The International Database of Efficient Appliances (IDEA): A New Resource for Global Efficiency Policy

Brian F. Gerke, Michael A. McNeil, Thomas Tu, and Feiyang Xu[1],
Lawrence Berkeley National Laboratory

ABSTRACT

A major barrier to effective appliance efficiency program design and evaluation is a lack of data for determination of market baselines and cost-effective energy savings potential. The data gap is particularly acute in developing countries, which may have the greatest savings potential per unit GDP. To address this need, we are developing the International Database of Efficient Appliances (IDEA), which automatically compiles data from a wide variety of online sources to create a unified repository of information on efficiency, price, and features for a wide range of energy-consuming products across global markets. This paper summarizes the database framework and demonstrates the power of IDEA as a resource for appliance efficiency research and policy development. Using IDEA data for refrigerators in China and India, we develop robust cost-effectiveness indicators that allow rapid determination of savings potential within each market, as well as comparison of that potential across markets and appliance types. We discuss implications for future energy efficiency policy development.

Introduction

In order to meet their Nationally Determined Contributions under the Paris climate agreement, many countries will need to initiate or ramp up national appliance energy efficiency (EE) programs. Such programs often take the form of minimum energy performance standards (MEPS), which set mandatory minimum EE levels that products must meet to be sold legally, as well as labeling programs, which provide consumers with information on energy consumption. Globally, the most common standards and labeling (S&L) programs take the form of categorical labeling, in which governments define a number of efficiency levels (ELs) , starting from a MEPS level, for each covered product, and require a label to be displayed on each product at the point of sale, indicating the EE level that it meets.

In recent years, the expansion of appliance S&L programs has been a central focus of a coordinated multinational effort, known as the Super-Efficient Appliance Deployment[2] (SEAD) initiative of the Clean Energy Ministerial[3]. Among the barriers to advancement identified by SEAD is a lack of accessible market data to support S&L policy development. Effective program development requires an accurate understanding of the mix of product efficiencies available on the market, as well as the pricess of efficient products and

---

[1] Current Address: School of Creative Science and Engineering, Waseda University, Japan.
[2] http://www.superefficient.org/
[3] http://www.cleanenergyministerial.org/

correlations between EE and product features. Similar data is needed to evaluate key program impacts, such as national energy savings or consumer financial savings. Historically, the requisite data in most markets has been fragmentary, expensive to obtain, or completely unavailable. Price data resides mainly with retailers or market research firms, complete product feature information resides with manufacturers, and efficiency data is either stored in government certification databases (if they exist) or is available inconsistently if at all.

To improve this situation, we are developing the International Database of Efficient Appliances (IDEA), which is the first fully functioning implementation of a global data-access framework commissioned by SEAD (Katzman, McNeil, and Gerke 2013). That framework defined the structure of a unified database of appliance information with global scope. With the capacity for frequent data updates from public online data sources, IDEA enables real-time tracking of market trends to measure intra-market EE progress or price trends for efficient technology (e.g., as in Gerke, Ngo, and Fisseha 2015). With its global reach, IDEA enables international EE benchmarking, supports policy prioritization efforts, and can yield insights into the international effects of national EE policies, such as cross-market spillover effects or the dumping of inefficient products in unregulated markets.

A functioning prototype of IDEA is now complete and is collecting data for several appliances and countries. In this paper, we demonstrate the potential of IDEA to produce insights that can inform S&L policy development. Specifically, we analyze IDEA data on refrigerators in the Chinese and Indian markets and develop EE cost-effectiveness indicators which allow direct comparison of EE savings potential between different markets and appliance categories.

In the next section we summarize key details of the IDEA data set, and we describe the data used in this study. The Methods section describes our approach to analyzing and cross-comparing the market for refrigerator efficiency in the two countries. We present the analytical results in the Analysis and Results section. In the Conclusion, we briefly discuss potential implications for the relevant S&L programs, as well as the broader potential of IDEA for global appliance efficiency policy.

The Database

An overview of the features and functionality of IDEA is given elsewhere (Gerke, McNeil, and Tu 2015), as is a more general discussion of the benefits to effective policy development that would be expected from such a database (Katzman, McNeil, and Pantano 2014). We summarize the most important details here.

