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Abstract. In recent years, household LED light bulbs (LED A lamps) have undergone a dramatic price decline. Since late 2011, we have been collecting weekly data on retail offerings of LED A lamps on the Internet. The resulting data set allows us to track the recent price decline in detail. This report extends and improves upon a previous report, released in 2014, by developing a regression model that accounts for the effects on lamp price of time, lumen output, brand, retailer, and color temperature. Significant effects on price are observed with time, lumen output, brand and retailer. If brand-name effects are ignored as price predictors, we find that LED A lamps declined in price by 32% per year between 2011 and 2015, after controlling for lumen and retailer effects. If we also control for brand-name effects the rate of price decline drops to 28% per year, suggesting that a portion of the price decline has been driven by competition among the many brands that have entered the market in recent years. If we attribute the remaining price decline to technological learning, we can combine the rate of price decline with public data on the growth in LED A lamp shipments to yield a power-law experience curve relating price to cumulative shipments. From this, we estimate that LED A lamp prices have recently fallen by 18% for each doubling in cumulative production.

1 Introduction

Solid state lighting (SSL) utilizing light-emitting diodes (LEDs) is in the process of transforming the lighting market. Since the start of 2011, US sales of A-shape household light bulbs (hereafter A lamps) using LEDs have increased approximately thirtyfold.[1] Meanwhile, the market price of LED A lamps has fallen dramatically,[2] by a factor of two or more, and a report issued by the U.S. Department of Energy (DOE) forecasts a further decline in LED lamp prices by a factor of several by 2030.[3]

A rapid price decline for LED A lamps was widely expected when these products were first introduced late in the last decade. Part of the reason for this was Haitz's law,[4,5] which is the observation that the per-lumen price of LEDs has fallen by a factor of 10 in each decade since their invention in the 1960s (corresponding to a decline of roughly 25% per year). The price of an LED-based A lamp involves many more components than the individual LEDs themselves, however, so Haitz's law alone is unlikely to fully explain the recent price decline for LED A lamps. A broader reason to expect a price decline for LED A lamps is the general observation that the cost of production for new technologies tends to fall as their production increases. This phenomenon is often discussed in the context of *experience curves* (sometimes referred to as learning curves), which mathematically characterize the cost of manufacturing for a given technology as a declining power law function of cumulative industry manufacturing experience. This implies that cost will fall by a fixed fraction for each doubling in cumulative production. A broad range of products have been observed to approximately follow such a curve. Since cumulative production doubles and redoubles very rapidly in the period following market introduction for new products, and more slowly for mature products, relatively rapid cost declines are generally predicted for new technologies such as LED A lamps. One would expect such declines in manufacturing costs to lead to similarly rapid declines in consumer prices.

To monitor LED A lamp prices in detail, since late 2011 we have been collecting weekly data on the price and features of LED A lamps sold on the Internet, using automated web-crawling software. In a previous study[6], we aggregated these data within each weekly data collection to produce measures of typical LED A lamp prices over time, and we fitted the resulting time series to mathematical models characterizing the price decline with time. We also combined the time series of typical price with lamp shipment indices[7] published by the National Electrical Manufacturers Association (NEMA) to derive an experience-curve relation between price and cumulative production for LED A lamps.

The approach we used in that study had the advantage of producing aggregate indicators of typical LED A-lamp prices that could be used to track price changes on a weekly timescale. However, there were a few disadvantages for the fitting of long-term price trends and experience curves. First, the aggregation step made it difficult or impossible to produce a full accounting of the uncertainty in the fitted price trends. In particular, the observed prices of individual lamps at a given retailer are expected to be strongly correlated over time, and this correlation will have an impact on the trend uncertainty, but it is impossible to take such correlations into account using only the aggregate price indicators. Second, the typical consumer price may not be an ideal metric from which to compute experience curves, since the relation between manufacturing cost and typical market price point may not be constant over time in a market containing a shifting range of product offerings and manufacturers. This is particularly true in a new, active, and competitive market, such as currently exists for LED A lamps, where the mix of brands and pricing strategies in the market may be shifting rapidly.

In this study, we expand the data set utilized in the previous study to include retail data collected in late 2014 and early 2015. We perform a series of regression analyses on the full, disaggregated dataset to explore the scaling of lamp price with lumen output, retail outlet, brand, and time. By performing a regression analysis on the full data set, we are able to use error analysis techniques that properly account for serial correlations in price with time for individual lamp models, yielding a more complete accounting of the uncertainty in the price trend. Including lumen output in the model allows us to explore the incremental price of increased luminosity and any time trends in that price increment, while separating such effects from the underlying price decline for the technology. Including brand and retailer as predictive variables in our model allows us to control for the most direct effects of competition on price, yielding a price trend with time that should more closely reflect the underlying decline in manufacturing costs. We combine this trend with a shipments growth trend derived from the NEMA shipments indices to derive an improved estimate of the experience curve for LED A lamps.

In the next section, we summarize our methods for collecting data from the Internet, as well as the additional data sources used in this study. Section 3 details our regression models and our error estimation methods, both for the retail lamp data and for the NEMA shipments data. We present and discuss the results of these analyses in section 4, and in section 5 we conclude.

2 Data

2.1 Crawling the web for LED data

To monitor the price and features of LED A lamps over time, we used automated web-crawling software to collect data on a regular basis from five separate online retail outlets from 1 November 2011 to 22 May 2015. The retailers included four online-only lighting retailers and the website of one national chain of large home-improvement centers. The retailers were selected in part because they had unique product offerings for LED A lamps, in an effort to give a reasonably broad cross-section of the limited set of such lamps available on the US market at the time data collection began in late 2011. The home-improvement retailer was included to allow exploration of any systematic offsets between the online-only retail prices and prices at physical stores, since the latter are expected to capture a majority fraction of household lamp sales[8].

The data collection software proceeds by loading a page from each website, listing the available LED A lamp options. It then follows links to each product offer in turn and extracts the desired data, including price and various lamp features, from the HTML code underlying the page. For lamps sold in multi-packs, the collected price data were corrected to represent the price per individual lamp**.** Data collection typically occurred on a weekly basis, but data-collection errors and differences in the commencement of data collection for each site led to varying numbers of total collections for the various sites. Rapid expansion of the LED market during the data-collection period led to a large time variation in the number of LED A lamps collected from the sites, as some retailers dramatically expanded their selection, while others focused on a narrower range of products. The collection statistics for the five retail sites are summarized in Table 1. **We used data collected in this** manner in our previous study[6]; the data used here extends that data set to include data collected since that study was completed.

