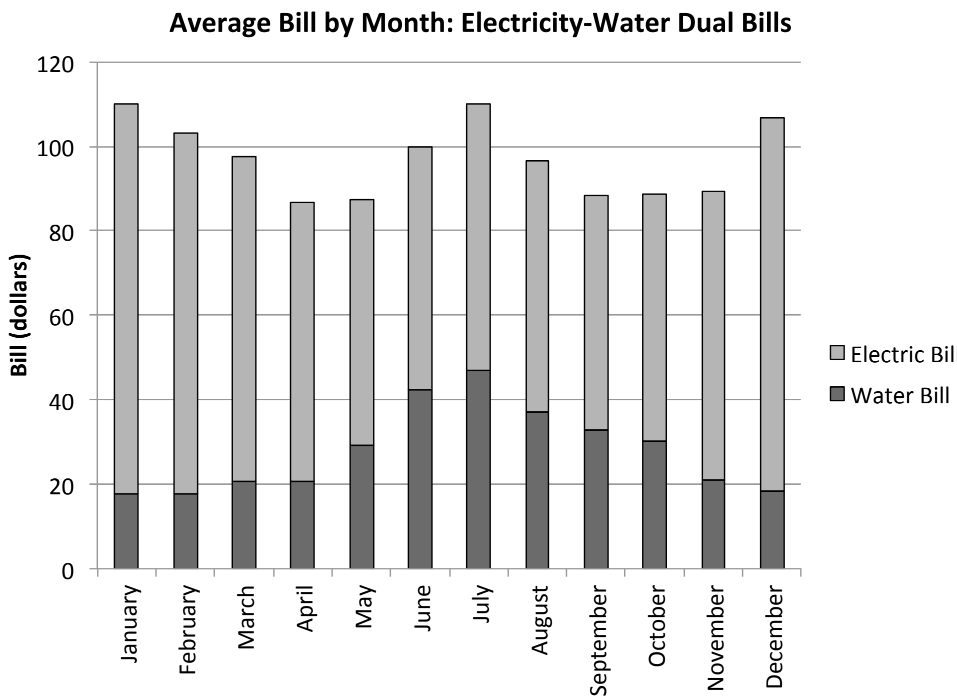


Figure 4.5. Electric & Water Dual-Bill Variation (A)

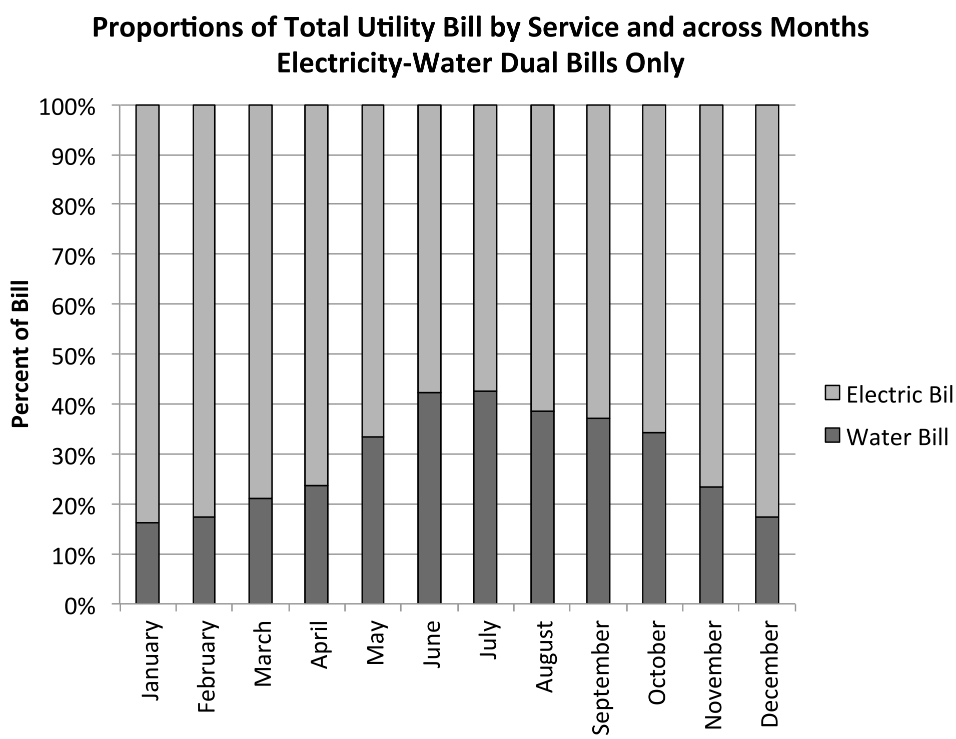


Figure 4.6. Electric & Water Dual-Bill Variation (B)

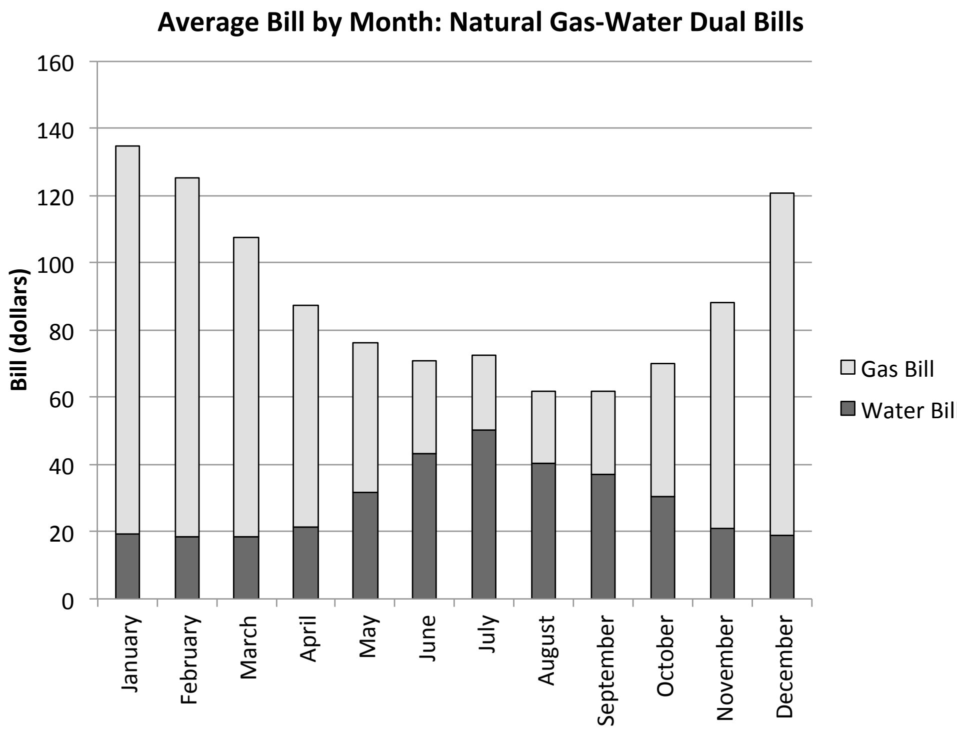


FIGURE 4.7. Natural Gas & Water Dual-Bill Variation (A)

