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Chapter 13 Light-emitting diode lighting products

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Chapter 13 (TBC)

LED Lighting Products

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Abstract:
Over a span of only a few years in the early to mid 2010s, the lighting industry was revolutionized by the arrival on the market of products using light emitting diodes (LEDs) for general lighting applications. During that period, LED lighting products underwent both a dramatic growth in sales along with a precipitous decline in price. In the US alone, sales of LED-based standard household light bulbs rose by more than two orders of magnitude, while falling nearly tenfold in price. This rapid rate of change in both price and production represented an excellent opportunity for tracking the effects of technological learning in real time. Measuring the learning effect directly on manufacturing costs is challenging, owing to a lack of available data on cost, as well as very rapid evolution in product design. Because LED products are sold directly to consumers through online retail channels, however, it was possible to use web-crawling techniques to track retail prices at high frequency and track the price decline in great detail. A variety of studies using web crawling and other retail tracking approaches pointed consistently to a steady 20-30% annual rate of price decline for household LED light bulbs from 2011 to 2018, in both the US and elsewhere. Coupling this with a public sales index for the US market, a picture emerges of a technological learning curve characterized by an 18% price decline for each doubling of cumulative sales. Projecting these trends forward implies that substantial price declines are still to come, with prices expected to drop by more than a factor of four between 2015 and 2030.

Key Words:
~~TBD~~Lighting – Light Bulbs – Lamps – Energy Efficiency – LEDs – Emerging Technology

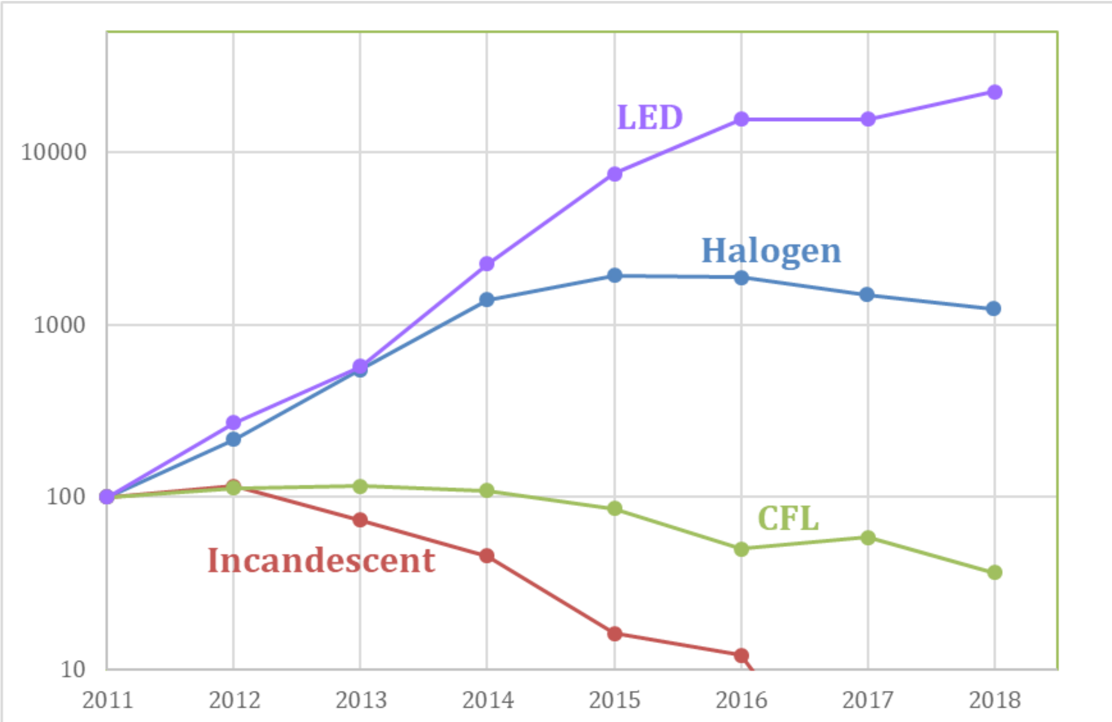
[Chapter Starts Here]

13.1. LED lighting technology in the 2010s

In the past decade, lighting products utilizing light emitting diodes (LEDs) have radically transformed the global lighting market. LEDs are semiconductor devices that emit light over a narrow wavelength band via electroluminescence when an electrical current is applied. Since their invention in the 1960s, LEDs have been valued for their highly efficient conversion of electrical energy into light, but for most of their history they have been low-intensity sources with emission in the red (long-wavelength) end of the visible spectrum, limiting their range of uses to indicator lighting and other low-output applications. In 1993, the breakthrough invention of blue-light LEDs (see Feezel and Nakamura, 2018, for a review) created the possibility of using LEDs to produce white light via phosphor down-conversion processes similar to those historically used in fluorescent lighting, or via color-mixing. Within little more than a decade, LED devices suitable for general lighting applications were available commercially and being used in lighting products ranging from replacement light bulbs (referred to in the lighting industry as *lamps*), to novel luminaire designs with directly integrated LEDs. Owing to these products' highly efficient production of visible light compared to traditional technologies, the potential was widely recognized for LED lighting products to drive a major reduction in global energy consumption.

Since then, LED lighting products have undergone rapid adoption in the lighting market. In the United States, for example, a study of the 2010 lighting market for the United States Department of Energy (US DOE) estimated that there were 67 million total LED lighting installations in the US, representing 0.8% of the national lighting stock (Ashe et al, 2012). By 2015, this value had increased tenfold, to an estimated 701 million total installations, representing 8% of the US lighting stock (Buccitelli et al., 2017). In terms of market share in the standard household light bulbs (technically referred to as *A-line lamps*), LED products have grown from a negligible presence in 2010 to capture more than 50% of the market by late 2017 in the US, according to a sales index[1] reported periodically by the National Electrical Manufacturing Association (NEMA, 2018b). Figure 13.1 shows the relative growth in sales from 2011 to 2018, for LED A-line lamps and A-line lamps using more traditional technologies. Traditional incandescent lamp sales show a sharp decline, driven by national efficiency standards that effectively phased out this technology starting in 2012. Over the same period, LED sales have grown by more than two orders of magnitude, while sales of halogen and compact fluorescent (CFL) lamps have begun to decline.