Table 1. Summary of data sources for LED retail data.

Retailer	Type	Number of data collections	Average LED Yield	Maximum LED Yield
1	Internet only	157	51.6	85
2	Internet only	204	10.9	40
3	Internet only	203	6.4	11
4	Internet only	201	91.6	348
5	Home-improvement center	141	66.5	110

2.2 Lamp shipment indices from NEMA

To obtain data on the relative shipment volume of LED A lamps over time, we digitally extracted data from the figures in NEMA's regular updates to its lamp shipment indices[1,7,9–17] for incandescent, CFL, Halogen, and LED A lamps, yielding data covering the period from the beginning of 2001 to the beginning of 2015. We detail our methods for extracting, correcting, and normalizing these indices in our previous study[6], which included data through the end of 2013. Here we add data for the quarters between the beginning of 2014 to the beginning of 2015, which has been released since the previous study was completed. Figure 1 shows the extracted shipment index data on a log-linear chart. For the sake of completeness, all tracked lamp types are shown, although only the LED data is used in this study.

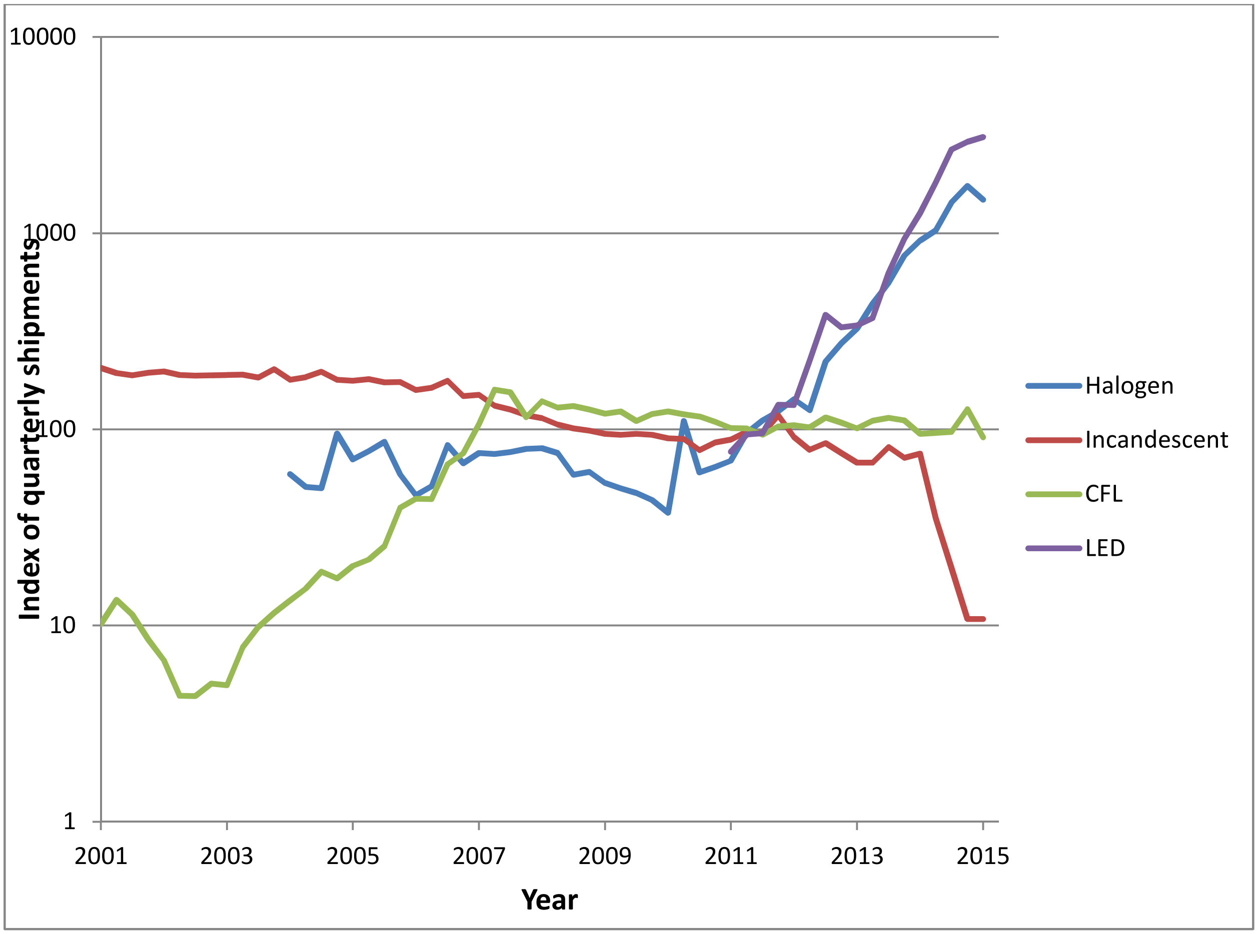

Figure 1. Quarterly NEMA lamp shipments index from beginning of 2001 to beginning of 2015 (average 2011 quarterly shipments = 100). Relative shipments are shown on a logarithmic scale.

As we will discuss in section 3.3, to estimate an experience curve for LED A lamps, it is necessary to have a time series of *cumulative* shipments relative to some reference year. We can convert the quarterly NEMA shipments index into a cumulative quarterly shipments index as follows. First we note that the LED shipments index time series starts after the year of LED market introduction; hence we must construct a model to estimate the cumulative shipments prior to the beginning of the data series in 2011. We note that LED A lamps are currently in a very early phase of their market adoption, a period during which market growth may be expected to approximately follow an exponential growth model. Furthermore, we note that the LED shipments curve shown in Figure 1 is reasonably well approximated by an exponential curve (i.e., it roughly describes a straight line on the log-linear plot). Therefore, we approximate the pre-2011 shipments of LED lamps by fitting an exponential curve to the LED shipments index and extrapolating back to the year of introduction in 2004. Summing this curve from 2004 through 2010 yields an estimate for the cumulative LED A lamp shipments through 2010 of 2.6 times the average quarterly shipments in 2011. By adding this value to the cumulative sum of the NEMA LED index, we can construct a quarterly cumulative shipments index from 2011 through 2015. This cumulative index, and the historical extrapolation, are shown in Figure 2. It is worth noting that the cumulative shipments between 2011 and 2015 also follow an approximately exponential trend.

