East West University

Department of Economics Working Paper Series

The Abuses of Net Present Value in Energy Efficiency Standards

By

Syed Abul Basher

David Raboy

Working Paper 2017-04

August 2017

Department of Economics
Aftabnagar, Plot No. A-2
Dhaka 1212, Bangladesh

: 09666775577 x. 209
economics@ewubd.ed
www.ewubd.edu/economics

The Abuses of Net Present Value in Energy Efficiency Standards

Syed Abul Basher[a] **David G. Raboy**[b]

a. Department of Economics, East West University, Aftabnagar Main Road, Dhaka 1212, Bangladesh.
syed.basher@gmail.com

b. Department of Economics, Northern Virginia Community College, Manassas Campus, VA 20109.
draboy@nvcc.edu

August 2, 2017

The Abuses of Net Present Value in Energy Efficiency Standards

Abstract. Consumers are often blamed for not making necessary investments in energy-efficient durables despite that these investments have positive net present value (NPV). Several papers have argued that when investments have option-like characteristics (e.g., irreversibility, uncertainty, flexible timing, and lumpiness), the aphorism "invest if the net present value of investing exceeds zero" isn't the best advice. Yet, curiously, the Department of Energy (DOE) in the United States proposes new regulations mandating higher energy efficiency standards for consumer durables on the basis of positive NPV over an investment's lifetime. In this paper, we provide a step-by-step deconstruction of DOE's NPV methodology and show that DOE's method purges volatility, volatility persistence, and nonstationarity that are otherwise present in energy prices. As a result, DOE's projections of future energy prices are artificially smooth and statistically biased, casting serious doubt on the reliability of the magnitude of energy savings from energy-efficient durables. Our results, therefore, support the notion that consumers' behavior isn't irrational.

Keywords: Net present value; energy efficiency; Nonstationarity; Volatility; Electricity and gas prices

JEL Codes: C22; Q40; Q41; Q47

1. Introduction

The rule, "invest if the net present value of investing exceeds zero" is still widely popular among managers and taught to students in business schools. Ross (1995) remarks that NPV "is the meat of most textbook and lies at the core of what financial academics think they have to offer CFOs, corporate treasurers, investment bankers, and practitioners of all stripes" (p. 96). Excel spreadsheets and financial calculators include an "NPV" function, which makes it very easy to calculate the net present value (NPV). Harvard Business Review sells a guide for businesses which includes an easy-to-use pre-filled spreadsheets for NPV and the other return on investment methods (Sheen and Gallo, 2015).

However, when investments have option-like characteristics (e.g., irreversibility, uncertainty, flexible timing, and lumpiness), simple NPV rules must be modified (McDonald and Siegel, 1986; Pindyck, 1991, 1999). The concept of NPV is built on the assumption that "the variance of the present value of future benefits and costs is zero" (McDonald and Siegel 1986, p. 708). But when investment decisions involve real options, variance "matter very much, so that an investment decision based on a mean-reverting process could turn out to be quite different from one based on a random walk" (Pindyck 1999, p. 2).

To appreciate the significance of irreversibility and option value of an investment, let us consider the evidence of underinvestment in energy-efficient technologies. Despite the considerable promise for reducing the costs and environmental damages associated with energy use, consumers and businesses are not investing in energy-efficient technologies to the extent they should, a paradox that has come to be known as the "energy-efficiency gap" (Gerarden et al., 2015). Over the last several decades, a burgeoning literature has emerged to explain the apparent market failures (and behavioral biases) associated with a suboptimal use of energy-efficient technologies – see Gerarden et al. (2015) for an excellent survey of this literature.

However, when viewing through the lens of irreversibility and option to wait, such underinvestment in energy-efficient technologies may not appear to be a paradox (Baker 2012). Uncertainty regarding future energy price or future benefits from technological change coupled with little resale value, among other unobserved costs, may cause consumers and firms to delay or postpone investment in energy efficient durable goods. Put differently, the presence of market imperfections, uncertainty, risk, and a host of other factors cause the implicit discount rate to be higher making expected present discounted value of the energy savings lower than is typically assumed. Numerous empirical studies have revealed that implicit discount rates substantially exceeding market interest rates – see Kim and Sims (2016) for an overview of the implicit discount rate from 19 energy-efficiency studies.

Over the years, the Department of Energy (DOE) in the United States has promulgated a set of new regulations mandating higher energy efficiency standards for consumer durables. These regulations are derived from the Energy Policy and Conservation Act of 1975[1] (EPCA) and the DOE is delegated to monitor the standards set by the EPCA over time. Hence, when considering amending a standard, the DOE follows the guidelines stipulated in the EPCA that the new standard must: "achieve the maximum improvement in energy efficiency . . . which the Secretary determines is technologically feasible and economically justifiable." In determining whether a standard is "economically justifiable" or not, the DOE depends on a set of techniques such as simple payback period, NPV and life cycle costing to evaluate potential savings from investment in energy efficient equipment.[2] What is required for the regulation to proceed is to show that the NPV is positive. In so doing, however, the DOE neglects other relevant costs or benefits, as highlighted above, that can drive the investment decision.

The primary goal of this paper is to deconstruct DOE's methodology in evaluating potential saving from purchasing or investing in energy efficient durables. We provide a step-by-step description of the nature of DOE projections to highlight the underlying limitations in DOE's methodology such that the empirical validity of the future projections about saving is in serious question. Although the issue of using simple NPV analysis in the context of energy efficient investments has long been discussed and debated in the past literature (more on this below), to the best of our knowledge this is the first paper to offer a systematic treatment of the question at hand. The results of our analysis reveal new insights that have subsequent implications for other areas of research and policy undertakings.

The rest of the paper is organized as follows. Section 2 briefly reviews the empirical literature on irreversibility, option value and the relevance of discount rates. Section 3 discusses the data and presents preliminary empirical evidence supporting the volatility and uncertainty in energy prices. Section 4 discusses DOE's predictive methodology in defense of the energy-efficient consumer-durable regulations. Section 5 offers a discussion of the main findings. Section 6 concludes the paper.

2. Literature review

This section briefly summarizes findings of past contributions that concern the shortcomings of conventional methods such as life-cycle cost, NPV for evaluating energy-efficient durables. The proponents (including the DOE) often frame purchases of energy-efficient durables as akin to investments in safe financial instruments like perfectly liquid and insured bank account. However, numerous studies have pointed out that the implicit discount rates for purchases of energy-related durables are well above the market discount rate. Hausman (1979) finds a discount rate of 20 percent for purchases of energy-efficient durables. In commenting on Hausman's paper, Gately (1980) provides discount rates in the range of 45 to 300 percent.

Hassett and Metcalf (1993) have made an interesting and useful contribution by conducting an option value analysis of energy-efficient investments. They find an implicit discount rate of around 20 percent due to a high option value to waiting, resulting in the slow diffusion of energy saving technologies. The model of Hassett and Metcalf has been extended in several directions. Sanstad et al. (1995) include the costs of delaying purchases that offset the value of the option to delay and find a hurdle rate (implicit discount rate) of only 6.8 percent. Likewise, Baker (2012) argues that when consumers care more about *which* products to choose (rather than *when*), uncertainty and irreversibility (or the "option value") play little role in explaining the slow diffusion of energy efficient technologies. Further, Kim and Sims (2016) update the option value analysis of Hassett and Metcalf (1993) using more recent fuel price data and find that the option value multiplier is lower than Hassett and Metcalf's results.

However, when investors' anticipation of future technological advance is incorporated in Hassett and Metcalf's (1993) model, Ansar and Sparks (2009) find a high implicit discount rate that is generally observed in the literature. Bauner and Crago (2015) extend the analysis by Ansar and Sparks (2009) for solar PV system and find an option value multiplier of 1.6, implying that the discounted benefits from solar PV need to exceed installation costs by 60% for investment to occur.

It is instructive to review the contributions that highlight the limitations of the so-called *ex-ante engineering* studies which tend to overestimate energy savings from investment in energy-efficient durables (see, e.g., Granade et al., 2009). The reason for overestimation is because ex-ante engineering analyses rely on predicted energy savings, whereas most impact evaluations are conducted on actual energy usage, among other explanations (see Gerarden et al., 2015). Nadel and Keating (1991) compare nine residential appliance and lighting programs and find that, except for two programs, the magnitude of energy saving ranged from negative to 74% of the engineering estimates. Likewise, in a randomized controlled experiment in Florida, Dublin et al. (1986) find that actual conservation is as much as 13% below engineering estimates for cooling and 8-12% below for heating. Recent studies that provide evidence that predicted savings from certain energy-efficiency programs are overstated include Allcott and Greenstone (2012), Davis et al. (2014), Fowlie et al. (2015), Gillingham and Palmer (2014), Houde and Aldy (2014), and Levinson (2014), to cite just a few contributions.

[1] Public Law 94-163 (42 U.S.C. 6291-6309, as codified) Authority and details are codified in Title 10 of the Code of Federal Regulations Parts 429 and 430 (10 CFR Parts 429, 430).

[2] 42 U.S.C. 6295(o)(2)(B)(i)(II)

We contribute to this voluminous literature of energy-efficiency gap in two ways. First, we apply recent advances in time series econometrics to test whether energy price evolves as a random-walk process (or unit root process) or can be described as a mean-reverting process. As uncertainty about future energy prices is often used as a non-market failure explanation of the energy-efficiency gap (Jaffe and Stavins, 1994), identifying the stochastic nature of prices is importing for consumers and firms making investment decisions. Second, and already stated in the Introduction, we provide a step-by-step description of the NPV methodology that constitutes as a building block of ex-ante engineering analyses such as the influential analysis of Granade et al. (2009), which has been cited in numerous publications by the DOE.

3. Empirics of energy prices

3.1 Data

We employ one basic data set. The Energy Information Agency (EIA) provides data on the retail residential prices of gas and electricity, disaggregated by month and state. We acquired these data for the period spanning January 2001 through December 2013. For each state plus the District of Columbia, then, our data comprise 156 observations.