[1] See https://www.nema.org/Intelligence/Pages/Lamp-Indices.aspx

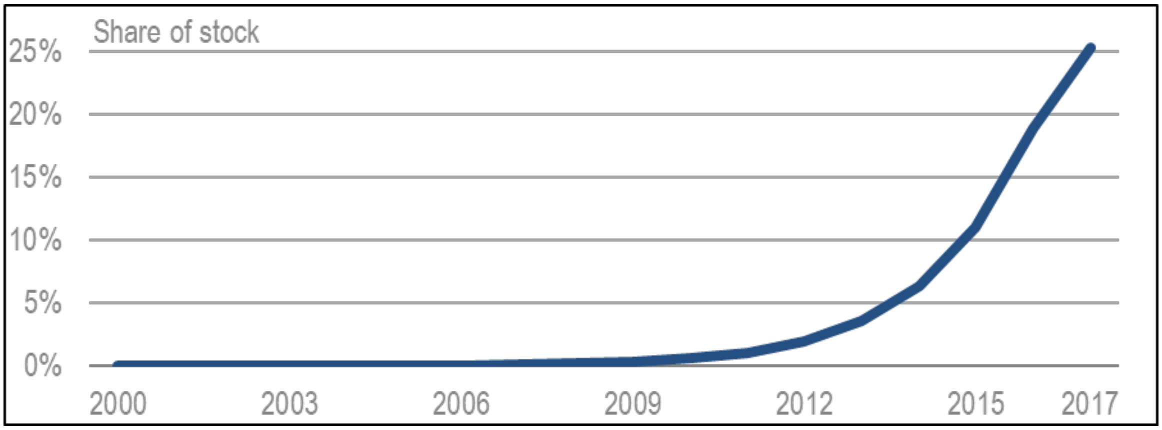


*** Insert Figure 13.1 ***

Caption: Relative annual sales of A-line lamps utilizing different technologies, compared to sales of each technology in 2011. LED lamp sales have grown by more than two orders of magnitude, while sales of incandescent, compact fluorescent (CFL), and halogen technologies have fallen in response.

Credit: Author's compilation of historical data from the NEMA A-line lamp indices.

This dramatic market growth for the LED technology has been observed worldwide across a broad range of lighting products. In India, for instance, a recent report on LED adoption observes a fivefold increase in sales of LED lighting products between 2014 and 2016, with a concurrent sales decline in other lighting technologies (Chunekar et al., 2017). Globally, the International Energy Agency (IEA) estimates that LED lighting products grew to make up up fully one quarter of lighting installations in 2017 (see Figure 13.2), despite less than a decade's significant presence in the market (IEA, 2018).



*** Insert Figure 13.2 ***
Caption: Evolution in the share of LED products in the installed stock of lighting products worldwide, as compiled by the IEA.
Credit: IEA, 2018.

The rapid adoption of LED technology has significant implications for global energy consumption, both now and in the future. The IEA estimates an annual worldwide electricity savings from LED lighting adoption in grid-connected applications grew from 20 TWh in 2010 to more than 140 TWh by 2016 (IEA, 2016). In the EU alone, annual energy savings from LED lighting technologies are projected to rise to more than 200 TWh (De Almeida, 2014) by 2030, while in the US, annual savings are projected to reach 3.9 EJ (3.7 quadrillion BTUs), corresponding to over 300 TWh, by 2035 (Penning et al., 2016). At the same time, ultra-efficient LED lighting technologies have also dramatically increased access to off-grid electric lighting in the developing world, with substantial positive implications for human health and economic development (Alstone & Jacobsen, 2018).

In light of their potential for energy savings, the development and adoption of LED lighting products have received considerable support from government policies aimed at reducing energy consumption and greenhouse gas emissions. Minimum efficiency standards that effectively banned traditional incandescent lamps, such as those implemented in the United States (US Congress, 2007) and the European Union (European Parliament, 2009), created a market for LED products to capture. Concurrently, other programs were implemented to support rapid deployment of LED lighting technology, such as US DOE's Solid State Lighting (SSL) program (US DOE 2018), which worked with industry to develop a roadmap, technological targets, and testing protocols to support LED development. In a highly visible example of such support, the US DOE's SSL program held the "L-Prize" competition, which helped to bring the first viable mass-market LED A-line lamp to the US market in late 2011 (US

DOE 2016a). Additionally, a wide variety of local and regional programs, typically managed by electrical utilities, encouraged adoption of LED products via subsidies, direct installation, or other means. In addition to the policy support, LED adoption was also encouraged by attractive features specific to LED lighting products, such as their capacity for dimming, directional control, and color tuning.

However, the most important driver of rapid adoption for LED lighting products was surely the precipitous decline in price that followed their early market entry. In 2008, the early market-entrant A-line LED lamps purchased for testing under the US DOE SSL program had prices in excess of USD 100 per kilolumen of light output, falling to prices around USD 50/klm in 2012 following the introduction of the L-prize lamp (Tuenge, 2013). By 2015, typical observed prices had fallen to USD 16/klm (Penning et al., 2016). Similar declines were seen worldwide. Again using the example of India, a fivefold drop in retail price was observed for LED lighting products from 2014 to 2018 (IEA, 2018).

A rapid price decline of this nature was widely anticipated when LED lighting products first entered the market at prohibitively high price points late in the first decade of this century. Part of the reason for this expectation was Haitz's Law (Haitz et al., 1999), which is the observation that the price of LEDs, per unit of light output, has declined tenfold every decade since their invention in the 1960s, corresponding to a decline of roughly 25% per year—a phenomenon that has also been observed for white-light LEDs since their introduction (Haitz & Tsao, 2011). Haitz's Law alone is insufficient to account for the dramatic price drop for LED lighting products, however, since these products also consist of other componentry besides the LED package itself, such as drivers and other electronics, heat sinks, electrical components, and optics. Moreover, combining all of the components into an omnidirectional lighting product required substantial investments in research and development, with significant additional opportunities for cost reduction associated with the assembly process. Industry estimates gathered by the US DOE's SSL program (Bardsley et al., 2014, 2016) indicate that, although the LED packages have seen the most dramatic decline, significant cost reductions are ongoing among most or all of these categories, and these are expected to drive a 40% reduction in manufacturing cost between 2015 and 2020.

Thus, the rapid mass-market adoption of LED lighting products that took place immediately following their market entry made these products an excellent laboratory for measuring the effects of technological learning, with limited confounding influence from inflation or other long-term economic trends. The rapid growth in demand for these products early in their existence yielded very rapid doublings in production—sometimes several times per year—which enabled learning analyses to be performed with only a few years of price tracking data.

In this chapter, we survey efforts to measure learning curves and other price trends for LED lighting products in the early to mid 2010s, during the period of their initial US market adoption. To focus on a concrete example, we devote most of our discussion to LED A lamps in the United States lighting market, since this market has seen the broadest range of studies relevant to technological learning. In section 13.2, we discuss the approaches taken to collect data on price and production for LED lighting products, and we summarize key issues related to data collection for a mass-market product in a competitive market environment. In section 13.3, we summarize the results from various price-trend studies for LED lighting products, which, taken as a whole, find that LED lighting products declined in price by some 20-30% per year in the early 2010s and that, in the US, these declines corresponded to a learning curve with an 18% price decline for each doubling of cumulative shipments to the US market. Section 13.4 presents the results of various price forecasts for LED lighting products, based on the measured price trends and expected future production. In Section 13.5, we conclude and discuss implications of the observed price declines for industry and policy.

13.2. Methodological issues and data availability

13.2.1 Price data for LED lighting products

Because lamps and luminaires are marketed directly to consumers and are widely available via conventional retail channels, data on the retail price of LED lighting products are relatively easy to find and collect. Retail prices present a conceptual challenge, in principle, for learning-curve analysis of LED lighting products, since these products consist of a new technology (the LEDs and associated electronics), whose cost may be declining rapidly, in a familiar package (the light bulb) whose componentry (such as the enclosure, electrical connectors, etc.) are largely technologically mature and likely declining only slowly in price. A multi-factor learning approach could be considered in this situation; however, comprehensive component-level cost and production data for LED lighting products is extremely difficult to obtain,[2] making such an analysis infeasible.

