Are LEDs the Next CFL:
A Diffusion of Innovation Analysis

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ABSTRACT

This paper examines properties of compact fluorescent lamp (CFL) adoption in the Pacific Northwest and early adoption characteristics of light emitting diode lamps (LED) to glean similarities and differences. CFLs were the emerging technology in the 90's competing against the dominant incandescent bulb. With the phase-out of incandescent bulbs due to Federal legislation (see EISA 2007), within the next few years, CFLs will initially be the dominant bulb and LEDs will be the emerging technology. There is much discussion as to whether LEDs can reach a price point that will make them cost-effective enough to displace the competition. Although there is limited LED data due to its infancy in the market, information may be inferred from the more mature CFL market. With 17 years of CFL data, diffusion of innovation parameters via Bass model estimation are calculated. Additionally, own-price and income elasticities are calculated with more simple logarithmic functions.

We find that CFLs are highly income elastic with a range of 6.10 to 7.80, implying that CFLs are a luxury good. Own-price elasticity ranges from -0.94 to -2.99 supports strong price sensitivity. Further, after 17 years, households in the Pacific Northwest have a CFL socket saturation of 24% while obtaining a peak market share of approximately 33% of all medium screw-based bulbs in 2008, suggesting that many consumers were never reached in this market. First cost and quality of CFLs were barriers that were never fully removed to attract these latter consumer groups, resulting in lost energy savings potential. LEDs provide the most energy saving in the residential lighting market, so from a conservation perspective are highly desirable. LEDs are on the right track as their price forecasts show precipitous declines, but may remain 2 to 3 times higher than CFLs. Therefore, given the evidence of strong consumer sensitivity to CFL price, LEDs may not reach their highest possible saturation rate unless prices can drop more than expected or non-financial benefits outweigh consumer cost concerns.

Introduction

The Energy Independence and Security Act (EISA 2007), phasing out most traditional medium screw-based incandescent bulbs over the next two years, has created a new playing field for LEDs, CFLs, and Halogen bulbs. LEDs and CFLs will get an additional market boost by a 'second' phase of EISA which will prohibit the manufacture of general service lamps unable to meet an efficacy standard of 45 lumens per watt by year 2020 thus eliminating most Halogens from the market (LightBulbChoice.com 2014). Navigant Consulting, Inc. and SAIC (2012) imply that the halogen market share is already in decline in light of the 2020 standard saying that the industry is foregoing investment of incandescent [infrared halogen] technology and instead focusing on LED technology. The LED market has already experienced modest gains over the last 8 years. In the DOE's 2002 Lighting Market Characterization, zero residential LED bulbs registered in the survey, whereas the DOE's 2010 Lighting Market Characterization reported over 9 million residential LED lamps, although still a fraction of 1% of the total residential lamp market. At least one regional residential stock assessment was consistent with the DOE. According to Ecotope's 2012 *Residential Building Stock Assessment* for the Pacific Northwest, LEDs filled 0.7% of sockets, while Incandescents, CFLs, and Halogens filled 57%, 25%, and 6.5%, respectively.

Although it is likely that incandescent bulbs still fill the majority of housing sockets, they will need to be replaced with EISA compliant halogen bulbs, CFLs, or LEDs fairly soon. The opinion about future consumer bulb choice is conflicting. A recent survey by Sylvania, when asking about switching to more efficient lighting as a result of EISA, found that 46% of respondents planned to switch to CFLs, 24% will choose LEDs, while 13% plan to switch to halogen. However, DNV KEMA Energy and Sustainability (herein referred to as DNV KEMA), in a 2013 lighting marketing study prepared for the Northwest Energy Efficiency Alliance, thinks that CFLs will be the least likely to succeed as a result of the EISA transition primarily due to quality issues surrounding the CFL. Some of the quality issues, such as light rendering and on/off cycling time have improved (Eartheasy.com 2014), but dimming ability, low-temperature applications, spot lighting, and cycling time still remain a challenge (Earth Easy 2014). After extensive searching, this author was unable to find any evidence that lighting manufacturers will further research and development to improve CFL quality.