IDEA is intended to serve as a comprehensive database of price, EE, and feature information for appliances marketed in a broad range of international markets. To accomplish this, the IDEA software can automatically collect data, on a regular cadence, from an array of online retailers and manufacturer websites across a range of different markets and appliance categories. The resulting raw data is then integrated into the database via a series of mapping and normalization steps. First, identical appliance models within each market are identified from among the different data sources and past collection events, so that their data can be combined. Basic information about each product, such as brand name, model number, and price, is extracted for each appliance model, as are category-specific features (e.g., volume and cooling method for refrigerators, or cooling capacity and speed control for air conditioners). The extracted attributes, which may have different names in the different data sources, are then mapped to a canonical set of attribute names in IDEA, so that the data can be aggregated into a simple, tabular form. The set of canonical names can be arbitrarily expanded to allow new features, or entire new appliance categories, to be added to the database as desired. Duplicate attribute information is eliminated by ranking the data sources in order of their expected data quality, except that price data from all sources is recorded and archived to allow analysis of price trends. The result of this procedure is a data set containing a single, unified record for each appliance model, containing a full price history and attribute information drawn potentially from multiple different data sources.

The IDEA software then cross-references these data records, by model number, against data from certification databases associated with government-run EE programs. A complication is introduced in this step, because many government certification databases contain generalized model numbers, in which certain characters have been replaced by wild-card characters, to account for model groups that have identical EE profiles (e.g., sets of models that differ only in aesthetic features). IDEA includes a toolkit for identifying and handling such wild-card characters in the cross-referencing process. EE metrics and other product attributes are then extracted from the certification data and stored in the unified database using the same approach as just described for the retail data.

Data used in this study

The data used in this study is part of a larger data set gathered in the summer of 2015 to commission the IDEA prototype and demonstrate its functionality. That commissioning data included refrigerators and air conditioners collected from retail sites in China and India, which both have well established categorical labeling EE programs with public certification databases that enable the extraction of reliable EE information. In this study, we focus on the refrigerator data, since the EE metric for refrigerators is simply the unit energy consumption (UEC) in a fixed period (e.g., kWh per day or per year). This makes it straightforward to compute the annual energy savings associated with a given efficiency improvement.[4]

We collected data on refrigerators offered for sale online for three retailers in the Chinese market and two retailers in the Indian market. The IDEA software combined the information from these sites and cross-referenced the resulting models against the certification data associated with each nation's appliance S&L program. In China, the China National Institute of Standardization (CNIS) provides model-level data associated with the China Energy Label program,[5] while in India, the Bureau of Energy Efficiency (BEE) provides similar data for the Indian efficiency star-rating program.[6]

After eliminating models without a certification match, as well as extreme outliers in price and volume, the, final data set comprised 833 unique Chinese and 344 unique Indian refrigerator models with government-certified efficiency data. The cleaned Chinese dataset

[4] Certified UEC values for refrigerators in India and China are based on different test procedures, so they may not be equivalent. However, for the purposes of this analysis, we assume that each nation's test procedure is designed to yield an estimate of energy consumption under typical usage patterns in that country, so that the energy savings can be taken to be representative of real-world conditions in each country.

[5] http://www.energylabel.gov.cn/NewsMore.aspx?para=uncc_bagg

[6] https://beestarlabel.com/Home/Searchcompare

represents 90% of the models collected in IDEA. In the Indian market, there is a high fraction of uncertified models, in part because certification is voluntary for direct-cool units (for more detail, see Gerke, McNeil, and Tu 2015). As a result, the cleaned Indian dataset represents only 51% of all models collected in IDEA. Thus, any conclusions drawn from this data will apply only to the segment of the market that bears a certified efficiency label.

Methods

Analysis of efficiency distributions

To get a quick snapshot of the state of EE in each market, our first step in analyzing each data set is to examine the overall distribution of efficiency, as well as the market breakdown by EL. For refrigerators, MEPS and EL definitions are typically defined by a formula that yields a threshold UEC (in kWh/yr or kWh/day) as a function of the *adjusted volume*, V_{adj}, which is a weighted sum[7] of the volumes of compartments operating at different temperatures (for an example, see BEE 2015a,b). To obtain a single EE metric that can be used to compare refrigerators having different adjusted volumes, it is common to make use of the *energy efficiency index* (EEI), which is the ratio of a refrigerator's UEC to the MEPS value for its adjusted volume:

$$EEI = UEC/UEC_{MEPS}(V_{adj})$$

Since all refrigerators on the market must have UEC below the MEPS level, $EEI < 1$ for all legal refrigerators, by construction.