That these data are characterized by extreme volatility is readily apparent. By way of example, Figure 1 portrays percentage changes in the monthly residential prices of gas and electricity, compared to those for the CPI, for Louisianna over the 156 months of data.

[**Place Figure 1 approximately here**].

3.2 Unit roots tests

Stationary data are mean-reverting (a price shock is temporary, and data naturally revert to trend). Non-stationary data are not mean-reverting, and a price shock will appear to be permanent. Consequently, non-stationary data are very difficult to forecast and past observations in levels are not of use in predicting the future (Phillips and Zhijie 1998).[3]

There are several unit root tests available that allow researchers to determine if data are nonstationary. In this paper we use the DF-GLS unit root test as introduced by Elliot et al. (1996), which is a powerful GLS variant of the standard Dickey-Fuller test. In particular, standard unit root tests such as the augmented Dickey-Fuller (ADF) test have very low power in discriminating between highly persistent

[3] Econometricians have tools to convert non-stationary to stationary data, some as simple as first-differencing data or differencing at higher orders, although energy-price predictions are illusive even for econometricians. Of course, none of these tools are available to untutored consumers attempting to form heuristics.

stationary processes and nonstationary processes. Moreover, the power of conventional unit root tests is lower as deterministic terms (such as a constant and trend) are added to the test regression (Maddala and Kim 1998). Because the DF-GLS test exhibits higher power than conventional tests when the series is highly persistent, it is often referred to as an efficient unit root test (Zivot and Wang 2006).

We apply the DF-GLS unit root test to monthly state-by-state electric and gas retail residential prices, in levels, for the period 2001 to 2013. The DF-GLS test is implemented with a constant as a deterministic component in the test regression. The null hypothesis of the test is that the series contains a unit root against the alternative hypothesis that the series is stationary around a mean. Since the DF-GLS method applies the conventional ADF test to locally detrended data, it is unnecessary to include a time trend in the test regression. However, our results remain unaffected even if we allow a linear time trend in the unit root test. Following Ng and Perron (2001), we use the modified Aikake Information Criterion (AIC) to select the optimal lag length in the test regression. Ng and Perron (2001) show that the combination of modified AIC and GLS detrended data yield the desirable size and power properties of the unit root test.

Table 1 provides the DF-GLS test statistics for the 50 states plus DC for both the constant-only case, and one where a linear trend is included in the test statistic. As is shown, we could not reject the null hypothesis of unit root for all 51 entities for electricity when only a constant is considered in the test regression.[4] Once a deterministic time trend is added, the null of unit root is rejected for six states at the 5% significance level. For natural gas the DF-GLS test produced the following results: the null hypothesis of a unit root is rejected for seven states with a constantly only, but rejected for only for two states with both a constant and linear time trend.

A key characteristic of electricity and gas prices is seasonality, since demand for these commodities tends to be highly weather-sensitive. Thus, for seasonal time series such as electricity or gas prices, the presence of a seasonal unit root may affect the properties of the nonseasonal unit root tests, which assume one unit root at zero frequency and no other unit roots at other frequencies such as seasonal. If seasonal data have only “deterministic seasonality,” it can be removed by simply seasonally adjusting the series. However, if the data contain “stochastic seasonality,” then we need to test for unit roots at the seasonal frequencies. The most widely used procedure for testing for seasonal unit roots is that proposed by Hylleberg et al. (1990), which focuses on quarterly time series. The test for stochastic seasonality in monthly data is discussed in Beaulieu and Miron (1993). To implement the seasonal unit root test on our data, we make use of the HEGY add-in implemented in Eviews 9.0.[5]

[4] A positive test statistic also rules out the likelihood of stability of the respective time series, implying that the series is nonstationary.

[5] Nicolas Ronderos, HEGY – Seasonal Unit Root Test, Eviews Add-in, June 25, 2015. http://www.eviews.com/Addins/addins.shtml

The seasonal unit root test is implemented using constant, trend, and seasonal dummies as deterministic components in the test regression. The lag length is chosen using the AIC. The critical values and p-values for the test are obtained using 1,000 Monte Carlo simulations. We have the following results. For electricity prices, there is evidence of one unit root at zero frequency (i.e., no seasonal unit root) for 26 states, two states display stationarity, and in remaining 23 states there is evidence of seasonal unit roots at almost all seasonal frequencies (2, 3, 4, 6, and 12 months per cycle). By contrast, the evidence of seasonal unit root is markedly more prevalent with gas prices. There is evidence of one unit root at zero frequency for 15 states, and the presence of seasonal unit roots at all seasonal frequencies for the remaining 36 states. These results are not presented in the paper to save space, but are available from the corresponding author on request.

Overall, the results of the unit root tests indicate that electricity and gas retail prices in virtually all U.S. states are nonstationary. The finding of unit root in aggregate prices is consistent with consumer beliefs that energy prices follow a random walk (Anderson et al., 2013). The unit root tests also serve as a basis for measuring persistence or inertia in economic series. Thus if a series contains a unit root, "its persistence is unquestionably large (infinite) and its variance is unbounded" (Fuhrer 2009, p. 13).

[Place Table 1 approximately here]

4. An analysis of the DOE methodology

Over the past decade, the DOE has promulgated a set of new regulations pertaining to the energy efficiency of consumer durables such as refrigerators and freezers (Docket-Number-EE-2008-BT-STD-0012)[6]; residential boilers (Docket Number EERE-2012-BT-STD-0047); residential furnace fans (Docket Number EERE-2010-BT-STD-0011); water heaters, direct heaters, and pool heaters (Docket Number-EE-2006-STD-0129); clothes washers, driers and dishwashers (Docket-Number-EE-RM-94-230A); and other appliances. These regulations emanate from the Office of Energy Efficiency (EE) pursuant to the Energy Policy and Conservation Act of 1975 (EPCA), as amended by the Energy Policy Act of 2005, and authority and details are codified in Title 10 of the Code of Federal Regulations Parts 429 and 430 (10 CFR Parts 429, 430).

An NPV analysis is statutorily required to assess potential impacts on consumers, and NPV must be positive for the regulation to proceed. In the case of energy-efficiency regulations, DOE has claimed that it is capable of accurate measurement, that NPV is net positive, and therefore regulations will result in private benefits. The essential element facing DOE is the ability to accurately predict future energy prices

[6] Dockets for each regulation, containing all related materials, can be accessed from the index at www.regulations.gov.

as these are the key inputs in the NPV calculation.

There are numerous highly shopisticated predictive models[7] in use in academia and private energy sector which specifically incorporate the extreme price volatility, nonstationary, and volatility persistent of historic data (Behmiri and Pires Manso 2013, Gabralla and Abraham 2013). DOE does not even attempt to base their predictive methodology on these widely used models, even though they're there for the asking. Indeed DOE seems to favor a "certainty model" which projects the stable future energy prices required for a clean NPV analysis. To validate this claim this section will recreate and analyze the DOE model mathematically and empirically. Section 4.1 will present the steps involved in the methodology, with subsections describing a step-by-step analysis which demonstrates the effects of each step on the data and a discussion of the consequences of the DOE approach. Our methodology will be to compare monthly historic results for a 13 year period, 2001-2013 to a matching set of DOE-methodology monthly projections over the 13 year period 2016-2028. In the interests of space, the DOE methodology is analyzed solely with respect to electricity.

4.1 Description of the DOE methodology

These are the steps in DOE's predictive methodology:[8]

1. DOE creates what they refer to as "factors" by dividing each monthly state price data point by the annual mean in the state associated with the year of the data point.

2. DOE next averages all factors from the entire data set by month and state to produce "final factors" for each state. For each month, regardless of projection year, there is a single factor that plays a prominent role in final predictions of future energy prices.

3. Future annual price projections (national) are derived from the Annual Energy Outlook (AEO), produced by EIA. The latest is AEO 2015 (EIA 2015). The annual projections start with an average annual national price for 2013 which then grows by an annual 2.5% (nominal) so the average national future price in year t is always $P_{t-1}(1+.25)$. This produces a linear trend that spans the entire 13-year projection period.

4. Future monthly state prices in each future year are determined by multiplying the projected average annual *national* price in each year by the 12 final factors for each state (the final factors repeat every year). So if P_t is the annual price in year t, then in state S, the January price is $P_t ff_{January\text{-}S}$, for February

[7] These include generalized autoregressive conditional heteroskedasticity (Kuper and van Soest 2006), artificial neural network (Panella et al. 2012), and unobserved components model (García-Martos et al. 2010), among others.

[8] The DOE methodology is described in DOE (2006). There are a few differences between our reconstruction and the original DOE method: We aggregate at the state level while DOE uses geographical regions. We also use a more recent historic data set covering 13 years from 2001-2013, while DOE's historic data set covers 1990-2007.

$P_t ff_{February\text{-}S}$, etc. where $ff_{j\text{-}S}$ is a final monthly factor for state S in month j.

4.2 Step-by-Step deconstruction of DOE's NPV methodology

Step 1. Before presenting the empirical evidence of the way in which Step 1 purges price volatility, nonstationarity, and other aspects of ambiguity from historic data, a simple algebraic analysis presents some curious characteristics of the factors of Step 1 which will also help explain the empirical evidence. Factors are produced in any period with N observations by dividing every price by the mean in the period. Treating factors as the new observations first consider the sum of these new observations which is the numerator of the mean:

$$S_f = \sum \frac{P_i}{\bar{x}} = \frac{\sum_1^n P_i}{\bar{x}} = \frac{\sum_1^n P_i}{\frac{\sum_1^n P_i}{N}} = N \qquad (1)$$

For any sample period with N observations, the sum of the factors will always be N. Since the mean is simply the sum of observations divided by N, the mean of any N factors will always be unity—the mean of DOE's factors in any given historic year will be unity. Indeed, despite the noise of dividing monthly prices by a different mean in each year, over the entire data period, the mean of the factors in each state will be very close to one.[9] This can be seen in Table 2 which compares descriptive statistics from actual prices to those from associated factors.