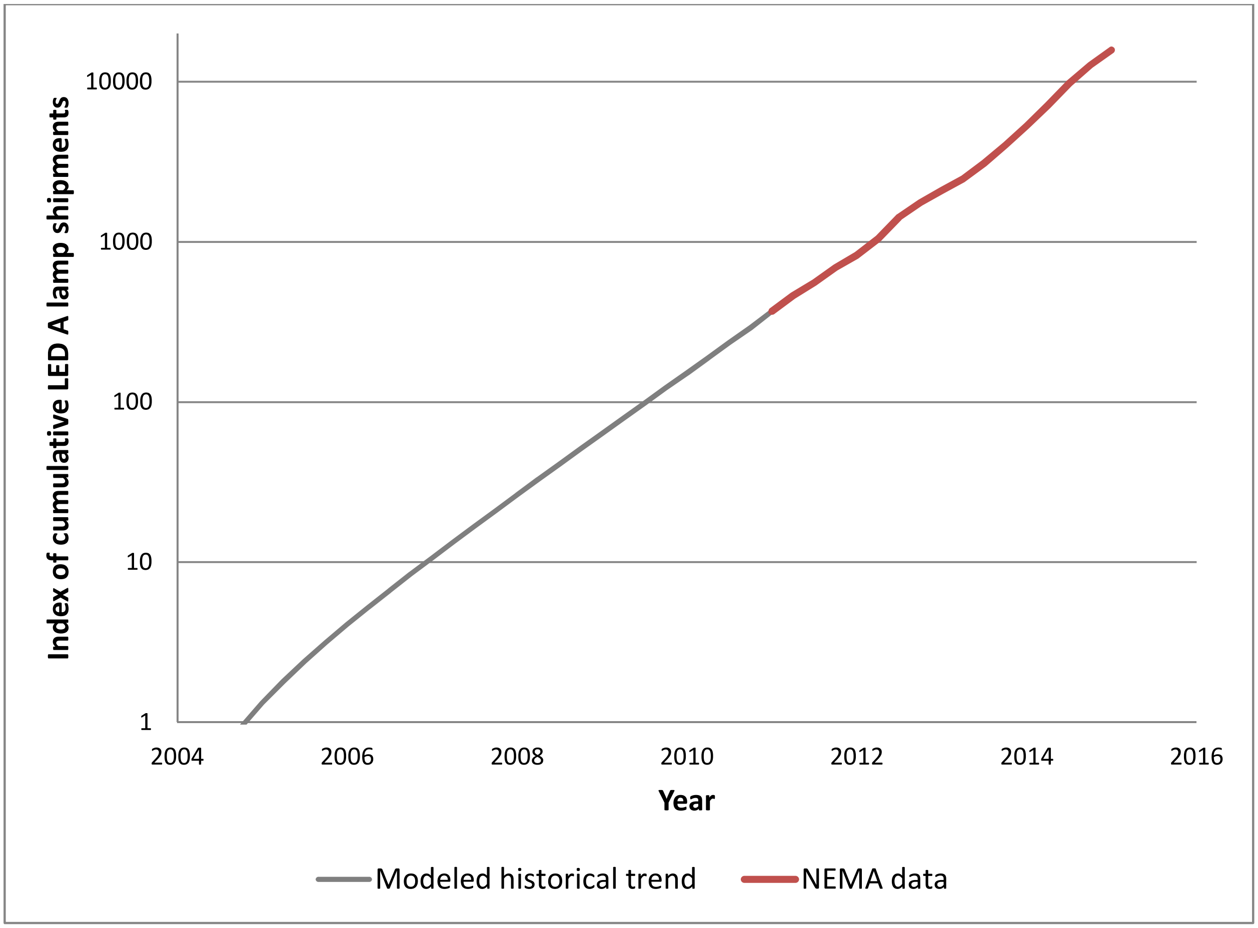

Figure 2. Quarterly index of cumulative LED A lamp shipments, as derived from the NEMA shipments index for these lamps shown in Figure 1 (average 2011 quarterly shipments = 100). Also shown is the fitted historical trend used to initialize the cumulative shipments in 2011.

3 Analysis

In this section we discuss the selection and processing of data to be analyzed in a multilinear regression model for the price of LED A lamps. We then discuss the considerations we used in developing that model, and we specify the variables and parameters to be considered in the analysis. Finally, we discuss a method for combining our regression results with a simple regression model for LED A lamp shipments in order to estimate an experience curve for LED A lamps.

3.1 Data selection and cleaning

Data fields collected by the web crawling software included the date of collection, price, brand, model number, retailer, retailer's product identifier (SKU), voltage, wattage, lumen output, color, correlated color temperature (CCT), color rendering index (CRI), bulb shape, and information about lamp dimmability. Many of these data fields were reported too inconsistently on the retail sites to be included in our regression analysis; however, there was sufficient data completeness to include the following fields in our analysis:

- Sale price
- Collection date
- Brand

- Retailer
- SKU
- Lumen output
- CCT

Wattage was also an available field with high completeness, but since it is very strongly correlated with lumen output, we excluded it from our analysis.

We restricted our analysis to lamps with lumen output between 310 and 1999 lumens. The lower bound allows us to exclude accent lighting products, which are used in different applications from the general-service lighting products that interest us here. The upper bound excludes lamps that are more luminous than typical traditional household light bulbs. LED A lamps in this latter category are currently quite rare, having only recently been introduced to the market. After restricting the data in this way, we are left with some 33,000 individual data records, each representing the record of a particular lamp's being offered for sale on a particular website on a particular date.

We then removed records that had missing data, or obviously incorrect data, on sale price, brand, SKU, or lumen output. We also eliminated lamps that were marketed as colored lamps (i.e., lamps producing red, blue, or other colors of light, rather than white light) and lamps with base types other than either the typical household medium screw base or the GU-24 base used commonly for high-efficacy lighting applications. Finally, we eliminated so-called "smart" lamps that are controllable through a wireless gateway, since such lamps have a significant price premium, which often includes the price of the gateway. We eliminated smart lamps by identifying relevant keywords in the product description text, such as "connected", "wireless" and "smart". After eliminating the records just described, we are left with some 30,000 records. In a portion of our analysis below, we also eliminate records with missing information on CCT; this yields 22,000 remaining records.