At least one major retailer seems to be less reticent in siding with LEDs. In October 2013, Walmart was offering a special promotion of 60 watt equivalent LEDs for $9 stating that consumers on average could save up to $134 over the lifetime of the bulb versus an incandescent bulb (The Verge 2013). These activities are more consistent with the DOE's LED prognostication, where they forecast LED lighting to represent 36% of the US market by 2020 and 74% by 2030 (Lighting.Com 2014). LEDs are the most cost-effective long-run option (Table 2). The long-run savings of both the CFLs and LEDs are significantly higher than the halogen bulb. And, with a longer-run savings of LEDs over CFLs of nearly $7.00 per bulb, filling several sockets could potentially create considerable cost and time savings.

Table 2. Cost comparison between LEDs, CFLs, Halogens, and Incandescent light bulbs. *Data Source*: Calem, R.E., December 2013, for lifespan, watts, and cost per bulb

	LED	**CFL**	**Halogen**	**Incandescent**
Light bulb projected lifespan	**25,000 hours**	**8,000 hours**	**4,000 hours**	**1,200 hours**
Watts per bulb (equiv. 60 watts)	**10**	**14**	**43**	**60**
Cost per bulb	**$11 - $22**	**$1.50 - $7.00**	**$1.00 - $2.75**	**$0.41 - $1.00**
KWh of electricity used over 25,000 hrs	**250**	**350**	**1075**	**1500**
Cost of electricity (@ 0.10per KWh)	**$25**	**$35**	**$107.5**	**$150**
Bulbs needed for 25k hours of use	**1**	**3.125**	**6.25**	**20.83**
Equivalent 25k hours bulb expense	**$16.5**	**$13.28**	**$11.72**	**$14.68**
Total cost for 25k hours	**$41.5**	**$48.28**	**$119.22**	**$164.68**

Substantial long-run savings would seem impetus enough for consumer decision-making, however first cost, as opposed to longer-run savings, is often times seen as a barrier to adoption (Kim et al. 2012) and was in particular for CFLs (Bonn 2012). Recently, Greg LaBlanc, keynote speaker at the 2014 Efficiency Exchange, provided rationale for seemingly irrational decisions to forego the benefits of energy efficient alternatives. He attributes consumers' ability to ignore the relative financial benefit of a product over their initial expenditures to 'hyperbolic' discounting or the consumer application of differing discount rates depending upon the immediacy of the benefits (greater detail can be found at LaBlanc's Efficiency Exchange transcript 2014). Given the importance of first cost and the potential for irrational consumer behavior, bulb price is an underlying focus of this study.

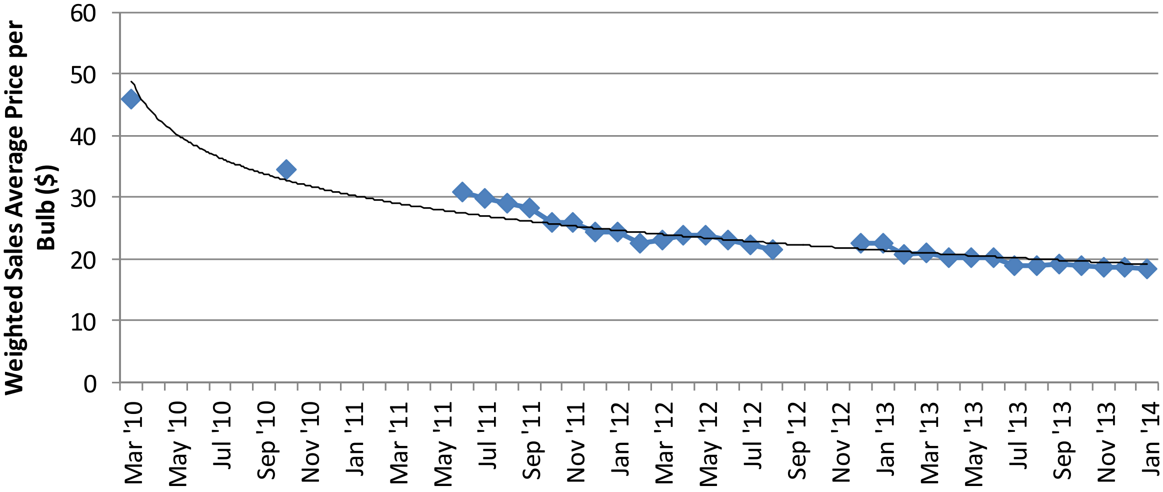

Figure 1. U.S. average monthly weighted LED prices based on 40 watt and 60 watt equivalent LEDs with trend line added. *Source*: LEDInside, CLEAResult, 2012 and 2013.

