# Paternalism and Energy Efficiency: An Overview

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## Keywords

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## Abstract

This article provides an overview of the application of behavioral public economics to energy efficiency. I document policy makers' arguments for "paternalistic" energy efficiency policies, formalize with a simple model of misoptimizing consumers, review and critique empirical evidence, and suggest future research directions. Although empirical results suggest that policies to address imperfect information and internalities may increase welfare in some cases, some existing policies may be mistargeted or miscalibrated.

# 1. INTRODUCTION

Governments frequently intervene to protect citizens from our own choices. For example, the United States and many other countries tax or ban hard drugs, alcohol, and cigarettes. Motorcycle helmet and automobile seat-belt laws are common, as are safety standards for food and other products. Usury laws and other regulations protect consumers from their own financial decisions. Life-cycle myopia is one potential justification for mandatory retirement savings programs (Feldstein & Liebman 2002).

Without models of imperfect information or misoptimization, economics would have little useful to say about these policies: With perfect information and optimizing consumers, any restriction of consumer choice mechanically reduces consumer welfare, essentially by assumption. Information economics and behavioral public economics provide the tools to formalize and test hypotheses about "mistakes" and to evaluate the welfare effects of "paternalistic" policies.[1] I use the term "mistakes" to cover any reason why our decisions do not maximize our own welfare, including that we do not know or do not properly value the consequences. In a world with mistakes, "paternalistic" is not a pejorative word—instead, it is a descriptive term that clarifies policy goals and defines empirical hypotheses.

This article provides an overview of the application of behavioral public economics to energy efficiency policy. Along with externality reduction, which of course would be best achieved through Pigouvian taxes, consumer mistakes are offered as an important justification for policies such as subsidies for energy-efficient goods and minimum energy efficiency standards.[2] I begin by reviewing the policy argument and formalizing it in a simple consumer choice model. I use the model to characterize three categories of empirical tests for mistakes: comparing demand responses to prices versus energy costs, measuring the effects of nudges, and belief elicitation. These tests have direct analogies with other domains such as consumer finance and health, and the categorization draws on similar discussions in DellaVigna (2009) and Mullainathan et al. (2012). I then discuss tests between different behavioral models, outline emerging policy implications, and suggest directions for future research.

This review does not cover the literature on how energy-conservation marketing campaigns, social norm information, goal setting, and other tools from applied psychology affect energy use.[3] Many of these interventions could act through persuasion instead of by correcting consumer mistakes, so the regulatory policy implications are unclear unless one can distinguish between these two channels and develop a model of socially optimal persuasion (see Allcott & Kessler 2015 for one initial step in this direction).

# 2. BACKGROUND

## 2.1. Why Energy Matters

Expenditures on energy and energy-using durables represent a significant share of the economy in industrialized countries. According to the 2014 Consumer Expenditure Survey, in 2011, US

[1]In the past 10 years, a growing number of papers have made empirical or theoretical contributions to behavioral public economics (e.g., Baicker et al. 2015; Bernheim & Rangel 2004, 2009; Carroll et al. 2009; Chetty 2015; Gabaix & Laibson 2006; Grubb 2015; Grubb & Osborne 2015; Gruber & Koszegi 2004; Gruber & Mullainathan 2005; Gul & Pesendorfer 2007; Mullainathan et al. 2012; O'Donoghue & Rabin 2006).

[2]Allcott & Greenstone (2012), Gerarden et al. (2015), Gillingham et al. (2009), and Gillingham & Palmer (2014) provide broader reviews of energy efficiency policy. Allcott & Sunstein (2015) discuss the regulation of internalities with a focus on energy efficiency.

[3]Recent work includes Allcott (2011b), Allcott & Rogers (2014), Asensio & Delmas (2015), Ayres et al. (2013), Costa & Kahn (2013), Delmas & Lessem (2014), Dolan & Metcalfe (2015), Harding & Hsiaw (2014), Ito et al. (2015), Sudarshan (2014), and Yoeli et al. (2015).

**Table 1 Major US energy efficiency policies**

| Policy | Years | Magnitude |
|---|---|---|
| **Standards** | | |
| Appliance efficiency standards | 1990–present | \$2.9 billion annual cost |
| Building codes | 1978–present | ND |
| CAFE standards | 1978–present | \$10 billion annual cost |
| **Prices** | | |
| Federal hybrid vehicle tax credit | 2006–2010 | \$426 million annual credit |
| Gas guzzler tax | 1980–present | \$200 million annual revenues |
| Weatherization Assistance Program | 1976–present | \$250 million annual cost |
| Demand-side management | 1978–present | \$7.6 billion annual cost |
| 2009 economic stimulus | 2009–2014 | \$17 billion total |
| **Information and marketing** | | |
| Fuel economy labels | Mid-1970s | ND |
| Appliance yellow tags | 1980–present | ND |
| Energy Star program | 1992–present | \$50 million annual cost |

Data in this table are primarily from Allcott & Greenstone (2012). Abbreviations: CAFE, Corporate Average Fuel Economy; ND, not determined.

households purchased \$361 billion worth of energy-using durable goods such as cars and air conditioners and spent another \$570 billion on gasoline, electricity, natural gas, and fuel oil. Even relatively small inefficiencies in such large markets could quickly add up to large welfare losses.

There is also increased policy interest in energy efficiency due to environmental externalities from energy use, including greenhouse gas and local pollution emissions and national security concerns related to oil imports. US household energy use imposes \$40 billion in carbon pollution externalities, plus additional externalities from local air pollution.[4] Any systematic consumer mistakes that increase energy use would also increase externalities.

## 2.2. Energy Efficiency Policies

The United States has a number of policies that encourage energy efficiency, many of which were introduced as energy prices rose in the 1970s. **Table 1** presents the most significant US policies, organized into three categories. Many other industrialized countries and large developing countries have similar policies.

The first category is standards. The Energy Policy and Conservation Act of 1975 called for minimum energy efficiency standards for home appliances. The first meaningful nationwide standards were finally implemented in 1990, and since then, the standards have been strengthened and additional products included. The Energy Independence and Security Act of 2007 set minimum lighting efficiency standards that banned most traditional incandescent light bulbs between 2012 and 2014 and will be tightened further in 2020. Argentina, Australia, Brazil, Canada, China, Cuba, the European Union, Israel, Malaysia, Russia, and Switzerland have also banned some or all incandescent light bulbs. Many states have building codes that mandate minimum insulation levels and other energy efficiency measures. Corporate Average Fuel Economy (CAFE) standards

[4]This number is the product of the \$38 social cost of carbon for 2013 estimated by the Interagency Working Group on Social Cost of Carbon (2013) and total household carbon emissions from energy use estimated by the US Energy Information Administration (2015).

require that each auto manufacturer's fleet of new cars and trucks meet a minimum average miles per gallon (MPG) rating.

The second category is price policies (i.e., taxes and subsidies). There were federal income tax credits of up to $3,400 for hybrid vehicles from 2006 to 2010, and credits of up to $7,500 are currently available for plug-in hybrids and electric vehicles. There are federal gas guzzler taxes that range from $1,000 to $7,700 on the sale of low-MPG passenger cars. The US Weatherization Assistance Program grants $250 million for improved insulation, air sealing, and other weatherization measures at approximately 100,000 low-income homes each year. Electricity bill surcharges fund billions of dollars of utility-implemented demand-side management programs, which include subsidized home energy audits, energy efficiency information provision, and subsidies for energy-efficient appliances, weatherization, and other investments. The 2009 American Recovery and Reinvestment Act included substantial increases in energy efficiency subsidies. In total, that legislation and related economic stimulus bills authorized $17 billion in energy efficiency spending, including additional weatherization subsidies and automobile and appliance cash-for-clunkers programs.

The final category is information and marketing. The US government requires all new vehicles to have fuel economy information labels, and appliances must be labeled with informational yellow tags. Furthermore, the Environmental Protection Agency runs the Energy Star labeling and marketing program. Although cost data are not available for all programs, information and marketing are cheap compared to the fiscal cost of subsidies or the production costs of energy-efficient goods.

## 2.3. The Paternalistic Rationale for Energy Efficiency Policy

Energy efficiency policies can address several different market failures, including environmental externalities and spillovers of returns to innovation. Imperfect information and misoptimization, however, are central to the policy discussion. This section documents this with several examples.

Some of the earliest behavioral language is from Hausman's (1979, p. 51) seminal analysis of the implied discount rates that rationalize consumers' trade-offs between purchase price and energy efficiency in air conditioner purchases:

> This finding of a high individual discount rate does not surprise most economists. At least since Pigou, many economists have commented on a "defective telescopic faculty." A simple fact emerges that in making decisions which involve discounting over time, individuals behave in a manner which implies a much higher discount rate than can be explained in terms of the opportunity cost of funds available in credit markets. Because this individual discount rate substantially exceeds the social discount rate used in benefit-cost calculations, the divergence might be narrowed by policies which lead to purchases of more energy-efficient equipment.

The next year, the US Department of Energy relied heavily on this argument in its regulatory impact analysis (RIA) of the first appliance energy efficiency standards. Using engineering analyses of appliance costs and energy savings, the RIA found that the proposed standards would generate large net private benefits for consumers. Of course, regulation can only generate *private* net benefits if consumers' original choices did not maximize their utility, i.e., if they were making what I refer to as mistakes. Given this realization, the Department of Energy and other federal agencies debated whether consumers were "uninformed" and "myopic" (see Regul. Anal. Rev. Group 1980).

Engineering cost calculations in subsequent RIAs have consistently found that further strengthened energy efficiency standards generate large net private benefits. For example, the RIA for the 2012–2016 CAFE standard (NHTSA 2010) found that $15 billion per year in consumer welfare gains will accrue to consumers who would be induced to buy higher-fuel economy vehicles. Without these private gains, the regulation is likely to be welfare reducing—such stringent CAFE standards cannot be justified by externalities alone:

> Although the economy-wide or "social" benefits from requiring higher fuel economy represent an important share of the total economic benefits from raising CAFE standards, NHTSA estimates that benefits to vehicle buyers themselves will significantly exceed the costs of complying with the stricter fuel economy standards this rule establishes . . . . This raises the question of why current purchasing patterns do not result in higher average fuel economy, and why stricter fuel efficiency standards should be necessary to achieve that goal. To address this issue, the analysis examines possible explanations for this apparent paradox, including discrepancies between the consumers' perceptions of the value of fuel savings and those calculated by the agency. (NHTSA 2010, p. 2)

Similarly, the RIA for Australia's phaseout of traditional incandescent light bulbs (DEHWA 2008, p. vii) argues that internalities and information failures justify the policy, as well as asymmetric information in housing markets:

> [Incandescent light bulbs] continue to sell remarkably well because, if their energy costs are ignored, they appear cheap . . . . There are significant information failures and split incentive problems in the market for energy-efficient lamps. Energy bills are aggregated and periodic and therefore do not provide immediate feedback on the effectiveness of individual energy saving investments. Consumers must therefore gather information and perform a reasonably sophisticated calculation to compare the life-cycle costs of tungsten filament lamps and CFLs. But many lack the skills. For others, the amounts saved are too small to justify the effort or they do not remain at the same address long enough to benefit fully from a long lived energy saving lamp.

