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The evolving price of household LED lamps: Recent trends and historical comparisons for the US market

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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 data, on a weekly basis, for retail offerings of LED A lamps on the Internet. The resulting data set allows us to track the recent price decline in detail. LED A lamp prices declined roughly exponentially with time in 2011-2014, with decline rates of 28% to 44% per year depending on lumen output, and with higher-lumen lamps exhibiting more rapid price declines. By combining the Internet price data with publicly available lamp shipments indices for the US market, it is also possible to correlate LED A lamp prices against cumulative production, yielding an experience curve for LED A lamps. In 2012-2013, LED A lamp prices declined by 20-25% for each doubling in cumulative shipments. Similar analysis of historical data for other lighting technologies reveals that LED prices have fallen significantly more rapidly with cumulative production than did their technological predecessors, which exhibited a historical decline of 14-15% per doubling of production.

1 Introduction

Solid state lighting (SSL) utilizing light-emitting diodes (LEDs) is in the process of transforming the market for lighting products. Since the start of 2011, US sales of A-shape household light bulbs (hereafter A lamps) using LEDs have increased approximately tenfold.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 threefold decline in LED lamp prices by 2030.³

There are two primary reasons that such a rapid price decline might be expected. The first is 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 is unlikely to be the full story. A second, broader reason to expect a price decline for LED A lamps is the general observation that new technologies tend to fall in price 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 (and hence the end-user price) as a declining power law in manufacturing experience, which is typically quantified by cumulative production⁶. A broad range of products have been observed to approximately follow such a curve, which implies that price falls by a fixed fraction for each doubling in cumulative production. 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 price declines are generally predicted for new technologies like LED A lamps.

In order to track the price decline 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 this study, we use these data to produce time series of typical LED A lamp prices, for different lumen ranges, with a weekly frequency; and we characterize these time series mathematically. Interestingly, we find that the price of LED A lamps has fallen at a faster rate than the Haitz's-law prediction for individual LEDs. We then combine the LED price time series with lamp shipment indices⁷ published by the National Electrical Manufacturers Association (NEMA) to derive an experience-curve relation between price and cumulative production for LED A lamps. For comparison, we also derive historical experience curves for traditional lighting technologies using data published by the U.S. Census Bureau, and we find that the

LED experience curve has recently been much steeper than historically observed for other lighting technologies.

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 analytical methods for computing aggregate time-series statistics from the Internet data, for computing cumulative production from the shipments data, and for fitting price trends and experience curves to our various data sets. We present results of these analyses in section 4, and in section 5 we discuss implications and conclude.

2 Data

2.1 Crawling the web for LED data

To allow the price and features of general service LED lamps to be tracked over time, we used automated web-crawling software to collect data on a regular basis from five separate online retail outlets from late 2011 to mid-2014. 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 general-service LED 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 sales⁸.

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 sites. Rapid expansion of the LED market during the data-collection period led to a large time variation in the number of general-service LED 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. Our approach to accounting and correcting for differences in collection frequency and yield is summarized in Section 3.1.2.

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

Retailer	Type	Number of data collections	Average LED Yield	Minimum LED Yield	Maximum LED Yield
1	Internet only	123	46.7	3	72
2	Internet only	163	7.9	2	17
3	Internet only	161	6.6	5	11
4	Internet only	161	56.7	13	177
5	Home-improvement center	103	55.7	1	110

The data collection software proceeds by loading a page from each website listing the available general-service LED options. It then follows links to each product offer in turn and extracts the desired data from the HTML code underlying the page. Data fields collected for general-service LED lamp offers included the price, brand, quantity of lamps being sold (e.g., in a multi-pack), voltage, wattage, lumen output,

correlated color temperature (CCT), color rendering index (CRI), bulb shape, and any information about dimmability. For lamps sold in multi-packs, the collected price data were corrected to represent the price per individual lamp.

2.2 Incandescent and CFL price and shipments data from the US Census Bureau

We obtained shipments and cost data for incandescent lamps and compact fluorescent lamps (CFLs) from the U.S. Census Bureau's Current Industrial Reports (CIR), Electric Lamps – MQ36B⁹. For incandescent lamps the data spans the years 1958-1994, and for CFLs 1992-1994. These reports survey all known manufacturers of electric lamps in the U.S. and report the number of units shipped from a factory or factory warehouse, and the value of products shipped. The value of products shipped represents the net free-on-board factory selling value of the lamp shipments, after discounts and allowances and exclusive of freight charges and excise taxes. This value, therefore, represents the cost to manufacture the product, plus a single markup to the original purchaser, likely a distributor. The category in the CIR that best represents incandescent A lamps is *General lighting, 150 watt and below, 100-130 Volts*, a subcategory of *Large incandescents, except photographic and Christmas tree*. For CFLs the category used is *Compact fluorescent lamps* under the *Electric discharge, except Christmas tree*, category.

Using the values in the CIR it is straightforward to calculate the cost of each unit by dividing the total value of shipments by the number of products shipped. The resulting unit cost, in nominal dollars, is then converted to real 2005 dollars using the GDP chained price index provided by the U.S. Department of Commerce's Bureau of Economic Analysis.¹⁰ These real dollar unit costs are used to calculate the experience curves as detailed in section 3.3.1 below.

2.3 Lamp shipment indices from NEMA

To obtain data on the relative shipment volume of A lamps over time, we digitally extracted data from the figures in NEMA's regular updates to its lamp shipment indices^{1,11-19} for incandescent, CFL, Halogen, and LED A lamps from the beginning of 2001 to the end of 2013. Prior to the third quarter of 2013, these indices were referenced to the average quarterly sales in 2006; afterward they were referenced to the average 2011 quarter. To correct for errors in the data-extraction process within each data set, all extracted data were first normalized with respect to the appropriate reference year for each report using the equation

$$NV_{(Q,Y)} = \frac{V_Q}{\langle V \rangle_Y} \times 100, \quad (1)$$

Where Y is the reference year, V_Q is the extracted value for quarter Q , $\langle V \rangle_Y$ is the average extracted value for the four quarters in year Y , and $NV_{(Q,Y)}$ is the normalized value for the quarter Q relative to year Y .

After normalizing all the extracted values, the 2006-referenced values were converted to a 2011 reference year. For reports released from the beginning of 2012 to the second quarter of 2013, which included data from all quarters in 2006 and 2011, the following equation was used to convert to data from values relative to 2006 average to values relative to 2011 average:

$$NV_{(Q,2011)} = NV_{(Q,2006)} \times \frac{\sum_{i=2006Q1}^{2006Q4} NV_{(i,2006)}}{\sum_{i=2011Q1}^{2011Q4} NV_{(i,2011)}}. \quad (2)$$

(Because of our initial normalization, the numerator of the fraction on the right-hand side of this equation is equal to 400 for each report.)