[2] The US DOE's SSL program does compile estimates, based on industry input, for the relative manufacturing costs of LED lamps, broken down into broad categories (Bardsley 2014, 2016). However, these are likely insufficiently precise and detailed to support a component-based learning analysis; and in any case they do not include estimates of cumulative production for each component, which would also be required.

Moreover, the unique challenges of using LED technology in general lighting applications, such as heat dissipation or overcoming LEDs' fundamentally directional nature, led to a diverse and fast-evolving set of product designs throughout the 2010s. This rapid churn in product design suggests that significant technological learning was occurring throughout the manufacturing and assembly process of LED lighting products, not just in the fabrication of the LEDs themselves, so that a learning analysis based on total product price is likely the most appropriate approach during this early phase of market adoption.

However, the rapid evolution in LED lighting products also introduced a wide variety of new product features that also affect price, posing a challenge for determining a single, well-defined price at any given point in time and confounding efforts to measure the underlying learning dynamics for the base technology. For instance, the earliest LED lighting products intended for general illumination had relatively low light output, similar to 40 or 60 Watt traditional incandescent bulbs. Over time, products with higher output (e.g., replacements for 75 and 100 Watt bulbs) were introduced to the market at a substantial price premium that eased with time. It is thus essential for any price-trend analysis to control for lumen output, to account for the varying maturity and market penetration of bulbs with different output. Additional features that can impact the price of LED lighting products, and whose relative market penetration varied significantly during the 2010s, include lifetime; color temperature (the perceived "warmth" or "coolness" of the light); color rendering (the ability of the light to reflect the true color of illuminated objects); dimmability; color tunability; remote controllability (e.g., via a smart-phone application); and the aesthetic appearance of the light bulb itself. In a highly competitive market such as generally exists for new technologies, one would naturally expect a degree of market differentiation on these features, with some products minimizing features in the interest of price, while others add desirable features at a price premium. It is important that a learning-curve analysis for LED products account for such market dynamics, whether via a multi-factor learning approach or by other means.

A common method of tracking the evolution of LED products since their introduction has been *web crawling*, using automated software tools to collect data on price and product attributes from online retail outlets (Gerke et al., 2014, 2015; McGaraghan 2015; Penning et al., 2016). This approach allows data to be collected repeatedly, on a regular cadence and at a high frequency (for instance, Gerke et al., 2014, 2015, collected LED light bulb prices on a weekly or biweekly basis for more than three years), with little additional effort required beyond the initial development of the web-crawling software. Thus, even very rapid price declines can be tracked in detail.

One downside to using retail web crawling in the context of learning curve analysis is that the market consists of a wide variety of products at different price points, and it may be challenging to aggregate these prices to estimate a typical price in each time period for which cumulative production has been measured. On the positive side, however, in addition to price, retail sites usually also display information about product specifications, so web-crawling software can also collect data on the diverse product features that may serve as confounding factors in a price trend analysis, enabling these features to be controlled for via multivariate regression (see Gerke et al., 2015). Web crawling also allows data collection to be easily extended to a broad range of different products, so that prices can be tracked separately for different LED lighting products, ranging from A-line and reflector lamps, to replacements for fluorescent tubes, to integrated LED luminaires. For instance, Penning et al. (2016) used web crawling to track prices for 24 different categories of LED lighting products over a period of seven years.

The confounding influence of product features on price trend analyses applies to a wide variety of consumer products, but for LED lighting products there are two additional concerns that could muddy the effects of technological learning. First, early in the decade, there was substantial concern about price volatility in the market for rare earth elements (which would impact the price of LED phosphors), so that analyses of cost-effectiveness for lighting efficiency policy took the impact of such volatility into effect (US DOE, 2014). However, in recent years, this volatility has eased, and it is not expected to significantly impact price trends for LEDs (US DOE, 2016b). Also, a large number of utilities and local policymaking bodies have provided subsidies to encourage adoption of LED products, and many of these programs are structured as so-called upstream or mid-stream incentives, in which the subsidy is paid directly to the manufacturer, distributor, or retailer, to produce a lower consumer-facing retail price (rather than providing a rebate to the consumer after purchase). These programs could obscure or enhance the underlying price decline if they are not accounted for. Fortunately, the web-crawling approach can overcome this issue, since it is possible to crawl prices as displayed to a customer outside of the geographic region covered by a subsidy (e.g., by crawling from a server location outside of the relevant country).

13.2.2 Approach to inferring cumulative production

While price data for LED lighting products are relatively easy to obtain, it is more difficult to find data that can inform estimates of cumulative production for these products. The market for LED lighting is a competitive one, and actual data on manufacturing output and sales tend to be very closely held by firms. A key source of information on this front for the US market are the sales indices for lighting products published roughly twice yearly by NEMA (NEMA, 2018a). These indices provide the relative quarterly sales of various lighting products, including household LED light bulbs (A-type lamps), compared to a selected baseline quarter.

From the perspective of determining a learning rate, having an index of relative sales like the NEMA indices, rather than absolute sales, presents no obstacle. A relative sales index is given by $I_p = q_p / q_0$, where q_p is the sales in time period p, and q_0 represents the sales in a selected reference period. Then the cumulative production Q_p can be computed in units of q_o by summing up from the period of introduction p_i:
$\widetilde{Q}_p \equiv Q_p / q_0 = \sum_{p'=p_i}^{p} q_{p'} / q_0 = \sum_{p'=p_i}^{p} I_{p'}$. Although the absolute sales multiplier q_0 remains unknown, this value cancels out of the learning curve equation when we write it as

$$P = \left(\frac{Q}{Q_0} \right)^{-b} = \left(\frac{\widetilde{Q}}{\widetilde{Q}_0} \right)^{-b}.$$

In this case, $\widetilde{Q}$ is the independent variable, while $\widetilde{Q}_0$ and b are the parameters being estimated. A residual challenge in developing a cumulative production estimate is that the NEMA lamp indices only began tracking LED sales figures as of 2011, several years after the first LED lamps were introduced to the market. Fortunately, the scale of LED shipments at this stage was sufficiently small that it is reasonable to back-cast the shipments to the year of introduction by assuming a simple trend, without introducing significant error to the estimate of cumulative production. (For more detail on this procedure, see section 13.3.2.)

A bigger challenge posed by the NEMA indices (or other sources of market tracking data) is that they represent sales in a limited geographic region (the United States); whereas the rapid adoption of LED lighting products is a worldwide phenomenon, and one would expect technological learning to be driven by the growth in cumulative global production. To perform a learning curve analysis using sales data from only one geographical region, one assumes that the market being analyzed represents an approximately constant fraction of the global market over the period being analyzed. Since the market growth may proceed at substantially different rates in different regions, this assumption, though necessary, may be a significant source of error in the estimated learning rate. Similarly, most market tracking data will focus on specific types of LED lighting product (e.g., household A-type lamps in the case of the NEMA indices), and there is a risk that these do not represent a constant fraction of total production for all LED products. Fortunately, because the US represents a significant fraction of the global lighting market, and since household A-type lamps are a dominant product category, the fraction of global production represented by the NEMA A-lamp indices is likely to be fairly stable, and so these can be used as a reasonably reliable proxy for global LED production, at least over a period of a few years.

13.2.3 Summary of data and methodological issues

Table 13.1 summarizes the data issues encountered in performing learning curve analysis for LED lighting products, as described in this section, and the approaches that have been taking to addressing them.