It was also necessary to perform some processing on the brand names present in the data set to eliminate alternate spellings. For example, some retailers sell lamps under the brand name *Philips Lighting*, while others simply use *Philips*. We searched the data for alternate spellings of each brand name and modified some records to enforce a single, consistent spelling for each brand.

3.2 Linear regression model for LED A lamp prices

3.2.1 Model development

It is manifestly apparent from casual market observation that the price of LED A lamps has been declining in recent years and that LED A lamp prices generally increase with increasing lumen output. Our previous study of LED A lamp prices[6] indicated that the typical price of LED A lamps has been falling roughly exponentially with time. Motivated by this, we will assume a declining exponential relation between price and time in our linear regression model: $P \propto \exp(\beta_t t)$, where β_t is a negative constant.

To model the impact of higher lumen output on price, we first note that the lumen outputs of LED A lamps are typically tightly clustered around four values, corresponding to the lumen outputs of the traditional incandescent A lamps they are intended to replace, at the long-standard incandescent wattages of 40, 60, 75, and 100 Watts. Further, exploratory inspection of our data suggests that the relation between price and lumen output is not a simple linear relation. Both of these observations suggest that it will be more natural and accurate to treat lumen output as a categorical variable in our regression model, rather than a continuous one. Thus, we categorized our data into four bins of lumen output, corresponding roughly to the four standard incandescent wattages. The bins, summarized in Table 2, are identical to the bins established for the regulation of general service incandescent lamps in the United States by the Energy Independence and Security Act of 2007 (EISA 2007)[18], with the exception of the brightest bin, which is truncated at 1999 lumens for consistency with our overall lumen-output limits discussed in section 3.1. In our regression model, we assign a multiplier to each lumen bin, which corresponds to assuming a constant fractional price difference on average between the lumen bins. We also explore the possibility that each of the lumen-bin multipliers varies exponentially with time, which would yield different overall price trends for lamps in each of the four lumen bins.

Table 2. The lumen bins within which lamps were analyzed for this study.

Lumen Range*	Approximate Incandescent Equivalent Wattage
310-759	40
750-1049	60
1050-1489	75
1490-1999	100

* These bins are identical to the bins established by EISA 2007, with the exception of the brightest bin, which is truncated to the maximum lumen output considered in this study.

It is also natural to expect that different retailers and different brands will have different pricing strategies. Therefore, we include brand and retailer as categorical variables in our model, and we again assign a multiplier to each category, corresponding to the assumption that different brands and different retailers have constant fractional price differences relative to one another on average. Finally, we note that, historically, there have been technical obstacles to producing LED lamps in the lower "warm-white" range of CCT that is often favored by consumers. Although LED A lamps with warm CCTs are now quite common, it is possible that a price premium persists for these lamps relative to lamps with higher CCT. Therefore we also consider in our model a multiplier for lamps with CCT below 4000K, corresponding to the assumption of a constant fractional price increment for warm-white lamps relative to other lamps.

The most comprehensive model using the variables described above can be represented by the following linear model for the ith price observation:

$$\ln(P_i) = \beta_t t_i + \sum_{\ell} \beta_{\ell} \mathbf{1}_{\ell}(L_i) + \sum_{\ell} \beta_{\ell t} \mathbf{1}_{\ell}(L_i) t_i + \sum_{r} \beta_r \mathbf{1}_r(R_i) + \sum_{b} \beta_b \mathbf{1}_b(B_i) + \beta_W \mathbf{1}_W(T_i) + C + \varepsilon_i. \quad \textbf{Eq. 1}$$

In this equation, P is the lamp price predicted by the model, t is the time since the commencement of the data collection, L is the lamp lumen output, R is the lamp retailer, B is the lamp brand, T is the CCT, C is a constant, and ε_i is the error term. The various β parameters are the regression coefficients for each variable or combination of variables. The indicator function $\mathbf{1}_C(X)$ indicates whether the variable X falls into the category C: it is equal to unity if $X \in C$ and zero otherwise. Our use of this function in Eq. 1 creates several categorical variables in the regression model. The index ℓ runs over the three of the four lumen bins defined in Table 2, which we identify by their equivalent incandescent wattage: $\ell \in \{L_{40}, L_{60}, L_{75}, L_{100}\}$. The index r runs over four of the five internet retailers from which data was collected, which we denote as *Retailer1* through *Retailer5*, and the index b runs over 50 of the 51 unique brand names in the data set, which we denote as *Brand1* through *Brand51*. The subscript W represents the "warm-white" category of lamps with CCT below 4000K. For each set of categorical variables, one category is not explicitly included in the model: the coefficients for a lamp in each of these categories is represented by the overall constant C, and the coefficients for the other categories represent the modeled price change relative to the categories that are not explicitly modeled.

Table 3. Models considered in the regression analysis. Each model includes a subset of the terms in Eq. 1, denoted here by the variables involved.

Model	Variables
1	t
2	t, L, R
3	t, L, R, B
4	t, L, R, B, T
5	$t, L, R, B, L * t$*

* The designation $L * t$ refers to the term involving both L and t.

In section 4, we consider models that include various subsets of the variables in Eq. 1. These models are summarized in Table 3. The simplest model, Model 1, is a simple time trend. We expect this to be a poor description of the data, since there are many variables that will have a large, time-varying impact on price. Nevertheless, Model 1 is a useful baseline against which to compare more complex models.

Model 2 adds two variables, retailer and lumen output, that we expect to have a large and varying impact on the average price of LED A lamps. It is clear from casual inspection of the data that lamp price increases with lumen output, and there were no lamps at all in the highest two lumen bins when we commenced data collection in late 2011. This changing mix of lumen outputs will confound the underlying time trend in price. Similarly , the relative market presence of different retailers has changed over the data-collection period; if there are systematic price differences among the various retailers, this will also cloud the underlying price trend. Model 2 assumes a constant multiplier for each lumen bin and for each retailer to account for these confounding price effects.

It is also possible that different lamp brands have systematically different prices, and if the mix of brands on the market has changed over the data collection period, this could also mask or enhance the underlying price trend in LED A lamp technology. To account for this, Model 3 includes a constant multiplier for each brand in the dataset.