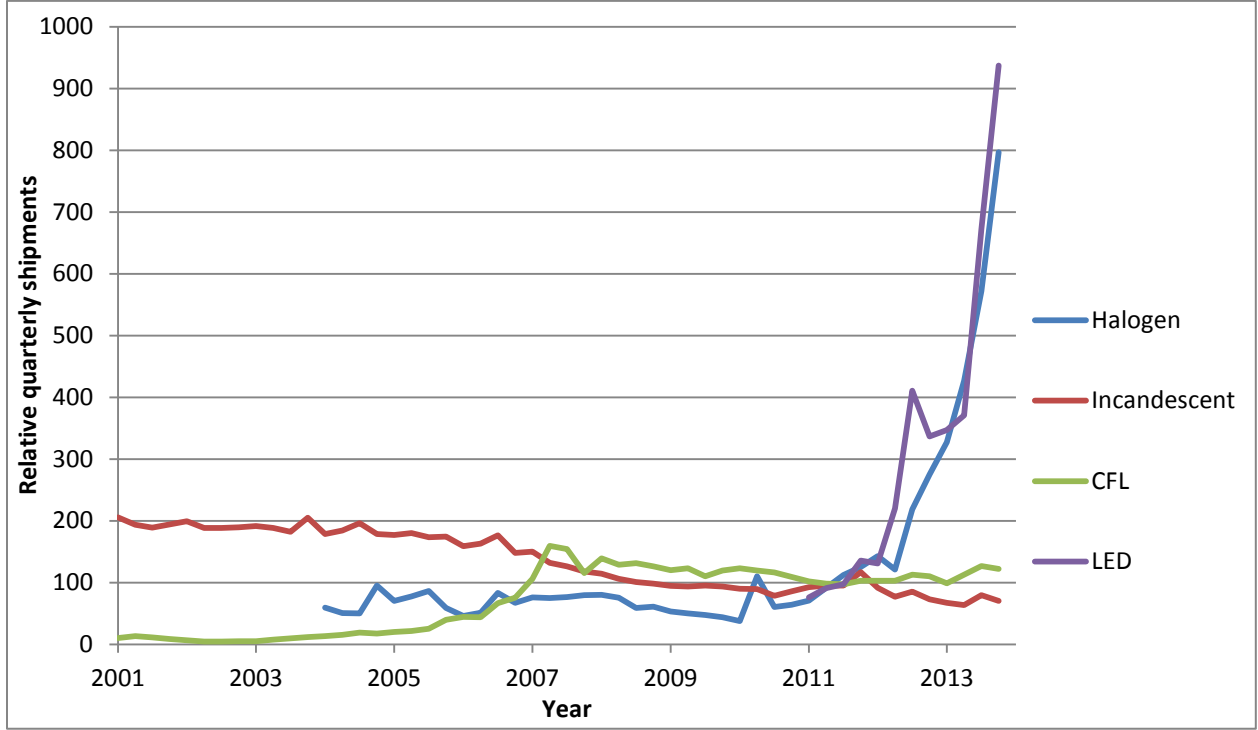


Figure 1. Quarterly NEMA lamp shipments index from beginning of 2001 to end of 2013 (average 2011 value = 100)

The reports that we were able to normalize in this manner yielded shipments index data back to 2004. Earlier reports provided 2006-referenced shipments-index data from 2001 through 2003. Because these reports did not contain data in 2011, we were unable to use equation (2) to convert them to 2011-referenced data. The 2006-to-2011 correction factor we computed in that equation varies slightly from report to report owing to data-extraction errors, so to correct the pre-2004 data to a 2011 reference year, we computed an average correction factor for each report:

$$CF = \frac{\sum_{Q=2004Q1}^{QL} CF_Q}{n}, \quad (3)$$

where QL is last quarter covered by the report, and n is the number of quarters from the beginning of 2004 to QL . The quarterly correction factor that is being averaged is given by the equation

$$CF_Q = \frac{\langle NV_{(Q,2011)} \rangle}{NV_{(Q,2006)}},$$

where CF_Q is the correction factor in quarter Q for report R ; $\langle NV_{(Q,2011)} \rangle$ is the average 2011-referenced value for quarter Q , where the average is taken across the reports released since the beginning of 2012; and $NV_{(Q,2006)}$ is the normalized value of quarter Q in report R , computed from Equation (1). The normalized and corrected data are presented in Figure 1. Only the data for LED lamps are used in this study, but we present all lamp types for completeness.

3 Analytical Methods

This section details the methods we used to convert our web-crawling data into several time series of characteristic price for LED A lamps, for fitting those time series to simple exponential models of price decline with time, and for fitting experience curves to our various sources of data for different lamp technologies.

3.1 Constructing aggregate price and efficacy time series for LED lamps

Regular data collection using the web-crawling software described in section 2.1 yields price and attribute data for a varying number (a few to more than 100) of LED A lamps on each collection date, from five different retailers. This section describes the procedure for aggregating those data to produce a single characteristic price measurement on each date, yielding a time series of characteristic lamp prices for trend analysis.

3.1.1 Lumen bins

Traditional incandescent A lamps have long been sold at a discrete set of standard wattages. The most common of these for household use are 40, 60, 75, and 100 watts, corresponding to light output levels of roughly 500, 800, 1200, and 1600 lumens, respectively. Energy-efficient A lamps are typically marketed as replacements for a particular incandescent wattage, based on their similar lumen output; however, precise lumen output varies from product to product. The technical barriers to producing a marketable LED lamp increase with increasing lumen output; thus, the earliest household LED A lamps for general illumination purposes were replacements for 40-watt incandescent lamps. 60-watt equivalent LED A lamps followed several years later, and in recent years 75 and 100-watt replacements have entered the market. Because of the phased market introduction of these lamps, and the increased technical difficulty at the higher lumen ranges, there is presently a very strong gradient in price across the different incandescent-equivalent wattages. Further, because of the phased market introduction, one might expect that price trends would differ for lamps with different lumen outputs.

Table 2. The lumen bins within which lamps were analyzed for this study. These bins are identical to the bins established by EISA 2007.

Lumen Range	Approximate Incandescent Equivalent Wattage
310-759	40
750-1049	60
1050-1489	75
1490-2600	100

To account for these issues, in this study we analyzed the prices of LED lamps in four different lumen bins, 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)²⁰.