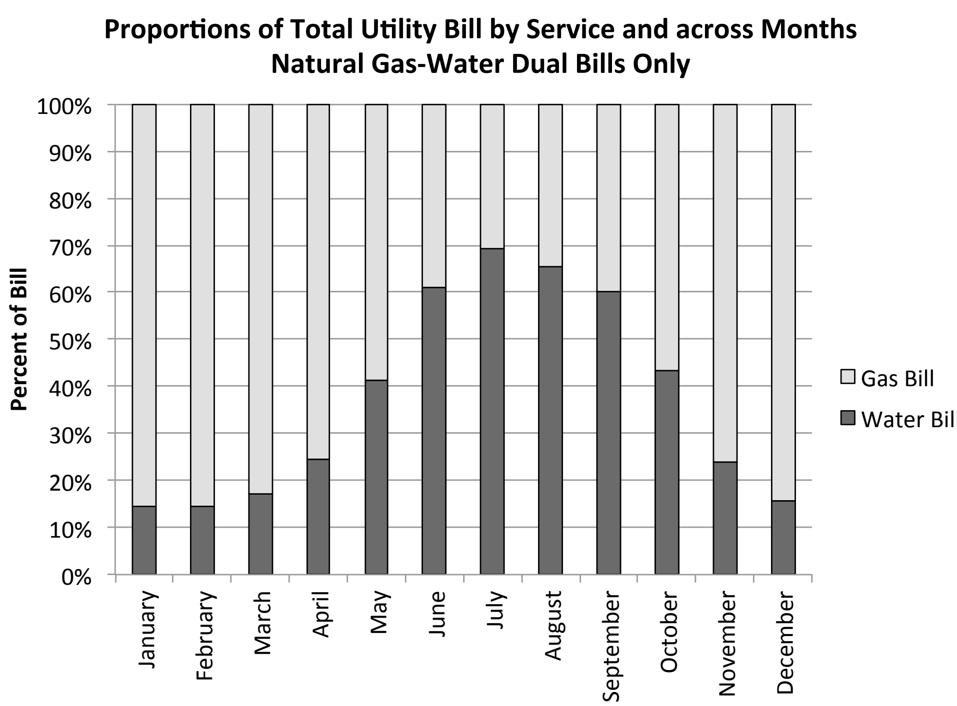


FIGURE 4.8. Natural Gas & Water Dual-Bill Variation (B)

4.5. Results

As shown in Table 4.3, the baseline model results provide initial evidence of differences in price elasticity across bill types. Those households who only receive water services from this utility have the highest price elasticity. Households with two or three services on their single bill exhibit less price responsiveness. We would expect that households with all three services on one bill would be less responsive to the price of water; however, this is not the case. Dual-bill households with natural gas are more responsive to the price of water than dual-bill households with electricity. This may be because charges for water consumption are on average always less than electricity charges for households with electric-water dual bills (see Figures 4.5 and 4.6), and thus these households may be more responsive to the electricity portion of their bills. Full model results can be found in Table B.2 in the Chapter 4 Appendix.

Table 4.3. Elasticity estimates without adjustment factor across Bill Type

	Price Elasticity
Tri-Bill	-0.758
Water & Electricity	-0.596
Water & Natural Gas	-0.642
Water Only	-0.956

Price Elasticity estimates presented only; all estimates presented are significant at the 1% level.

4.5.1. Salience Model Results

Referring back to the summary statistics in Table 4.2, average water consumption is not notably different across bill types. Yet, in the baseline results above, there is evidence of different price responsiveness across bill types. Using the salience model, I illustrate that the portion of the total bill stemming from water services affects water price responsiveness.

Table 4.4 presents the results for the tri-bill population across four different specifications of the salience model. These specifications represent various ways to control for household-level heterogeneity as well as ways to account for possible endogeneity in the co-determination of consumption and average price. The fixed effect (FE) specifications controls for household heterogeneity with household-level fixed effects. The instrumental variables (IV) specifications instrument for both the base price variable and the interaction term; the instruments are the parameters of the water block rate structure, including fixed charge per day and the marginal prices of each block, as well as fixed charges per day for electricity and natural gas. The IV specification without fixed effects includes zip code dummy variables as well as the low-to-high categorical variable, which controls for different levels of outdoor water use. Ignoring the IV component for a moment, the results are similar between specifications (1) to (2) and the results are similar between specifications from (3) to (4). This suggests that when a researcher does not have observations attributed to a specific household, controlling for differences across observations using more granular variables (like zip code) may be a reliable alternative. While the magnitude varies across specifications, the story remains the same.

Table 4.4. Salience Model Results

Specification	(1)	(2)	(3)	(4)
Dependent variable: $ln(w_{it})$	OLS	FE	IV	FE+IV
$ln(AP_{i,t-1})$	-1.072	-0.536	-0.188	-0.172
	(.004)***	(.004)***	(.010)***	(.008)***
$ln(AP_{i,t-1}) \times (Wbill_{i,t-1}/Tbill_{i,t-1})$	-0.672	-0.617	-0.281	-0.302
	(.002)***	(.002)***	(.023)***	(.018)***
#BP days	0.040	0.041	0.042	0.042
	(.001)***	(.001)***	(.001)***	(.001)***
BlockRate	-0.039	-0.046	-0.067	-0.067
	(.003)***	(.002)***	(.003)***	(.002)***
02Volun	-0.534	-0.346	-0.129	-0.137
	(.007)***	(.006)	(.010)***	(.008)***
OneDayRestrict	-0.145	-0.119	-0.120	-0.123
	(.002)	(.002)**	(.004)***	(.003)***
TwoDayRestrict	-0.149	-0.105	-0.087	-0.091
	(.003)***	(.003)***	(.004)***	(.003)***
ThreeDayRestrict	-0.018	-0.030	-0.045	-0.050
	(.004)***	(.003)	(.005)***	(.003)***
0506Volun	0.084	-0.131	-0.089	-0.095
	(.003)***	(.002)	(.004)**	(.003)***
MaxTemp	0.010	0.012	0.017	0.017
	(.001)***	(.001)***	(.003)***	(.001)***
Precip	-0.042	-0.050	-0.050	-0.051
	(.001)***	(.001)***	(.001)***	(.001)***
Unemp	0.066	0.023	-0.003	-0.005
	(.001)***	(.000)***	(.001)***	(.001)***
constant	0.071	2.441	3.389	3.876
	(525.4)	(.020)***	(.367)***	(.033)***
Month Dummies	✓	✓	✓	✓
Zip Code Dummies	✓		✓	
R^2	0.6527	0.5846	0.5597	0.4779
$n = 497384$			*(groups = 4291)*	

Standard errors are in parentheses.
*, **, *** denotes p-values of 0.10, 0.05 and 0.01 respectively.
Both price-related variables are instrumented for using the parameters of the water block rate structure, including fixed charge per day and the marginal prices of each block, as well as fixed charges per day for electricity and natural gas.

Responsiveness to the lagged average price of water is a function of the proportion of the total bill attributable to water services. As shown in Table 4.5, the base price elasticity ranges from -0.172 to -1.072 and the adjustment factor varies from -0.281 to -0.672, depending on the model specification. Regardless, the larger the bill portion that is attributable to water services, the larger the price responsiveness. These results resonate with the existing literature and anecdotal evidence, by showing that household responsiveness to water prices is inelastic (range is typically between -0.3 and -0.7), and that households are less responsive as water services contribute less to their overall utility bill expenditures (Arbués et al., 2003).

Regardless of specification, there is consistency across the coefficients of the other variables included. They are also of the expected sign and are statistically significant. An additional day in the billing period, increases water consumption by around 4%. Mandatory restrictions reduce water consumption. The presence of a block rate structure reduces water consumption by 4.4%, on average. Higher levels of precipitation reduce water use, whereas higher average maximum temperatures increase water use. These weather results are likely largely driven by variation across summer months.

Table 4.5 boils down the essential information from the results in Table 4.4. The first column of elasticities are the base elasticities from each of the four specifications. The second column contains the adjustment factor. Using the minimum, mean, and maximum water bill proportions found in Table 4.2, I calculated the price elasticities for each category across each specification. This illustrates the range of elasticities, given the range of the proportion of the total bill driven by water charges.

Table 4.5. Elasticity Estimates: Tri-Bills Only

			Based on Water Bill Proportions		
Specification	Base Elasticity	Adjustment Factor	Min	Mean	Max
(1)	-1.072	-0.672	-1.082	-1.218	-1.6835
(2)	-0.536	-0.617	-0.545	-0.671	-1.097
(3)	-0.188	-0.281	-0.192	-0.250	-0.444
(4)	-0.172	-0.301	-0.176	-0.240	-0.446

Min, Mean and Max water bill proportions can be found the the summary statistics table.
Sample calculation for specification (1) overall elasticity:

As discussed in the literature, some authors use lagged prices to address the co-determination of contemporaneous price and consumption variables because lagged price variables do not co-determine current water consumption. Other authors use instrumental variables to address the issue. Given that the literature suggests that households respond to lagged average price, this is the price variable used in this study. I present the results with and without the IV technique to illustrate the impact on the estimates. Using IV results in a significantly smaller base price elasticity and adjustment factor. The first stage of the IV process predicts just under 60% of the variation in the price variables (base elasticity and the adjustment factor). Using the IV technique tends to result in smaller estimates and generally larger standard errors. Given that lagging prices is a means to account for co-determination and that estimates without the IV technique fall in line better with existing estimates, the fixed effects specification is likely the most appropriate.