Using similar arguments, light-bulb manufacturers and environmental groups lobbied together for the US lighting efficiency standards. In congressional testimony, the National Electrical Manufacturers Association argues, "New standards-setting legislation is needed in order to further educate consumers on the benefits of energy-efficient products" (US Gov. Print. Off. 2007).[5] The Natural Resources Defense Council (2011, p. 1) writes, "Some in Congress are considering repealing the new efficiency standards before they even take effect. That would take away $12.5 billion in consumer savings—something none of us can afford." The RIA for the Energy Independence and Security Act (EISA) of 2007, which included the lighting efficiency standards, argues that after accounting for incremental production costs, the lighting standards will save consumers a net present value of $27 to $64 billion over 30 years (US Dep. Energy 2009). As with CAFE standards, private net benefits are considerably more important than carbon externality reduction, which the EISA RIA values at no more than $16 billion over 30 years.

Gayer (2011, p. 17) succinctly summarizes the argument:

[5]US Senator Rand Paul has strong views on this argument. During congressional testimony by Kathleen Hogan, Deputy Assistant Secretary for Energy Efficiency at the Department of Energy, Paul says (ABC News 2011), "You' re really anti-choice on every other consumer item that you' ve listed here, including light bulbs, refrigerators, toilets—you name it, you can't go around your house without being told what to buy. You restrict my choices, you don' t care about my choices." Paul continues, "This is what your energy efficiency standards are. Call it what it is. You prevent people from making things that consumers want."

> Energy-efficiency regulations and fuel economy regulations are therefore justified by [cost-benefit analyses] only by presuming that consumers are unable to make market decisions that yield personal savings, that the regulator is able to identify these consumer mistakes, and that the regulator should correct economic harm that people do to themselves.

Additional academic articles have followed Hausman (1979). Fischer et al. (2007) and Parry et al. (2010) use simulation models to analyze whether mistakes might justify energy efficiency policies. In a review of fuel economy policies in the *Journal of Economic Literature*, Parry et al. (2007, p. 390) conclude that

> Higher fuel economy standards significantly increase efficiency only if carbon and oil dependence externalities greatly exceed the mainstream estimates . . . or if consumers perceive only about a third of the actual fuel economy benefits . . . . Unfortunately, there is little in the way of solid empirical (as opposed to anecdotal) evidence on this hotly contested issue.

The rest of this article formalizes these policy assertions in a model and provides an overview of recent empirical evidence. Such empirical evidence is crucial: An alternative explanation for the RIAs' findings of large private net benefits is that their engineering cost calculations are overly optimistic. If this is true, then energy efficiency policies based on these RIAs might actually be welfare reducing.

## 3. MODEL

### 3.1. Setup

This section formalizes policy assertions about consumer mistakes in a very simple model. It roughly follows Allcott & Taubinsky (2015) and Allcott et al. (2014), but it also draws on work by Heutel (2016) and Sallee (2014), and the frameworks of DellaVigna (2009) and Mullainathan et al. (2012).

Consumers have unit demand and choose between two energy-using durable goods, indexed $j \in \{E, I\}$. Good $E$ is more energy efficient than good $I$, with energy requirement $r_E < r_I$ per unit of usage. The goods are produced at marginal cost $c_j$, and markets are perfectly competitive, with $p_j = c_j$ in the absence of a subsidy. Time is indexed by $t$, and the durables have fixed lifetime $T$. Consumers have exogenous utilization of $m$ units per unit time, the energy cost is $e$, and consumers use discount factor $\delta$. Predicted total lifetime energy costs for good $j$ are thus

$$g_j \equiv \sum_{t=0}^{T} \delta^t m r_j e. \tag{1}$$

Consumers receive usage utility $v_j$ from owning good $j$. I define differences $p \equiv p_E - p_I$, $v \equiv v_E - v_I$, and $g \equiv g_I - g_E$. Notice that this defines $g \equiv g_I - g_E$ instead of $g \equiv g_E - g_I$, so $g > 0$, and $g$ is energy cost savings.[6]

### 3.2. Specific Behavioral Models of Mistakes

Fully informed and optimizing consumers purchase good $E$ if and only if the net benefits (usage utility difference plus energy cost savings) outweigh the relative purchase price (i.e., if $v + g > p$).

[6] I assume here that $g$ is certain and that the choice between $E$ and $I$ cannot be delayed (see Hassett & Metcalf 1993 for a model of these issues).

By contrast, a biased consumer might misperceive energy cost savings by amount $b$, purchasing good $E$ if and only if $v + g - b > p$. Bias $b$ could be positive, negative, or zero. As defined, $b > 0$ implies that a consumer undervalues energy cost savings and is thus less likely to buy good $E$, whereas $b < 0$ implies the opposite. In the language of Herrnstein et al. (1993), $b$ is an "internality": an externality that decision makers impose on themselves by not correctly valuing all consequences of a decision.

Mistakes might arise through mechanisms such as present bias, bias toward concentration, biased beliefs, costly information acquisition, exogenous inattention, and endogenous inattention.

If consumers are present biased with $\beta$ and $\delta$ preferences, as in Laibson (1997), and if they cannot save or borrow between periods, they downweight the future energy cost savings $g$ by factor $\beta < 1$, purchasing good $E$ if $v + \beta g > p$.

In the Koszegi & Szeidl (2013) model of bias toward concentration, consumers underweight future cash flows that, similar to energy bill savings, accrue in small amounts over many future dates. Although many predictions differ from those of the present bias model, the implication is the same in this simple framework: Consumers downweight energy cost savings by $\beta < 1$.

Consumers' beliefs about energy costs could also be biased by factor $\phi$. For example, they could perceive that energy prices are $\tilde{e} = \phi e$, or that the total energy cost difference is $\tilde{g} = \phi g$. In this case, they purchase good $E$ if $v + \phi g > p$.

In costly information acquisition models, consumers might learn $g_E$ and $g_I$ only by incurring some cost. Otherwise, they remain imperfectly informed. In some rational expectations models, imperfectly informed consumers might assume that both $g_E$ and $g_I$ equal their average, purchasing good $E$ if $v > p$.

Similar to Chetty et al. (2009), share $\lambda$ of the population could be attentive to energy costs $g$, whereas share $1 - \lambda$ is exogenously fully inattentive, purchasing $E$ if $v > p$.

Finally, in rational inattention models such as Gabaix (2014) and Sallee (2014), consumers are more likely to pay attention to an attribute if it is more likely to matter in their purchase decision. A simple way to capture this is to allow $\lambda = \lambda(g)$, with $\partial\lambda/\partial g > 0$.

With present bias and bias toward concentration, we have $b = (1 - \beta)g$, and in the biased beliefs model, $b = (1 - \phi)g$. Uninformed or inattentive consumers have $b = g$.

## 3.3. Policy Implications of Mistakes

If factors such as these can cause mistakes, the first-best policy would be some nudge that eliminates the distortion. For example, if consumers are imperfectly informed or have biased beliefs, one natural policy is to provide information. In practice, however, the ideal nudge may not be feasible, and the policy maker must resort to a price or quantity instrument. The logic of O'Donoghue & Rabin (2006) suggests that a tax or subsidy could increase welfare by offsetting the bias, even if the first best is not achieved.

To see this, define $F$ as the cumulative density function (CDF) of true valuations $v + g$, $G(b|v + g)$ as the CDF of $b$ conditional on $v + g$, and $H$ as the CDF of perceived valuations $v + g - b$. Let $D_B(p) = 1 - H(p)$ denote the market demand curve for good $E$, and assume that $F(\cdot)$ and $H(\cdot)$ are both smooth and strictly increasing. Also assume quasi-linear utility, which is reasonable if $p$ and $g$ are small relative to total expenditures, and assume that there are no distortions other than consumer mistakes.[7]

[7]Allcott & Taubinsky (2015), Allcott et al. (2014), Heutel (2016), and Tsvetanov & Segerson (2013, 2014) consider the case with both internalities and externalities. In these models, the optimal policy is a combination of product subsidies and energy taxes, although the energy tax will not necessarily equal the externality. One result of these models is that externality taxes

Consider a social planner that sets subsidy $s$ for good $E$ using public funds raised from lump-sum taxation, so $p = c - s$, and denote $Z(s)$ as consumers' after-tax income. The social planner maximizes social welfare

$$W(s) = Z(s) + v_I - g_I - p_I + \int_{v+g-b\geq p} (v + g - p)dFdG. \tag{2}$$

If all consumers have homogeneous bias $b^\dagger$, then subsidy $s = b^\dagger$ causes consumers to purchase good $E$ if and only if $v + g - b^\dagger > c - s$. The $s$ and $b^\dagger$ cancel, and the first best is achieved: Consumers make the same purchase that they would make if they were rational and perfectly informed and had to pay marginal cost. Thus, the welfare-maximizing subsidy is $s^* = b^\dagger$, a subsidy that exactly offsets the bias.

When consumers have heterogeneous bias, Allcott & Taubinsky (2015) show that the average marginal bias function $B(p)$ is a sufficient statistic for the optimal subsidy. Formally, $B(p)$ is the average $b$ of all consumers that are marginal at price $p$: $B(p) = E_G(b|v + g - b = p)$. The welfare change from a marginal change in the subsidy is

$$W'(s) = (s - B(p))D'_B(p). \tag{3}$$

Relative to no subsidy, the welfare effect of a subsidy of amount $s$ is approximately

$$\Delta W(s) \approx \underbrace{\frac{s^2}{2} D'_B(p)}_{\text{Harberger distortion}} \underbrace{- s\, D'_B(p) \cdot E_H\left(B(x)|p - s \leq x \leq p\right)}_{\text{Internality reduction}}. \tag{4}$$

Using this equation, Allcott & Taubinsky (2015) highlight the two effects of a corrective subsidy. First, the subsidy increases allocative efficiency through internality reduction, which is the product of the change in quantity demanded $-sD'_B(p)$ and the average marginal bias $E_H(B(x)|p - s \leq x \leq p)$. Second, however, it distorts consumers' perceived optimal decisions, generating a standard Harberger deadweight loss triangle.

By setting the welfare derivative in Equation 3 equal to zero, one finds that the optimal subsidy $s^*$ equals the average marginal bias:

$$s^* = B(c - s^*). \tag{5}$$

Allcott & Taubinsky (2015), Allcott et al. (2014), Baicker et al. (2015), and Mullainathan et al. (2012) derive the basic result that the optimal internality tax equals the average marginal internality. This directly parallels the findings of Diamond (1973), who shows that the optimal externality tax equals the average marginal externality.