3.1.2 Computing aggregate statistics across retailers

The automated web-crawling software typically collected multiple LED A lamps from each website on each visit. To compute a time series of the typical price or efficacy of an LED A lamp in each lumen bin, it was necessary to compute aggregate statistics over all of the lamps collected in each bin on each data-collection date. As shown in Table 1, the yield of lamps varied by an order of magnitude among the different web sites considered and by an even greater margin at individual retailers across time. In this situation, simple approaches to aggregation, such as taking the mean or median of all lamps collected on each date, can be heavily skewed by changes in the lamp offerings or pricing strategy at the retailers with the largest selection on any given date. Because the relative size of the different retailers' lamp selection also varied significantly across time, the impact of individual retailer would be different at different times: a sale on LED A lamps at retailer number 4, for example, might have a wildly different impact on the average lamp price in 2012 than in 2013. This will make it difficult to interpret any time trends observed for statistics that are computed across all lamps collected on each date.

To guard against such issues, we chose to compute aggregate statistics by first computing the statistic for each retailer separately and then averaging the values obtained for each of the five retailers. For example, we might compute the average retailer's median price by computing the median of the prices collected at each retailer on a given date, then averaging these five median prices. In mathematical notation, our approach to computing a statistic $s(d)$ on date d can be written as

$$\bar{s}(d) = \frac{1}{N_{ret}} \sum_R s_R(d), \quad (5)$$

Where s is the statistic being computed (mean, median, percentile, etc.), d is the date N_{ret} is the number of retailers being considered, and R is an index across all of the individual retailers. For example, if the statistic s is the mean, then $\bar{s}$ is the grand mean across retailers. We compute the aggregate statistics separately for each of the lumen bins described in section 3.1.1.

An arguably preferable approach to the one we have outlined here would be to compute a sales-weighted average across all the different retailers. However, we lack detailed quantitative information on the sales volumes of the different retailers. Fortunately, our primary interest in this study is the computation of price trends, rather than absolute prices. Falling prices in the market as a whole will tend to exert downward price pressure on all retailers, so one would expect that the trends computed by simple averaging across retailers should be very similar to the trends computed via a sales-weighted mean, even if the absolute prices are systematically different from the sales-weighted value.

After computing aggregate statistics on each date using Equation (5), we are left with a time series of aggregate price data. Before using this data to compute price trends, it is important to adjust it for the effects of inflation. Since the prices we gather from the web are consumer purchase prices, we correct our

time series data to real January 2012ⁱ dollars, using the monthly chained consumer price index (CPI) published by the Bureau of Labor Statistics²¹. The monthly CPI values are interpolated to yield correction factors at each date in the time series.

3.1.3 Selecting appropriate statistics for time-series analysis

In using Equation (5) to compute a time series of characteristic price from our web-crawled data, it is important to choose a statistic s that properly characterizes typical prices on the market on a given date. As discussed above, the ideal statistic would be a sales-weighted average, but since the web crawling process yields no information on relative sales, this statistic is unavailable. The unweighted average price is a poor alternative for two reasons. First, because LED lamps are a rapidly changing technology, there are typically a few very new, high-priced products on the market, which can cause the unweighted average to be well above the sales-weighted average. Second, the entry of these high-priced products into the market, coupled with temporarily low-priced products in sale events, causes the unweighted average to be a fairly volatile metric.

Using a percentile of the price distribution to represent the characteristic price is more robust to such outlier effects, but it is not immediately obvious which percentile should be used. To investigate this, we commissioned a survey through Google Consumer Surveysⁱⁱ. The survey asked a single question: *If you've purchased a 60-watt equivalent LED light bulb (not including reflector bulbs) in the past six months, how much did you pay?* Respondents were prompted to select a price range from a list of options that were chosen to approximate percentiles of the price distribution in our web data from the large home-improvement retailer. We used percentiles from the home-improvement retailer since it is expected to have the largest sales volume and thus be most directly representative of the market price distribution at any given time. Respondents were also allowed to indicate that they had not purchased any such lamps or to fill in a free-form response.

The survey question was posed to 9706 internet users and received 5024 valid responses. Results were weighted to match the demographic distribution of the population of US Internet users; they are presented in Table 3. More than half of respondents who had recently purchased an 60-watt-equivalent LED A lamp paid a price at or below the tenth percentile of the overall price distribution for such lamps. More than 80 percent of such respondents purchased a lamp at or below the 25th percentile price, and more than 90 percent purchased at or below the median price. Nearly two thirds of respondents had not purchased such a lamp in the preceding six months.

Based on these results, the 10th-percentile price is an attractive statistic to use as a characteristic price, since it is approximately equal to the median purchase price. However, this statistic, like the unweighted mean, is somewhat sensitive to the deep, short-term discounting that occurs during sale events, which makes it a somewhat volatile metric. Since our goal in this study is to measure price trends over a period of several years, a more stable statistic is desirable. The 25th-percentile price is also a reasonable statistic to use as a characteristic price, since the bulk of purchases fall at or below that level; whereas the median

ⁱ When correcting the CIR data for inflation in section 2.3, we used a 2005 reference year. Our web-crawled data on consumer price are not directly comparable to the CIR data, and we choose a different reference year here in part to highlight that fact. The choice of reference year does not impact the experience rates we measure, which will be directly comparable.

ⁱⁱ <https://www.google.com/insights/consumersurveys/home>

price is likely to be on the tail of the purchase distribution. For these reasons, we adopt the 25th percentile as our primary statistic for computing the various time series of price that we analyze in this study. For most of the price-trend analyses discussed below that make use of this statistic, we also repeated the analysis using the 10th percentile and the median; these alternative analyses yielded similar rates of LED price decline to those we obtain from the 25th percentile.

Table 3. Response percentages for 5024 total responses to the Google survey question “If you've purchased a 60-watt equivalent LED light bulb (not including reflector bulbs) in the past six months, how much did you pay?”. Results were weighted by age, gender, and region to reflect the demographic distribution of the total Internet-using population.

Response	Price percentile range (approximate)	Percentage of all respondents	Percentage of LED purchasers
\$8 or less	0-10	21.1	56.9
Between \$8 and \$10	10-25	9.26	25.0
Between \$10 and \$12	25-50	3.84	10.4
\$12 or more	50-100	2.87	7.74
I have not made such a purchase	-	62.7	-
Other response**	-	0.21	-

*Approximate percentiles represented by the response's price range, for lamps sold by a large home improvement retailer in early 2014.

**The survey included a free-form field for alternate responses.

3.1.4 Data cleaning and correction

The automated web-crawling software discussed in Section 2.1 gathers data and crawls to additional products by looking for data and links in specified locations on the product listing web pages served by each retailer. If the retailers modify or redesign their websites, the web-crawling software may fail to gather certain data if it is no longer located where expected, or it may fail to gather data at all if the format or location of the relevant links has changed. Because of this, in any given week it was possible that one or more websites yielded incomplete data or no data at all.