LED prices have dropped precipitously since 2010 (Figure 1). The prices in the graph below represent average selling prices of LED sales weighted averages of 40 watt and 60 watt equivalent medium screw-based bulbs. From March 2010 and January 2014, approximately the first four years of commercialization for which market prices were reported; average LED price has fallen nearly 60%. Comparatively, in the first four years of CFL commercialization, CFL prices fell by only 37.5% (Figure 2). The next figure illustrates the larger drop in LED prices relative to CFL price (Figure 3). This graph shows price indices for both CFLs and LEDs since their time of tracking inception. For example CFLs were normalized by their 1997 price and LEDs were normalized by their 2010 price. This relative drop in price illustrates that LEDs may 'take-off' more quickly than CFLs. Golder and Tellis (2004) explain take-off as the first dramatic increase in sales that often leads to a sustained growth in a new product's sales. They found that a 1% decrease in price leads to a 4.2% increase in the probability of take-off. In addition to LED price declines that are supportive of increased sales, utilities are beginning to provide promotions for LEDs. DNV KEMA (2013) showed that of the 18 utilities surveyed in the Pacific Northwest with 2012 outreach efforts that 4 utilities provided incentives for LED lamps, up from zero utilities the year before.

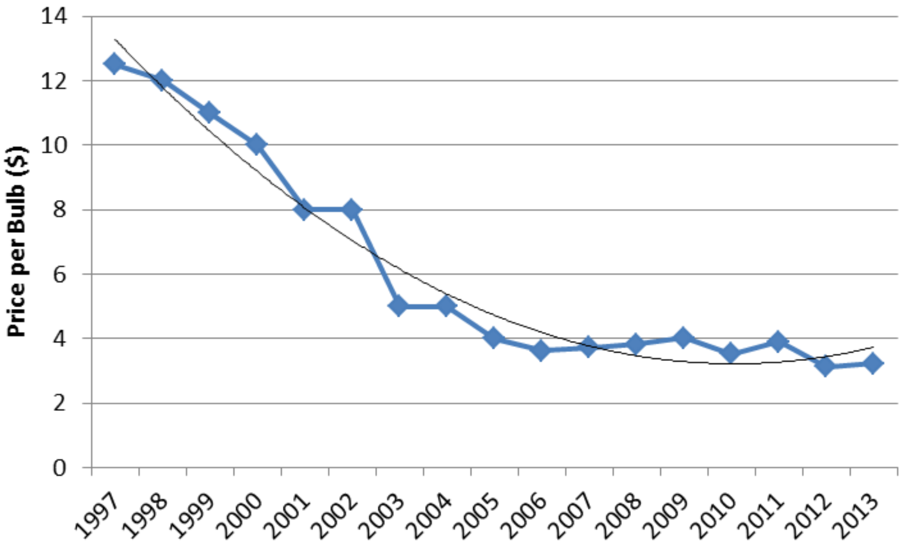

Figure 2. Average general purpose CFL bulb price and trend. *Source*: DNV KEMA, CLEAResult 2012 and 2013.

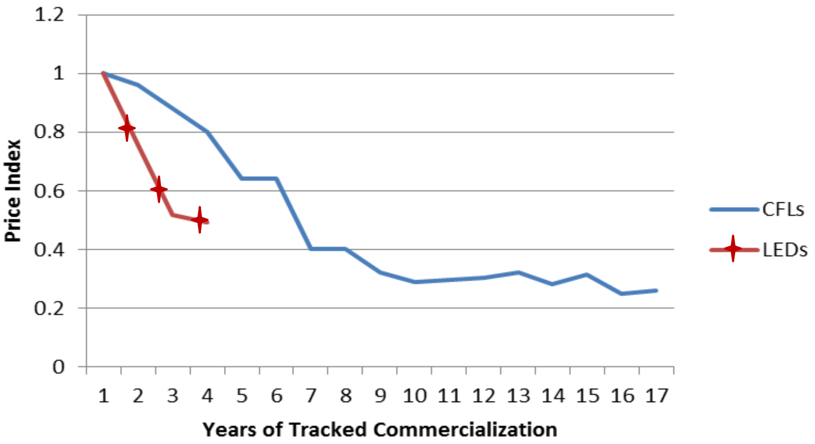

Figure 3. Price indices for CFLs and LEDs normalized by their respective first year prices. *Source*: Holland 2014.