[Place Table 2 approximately here]

The information in Table 2 also shows how volatility or dispersion from mean is very small in factors, relative to the actual prices from which they are derived. The Coefficients of Variation (CV) in most states for actual prices are many multiples of the those for the factors calculated from these prices. Noting that any observation X_i can be expressed as $X_i = \bar{X} + d_i$ where d_i is a positive or negative deviation from the mean, the sample Standard Deviation (SD) of the factors is:

$$SD = \sqrt{\frac{\sum(1+d_i-1)^2}{N-1}} = \sqrt{\frac{\sum(d_i)^2}{N-1}} \qquad (2)$$

Where $\sum d_i = 0$

Observation of the factors shows that $0 < |d_i| < 1$. Therefore the square of any deviation is smaller than the deviation and the square route of the sum of the squared deviations divided by N-1 is a small number, relative to the SDs of the underlying true historical prices. Also, with a mean of 1, since the factors are all positive, the SD always equals the CV.

[9] 14 states have means that deviate from unity by .01, and 2 by .02. All the rest are 1.

Step 2. Even with the noise introduced by averaging factors, the results for Step 1 generally apply to Step 2. Here the sum of observations is 12, with 17 states that deviate by an absolute value of .1 and one state deviating by .3. The other 33 have sums of 12. The means for all states are unity, with very little deviation. The additional averaging reduces the final factor SDs to levels even lower than those for the factors derived in Step 1, sometimes dramatically so, and commensurately for CVs as they equal the SDs. Table 3 presents the Final Monthly Factors and associated descriptive statistics.

[Place Table 3 approximately here]

Step 3. The literature on DOE price projections has been criticized regarding methodology recently. Rather than reflecting the many choices of empirical models, EIA out-of-sample forecasts "have been largely judgemental, making them difficult to replicate and justify" (Baumeister and Kilian 2015, p. 338). Baumeister and Kilian (2015) offered an alternative by constructing six econometric models and then combining them, a method they found to be quite accurate. With respect to the EIA model Baumeister and Kilian (2015) had this to say:

In contrast, the EIA oil price forecasts not only tend to be less accurate than the no-change forecasts, but are much less accurate than our preferred forecast combination. Moreover, including EIA forecasts in the forecast combination systematically lowers the accuracy of the combination forecast (Baumeister and Kilian 2015, p. 338) [emphasis added].

Yet DOE feels comfortable imposing a judgemental linear trend on their projections. Figure 2 compares historic (downloaded from EIA) annual national retail residential electricity prices from 2001-2013 to DOE projected annual prices for the matching 13-year period 2016-2028. As is obvious, DOE's linear methodology purges all price volatility from annual national prices, which bears no relation to history.

[Place Figure 2 approximately here]

The DOE linear trend and annual growth rate ascribed to future annual national prices are based on a *subjective assumption*, not on any econometric analysis of time-series data as would be standard econometric practice. Just viewing Figure 2 shows that there is no relationship between historic national annual price observations and DOE projections. This is especially disconcerting because the assumed national prices through 2028 dominate the projections.

Step 4. The final step for DOE projections is the multiplication of the linear projected annual national prices by the smooth single set of monthly state-specific factors to project future monthly state-level prices. The first task in our analysis is to calculate the mean monthly price in each projected year *t* from 2016-2028, (appropriate for each state) where *j* denotes month.

$$\overline{P_t} = \frac{\sum P_t ff_j}{N} = \frac{P_t \sum ff_j}{N} = P_t \tag{3}$$

Equation (1) establishes that the sum of the factors *j* always equals N, therefore the mean monthly projected price in any year *t* is P_t.. The DOE projected price total monthly mean, over the entire projection period, will deviate some in each state from the total annual mean, due to accumulated noise from 156 observations for each state.

As to volatility the formula for monthly projected price SD is:

$$SD = \sqrt{\frac{\sum\left(P_t ff_j - P_t\right)^2}{N-1}} = \sqrt{\frac{\sum P_t^2\left(ff_j - 1\right)^2}{N-1}} = \sqrt{\frac{P_t^2 \sum\left(ff_j - 1\right)^2}{N-1}} = \sqrt{\frac{P_t^2 \sum(1+d_j-1)^2}{N-1}} = \sqrt{\frac{P_t^2 \sum\left(d_j\right)^2}{N-1}} = P_t\sqrt{\frac{\sum d_j^2}{N-1}} \tag{4}$$

The SD is dominated by the SD of the final factors, because in any year *P* is a constant and over time follows a linear trend. However, the factor SDs are small and result from small deviations from factor mean (unity) in each month in each state, a pattern which repeats year after year.

The evidence of volatility dampening is a comparison of the CVs of historic monthly state prices from 2001-2013 and DOE projections of monthly prices from 2016-2028. These CVs are displayed in Table 4. All of the purging of volatility, volatility persistence, and nonstationarity in energy-price data are shown in Figures 3-6, which compare historic monthly prices over the 13 year test period to those of the DOE projected prices for four states. The nonstationarity, volatility, and volatility persistence are obvious in the historic data. Yet they are completely absent in the DOE projections, in patterns that are seen nowhere in the retail residential energy sector.

[Place Table 4 approximately here]

[Place Figures 3-6 approximately here]

The analysis above clearly shows the limitations of the DOE's methodology for calculating NPV. The demonstrably artificial and statistically biased nature of DOE projections cannot, therefore, be considered appropriate for plausible NPV analysis. While the government might have an incentive to use lax statistical methods to promote energy efficiency products, in reality, it is the divergence in incentives between economic agents (for example, landlord–tenant or builder–buyer) that is inhibiting energy-efficient decisions, among other factors.

5. The perils of forecasting

"Before purchasing a good, consumers project the satisfaction it will bring them" (Beckert 2016, p. 217). This involves some form of expectation building (or forecasting) about the future return before it happens. Humans are bad at forecasting because we fail to factor the possibility of randomness and uncertainty that shape the future. For example, we can't even get it right when estimating the cost of building, say, our own house. Similarly, private sector or government too forget about unpredictability when they end up with the massively over-budget construction projects such as Sydney Opera House or the New Wembley Stadium (The Economist 2007).

Using economic or technological forecasting models do not help to improve forecast accuracy either. The voluminous literature on economic forecasting, as scrutinized systematically in Elliott and Timmermann (2008) and Taleb (2010), teaches us that it is impossible to predict the future. Beckert (2016, p. 222) provides several anecdotes of the spectacular failure of predictions. First, just weeks after the stock market crash, in December 1929, the Harvard Economic Society predicted a quick recovery. Similarly, a transcript of the Federal Open Market Committee shows that, even as late as December 2007, the expert members did not take any notice of the impending financial crisis. Even more interestingly, in 1954, the head of the American Atomic Energy Commission predicted that the electricity would be so cheap that there would be no need to meter by the end of the twentieth century (Beckert 2016, p. 225).

These examples show that, even when equipped with sophisticated econometric models, hardly anything can be foreseen. Consequently, a large number of papers have been written discussing what causes predictions to fail. The earliest explanation for the failure of forecast that we know comes from Oskar Morgenstern (1928), who pointed that prediction fails in part because "forecasts create expectations that alter the conditions they assume, which renders them meaningless".[10] More recently, Taleb (2010) coined the term "black swans" (i.e., highly unlikely long-tail events such as unexpected political decisions) and criticized forecasters for underestimating black swan-type events. But, more often, predictions fail due to endogenous factors such as misleading or insufficient data, technical shortcomings of the instruments and methods used, and forecasters' tendency to align their predictions with those of other institutions (the so-called "consensus forecasts") – see Beckert (2016) for further discussion.

Where do consumers stand in all this? A question that is relevant for us is: "how do consumers forecast future price changes?" Anderson et al. (2013) address this question by examining two decades of data from the Michigan Survey of Consumers. They find that, on average, consumers expect that the real price of gasoline five years in the future will be equal to the current real price. That is, the forecast of future gasoline price looks very similar to a random walk or a "no-change" forecast. An implication of this result is that consumers beliefs about future energy prices do not contribute to the energy-efficiency gap.[11] In a classic paper about judgment under uncertainty, Tversky and Kahneman (1974) acknowledge

[10] Cited in Beckert (2016, p. 227).

[11] See Gerarden et al. (2015) for further discussion.

that, in a world of uncertainty, people tend to rely on "heuristics" (or mental shortcuts) to make a decision, rather than taking into account every tiny detail. Such cognitive bias threatens to break the logic of public choice theory, which suggests, among other arguments, that consumers have stronger incentives to acquire information to overcome behavioral biases. A large body of research shows that, more often than not, financial decision making is influenced by behavioral biases such as loss aversion or procrastination.[12]

The upshot of this discussion is that prediction about future is very difficult. And even if such predictions about future energy savings are available, they cannot confidently be treated as cardinal due to, among other barriers, inconsistency with actual conditions in the home. But, much more importantly, when future energy prices are extremely volatile and also unpredictable, even forming plausible heuristics to predict future energy prices becomes very difficult. Viewing the problem through the lens of uncertainty, it then becomes clear that there is no private behavioral market failure if individuals do not consider purchasing durables as an "investment."

5. Conclusion

In this paper, we have seen that energy prices are highly volatile and follow a random walk process. This implies that energy prices have time-dependent variance, making forecasting of future energy prices very difficult. Our second and major finding is that the DOE methodology for NPV analysis cannot be reliably used for calculating return on investment in energy-efficient durables. This is because, the DOE method purges volatility, volatility persistence, and nonstationarity that are otherwise present in the original data. In a nutshell, our results do not imply that consumers are irrational for undervaluing energy savings from investment in energy durables.

[12] See Raboy and Basher (2016) for application of behavioral economics in energy efficiency.

References

Allcott, H. and Greenstone, M. (2012). Is there an energy efficiency gap? Journal of Economic Perspectives 26, 3-28.

Anderson, S.T., Kellogg, R. and Sallee, J.M. (2013). What Do Consumers Believe about Future Gasoline Prices? Journal of Environmental Economics and Management 66, 383-403.