If multiple websites had missing data in a given week, we excluded that week's data from consideration. If only one website had missing data, we eliminated any partial data collected for that website in that week, computed our aggregate statistics from the remaining web sites, and then computed correction factors to account for the absent data. To construct the correction factors for a given statistic, we compiled a list of “good” dates, $\{D_{good}\}_w$, for each web site w , on which the crawling software collected a complete data set for that site. Using Equation (5) we then re-computed the aggregate statistic on those dates, excluding site w . We denote this re-computed statistic $\bar{s}_{\sim w}(d)$. The correction factor is then given by taking the ratio between $\bar{s}_{\sim w}$ and $\bar{s}$ and averaging over the “good” dates:

$$c_w = \frac{1}{N_{good,w}} \sum_{d \in \{D_{good}\}_w} \frac{\bar{s}(d)}{\bar{s}_{\sim w}(d)}, \quad (6)$$

where $N_{good,w}$ is the number of dates in the set $\{D_{good}\}_w$. The final corrected statistic can then be computed as $\bar{s}_{cor}(d) = \bar{s}(d) \times C_w$.

3.2 Time trend fits for absolute LED A lamp price and the incremental price of lumen output

Having computed aggregate statistics as a function of time and corrected them for missing data, we can fit these data to mathematical models describing overall trends with time. All fits, in this section and the following one, are performed via least-squares minimization.

Since price must be nonnegative, the simplest models that can be used to describe our time-series price data are exponential or power-law trends with time. The data describe approximately straight lines on a semilog plot (e.g., as shown in Figure 5), which implies that they will be well described by exponential models. Thus, we fit our aggregate price time series data to the following exponential model:

$$P(y) = e^{-\alpha(y-y_0)}, \quad (7)$$

where y is the year, α is the fractional annual rate of price decline, and y_0 is the reference year, defined to be the year in which the modeled price is equal to \$1.

LED A lamps in each of the lumen bins were introduced to the market at different times, spanning approximately a decade, with the most luminous lamps only being introduced in late 2012 and having substantially higher prices than their less luminous counterparts had at that time. It is apparent from inspection of the data (e.g., Figure 5) that the more luminous lamps have lately been declining in price far more rapidly than the less luminous, more mature product options. The price differential between the lumen bins has been shrinking in a manner that also appears roughly exponential with time. It is thus also interesting to fit a model to the difference in price between the lowest lumen bin listed in Table 2 and the higher lumen bins:

$$\Delta P_L(y) = e^{-\alpha_\Delta(y-y_{0,\Delta})}, \quad (8)$$

where $\Delta P_L(y)$ is the difference in price in year y between lumen bin L and the lowest lumen bin (310-749 lm), and $y_{0,\Delta}$ is the reference year in which the price difference is equal to \$1.

We fitted the two equations in this section to the aggregate price statistics via ordinary least-squares regression in semi-log space. That is, we regress $\log P$ and $\log \Delta P$ on the variable y and a constant with equal weighting of all data points in the time series of aggregate price. Results of the fits are given in section 4.2.1.

3.3 Experience curve fits

Prices for a broad range of products and technologies have generally been observed to decline as a function of increasing production. In many cases, these declines approximately obey a power law relation between price P and the cumulative number of units produced Q since the technology was first brought to market⁶, often referred to as an experience curve:

$$P = \left(\frac{Q}{Q_0}\right)^{-b} \quad (9)$$

where b and Q_0 are technology-specific constants. The power-law index b represents the fractional decline in price that occurs for each fractional increase in cumulative production. A useful quantity that can be computed from the power-law index b is the experience rate $r = 1 - 2^{-b}$, which represents the fractional price reduction that occurs for each doubling in cumulative shipments. Experience curves have been suggested as a useful tool for forecasting the future cost-effectiveness of energy-efficient technologies,²² so it will be interesting to fit our data to such models.

Experience curves are often referred to in the literature as a learning curve, on the principle that manufacturers of new products will learn new methods to improve the efficiency of their production, and thus reduce their costs, at a roughly fixed rate as their cumulative experience grows. Although this may be an accurate description of the process for individual manufacturers, when one considers the market as a whole, there are many economic phenomena besides learning that can cause price to decline with cumulative production, including economies of scale and competitive market pressure. Nevertheless, an approximate power-law relation between price and cumulative production appears with remarkable regularity across product types and market sector. To avoid attributing this phenomenon to the particular mechanism of learning, we have chosen to use the term *experience curve* throughout this study. In the remainder of this section, we describe our methods for fitting price and production data to experience curves for LED, CFL, and incandescent A lamps.

Equation (9) depends on the cumulative number of units produced since the product was introduced to market. For each of the products we consider here, we have annual shipments data starting in some year after the year of introduction. To convert these annual shipments into approximate cumulative production, it is necessary to estimate the annual shipments data for the years prior to the first year of the data set. To make these estimates, we start by assuming a year of market introduction for each product. In particular, we assume that incandescent lamps entered the market in 1880²³, CFLs in 1980²⁴, and LED A lamps in 2008²³. We discuss our approach to estimating shipments prior to the start of our data sets in sections 3.3.1 and 3.3.2.

3.3.1 Estimating cumulative shipments for CFL and incandescent lamps

The Census data described in section 2.2 yield a time series of annual shipments and per-unit value. To fit an experience curve, it is necessary to convert the annual shipments data into a time series of cumulative shipments by estimating the annual shipments that occurred in years prior to the start of the data series.

For CFLs, we have quarterly census shipments data between 1992 and 1994. CFLs did not achieve substantial market penetration in the US until the late 1990s and early 2000s, so we assume that the Census represent the early-adoption phase of the CFL market. The growth of shipments during this phase of can be well represented for many products by a Bass adoption curve²⁵:

$$S(t) = S_{max} \frac{1 - e^{-(p+q)(t-t_0)}}{1 + \frac{q}{p} e^{-(p+q)(t-t_0)'}}$$

(10)

where $S(t)$ is the shipments in time period t , S_{max} is the shipments at market saturation, t_0 is the time of introduction, and p and q are parameters representing the fraction of consumers who are early adoptors and imitators, respectively. To estimate the shipments of CFLs prior to 1992, we fit the Census data to this model, assuming $y_0 = 1980$ and treating S_{max} , p , and q as free parameters. The fit yielded parameter values of $p = 0.01$, $q = 0.12$, and $S_{max} = 3.2 \times 10^6$. The resulting curve is shown in Figure 2. Summing the resulting model from 1980 through 1991 yields an estimate for the cumulative shipments prior to the beginning of the Census data of 130 million units.