Moving forward, I employ specification (2) only. I do this for a two main reasons: First, given that we have household identifiers for each observation and little other household-specific data, then household-level fixed effects will be a more valuable way to control for household heterogeneity than the broader zip code dummy variable approach. Second, with the smaller number of observations across the remaining bill types, and given that there is support for lagging average price as a reasonable means to address any endogeneity, there is no pressing need for instrumental variables. Table 4.6 presents only the estimates for the price variables for across each bill type. Along with the base elasticity and the adjustment factor, I include the range of overall elasticities for each bill type based on the minimum, mean and maximum proportion of the total bill stemming from water charges.[60] These results maintain the patterns across bill type found above, but highlight the range of elasticities once we account for varying price salience from the combined bill. Full model results can be found in Table B.3 in the Chapter 4 Appendix.

Table 4.6. Estimates across Bill Type

			Overall Elasticity		
	Base Elasticity	Adjustment Factor	Min	Mean	Max
Tri-Bill	-0.536	-0.617	-0.545	-0.671	-1.097
Water & Electricity	-0.293	-0.449	-0.309	-0.432	-0.704
Water & Natural Gas	-0.467	-0.319	-0.487	-0.602	-0.782
Water Only	-0.959	N/A	-0.959	-0.959	-0.959

Estimates are from the Salience Model run with household level fixed effects, but no IV. All estimates presented are significant at the 1% level.
Min, Mean and Max water bill proportions can be found the the summary statistics table.
Sample calculation: $-0.536 + (-0.617) * (0.219) = -0.671 =$ Tri-Bill overall elasticity for the mean bill ratio

Table 4.6 illustrates that there are indeed differences in responsiveness across bill types; the range in estimates across bill type echoes the preliminary results presented in Table4.3. Households receiving only a separate water bill are the most responsive, with the exception of tri-bill households whose bill is over 90% driven by water consumption. Households paying tri-bills that look like this might be the most responsive to water prices because most of the bill is driven by water use, and the average total bill for tri-bill households is greater that total bills for households only subscribing to water services. Tri-bill households exhibit a

[60] See the summary statistics (Table 4.2) for the specific ratios.

wider range of responsiveness than the other bill types, which is in part because the majority of customers in this dataset are tri-bill households. There is naturally going to be greater heterogeneity across this group.

For the gas-water dual bills, responsiveness to water is on average higher than for households receiving electric-water dual bills. On average, households with only gas and water services tend to have natural gas use dominate their bills in the winter, and water use dominate the bill in the summer. For households with only electricity and water services, electric bill is on average always more than half of the total utility bill, regardless of the season. During the summer months, total bills tend to be lower for natural gas-water dual bill and tri-bill households, whereas electric-water dual bill households' total bills tends to be lowest in the shoulder months (April-May; September-October). When the total bill is on average lower while the water proportion is usually higher, like it is for natural gas-water dual bills and tri-bill households, the water price signal is more salient (because the other services are lower and less significant drivers of expenditures). This also may explain why electric-water dual bill households are less responsive to water prices; they may be more responsive to electricity prices instead. Finally, both dual bill types are less responsive than tri-bill types because tri-bill totals tend to be larger than either of the dual bill totals.

4.6. Conclusion

This study provides new evidence explaining residential responsiveness to water prices. The analysis shows that the informational environment of the utility bill and the salience of the water price driven by the water bill contribute to varying levels of responsiveness. Responsiveness varies by the number and type of services bill through the single utility bill. Responsiveness to the lagged average price of water is a function of the proportion of the total utility bill stemming from water services. Households may be thinking of utilities as a combined area of expenditure, especially since they only see a single bill. Given the pattern of energy and water use over the course of a year, it may be that households are responding to higher utility bills by reducing energy or natural gas consumption instead of water consumption. While we cannot expect that a utility will switch its billing process to individual bills per service, the results do highlight why household responsiveness to water prices may be inelastic and what drive some of the variation. If the utility desires greater responsiveness to water price, they will need to make the price signal more salient. With greater use of smart meter technology, online web portals and in-home displays, there are many opportunities on the horizon for communicating consumption and prices to consumers. Some possibly extensions of this research will be discussed in Chapter 5, the Conclusion.

CHAPTER 5

Conclusion

This collection of research provides new evidence on how the informational setting influences household water and energy use decision-making. Water and energy use fit into a category of decision-making that is quite complex, though not wholly unique to these goods.[61] There are many reasons to expect decision-making in this environment to not perfectly conform to the assumptions nor the results of rational decision-making theory. Households make choices armed with imperfect, infrequent information and face uncertainty (and/or do not easily have access to information) about how much they are consuming and what prices they face. This research has investigated how the timing of information can reduce uncertainty and affect consumption choices, how the effect of the timing of information changes under different price structures and, how a combined bill for multiple services dampens the price signal of any individual service.

As discussed in the Introductory Chapter, there exists a pressing need to manage use of natural resources more efficiently and effectively. The two major environmental issues addressed here are (1) increasing greenhouse gas emissions and, (2) increasing variability and scarcity of water. Households contribute to these problems through common, routine activities like watering their lawns and watching television. Supply expansion of energy and water resources is limited and contains serious environmental trade-offs.[62] To meet future needs, utilities need demand-side management (DSM) policies to result in more reliable and consistent consumer responsiveness. However, it is clear that most households do not know

[61] The decision-making environment present here can apply to energy use, healthcare, cell phone use, credit cards, and labor supply.

[62] Expanding supplies is increasingly less reliable, more regulated, and more taxing on the environment.

how much energy or water they consume, do not know the prices they face, and do not know the best way to reduce use. Given the existing technology and infrastructure, households do not have the information or tools to effectively manage their consumption or the resulting costs. By improving the informational environment surrounding household water and energy use, there will be great capacity for households to use water and energy more efficiently and ultimately make choices that will help reduce the severity of climate change and water issues.

Consumers need to have greater control over consumption and costs. The United States government sees the smart grid as a means to modernize the U.S. electricity transmission and distribution system, which involves the "integration of 'smart' appliances and consumer devices" as well as "provision to consumers of timely information and control options" (Congress, 2007).[63] The Energy Independence and Security Act of 2007 notes that "for the United States to realize its full [energy] demand response potential, customers must have access to, and a better understanding of, information about real-time or near-real-time prices" (Congress, 2007). Though much of the focus is currently on the role of advanced metering infrastructure (AMI) technology in the electricity industry, there is increasing installation of AMI on the water side, too (John, 2012). Historically, water utilities tend to lag, but eventually follow, the direction of electric utilities.

In order for utilities to forecast demand, predict revenue streams, and plan for long-term capital projects, they need to know how their customers respond to price. The costs of addressing aging infrastructure and future supply development will definitely lead to increases in retail prices. For example, Parkville Water District in Leadville, Colorado is increasing the fixed charge portion and the price of each block in their tier rate structure; from

[63] Though much of the attention is on smart grid development in the energy sector, there is growth on the water side, too. See the summarizing article: John (2012). Historically, water utilities tend to lag, but eventually follow, the direction of electric utilities.

their recent press release: “The rate increase is necessary to keep up with expenses, he [Greg Teter, Parkville general manager] said. The district would like to put away something in a capital-reserve fund, but its hard to project what the expenses will be each year. Parkville is looking at $500,000 in capital expenses this year as it deals with 130-year-old water lines and 120-year-old dams, Teter said” (Martinek, 2014).