Refrigerator MEPS and EL definitions also typically vary by cooling method, since frost-free refrigerators use more energy than direct-cool units, all else being equal. It will thus be important to divide our dataset by cooling method as well. The IDEA data for China contains information on cooling method, so this division is straightforward to perform. For India, information on cooling method was not directly available, but it was possible to categorize refrigerators by number of doors. Inspection of the correlations between energy and volume, compared to the India star-rating thresholds, suggests that refrigerators in India having a single door are almost universally direct cool, while multi-door units are nearly all frost-free. Thus, we used door count as a proxy for cooling method for Indian refrigerators.

The CNIS database provides EEI values for all certified Chinese refrigerators, computed relative to the original Chinese MEPS level, which has since been updated. It is simple to rescale these to the current MEPS level by dividing through by the maximum reported value. The BEE database does not report EEI, and it reports total volume, rather than adjusted volume, so EEI for Indian refrigerators cannot be computed from the BEE data alone. Fortunately, the retail data in IDEA frequently includes information on both refrigerator and freezer volume, allowing us to compute an average volume-adjustment factor for Indian refrigerators, from which we can compute an approximate EEI relative to the MEPS that were in force for Indian refrigerators in 2015 (BEE 2015a,b).

[7] Freezers, for example, have a larger weight than fresh-food compartments, because of their higher energy intensity

The cost of conserved energy

A useful metric for the cost-effectiveness of a particular EE measure is the *cost of conserved energy* (CCE), which is the cost of the measure per unit of energy conserved (Rosenfeld et al. 1993). For instance, a utility demand-response program that pays consumers one cent for an immediate reduction in demand of one kWh would have a CCE of $0.01/kWh. In the case of appliances, the measure cost is equal to the increase in appliance purchase price associated with a given EE improvement, and the conserved energy is the total energy saved over the product lifetime. If the CCE is smaller than the relevant energy price (e.g., the price of electricity in the case of refrigerators), then the EE improvement is cost-effective. The primary value of the CCE metric is that it allows disparate energy-conserving measures to be compared on an equal footing. It has been used in the past (e.g., McNeil and Bojda 2012) to compare the relative cost-effectiveness of different EE improvements for various appliances in the US market; here we will use it to compare appliance EE improvements both within and across international markets.

Since the energy savings from appliance EE improvements are not instantaneous but rather occur over the lifetime of the product, it is important to account for the time value of money when computing the CCE. Future energy-cost savings have lower value to a consumer than an equal amount of present-day savings because the present savings could be invested at some rate of return. This can be accounted for by annualizing the price increment—i.e., by computing the annual outlay over the product lifetime that would have a present value equal to the price increment for the EE improvement. Thus, the CCE for an improvement in appliance efficiency over some baseline EE level is

$$CCE \equiv \frac{\Delta P}{|\Delta UEC|} \times \frac{r}{1-(1+r)^{-L}}.$$

where ΔP is the price increase associated with the EE improvement, ΔUEC is the resulting change in UEC, L is the product lifetime and r is a discount rate that accounts for the time value of money. The term involving r and L is the annualization factor, also called the capital recovery factor, which converts ΔP into its annualized value.

In this study, we compute the CCE for refrigerators in China and India, using the predictions of regression models for price and UEC that have been constrained using IDEA data. For a given fixed representative feature set, we compute the CCE of EL k relative to a baseline level k_0 using $\Delta P = \hat{P}_k - \hat{P}_{k_0}$ and $\Delta UEC = \widehat{UEC}_k - \widehat{UEC}_{k_0}$, where $\hat{P}_k$ and $\widehat{UEC}_k$ are the price and UEC values predicted by the regression models for a product at EL k.

Regression analysis of refrigerator price and energy consumption

To demonstrate the power of the cross-referenced IDEA dataset, we used the data to constrain regression models for the retail price and the annual UEC, as a function of product features and efficiency labeling information. For the purposes of this analysis, we use the most recently observed online retail price and the UEC as reported in the relevant government certification database. As discussed above, our ultimate purpose in constraining these models is to compute the CCE for various EE improvements.