Table 13.1. Data issues related to LED lighting learning curve analysis, and resolutions applied.

Issue	Resolution applied	Applicability
Data is not for cost but for price	Use price data as indicator for costs	☑
Data not available for desired cost unit		
Data is valid for limited geographical scope	Assume regional production tracks global production	☑
Cumulative production figures not available	Use relative sales index	☑
Data is in incorrect currency or currency year	Correct for inflation	☑
Early cumulative production figures are not clear or available	Back-cast early cumulative production from trend in available data.	☑
Supply/demand affecting costs significantly		
Lack of empirical (commercial scale) data		

13.3. Results

13.3.1 Time trend analyses

Owing to the ready availability of price data for LED lighting products, alongside the challenges described in the previous section in estimating cumulative production, numerous studies have estimated price trends for different categories of LED lighting products assuming an exponential decline with time (or some other time trend), rather than a learning-curve model based on cumulative production. In this section, we summarize the various time trend analyses and compare the various annual rates of price decline obtained, using A-line lamps as a common technology for comparison. Table 13.1 presents a summary of the studies considered and the estimated rates of price decline.

In an early example, a report from the US DOE's SSL program (Tuenge, 2013) used the purchase price of lamps acquired for performance testing within the program to track the price of various LED lighting products, ranging from household LED lamps, to integrated LED fixtures, to street lights, during the period from 2008 through 2012, during the very early years of market entry for the technology. As may be expected for a very new technology, the observed price declines were quite extreme, ranging from a factor of 2 to a factor of 6 in average price over the 4-year period of observation. Although the report used a power-law trend with price and did not report fit parameters explicitly, we can estimate the annual rate of price decline that would be obtained from an exponential fit, based on the fractional price decline over the observation period. For A-line lamps, the fit suggests a decline rate of 65% per year during the period of observation.

Several years later, two reports from Lawrence Berkeley National Laboratory (LBNL) (Gerke et al., 2014, 2015) used web crawling data to estimate learning curves for LED A-line lamps. As a prelude to the learning analysis, both studies also estimated a declining exponential trend of price with time. The 2014 analysis divided the data sample into ranges of lumen output corresponding to the standard traditional incandescent wattages. Finding a faster price decline as lumen output increases, and noting that more luminous lamps had entered the market more recently than dimmer lamps, the authors focus on the lowest lumen range (310-749 lumens, corresponding to a 40 Watt incandescent lamp) as the best estimate of the baseline decline rate, at 28% per year. The 2015 report undertook a more thorough regression analysis, including lumen output and other features as explicit regression variables impacting the lamp price. The result was a more rigorous estimate of the underlying price decline rate, which happened to be unchanged from the 2014 report at 28% per year.

In a formal comment on proposed energy consumption standards for LED lighting products in California (McGaraghan, 2015), prepared by the consultancy Energy Solutions on behalf of the California Investor Owned Utilities, web crawling data were used to monitor price declines for LED A-line lamps categorized by their color-rendering index (CRI) into typical and high-CRI ranges. The authors found a price decline rate of approximately 21% per year for the typical products, while the high-CRI lamps, which had entered the market later, were falling at a faster rate of roughly 35% per year. This difference in price decline rates highlights a challenge, mentioned in section 13.2, in using web crawling data to estimate a learning rate: lamps with the high-CRI feature were a growing fraction of the market and had a more rapidly declining price, which could confound efforts to estimate a learning rate for the underlying technology.

A 2016 forecast of energy savings potential from LED products from the US DOE Solid State Lighting (SSL) program (Penning et al., 2016) developed price forecasts for numerous different categories of LED lighting products by using web crawling data to estimate learning-based price trends, using the same regression model as Gerke et al. (2015). Although the report did not report fit parameters explicitly, for the purpose of comparing to other studies we can infer the measured rate of price decline from the forecasted price declines early in the forecast period, when the trend would still be expected to be approximately exponential. For LED A-line lamps, the report forecasts a price drop of a factor of four from 2015 to 2020, which would correspond to an exponential decline at a rate of 28% per year.

The picture that emerges from these studies is of a steady 20-30% annual price decline for LED lamps in the US market. Relatively fewer studies have been published on LED lamp price trends outside the US market, so it is difficult to know how well these results scale to the rest of the world. However, in 2018, the IEA referenced an 80% price decline between 2014 and 2018 for India's LED bulk procurement program, UJALA (IEA, 2018), which translates to a roughly 33% annual price decline, broadly in line with (or even slightly faster than) trends observed in the US. Most recently, a study from the University of Geneva (Heidari et al., 2018) presented data on the price of LED lamps (as well as other technologies) in Switzerland, between 2010 and 2016, based on a compilation of data from a variety of online and other sources. They fitted an exponential model of price decline, with an additional constant term based on an assumed price floor. Based on the data reported in this study, the price of LED lamps on the Swiss market fell by a factor of four over the period considered, from CHF 35.3 in 2010, to CHF 8.7 in 2016. An exponential fit to the reported data implies a 22% annual rate of price decline over the period, which is similar to trends observed in the US.

Table 13.1. Estimated annual rates of price decline for LED A-line lamps from various studies of LED price trends.

Study	Region	Period of data collection	Estimated annual price decline rate	Note
Tuenge, 2013	USA	2008-2012	65%	Estimated from the results of a power-law fit.
Gerke et al., 2014	USA	2011-2014	28%	Based on 25th percentile observed lamp price for low-

				lumen lamps only.
Gerke et al., 2015	USA	2011-2015	28%	Based on multivariate regression, including controls for various product features.
McGaraghan, 2015	California	2013-2015	21-35%	Trend range represents separate estimates for low and high CRI products.
Penning et al., 2016	USA	2010-2016	28%	Estimated from the early-adoption period of a learning-based model.
IEA, 2018	India	2014-2018	33%	Estimated from a reported 80% price decline over the period, for bulk procurement (not consumer price).
Heidari et al., 2018	Switzerland	2010-2016	22%	Based on exponential fit to reported data.