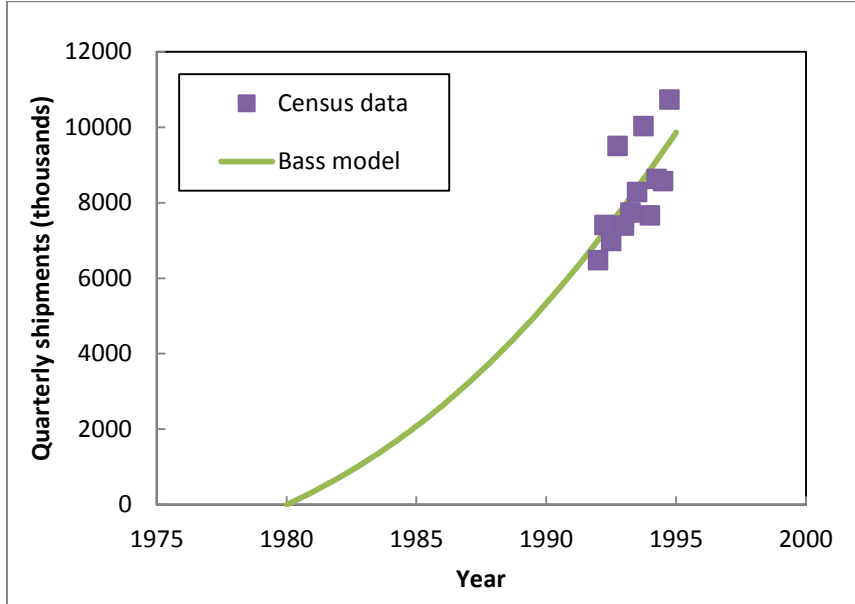


Figure 2. Quarterly shipments data for CFLs from the US Census Bureau fitted to the Bass adoption curve given in Equation (10).

In the case of incandescent lamps, the Census data are much more extensive and fall well within the period of market maturity, running from 1957 through 1994. We note that the data, shown in Figure 3, exhibit a roughly linear growth over the entire sampled period. A backward linear extrapolation of this trend, also shown in the figure, reaches zero shipments in 1907, at which time the market saturation of incandescent lamps was indeed extremely low. A more sophisticated model built to capture the dynamics in the early-adoption period would have negligible impact on the cumulative shipments to 1957 that we infer from this simple extrapolation, so for the purposes of this study we consider the linear extrapolation to be sufficiently accurate. Summing this linear model from 1907 through 1956 yields an estimate of 20 billion cumulative shipments from market introduction through 1956.

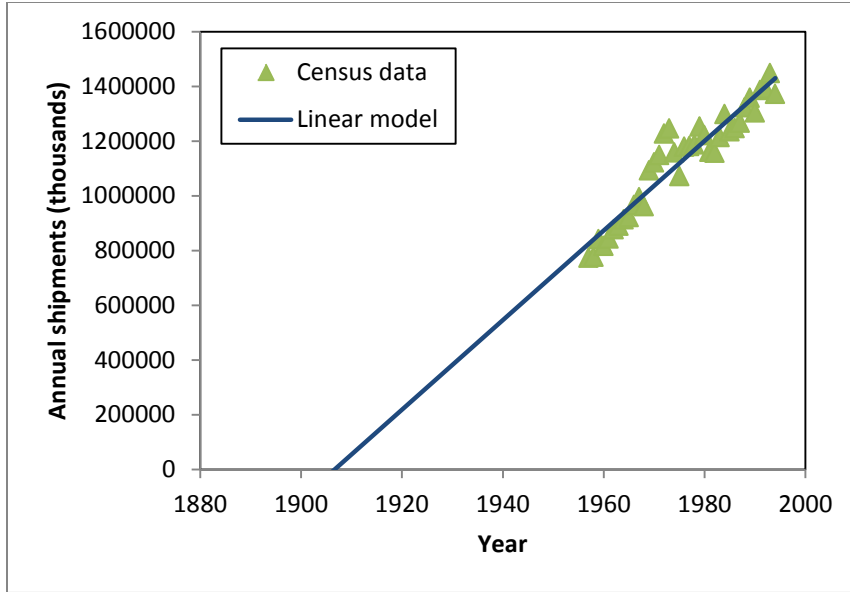


Figure 3. Annual shipments data for incandescent lamps from the US Census Bureau fitted to a linear growth model.

Using these initial cumulative shipments estimates for CFLs and incandescent lamps, we can construct time series of cumulative shipments by adding the estimates to the cumulative sums of the Census shipments data. The Census data also yield estimates of the average value per unit, as discussed in section 2.2. This is sufficient data to perform a fit to Equation (9), yielding an estimate of the experience curves for these two products. Results of these fits are presented in section 4.1.

3.3.2 Experience curve data for LED lamps

In the case of LED lamps, we do not have data on absolute shipments; instead we have a shipments index normalized to a quarterly average value of 100 in 2011, as described in section 2.3. Fortunately, the form of Equation (9) allows us to simply express our cumulative shipments in units where the average of the 2011 quarterly shipments is equal to 100. The power-law index b that we obtain from our fit will be independent of the units we use for Q .

As with the incandescent and CFL data, 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 a Bass adoption curve is very well approximated by an exponential growth model. Furthermore, we note that the LED shipments curve shown in Figure 1 is very well approximated by an exponential curve. Therefore, we simply approximate the 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 LED index we can construct a quarterly cumulative shipments index from 2011 through 2013.

To fit an experience curve, it is then necessary to construct a quarterly time series of LED price data. To do this, we can use the aggregate time-series price statistics that we developed in section 3.1. However, the large differences in prices and price trends among the various lumen bins, along with the varying times of introduction for lamps in each bin, will complicate any attempts to construct a meaningful price statistic across all bins that is comparable over time. Instead, we note that lamps in the lowest lumen bin (350-710 lm) have had the longest presence on the market, and, as we will discuss in section 4.2.1, prices for all brighter lumen bins are declining relative to the lowest bin. Therefore, we take lamps in lowest lumen bin to be representative of a baseline technology, with lamps in higher lumen bins representing incremental technology improvements that require a price increment which is declining over time. In estimating an experience curve, for LED A lamps as a whole, we wish to analyze the decline in price of a technology at a constant quality level, so in this analysis we consider only the time series price data for the lowest lumen bin (350-710 lm) in the experience-curve analysis.

In addition, our time-series price data from web crawling has a weekly frequency. For comparison against the cumulative shipments data, we down-sample to a quarterly frequency by taking the six-week average of our price time series about the beginning of each quarter. This yields a set of quarterly price data that can be fitted against our quarterly cumulative shipments index to produce an estimated experience curve for LED A lamps. We perform the fit using ordinary least-squares in log-log space. That is, we regress $\log P$ on $\log Q$ and a constant with equal weighting of all data points. Results of this fit are presented in section 4.2.2.

4 Results

4.1 Incandescent and CFL experience curves

Figure 4 shows the Census data on cumulative shipments and average value per unit for Incandescent and CFL A lamps (Sections 2.2 and 3.3.1). Also shown are fits to these data of the power-law experience curve given in Equation (9). The fit parameters and derived experience rates and their uncertainties are presented in Table 4. The rates of price decline with production are remarkably similar for the two technologies, with prices falling at 14-15% per doubling in cumulative shipments.