In areas like the Western United States, nearly every utility has a set of policies designed to reduce consumption. Conservation pricing policies can be used to effectively influence consumption if people have better information about quantity, rate structures and prices. As noted by Jessoe et al. (2013), there is “a recent tendency for electricity and water regulators to eschew market-based approaches in favor of non-market instruments. Electric utilities have made social pressure a cornerstone of recent energy conservation efforts and federal authorities rely heavily on efficiency standards. To respond to droughts, water authorities tend to use non-pecuniary approaches (Olmstead and Stavins 2009). And while these programs have been shown to achieve conservation (Allcott 2011b, Ferraro and Price 2011), under full information policymakers should view price as an effective tool to achieve their objective.” As more dynamic pricing systems are put in place, information and ‘smart’ technology will be critical in enabling customers to respond efficiently, reduced the system demand (peak demand) by reducing their own demand (and their own bills). Utilities need to provide “timely and actionable information to consumers in order to maximize the effectiveness of nonlinear retail price schemes” (Kahn and Wolak, 2013). This dissertation shows how important the informational setting is: Without the proper level of information and understanding, economic incentives may be less effective. Improving information may increasing efficiency, reduce consumption, reduce or put off long term supply expansion. Utilities can use technology like smart meters to render existing and developing DSM programs more effective, and result in a greater impact that under the less certain, less informed world.

Each chapter of this dissertation addresses an aspect of the informational setting in the decision-making environment characterizing household water and energy use. In Chapter 2, I present a theoretical model of decision-making under quantity uncertainty. While a household knows the benefit they receive from setting the thermostat to a comfortable temperature, they do not know the energy requirement nor the cost of this choice. The expected utility model describes an individual making multiple consumption choices over a billing period where the benefit of is known at the time of consumption but the input requirement and therefore the total cost is not known. This individual faces two types of quantity uncertainty: 'backward uncertainty,' since it is difficult or inconvenient to know total consumption up to any given point in the period, and 'forward uncertainty,' because the household is unlikely to know how much they will consume throughout the remainder of the period. As a result, when making decisions within a bill period, consumers are unaware of how much they have consumed to that point and how much they are likely to consume, in total, throughout the period. I show how consumption decisions in total and within the period change when backward quantity uncertainty is removed.

These results depend on risk preferences and the rate structure in place. In general, risk averse individuals will, all else equal, increase consumption when backward uncertainty is removed, whereas risk seeking individuals will reduce consumption instead. When a consumer faces an increasing block rate structure, the presence of quantity uncertainty can lead to marginal price uncertainty. This alters behavior: for example, an individual who is risk neutral but faces a positive probability of total consumption falling in the second block (and facing a higher marginal price) may appear to act risk averse. Overall, the theoretical model suggests that consumer behavior depends on 1) the level of uncertainty, which is dictated by the frequency of information provided within a period, 2) the content of the information (i.e., the value of the input requirement), 3) the individual's risk preferences, and 4) the rate structure.

This theoretical model contributes to the literature on decision-making under uncertainty in two major ways: First, I model multiple sequential choices within a billing period. Existing models do not capture this aspect of the decision-making environment; instead they essentially model the billing period as the unit of decision-making, even in models of sequential decision-making under uncertainty. In household water and energy use, *many* choices are made within the billing period. When the household only receives an end-of-period bill, they make all of the period's decisions before any uncertainty is realized. Even when the uncertainty is realized, the multiple-choice nature of the environment keeps the individual from knowing the true values of individual input requirement. Second, I allow for a spectrum of risk preferences. Other models, typically via their choice of functional form, assume the individual is risk averse or risk neutral. Without allowing for many types of risk preferences, we would not be able to illustrate the variety of possible sets of choices made with and without uncertainty, especially when facing a non-linear rate structure. While this theoretical model is designed to illustrate how more frequent feedback may influence household water and energy use, the findings here can also be applied to any other setting where multiple decisions are made facing uncertainty and are made prior to realization of cost.

This model could be extended in a number of ways. It could be adapted to test the influence of different probability distributions for the uncertain variables. This model could also be melded with the literature on learning and allow for the potential for the individual to learn over time, which may better match how household with smart meters will adapt to this new technology. Finally, while the motivation in water and energy consumption, this model can be applied to other settings with similar characteristics.

In Chapter 3, I create a computerized laboratory experiment that tests some of the predictions generated by the expected utility model presented in Chapter 2. The experimental setting is simplified to an individual making consumption choices under input quantity uncertainty due to imperfect information. In the computerized laboratory experiment, participants are incentivized to maximize profit: a sequence of decisions are made facing either complete uncertainty about input requirements or only forward uncertainty if the individual receives feedback on her input use resulting from previous decisions within the period. The feedback effect is tested under three rate structure treatments: a constant marginal price structure and two versions of a two-tier increasing block rate structure.

Results show that more frequent feedback increased average consumption, increased variance in weekly output levels and lowered price responsiveness, independent of rate structure. Results from the IBR sessions suggest that the effect of prices and the block boundary depend on the distribution of user preferences relative to the block boundary. Participants with preferences consistent with expected use below (above) boundary increased (decreased) use. There was notable heterogeneity in the decision-making of participants, which can partially be explained by differences in risk preferences and gender. Using estimates of risk preferences elicited through a Holt and Laury (2002) lottery, I find that risk averse and risk neutral participants are positively responsive to feedback and more price responsive than risk seeking participants.[64] I also find evidence of rate structure induced risk behavior in the IBR sessions (i.e., risk neutral participants acting like they are risk averse due to the positive probability of facing a higher marginal price). This behavior sometimes makes participants appear to target the block boundary, however, the risk preferences explanation fits the data better. Finally, female participants are more responsive to feedback than their male counterparts, a result which is interestingly independent of the other experiment treatments and risk preferences.

Though the Department of Energy is taking the steps to encourage more utilities to install AMI system, few utilities have yet to take advantage of the utility-to-household smart meter communication opportunities and even where this data exists, program implementation often confounds clear analysis and privacy laws make it difficult to study household level data. Beyond these barriers to accessing real world data, it is difficult and costly to apply different treatments (like different bill design, bill frequency or prices) to different subsets of customers. An experiment is a great way to test economic theories without disrupting real world activities; this tool can be used before incurring the risk and expense of a real world application or field test. The experiment can shed light on unintended results or consequences and suggest factors that should be considered in final policy design (Croson 2005). The results give insight into how water consumers may respond to more frequent information, and provide guidance to design and implementation of utility demand-side policies. I am not aware of any previous studies that have considered the effect of resolving backward

[64]The expected utility model developed in the conceptual framework section predicts much of the risk-preference related behavior seen in the experiment.

uncertainty in a controlled experimental setting or the impact of information under alternative pricing schemes. This work complements a growing literature on price and quantity salience, as well as household water and energy use.

There are a variety of ways to extend the research presented in Chapter 3. First, elements of the experimental design could be changed to test the effect. For example, in most economic experiments, participants earn money based on their decisions within the experiment, otherwise the experiment is not incentive compatible. I argue that since participants typically expect to earn *some* amount of money for their time, that it does not perfectly match up with reality. I would like to explore how experiment incentive structure where participants perceive to be losing money rather than gaining money influences decision-making, specifically under uncertainty. Another example would be to explore the frequency of feedback more. What is the optimal frequency of providing updated information? Finally, like the theoretical model, this experiment could be adjusted to explore the role of learning.

Another possible extension would be to test the effect of combinations of policies and incentives. What is the optimal combination of price and non-price policies (like information)? For example, how does the combination of social norm-related energy use messaging and dynamic time-of-use pricing affect energy use? What is the optimal frequency of feedback given a utility's overall or a household's personal consumption goals? While research on price and non-pricing policies can inform questions in household energy and water use, it can also easily extend to other economic applications.

Finally, given the initial evidence of heterogeneity in decision-making under uncertainty, it would be of interest to find ways to identify different types of decision-makers and different types of households. For example, results from the experiment suggest that the socio-demographics of who in a household pays the utility bills and influences water and energy consumption decisions matters. Identifying different segments of a population will help identify how policies will impact welfare and responsiveness at a more refined level.

In Chapter 4, I explore the role of billing for multiple utility services through a single monthly bill. I test the hypothesis that household responsiveness to the price of a water is influenced by the number of other services on the bill and the proportion of the total bill driven by water charges. I find differences in responsiveness when there are different numbers and combinations of utility services billed on the single bill. For example, households only subscribing to electricity and water services are less price responsive than households who only receive natural gas and water services from the Utility. Households only receiving a bill with water charges on it are typically the most responsive to price. Through an empirical model of price salience, I find that responsiveness to water prices increases as the proportion of the total bill attributable to water services increases. Households pay more attention to water prices, when their water use contributes to a greater portion of their total utility spending. This study provides additional support of households being generally inelastic, but not unresponsive, with respect to water prices. Given this unique data set I am able to provide evidence of how different combinations of bills, and the varying proportion of a bill attributable to water, affects water responsiveness.