Model 4 adds to Model 3 a multiplier for warm-white lamps, to account for the possibility that they have a systematic price offset from other lamps. Model 5 adds to Model 3 an interaction term between lumen output and time to account for the possibility that the fractional price differences among the lumen bins are varying with time. We do not consider a model that includes all of the terms in Eq. 1 because, as discussed in section 4, the inclusion of certain terms is not supported by the data.

3.2.2 Estimation of parameters and standard errors

We use use ordinary least squares (OLS) regression for our primary parameter estimates. However, as we discuss further in section 4, the data set appears to contain a small number of outliers, so we also explore the impact on the parameter estimates of using outlier-robust regression techniques. Estimating the uncertainty the parameter estimates is complicated by the fact that our the data are made up of weekly reobservations of the price for the various individual LED A lamp models sold at each retailer. From week to week, the price of a given lamp at a given retailer is likely to be unchanged, or nearly so. In general, we expect that the decline in LED prices will arise not from strong or rapid declines in the prices of individual lamp models, but rather from the introduction of new models that incorporate improvements that reduce the cost of production.

This situation means that there is strong serial correlation among the repeat observation of each individual lamp. When observations are serially correlated, standard techniques for estimating parameter uncertainty from the variance in the data will tend to underestimate the true uncertainty. In our particular case, with many independent entities whose observations are serially autocorrelated, the recommended approach is to use the clustered variance estimator, in which (broadly speaking) the data are divided into serially correlated clusters, and the parameter uncertainty is estimated from the variance both within and among the clusters. In our analysis, we divide the LED A lamp data into clusters by model and by retailer; that is, each model offered at a particular retailer is treated as a serially correlated cluster for the purposes of estimating the uncertainty in the regression coefficients.

3.3 Estimation of an LED A lamp experience curve

The regression models we described in section 3.2 will yield an estimate of the annual rate of price decline for LED A lamps. We are also interested in estimating an experience curve for these lamps. We can do this by combining the results of our regression model with a regression performed on the NEMA shipments indices as follows.

3.3.1 Approach

The experience curve is often quantified by a relation between product price and cumulative product shipments[19]: $P = AQ^{-b}$, where P represents price, Q represents cumulative product shipments since market introduction, and A and b are constants. This equation can be rewritten in a form that manifestly yields the fractional change in price for each fractional change in cumulative shipments:

$$\frac{P}{P_0} = \left(\frac{Q}{Q_0}\right)^{-b},$$

Eq. 2

where P_0 and Q_0 are constants. The power-law index can also be converted into a learning-rate parameter, $r = 1 - 2^{-b}$, which is the (fixed) fractional price decline that occurs each time Q doubles. Our regression model assumes that price declines exponentially with time: $P/P_0 = e^{\beta_t t}$. If we also assume that cumulative shipments are growing exponentially as $Q/Q_0 = e^{\gamma t}$ (as suggested by the shape of the cumulative shipments index in Figure 2), then we can insert these formulas into Eq. 2 and obtain a relation between the learning-curve exponent and the exponential rates of price decline and shipment growth:

$$b = -\frac{\beta_t}{\gamma}.$$

Eq. 3

Given β_t, γ, and the price at some reference time t_0, we can then use the learning curve to predict the price at time t from the change in cumulative shipments between t_0 and t. Importantly, this equation does not depend on the absolute scale of the cumulative shipments, Q_0, so a time series of *relative* cumulative shipments, such as the one we derived in section 2.2, is sufficient to obtain b.

3.3.2 Cumulative-shipments-index regression and error estimation

The regression model described in section 3.2 yields an estimate for β_t. To estimate γ we fit the a simple regression model to the cumulative shipments index for LED A lamps presented in section 2.2. The fit was performed only for the quarters in which NEMA data exists, from 2011 to 2015. Our linear regression model for cumulative shipments is the following:

$$\ln(Q_i) = \gamma t_i + K + \varepsilon_i,$$

Eq. 4

where t_i is the time period of the ith shipments index value Q_i, γ is the associated regression coefficient, K is a constant, and ε_i is an error term. We can use OLS to straightforwardly estimate the parameters of this model. However, because Q is a cumulative time series, it is manifestly (and strongly) autocorrelated. In this situation, as before, the usual OLS standard errors are likely to be underestimates of the true uncertainty in the parameters. Clustered variance is not appropriate in this case (since there is only one "cluster" in our analysis), so we use the Newey-West heteroskedasticity and autocorrelation consistent (HAC) variance estimator to compute the uncertainty in the regression parameters.

4 Results

4.1 Lamp price regression

Table 4 shows the coefficients we obtained upon fitting our data with the five regression models summarized in Table 3, their estimated uncertainty and statistical significance, and the adjusted R^2 statistic for each model. Since our primary interest is in estimating the price decline rate, we will focus on the coefficient of the time variable t, which is the exponential rate of price decline (percent per year). Model 1 indicates that the typical price of an LED A lamp fell at a rate of 20% per year between 2011 and 2015, despite the introduction into the market of more expensive, higher lumen lamps during that period. However, as expected, this model has a rather low R^2 value of 0.1, since there are many variables besides time driving the variance in the observed lamp prices.

Model 2 introduces multipliers for the lumen bins and retailers, to control for their effects on price. The R^2 value with these added variables jumps substantially, to 0.4. Inspection of the coefficients shows that there are significant differences among the typical prices offered at some of the retailers. We also find that lamps in the 75W, 60W, and 40W-replacement lumen bins are significantly (and increasingly) less expensive than lamps in the 100W-replacement bin, as expected. Because the 100W and 75W-replacement bins only became available after the commencement of data collection, and the 60W-replacement bin grew substantially, it is unsurprising that the rate of price decline in Model 2 is higher, at 32% per year, than in Model 1, where we did not control for the effects of lumen output on price. We thus estimate that the typical price of an LED A lamp, at fixed lumen output and sold by a given retailer, has fallen by roughly 32% per year since 2011.

Model 3 adds a categorical variable for each of the 51 brand names present in the data set. With R^2 increasing to 0.6, this model appears to yield a substantially improved description of the data compared to Model 2. The regression results show that there frequently are significant differences in the typical prices for lamps marketed by different brands. Interestingly, the rate of price decline in Model 3, 28% per year, is significantly lower than in Model 2, at better than 95% confidence. This suggests that a portion of the price decline rate observed in Model 2 was driven by market competition among a changing mix of brands on the market, as, for example, new players enter the market and undercut the existing brands.