Nearly as important as price, income is also examined due to its relevance in the adoption process. Meade and Islam note that 'heterogeneity of income distribution has been cited by several authors as the driver of the S shape' famously associated with Roger's diffusion of innovation theory. In brief, Roger's theory espouses that the adoption process is successively made up of groups of adopters (Figure 4). The adoption groups typically have similar socio-economic characteristics and behavioral/risk characteristics within group, but are heterogeneous between groups. The earlier groups of adopters, such as the Innovators, typically have higher disposable incomes, higher education, and higher risk tolerance than later groups of adopters. As a result, it is possible for an innovation to never reach full market saturation if the benefits do not outweigh the risks for the later groups. The most commonly cited reason for failure of market adoption progress is inadequate price decline (Golder and Tellis 2004).

Additionally, CFL diffusion parameters associated with the adoption of innovation and the S curve shape may provide some insights into LED adoption. Golder and Tellis (2004) and Lund (2009) estimate take-off periods for several products ranging from consumer durables to electronics. Peres et al. contends that take-off is a result of price reductions, which in turn reduces consumer risk. This explains why take-off is much longer for durable goods, 35 – 45 years, as opposed to less expensive White Goods (appliances and housewares), whose take-off ranges from 6 – 23 years. Brown Goods (leisure goods and electronics) had the lowest take-off time period ranging from 2 – 17 years. Lighting is not considered part of the Brown Good or 'status enhancing' goods. Instead, lighting is considered more of a houseware, and could expect similar take-off time periods.

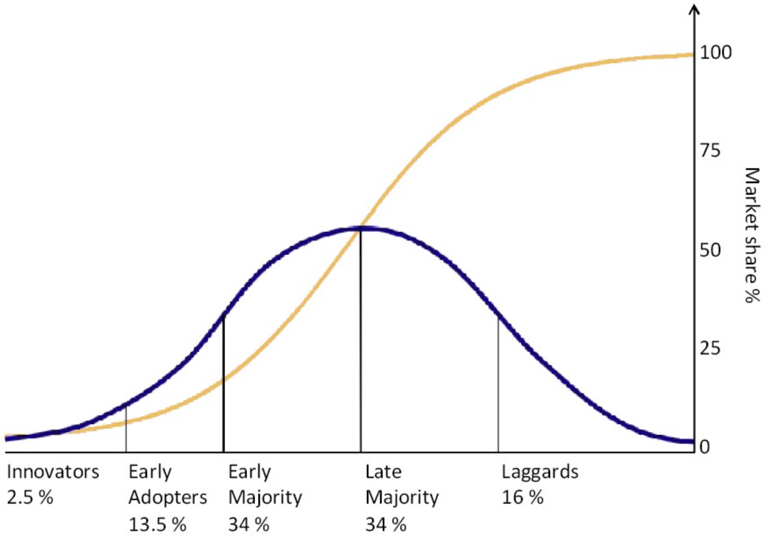

Figure 4. Adopter groups according to Roger's Diffusion of Innovation theory. *Source*: Roger's 1995.

Another aspect of diffusion research which may provide analytical insights into new lighting products are the coefficient of imitation and the coefficient of innovation, two parameters of the Bass model (Bass 1969). The coefficient of imitation accounts for internal influences or 'word of mouth' effects, while the coefficient of innovation is widely viewed as the effect of external or advertising effects. These coefficients influence the shape of the curve. The coefficient of innovation has a greater impact on the front end of the curve. A purely innovative diffusion curve creates a more aggressive exponential shape. Alternatively, a more imitative process creates the S curve shape. The coefficient of imitation is always higher than the coefficient of innovation, hence the pervasiveness of the S shape. Review articles on diffusion on innovation by Kohli, Lehmann, and Pae (1999) and Chandrasekaran and Tellis (2007) provide the following ranges for the diffusion parameters:

Table 3. Value ranges for coefficient of innovation and imitation from review of more than 200 products. *Source*: Kohli, Lehmann, and Pae 1999 and Chandrasekaran and Tellis 2007

Coefficient of Imitation	0.38 – 0.53	Chandrasekaran and Tellis
	0.23 – 0.34	Kohli et al.
Coefficient of Innovation	0.0007 – 0.03	Chandrasekaran and Tellis
	0.0052 – 0.0115	Kohli et al.