Interestingly, the experience rates we derive here are nearly identical to the rate estimated by DOE for linear fluorescent lamps in a recent regulatory analysis²⁶. That analysis found an experience curve power-law index $b = 0.226$ and experience rate $r = 0.145$ for linear fluorescent lamps. The similarity in the experience curves for incandescent, CFL and linear fluorescent lamps suggests that a common experience rate may have historically applied to many commodity lamps used for general illumination.

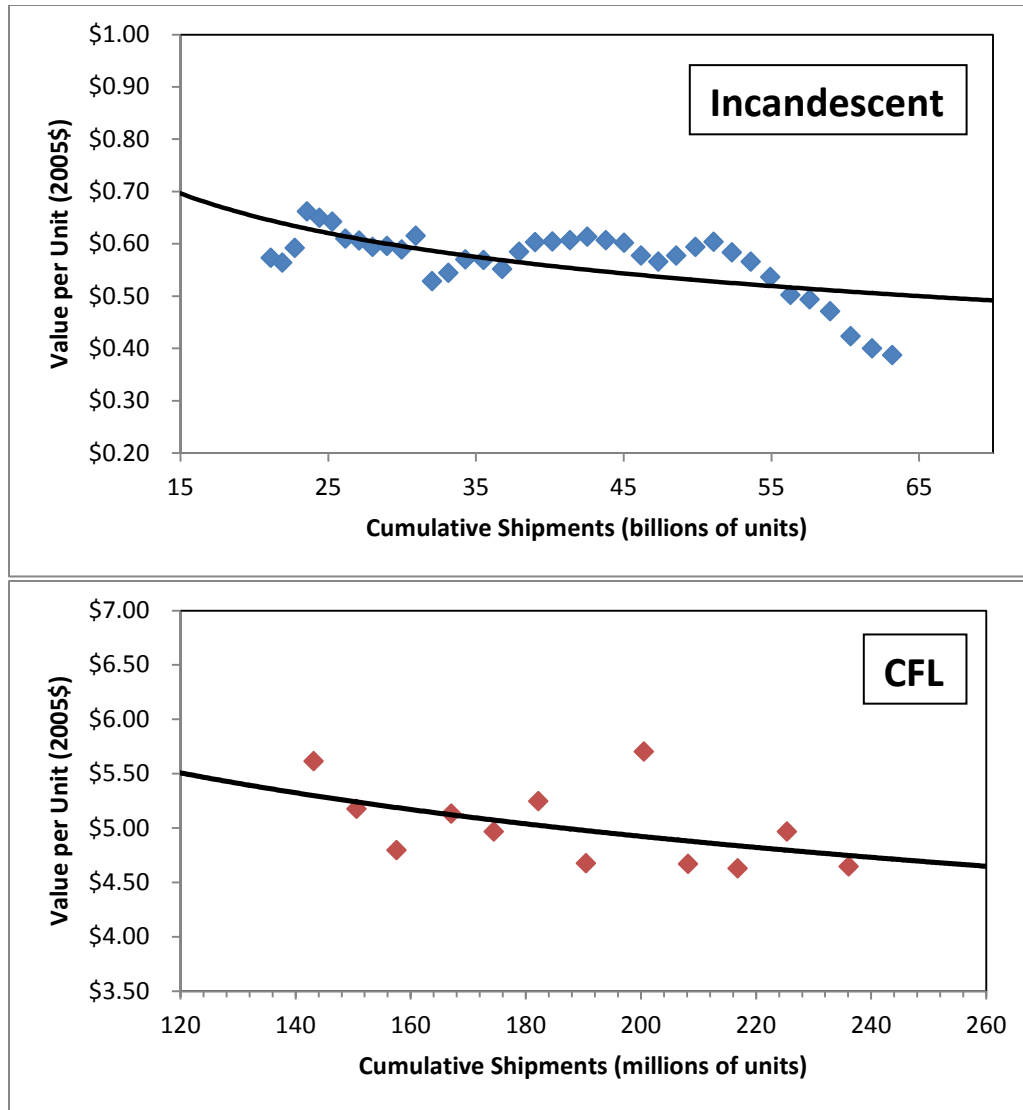


Figure 4. Experience curves for Incandescent (top) and CFL (bottom) A lamps. Data points are from the US Census Bureau⁹ and curves are fits to Equation (9).

Table 4. Fit parameters and derived experience rates, with ordinary-least-squares standard error estimates, for the experience curve fits shown in Figure 4.

	Power law index b	Reference Quantity Q_0 ¹	Experience rate r
Incandescent	0.226 ± 0.048	$10^{0.480 \pm 0.341}$	0.145 ± 0.029
CFL	0.219 ± 0.121	$10^{5.45 \pm 1.26}$	0.141 ± 0.078

¹Millions of units

4.2 Trends in LED A lamp prices

4.2.1 Time trends of absolute and differential price

Figure 5 is a semilog plot showing time series of the 25th percentile lamp price, averaged across retailers as described in section 3.1.2, for LED A lamps in each of the four lumen bins we consider. Correction factors for missing data have been applied as described in section 3.1.4. Data series for the two lower-lumen bins begin at the commencement of data collection in late 2011. For the two higher-lumen bins, the data series begin later, since products in those lumen ranges were only widely introduced to the market in 2012. For each lumen bin, significant declines in price are evident.

Gray lines in the figure show fits of equation (7) to the time series trends. Fit parameters and uncertainties are presented in Table 5. As shown, prices declined at an annual rate of 28-44% during the time period sampled. If these trends were to continue uninterrupted, prices for LED A lamps in all lumen bins would fall to one dollar by the early 2020s.

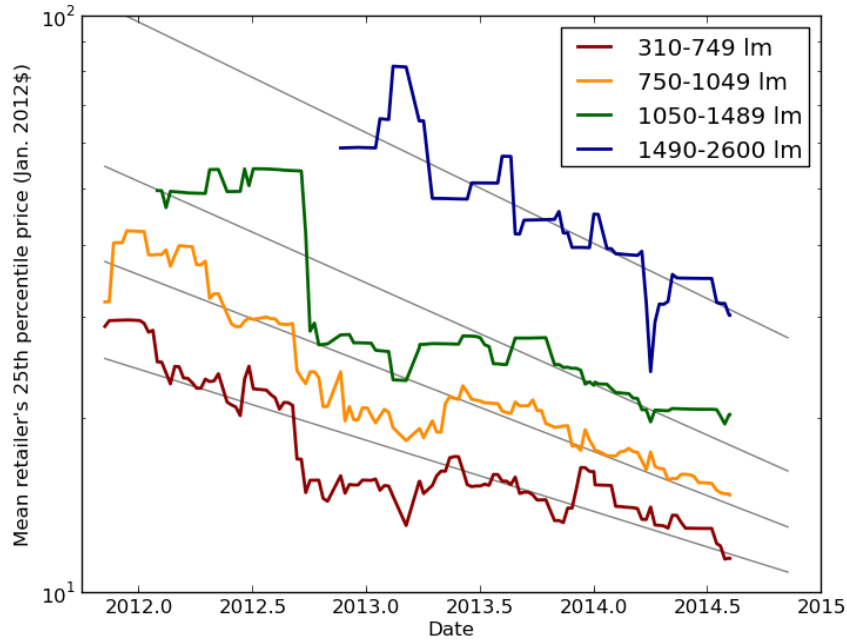


Figure 5. Trends in the mean retailer's 25th percentile price for LED A lamps, by lumen bin. Trends are shown on a semilog plot, so that exponential curves describe straight lines with slope equal to the exponential decline rate α .