In the early days of white LED lighting products, lamps with high CCT values were more common than low-CCT, warm-white products, and, anecdotally at least, warm-white lamps came at a price premium. To investigate such a price effect in our data, Model 4 adds to Model 3 a dummy variable for warm-white lamps. When fitting this model, we restricted our data set to the subset of records containing CCT information, which diminishes the dataset by roughly 25%. This model does not yield a substantial improvement in R^2 compared to Model 3, and the warm-white coefficient we obtain is not statistically significant. We therefore exclude this variable from further consideration. In Model 5, we consider the possibility that the effect of lumen output on price has been varying with time, by adding to Model 3 interaction terms between lumen bin and time. This model also does not yield a substantial further improvement in R^2, and none of the new coefficients are statistically significant. Because neither Model 4 or Model 5 yields an improved fit, we do not expect improvement from a model including all of the variables in Eq. 1, so we do not explicitly consider such a model.

Based on the results shown in Table 4, we select Model 3 as our preferred model for further analysis. In particular, we estimate the rate of price decline for LED A lamp technology, after controlling for lumen output and the effects of competitive pricing strategies among retailers and brands, to be $\beta_t = 28.0\% \pm 1.7\%$ per year. It is also interesting to note the impact of lumen output on price in this model: on average, LED A lamps in the lumen bins that are approximately equivalent to 40W, 60W, and 75W incandescent bulbs have prices that are 48%, 43%, and 16%, respectively, lower than LED A lamps intended to replace 100W incandescents. Figure 3 shows the modeled price over time (red curve) for an LED A lamp having brand Brand1, sold at retailer Retailer1, in the 750-1049 lumen (60W incandescent equivalent) bin. The blue points are the model residuals added to the modeled curve, to show the scatter in the data. Strong horizontal striping is apparent in the residuals. This is the visual representation of the clustered serial correlation discussed in section 3.2.2: individual lamp models sold at individual retailers tend to have prices that are very similar or identical from week to week. The use of the clustered variance estimator, with clustering performed at the per-model, per-retailer level, ensures that this serial correlation is properly accounted for in our parameter uncertainty estimates.

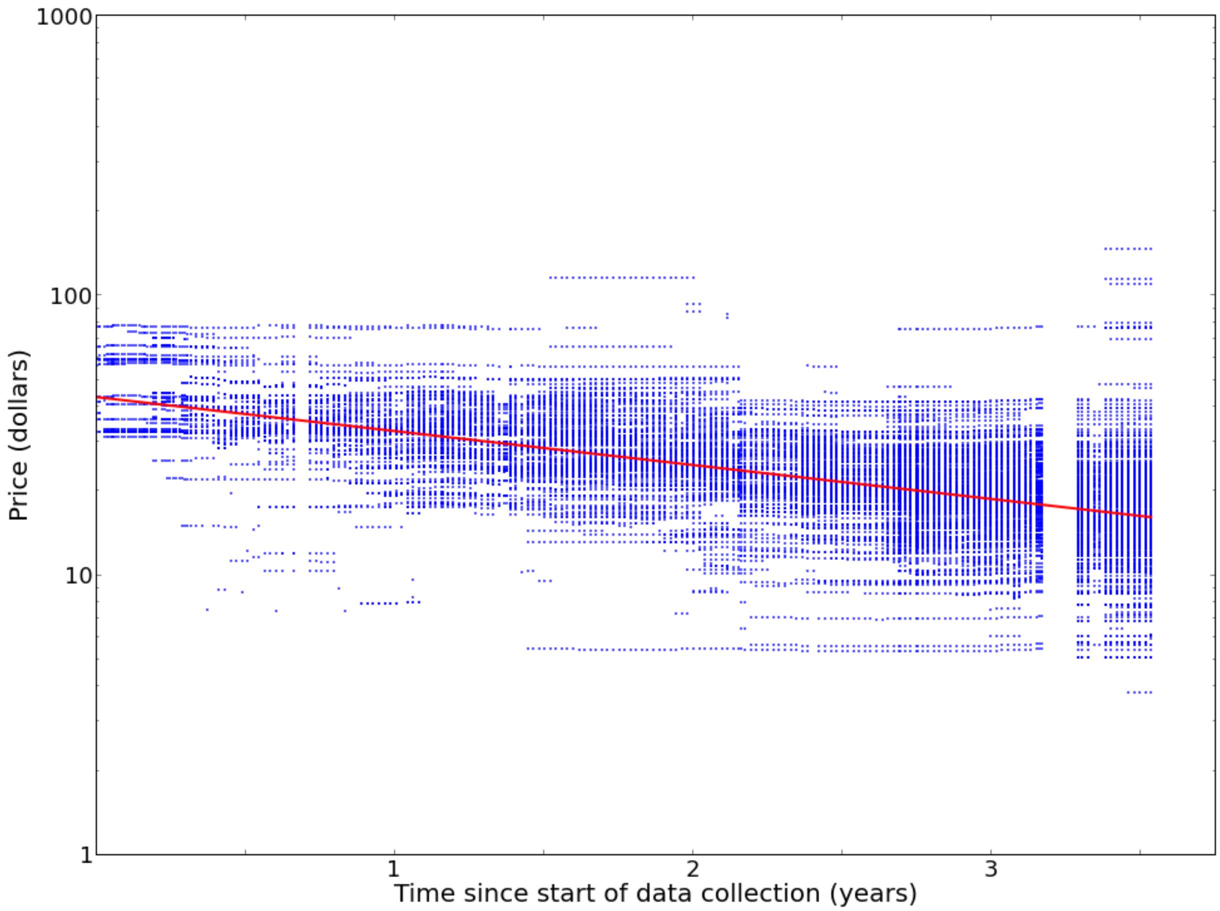

Figure 3. Modeled price versus time for a particular LED A lamp. The red curve shows the modeled price of an LED A lamp in the 750-1049 lumen (60W incandescent equivalent) bin, when sold at Retailer1 and manufactured by Brand1. Blue points are the residuals about this model (i.e., the overall model residuals plus the model shown here). The significant clustered serial correlation in the residuals is visually apparent.