Ansar, J. and Sparks, R. (2009). The experience curve, option value, and the energy paradox. Energy Policy 37, 1012-1020.

Baker, E. (2012). Option value and the diffusion of energy efficient products. Energy Journal 33, 49-59.

Baumeister, C. and Kilian, L. (2015). Forecasting the real price of oil in a changing world: A forecast combination approach. Journal of Business & Economic Statistics 33, 338-351.

Bauner, C. and Crago, C.L. (2015). Adoption of residential solar power under uncertainty: Implications for renewable energy incentives. Energy Policy 86, 27- 35.

Beaulieu, J.J. and Miron, J.A. (1993). Seasonal unit roots in aggregate U.S. data. Journal of Econometrics 55, 305-328.

Becker, J. (2016). *Imagined Futures: Fictional Expectations and Capitalist Dynamics*. Cambridge, MA: Harvard University Press.

Behmiri, N.B. and Pires Manso, J.R. (2013). Crude oil forecasting techniques: A comprehensive review of the literature. Alternative Investment Management Review 2, 18-23.

Davis, L.W., Fuchs, A. and Gertler, P.J. (2014). Cash for coolers: Evaluating a large-scale appliance replacement program in Mexico. American Economic Journal: Economic Policy 6, 207-238.

DOE, 2006. APPENDIX 8-E Monthly Price Factor Calculations for Water Heater Analysis. Technical Report EE-2006-STD- Comment 56.10, Department of Energy, Washington DC, pp. 8-E-i-8-E-15.

Dubin, J.A., Miedema, A.K. and Chandran, R.V. (1986). Price effects of energy-efficient technologies: A study of residential demand for heating and cooling. RAND Journal of Economics 17, 310–25.

The Economist. (2007). The perils of forecasting. May 31st. London.

EIA, Energy Information Agency. (2015). Annual Energy Outlook 2015. Data Report, Department of Energy, Washington DC, pp. i-G1.

Elliott, G., Rothenberg, T.J., Stock, J.H. (1996). Efficient tests for an autoregressive unit root. Econometrica 64, 813–836.

Elliott, G. and Timmermann, A. (2008). Economic forecasting. Journal of Economic Literature 46, 3-56.

Fowlie, M., Greenstone, M. and Wolfram, C. (2015). Do energy efficiency investments deliver? Evidence from the Weatherization Assistance Program. https://nature.berkeley.edu/~fowlie/WAP.pdf.

Fuhrer, J.C. (2009). Inflation persistence. Working Paper No. 09-14, Federal Reserve Bank of Boston.

Gabralla, L.A. and Abraham, A. (2013). Computational modeling of crude oil price forecasting: A review of two decades of research. International Journal of Computer Information Systems and Industrial Management Applications 5, 729-740.

García-Martos, C., Rodríguez, J. and Sánchez, M. (2010). Unobserved components model for forecasting electricity prices and their volatilities. Working Paper, Universidad Politécnica de Madrid, 1-31.

Gately, D. (1980). Individual discount rates and the purchase and utilization of energy-using durables: Comment. Bell Journal of Economics 11, 373-74.

Gerarden, T.D., Newell, R.G. and Stavins, R.N. (2015). Assessing the energy-efficiency gap. NBER Working Paper No. 20904. Cambridge, MA: National Bureau of Economic Research.

Gillingham, K. and Palmer, K. (2014). Bridging the energy efficiency gap: Policy insights from economic theory and empirical evidence. Review of Environmental Economics and Policy 8, 18-38.

Granade, H.C., Creyts, J., Derkach, A., Farese, P., Nyquist, S. and Ostrowski, K. (2009). *Unlocking Energy Efficiency in the U.S. Economy. McKinsey & Company.* www.mckinsey.com/

Hasset, K. and Metcalf, G. (1993). Energy conservation investment: Do consumers discount the future correctly? Energy Policy 21, 710-716.

Hausman, J. A. (1979). Individual discount rates and the purchase and utilization of energy-using durables. Bell Journal of Economics 10, 33-54.

Houde, S. and Aldy, J.E. (2014). Belt and suspenders and more: The incremental impact of energy efficiency subsidies in the presence of existing policy instruments. NBER Working Paper No. 20541. Cambridge, MA: National Bureau of Economic Research.

Hylleberg, S., Engle, R.F., Granger, C.W.J., Yoo, B.S. (1990). Seasonal integration and cointegration. Journal of Econometrics 44, 215-238.

Jaffe, A.B. and Stavins, R.N. (1994). The energy-efficiency gap: What does it mean? Energy Policy 22, 804–10.

Kim, B. and Sims, C. (2016). Why is energy efficiency such a hard sell? White Paper 1:16. The Howard H. Baker Jr. Center for Public Policy, University of Tennessee.

Kuper, G. and van Soest, D. (2006). Does oil price uncertainty affect energy use? Energy Journal 27, 55-78.

Levinson, A. (2014). California energy efficiency: Lessons for the rest of the world, or not? Journal of Economic Behavior & Organization 107, 269-289.

Maddala, G.S., Kim, I.M. (1998). *Unit Roots, Cointegration, and Structural Change.* Cambridge University Press, Cambridge.

McDonald, R. and Siegel, D.R. (1986). The value of waiting to invest. Quaterly Journal of Economics 101, 707-27.

Morgenstern, Oskar. 1928. *Wirtschaftsprognose: Eine Untersuchung ihrer Voraussetzungen und Möglichkeiten.* Vienna: Julius Springer.

Nadel, S. and Keating, K. (1991). *Engineering Estimates vs. Impact Evaluation Results: How Do They Compare and Why?* Research Report U915. Washington, D.C.: American Council for an Energy-Efficient Economy.

Ng, S., Perron, P. (2001). Lag length selection and the construction of unit root tests with good size and power. Econometrica 69, 1519-1554.

Panella, M., Barcellona, F. and D'Ecclesia, R.L. (2012). Forecasting energy prices using neural networks. Advances in Decision Sciences 2012, 1-26.

Phillips, P. and Zhijie, X. (1998). A primer on unit root testing. Journal of Economic Surveys 12, 423-469.

Pindyck, R.S. (1991). The long-run evolution of energy prices. Energy Journal 20, 1-27.

Pindyck, R.S. (1999). Irreversibility, uncertainty, and investment. Journal of Economic Literature 39, 1110-1148.

Raboy, D.G. and Basher, S.A. (2016). Paternalism and new durable-goods energy efficiency standards: Consumers ain't misbehavin'. Available at SSRN: https://ssrn.com/abstract=2800806

Ross, S.A. (1995). Uses, abuses, and alternatives to the net-present-value rule. Financial Management 24, 96-102.

Sanstad, A.H., Blumstein, C. and Stoft, S.E. (1995). How high are option values in energy-efficiency investments? Energy Policy 23, 739–43.
Sheen, R. and Gallo, A. (2015). HBR Guide to Building Your Business Case. Harvard Business Review Press.
Taleb, N.N. (2010). *The Black Swan: The Impact of the Highly Improbable.* 2nd ed. New York: Random House.
Tversky, A. and Kahneman, D. (1974). Judgement under uncertainty: Heuristics and biases. Science 185, 1124-1131.
Zivot, E. and Wang, J. (2006). Modeling Financial Time Series with S-PLUS. Springer, New York.

Table 1. DF-GLS unit root test statistics

	Electricity Prices		Gas Prices	
States	Constant	Trend	Constant	Trend
AL	0.757	-1.132	-0.055	-0.633
AK	0.669	-1.527	0.334	-1.035
AZ	2.347	-2.248	-0.134	-1.178
AR	0.394	-2.026	-0.916	-1.128
CA	1.189	-2.311	-2.107**	-2.476
CO	1.053	-1.505	-0.986	-1.772
CT	-0.224	-1.368	-1.142	-1.645
DE	-0.406	-1.939	0.157	-0.646
DC	0.498	-0.997	-1.620	-1.888
FL	-0.016	-1.411	0.142	-0.676
GA	1.229	-2.810**	-0.503	-1.120
HI	-0.474	-2.818	-0.073	-3.615**
ID	1.358	-2.463	-0.744	-0.891
IL	-0.178	-1.584	-2.811**	-2.845
IN	1.828	-3.376**	-1.445	-1.109
IA	2.294	-1.925	-2.126**	-2.159
KS	2.713	-1.534	-1.247	-1.662
KY	1.466	-1.920	-1.116	-2.137
LA	-1.447	-2.195	-1.959	-2.013
ME	-0.930	-1.429	-0.689	-1.137
MD	-0.141	-2.090	-0.875	-1.251
MA	0.069	-1.506	-0.967	-1.671
MI	1.076	-1.062	-0.136	-0.693
MN	2.404	-2.213	-1.945	-2.670
MS	0.585	-1.559	-2.110**	-2.237
MO	3.253	-2.890**	-0.271	-1.041
MT	1.705	-1.274	-1.439	-2.257
NE	3.105	-2.878**	-1.151	-1.429
NV	0.801	-1.191	-0.594	-1.571
NH	-0.741	-1.787	-0.785	-1.150
NJ	0.183	-0.928	-0.378	-0.445
NM	2.014	-1.819	-0.568	-1.093
NY	0.404	-1.441	-0.972	-1.331
NC	2.594	-2.913**	-0.569	-1.037
ND	2.861	-2.858	-2.743**	-2.688
OH	1.842	-2.319	-0.907	-1.399
OK	0.540	-1.690	-0.643	-1.305
OR	1.345	-1.981	-0.701	-1.306
PA	0.612	-2.601	-0.934	-1.398
RI	-0.806	-2.238	0.001	-1.174
SC	1.975	-2.010	-0.805	-1.225
SD	4.194	-3.090**	-2.720**	-2.914**
TN	0.614	-2.060	-1.022	-1.008
TX	-0.366	-1.384	-1.571	-1.950
UT	2.254	-1.793	-1.906	-2.216
VT	1.576	-0.851	-0.419	-1.326
VA	0.454	-1.967	-0.834	-1.317
WA	1.303	-2.036	-0.595	-1.747
WV	-0.413	-1.456	-0.422	-0.954
WI	1.024	-0.685	-2.498**	-2.725
WY	2.471	-2.671	-1.281	-2.421

Sample period is 2001M1 – 2013M12. The DF-GLS unit root test is developed by Elliott et al. (1996). The optimal lag length has been chosen using the modified AIC procedure. ** indicates rejection of the unit root null hypothesis at the 5% level of significance.