One could expect the diffusion parameters for LEDs to be somewhat similar to CFLs. Relative values of the CFL parameters within the suite of goods listed above may provide intuition into how a new lighting innovation may adopt. With regard to price/adoption relationships, Kohli et al. echo the sentiment of Peres et al. They explain that cheaper, less risk products, such as housewares have relatively higher coefficients of innovation. Since, lighting falls within the housewares category, it may also be subject to the relative price sensitivity noted above.

Other measurements of price sensitivity are income elasticity of demand and own-price elasticity of demand. Income and price elasticities refer to the responsiveness of demand associated with income change and changes in price, respectively. Elastic goods are price sensitive and will have an elasticity greater than 1. Inelastic goods have elasticities between 0 and 1. A normal good means an increase in income causes an increase in demand. A normal good can be income elastic or inelastic. A luxury good means that an increase in income causes a bigger percentage increase in demand and would therefore have an elasticity greater than one. Allcott and Taubinsky (2013) found own-price elasticity of demand for CFLs to be very elastic. Using a test group and incentives equal to 20% of the bulb cost, they estimated CFL price elasticity to be approximately -1.5.

This paper also examines income and price elasticities of CFLs to use as reference points for LED adoption[1]. Next, we examine the CFL market adoption characteristics and some economic characteristics. Examining these adoption, or diffusion characteristics will help explain how many years it took for the market to 'take-off', when it hit its maximum penetration rate, and provide estimates of its total penetration, or cumulative sales volume. It is well known that the cumulative sales of many new innovations follow an adoption path that is sigmoidal or S shaped based on Roger's theory of diffusion. One of the most prolifically used models which captures this shape is the Bass (1969) model. Therefore, this paper uses the Bass model to estimate the coefficients of imitation and innovation for CFLs to see what may be in store for LEDs. Lastly, this paper estimates a future price trajectory of LEDs based on the existing price trend to draw some inferences about LEDs ability to saturate the market.

Methodology

As mentioned in the introduction, the focus of this paper is on the adoption characteristics of CFLs as a means to glean insights into possible adoption paths for LEDs. Although both sales and price data are available for CFLs, sales data was unobtainable for LEDs. An LED price series was created through actual and interpolated data. LED prices were sporadically available

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[1] Due to declining investment in halogen R&D, along with increasing efficacy standards of EISA's phase 2, halogens are not part of the analysis.

from LEDinside (2010 – 2014). More specifically, monthly prices for sales weighted averages of 40w and 60w LEDs in the US market were taken from LEDinside's online articles. Also, approximately, 30% of the monthly values were missing, in which case prices were estimated via logarithmic interpolation. Further, if monthly shelf survey data was available by CLEAResult (2012 and 2013), this data was used for any missing values. There were some minor discrepancies between U.S. average prices and regional prices in the Pacific Northwest, however, the overall data trend looked reasonable (Figure 1). LED forecasted prices are estimated based on the logarithmic trend produced in Figure 1 and expressed in Equation 1.

$$P_t = -7.777\ln(t) + 49.024 \qquad (1)$$

where P is price at time t. It is the first cost comparison of the LED price forecast with CFLs that will provide insights into the potential success of LEDs. Annual general purpose CFL prices were taken from annual shelf surveys conducted by KEMA DNV as part of NEEA's CFL initiative.

In addition to price analysis, we examine some CFL adoption characteristics using the following Bass estimation:

$$\mathrm{Y}(t) = m[(1-e^{-(p+q)t})/(1 + (q/p)e^{-(p+q)t})] \qquad (2)$$

where, Y(t) denotes cumulative adoptions at time t, m is the market size, p is the coefficient of innovation, q is the coefficient of imitation, and e is the exponential function. For a full derivation of equation 1 refer to Bass (1969). Adoptions are gross sales of CFLs in the Pacific Northwest, including sales that are used for replacements. A nonlinear estimation technique is used to derive the parameters.