Although this framework is highly stylized, it generates insights for a broad class of policies: At least in simple models, the most important policies listed in **Table 1** are isomorphic to a subsidy $s$. Subsidies for Energy Star appliances and weatherization can be analyzed directly, although typically it would be necessary to extend the model to incorporate more than two products. With unit demand and lump-sum taxation or revenue recycling, a gas guzzler tax or analogous tax on good $I$ is isomorphic to a subsidy, and a minimum energy efficiency standard is an infinite tax on good $I$. CAFE standards impose a shadow cost on vehicle sales that can be approximated as a subsidy for high-MPG vehicles.

Equations 4 and 5 emphasize the importance of empirical work that can identify $B(p)$. Some issues matter for welfare analysis, whereas others do not. First, $B(p)$ could naturally be heterogeneous at different $p$, and different types of consumers could be marginal to different policies.

can actually increase consumer welfare (even without including externality benefits) if they also reduce internalities; Allcott et al. (2014) call this the "internality dividend."

Thus, to set and evaluate subsidies and standards, it is insufficient to know just the population average bias. Second, $B(p)$ is a reduced-form description of the behavioral models described in Section 3.2. Once we know $B(p)$, the optimal subsidy and welfare evaluation do not depend on whether consumers are present biased, inattentive, or biased in some other way.

## 4. EMPIRICAL TESTS

This section discusses categories of three empirical tests: comparing demand responses to prices versus energy costs, measuring the effects of nudges, and belief elicitation. These tests are directly analogous to the three empirical studies in Chetty et al. (2009) and are parallel to categories of tests described in Mullainathan et al. (2012). The first two tests also parallel two of DellaVigna's (2009) proposed methods of testing for inattention, although, as shown below, they are joint tests of inattention and other behavioral models.

### 4.1. Comparing Demand Responses

A general test for systematically misperceived costs is to compare demand response to a correctly perceived cost versus a potentially misperceived cost. This is the approach followed by Abaluck & Gruber (2011), Barber et al. (2005), Chetty et al. (2009), Finkelstein (2009), Hossain & Morgan (2006), and others when studying sales taxes, shipping and handling charges, highway tolls, and other potentially shrouded costs.

The energy efficiency version of this test is to compare demand response to price versus energy cost. Consumers should care only about the total lifetime cost of using a car, not the individual components of that cost. Thus, consumers should be indifferent between a dollar of upfront price and a present discounted dollar of energy costs. Many papers have implemented this test, including Dubin (1992), Dubin & McFadden (1984), Goldberg (1998), Grigolon et al. (2014), Hausman (1979), and Houde & Spurlock (2015). A simple representation of the approach is to imagine cross-sectional data on market shares and product attributes in a logit model. Define $s_j$, $X_j$, and $\xi_j$ as the market share, observed characteristics, and unobserved characteristics of product $j$. In the representative consumer logit model, the market share equation is

$$\ln(s_j) = -\eta(p_j + \gamma g_j) + \alpha X_j + \xi_j. \tag{6}$$

If the estimated $\hat{\gamma}$ is smaller (larger) than 1, this implies that consumers undervalue (overvalue) one dollar of energy cost $g_j$ relative to purchase price $p_j$.

A crucial part of the approach is estimating $g_j$. This requires expectations of future energy costs, utilization patterns, and discount rates.[8] Of course, estimating the implied discount rate that gives $\gamma = 1$ does not eliminate the need to take a stand on discount rates because once an implied discount rate is estimated, it must be compared to some benchmark rate to determine if consumers are behaving according to some benchmark model. The need to make assumptions to calculate $g_j$ makes it more complicated to implement this test with energy efficiency relative to sales taxes, shipping and handling fees, or other costs that are easily quantified and are paid at the

[8] Allcott (2011a), Allcott & Wozny (2014), and Anderson et al. (2013) provide evidence on consumers' energy price predictions. Anderson et al. (2013) use Michigan Survey of Consumers (MSC) data from 1993 to 2010 to show that on average, consumers believed that the future real price of gasoline would equal the current price. However, both oil futures markets and MSC consumers believed that the price shocks of 2008 were temporary. Allcott & Wozny (2014) show that used vehicle prices move as if consumers' forecasts are some combination of current and futures prices.

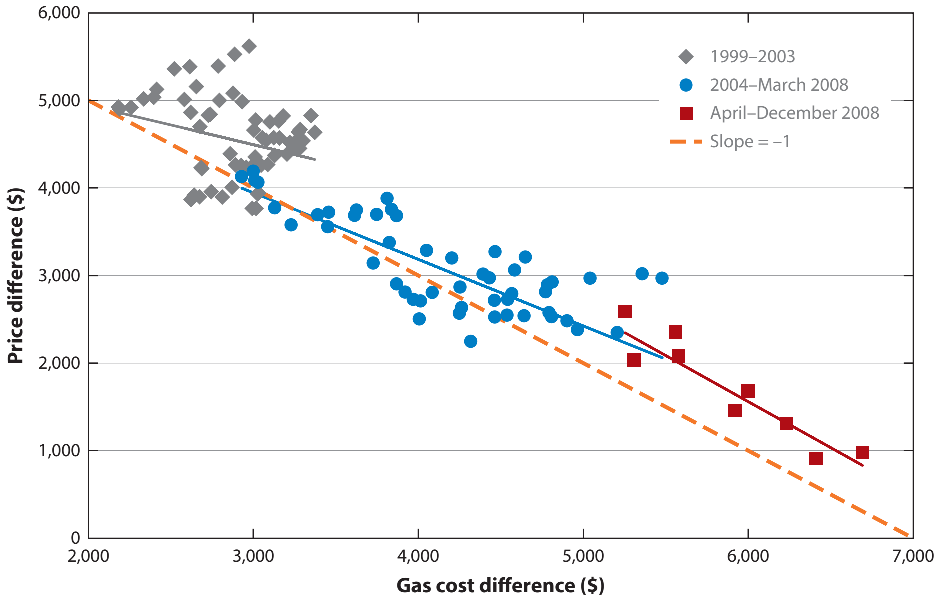


**Figure 1**

Comparison of demand responses. The vertical axis presents the difference in average prices between below-median miles per gallon (MPG) and above-median MPG used vehicles. The horizontal axis presents the difference in the average present discounted value of gasoline costs. Each symbol represents a month of the sample, from January 1999 through December 2008. Data are from Allcott & Wozny (2014).

time of purchase. Conversely, many other product attributes—a car's horsepower, the sweetness of strawberry jam, etc.—cannot be monetized, and this test could not be implemented at all.

One immediate problem with the cross-sectional test is the endogeneity of both $p_j$ and $g_j$. As Berry et al. (1995) and others point out, prices are likely to be correlated with unobserved characteristics $\xi_j$. Furthermore, energy efficiency, which generates the cross-sectional variation in $g_j$, is also likely to be correlated with $\xi_j$. For example, an "economy" car has both high fuel economy and fewer amenities, and not all amenities are observed by the econometrician. Allcott & Wozny (2014) show that fuel economy is highly negatively correlated with price in a cross section of vehicles, suggesting the low-fuel economy vehicles have more observed and unobserved amenities.

To address these issues, Allcott & Wozny (2014), Busse et al. (2013), and Sallee et al. (2016) exploit variation in $g$ and $p$ from panel data on used auto markets. Allow $jat$ to index a model $j$ of age $a$ at time $t$, for example, a three-year-old Honda Civic DX in 2006. In used markets, $s_{ja}$ is fixed over time by definition because vehicles of a given model year have already been produced.[9] Defining $\xi_{ja}$ as a model fixed effect and including time indicators $\tau_t$, one can rearrange Equation 6 as

$$p_{jat} = \gamma g_{jat} + \xi_{ja} + \tau_t + \epsilon_{jat}. \qquad (7)$$

**Figure 1** gives graphical intuition for the identification, using data from Allcott & Wozny (2014). It is constructed by grouping above-median and below-median fuel economy vehicles into

[9] Allcott & Wozny (2014) exclude vehicles older than 15 years, as they reject that scrappage is exogenous to gasoline prices for these older vehicles.

composite groups, analogous to goods $E$ and $I$. Each point on the graph is a month of the sample, from 1999 through the end of 2008. The $y$ axis plots the mean price difference $p_I - p_E = -p$, and the $x$ axis plots the mean gas cost difference $g_I - g_E = g$. Notice that low-MPG cars are both more expensive and have higher $g_j$, so both $-p$ and $g$ are positive. This figure plots raw data, before removing fixed effects or including other controls. The best-fit lines slope downward: As gas prices increase, the relative gas costs of good $I$ increase, and relative prices drop in response. Thus, consumers are clearly highly responsive to gas prices. The more responsive are relative prices to gasoline costs, the more we infer that consumers value fuel economy.

Allcott & Wozny (2014) estimate a 15% implied discount rate, meaning that $\gamma = 1$ when they assume $\delta = 1/1.15$. They calculate consumers' weighted average intertemporal opportunity cost of capital based on used car loan interest rates from the Survey of Consumer Finances and returns to the S&P 500, and weight these two by the share of consumers who pay with loans versus cash. This weighted average is 6%, which gives $\delta = 1/(1 + 6\%)$. At this $\delta$, the $\hat{\gamma}$ in Allcott & Wozny's (2014) primary specification is 0.76. They also estimate $\hat{\gamma}$ for a range of alternative assumptions and specifications.

Using an analogous approach that compares vehicles in different quartiles of the MPG distribution, Busse et al. (2013) report a range of implied discount rates from −6.8% to 20.9%, depending on the assumptions used to calculate $g$ and the quartiles being compared. When using assumptions that correspond most closely to Allcott & Wozny's (2014) primary specification (vehicle miles traveled and survival probabilities from the National Highway Transportation Safety Administration), the average implied discount rate for used vehicles is 13%. At $\delta = 1/(1 + 6\%)$, this gives $\hat{\gamma} = 0.78$. However, Busse et al.'s (2013) implied discount rates drop under alternative estimates of vehicle miles traveled, and the auto loan interest rates in Busse et al.'s (2013) data appear to be higher than in the Survey of Consumer Finances, so their benchmark $\delta$ is different. Thus, Busse et al. (2013) find little evidence that auto consumers undervalue future gasoline costs.

Sallee et al. (2016) have a slightly different empirical specification: They include separate model-age fixed effects for every month in their sample, as well as flexible controls for each transacted vehicle's odometer reading. Autos with less past mileage have a longer future life, so their transaction prices should be more responsive to changes in gas prices. Sallee et al. (2016) are thus testing a different hypothesis than Allcott & Wozny (2014) and Busse et al. (2013): whether consumers recognize that gas price changes should differentially affect older versus newer vehicles, instead of high-MPG versus low-MPG vehicles. Although Allcott & Wozny's (2014) and Busse et al.'s (2013) question is one step closer to the policy question of how consumers value fuel economy, Sallee et al. (2016) can include a larger set of controls, and their test is plausibly a nested test: If consumers fully value how gas prices differentially affect vehicles of the same model and model year with different odometer readings, it is likely that they fully value how gas prices differentially affect models with different MPG ratings. Sallee et al.'s (2016) baseline model gives robust estimates consistent with full valuation, but they emphasize that different assumptions around the construction of $g_j$ can shift the coefficient estimate in either direction.