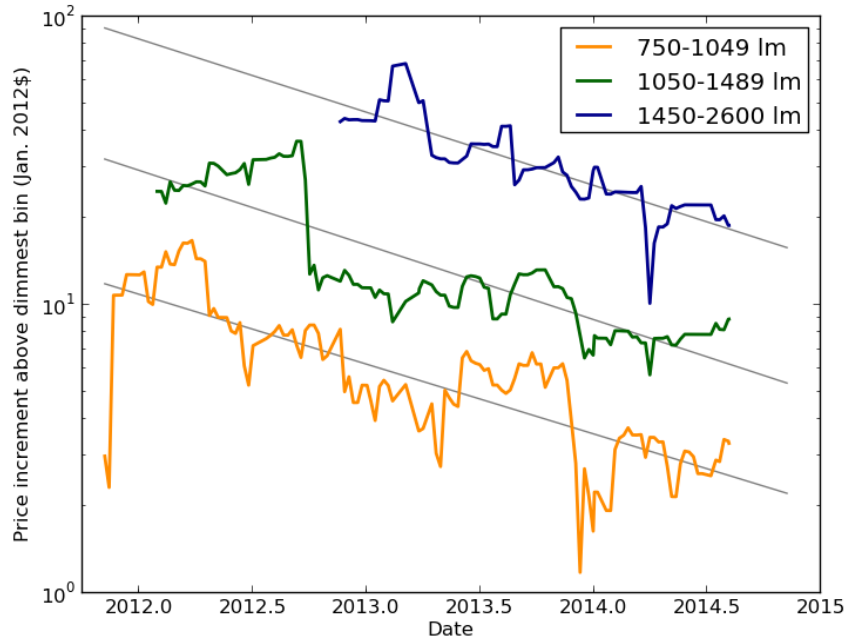


Figure 6. Trends in the incremental price of each lumen bin, relative to the lowest bin. Trends are shown on a semilog plot, so that exponential curves describe straight lines with slope equal to the exponential decline rate α .

Table 5. Absolute price decline for LED A lamps: parameters of the exponential fit with ordinary-least-squares standard-error estimates.

Lumen bin	Rate of price decline α (yr ⁻¹)	Reference year y_0
310-749	0.284 ± 0.012	2023.2 ± 0.5
750-1049	0.353 ± 0.012	2022.1 ± 0.3
1050-1489	0.406 ± 0.019	2021.7 ± 0.5
1490-2600	0.442 ± 0.020	2022.4 ± 0.5

Table 6. Incremental price decline for LED A lamps of increasing lumen output: parameters of the exponential fit and ordinary-least-squares standard error estimates.

Lumen bin	Rate of price decline α_Δ (yr ⁻¹)	Reference year $y_{0,\Delta}$
750-1049	0.558 ± 0.036	2016.3 ± 0.3
1050-1489	0.596 ± 0.032	2017.7 ± 0.3
1490-2600	0.585 ± 0.032	2019.6 ± 0.4

Figure 6 shows time series of the typical price increment ΔP_L between the three highest lumen bins and the lowest lumen bin. These time series are computed by differencing the time series shown in Figure 5. These differenced time series are somewhat more volatile than the absolute price trends, but significant declines are still readily apparent, with incremental prices dropping by factors of 3-5 over the time period shown. Gray curves show fits of equation (8) to these time series; fit parameters and uncertainties are

presented in Table 6. The incremental price of increased lumen output has declined by 55-60% annually over the time period analyzed, and if these trends continue uninterrupted, the price increments over the lowest lumen-bin price will fall to one dollar by late in the current decade.

4.2.2 Experience curves

Figure 7 shows quarterly data on price and cumulative shipments for LED A lamps, as developed using the methods described in section 3.3.2. (As explained in that section, the prices used in this part of the analysis are the prices of lamps in the 310-710 lumen bin.) For the reasons laid out in section 3.1.3 we consider the 25th-percentile price, averaged across retailers, for our primary analysis (red points). By contrast, however, when we estimated experience curves for incandescent and CFL A lamps in section 4.1, we derived price data from the average value of shipments, which corresponds to a shipments-weighted average. This may not be directly comparable to trends in the 25th percentile price. We therefore also analyze the mean price, averaged across retailers.

Since this mean is a model-weighted mean, not a shipments-weighted one, it is also not directly comparable to the Census data. In particular, because some LED sales will occur at very high price points as new, more advanced LED lamps enter the market, the unweighted mean price is likely to be much higher than the median price. Because the bulk of purchases occur well below the median price, the unweighted mean is therefore also likely much higher than the shipments-weighted mean. Thus, we can take the unweighted mean values we compute as an upper limit on the shipments-weighted mean.

Figure 7 also shows fits to the data of the experience curve formula given in Equation (9). The fit parameters and derived experience rates, with their associated uncertainties, are summarized in Table 7. In the 2012-2013 period, cumulative shipments of LED A-lamps to the US market doubled more than twice, while prices fell dramatically. The mean and 25th percentile price declined by 20% and 26%, respectively, for each doubling in the cumulative shipments. These experience rates are substantially higher than the 14-15% observed for CFL and incandescent A lamps in section 4.1 and for linear fluorescent lamps observed by DOE.²⁶ Given the parameter uncertainties, the learning rate for the mean LED A lamp price is marginally consistent (within 95% confidence) with the learning rates for the other technologies, but the learning rate for the 25th percentile LED lamp price is very significantly higher than the learning rates for the other technologies. It thus appears that LED A lamps have recently been following a steeper experience curve than has historically been observed for other lighting technologies.