The IDEA data contained sufficient information to consider the following types of regression variables for predicting price and UEC: total refrigerator volume, brand name, cooling method (direct cool vs. frost free), and labeled EL. It is natural to suppose that, among these variables, volume will have the largest impact on refrigerator price and energy consumption, since this drives both the bill of materials for manufacturing and the total amount of cooling required. In both cases one would expect the relation to take the form of a power law on simple physical grounds. On similar grounds, one might also expect that changes in energy efficiency or refrigerator features would have a multiplicative effect on price and energy consumption, rather than an additive effect, since the impact of a given improvement should scale with volume. As discussed in the Analysis and Results section, exploratory analysis of the data confirms this basic picture.

Because we expect power law and multiplicative relations, it is appropriate to consider regression models for the natural logarithm of the dependent variables; that is, we build regression models that predict the quantities $\ln(P)$ and $\ln(UEC)$. We detail our selection of specific regression variables in the Analysis and Results section.

Selection of the baseline efficiency level

To determine the CCE for a particular EL, it is necessary to compare the costs associated with that level to some baseline level. In India, products are divided into five ELs, rated from one star to five stars, with one star being the least efficient. The China Energy Label divides the market into three numbered ELs, with level 3 being the least efficient. In the simple picture often used to conceptualize EE impacts, price is assumed to increase steadily with efficiency, so the baseline is taken to be the least efficient product on the market. This picture may not hold in dynamic real-world markets, however, especially during periods of policy transition. In particular, India in 2015 was in the midst of a series of regular MEPS and labeling updates, so that the 2015 2-star (3-star) level is now the MEPS level for frost-free (direct-cool) refrigerators (BEE 2015a,b). In 2015, the Chinese government was also expected to update its MEPS in the near future, so it was a reasonable expectation that level 3 refrigerators, at least, would soon be eliminated. It is possible, therefore, that the lowest ELs in each market are in the process of being depopulated and no longer contain a representative product mix. This would make our regression fits for these ELs unreliable. For this reason, we choose our baseline in each market to be the lowest EL that may reasonably have been expected to remain available in the future, at the time of data collection—namely, the 2-star level in India and level 2 in China.

Analysis and Results

Figure 1 shows the EEI distribution of models in IDEA, for each market and cooling method[8]. The EL definitions used for EE labeling in both India and China are constructed as

[8] Note that efficiency labeling is voluntary for direct-cool refrigerators in India, so the EEI distribution may not be representative of this market segment.

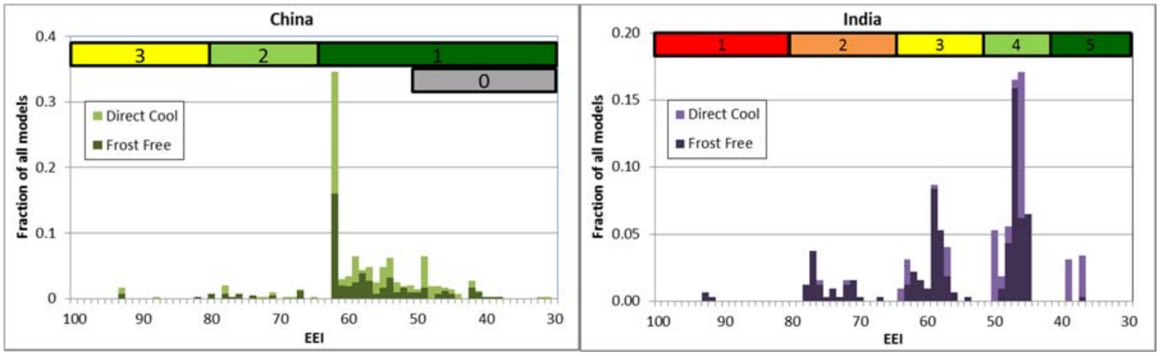

Figure 1. Stacked histograms showing the distribution of refrigerator models by energy efficiency index, separated by cooling method, in China (left) and India (right). Colored bars at top show the EL definitions for labeling programs in each nation, as well as our definition of an ultra-efficient level 0 for the Chinese market.

simple fractions of the MEPS level, with the lowest EL having its threshold at the MEPS level, and each subsequent EL having a threshold that is 80% of the previous threshold. This makes it simple to use the EEI to determine the breakdown of each market among the ELs. The EL definitions are indicated by colored bars in the figure.