We also want to examine income and own-price elasticity. Ideally, one would want to control for underlying sales dynamics resulting from diffusion (Tellis 1988; Parker 1992) with functional forms suggested by Jain and Rao (1990). However, the limited number of observations does not allow for the inclusion of the explanatory variables, income and CFL price, in Eq 2. Another consideration is that autocorrelation is common in time series, so a simple autoregressive model (AR1) corrected for first order autocorrelated errors is used to estimate elasticities with the following function

$$\mathrm{Y}(t) = ln(\mathrm{X}_t)\,\beta + \mu_t\,, \qquad (3)$$

$$\mu_t = \rho\mu_{t-1} + \varepsilon \qquad (4)$$

where β's and ρ are coefficients, and $X_t = x_1, x_2$ represent logged price and logged income. Prices reflect general purpose, medium screw-based CFLs (DNV KEMA 2013). Income reflects population weighted average state income for Washington, Oregon, Idaho, and Montana. All models were estimated using the software package, Regression of Time Series Analysis by Estima 2010.

Results

As expected, there were not enough observations to get the Bass model to converge while including the independent variables, income and price. However, the simplified Bass model provided a reasonable fit of the data. Graphs of the annual and cumulative actual data, and their Bass prediction curves (Figures A1 and A2), followed by the estimation results are provided in the appendix (Table A1). The coefficient of innovation for CFLs is 0.001, falls within the coefficient range supplied by Chandrasekaran and Tellis, but below the range of surveyed good analyzed by Kohli et al. in Table 2. This may be due to the relatively high price of CFLs compared to incandescent bulbs, as well as the degree of their 'innovativeness', ie. the bulbs look quite different from incandescent bulbs and are perceived to not perform as well (DNV KEMA 2013). Conversely, the coefficient of imitation is relatively high at 0.48 suggesting most of the growth in sales occurred in the latter stages of the CFL life cycle. Correspondingly, the period of most rapid growth occurred in 2006, nine years after marketing efforts began. Additionally, CFLs reached a maximum market saturation rate of 33% in 2008. Although it is expected that bulb sales will decline as sockets are filled with more efficient bulbs, the fact remains that CFL socket saturation only reached 24% suggesting that the latter adoptive groups were never reached.

In addition to the diffusion parameters, income and own-price elasticities were also calculated. The first equation estimated was a simple log linear model, however, the errors presented autocorrelation, as predicted. The estimation was then run using an AR(1) model, as defined by Equations (3) and (4) in the methodology, of logged price and income on logged sales (Table A2). This estimation was challenged given a usable observations limit of 16. However, the results of this model gives reasonable results, i.e. realistic coefficient values, correct signs, and reasonable significance given the limited data. It is most likely that collinearity exists. Due to limited data the model is unable to distinguish between price and income effects as evidenced by a high R2 of 0.89 when logged income is regressed on logged price (not shown in the Appendix). As a result, individual AR(1) regressions of price and income against sales were used to provide elasticity relationships (Tables A3 and A4). Elasticity results from all three regressions provide a range of elasticities. The own-price elasticity ranges from -0.94 to -2.99 indicating strong price sensitivity. Income elasticity ranges from 6.10 to 7.80 strongly indicating that CFLs are a luxury good.

Lastly, estimated LED prices using the existing price trend, indicates that average annual price per bulb may drop to $11.50 by the year 2020 (Figure 5). Assuming that the CFL price trajectory will also follow its historic path, future CFL price will hover around $4.00, making LEDs 2 to 3 times more expensive by the year 2020. This LED estimate may be high. IHS forecasts an average of $12.70 per bulb in 2014, much lower than the extrapolated average of $18.24. Further, Huston contends that a LED "price war" will erupt in 2014 possibly driving prices downward at a rate exceeding the forecasted trend.

Conclusions

For long-run adoption success, the question is 'can the benefits of long-run savings outweigh the barrier of first cost?' To examine this question, the adoption characteristics of CFLs are examined. The Bass model estimation suggests that CFLs are in a decline phase despite the advent of EISA. Often cited reasons for the decline are quality concerns and the availability of cheap substitutes such as halogens bulbs. Although to a much lesser extent, LEDs seem to have some of similar quality issues that have nagged CFLs (Green American 2010; AZCentral.com 2014). However, Philips, Osram, GE and other major manufacturers seem highly motivated given price their price incentives. Additionally, utilities will start to provide significant rebates which will reduce the price even further. Some believe that LEDs will eventually replace all incandescent bulbs with CFLs only a temporary solution. Nonetheless, the results of this research suggest that in the lighting market, CFL bulbs are highly income and price elastic. It is the belief of this researcher that LEDs may be subject to similar price sensitivity. Time will tell consumers how consumers will weigh the non-financial benefits of the LEDs over LED first cost.