13.3.2 Learning curve analyses

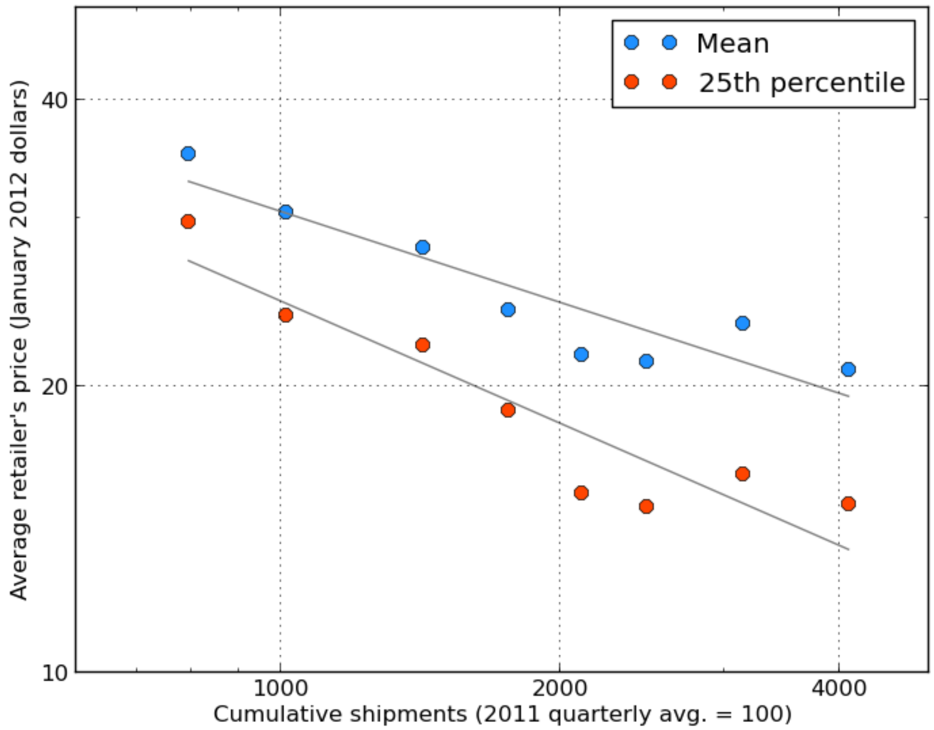
If an emerging technology follows a learning curve, one would naturally expect an exponential price decline with time in the early adoption period, based on commonly used models for market adoption. Growth in the adoption of new technologies is often observed to obey an S-shaped curve (Bass, 1969) that is well approximated by an exponential growth curve in the early adoption period. By the properties of exponential functions, exponential growth in production implies that the *cumulative* production Q is also growing exponentially: $Q \propto e^{\beta t}$. If we insert this relation into the learning curve equation, we find that the price is expected to fall exponentially when production is growing exponentially:

$$P \propto Q^{-b} \propto e^{-b\beta t} = e^{-\alpha t}.$$
(Eq. 13.1)

Since LED lighting products are still early in their market penetration curve, then, the exponential price-decline models in the studies mentioned above are consistent with an assumption that prices followed a technological learning curve. If overlapping production data become available in the future, a learning parameter could be estimated from the exponential price trends by combining the rate of price decline with the growth rate of production: $b=\alpha/\beta$.

More explicit attempts to estimate a learning curve for standard A-type LED light bulbs were undertaken in the two reports from LBNL (Gerke et al. 2014, 2015). In both studies, the authors used web-crawling data that had been collected on a weekly or biweekly basis from online retailers in the US market, starting in late 2011 and continuing through the year of publication. The authors then combined the web-crawled price data with the quarterly NEMA shipments index to estimate a learning curve. Because the NEMA indices did not include LED lamps prior to 2011, the authors extrapolate an exponential growth curve backward to an assumed introduction year of 2004, prior to which shipments were assumed to be zero. With this back-cast, it was then possible to compute an index of cumulative shipments.

As discussed in section 13.3, the broad diversity in product features and prices captured in high-frequency web-crawling data presented a challenge for estimating a typical price value that can be fitted against the cumulative shipments index. The 2014 report estimates a learning curve based on the price of LED light bulbs having relatively low lumen output, comparable to a traditional 40-Watt incandescent bulb (approximately 500 lm), to avoid the confounding effects of higher-lumen bulbs that had entered the market at a significant price premium during the analysis period. The report aggregates the prices of different light bulbs offered on the market by selecting either the mean price (to represent a typical overall price) or the 25th percentile (to represent a typical price for a purchased item) from each retailer, and then averaging this statistic across retailers to smooth out differences in pricing strategy. To convert the resulting weekly prices into a quarterly price, the authors took a 6-week average about the end date of each quarter. Figure 13.3 shows the result of fitting these aggregated quarterly prices against the cumulative NEMA shipments index to estimate a learning curve. The study found learning parameters of $b=0.32\pm0.05$ for the mean price and $b=0.43\pm0.07$ for the 25th percentile price (corresponding to a 20% and 26% price decline per doubling of cumulative shipments, respectively).



*** Insert Figure 13.3 ***
Caption: Learning curves fitted to the mean and 25th percentile in price for A-type LED light bulbs near 500 lumens, offered for sale at US online retailers in the period from late 2011 to 2014. Cumulative shipments are shown in units where the average quarterly shipment volume in 2011 is equal to 100. The mean and 25th percentile learning curve fits imply a 20% and a 26% drop in price for each doubling of cumulative shipments, respectively.
Credit: Reproduced from Gerke et al. 2014.

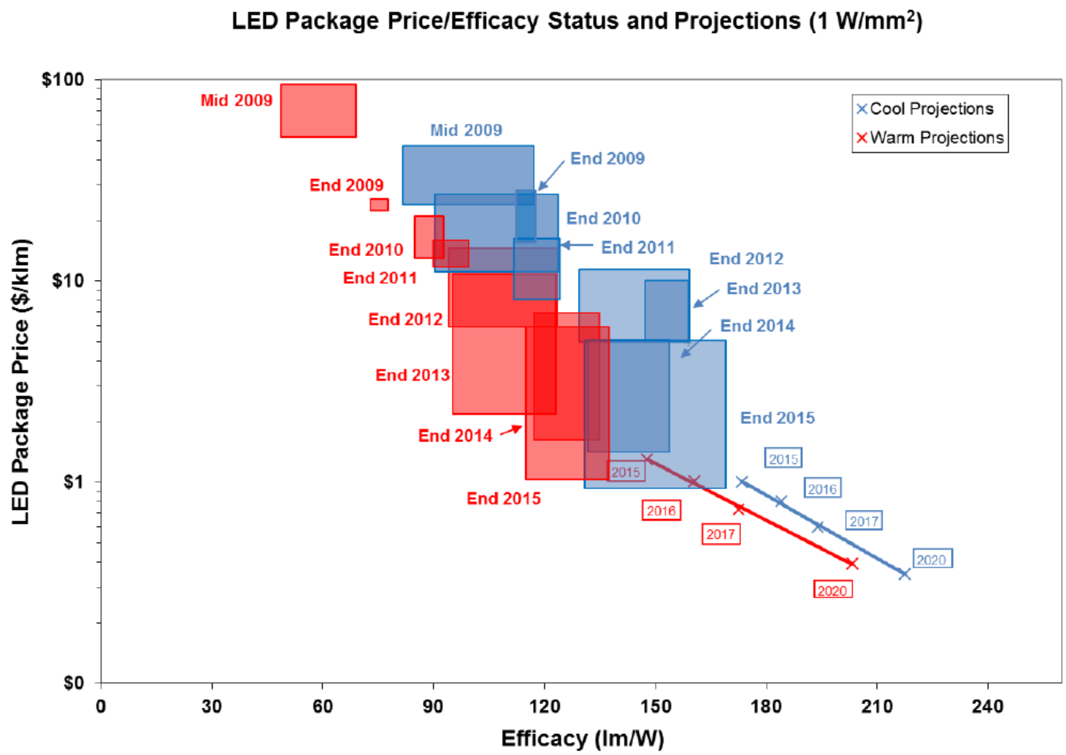
The growing difference between the mean and 25th percentile price observed in Gerke et al., 2014, is suggestive of a market whose price structure is undergoing differentiation on product features. To better account for these market dynamics, the same authors took a different approach in their 2015 study. Sidestepping the issue of aggregating the weekly price data to a quarterly value, they instead fitted price and cumulative shipments as exponential functions of time, then estimated a learning parameter via Equation 13.1. This approach allowed the use of a more thorough regression model for price, utilizing all of the web-crawled data, and including as variables additional product features such as lumen output, color temperature, and brand name. They found that including the product features--especially brand name—resulted in a slower estimated price trend, suggesting that an evolving market landscape, with brands competing on price and other features, was driving a steeper price decline than the baseline trend from technological learning. Using a regression model that accounts for these effects results in an estimated learning parameter $b = 0.30$, corresponding to an 18% price decline per doubling of cumulative production.