The Indian market has significant representation from several different ELs; by contrast, the Chinese refrigerator market is heavily concentrated at the highest EL. In both markets, EEI is clustered within the ELs, suggesting that the labeling programs are impacting product design decisions. Notably, in both markets, there are very few models at the lowest EL, suggesting that the 2015 markets in both countries may already have been responding to the upcoming MEPS updates. In addition, models meeting level 1 in China populate a strikingly wide range in efficiency, as broad as the other two levels combined. This suggests that the current China Energy label definitions for refrigerators may have fallen behind recent technological EE improvements. To allow a more granular accounting for efficiency in our regressions, it will be helpful to subdivide this level. For the remainder of this analysis, we proceed as if the Chinese refrigerator label had a fourth EL, which we refer to as level 0, having a minimum threshold 20% more efficient than the level 1 threshold, as shown in Figure 1.

Refrigerator regression models

We now turn to developing detailed regression models for refrigerator price and UEC in India and China. Figure 2 shows the relation between price and volume for various market segments, illustrating some of the primary correlations to be included in the price models. In both markets, a correlation between price and volume is apparent, taking the approximate form of a power law. In addition, systematic differences in price between different ELs are apparent in certain cases: for example, prices for level 3 models in China, and for 1-star models in India, appear to be systematically higher than average. Finally, in the Chinese market especially, it appears that direct cool units (triangles) may follow a different price-volume relation from frost-free units (circles). Therefore, our regression models for price include each of the explanatory variables represented in the figure, as well as an interaction

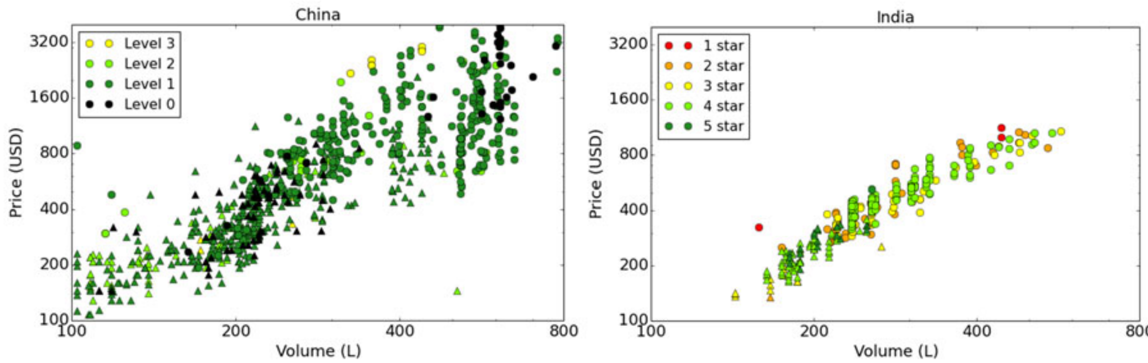

Figure 2. Scatter plots of price versus volume for refrigerators in China (left) and India (right). Refrigerator models are color-coded by efficiency level. In each plot, triangles indicate direct-cool refrigerators, and circles denote frost-free units. In both plots, the horizontal and vertical axes have a logarithmic scale.

term between volume and cooling method for the Chinese market. Similar considerations drive us to select a similar set of explanatory variables in our regression models for UEC.

Even after controlling for the variables displayed in the figure, we find that there remains substantial scatter in price, which is likely attributable to additional refrigerator features that have varying levels of consumer desirability. Further exploration of the data sets reveals that a significant amount of this scatter is correlated with product brand names. Each market can be fairly straightforwardly subdivided into relatively low-priced mass-market brands and relatively high-priced luxury brands. Thus, we additionally include a categorical variable to distinguish luxury from mass-market brands in our price regression model. Further exploratory data analysis shows no significant impact on price or UEC for the other variables available in IDEA.