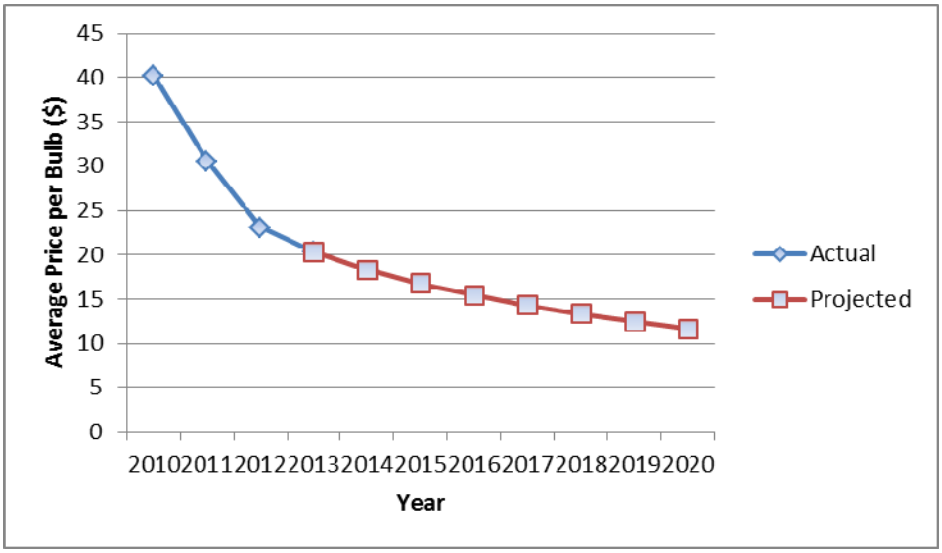

Figure 5. Actual and projected LED average prices for 40 watt and 60 watt equivalents. *Source*: Holland, 2014.

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Appendix

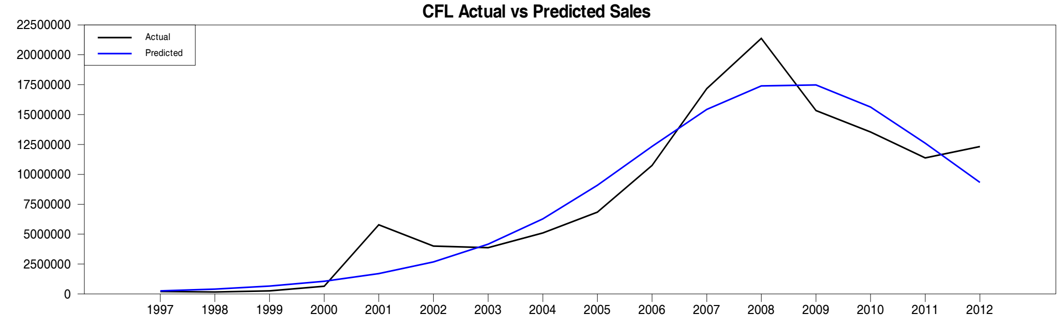

Figure A1. Annual CFL sales versus estimated annual sales produced by a simple Bass model.

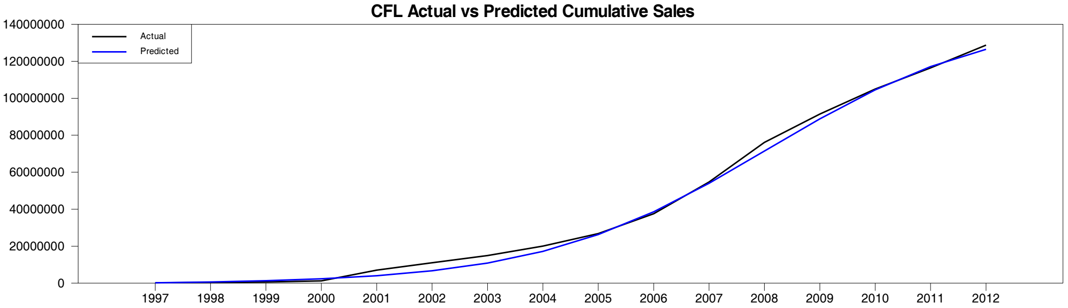

Figure A2. Cumulative CFL sales versus estimated cumulative sales produced by a simple Bass model.