As discussed further in Section 6.2, although these three papers differ, their results are consistent in showing that consumers are highly responsive to gas prices, and they can rule out the magnitude of mistakes that would be required to justify the stringency of the current CAFE standard.

Houde (2014b) estimates a model of the refrigerator market that can also be categorized as comparing demand responses. He first estimates an analog to Equation 6 with model fixed effects, identifying the $\gamma$ parameter using the fact that consumers in different counties and states pay different electricity prices. This variation consistently identifies $\gamma$ as long as geographic variation in models stocked and consumer preferences is not correlated with electricity prices. The base specification gives an implied discount rate of 62%. Houde then posits a structural model in which some consumers are fully inattentive to electricity costs, some are fully attentive, and some form expectations of electricity costs using only the Energy Star label. The model is identified by changes in the choice set over his 2007–2011 sample: Models enter and exit, prices change, and some models lose their Energy Star certification due to the discovery of a testing error. The share of consumers that substitute equally to models regardless of electricity use represents the share of inattentive consumers, and the share that substitute equally to all Energy Star models regardless of electricity use, but prefer Energy Star to non–Energy Star models, is the share that attend only to Energy Star. Consistent with his high implied discount rate, Houde finds that the modal consumer is fully inattentive, and many other consumers are attentive only to the Energy Star label and not the exact level of electricity use.

What parameters do the used vehicle market studies identify? Allcott & Wozny (2014), Busse et al. (2013), and Sallee et al. (2016) all estimate the $\hat{\gamma} = -dp/dg$ from Equation 7 using the identification strategy of comparing demand responses. In the choice models from Section 3, what does this $\hat{\gamma}$ represent? Allcott et al. (2014, section 4.3) show that if the bias is exogenous to gas price changes, $\hat{\gamma}$ can measure the average marginal bias. When bias is endogenous, however, as in the models with endogenous attention and costly information acquisition, relative prices move more than would be predicted in exogenous bias models. Intuitively, as gas prices increase, the relative prices of high-MPG vehicles increase both because they are more valuable to attentive consumers and because more consumers become attentive and thus are willing to pay for fuel economy. Thus, when attention or information acquisition is endogenous, the identification strategy of comparing demand responses will overstate the share of attentive consumers $\lambda$ at initial prices. This is an issue not just for Allcott & Wozny (2014), Busse et al. (2013), Sallee et al. (2016), and other energy papers, but also for papers in other domains, such as Chetty et al. (2009), that use an analogous approach to identify the magnitude of inattention.[10]

## 4.2. Estimating Effects of Nudges

Building on Thaler & Sunstein (2008), Allcott & Taubinsky (2015) define a pure nudge as an intervention that eliminates bias but has no other effects. For example, providing information on energy costs can cause consumers who were previously uninformed or inattentive to make privately optimal decisions. In theory, pure nudges can identify the average marginal bias function. To see this, consider the set of consumers who have baseline willingness to pay (WTP) of $v + g - b = p$ and are thus marginal at price $p$. Because the pure nudge causes consumers to make the same decisions they would make if they were informed and rational, their average WTP after being given a pure nudge is just the average of their $(v + g)$. Thus, $\tau(p)$, the average WTP change from a pure nudge for consumers marginal at price $p$, equals the average marginal bias:

$$\tau(p) = E_G((v+g) - (v+g-b)|v+g-b=p) = E_G(b|v+g-b=p) = B(p). \tag{8}$$

Carrera & Villas-Boas (2015), Chetty et al. (2009), Choi et al. (2010), Kling et al. (2012), and others measure the effects of information in choices between generic and branded drugs, sales taxes, retirement savings, health insurance, and other domains. DellaVigna (2009) points to Chetty et al. (2009) as an example of how treatment effects from experimentally provided information can be a measure of bias from inattention. Of course, nudges only identify the magnitudes of the specific biases they target: Information provision can eliminate imperfect information and inattention, but

[10] Allcott & Taubinsky (2015) also show that even when each consumer's attention or bias is exogenous, comparing demand responses only approximates the average marginal bias $B(p)$ when $b$ is heterogeneous across consumers and not independent of $v$. They show that the approximation can be highly inexact, which provides a further challenge to this approach.

it does not affect or identify present bias. Offering state-contingent commitment contracts could identify present bias for sophisticates, but this does not affect or identify imperfect information.

In the context of energy efficiency, the nudge identification strategy might take the form of measuring effects of durable-good energy cost information. Allcott & Taubinsky (2015) run two informational field experiments with light-bulb buyers. Their study is motivated by the fact that only 28% of light sockets in US homes that could accommodate compact fluorescent light bulbs (CFLs) actually had them as of 2010, despite the fact that a standard 60-watt-equivalent CFL saves \$40 in electricity and bulb replacement costs over its rated eight-year life relative to traditional incandescent bulbs. Is this low market share a result of preferences, i.e., the distribution of $v$ in the model above? Or is this a result of imperfect information or inattention?

Only very specific experimental designs can plausibly use Equation 8 to identify $B(p)$. First, experimental or quasi-experimental designs are obviously needed to consistently identify a treatment effect $\tau$. Second, one needs a design that allows the measurement of $\tau(p)$ at different $p$. To do this, one must observe consumers' WTP before being given a pure nudge to know which consumers are marginal at a given $p$ and then measure the nudge's effect on WTP for these marginal consumers. Third, the treatment must be a pure nudge, without affecting consumers through persuasion, demand effects, or other mechanisms. This highlights perhaps the crucial drawback of this identification strategy: It is difficult to design interventions that plausibly approximate a pure nudge, and it is not clear how such an assumption could be decisively tested.

Allcott & Taubinsky's (2015) experiment using Time-Sharing Experiments for the Social Sciences (TESS) attempts to satisfy these three criteria. A crucial feature is the within-subject design. All consumers in the experiment were given a \$10 shopping budget and asked to make choices between CFLs (good $E$) and incandescents (good $I$). Each consumer made baseline choices using a 15-part multiple price list. The treatment group was then given hard information about cost savings from CFLs, whereas the control group received information that was parallel in form but vacuous in content. Each consumer then made end-line light-bulb choices on an identical 15-part multiple price list. Consumers' decisions were incentive compatible: One of the 30 choices was randomly selected to be the consumer's official purchase, and consumers were shipped the light bulbs that they had chosen at that relative price and given the remainder of their \$10 shopping budget. This within-subject design identifies $\tau(p)$ by measuring the average treatment effect on WTP for consumers at each level of baseline WTP. In this context, WTP refers to incremental WTP for the CFL relative to the incandescent.

The information treatment was designed to plausibly approximate a pure nudge. It provided only hard information on light-bulb costs, without persuasive cues such as social comparisons or environmental framing. Care was taken to avoid demand effects, where experimental subjects might be more or less likely to purchase energy-efficient goods not due to new information but because they wish to comply with (or perhaps defy) the perceived wishes of the experimenter. In addition, Allcott & Taubinsky (2015) take steps to ensure and document that treated consumers understood, believed, and internalized the information. Despite this, they view their information treatments as only approximations to a pure nudge, and they carry out analyses under alternative assumptions.

**Figure 2** gives the intuition for Allcott & Taubinsky's (2015) main results. The graph presents a discrete version of Equation 4. Because the CFL and incandescent light-bulb packages were chosen to have the same unsubsidized retail price, the unsubsidized market equilibrium is at a relative price of \$0. At this price, the CFL market share is approximately 70%. By the assumptions for Equation 8, the average treatment effect for consumers whose baseline relative WTP for the CFL is between \$0 and \$$-1$ equals the average marginal bias $B(p)$. A subsidy of \$1 moves the CFL market share to approximately 0.82, generating both the internality reduction and the Harberger distortion indicated in the figure. Subtracting the loss from the gain, it is clear that this

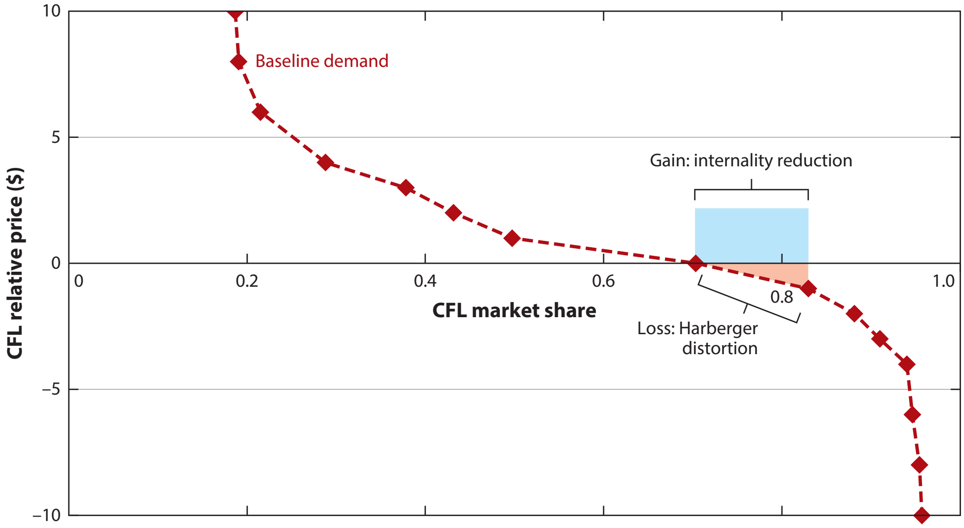


**Figure 2**

Welfare effects of a $1 compact fluorescent light bulb (CFL) subsidy. Observations are weighted for national representativeness. The dashed line is the demand curve from the baseline multiple price list. The shaded rectangle above the $x$ axis is the average treatment effect for consumers whose baseline relative willingness to pay for the CFL is between $0 and $−1. The triangle below the $x$ axis is the Harberger distortion from the subsidy, in which the subsidy moves consumers away from their perceived private optima. Data are from Allcott & Taubinsky (2015).

$1 subsidy increases welfare. Incremental increases in the subsidy raise welfare until the incremental internality reduction above the $x$ axis is larger than the incremental Harberger distortion below the $x$ axis. Using this logic, Allcott & Taubinsky (2015) find that the optimal subsidy to address imperfect information and inattention is $3.

In the model with unit demand and lump sum revenue recycling, a ban on good $I$ is equivalent to subsidy $s = \infty$. Any incremental subsidy increases beyond $3 decrease welfare, and the ban on incandescent light bulbs is so stringent as to fully reverse the possible welfare gains from the $3 subsidy. This result is driven by the fact that there is a large group of consumers who strongly prefer incandescent light bulbs, even after being informed about the cost advantages of CFLs.