As we discussed in the Methods section, because we expect power-law and multiplicative relations, it is appropriate to build logarithmic regression models that predict $\ln(P)$ and $\ln(UEC)$. We construct separate regression models for price and UEC in each country considered. Table 1presents the regression variables included in each model, and the associated coefficients that we obtained from our regression fits. For each categorical variable considered (EL, cooling method, and brand type), one category is excluded from the variable set, since it is implicit in the overall constant that we include in each model. In each case, we are free to select which level to exclude, and in particular we have chosen to exclude the EL category corresponding to the lowest predicted price, which happens to be the same as our selected baseline for computing the CCE in each country. (That is, we have excluded level 2 in the Chinese market and the 2-star level in the Indian market.) Given this selection, all EL coefficients included in the price model are positive by construction.

The cost of conserved energy

We used the regression fits to predict the CCE for refrigerators having a fixed representative set of features for the Chinese and Indian markets. In both cases, we constructed a separate set of representative features for the direct-cool and frost-free categories, as follows. We suppose that mass-market brands are typical, so each representative unit is assumed to bear a mass-market brand name. Then, for each cooling

Table 1. Regression variables, coefficients, and standard errors (in parentheses) for price and UEC models estimated using the IDEA dataset.

	China		India	
Regression variable	Price model	UEC model	Price model	UEC model
ln(volume)	1.18 (0.05)	0.50 (0.02)	1.39 (0.04)	0.06 (0.02)
frost-free	1.71 (0.05)	-1.15 (0.15)	0.17 (0.02)	-1.46 (0.14)
luxury brand	0.44 (0.04)	-	0.07 (0.02)	-
ln(volume)*frost-free	-0.25 (0.08)	0.24 (0.03)	-	0.26 (0.03)
1 star	-	-	0.25 (0.08)	0.25 (0.01)
2 star/level 3	0.40	0.15 (0.03)	-	-
3 star/level 2	-	-	-0.03 (0.03)	-0.24 (0.01)
4 star/level 1	0.01 (0.04)	-0.29 (0.01)	0.01 (0.03)	-0.48 (0.01)
5 star/level 0	0.13 (0.06)	-0.51 (0.02)	0.09 (0.04)	-0.69 (0.01)
constant	-0.46 (0.25)	-3.11 (0.08)	-1.92 (0.21)	5.70 (0.12)
R^2 statistic	0.81	0.92	0.92	0.97
Units of prediction	USD	kWh/day	USD	kWh/yr

Note—where no coefficient is shown, the variable was not included in the model. Standard errors are computed using techniques robust to heteroscedasticity and covariance.

method in each market, we select a characteristic value for the volume. In the Indian market, our representative direct-cool and frost-free refrigerators have volumes of 193 liters and 293 liters, respectively, which are the average values for each cooling method in our dataset. In the Chinese market, the volume distributions are multimodal, so average values are not necessarily representative. Hence we choose representative volumes that are near the values most commonly observed for direct-cool and frost-free refrigerators on the Chinese market. These are 200 and 550 liters, respectively. For these representative feature sets, we use our regression models to predict the price and UEC for a refrigerator at each efficiency level. From these predicted values, it is straightforward to compute the CCE associated with changing the representative unit's efficiency level while holding other features fixed.

Figure 3 shows the average CCE, for each representative refrigerator, associated with moving from the baseline to a higher EL (movement to lower ELs is not shown, since those ELs are assumed to be exiting the market under upcoming MEPS updates). CCE is plotted as a function of the average annual energy savings associated with the change in EL, according to the UEC regression model. Error bars represent the standard error on the predicted CCE value. Purple and green dashed lines show representative urban residential electricity tariffs for each country, in New Delhi (Delhi Electricity Regulatory Commission 2015) and Beijing (eBeijing 2016), respectively. Where the CCE falls below the local electricity price, the EE improvement is nominally cost-effective.

The figure gives a compact summary of the state of the market for efficient refrigerators in China and India which can be used to inform and prioritize policymaking efforts. Cost-effective energy savings above the baseline appear to be available to typical urban consumers for all representative refrigerators considered. In the Indian market, moving to 3-star or 4-star products (as defined in 2015) is achievable at a price increment that is