Table 2: Descriptive Statistics Comparison--Historic Monthly Prices vs DOE Monthly Constructed Factors

(2001 through 2013--Actual Prices in ¢/kwH)

STATE	Price Mean	Price SD	Price CV	Factor Mean	Factor SD	Factor CV
AL	9.28	1.696	18.27%	1.00	0.047	4.74%
AK	15.10	2.392	15.84%	1.00	0.037	3.67%
AZ	9.64	1.433	14.87%	0.98	0.080	8.13%
AR	8.47	0.969	11.44%	1.00	0.059	5.95%
CA	13.81	1.475	10.68%	1.00	0.051	5.14%
CO	9.57	1.528	15.96%	1.00	0.048	4.82%
CT	15.93	3.562	22.36%	1.00	0.037	3.67%
DE	11.64	2.511	21.57%	1.00	0.076	7.55%
DC	10.72	2.583	24.08%	0.99	0.097	9.83%
FL	10.47	1.423	13.59%	1.00	0.028	2.77%
GA	9.27	1.477	15.93%	0.99	0.067	6.79%
HI	25.28	7.798	30.85%	1.00	0.055	5.51%
ID	7.15	1.142	15.98%	1.01	0.062	6.12%
IL	9.90	1.559	15.74%	1.00	0.064	6.34%
IN	8.66	1.476	17.04%	1.01	0.058	5.74%
IA	9.62	1.112	11.56%	1.00	0.069	6.87%
KS	8.95	1.522	17.01%	0.99	0.064	6.48%
KY	7.53	1.485	19.73%	1.00	0.043	4.24%
LA	8.61	1.013	11.76%	1.00	0.070	7.04%
ME	14.34	1.535	10.70%	1.00	0.043	4.24%
MD	11.04	2.903	26.28%	1.00	0.081	8.12%
MA	14.43	2.237	15.50%	1.00	0.046	4.62%
MI	10.63	2.322	21.85%	1.00	0.040	3.97%
MN	9.33	1.570	16.82%	1.00	0.054	5.39%
MS	9.22	1.315	14.26%	1.00	0.054	5.41%
MO	8.15	1.582	19.41%	0.99	0.113	11.38%
MT	8.68	1.138	13.11%	1.01	0.050	4.97%
NE	8.02	1.578	19.67%	0.99	0.123	12.41%
NV	11.05	1.363	12.34%	1.01	0.041	4.10%
NH	14.58	1.834	12.58%	1.00	0.034	3.37%
NJ	13.53	2.605	19.25%	0.99	0.068	6.82%
NM	9.71	1.192	12.27%	1.00	0.056	5.59%
NY	16.53	1.992	12.05%	1.00	0.049	4.86%
NC	9.42	1.046	11.10%	1.00	0.040	3.95%
ND	7.68	1.276	16.62%	1.02	0.110	10.73%
OH	9.88	1.518	15.37%	1.00	0.062	6.15%
OK	8.41	1.251	14.87%	1.00	0.096	9.67%
OR	8.16	1.162	14.24%	1.00	0.031	3.05%
PA	11.13	1.443	12.96%	0.99	0.055	5.50%
RI	13.95	2.219	15.90%	1.00	0.071	7.09%
SC	9.57	1.499	15.67%	1.00	0.036	3.63%
SD	8.46	1.144	13.52%	1.01	0.071	7.03%
TN	8.21	1.464	17.84%	1.00	0.044	4.34%
TX	10.90	1.629	14.95%	1.00	0.051	5.11%
UT	8.08	1.182	14.62%	1.00	0.051	5.16%
VT	14.42	1.639	11.37%	1.00	0.024	2.40%
VA	9.25	1.388	15.00%	1.00	0.057	5.72%
WA	7.26	0.965	13.29%	1.00	0.029	2.89%
WV	7.49	1.425	19.02%	1.01	0.036	3.62%
WI	10.84	1.955	18.04%	1.00	0.030	2.97%
WY	8.21	1.171	14.26%	1.01	0.062	6.11%

Table 3: Final Factors and Descriptive Statistics

STATE	Jan.	Feb.	March	April	May	June	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.	SUM	MEAN	SD	CV
AL	0.923	0.944	0.977	1.022	1.004	1.034	1.028	1.040	1.031	1.029	1.007	0.961	12.00	1.000	0.0395	3.95%
AK	0.951	0.958	0.984	0.993	1.022	1.025	1.051	1.039	1.010	1.015	1.005	0.997	12.05	1.004	0.0301	2.99%
AZ	0.866	0.890	0.912	0.966	1.083	1.065	1.059	1.054	1.048	1.037	0.919	0.911	11.81	0.984	0.0807	8.20%
AR	0.904	0.920	0.956	1.002	1.021	1.060	1.049	1.054	1.052	1.003	1.008	0.951	11.98	0.998	0.0540	5.41%
CA	0.999	0.971	0.958	0.955	0.997	1.046	1.055	1.045	1.004	0.932	1.001	1.012	11.97	0.998	0.0390	3.91%
CO	0.934	0.956	0.963	0.989	1.017	1.043	1.033	1.033	1.045	1.015	0.996	0.972	12.00	1.000	0.0371	3.71%
CT	0.964	0.974	0.981	1.012	1.028	1.016	1.004	1.016	1.018	1.030	1.005	0.981	12.03	1.002	0.0221	2.21%
DE	0.908	0.908	0.932	0.976	1.034	1.069	1.049	1.050	1.059	1.048	1.028	0.979	12.04	1.003	0.0602	6.00%
DC	0.918	0.922	0.924	0.925	0.989	1.082	1.097	1.092	1.065	0.982	0.931	0.957	11.88	0.990	0.0731	7.38%
FL	0.968	0.986	0.992	1.013	0.997	0.991	1.002	1.009	1.014	1.012	1.019	1.000	12.00	1.000	0.0144	1.44%
GA	0.901	0.927	0.956	0.972	1.002	1.070	1.079	1.092	1.055	0.996	0.957	0.912	11.92	0.993	0.0672	6.77%
HI	0.959	0.960	0.954	0.967	0.987	1.007	1.013	1.025	1.023	1.039	1.036	1.027	12.00	1.000	0.0324	3.24%
ID	0.948	0.952	0.956	0.960	0.999	1.069	1.073	1.074	1.010	1.033	1.003	0.984	12.06	1.005	0.0479	4.77%
IL	0.904	0.950	0.975	1.021	1.059	1.052	1.035	1.031	1.043	1.044	0.993	0.921	12.03	1.002	0.0532	5.31%
IN	0.909	0.939	0.976	1.056	1.070	1.019	0.996	1.007	1.043	1.083	1.039	0.962	12.10	1.008	0.0539	5.35%
IA	0.897	0.915	0.949	1.002	1.033	1.067	1.078	1.089	1.068	1.022	0.964	0.935	12.02	1.002	0.0678	6.77%
KS	0.889	0.923	0.959	1.001	1.020	1.051	1.070	1.069	1.058	1.003	0.964	0.917	11.92	0.994	0.0630	6.34%
KY	0.931	0.951	0.966	1.018	1.035	1.023	1.019	1.020	1.022	1.052	1.026	0.995	12.06	1.005	0.0367	3.65%
LA	0.924	0.953	0.981	0.990	1.013	1.019	1.031	1.036	1.037	1.044	0.974	0.947	11.95	0.996	0.0402	4.04%
ME	0.979	0.995	1.013	0.996	1.017	1.015	1.001	1.001	1.021	1.009	1.003	0.980	12.03	1.002	0.0136	1.35%
MD	0.915	0.919	0.932	0.951	1.012	1.082	1.079	1.083	1.074	1.013	0.974	0.963	12.00	1.000	0.0663	6.63%
MA	0.995	0.995	0.997	0.989	1.000	1.004	0.987	0.999	1.023	1.001	0.996	1.022	12.01	1.001	0.0113	1.13%
MI	0.954	0.961	0.961	0.976	0.997	1.040	1.047	1.054	1.023	0.997	0.983	0.984	11.98	0.998	0.0350	3.50%
MN	0.931	0.942	0.950	0.973	1.010	1.074	1.076	1.068	1.032	1.006	0.977	0.959	12.00	1.000	0.0528	5.28%
MS	0.915	0.934	0.976	1.024	1.040	1.032	1.029	1.028	1.017	1.006	1.017	0.969	11.99	0.999	0.0410	4.11%
MO	0.839	0.860	0.901	0.958	1.085	1.146	1.143	1.137	1.036	0.982	0.938	0.880	11.91	0.992	0.1145	11.54%
MT	0.932	0.947	0.957	0.971	1.008	1.047	1.062	1.060	1.068	1.044	1.005	0.978	12.08	1.007	0.0490	4.87%
NE	0.819	0.864	0.887	0.939	0.988	1.127	1.142	1.139	1.140	0.997	0.948	0.880	11.87	0.989	0.1201	12.14%
NV	0.964	0.995	1.008	1.029	1.017	0.992	0.989	0.983	0.998	1.028	1.054	1.012	12.07	1.006	0.0243	2.42%
NH	0.977	0.989	0.998	1.020	1.016	1.003	0.998	0.988	1.005	1.030	1.000	0.995	12.02	1.001	0.0148	1.48%
NJ	0.933	0.943	0.944	0.947	0.966	1.050	1.077	1.086	1.057	0.967	0.962	0.962	11.89	0.991	0.0579	5.84%
NM	0.933	0.945	0.953	0.972	1.001	1.046	1.054	1.069	1.036	1.044	0.971	0.953	11.98	0.998	0.0491	4.92%
NY	0.941	0.958	0.950	0.967	0.997	1.038	1.050	1.048	1.048	1.023	0.989	0.967	11.98	0.998	0.0416	4.17%
NC	0.934	0.963	0.977	1.015	1.015	0.998	1.019	1.025	1.046	1.070	1.017	0.964	12.04	1.004	0.0383	3.82%
ND	0.861	0.889	0.912	0.973	1.058	1.158	1.140	1.147	1.154	1.075	0.984	0.928	12.28	1.023	0.1120	10.95%
OH	0.904	0.924	0.948	1.003	1.051	1.073	1.071	1.065	1.048	1.021	0.995	0.937	12.04	1.003	0.0615	6.13%
OK	0.854	0.923	0.965	1.025	1.020	1.059	1.052	1.059	1.108	1.069	0.969	0.863	11.97	0.997	0.0826	8.29%
OR	0.967	0.977	0.980	0.988	0.995	1.013	1.021	1.021	1.021	1.021	1.020	1.010	12.03	1.003	0.0201	2.00%
PA	0.925	0.941	0.951	0.981	1.019	1.048	1.041	1.037	1.024	1.014	0.990	0.958	11.93	0.994	0.0424	4.26%
RI	0.985	0.998	0.994	0.971	1.000	0.994	0.984	1.001	1.028	0.986	1.008	1.051	12.00	1.000	0.0215	2.15%
SC	0.946	0.964	0.966	1.021	1.020	1.018	1.010	1.020	1.020	1.034	1.032	0.981	12.03	1.003	0.0298	2.98%
SD	0.897	0.914	0.935	0.980	1.043	1.093	1.082	1.065	1.083	1.067	0.999	0.947	12.10	1.009	0.0721	7.15%
TN	0.957	0.955	0.977	1.010	1.027	1.010	1.002	0.998	1.000	1.047	1.043	1.018	12.04	1.004	0.0295	2.93%
TX	0.933	0.944	0.973	0.993	1.011	1.038	1.036	1.032	1.021	1.006	0.984	0.969	11.94	0.995	0.0354	3.56%
UT	0.933	0.951	0.947	0.968	1.012	1.051	1.065	1.069	1.040	0.987	0.957	0.962	11.94	0.995	0.0498	5.01%
VT	0.967	0.978	0.982	1.003	1.008	1.015	1.005	1.005	1.013	1.028	1.023	0.992	12.02	1.002	0.0185	1.85%
VA	0.915	0.934	0.955	0.995	1.037	1.054	1.065	1.063	1.048	1.023	0.993	0.948	12.03	1.003	0.0535	5.34%
WA	0.962	0.983	0.983	0.990	0.995	1.013	1.016	1.019	1.023	1.020	1.018	1.018	12.04	1.003	0.0198	1.98%
WV	0.949	0.960	0.979	1.011	1.045	1.016	1.011	1.018	1.029	1.055	1.028	0.982	12.08	1.007	0.0329	3.27%
WI	0.953	0.967	0.973	0.999	1.019	1.037	1.019	1.023	1.032	1.017	1.003	0.979	12.02	1.002	0.0277	2.76%
WY	0.912	0.936	0.950	0.985	1.025	1.059	1.071	1.058	1.086	1.077	1.012	0.960	12.13	1.011	0.0607	6.00%