Within the reported uncertainty, the results of the 2015 study on learning rate are consistent with the results for the learning rate estimated for the mean price statistic in the 2014 report. This suggests that a value of approximately 0.30 is a reasonably robust estimate of the learning parameter b for A-type LED light bulbs in the US market, and that steeper observed price declines may be driven in part by product differentiation on features, or other competitive effects.

In addition to the LBNL studies, as discussed in section 13.3.1, an LED energy-savings forecast from US DOE (Penning et al. 2016) also used web-crawling data to fit price trend regression models for LED lighting products. Although that report did not estimate learning parameters, it does provide forecasts out to 2030 for an impressively broad array of products, which we discuss in section 13.4.

13.3.3. Main drivers of the price decline

As discussed previously, actual cost data are difficult to obtain for the componentry and manufacturing processes of LED lighting products. However, the US DOE's SSL program periodically polls manufacturers to build a picture of the relative cost for different components of the manufacturing process and their evolution over time. The main manufacturing cost components for an LED lighting product can be subdivided into several categories: the LED packages themselves; the driver and other electronics; thermal, mechanical, and electrical components; optics; assembly; and overhead costs, including research and development, engineering, regulatory compliance, packaging, and distribution (Bardsley et al, 2014, 2016). The relative costs in each of these categories varies substantially among different lighting products, but as of 2016, the dominant cost category was generally the thermal, mechanical, and electrical components (such as heat sinks, electrical connectors, fasteners, and housing), which made up more than one quarter of costs. These were followed in importance by the driver electronics, the LED packages, assembly, overhead, and optics (Bardsley et al, 2016).



*** Insert Figure 13.4 ***

Caption: Typical ranges of retail price and luminous efficacy for LED packages from 2009 to 2015, with projections to 2020. As noted in the original source, efficacies are as obtained when operating the packages with power density of 1 W/mm^2 at an operating temperature of 25°C; cool white packages are assumed to have coordinated color temperature (CCT) of 5700K and color rendering index (CRI) of 70, while warm white packages assume CCT=3000K and CRI=80; and, while rectangles represent the full region mapped by maximum efficacy and lowest price for each time period, the maximum efficacy may not have been available for purchase at the lowest price. Credit: US DOE SSL Program, "R&D Plan", edited by James Brodrick, Ph.D. (Bardsley et al. 2016).

In the early to mid 2010s, the LED package category underwent the most dramatic cost decline: LED packages were by far the dominant cost component at the start of the decade (Bardsley et al., 2014), but by 2016 they had fallen to less than 20% of total manufacturing cost across a range of product types (Bardsley et al., 2016). This decline was driven by a more than tenfold decline in the price of LED packages between 2009 and 2016, as shown in Figure 13.4. Over the same period, the luminous efficacy of LED packages (lumens of output per Watt of electricity) roughly doubled, facilitating new product designs utilizing fewer packages per lamp or luminaire, further reducing overall costs in the LED package category. Costs in the other main categories declined as well, though at a slower pace. Notably, there were numerous changes to the overall design of LED lighting products as their market adoption increased (Bardsley et al, 2016). New system designs can significantly impact overall costs owing to changes in the bill of materials and assembly process, even if the per-unit cost of components remains unchanged. Because of this, it can be difficult to account for the full price trend using a reductive, purely component-based approach. In this situation, a more holistic learning analysis at the product level, like those described earlier in this section, may be more effective at capturing the full effect of learning.

13.4. Future outlook

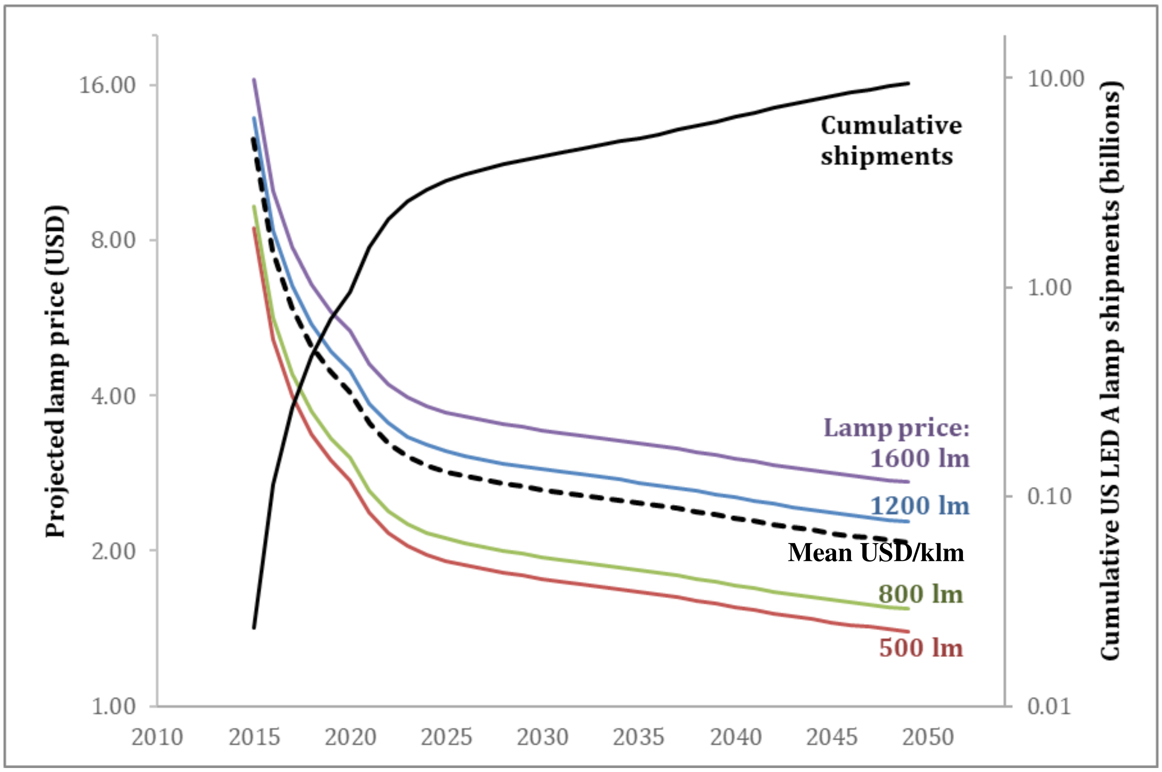
13.4.1. Product-level price projections

Two different 2016 studies from US DOE projected future prices for LED lighting products, using learning curves estimated from historical data combined with forecasts of shipments to the US market. The agency published a Notice of Proposed Rulemaking (NOPR) (US DOE 2016b) proposing new energy efficiency standards for General Service Lamps (GSLs), along with a detailed analysis of the expected national impacts of such standards (US DOE 2016c). The analysis included a projection of the shipments of LED A-line lamps under different policy scenarios, based on a model of stock turnover and consumer adoption, and it used the learning curve estimated by Gerke et al. (2015) to project the price declines expected to occur in each case. In addition, as discussed in section 13.3, a broader energy savings forecast from the US DOE's SSL program used a learning-based model, along with a shipments projection, to forecast price declines for a variety of different LED lighting products (Penning et al., 2016). In both cases, the forecasts were based on analysis of trends in the total product retail price, rather than a bottom-up component-based analysis of manufacturing costs.