This nudge-based identification strategy has several important advantages. First, the nudge approach provides a consistent estimate of the baseline level of bias even if the bias is endogenous or heterogeneous. As discussed above, this is not necessarily true for the approach of comparing demand responses. Second, the nudge approach requires none of the assumptions on discount rates, energy price forecasts, and utilization that are required to calculate $g_j$ in order to compare demand responses. Third, when paired with the multiple price lists and within-subject design of the light-bulb experiment, the nudge approach allows the analyst to infer the joint distribution of baseline demand and $B(p)$, which is required both for setting the globally optimal subsidy and for evaluating the welfare effects of a ban. An important future research area would be to design a natural field experiment that has the conceptual advantages of Allcott & Taubinsky's (2015) experiment without the artifactual setting.

Because their nudge identifies only the effects of imperfect information and inattention, Allcott & Taubinsky (2015) cannot rule out that other mistakes might justify a ban on incandescent light bulbs. Indeed, there are two interesting results that suggest other potential mistakes. First, Allcott & Taubinsky (2015) point out that the demand curve in **Figure 2** is highly elastic around zero relative price. Interestingly, $g$ is typically very large and positive, because CFLs can save significant amounts of money on electricity costs. For $v+g$ to have significant mass around zero, the distribution of $v$ must be closely symmetric to the distribution of $g$ (i.e., typically very large and negative.) Although many people dislike CFLs, the required symmetry of this disutility might not be plausible. One alternative explanation is that there is some alternative bias, such as bias toward concentration with $\beta$ close to zero, such that the distribution of WTP largely reflects a distribution of $v$ centered close to zero.

Second, Allcott & Taubinsky's (2015) survey participants compose a nationally representative sample with at least one person in every US state other than Alaska. There is substantial variation in electricity prices across states: Using data from the US Energy Information Administration, the mean across states is 12.7 cents per kilowatt-hour, with a standard deviation of 4.3. Using Equation 1, I calculate $g_s = g_{Es} - g_{Is}$ for CFLs versus incandescents in each state $s$ using a 6% discount rate over the eight-year rated life of a CFL; this averages \$39. If $v \perp g_s$, then the coefficient on $g_s$ in a regression of WTP on $g_s$ should be 1. In other words, as long as people's nonmonetary preferences for light bulbs are not correlated with state electricity prices, people should be willing to pay \$1 more for a CFL if their state electricity prices imply an additional \$1 savings.

**Table 2** presents results. Regardless of whether I control for additional covariates that might be correlated with $v$ and electricity prices, the coefficient is statistically indistinguishable from zero and easily distinguishable from 1. This is again consistent with the idea that there is some additional bias that would not be addressed by an information provision nudge, such as bias toward concentration with $\beta$ close to zero. Using state-by-year panel data, Jacobsen (2015) similarly shows that electricity prices have an economically and statistically insignificant impact on market shares of Energy Star appliances.

## 4.3. Belief Elicitation

Starbucks customers tend to overestimate the calories in drinks and underestimate the calories in food (Bollinger et al. 2011). People signing up for gyms are overconfident about their future attendance and about their likelihood of canceling automatically renewed memberships (DellaVigna & Malmendier 2006). More than 70% of seniors choosing between Medicare plans underestimate potential cost savings from switching (Kling et al. 2012). Spinnewijn (2015) shows that the unemployed overestimate how quickly they will find work. Could consumers have systematically biased beliefs about the financial benefits of energy efficiency?

There is some evidence of misperceived energy costs from the psychology literature. Attari et al. (2010) show that consumers underestimate the energy use from heating and cooling and other large energy uses relative to the energy use of a light bulb. Larrick & Soll (2008) document the concept of MPG illusion: People intuitively think as if automobile fuel costs scale linearly in MPG, whereas they in fact scale linearly in gallons per mile. Turrentine & Kurani (2007) show that even well-educated auto owners with quantitative jobs have trouble with the net present value calculations required to estimate $g_j$.

Although these results are interesting and important, this evidence that consumers misperceive energy costs does not directly test whether consumers systematically overestimate or underestimate the value of energy efficiency, i.e., whether $B(p)$ is nonzero. The Vehicle Ownership and Alternatives Survey (VOAS) (Allcott 2011a, 2013) is a nationally representative survey on the TESS platform, designed to test whether consumers systematically underestimate the fuel cost savings from higher-MPG vehicles. The VOAS asks consumers what vehicle they currently drive, how much they spend on gasoline, and how much they would spend on gasoline if they had bought

**Table 2 Correlation of willingness to pay (WTP) for a compact fluorescent light bulb (CFL) with electricity cost savings**

| | (1) | (2) |
|---|---|---|
| CFL electricity cost savings | −0.031<br>(0.031) | −0.025<br>(0.031) |
| Income ($ millions) | | 1.903<br>(6.167) |
| Education (years) | | −0.032<br>(0.147) |
| Age | | −0.012<br>(0.019) |
| Male | | 0.707<br>(0.537) |
| Liberal | | −0.071<br>(0.385) |
| Party | | 0.572<br>(0.346)* |
| Environmentalist | | 1.168<br>(0.847) |
| 1(Homeowner) | | 0.262<br>(0.695) |
| $N$ | 1,229 | 1,217 |
| $R^2$ | 0.00 | 0.01 |

The dependent variable is incremental WTP for a CFL relative to an incandescent light bulb, using data from Allcott & Taubinsky (2015). Liberal and Party are self-reported political variables, normalized to mean zero, a standard deviation of 1, with more positive meaning more liberal and more Democratic. Environmentalist is the consumer's response to the question, "Would you describe yourself as an environmentalist?" "Yes, definitely," "Yes, somewhat," and "No" are coded as 1, 1/2, and 0, respectively. Robust standard errors are in parentheses. *, **, and *** denote statistically different from zero with 90%, 95%, and 99% confidence, respectively.

their second-choice vehicle or another "replacement vehicle" with randomly selected MPG difference. These questions are used to construct valuation ratios: the share of true fuel cost differences that consumers perceive. This is denoted $\phi$ in the model in Section 3. Indexing the current vehicle as $j = o$ and an alternative vehicle as $j = a$, the valuation ratio for consumer $i$ is

$$\phi_{ia} = \frac{\tilde{g}_{ia} - \tilde{g}_{io}}{g_{ia} - g_{io}}. \tag{9}$$

Consumers were told to assume that they drove the alternative vehicles the same amount as their current vehicle, which allows $m$ to be assumed constant. To measure and limit potential confusion, various response frames were randomized across consumers. For example, some were told to report annual gasoline cost estimates, whereas others were told to report estimates over the full vehicle life. Some consumers were asked for absolute levels of gasoline costs, whereas others were told to report cost savings or additional costs relative to their current vehicle.

**Figure 3** plots the distribution of valuation ratios between current vehicles and second-choice vehicles. If all consumers were perfectly informed and reported correctly on the survey, the distribution would have point mass at $\phi = 1$. In fact, the figure shows that valuation ratios are quite dispersed, likely reflecting a combination of truly dispersed beliefs and reporting error. The large mass at zero represents consumers who incorrectly report that their current vehicle

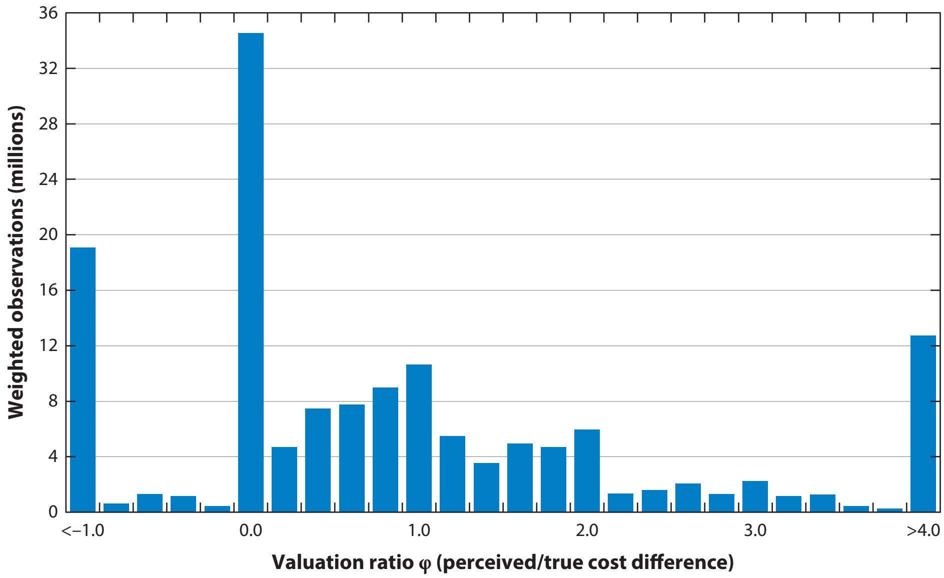


**Figure 3**

The distribution of valuation ratios for second-choice vehicles from the Vehicle Ownership and Alternatives Survey. Observations are weighted for national representativeness. Data are from Allcott (2013).

and second-choice vehicle have "exactly the same" fuel economy. Allcott (2013) shows that on average, consumers correctly estimate or perhaps slightly underestimate the financial benefits of higher-MPG vehicles.

There are two concerns with the belief elicitation approach to measuring bias. The first is that because the goal is to measure beliefs as they existed at the time of purchase, the survey must induce accurate recall without additional calculation. Making the belief elicitation fully incentive compatible could induce survey respondents to look up fuel economy ratings and calculate answers on a calculator or spreadsheet. Conversely, providing no incentives could lead to thoughtless answers. The VOAS offered moderate incentives (up to $10) with a vague criteria for payout: if an answer "makes sense" given answers to other questions. Allcott (2013) shows that results are indistinguishable between consumers randomly assigned to be offered incentives versus not offered incentives.

The second concern is that stated beliefs have wide variance, and it is not clear whether this reflects true variation in beliefs or reporting error. The average marginal $\phi$ represents an estimate of $B(p)$, but the standard error on the estimated mean can be large. Allcott (2013) also estimates median regressions as an alternative measure of central tendency.

One benefit of belief elicitation is that it provides a direct measure of biased beliefs, whereas the comparing demand responses approach could estimate a combination of biases, and the informational nudge could estimate effects of biased beliefs, costly information acquisition, and inattention.

## 5. TESTING BETWEEN BEHAVIORAL MODELS

Section 3 proposed several behavioral models, and the three empirical approaches discussed in Section 4 identify different subsets of these models. This section provides additional evidence for and against two of the proposed models.