A small number of large outliers are apparent in the residuals plotted in Figure 3. To investigate the possibility that these may be significantly affecting the fit, we also fit Model 3 to the data using standard outlier-robust regression modeling techniques (in brief, this approach iteratively fits and re-fits the model to the data, excluding strong outliers from the previous fit at each iteration, until convergence is achieved and no strong outliers remain). All but two of the parameter estimates changed by less than the uncertainty in the original fit, and none changed by more than 115% of the original uncertainty. We therefore conclude that the outliers present in the data are not substantially affecting the fit parameters, so we use OLS parameter estimates throughout this study for the sake of analytical simplicity.

4.2 Learning curve parameter estimate

Upon fitting the model in Eq. 4 to the cumulative shipments index for LED A lamps derived in section 2.2, we obtain parameter estimates of $\gamma = 0.976 \pm 0.023$ and $K = 6.53 \pm 0.04$. The parameter uncertainty estimates are computed using the HAC-robust estimator discussed in section 3.3.2. When we combine this estimate of γ with the estimate of β_t in section 4.1, Eq. 3 yields an estimate of the learning curve power-law index: $b = 0.294 \pm 0.028$, where the uncertainty is the quadrature sum of the uncertainties on γ and β_t. This corresponds to an 18% reduction in price for each doubling of cumulative LED A lamp shipments.

5 Discussion and Conclusions

From late 2011 through mid-2015, we have collected weekly data on LED A lamp prices and features from five Internet retail sites. In this study we fit the data to a series of regression models to yield an estimate of the annual rate of price decline for LED A lamps after accounting for other variables affecting price whose influence on the sample may be changing with time. Of the variables considered we find that, in addition to time, the lamp's lumen output and brand name, and the specific retailer offering the lamp, have statistically significant effects on the lamp price. Since the distribution of lamps among brands, retailers, and lumen levels has been rapidly evolving over the period of data collection, it is important to control for these additional price effects; upon doing so (in Model 3), we estimate that the price of an LED A lamp with fixed properties has been falling by $28.0\% \pm 1.7\%$ per year.

Interestingly, if we do not account for brand-name effects in our model (as in Model 2), we estimate a slightly higher rate of price decline, at $32.0\% \pm 1.7\%$ per year, a difference that is statistically significant at greater than 95% confidence. This suggests that inter-brand competition and a changing market landscape have caused the typical price of LED A lamps encountered by consumers to fall slightly faster than would be expected from declines in cost for the underlying technology due, e.g., to technological learning.

If we wish to estimate an experience curve for LED A lamps, then, it is most appropriate to use the price decline rate that controls for such competitive effects. Combining our 28% per year measured price decline with an estimate of the growth in cumulative shipments derived from the NEMA lamp indices, we compute an experience-curve power-law index of 0.294 ± 0.028, corresponding to an 18% price reduction for LED A lamps for each doubling of their cumulative shipments.

It is interesting to compare these results to the results we obtained using substantially different methods in our 2014 study.[6] In that report, we fitted simple exponential decline models to time series of aggregate price indicators that were developed from the same web crawling data used here, covering a shorter time period. To account for the impact of lumen output on price in that study we fitted separate time trends to lamps in each of the four lumen bins considered here. To account for differences in pricing among retailers, we averaged our aggregate price statistics across the five retailers considered. We made no attempt to control for differences in pricing among brands in that work. Using that approach we estimated an annual price decline rate of 28% per year for LED A lamps in the 310-749 (40W incandescent equivalent) lumen bin, essentially identical to the decline rate we derive in this analysis. This agreement is striking, given the vastly different statistical approaches taken in the two studies. For the higher lumen bins, the previous analysis indicated a much higher rate of decline, but our analysis here (Model 5) shows no evidence for different price-decline rates in different lumen bins, after accounting for brand-name effects. This suggests that the differential rates of price decline observed previously may have been driven largely by the shifting mix of brand names in each lumen bin.

Additionally, our previous study used a different methodology to estimate experience-curve parameters for LED A lamps. Our primary estimate of the power-law index, which was based only on lamps in the 310-749 lumen bin, was substantially higher, at 0.430, than the value of $b = 0.294$ measured here. This difference appears to be driven largely by a very rapid increase in cumulative shipments that has occurred for LED A lamps during the period between the previous study and today. This faster growth in shipments, while the rate of price decline has remained steady, yields a slower estimate of the experience curve. It is worth noting that an alternate estimate of the experience-curve parameter, presented in the previous study, was consistent with the estimate we derive here, but we believe this agreement is likely to be coincidental. The increased rate of shipments growth since 2014 would reduce that estimate as well, if we were to repeat the previous analysis today.

Because the present analysis covers a longer time period, accounts for a wider range of effects that may confound the underlying price trend, and utilizes methods that can account more fully for the parameter uncertainties, we view our results here on time trends and learning curves as a significant improvement over the results of the previous analysis. At present, based on weekly collection of Internet retail price data over nearly four years, our best estimate of the rates of price decline for LED A lamps are 28% per year and 18% for each doubling in cumulative shipments.

Table 4. Regression coefficients for the variables from Eq. 1, as used in the five models summarized in Table 3, upon fitting to the LED A lamp web crawling data. The adjusted R^2 statistic for each model fit is also displayed.