The supporting analysis for the GSL NOPR included a detailed projection of annual US shipments and price points for LED A-line lamps having different lumen outputs and efficiency levels, from 2015 through 2049 (US DOE 2016c). Figure 13.5 displays the results of this projection for the scenario with no new efficiency standards.[3] Shown on a semilog plot are the projected cumulative shipments of LED A-line lamps to the US market (solid black curve); the projected lamp price for lamps having four different lumen outputs, corresponding approximately (from bottom to top) to the output of standard 40, 60, 75, and 100 Watt traditional incandescent lamps (colored curves); and the per-kilolumen price averaged across all four lumen outputs (dashed black curve), for

[3] Since neither the proposed standard nor any other new efficiency standard covering LED A-line lamps had not been finalized at the time of writing, the no-new-standards scenario represents the current status quo.

ease of comparison to other results[4]. The projection indicates a rapid growth of cumulative shipments through the early 2020s, as LED market adoption rates increase, followed by a slower rate of growth due to natural stock replacement and market growth after market saturation is reached. The lamp prices mirror the cumulative shipments growth, undergoing a dramatic drop of approximately a factor of four from 2015 through the early 2020s[5], followed by a slower, yet steady, price decline. The ultimate result is a projected sixfold price decline from 2016 through 2049, with the per-kilolumen price falling to USD 2.60 by 2030 and to approximately USD 2 by the end of the period.



*** Insert Figure 13.5 ***

Caption: Projected cumulative shipments and price for LED A-line lamps in the US market, from an analysis performed in support of proposed energy-efficiency standards for General Service Lamps. The price trends indicate price projections for lamps with four different lumen outputs, corresponding to the standard wattages of (from bottom to

[4] Averaging across the lumen ranges is necessary, since lamp luminous efficacy (lumens per Watt) increases with increasing lumen output, so that the higher-output lamps tend to be less expensive per kilolumen than the lower-output ones.

[5] A particularly sharp feature is visible in Figure 13.5 around 2020, where there is a sudden sharp increase in cumulative shipments, and a corresponding acceleration in the price decline due to learning impacts. This represents the projected impact of a provision in US law that would effectively eliminate most A-line halogen incandescent lamps in 2020, if certain conditions are met (US Congress, 2007).

top) 40, 60, 75, and 100 historically used for incandescent lamps. Also shown is the normalized price per kilolumen of light output, averaged across all four lamp types shown.
Credit: Developed from data in US DOE 2016d.

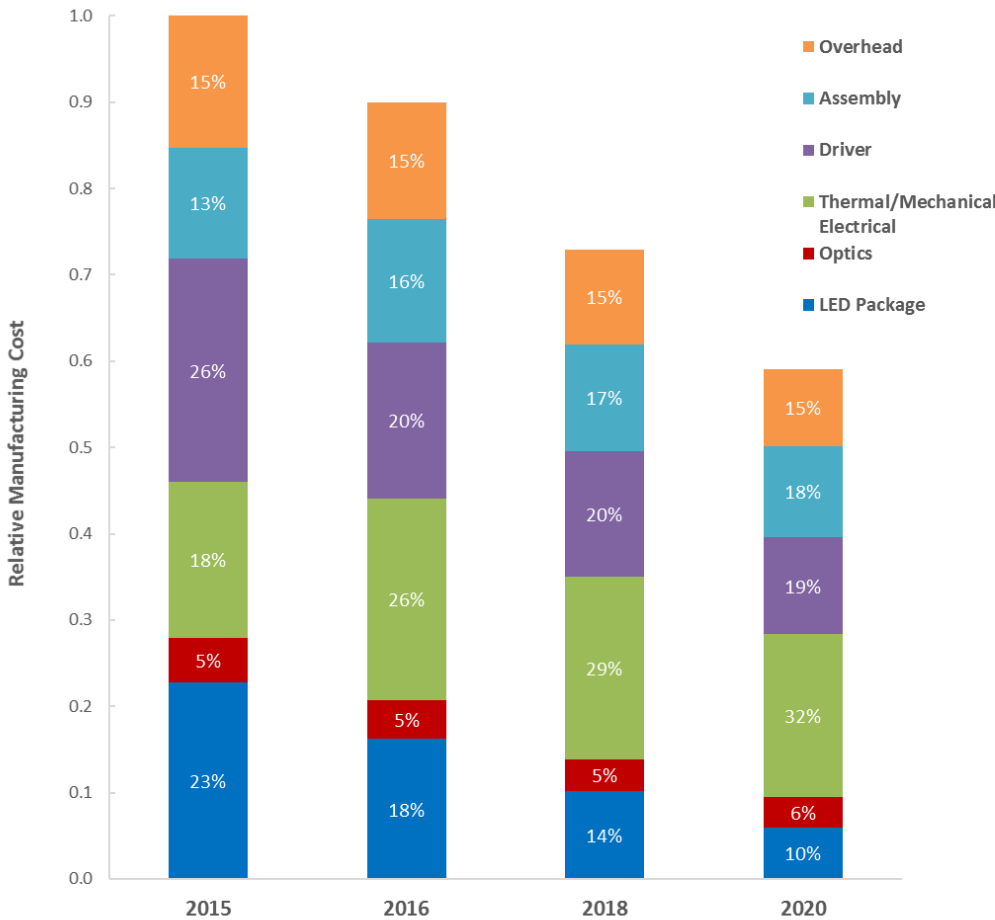
The forecasts from the US DOE SSL program (Penning et al., 2016) cover a much broader range of LED lighting products, but with less detail than the standards analysis. Table 13.3 shows price forecasts out to 2035 for a selection of different commonly used lamp types; the full report covers a wider range of products, including integrated LED luminaires. The results overall indicate a substantial price drop for all LED lighting products, ranging from a factor of two to a factor of more than six out to 2030. As expected for an emerging technology, the bulk of the price decrease occurs in the early part of the forecast period, with a flatter trend for all products in the later years. The forecast for A-line lamps is broadly in line with the standards analysis, indicating a roughly fivefold price decline from 2015 through 2030 (although the standards analysis has marginally lower absolute price estimates throughout).

Table 13.3. Price forecasts from Penning et al. (2016) based on learning-curve analysis for various types of LED lamps. All values are forecast lamp price in USD per kilolumen.