## 5.1. Evidence of Endogenous Attention

Sallee (2014) describes reasons to believe that auto buyers might be rationally inattentive to gas costs. First, he argues that some cognitive cost is required to calculate the lifetime present discounted value of gas costs, both because fuel economy information labels can be incomplete and inaccurate and because the labels provide average cost information that consumers must then adjust to their own energy costs and usage patterns. Second, he shows that in many cases, fuel economy may not be worth paying attention to. The variation in lifetime gas costs across vehicles is dwarfed by the variation in prices, and only approximately 10% of new vehicle buyers would change their decisions if they ignored versus fully attended to within-class fuel economy differences, generating a welfare loss of only approximately $100–200 per purchase.

Below, I provide three pieces of empirical evidence in support of endogenous attention models. I use the phrase endogenous attention as shorthand—these tests measure both endogenous information acquisition and endogenous attention to that information. I use the term endogenous instead of rational because these tests do not necessarily imply that attention responds optimally.

In rational attention models such as those of Gabaix (2014) and Sallee (2014), consumers are more likely to pay a cost to attend to an attribute if it is more likely to affect their decisions. In the context of the model in Section 3, this implies that $\lambda$ is increasing in energy price $e$ and utilization $m$. Furthermore, attention might vary across consumers due to variation in cognitive costs, not just gains from attention. These models guide the evidence below.

The first piece of evidence comes from the VOAS, originally reported in Allcott (2011a). The median completion time for this survey was ten minutes. The final question was, "In this survey, we asked you to calculate fuel costs fairly mathematically and precisely. Think back to the time when you were deciding whether to purchase your vehicle. At that time, how precisely did you calculate the potential fuel costs for your vehicle and other vehicles you could have bought?" There were five possible responses, ordered from "I did not think about fuel costs at all when making my decision" to "I calculated more precisely than I did just now during this survey." Forty percent of Americans reported that they did not think about fuel costs at all during their most recent purchase. I construct a measure of calculation effort by coding the five responses as integers from 1 to 5 and normalizing to mean zero, with a standard deviation of 1.

**Table 3** reports regressions of calculation effort on potential explanatory factors available in the VOAS. Column 1 shows that a $1 increase in gasoline prices is associated with a 0.148 standard deviation increase in calculation effort. Consumers that drive more miles per year also calculate more. These two results are consistent with a model in which consumers pay more attention to fuel economy when it has larger financial implications, either because they drive more miles or because gas prices are higher. Column 2 repeats the regression with the addition of the interaction between gas prices and miles per year. As the same model would predict, gas prices have an especially large association with calculation effort for consumers who drive more. Calculation effort is also positively associated with education, which is consistent with a model in which education is correlated with lower cognitive costs. Self-described environmentalists also are more attentive to fuel costs, a result that I return to in Section 6.1.

A second piece of evidence for endogenous attention comes from the used vehicle markets studied by Allcott & Wozny (2014), Busse et al. (2013), and Sallee et al. (2016). As gas prices rose between 2003 and 2008, endogenous attention predicts that the estimated $\gamma$ parameter should increase. **Figure 1** shows graphical evidence of this using data from Allcott & Wozny (2014). From 1999 to 2003, gasoline prices were relatively low, and the slope of $dp/dg$ is relatively flat. From 2004 to March 2008, gasoline prices were at a higher average, and the slope becomes steeper. From April to December 2008, as gas prices reached almost unprecedented highs, the slope of

**Table 3 Correlates of fuel cost calculation effort**

| | (1) | (2) |
|---|---|---|
| Gas price at purchase ($/gallon) | 0.148<br>(0.046)*** | −0.801<br>(0.431)* |
| ln(Implied miles/year) | 0.069<br>(0.034)** | −0.205<br>(0.124)* |
| Environmentalist | 0.254<br>(0.115)** | 0.251<br>(0.115)** |
| Income ($ millions) | 0.201<br>(0.859) | 0.216<br>(0.860) |
| Education (years) | 0.051<br>(0.015)*** | 0.052<br>(0.015)*** |
| Age | −0.006<br>(0.002)** | −0.006<br>(0.002)*** |
| 1(Male) | 0.211<br>(0.070)*** | 0.204<br>(0.070)*** |
| 1(Rural) | −0.132<br>(0.082) | −0.137<br>(0.083)* |
| Gas price × ln(Implied miles/year) | | 0.106<br>(0.049)** |
| *N* | 1,444 | 1,444 |

The dependent variable is a measure of fuel cost calculation effort from the Vehicle Ownership and Alternatives Survey, normalized to a standard deviation of 1. Gas price at purchase is the US average retail gasoline price in the month that the vehicle was purchased from the US Energy Information Administration, inflated to 2014 dollars. Implied miles/year is backed out from self-reported gasoline expenditures using the current vehicle MPG rating and gasoline prices. Environmentalist is the consumer's response to the question, "Would you describe yourself as an environmentalist?" "Yes, definitely," "Yes, somewhat," and "No" are coded as 1, 1/2, and 0, respectively. Robust standard errors are in parentheses. *, **, and *** denote statistically different from zero with 90%, 95%, and 99% confidence, respectively.

$dp/dg$ is close to $-1$. More formally, Allcott & Wozny (2014) show that the estimated $\gamma$ is larger when excluding 1999–2003 and smaller when excluding April to December 2008.

A third piece of evidence comes from direct observation of information acquisition: Internet search volumes for terms related to fuel economy and page visits to the fueleconomy.gov informational website. This analysis parallels that of Hoopes et al. (2015), who show that Google searches for tax-related terms respond to stock market activity, policy changes, and news events.

For search volume data, I use Google Trends, which provides weekly data beginning in January 2004. I consider searches for five fuel economy-related phrases (gas mileage, fuel economy, fuel efficiency, miles per gallon, and mileage calculator) in the Vehicle Shopping category.[11] Search counts are normalized by total Vehicle Shopping category search volume in order to control for time variation both in the number of consumers currently in the auto market and in the use of web search. To corroborate the Google Trends data, I also acquired monthly counts of visits to fueleconomy.gov, the official US government fuel economy information website, beginning in

[11] These search terms were chosen to measure information acquisition, not product demand. Although one could also show that search terms such as "hybrid vehicles" and "Toyota Prius" covary positively with gasoline prices, this effect could be driven by informed consumers searching for information about vehicles already known to have higher MPG, instead of searches motivated by determining which vehicles have higher MPG.

October 2002. A "visit" is as defined by Google Analytics: a series of one or more page views by a unique visitor, which ends after 30 minutes of inactivity or when the browser is closed. There are an average of 2.3 million visits per month.

**Figure 4*a*** plots weekly Google searches for fuel economy on the left axis and gas prices on the right axis. Search volumes track gas prices extremely closely. **Figure 4*b*** plots the monthly data on visits to fueleconomy.gov, which also closely track gas prices. Unlike the Google Trends data, fueleconomy.gov visits are not normalized by any measure of web traffic or vehicle consumers in the market, and there is a general upward trend over time. Both graphs show a sharp uptick in search volume in June–August 2009, as the Cash for Clunkers program made government subsidies conditional on fuel economy ratings.

To formally test the relationship, I regress search volume in week $t$ (or website visits in month $t$) $S_t$ on gasoline price as $e_t$, controlling for a Cash-for-Clunkers indicator for June–August 2009 $C_t$, linear time trend $L_t$, and week-of-year (or month-of-year) indicators $\mu_t$:

$$\ln S_t = \eta \ln e_t + \psi C_t + \zeta L_t + \mu_t + \varepsilon_t. \tag{10}$$

**Table 4** presents results, with Newey-West standard errors allowing for one year of lags (52 weeks or 12 months). Columns 1 and 3 show that information acquisition is highly statistically significantly correlated with gas prices in both the Google Trends and fueleconomy.gov data, with very similar elasticities of approximately 1.9. Column 2 shows that Google searches for four alternative vehicle attributes (horsepower, torque, warranty, and safety ratings) are not correlated with gas prices, suggesting that attention to gas costs may not draw attention away from other attributes, but instead may increase total decision-making effort.

### 5.2. Is Present Bias a Plausible Model?

Across many nonenergy domains, there is strong evidence consistent with present bias and temptation models. Heutel (2016) and Tsvetanov and Segerson (2013, 2014) theoretically model the welfare effects of energy efficiency policy in present bias and temptation models, respectively. Above I suggest the possibility of a present bias model, as do Allcott & Taubinsky (2015), Allcott et al. (2014), Gillingham & Palmer (2014), and others. Is there empirical evidence consistent with such models?

There is one theoretical reason to question the relevance of present bias models for choices of energy-using durables. Taken literally, agents in these models are present biased over consumption, not cash flows. Because consumers in developed countries often can save and borrow to buy energy-using durables, paying additional money for an energy-efficient good does not affect consumption in the present. Instead, it affects consumption over many future periods—perhaps the same future periods in which energy cost savings accrue. Similarly, the actual consumption value from energy-using durables, by which I mean the enjoyment of driving a large SUV or a sporty car with lots of torque, also accrues over many future periods. Home buying is a clear example: Because of mortgages, the purchase price, home energy costs, and consumption value of the home are all flows that occur in the future. Thus, although present bias might cause consumers to delay the effort of buying a home or car, it should not cause consumers to underweight energy costs relative to purchase prices. This suggests that any mistakes in this domain would be more likely driven by imperfect information, inattention, or bias toward concentration.

One might propose an alternative present bias model in which agents are present biased over cash flows. Bradford et al. (2014) estimate time-consistent discounting and present bias parameters using multiple price lists that trade off cash flows at different times. They find that the present bias parameter $\beta$ is statistically associated in the predicted direction with driving a fuel-efficient car,