Model	1	2	3	4	5
Adj. R^2	0.107	0.409	0.610	0.610	0.612
t	-0.203 (0.021)***	-0.320 (0.017)***	-0.280 (0.017)***	-0.281 (0.016)***	-0.239 (0.137)
L_{40}	-	-0.694 (0.104)***	-0.663 (0.105)***	-0.673 (0.106)***	-0.600 (0.484)
L_{60}	-	-0.592 (0.101)***	-0.565 (0.103)***	-0.571 (0.104)***	-0.335 (0.484)
L_{75}	-	-0.236 (0.113)*	-0.175 (0.108)	-0.178 (0.109)	-0.112 (0.491)
$L_{40}*t$	-	-	-	-	-0.018 (0.138)
$L_{60}*t$	-	-	-	-	-0.088 (0.138)
$L_{75}*t$	-	-	-	-	-0.019 (0.142)
W	-	-	-	0.010 (0.028)	-
Retailer2	-	0.256 (0.065)***	0.022 (0.057)	-0.004 (0.051)	0.024 (0.058)
Retailer3	-	-0.112 (0.092)	0.079 (0.073)	0.074 (0.073)	0.082 (0.073)
Retailer4	-	0.583 (0.044)***	0.375 (0.034)***	0.368 (0.034)***	0.374 (0.034)***
Retailer5	-	0.021 (0.047)	-0.256 (0.042)***	-0.227 (0.042)***	-0.259 (0.043)***
Brand2	-	-	-1.143 (0.117)***	-1.109 (0.115)***	-1.102 (0.141)***
Brand3	-	-	-0.380 (0.081)***	-0.335 (0.079)***	-0.364 (0.084)***
Brand4	-	-	-1.482 (0.071)***	-1.438 (0.074)***	-1.474 (0.073)***
Brand5	-	-	0.016 (0.065)	0.054 (0.063)	0.050 (0.065)
Brand6	-	-	-0.383 (0.049)***	-0.370 (0.049)***	-0.363 (0.05)***
Brand7	-	-	-0.906 (0.071)***	-0.873 (0.069)***	-0.868 (0.083)***
Brand8	-	-	1.540 (0.035)***	1.542 (0.035)***	1.590 (0.043)***
Brand9	-	-	-2.102 (0.058)***	-2.069 (0.056)***	-2.072 (0.06)***
Brand10	-	-	-0.302 (0.209)	-0.263 (0.209)	-0.246 (0.208)
Brand11	-	-	-0.226 (0.072)**	-0.220 (0.073)**	-0.204 (0.072)**
Brand12	-	-	-0.251 (0.115)*	-0.211 (0.114)	-0.226 (0.116)
Brand13	-	-	-0.117 (0.082)	-0.079 (0.08)	-0.098 (0.083)
Brand14	-	-	-0.345 (0.073)***	-0.309 (0.074)***	-0.290 (0.077)***
Brand15	-	-	-1.163 (0.176)***	-1.124 (0.175)***	-1.151 (0.176)***
Brand16	-	-	-1.224 (0.059)***	-1.192 (0.057)***	-1.153 (0.064)***
Brand17	-	-	-1.112 (0.157)***	-0.799 (0.041)***	-1.068 (0.159)***
Brand18	-	-	0.318 (0.106)**	0.362 (0.107)**	0.334 (0.107)**
Brand19	-	-	-0.540 (0.065)***	-0.501 (0.065)***	-0.520 (0.068)***
Brand20	-	-	0.678 (0.079)***	0.670 (0.075)***	0.699 (0.083)***
Brand21	-	-	-0.555 (0.074)***	-0.517 (0.072)***	-0.530 (0.078)***
Brand22	-	-	-0.176 (0.109)	-0.135 (0.107)	-0.150 (0.11)
Brand23	-	-	-0.356 (0.097)***	-0.309 (0.097)**	-0.342 (0.096)***
Brand24	-	-	-0.696 (0.064)***	-0.657 (0.064)***	-0.680 (0.065)***
Brand25	-	-	-0.039 (0.074)	-0.002 (0.074)	-0.013 (0.074)
Brand26	-	-	-0.164 (0.085)	-0.126 (0.083)	-0.161 (0.088)

Brand27	-	-	-0.333 (0.07)***	-0.301 (0.07)***	-0.311 (0.068)***
Brand28	-	-	0.209 (0.067)**	0.251 (0.064)***	0.208 (0.069)**
Brand29	-	-	-0.299 (0.08)***	-0.255 (0.077)**	-0.283 (0.082)**
Brand30	-	-	-0.602 (0.078)***	-0.559 (0.077)***	-0.575 (0.083)***
Brand31	-	-	-0.319 (0.08)***	-0.275 (0.076)***	-0.296 (0.079)***
Brand32	-	-	-0.518 (0.097)***	-0.472 (0.094)***	-0.492 (0.1)***
Brand33	-	-	0.004 (0.068)	0.051 (0.066)	-0.001 (0.071)
Brand34	-	-	-0.373 (0.079)***	-0.316 (0.07)***	-0.332 (0.08)***
Brand35	-	-	-0.444 (0.08)***	-0.413 (0.079)***	-0.389 (0.082)***
Brand36	-	-	-0.203 (0.053)***	-0.196 (0.053)***	-0.188 (0.055)**
Brand37	-	-	-0.965 (0.094)***	-0.932 (0.093)***	-0.946 (0.098)***
Brand38	-	-	-0.544 (0.116)***	-0.512 (0.114)***	-0.519 (0.121)***
Brand39	-	-	-1.011 (0.161)***	-0.980 (0.16)***	-0.996 (0.156)***
Brand40	-	-	-0.879 (0.095)***	-0.850 (0.088)***	-0.868 (0.106)***
Brand41	-	-	-0.541 (0.214)*	-0.501 (0.215)*	-0.511 (0.216)*
Brand42	-	-	-0.813 (0.058)***	-0.783 (0.057)***	-0.763 (0.062)***
Brand43	-	-	-0.667 (0.069)***	-0.625 (0.065)***	-0.673 (0.071)***
Brand44	-	-	-0.883 (0.15)***	-0.850 (0.149)***	-0.863 (0.151)***
Brand45	-	-	0.192 (0.118)	0.232 (0.114)*	0.208 (0.119)
Brand46	-	-	-0.177 (0.098)	-0.140 (0.097)	-0.157 (0.096)
Brand47	-	-	-0.424 (0.056)***	-0.376 (0.055)***	-0.399 (0.058)***
Brand48	-	-	-0.319 (0.17)	-0.288 (0.17)	-0.276 (0.17)
Brand49	-	-	1.105 (0.045)***	1.102 (0.051)***	1.108 (0.048)***
Brand50	-	-	-0.711 (0.116)***	-0.669 (0.114)***	-0.681 (0.118)***
Brand51	-	-	-0.264 (0.088)**	-0.214 (0.089)*	-0.231 (0.089)*
C	3.406 (0.058)***	3.956 (0.115)***	4.335 (0.125)***	4.306 (0.127)***	4.201 (0.486)***

Notes: Each entry in the table includes the estimated value of the coefficient, and, in parentheses, the parameter uncertainty computed using the clustered variance estimator. Asterisks indicate the statistical significance with which each parameter can be distinguished from zero: one, two, and three asterisks indicate 95%, 99%, and 99.9% confidence, respectively.

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