There is evidence that household water demand is inelastic but not unresponsive with respect to water prices. Responsiveness is influenced by the salience of the given price signal, the relative weight of those charges within total utility spending and the combination of services billed through a single monthly bill. If a utility desires greater responsiveness to water price, they will need to make the price signal more salient. With greater use of smart meter technology, online web portals and in-home displays, there are many opportunities on the horizon for communicating consumption and prices to consumers.

A next step of this study will be to extend analysis to energy responsiveness and cross-price elasticities. The effect of water and energy prices on their respective residential demands have been studied separately, but little attention has been given to the effect of energy prices on household water use and vice versa (Hansen, 1996).[65] There is a direct relationship between water and energy consumption for a considerable portion of household activities (e.g., dishwashers and washing machines) and energy for water heating alone accounts for around 18% of a home's energy bill (EIA, 2009). There is potential that limiting the scope of analysis to own-price sensitivity ignores the significant functional connection between water and energy use and likely generates flawed estimates.[66]

To my knowledge, only one study has directly acknowledged how electricity and water prices may impact household demand of either. Hansen (1996) noted that at the time water use for services where the water is heated accounts for about two-thirds of water use, but the price of electricity on water demand doesn't receive much attention. He uses a pooled time-series approach and finds significant cross-price elasticities and suggests that further research be conducted for other populations, especially in terms of indoor use. His results

[65] Arbués et al. (2003) and Worthington and Hoffman (2008) provide good summaries of water demand modeling, and water own-price elasticity estimates under different price specifications. See Espey and Espey (2004), Reiss and White (2005) for similar reviews of electricity demand estimation.

[66] In the Western U.S., these may only be evident during winter months, as during the summer water use is primarily driven by outdoor irrigation and summer energy use is driven by air conditioning (i.e., hot weather). However, evidence during the summer may be difficult to tease out since water consumption is relatively low in the winter.

suggest that trends about changing energy prices could have significant impacts on water demand. The cross-price effect may not be easy to study since not many utilities provide both water and energy services, therefore the data requirements of a household-level study in this area would be daunting. It would require collection of data from separate utilities, both of which would be willing to provide household-level identifying information so that the researcher could connect water and energy consumption observations to the same household. This type of analysis could be possible with the data used in this study, yet I leave it for a future project.

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APPENDIX A

Chapter 3 Appendix

A.1. Summary Statistics

Table A.1 presents the summary statistics of the participant characteristics:

Table A.1. Summary Statistics

Participant Characteristics

	Average	Min	Max
Gender (1=female)	0.38	0	1
Age (years)	19.26	18	33
Year in College (1=Freshman)	1.61	1	4
Semesters of Econ Courses	1.27	0	15

A.2. Additional Tables and Figures

Table A.2. Week Output Correlation Coefficients by Feedback and Producer Type

Low-Value Producer: No Feedback				High-Value Producer: No Feedback		
	x_1	x_2	x_3	x_1	x_2	x_3
x_2	0.442	–	–	0.345	–	–
x_3	0.549	0.461	0.382	0.405	–	
x_4	0.434	0.596	0.426	0.453	0.536	0.541
Low-Value Producer: Feedback				**High-Value Producer: Feedback**		
	x_1	x_2	x_3	x_1	x_2	x_3
x_2	0.345	–	–	0.482	–	–
x_3	0.382	0.405	–	0.451	0.457	–
x_4	0.343	0.345	0.544	0.297	0.453	0.563

Figure A.1. Example: Correlation Coefficients across Weekly Output Choices, with and without Feedback

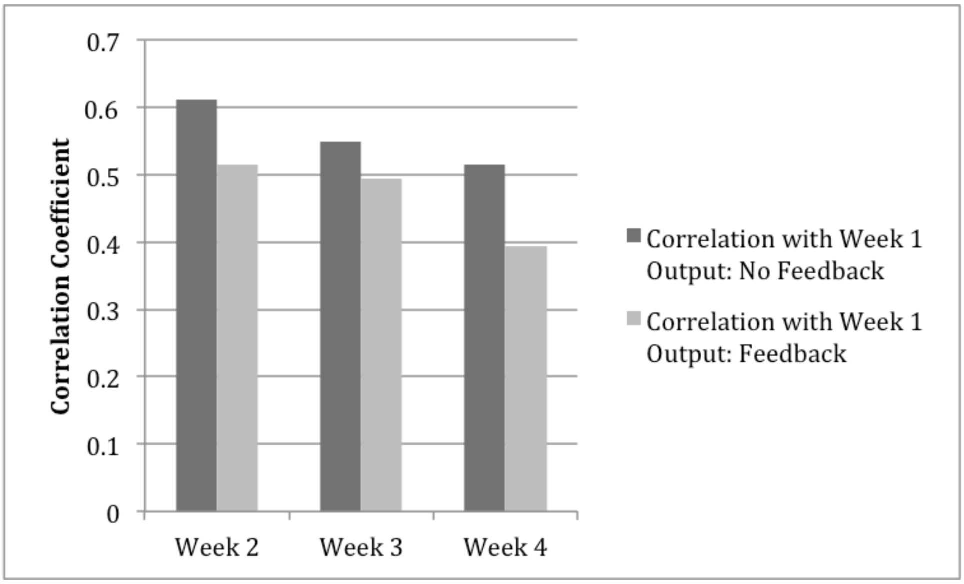

Table A.3. Relative Strength of Feedback and Price Effects across Rate Structures

Partial Effects on Monthly Input Demand

	CMP	IBR41	IBR82
Baseline Low Price D_{inputs}	26.154	29.275	29.538
Marginal Effects:			
Feedback*Low Price†‡	1.637	1.375	-3.40
	(3.377)	(2.664)	(2.809)
Medium Price Level†‡	-6.773*	-9.883***	-8.593***
	(3.660)	(2.878)	(3.034)
Feedback*Medium Price†‡	2.321	0.650	9.4125***
	(1.952)	(2.664)	(2.809)
High Price Level†‡	-18.059***	-17.676***	-8.578***
	(3.509)	(2.769)	(2.919)
Feedback*High Price†‡	9.279***	7.488***	-1.887
	(3.377)	(2.665)	(2.809)

*, **, *** denotes p-values of 0.10, 0.05 and 0.01 respectively.

† Estimates from a version of the random effects model 8 as seen in Table 3.4, but with price-feedback interaction terms and the sample split by rate structure.

‡ Relative to lowest price level.

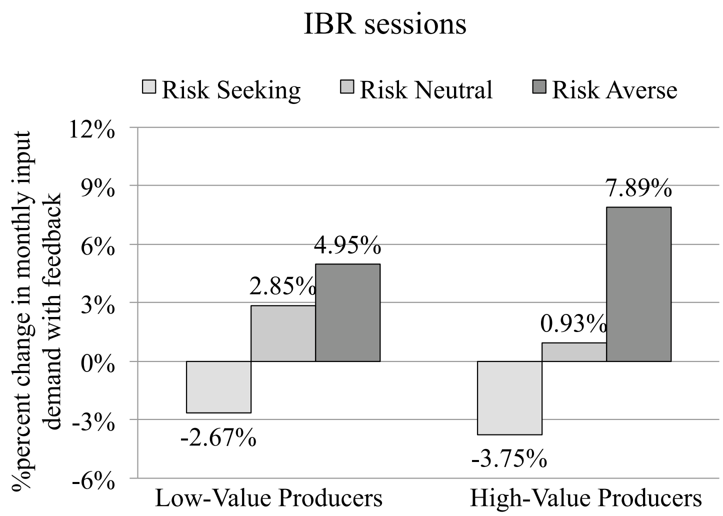

FIGURE A.2. Percent Change in Average Input Demand with Feedback IBR sessions only, Split: Producer Value Type

TABLE A.4. Role of Gender
Random Effects Model

Partial Effects on Monthly Input Demand		
Independent Variable	Male	Female
Feedback	1.577	5.245***
	(1.230)	(1.504)
Medium Price Level	-4.684***	-8.920***
	(1.832)	(2.126)
High Price Level	-12.241***	-12.158***
	(1.709)	(1.983)
IBR82	15.164***	10.462*
	(4.982)	(5.596)
IBR41	2.409	14.142**
	(4.670)	(6.195)
Producer Type	25.055***	15.563***
	(3.937)	(4.831)
Average Input Requirements	28.111***	21.397***
	(1.127)	(1.308)
constant	-15.860***	-3.624
	(5.395)	(6.156)
Overall R^2	0.5172	0.4430

Standard errors are in parentheses.
*, **, *** denotes p-values of 0.10, 0.05 and 0.01 respectively.
Estimates from a version of the random effects model 8 as seen in Table 3.4, but with the sample split by gender.