Product category	**2015**	**2020**	**2025**	**2030**	**2035**
A-line lamps	16	4	3	3	3
Large directional	21	12	9	8	7
Small directional	47	13	10	9	9
Linear tube	20	7	5	4	3
Low and High Bay	30	17	13	11	10
Decorative	28	8	6	6	5
Area and Roadway	23	15	12	11	10

13.4.2. Component-based manufacturing cost projections

As discussed in section 13.3.3, although specific component-level price data for LED lighting products are difficult to obtain, the US DOE SSL program periodically polls manufacturers for cost information to develop an overview of relative manufacturing costs for LED lighting products. The information gathered through that effort includes the best estimates of manufacturers for near-term cost declines. Figure 13.6 shows the resulting estimates for the case of A-line LED lamps, as of 2016 (Bardsley et al., 2016). Overall, manufacturing costs were expected to decline by 40% by 2020, led by a continuing rapid decline in the cost of LED packages, with a more modest decline across all other categories, with the exception of thermal, mechanical, and electrical components, which were expected to undergo a modest cost increase.



*** Insert Figure 13.6 ***

Caption: Projected evolution of relative manufacturing costs in different cost categories for LED A-type lamps, based on manufacturer input gathered by the US DOE SSL Program.

Credit: US DOE SSL Program, “R&D Plan”, edited by James Brodrick, Ph.D. (Bardsley et al. 2016).

13.4.3. Discussion

Both the product-level price forecasts and the component-level cost projections indicate that fairly dramatic price declines are expected to continue for LED lighting products. Nevertheless, there is a clear tension between the two approaches, with manufacturers projecting a 40% decline in costs from 2015 to 2020, while the price-based forecasts point to a fourfold price drop over the same period. Some discrepancy is perhaps to be expected, given that the price forecasts are based on historical trends, whereas the cost projections reflect manufacturer expectations for componentry and labor, as informed by current manufacturing practice. One explanation for this difference could involve changing margins for manufacturers. Indeed, prices for emerging technologies have been observed, in certain cases, to fall at different rates from manufacturing costs, when an “umbrella” pricing period maintains prices at an elevated level, relative to the declining manufacturing costs, followed by a competitive “shakeout” period that drives prices down at a faster rate than costs, before the price decline settles to the same rate as the cost trend (Hedley, 1976).

Alternatively, or in addition, future evolution in product designs could reduce the required bill of materials for manufacturing, or simplify the assembly process, leading to faster declines in total manufacturing cost (and ultimately product price) than would be expected based only on the component-level projections (see Bardsley et al., 2016, for further discussion of this point). For example, as LEDs have become more efficient, the need for thermal management has become less acute, reducing the amount of material needed for heat sinks, so the contribution of these components to total cost may fall more rapidly than the material cost evolution would imply. This represents a technological learning effect that is not captured by a cost forecast for the individual components of current manufacturing practice; in this sense, the more holistic price-based approach may lead to more accurate forecasts.

Indeed, there is some indication that even the more rapid price-based forecasts may underestimate the true rate of price decline. There have been recent anecdotal observations of LED A lamp prices that have *already* fallen below the USD 3/klm price that was forecast for 2030 in the circa-2016 price-based forecasts. Observations of lower than expected prices, occurring earlier than expected, may simply stem from evolving utility or governmental incentives, or they may arise from changes to lamp quality and features, as competition for customers drives firms to pursue lower prices, at the expense of reduced product quality or features (e.g., lifetimes, color rendering, or dimmability). It is also possible that the learning-based forecasts of A-lamp prices underestimate the price decline because they use the cumulative shipments of A-lamps only, whereas the cumulative shipments of all LED lighting products may have grown more rapidly (since LED A lamps were a relatively early entrant to the market).

13.5. Conclusions and recommendations for science, policy and business

The 2010s decade saw a steady and rapid decline in price for LED lighting products, with prices falling several fold from the high initial market-entry prices observed near the beginning of the decade. For LED A-line lamps sold in the US market, a steady decline of 20-30% per year was observed through the first half of the decade. At the same time, LED lighting products were also experiencing fast growth in consumer uptake, resulting in a many-fold increase in cumulative production over a period of only a few years. This situation presented an unusual opportunity to observe significant technological learning effects in near real time as they occurred over a period of only a few years. In the instance of A-line lamps in the US, researchers were able to measure a learning curve robustly using only 2-3 years of data on price and lamp sales, finding a price decline of 18% for every doubling in cumulative production (Gerke et al., 2015).

Despite the unmistakable price declines and production growth, there are nevertheless challenges to measuring the effects of technological learning for a consumer product like LED lighting products in the context of a rapidly evolving and highly competitive market. In such a market, data on absolute component costs and production output tend to be closely held by manufacturing firms, rendering relevant data difficult to obtain. Because LED lighting products are distributed through mass-market and online consumer-facing channels, however, gathering information on retail price was straightforward using web-crawling approaches, permitting price trends to be easily tracked. However, during the early years of market adoption for LED lighting products there was also dramatic evolution in the mix of products and product features available in the market, such as the introduction of lamps with increasingly higher lumen output. This churn in the mix of product features creates a significant confounding factor for measuring the price effects of learning; to isolate learning effects it was essential to control for features either by restricting the sample under consideration (Gerke et al. 2014) or by using multivariate regression (Gerke et al. 2015). Generally speaking, evolving product features should be expected to pose challenges when undertaking any learning analysis based on the retail prices of consumer products. Thus, for researchers analyzing learning effects based on retail price, it will be important, in addition to price and production data, to also collect data on product features that might significantly impact price, and control for these in any analysis of learning.

The dramatic price drop for LED lighting products observed in the past decade, and the future declines still projected to occur, are also a reminder that it is important to account for the effects of technological learning when making strategic business or policy decisions regarding new and emerging technologies. Early LED lighting products entered the market at price points on the order of $100/klm, and, despite their energy efficiency and lifetime advantages, they were not cost competitive with the most efficient incumbent technologies (see Garbesi et al. 2018, for a cost-effectiveness comparison between early LED products and incumbent technologies). Nevertheless, rapid price declines meant that LED lamps had captured a majority of the US A-line lamp market by late 2017 (NEMA, 2018b) which likely conferred a significant market share advantage on firms that entered the LED market early, despite the prohibitive early price points.

In the context of policy, the LED price decline was a strong reminder of the importance of including the effects of technological learning when considering the economic impacts of energy efficiency policy: a projected fourfold decline in the price of LED lighting products by 2050 (US DOE 2016b) is likely to have substantial implications for the expected impacts of policies that impact these products. (For a broader discussion of technological learning in the context of developing energy efficiency policy, see Desroches et al., 2013). Moreover, forward-looking approaches to policy development may have interacted positively with technological learning effects to help encourage the transition to LEDs. Few or no viable LED lighting products existed that could replace incumbent technologies when the US and EU announced the phase-out of less efficient traditional lighting technologies (in 2007 and 2009, respectively) but these announcements themselves helped to create a market for LED lighting products, by effectively displacing an incumbent technology. In concert with directly supportive policies, such as state and utility efficiency programs and the US DOE's SSL program, the phaseout announcements may themselves have helped to spur research and development, driving a faster price decline for LED lighting products, and a faster technological transition, than would have occurred in the absence of the policies. (For a broader discussion of the potential interactive effects between energy efficiency policy and price trends, see Van Buskirk et al, 2013.)

Thus, a key lesson from the market for LED lighting products in the 2010s is that an appreciation for the effects of technological learning is essential for sound decision-making with regard to emerging technologies, both for market actors and for policymakers. Decisions that may seem bold, or even foolhardy, in the context of status-quo market conditions may in fact appear wise and beneficial once the full effects of technological learning are considered.

Acknowledgments

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