Table 4: DOE Projections vs. Historic Retail Residential Electricity Prices: Comparison of CVs

STATE	CVs for Historic State Prices: 2001-2013	CV's for DOE Projections: 2016-2028
AL	18.27%	9.91%
AK	15.84%	9.59%
AZ	14.87%	12.09%
AR	11.44%	10.53%
CA	10.68%	9.90%
CO	15.96%	9.82%
CT	22.36%	9.39%
DE	21.57%	10.83%
DC	24.08%	11.59%
FL	13.59%	9.25%
GA	15.93%	11.24%
HI	30.85%	9.67%
ID	15.98%	10.24%
IL	15.74%	10.48%
IN	17.04%	10.50%
IA	11.56%	11.24%
KS	17.01%	11.01%
KY	19.73%	9.80%
LA	11.76%	9.94%
ME	10.70%	9.24%
MD	26.28%	11.16%
MA	15.50%	9.21%
MI	21.85%	9.75%
MN	16.82%	10.47%
MS	14.26%	9.97%
MO	19.41%	14.41%
MT	13.11%	10.28%
NE	19.67%	14.86%
NV	12.34%	9.44%
NH	12.58%	9.26%
NJ	19.25%	10.75%
NM	12.27%	10.31%
NY	12.05%	9.99%
NC	11.10%	9.86%
ND	16.62%	13.97%
OH	15.37%	10.89%
OK	14.87%	12.15%
OR	14.24%	9.35%
PA	12.96%	10.03%
RI	15.90%	9.38%
SC	15.67%	9.59%
SD	13.52%	11.46%
TN	17.84%	9.58%
TX	14.95%	9.77%
UT	14.62%	10.35%
VT	11.37%	9.32%
VA	15.00%	10.50%
WA	13.29%	9.35%
WV	19.02%	9.68%
WI	18.04%	9.53%
WY	14.26%	10.83%

FIGURE 1: MONTHLY Δ% IN LOUISIANA RETAIL RESIDENTIAL PRICES FOR GAS AND ELECTRICITY, AND CPI

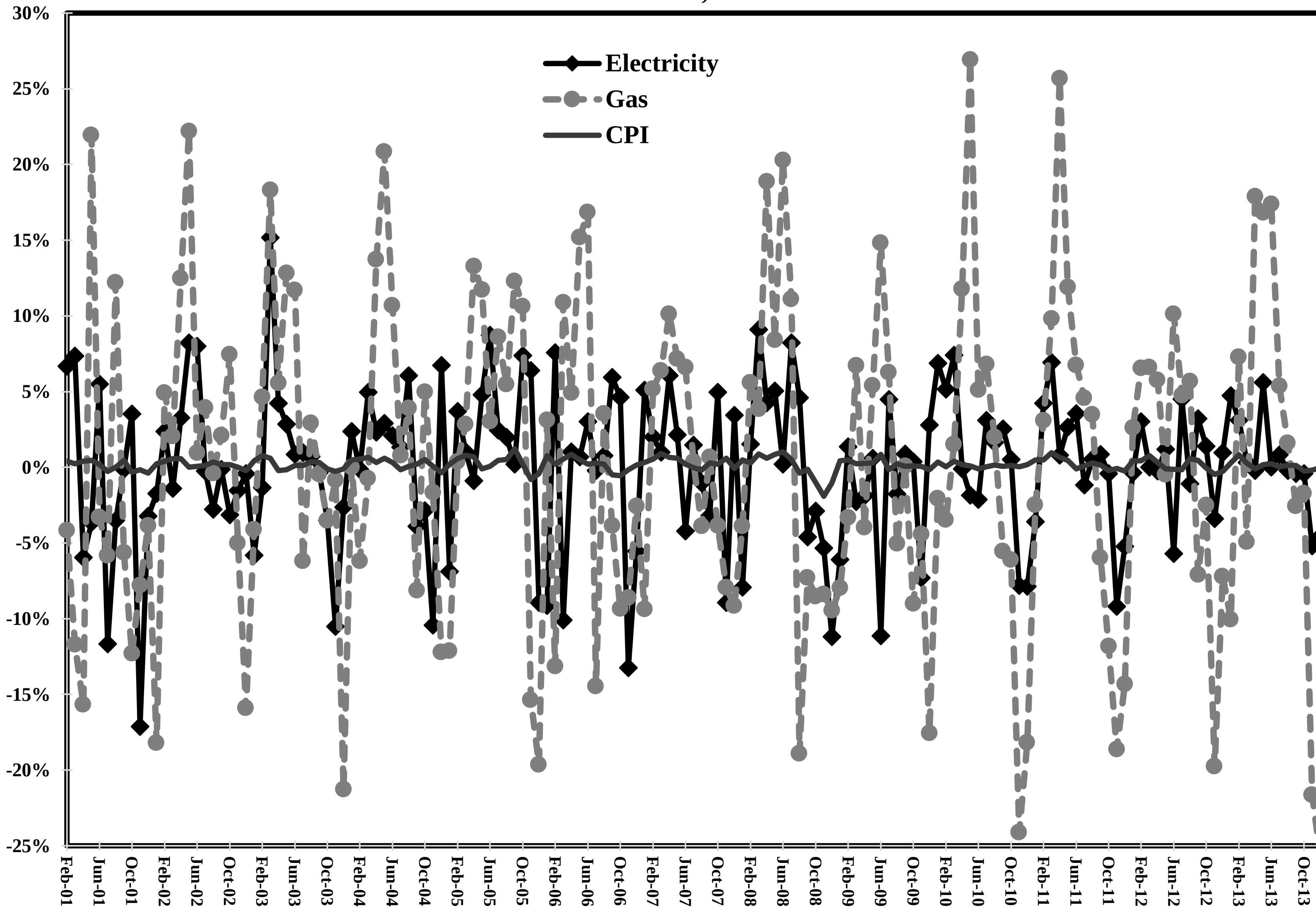
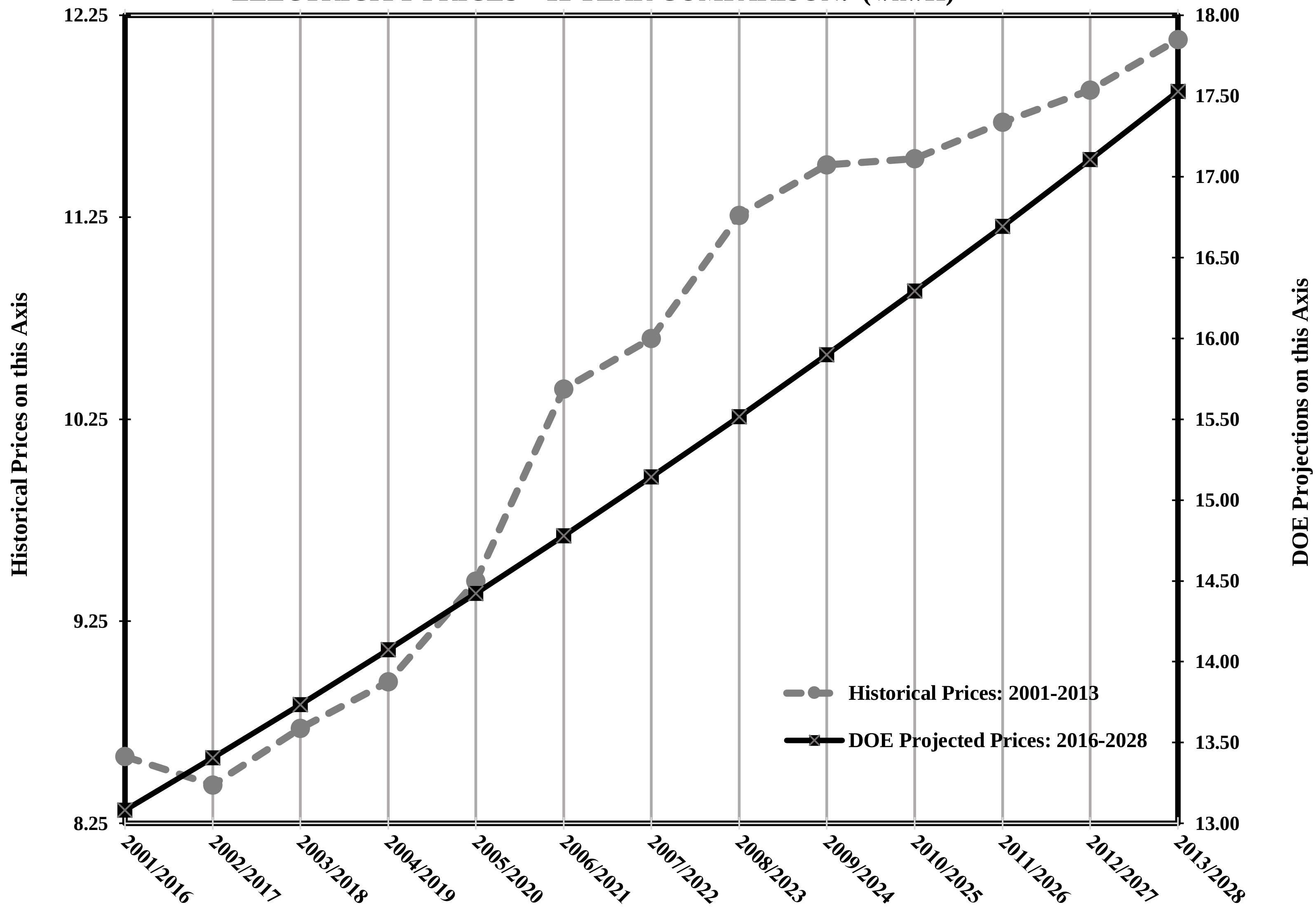