A.3. Sample Experiment Instructions

You are about to participate in an experiment on the economics of decision-making. This experiment should take about an hour and a half of your time. This experiment is funded by the Colorado State University Department of Agricultural and Resource Economics. You have the opportunity to earn cash, paid to you at the end of the session. Your payout depends on your decisions and chance: please read the following instructions carefully. Earnings in this experiment will be in Lab dollars.

X lab dollars = 1 U.S. dollar

During the entire experiment communication of any kind is strictly prohibited. Communication between participants will lead to your exclusion from the experiment and the forfeit of all earnings. Please raise your hand if you have any questions and a member of the research team will come to you and answer your questions privately. Also, please silent your cell phones to minimize disruption during the experiment. Your decisions are not related to any of the other participants decisions. You may notice that other participants seem to be moving faster or slower than you, or may have different looking screens. Your game is completely independent from other participants, so please proceed at the pace which guarantees that you are making the best decisions possible.

Experiment Overview and Timeline

In this experiment you are a producer of a single good. You will make decisions regarding how much of that good to produce. The experiment consists of a series of Months. Each Month consists of four Weeks. Each week you will have 30 seconds to decide how much of the good to produce. At the end of each week you will be shown a screen summarizing your decisions, including the amount of revenue earned based on the number of units of output produced. An example of this screen will be presented later in the instructions. At the end of each month you will be billed for the inputs required to produce the good during the previous four weeks. At the end of each month you will be shown a screen summarizing your decisions over the previous four weeks. An example of this screen will be presented later in the instructions.

The revenues you earned, and the costs you incurred, will be used to calculate your total profit for that month. Total profit in any given month will be calculated as:

$$\text{Profit} = \text{Total Revenue} \quad \text{Total Cost}$$

Note that months are independent from each other; your profits will always reset to zero in Week 1 of every month. Figure A.3 provides a timeline of the experiment:

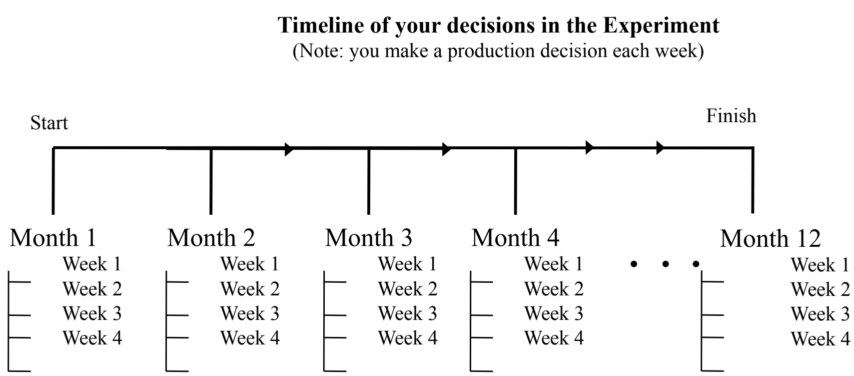

FIGURE A.3. Experiment Timeline

At the end of the experiment we will add up all of your profits and convert them into U.S. dollars using the exchange rate presented above.
The following three sections provide a detailed overview of how revenues and costs will be calculated.

A. Production Revenues The amount of revenue you earn each week will be based on how many units you produce. At the beginning of the experiment you will be given a

Production Revenue Sheet. This sheet will detail the amount of revenue you will earn for each unit of output produced in a given week. An example Production Revenue Sheet is included in your packet. Please take out the sheet of paper labeled Example Production Revenue Sheet at this time.
To better understand how to use your Production Revenue Sheet we will now walk you through an example using the Example Production Revenue Sheet. For this example assume that you decided to produce 6 units of output in Week 1, 4 in Week 2, 8 in Week 3, and 2 in Week 4. Table A.5, which is similar to the summary table you will see at the end of each month, provides a detailed breakdown of the revenue you would earn using the Example Production Revenue Sheet. Note: we have intentionally left blank the columns/rows corresponding to inputs and costs as these will be discussed later.

TABLE A.5. Example Revenue Calculations

Week	Units Produced	Total Revenue	Input Conditions	Inputs per Unit of Output	Total Inputs Used
1	6	20+18+16+14+12+10=**90**			
2	4	20+18+16+14= **68**			
3	8	20+18+16+14+12+10 +8+6=**104**			
4	2	20+18= **38**			
Total	20	**300**			

Total Revenue for Month _ is **300** lab dollars.
Total Cost of production is [intentionally left blank]
Your **Profit** this month is [intentionally left blank]

Note that, in this example, if you produced one more unit of output in Week 1 you would earn an additional $8. However, if you instead increased production by 1 in Week 4 you would earn an additional $16.
Alternatively, if you produced one less unit of output in Week 1 your total revenue would fall by $10. However, if you instead decreased production by 1 in Week 4, your total revenue would fall by $18.

Important: this is only the revenue component of your overall payoff. You must weigh your production decisions, which earn you revenue, with the costs you incur when producing your output. A detailed description of how your costs are calculated is presented in the next section.

B. Production Costs At the end of each month, the cost to produce each unit of output will be subtracted from your revenues. The cost of producing is based on the number of inputs used over the course of the entire month. Note that while revenues are calculated on a weekly basis, your costs are calculated at the end of each month, based on the total number of inputs used over the course of the month (the total from all 4 weeks) and the price of inputs in that month.
Input Requirements
The total amount of inputs you use will depend on the number of goods you produce and chance. The number of inputs needed to produce a single unit of the good will vary from week to week. Five different types of input conditions are possible: Very Low, Low, Normal, High, and Very High. Table A.6 outlines the input requirements and probabilities associated with each of these conditions that will be used throughout the experiment. On average each unit of the good produced will require 3 units of input.

TABLE A.6. Input Requirements per Unit of Output: Conditions and Probabilities

Input Condition	Input Requirement*	Probability**
Very Low	1	0.2
Low	2	0.2
Normal	3	0.2
High	4	0.2
Very High	5	0.2

Input Requirement: indicates the number of inputs required to produce each unit of output. For example, if you decide to produce 4 units of the good you will use 4(Input Requirement). If it was a Very Low week 4 units of output would require 4 units of input (4*1). By comparison, in a Very High week producing 4 units of output would require 20 units of the input (4*5).
**The probabilities listed mean that, on average, 2 out of every 10 weeks will have Very Low input requirements, 2 out of 10 weeks will have Low input requirements, 2 out of 10 will have Normal input requirements, 2 out of 10 will have High input requirements, and 2 out of 10 will have very high input requirements. However, the computer chooses randomly, so it is possible to have several weeks with Very Low (or Very High) input requirements in a row, and the probabilities are the same in each week, independent of what happened in previous weeks.

To better understand consider again the example from above where you decided to produce 6 units of output in Week 1, 4 in Week 2, 8 in Week 3, and 2 in Week 4. Table A.7 presents the inputs required assuming input conditions were High in Week 1, Very High in Week 2, Normal in Week 3, and Very Low in Week 4.