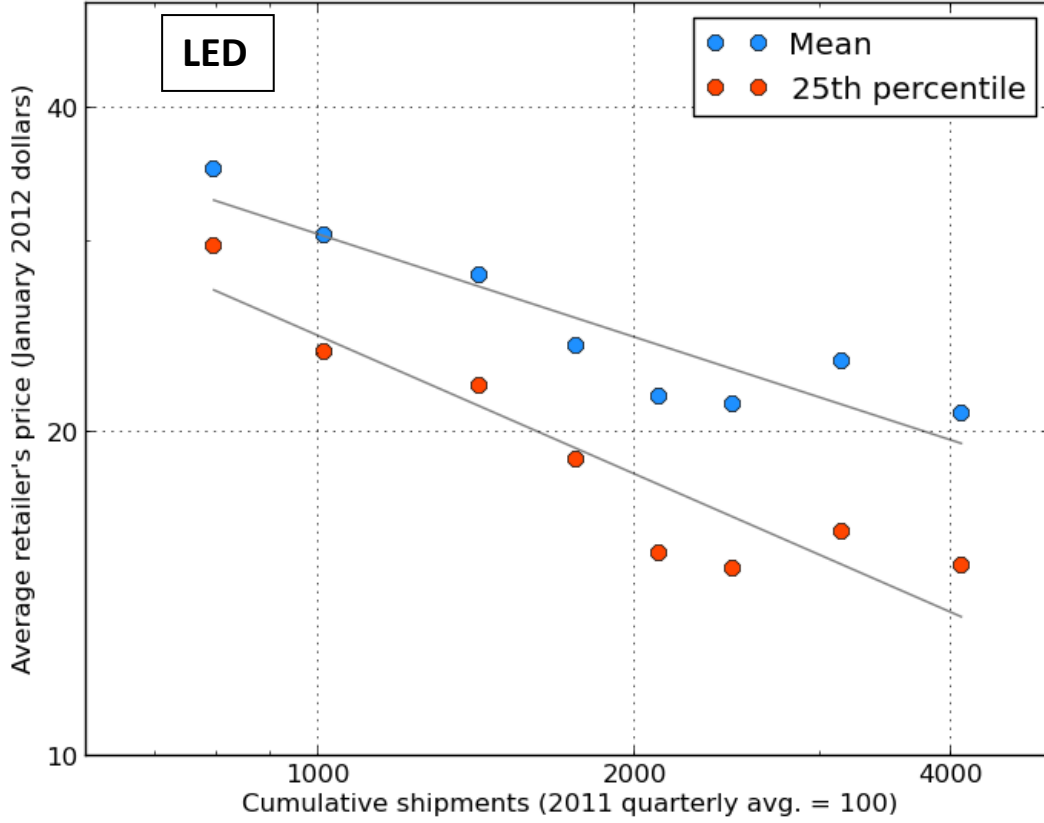


Figure 7. Price decline for LED A-lamps in the 310-749 lm bin of luminous flux, as a function of the quarterly time series index of cumulative shipments from 1Q 2012 through 4Q 2013. Data are shown on a log-log plot (so that power-law models describe straight lines), and cumulative shipments are normalized to 1Q 2012. Price data are shown for the average retailer's model-weighted mean and first-quartile prices. Gray lines show fits of the power-law function given by Equation (9) to the price-shipments trend for each of these price statistics. Fit parameters are summarized in Table 7.

Table 7. Parameters of the power-law fits shown in Figure 7 of Equation (9) to the relation between price and cumulative shipments.

Price statistic	Decline parameter b	Reference Quantity Q_0 [†]	Experience rate r
Mean	0.317 ± 0.053	$10^{7.69 \pm 0.54}$	0.197 ± 0.033
25 th percentile	0.430 ± 0.066	$10^{6.23 \pm 0.50}$	0.256 ± 0.039

[†]In units of the total shipments in year 2011.

5 Discussion and Conclusions

From late 2011 through mid-2014, we have collected weekly data on LED A-lamp prices and features from five Internet retail sites. In this study we use the data to construct four time series of characteristic prices for LED A lamps in lumen bins corresponding to the standard incandescent wattages used

historically for household applications. To establish a characteristic price statistic, we commissioned a brief consumer survey which found that the median recent purchase of an LED A lamp has occurred at approximately the 10th percentile in price, and roughly 80% of purchases occur at or below the 25th price percentile.

The LED A lamp price data exhibit a roughly exponential rate of decline in each lumen bin. Fitting the time series data to a simple exponential decline model, we find price-decline rates ranging from 28 to 44 percent per year, with faster rates of price decline for lamps with higher lumen output. Notably, these rates of decline are all faster than the 25 percent annual decline rate in per-lumen price that is observed for individual LED elements in Haitz's law. This suggests that Haitz's law, by itself, is not the primary driver of the recent price declines for LED A lamps. Declines in the costs of other components, economies of scale in manufacturing, competitive pressure, and policy support for research and development may all have contributed to the rapid price declines observed for LED A lamps.

Combining our Internet price data with data from NEMA's lamp shipments indices, we estimated an experience curve for LED A lamps. Additionally, we used price and shipments data from the U.S. Census Bureau to estimate experience curves for incandescent and compact fluorescent A lamps, following DOE's methodology for estimating an experience curve for linear fluorescent lamps. Prices for LED A lamps (in the lowest EISA lumen bin, which we take as representative of the baseline technology) have recently fallen by 20-26% for each doubling in cumulative shipments. By comparison, prices for incandescent, compact fluorescent, and linear fluorescent lamps have all historically fallen by roughly 15% for each doubling in cumulative shipments.

There are numerous potential reasons that LED A lamps might have a faster experience curve than other lighting technologies. The first is Haitz's law: a primary manufacturing input that is falling rapidly in price will enhance overall reductions in manufacturing costs and, ultimately, consumer prices. As we have already noted, however, Haitz's law is likely not the only explanation for the speed of the price decline. Since the other manufacturing costs for LEDs (e.g., electronics, lamp envelopes, lamp assembly) are similar to those for CFLs, it also seems unlikely that declines in these costs explain the faster experience curve for LEDs.

Heightened competition is another possible driver of the rapid experience rate for LED lamps. The manufacture of traditional lighting technologies for the U.S. market has long been dominated by a small number of large companies with a long history in the lighting market, but the advent of LED lighting has seen the entry of numerous new players into the market, including large consumer-electronics firms and small startup companies. The increased competitive pressure may be driving more rapid declines in consumer prices for LED products than occurred for traditional lighting products.

Finally, the introduction of LED A lamps has occurred in a very supportive policy environment. In particular, the Manufacturing R&D Initiative of DOE's SSL program identifies the facilitation of manufacturing-cost reductions as one of its primary goals²⁷. Additional federal, state, and local programs have aimed to reduce barriers to market entry and boost consumer adoption of LED products. Although a direct causal link cannot be drawn from the data considered here, it is plausible that the rapid experience curve we observe for LED A lamps reflects, at least in part, the success of these efforts.

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