Table A1. Results from bass model estimation

```
Nonlinear Least Squares - Estimation by Gauss-Newton
Dependent Variable SALES                  ; Annual Data From 1997:01 To 2012:01
Centered R^2                 0.90112;     ;  Uncentered R^2              0.96117
Mean of Dependent Variable   8044928.375  ;  Std Error of Dependent Variable    6680220.6536
Standard Error of Estimate   2256368.578  ;  Sum of Squared Residuals        6.6185e+013
Log Likelihood               -255.1102    ;  Durbin-Watson Statistic           1.5864

        Variable          Coeff          Std Error        T-Stat        Signif
    1.  P              0.489063         0.054508         8.97233       0.00000062
    2.  Q              0.001334         0.000685         1.94630       0.07355930
    3.  M              144658398.318    11822539.005     12.235        0.00000002
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Table A2. Results from autoregressive model of logged price and income on logged sales.

```
Regression with AR1 - Estimation by Beach-MacKinnon
Dependent Variable LNSALES                          ;  Annual Data From 1997:01 To 2012:01
Centered R^2                        0.94813         ;  Uncentered R^2                    0.99941
Mean of Dependent Variable          15.15182        ;  Std Error of Dependent Variable   1.67517
Standard Error of Estimate          0.44551         ;  Sum of Squared Residuals          2.18331
Log Likelihood                      -7.1040         ;  Durbin-Watson Statistic           1.19950

   Variable            Coeff              Std Error       T-Stat          Signif
1.  Constant        -47.05411576          26.25260737   -1.79236          0.10058941
2.  LNINCOME          6.10350494          2.41790436     2.52430          0.02825876
3.  LNPRICE          -0.94540904           0.77473377   -1.22030           0.24786567
4.  DUM2001           1.16199221           0.37149532    3.12788          0.00961396
5.  RHO             0.69875280            0.31200375     2.23957          0.04673684
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Table A3. Results from autoregressive model of logged income on logged sales

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Regression with AR1 - Estimation by Beach-MacKinnon
Dependent Variable LNSALES                          ;  Annual Data From 1997:01 To 2012:01
Centered R^2                 0.94303                ;  Uncentered R^2              0.9993546
Mean of Dependent Variable     15.15182             ;  Std Error of Dependent Variable   1.67517
Standard Error of Estimate     0.44700              ;  Sum of Squared Residuals          2.39772
Log Likelihood                 -8.0044              ;  Durbin-Watson Statistic        1.0210

   Variable            Coeff              Std Error       T-Stat          Signif
1.  Constant        -66.48776223          18.43731957     -3.60615        0.00360499
2.  LNINCOME          7.80585242          1.76956319      4.41117         0.00084861
3.  DUM2001          1.23892110           0.35127181      3.52696         0.00416969
4.  RHO              0.78845864           0.18958101      4.15895         0.00132526
```

Table A4. Results from autoregressive model of logged price on logged sales

```
Regression with AR1 - Estimation by Beach-MacKinnon
Dependent Variable LNSALES                              ;Annual Data From 1997:01 To 2012:01
Centered R^2     0.91700 ;  R-Bar^2      0.89625         ;  Uncentered R^2                0.99905
Mean of Dependent Variable              15.15182         ;  Std Error of Dependent Variable   1.67517
Standard Error of Estimate              0.53957          ;  Sum of Squared Residuals       3.49365
Log Likelihood                          -10.6238         ;  Durbin-Watson Statistic            1.7471


   Variable                Coeff                Std Error          T-Stat              Signif
1.  Constant              20.19694647           0.75746749         26.66378            0.00000000
2.  LNPRICE               -2.99927162           0.41945411         -7.15042             0.00001164
3.  DUM2001               1.13952822            0.50292272          2.26581            0.04276009
4.  RHO                   0.41385777            0.31759338         1.30311             0.21698845
```