TABLE A.7. Example Input Calculations

Week	Units Produced	Total Revenue	Input Conditions	Inputs per Unit of Output	Total Inputs Used
1	6	90	High	4	6*4=**24**
2	4	68	Very High	5	4*5=**20**
3	8	104	Normal	3	8*3=**24**
4	2	38	Very Low	1	2*1=**2**
Total	20	**300**			**70**

Total Revenue for Month _ is **300** lab dollars.
Total Cost of production is [intentionally left blank]
Your **Profit** this month is [intentionally left blank]

The input conditions assumed in Table 3 are for illustration purposes only. In the actual experiment, input requirements will vary from week to week and from the average of 3. You will not know with certainty the actual input requirements for a given week before you make your production decision. Depending on chance, in some weeks it will be relatively cheap to produce your output. In other weeks it will be relatively expensive to produce your output.

Input Costs

The final step to calculating your profit involves subtracting the cost of the inputs you use in producing your output from the revenues you earn from production.

You will be charged a constant per unit price for each input used. At the beginning of each month you will be told which price you will face. This price will not change over the course of a month, but may differ from month to month. At the end of each month we will add up the total number of inputs you used over the course of the previous four weeks and multiply that number by the input price per unit.

To better understand, consider again the case when you decide to produce 6 units of output in Week 1, 4 in Week 2, 8 in Week 3, and 2 in Week 4. Table A.8 presents the cost associated with this level of production given a price of $3 dollars per unit of input and assuming the same input conditions used in the previous example (i.e. High in Week 1, Very High in Week 2, Normal in Week 3, and Very Low in Week 4).

TABLE A.8. Example Cost and Profit Calculation

Week	Units Produced	Total Revenue	Input Conditions	Inputs per Unit of Output	Total Inputs Used
1	6	90	High	4	24
2	4	68	Very High	5	20
3	8	104	Normal	3	24
4	2	38	Very Low	1	2
Total	20	**300**			70

Total Revenue for Month _ is **300** lab dollars.
Total Cost of production is 70*34=**210** lab dollars.
Your **Profit** this month is 300-210=**90** lab dollars.

Note that in this example the cost associated with producing one additional unit of output would be different across each of the four weeks. In Week 1, producing 1 additional unit of output would require 4 units of input; increasing your total costs by 12 dollars (4*3). By comparison, producing an additional unit of output in Week 4 would require only 1 unit of input; increasing your total costs by 3 dollar (1*3).

Similarly, the savings associated with producing one less unit of output would also differ across each of the four weeks. In Week 1, producing 1 less unit of output would require 4 fewer units of input; decreasing your total costs by 12 dollars (4*3). By comparison, producing one less unit of output in Week 4 would require only 1 unit of input; increasing your total costs by 3 dollars (1*3).

C. Information on Input Requirements

Prior to deciding how many units of output to produce you will not know the input conditions for that week or for any future weeks. However, in some months we will tell you how many inputs you needed at the end of each week. i.e. after you have made your production decision we will tell you what the input conditions were for that week and how many inputs you have used up to that point in the month. This information will be included as part of your weekly summary. Figure A.4 provides an example of screen you will see at the end of each week during those months when this information is provided.

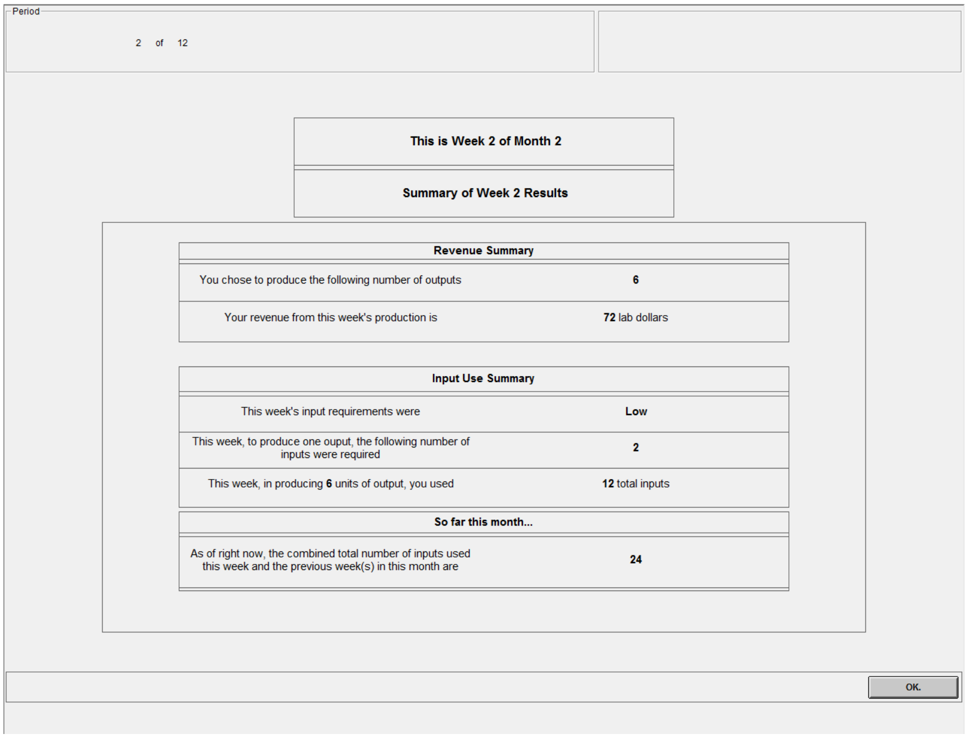

FIGURE A.4. Screenshot - with Weekly Feedback

In other months the weekly updates you receive will contain this information; each of the rows in the "Input Use Summary" and "So far this month" sections will indicate that the information is not available. In those cases you will have to wait until the end of the month to learn how many inputs you used in production of your output over the 4 weeks. Figure A.5 provides an example of screen you will see at the end of each week during those months when this information is not provided.

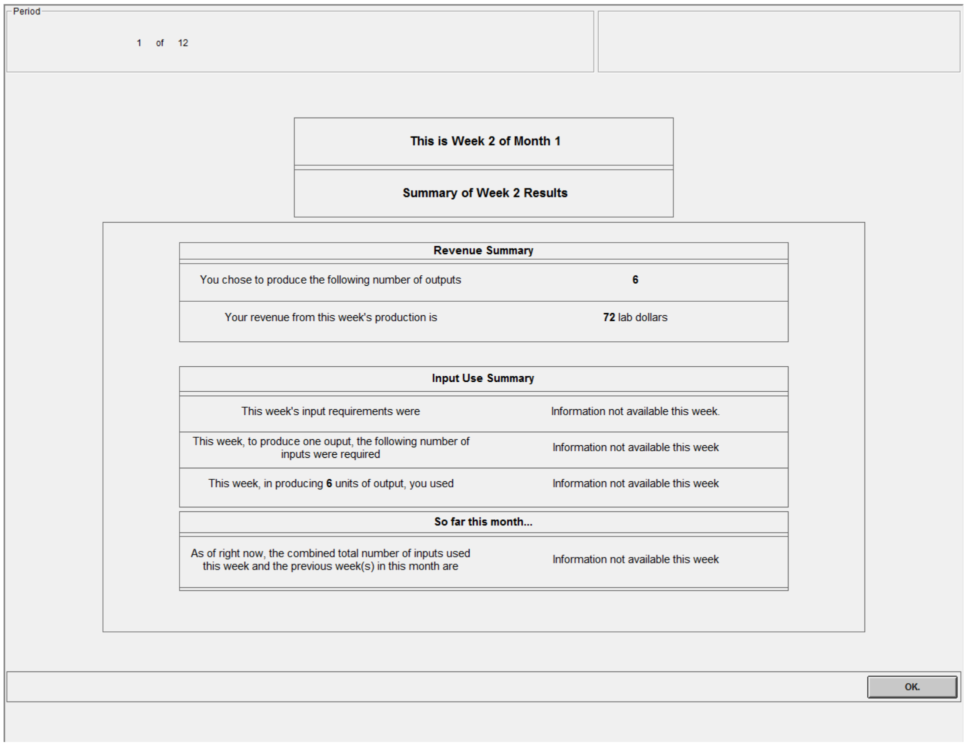

FIGURE A.5. Screenshot - with Weekly Feedback

At the beginning of each month, in addition to being given information on the price of inputs, you will be told whether or not you will receive weekly information updates.