FIGURE 2: DOE PROJECTED VS. HISTORIC ANNUAL RETAIL RESIDENTIAL ELECTRICITY PRICES---12 YEAR COMPARISON: (¢/kwH)



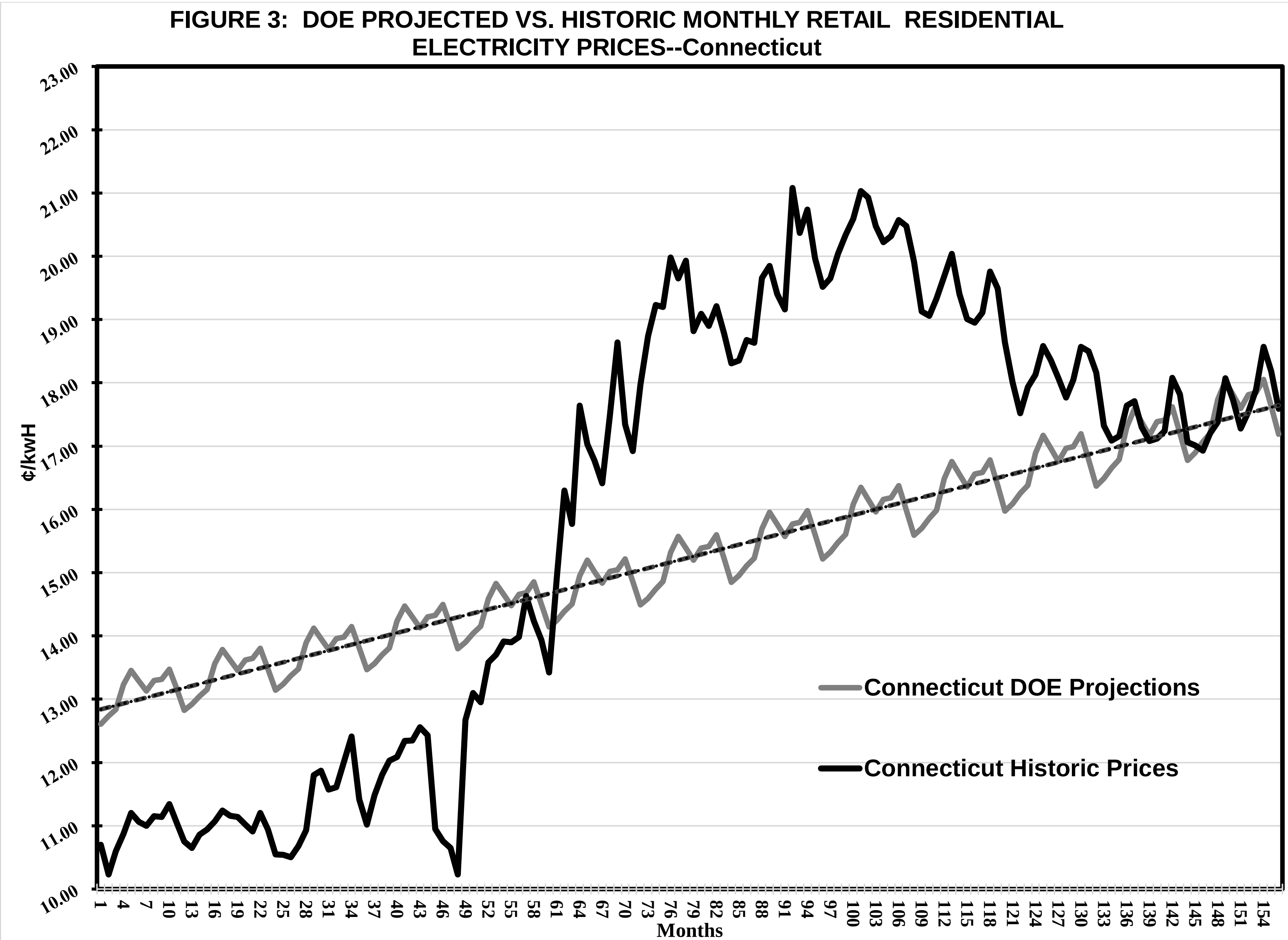


FIGURE 3: DOE PROJECTED VS. HISTORIC MONTHLY RETAIL RESIDENTIAL ELECTRICITY PRICES--Connecticut
¢/kwH
23.00
22.00
21.00
20.00
19.00
18.00
17.00
16.00
15.00
14.00
13.00
12.00
11.00
10.00
Connecticut DOE Projections
Connecticut Historic Prices
1 4 7 10 13 16 19 22 25 28 31 34 37 40 43 46 49 52 55 58 61 64 67 70 73 76 79 82 85 88 91 94 97 100 103 106 109 112 115 118 121 124 127 130 133 136 139 142 145 148 151 154
Months