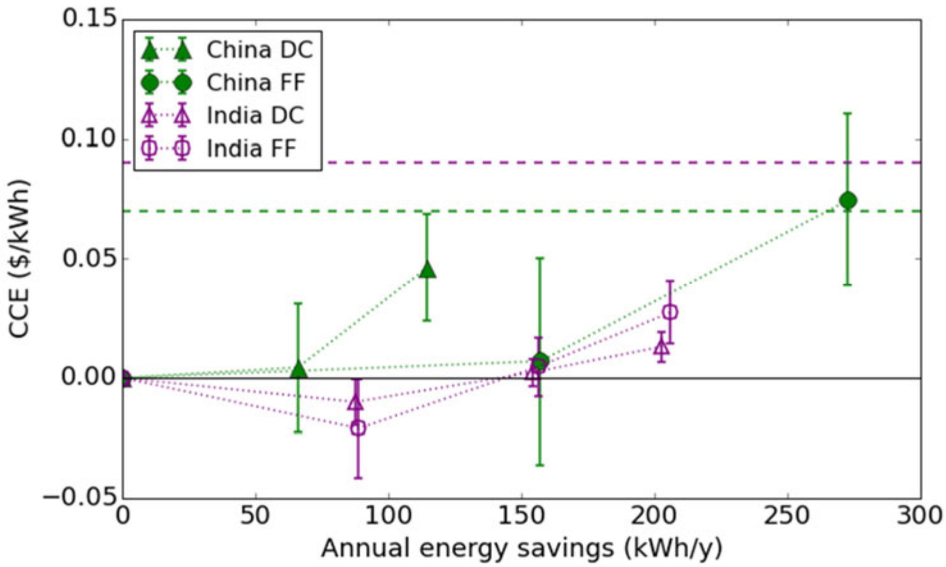

Figure 3. Cost of conserved energy for EE improvements to representative direct cool (DC) and frost-free (FF) refrigerators in the Chinese and Indian markets, as a function of the annual energy saved relative to the selected baseline. The assumed features of each representative refrigerator are described in the text. Error bars show the standard error for each predicted value. Purple and green dashed lines indicate representative urban electricity tariffs for India (New Delhi) and China (Beijing), respectively.

statistically indistinguishable from zero. Moreover, moving to the 5-star EL appears to be cost-effective, with high confidence, for all typical Indian refrigerators, yielding UEC savings in excess of 200 kWh/yr. (It is important to caution, however, that there is limited data for frost-free refrigerators at this EL.) Moving to EE level 1 appears to be cost-effective for all Chinese refrigerators, with marginal confidence, yielding savings exceeding 50 (150) kWh/yr for direct-cool (frost-free) refrigerators. Even larger savings, may be available at level 0, but there is lower confidence in the cost-effectiveness.

Moreover, it is worth noting that our CCE estimates are based on the observed retail price increment for each EE improvement, which may not have a perfect correlation with the associated manufacturing costs. Indeed, recent studies (Spurlock 2013, Van Buskirk et al. 2014) suggest that MEPS updates in the US have yielded *lower* overall appliance prices, possibly because they eliminate a form of price discrimination that pairs high-efficiency products with higher markups. If this is also the case in the markets studied here, then the CCE values we estimated here may overstate the costs associated with EE policy updates.

Conclusion

This paper demonstrates some of the ways in which IDEA can open new windows on international appliance EE markets and policies. First, we developed a simple snapshot of the status of refrigerator efficiency in India and China relative to current S&L policy definitions. This analysis yields some evidence that both markets may already be responding to expected MEPS updates by eliminating models at the lowest efficiency levels. We then demonstrated regression-based techniques for using IDEA data to construct a metric of cost-effectiveness, based on the CCE, that can be compared across markets and appliance categories. This metric shows that substantial cost-effective EE savings may still be available in both markets, even after planned policy updates are complete.

This kind of analysis could be valuable for prioritizing EE policy measures from within a range of possibilities, to focus on those actions that are most likely to be impactful and cost-effective. For instance, it appears that there is ample space for new, higher EL definitions within the Chinese EE labeling program. Near-term adoption of new ELs could thus drive higher consumer uptake of efficient technologies, even without the adoption of more stringent MEPS (which would typically have a slower time frame for implementation). With regard to potential MEPS updates, in India it may be possible to move to near the market-maximum EL in a cost-effective manner, suggesting that continued MEPS updates might pay dividends. In China, only a portion of the savings available on the market is likely to be cost-effective, indicating that a more measured approach may be advisable.