Test Questions

The next two pages contain a series of test questions that we would like you to answer before we continue. Please follow the instructions below and, using your Example Production Revenue Sheet, do your best to answer each question. If you have any questions about how to interpret the table or if you have any difficulty answering the questions, raise your hand and one of us will come help you.

Please raise your hand once you have reached the end of each section of questions. We will come around to review your answers. Do not proceed to the next section of questions until we have met with you.

Section 1: Calculating Total Revenue
For all of the questions in this section assume that you decided to produce 6 units of output in Week 1, 5 units in Week 2, 7 in Week 3, and 2 in Week 4. Using your Example Production Revenue Sheet, fill in the blanks:

(1) In Week 1 your total revenue will be _______ lab dollars.
(2) In Week 2 your total revenue will be _______ lab dollars.
(3) In Week 3 your total revenue will be _______ lab dollars.
(4) In Week 4 your total revenue will be _______ lab dollars.

(5) Your total revenue for the month will be ______ lab dollars.
(6) If you had decided to produce 1 additional unit of output in Week 1, your total revenue for the month would have increased by ______ lab dollars.
(7) If you had decided to produce 1 additional unit of output in Week 4, your total revenue for the month would have increased by______ lab dollars.

Section 2: Calculating Input Use

For all of the questions in this section assume that you decided to produce 6 units of output in Week 1, 5 units in Week 2, 7 in Week 3, and 2 in Week 4. Also assume that input conditions for each week are as follows: Normal for Week 1; Very Low for Week 2; High for Week 3; and Normal for Week 4. Using this information fill in the blanks:

(8) In Week 1 each unit of output produced would require _____ inputs and you would use _____ inputs in total.
(9) In Week 2 each unit of output produced would require _____inputs and you would use _____ inputs in total.
(10) In Week 3 each unit of output produced would require _____ inputs and you would use _____ inputs in total.
(11) In Week 4 each unit of output produced would require _____inputs and you would use _____ inputs in total.
(12) The total number of inputs used for the entire month would be _____.
(13) If you had decided to produce 1 additional unit of output in Week 1, the total number of inputs used for the month would have increased by _____.
(14) If you had decided to produce 1 additional unit of output in Week 3, the total number of inputs used for the month would have increased by _____.

Section 3: Calculating Total Cost and Profit

For all of the questions in this section assume that you are charged a constant per unit price of $1 for each input used. As in the previous sections, continue to assume that 6 units of output were produced in Week 1, 5 units in Week 2, 7 in Week 3, and 2 in Week 4 and that input conditions for each week are as follows: Normal for Week 1; Very Low for Week 2; High for Week 3; and Normal for Week 4. Using this information fill in the blanks:

(15) The total cost of production for this month would be _____ lab dollars.
(16) Your total profit for this month would be _____lab dollars.
(17) If you had decided to produce 1 additional unit of output in Week 1, your total profit for the month would have increased by _____ lab dollars.
(18) If you had decided to produce 1 additional unit of output in Week 3, your total profit for the month would have increased by _____.

APPENDIX B

Chapter 4 Appendix

B.1. Variable Definition

The Low-to-High variable is only used as a means to identify different types of household in the model specifications where household-level fixed effects are not employed. This categorical variable described in Table B.1 is defined based on the difference between peak winter water consumption (the average across December, January and February) and peak summer water consumption (the average across June, July and August). Peak winter consumption will match well with average indoor water use, which doesn't vary much. Thus the difference between peak winter and peak summer use will capture the level of outdoor water consumption. I use data from 1999 to construct this variable, which is not included in the analysis in the main body of this paper. In the West, average winter water use is about 800cf and average outdoor water use is 3000cf. The difference is 2200 cf, which falls in the middle of the categorical variables below.

Table B.1. Low-to-High Categories

Category	Definition	Percent of Households
(1)	133cf $<$ w $<$ 600 cf	12.35%
(2)	601 cf $<$ w $<$ 1200 cf	13.13%
(3)	1201 cf $<$ w $<$ 1800 cf	15.29%
(4)	1801 cf $<$ w $<$ 2400 cf	15.96%
(5)	2401 cf $<$ w $<$ 3200 cf	17.55%
(6)	3201 cf $<$ w $<$ 4000 cf	11.00%
(7)	4001 cf $<$ w $<$ 10,000 cf	14.72%

B.2. Supplementary Tables

Table B.2. Baseline Model Results

Specification	(1)	(2)	(3)	(4)
Dependent variable: $ln(w_{it})$	Tri-Bill	EW Dual	GW Dual	W Only
$ln(AP_{i,t-1})$	-0.758	-0.596	-0.642	-0.956
	(.005)***	(.004)***	(.080)***	(.051)***
#BP days	0.039	0.029	0.034	0.037
	(.001)***	(.004)***	(.008)***	(.006)***
BlockRate	-0.070	-0.005	-0.079	-0.113
	(.003)***	(.027)	(.053)	(.037)***
02Volun	-0.244	-0.112	-0.114	-0.352
	(.008)***	(.078)	(.127)	(.101)***
OneDayRestrict	-0.194	-0.075	-0.187	-0.210
	(.003)	(.026)**	(.045)***	(.034)***
TwoDayRestrict	-0.171	-0.111	-0.235	-0.173
	(.003)***	(.035)**	(.065)***	(.046)***
ThreeDayRestrict	-0.053	-0.059	-0.070	0.001
	(.004)***	(.043)	(.080)	(.058)
0506Volun	0.060	-0.102	-0.084	0.007
	(.003)***	(.031)**	(.059)	(.040)***
MaxTemp	0.018	0.019	0.023	0.012
	(.001)***	(.001)***	(.003)***	(.002)***
Precip	-0.037	-0.022	-0.042	-0.012
	(.001)***	(.006)***	(.013)***	(.009)
Unemp	0.040	0.021	0.037	-0.072
	(.001)***	(.006)***	(.010)***	(.007)***
constant	1.647	2.648	2.049	0.889
	(0.027)***	(.221)***	(.417)***	(.297)***
Month Dummies	✓	✓	✓	✓
Household Fixed Effects	✓	✓	✓	✓
R^2	0.4480	0.3848	0.3908	0.4113
n	339,975	6,681	1,871	3,750
groups	2833	1518	681	919

Standard errors are in parentheses.
*, **, *** denotes p-values of 0.10, 0.05 and 0.01 respectively.

Table B.3. Salience Model Results

Specification	(1)	(2)	(3)
Dependent variable: $ln(w_{it})$	Tri-Bill	EW Dual	GW Dual
$ln(AP_{i,t-1})$	-0.534	-0.390	-0.504
	(.004)***	(.040)***	(.078)***
$ln(AP_{i,t-1}) \times (Wbill_{i,t-1}/Tbill_{i,t-1})$	-0.612	-0.505	-0.297
	(.002)***	(.016)***	(.029)***
#BP days	0.040	0.041	0.039
	(.001)***	(.001)***	(.008)***
BlockRate	-0.048	-0.046	-0.070
	(.002)***	(.002)***	(.051)
02Volun	-0.345	-0.226	-0.193
	(.007)***	(.071)***	(.010)***
OneDayRestrict	-0.119	-0.034	-0.143
	(.002)	(.024)	(.043)***
TwoDayRestrict	-0.104	-0.108	-0.208
	(.003)***	(.032)***	(.062)***
ThreeDayRestrict	-0.024	-0.071	-0.064
	(.004)***	(.039)*	(.078)
0506Volun	0.007	-0.080	-0.053
	(.002)**	(.020)***	(.057)
MaxTemp	0.013	0.015	0.017
	(.001)***	(.001)***	(.003)***
Precip	-0.050	-0.030	-0.058
	(.001)***	(.005)***	(.001)***
Unemp	0.024	0.006	0.028
	(.001)***	(.005)	(.010)***
constant	2.436	3.088	3.389
	(.024)***	(.020)***	(.367)***
Month Dummies	✓	✓	✓
Household Fixed Effects	✓	✓	✓
R^2	0.5909	0.5247	0.4884
n	339,975	6,681	1,871
groups	2833	1518	681

Standard errors are in parentheses.
*, **, *** denotes p-values of 0.10, 0.05 and 0.01 respectively.