FIGURE 4: DOE PROJECTED VS. HISTORIC MONTHLY RETAIL RESIDENTIAL ELECTRICITY PRICES--
Massachusetts

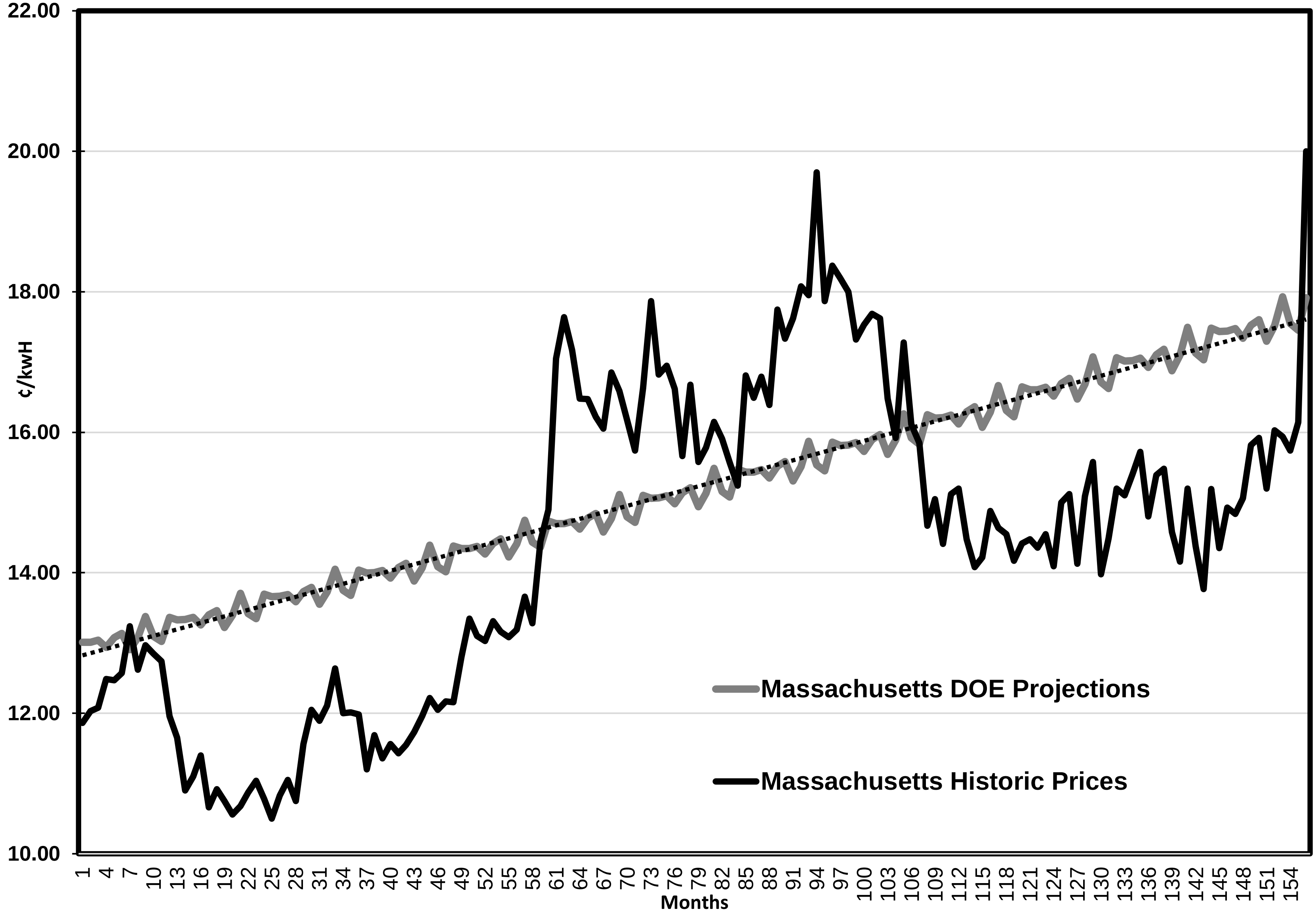
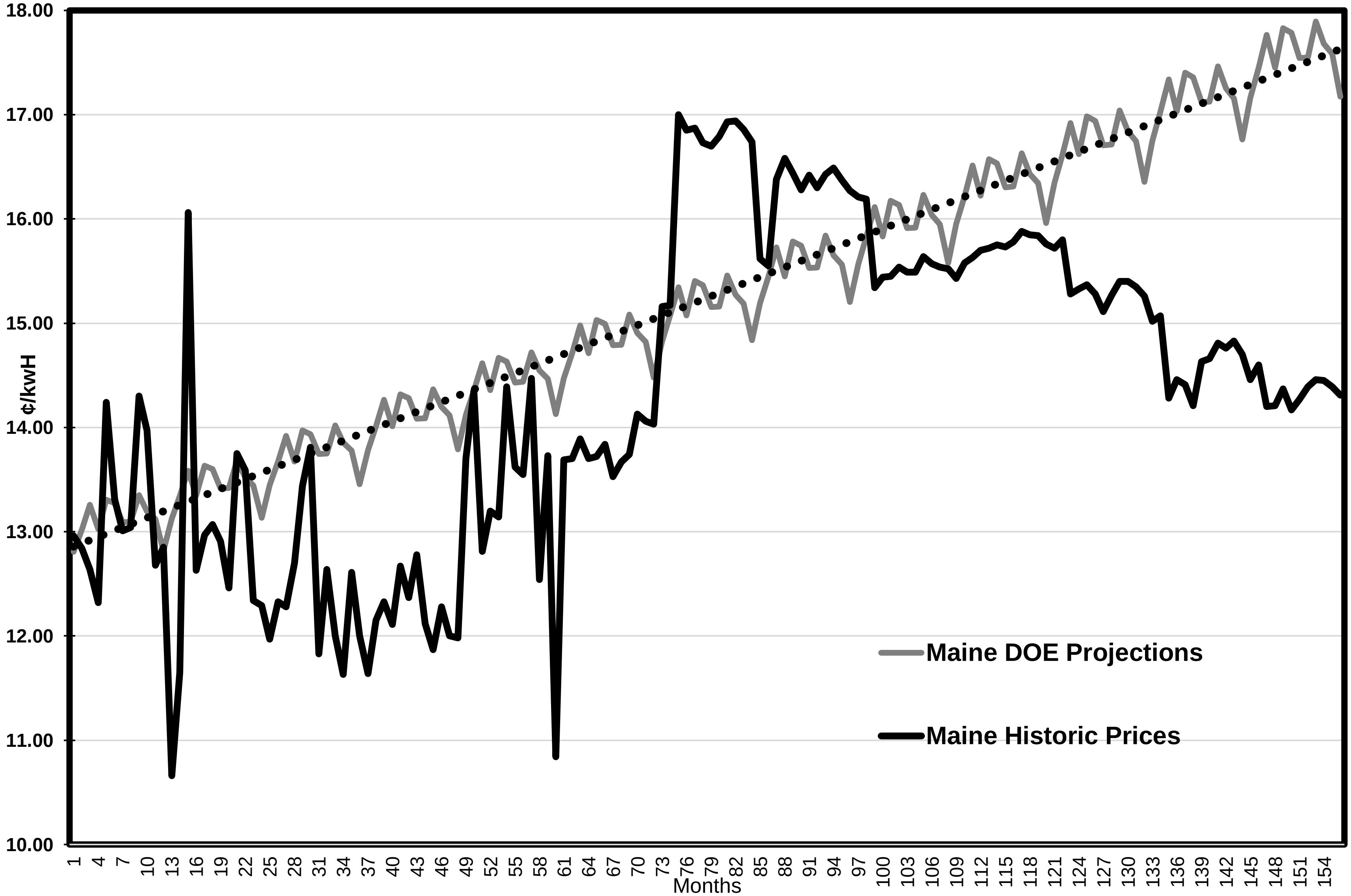


FIGURE 5: DOE PROJECTED VS. HISTORIC MONTHLY RETAIL RESIDENTIAL ELECTRICITY PRICES--Maine



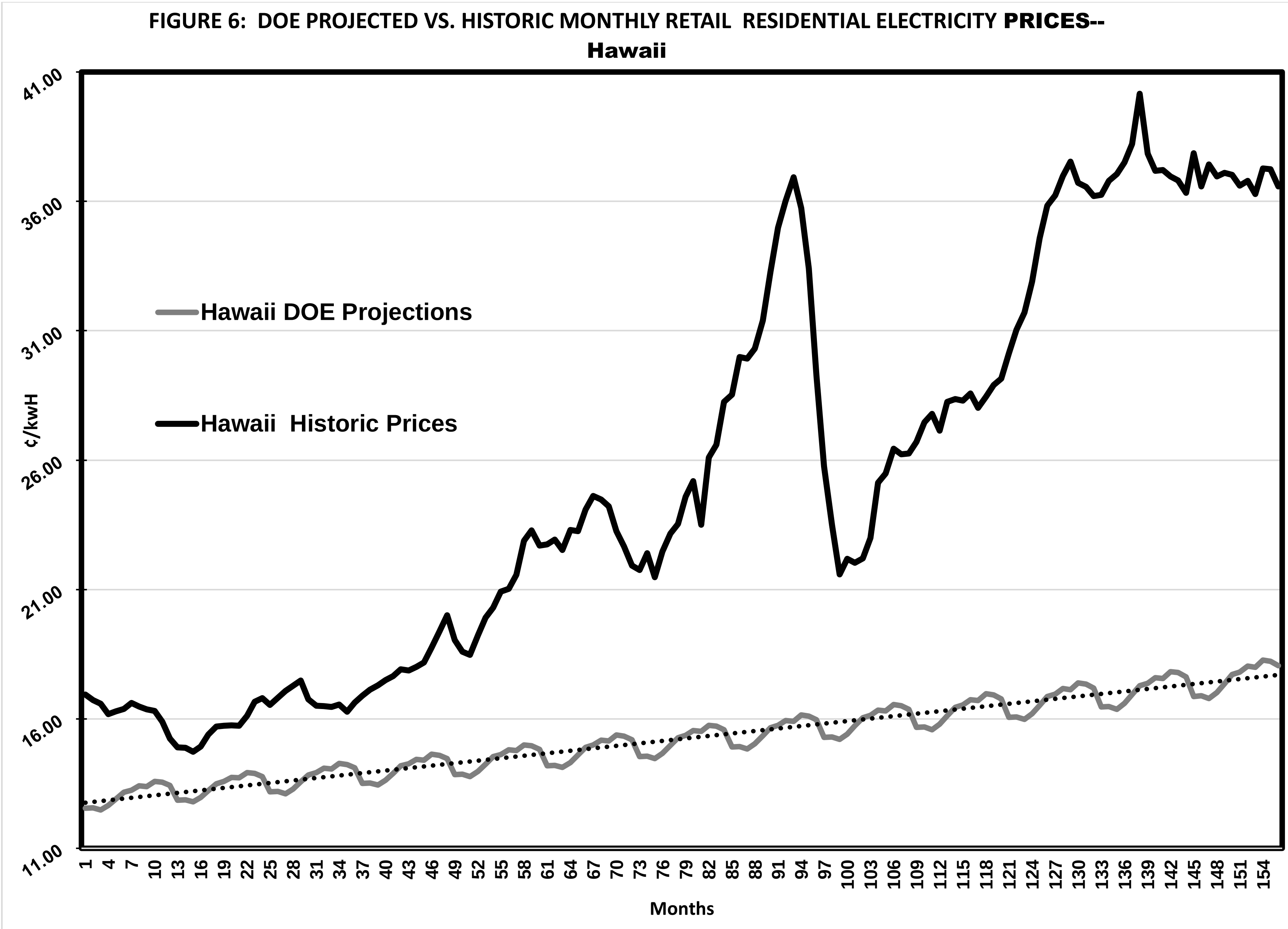


FIGURE 6: DOE PROJECTED VS. HISTORIC MONTHLY RETAIL RESIDENTIAL ELECTRICITY PRICES-- Hawaii
Hawaii DOE Projections
Hawaii Historic Prices
¢/kwH
41.00
36.00
31.00
26.00
21.00
16.00
11.00
Months