It is important to emphasize, however, that the present analysis alone is not sufficient to recommend any particular policy actions, or to predict the impacts thereof. For instance, one might be tempted to conclude definitively that India’s MEPS levels should be updated to the maximum EL. Significant caution is warranted, however: the present analysis deals only in market averages for consumers in representative urban areas and does not account for the full range of consumers and product options. It is also possible that there are unique elements of consumer utility that are only available at the lower ELs but are not included in our model. A more detailed analysis of the distributions of prices, features, and consumer profiles would thus be necessary to support any further updates to MEPS in either country.

The current results do suggest, though, that a more careful analysis could yield substantial cost-effective energy savings. IDEA can serve as a valuable resource in this context as well, since it enables a much more detailed consideration of market distributions than we carried out here. Moreover, with the capacity for real-time market tracking during periods of policy transition, IDEA will have an important future role to play as a tool for real-time evaluation of policy impacts. We plan to explore this capacity in future work.

Acknowledgement

This work was supported by the Laboratory Directed Research and Development Program of Lawrence Berkeley National Laboratory under U.S. Department of Energy Contract No. DE-AC02-05CH11231.

References

BEE (Bureau of Energy Efficiency, India). 2015a. “Schedule 1: Frost-Free (No Frost) Refrigerator.” https://beestarlabel.com/Content/Files/Schedule1_FFR.pdf

———. 2015b. “Schedule 5: Direct Cool Refrigerator.” https://beestarlabel.com/Content/Files/Schedule5-DCRefrigerator.pdf

Delhi Electricity Regulatory Commission. 2015. "Order on True Up for FY 2013-14, Aggregate Revenue Requirement and Distribution Tariff (Wheeling & Retail Supply) for FY 2015-16 for Tata Power Delhi Distribution Limited (TPDDL)." http://www.derc.gov.in/ordersPetitions/orders/Tariff/Tariff%20Order/2015-16/TPDDL.pdf

eBeijing. 2016. "Guide to Heating, Electricity, Water, and Gas – Policies and Procedures." Accessed February 29, 2016. http://www.ebeijing.gov.cn/feature_2/GuideToHeatingElectricityWaterAndGas/PriceGuide/t1107813.htm.

Gerke, B. F., McNeil, M. A., and Tu, T. 2015. "International Database of Efficient Appliances (IDEA): A Novel Tool for Efficiency Program Development and Evaluation." In *Proceedings of the 2015 International Energy Program Evaluation Conference.* Long Beach: IEPEC. http://www.iepec.org/wp-content/uploads/2015/papers/026.pdf.

Gerke, B. F., Ngo, A., and Fisseha, K. 2015. "Recent price trends and learning curves for household LED lamps from a regression analysis of Internet retail data." LBNL Report No. 184075. Berkeley: LBNL. http://eetd.lbl.gov/publications/recent-price-trends-and-learning-curv

Katzman, A. McNeil, M. and Gerke, B. 2013. "SEAD Energy Efficiency Data Access Project: Final Report." Washington DC: SEAD. http://www.superefficient.org/~/media/Files/SL%20Project%20Reports/SEAD%20Data%20Access%20Report/SEAD%20Data%20Access%20Final%20Report.pdf.

Katzman, A., McNeil, M, and Pantano, S. 2014. "The benefits of creating a cross-country data framework for energy efficiency." *Proceedings of the 7th International Conference EEDAL'2013 - Energy Efficiency in Domestic Appliances and Lighting*. Luxembourg: Publications Office of the European Union.

McNeil, M. A. and Bojda, N. 2012. "Cost-effectiveness of high-efficiency appliances in the U.S. residential sector: A case study." *Energy Policy* 45: 33-42.

Rosenfeld, A., Atkinson, C., Koomey, J., Meier, A., Mowris, R. J., and Price, L. 1993. "Conserved Energy Supply Curves for U.S. Buildings." *Contemporary Economic Policy* 11: 45-68.

Spurlock, C. A. 2013. "Appliance Efficiency Standards and Price Discrimination." LBNL Report No. LBNL-6823E. Berkeley: LBNL. http://eetd.lbl.gov/publications/appliance-efficiency-standards-and-pr

Van Buskirk, R. D., Kantner, C. L. S., Gerke, B. and Chu, S. 2014. "A retrospective evaluation of energy efficiency standards: policies may have accelerated long term declines in appliance costs." *Environ. Res. Lett.* 9, no 11: 114010.