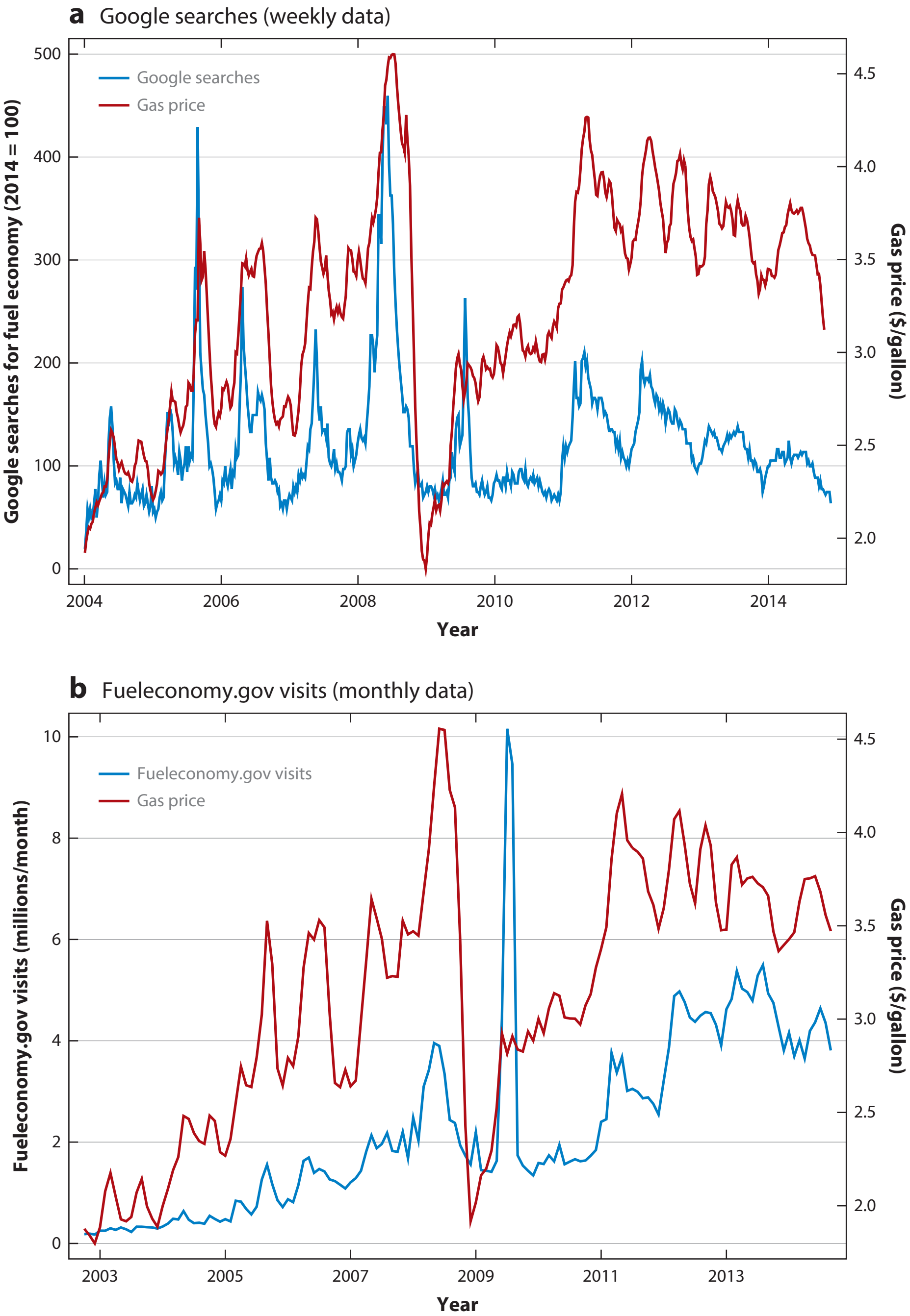


**Figure 4**

Gasoline prices and search volume. In panel *a*, Google searches represent the relative popularity of five fuel economy-related search terms (gas mileage, fuel economy, miles per gallon, fuel efficiency, and mileage calculator) from Google Trends data. In panel *b*, fueleconomy.gov visits represent unique sessions as defined by Google Analytics. Gas price is the "US All Grades All Formulations Retail Gasoline Price" from the US Energy Information Administration.

**Table 4 Fuel economy information acquisition as a function of gas prices**

| | (1) Google Trends | (2) Alternative attributes | (3) Fueleconomy.gov website |
|---|---|---|---|
| ln(Gas price) | 1.925 | −0.114 | 1.905 |
| | (0.320)*** | (0.116) | (0.409)*** |
| 1(Cash for Clunkers) | 0.398 | −0.099 | 1.615 |
| | (0.077)*** | (0.048)** | (0.114)*** |
| Time (years) | −0.049 | −0.038 | 0.147 |
| | (0.014)*** | (0.009)*** | (0.023)*** |
| Number of observations | 565 | 565 | 144 |
| Data frequency | Weekly | Weekly | Monthly |

The dependent variable in column 1 is the natural log of relative popularity of five fuel economy-related search terms (gas mileage, fuel economy, miles per gallon, fuel efficiency, and mileage calculator) from Google Trends data. The dependent variable in column 2 is the natural log of relative popularity of four search terms for alternative vehicle attributes (horsepower, torque, warranty, and safety ratings). The dependent variable in column 3 is the natural log of the count of visits to the fueleconomy.gov website. Columns 1 and 2 include 52 week-of-year indicators, and column 3 includes 12 month-of-year indicators. Newey-West standard errors, with 52 lags (columns 1 and 2) and 12 lags (column 3), are in parentheses. *, **, and *** denote statistically different from zero with 90%, 95%, and 99% confidence, respectively.

having a well-insulated home, and the temperature setting on one's thermostat, along with other nonenergy behaviors such as smoking, binge drinking, and savings. Interestingly, however, both Bradford et al. (2014) and Allcott & Taubinsky (2015) find no correlation between the $\beta$ from multiple price lists and demand for energy-efficient light bulbs.

Both present bias and temptation models predict that sophisticated agents will want to restrict their choice sets, perhaps by taking up commitment devices. Casual observation suggests that this is uncommon: Many people seem to want to get their future selves to lose weight or quit smoking, but one rarely hears people saying that they hope to be able to get their future self to buy an Energy Star air conditioner. There are two ways to corroborate this observation with data. First, one highly publicized commitment device is stickK.com, which allows people to individually tailor commitment contracts. stickK.com shared with me their data through mid-2014. Only 0.3% of their commitment contracts are categorized as "green initiatives," whereas 0.8% are "home improvement and DIY" and 3% are "money and finance." Energy efficiency contracts are likely to be a small subset of these three categories. By contrast, other categories are much more popular, such as weight loss (35%), exercise (21%), other health and wellness (17%), career (8%), and education and knowledge (7%).

Another piece of evidence is provided by Harding & Hsiaw (2014), who study a program that invited electricity consumers to set energy conservation goals and also provided conservation information and usage feedback. In their model, failing to reach a goal imposes a utility cost due to reference-dependent preferences, and present-biased consumers thus view the program as a commitment device. Although it is difficult to measure takeup rates conditional on being aware of the program, the authors present two statistics that suggest that these rates are low. First, although the program was marketed throughout the greater Chicago metropolitan area, only 2,487 households enrolled. Second, when the authors took a random sample of 10,000 households in the zip codes where there was any enrollment, only 36 had actually enrolled.

In summary, commitment device takeup rates from stickK.com and Harding & Hsiaw (2014) suggest that few consumers are sophisticated in a present bias or temptation model. Unless the ratio of sophisticates relative to naifs is somehow very large for energy conservation, this suggests that these models are not very relevant for energy-using durables. Although this does not say that low-cost commitment devices should not be offered, it does imply that present bias and temptation are unlikely to justify energy efficiency subsidies and standards.

Notwithstanding, present bias may be relevant through an indirect channel: through effects on household finances. Specifically, present bias leads households to hold savings disproportionately in illiquid retirement accounts and home equity (Laibson et al. 2003, 2007). The resulting liquidity constraints might keep consumers from buying higher-cost durables, even those that would increase present discounted utility at their long-run discount rates. Put simply, when you have little money in the bank and lots of credit card debt, buying an energy-efficient \$1,100 refrigerator is much harder than buying an energy-inefficient \$900 refrigerator. If this is quantitatively important, one way to address it would be to provide credit to present-biased consumers for investments such as energy-efficient durables.



## 6. POLICY IMPLICATIONS

### 6.1. Targeting

Mistakes, when they occur, are almost certainly heterogeneous. For example, **Figure 3** suggests that some consumers overestimate the private value of energy efficiency, even as other consumers underestimate. The optimal subsidy to address heterogeneous bias would be consumer-specific subsidies tailored to each consumer's bias $b$. Given that consumer-specific subsidies are not practically feasible, Equation 5 shows that the optimal uniform subsidy $s$ is a compromise between (i.e., the average of) the optimal consumer-specific subsidies for the marginal consumers. However, this uniform subsidy distorts decisions of less biased consumers even as it improves decisions by more biased types.

A well-targeted policy approximates a pure nudge by preferentially affecting decisions by biased types without affecting the already-optimal decisions of rational types. A poorly targeted policy, by contrast, preferentially affects decisions by less-biased types. At best, poorly targeted subsidies are disadvantageous because they might address only a small share of the total allocative inefficiency caused by consumer mistakes. At worst, a poorly targeted subsidy could reduce welfare if $s > 0$ but the marginal consumers have $B(p) < 0$. Bernheim & Rangel (2004) give an intuitive example: If addicts are more biased but are highly inelastic to sin taxes, then a sin tax addresses little of the welfare losses from addiction. Furthermore, if rational types are relatively elastic, then a sin tax of any nontrivial magnitude might reduce welfare by inducing many rational types to underconsume the sin good.

Allcott et al. (2015) provide suggestive evidence on the targeting of energy efficiency subsidies. They propose two mechanisms that might cause some energy efficiency subsidies to be poorly targeted. First, many consumers are unaware of subsidies such as the weatherization incentives offered by local utilities, and the consumers who are most aware of and attentive to energy costs should also be more likely to be aware of energy efficiency subsidies. Because consumers will not respond to a subsidy if they are unaware of it, this mechanically makes the marginal consumers better informed and more attentive. Second, some energy efficiency investments are niche goods, such as hybrid cars and weatherization, with small market shares and only environmentalists near the margin. Thus, environmentalists are more likely to be marginal to anything other than a large subsidy, and environmentalists might have less bias against energy efficiency (i.e., lower $b$).

Allcott et al. (2015) first confirm that environmentalism is correlated with lower $b$. Environmentalist consumers believe that energy-efficient light bulbs and water heaters save more money, and as shown in **Table 3**, they pay more attention to fuel costs when buying autos.[12] Allcott et al. (2015) also show that environmentalists are more likely to be aware of energy efficiency subsidies offered in their area.

Allcott et al. (2015) then test what observable characteristics are correlated with takeup of major energy efficiency subsidies: the federal residential energy credit, hybrid vehicle subsidies, and energy efficiency subsidies from a major utility. They find that environmentalism (as measured by self-reports, owning a home solar energy system, and voluntarily paying for green energy) and the calculation effort variable from **Table 3** are correlated with takeup, which strongly suggests that the average adopter is less biased against energy efficiency (i.e., has lower $b$) than the average consumer. They also show that wealthy people and homeowners are more likely to take up subsidies, which suggests that these policies are also not well-targeted to address credit constraints and landlord-tenant information asymmetries.[13] Using much more extensive tax microdata, Borenstein & Davis (2015) fully develop the result that high-income people are more likely to take up the residential energy credit.

These results suggest that some energy efficiency subsidies may not target the market failures they were designed to target. Instead, they primarily pay wealthy environmentalists to become even more green. Notwithstanding, this empirical evidence is only suggestive. In particular, Allcott et al.'s (2015) regressions show that the average (instead of marginal) subsidy adopters have characteristics likely to be correlated with lower $b$. It would be an interesting and important contribution to (*a*) convincingly identify biased consumers and (*b*) convincingly test whether consumers marginal to a policy are more or less biased.[14]

## 6.2. Calibrating Magnitudes

Sections 3 and 4 walk through the process of defining a socially optimal policy and calibrating it using data. By contrast, the processes that most utilities and government agencies undertake when setting subsidies for weatherization or energy-efficient goods bear little resemblance to this theoretically grounded process. Instead, the subsidies are often set to exhaust the available budget or to maximize effects per subsidy dollar spent. As a result, the subsidies in effect are almost certain to be inefficiently large or small.[15]

As a stark example of the importance of calibration, notice that $\Delta W(s) < 0$ in Equation 4 whenever $s > 2E_H(B(x)|p - s \leq x \leq p)$, i.e., whenever the subsidy is more than twice the average marginal bias. In other words, even if the policy maker correctly infers the sign of consumer bias, a subsidy can easily be worse than no policy if the subsidy is not optimally calibrated. This highlights the importance of not only measuring market failures, but also ensuring that policy makers correctly use the estimates.

[12]The differences in beliefs are interesting per se, because energy cost savings are a factual issue, not an ideological viewpoint, and the light bulb and water heater survey instruments were apolitical. This finding relates to earlier work by Kahn (2007), Costa & Kahn (2013), and Gromet et al. (2013) showing political differences in energy efficiency behaviors.

[13]Davis (2012), Gillingham et al. (2012), and Myers (2014) study the landlord-tenant information asymmetry.

[14]This point about optimal targeting is different than the point made by Boomhower & Davis (2014), Joskow & Marron (1992), and Ito (2015) about additionality. These papers argue that a policy's cost-effectiveness (subsidy disbursed per kilowatt-hour saved) is worse if the subsidy has many inframarginal consumers. Thus, from a cost-effectiveness perspective, it is better if marketing or program design can target a subsidy at consumers who are more likely to be marginal. By contrast, in the simple framework from Section 3, inframarginal consumers do not matter for welfare because subsidy funds are raised through nondistortionary lump-sum taxes.

[15]By contrast, the US Department of Energy sets energy efficiency standards so as to equate the marginal cost of more energy-efficient (lower $e_j$) goods with the marginal reduction in $G_j$. Although this is nontrivial to implement in practice, at least the process is theoretically optimal in a simple model.

A large set of papers (Allcott et al. 2014, Fischer et al. 2007, Heutel 2016, Parry et al. 2010) uses different models to show that CAFE standards are much more stringent than can be justified by the largest estimates of consumer bias from multiple papers (Allcott 2013, Allcott & Wozny 2014, Busse et al. 2013, Sallee et al. 2016). This poses a significant challenge to CAFE standards: The RIAs have relied heavily (although not exclusively) on consumer mistakes to justify the policy, so they will likely have to come up with some alternative explanation for why the engineering models predict such large consumer welfare gains from regulation. One potential explanation is that the engineering models understate the development and manufacturing costs or vehicle performance trade-offs of fuel economy improvements.[16]

### 6.3. Information Provision

As discussed in Section 3, the United States has several major information provision programs: yellow tags for appliances, MPG labels for autos, and the Energy Star marketing campaign. There are now several papers on energy cost information provision for durable goods, largely in artifactual settings with stated preferences, but some in field settings. What are we learning from a policy perspective?

First, although it is hard to object to the basic idea of information provision, existing policies can be improved. Regulatory implementation costs and firms' compliance costs are low relative to subsidies and standards, so as long as some consumers benefit, it is plausible that benefits outweigh costs. Notwithstanding, Davis & Metcalf (2016) point out one way that energy information labels could be improved: Because electricity costs vary substantially across states, presenting national average costs could mislead many consumers. In a stated choice experiment, they find that better information leads to better choices: Consumers in high (low) energy cost states are more (less) likely to choose an energy-efficient air conditioner with state-specific energy cost information relative to the national average. Larrick & Soll's (2008) finding of MPG illusion is another example of how information can be presented more clearly and understandably, and fuel economy labels have since been redesigned to include information in gallons per mile.

A second lesson is that although some have argued that information provision programs are sufficient to address consumer mistakes, this may not be true. Gayer & Viscusi (2013, p. 263) write,

> How can it be that consumers are leaving billions of potential economic gains on the table by not buying the most energy-efficient cars, clothes dryers, air conditioners, and light bulbs? . . . If the savings are this great, why is it that a very basic informational approach cannot remedy this seemingly stunning example of completely irrational behavior? It should be quite simple to rectify decisions that are this flawed.

Similarly, Mannix & Dudley (2015) argue that energy efficiency policies should be designed to address only what they call "classical" market failures. They then write, "Information asymmetry is an example of such a market failure, and we have long had fuel economy and energy-efficiency labels on cars and appliances to remedy it. This is a reasonable policy 'nudge,' and ought to be sufficient to the task" (Mannix & Dudley 2015, p. 708).

In other words, Gayer & Viscusi (2013) and Mannix & Dudley (2015) argue first that imperfect information is the primary (or only) consumer mistake that merits regulatory intervention,

[16]One scenario that would be useful to see in future RIAs is to adjust the fuel economy cost curves upward until the models correctly predict the current market equilibrium. This explicitly loads the discrepancy between model predictions and market equilibrium onto modeling error instead of an unknown market failure. Then the adjusted engineering model would be used to predict the socially optimal CAFE standard to address uninternalized externalities. The optimal CAFE standard under these assumptions would be much less stringent.

and second that existing information provision regulations should completely address this. These arguments are hard to square with the results of Houde (2014b), who estimates that large shares of refrigerator buyers do not value electricity costs despite the refrigerators having both yellow tags and Energy Star labels. Houde's evidence implies that either some noninformational mistake causes these consumers to undervalue electricity costs or the existing information provision regulations do not completely address imperfect information. This second possibility is consistent with casual observation—in some appliance showrooms, the yellow tags are hidden inside washing machines or not posted, and when buying online, energy cost information often requires extra clicks that many consumers might not make.

A third potential lesson is that regulators should think carefully about the distinction between information provision and persuasion. One view is that regulators should only be involved in the former. But the psychology literature provides many examples of how people respond differently to subtly different variations that would all be classified as hard information in a neoclassical model. For example, Camilleri & Larrick (2014) point out that presenting fuel economy information in gallons per 100,000 miles increases preferences for high-MPG vehicles relative to providing information in gallons per 100 miles. They suggest that policy makers should use the metric that induces more demand for high-MPG vehicles, but it is not clear that this increases allocative efficiency.

Indeed, two recent papers find that some energy information labels cause consumers to overvalue energy efficiency. Houde (2014b) estimates that the implied value that refrigerator buyers place on the Energy Star label is 15–83% larger than the true average electricity cost savings from Energy Star models. Newell & Siikamaki (2014) find that showing the Energy Star label causes 50% overvaluation of energy savings for water heater purchases in a stated choice experiment, when discounting future savings at individual-specific discount rates. They also find that a letter grade similar to the European Union's energy cost labels causes similar or greater overvaluation. These findings reinforce that policy makers should carefully consider whether current and future information labels are and should be used for marketing and persuasion instead of to help consumers minimize monetary costs. Glaeser (2006, 2014) expresses concern about using persuasion as a policy tool, pointing out that many nudges are in fact "emotional taxes" that decrease consumer utility but do not raise revenues.

## 7. OPEN RESEARCH QUESTIONS

Many research questions remain. In this section, I sketch five of them. First, what discount factor $\delta$ should be used in the empirical tests comparing demand responses? Many empirical papers, such as Allcott & Wozny (2014), Busse et al. (2013), and Sallee et al. (2016), use market average discount rates inferred from different estimates of the opportunity costs of capital. These approaches ignore consumer heterogeneity and may not reflect the correct opportunity cost of the marginal dollar, given that many consumers have savings, car loans, and credit card debt with widely varying interest rates. Newell & Siikamaki (2015) make progress on this issue by eliciting preferences over hypothetical cash payments of $1,000 in one month versus larger amounts in 12 months. They show that the elicited discount rates vary significantly across consumers and strongly predict stated preference for energy efficiency. Ideally, this approach could be extended to be incentive compatible, perhaps by paying respondents with some small probability, and to cover a longer time horizon relevant for most energy-using durables.[17]

[17]Laibson et al. (2007) estimate that consumers use much higher discount rates over shorter horizons, which also poses a challenge to the idea of using one time-consistent $\delta$.

Second, if consumers misoptimize, how does this affect firms' incentives to develop, offer, and price energy-efficient goods? Gabaix & Laibson (2006) study firms' incentives to debias consumers about add-on costs such as energy use, but a key feature of that model is that the firm selling the base good also sells the add-on at some profit. By contrast, retailers of durable goods do not sell energy, so depending on markups, they may have stronger incentives to debias compared to Gabaix & Laibson's (2006) "curse of debiasing." There is a growing literature on firms' incentives in marketing energy efficiency. Allcott & Sweeney (2016) use a field experiment to study one retailer's ability to inform consumers about energy efficiency. Houde (2014a) shows how firms bunch product characteristics around the minimum Energy Star eligibility cutoffs, and Houde & Spurlock (2015) show how energy efficiency standards can increase welfare by increasing competition (and thus decreasing markups) among products that comply with the standard. Fischer (2010) studies how internalities interact with market power in firms' decisions to provide higher-fuel economy vehicles and how this affects the optimal determination of minimum standards and gasoline taxes.

Third, could bias toward concentration be relevant for some energy efficiency decisions? Because the benefits of energy efficiency come in small flows every time an electricity bill is paid or the gas tank is filled, this is a natural application of Koszegi & Szeidl's (2013) model. Even a lab experiment framed in an energy use context would be interesting if it measured and distinguished bias toward concentration from other potential mistakes.

Fourth, many utilities have on-bill financing programs that essentially offer a loan to consumers for energy efficiency upgrades, which they pay back monthly on their energy bills. In theory, such a program could address present bias, bias toward concentration, and credit constraints. How effective are these programs, and why?

Fifth, in an endogenous inattention model, how do consumers form initial beliefs about the importance of energy efficiency when deciding whether to attend to this attribute? In Sallee (2014), for example, consumers have beliefs about the variance of energy costs across products, and in Gabaix (2014), consumers must have analogous initial beliefs about how much any attribute matters. Conlisk (1996), Gabaix et al. (2006), Lipman (1991), and others provide insight from other contexts.

## 8. CONCLUSION

As documented in Section 2.3, paternalism is an important factor used to justify energy efficiency policies. In recent years, models like the one in Section 3 have formalized this rationale, and three categories of empirical tests from Section 4 have been used to estimate consumer bias. Although the results are far from ironclad or comprehensive, there is some evidence that some consumers make systematic mistakes when purchasing some energy-using durables. In cases such as the vehicle market, however, the weight of the evidence suggests that if there are any systematic mistakes, they are small. In the absence of other market failures, the estimated consumer bias cannot justify the stringency of the current CAFE standards, and other energy efficiency subsidies and standards may also be miscalibrated. Furthermore, some existing policies do not appear to effectively target the market failures that they were designed to address. There is much work still to be done, and as rigorous evidence grows, it will be crucial to bring these results to policy makers.

## DISCLOSURE STATEMENT

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## Errata

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