Designing efficiency standards and labelling programs to accelerate long-term technological innovation

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Abstract
In this paper, we discuss how redesigning certain aspects of energy efficiency policies and programs might support the increasingly urgent goal of accelerating long-term technological innovation rates for efficiency technologies. We conduct this discussion in terms of a "Moore's Law of Energy Efficiency" (MLEE) hypothesis which provides a quantitative relationship between the long-term rate of energy efficiency improvement and key market parameters. An equation for a MLEE hypothesis is derived in an appendix to this study assuming conditions of steady EE improvement, of continuous EE adoption and a constant log (i.e. relative) variance in the range of EE performance in the product market distribution. The specific modifications of the policy features and measures discussed in this paper include: (1) *Market transparency:* enhancement of market monitoring and market transparency (e.g. using Internet data) so that energy efficiency accurately identified and incentivized, (2) *Improved savings estimation:* technical improvement in energy savings monitoring and measurement, (3) *Crowd-sourced data:* crowd-sourcing empirical energy use and product performance data so that product performance measurement can be freed from the constraint of test lab measurements that do not fully factor in behavior or consumer diversity, (4) *Correlating energy savings with consumer value:* aligning energy savings improvements with product features and attributes that provide other dimensions of consumer value, (5) *Off-grid products/appliances:* development of policy support and product rating infrastructure for the off-grid and autonomously powered product markets, and (6) *Enhanced technology road-mapping:* the development of long term technology roadmaps to set improvement expectations and to address the large off-grid market potential for super-efficient products. For each policy and program enhancements, we discuss how the feature or measure might be implemented and why it may accelerate long term efficiency improvement rates in the context of the MLEE hypothesis.

Introduction
It has been recognized – for as long as two decades – by economists and policy analysts that it will be necessary to accelerate the process of technological innovation for clean energy technologies, in order to meet the global policy objective of constraining greenhouse gas (GHG) emissions at reasonable levels and at relatively modest incremental investment cost (Grubb, Chapuis & Dong, 1995; Nakićenović, Victor & Morita 1998; Weyant & Olavson, 1999). More recently, there has been a growing recognition amongst governments and the energy and climate mitigation policy community that accelerating technology innovation is going to be a cornerstone for any strategy that is likely to meet medium and long term climate change mitigation and energy policy goals (Newell, 2010; Stern, 2006).

In the academic economics and policy analysis community, innovation has long been recognized as a key driver of economic progress (Schumnpeter, 1934) and a key means for solving environmental problems (Stewart, 2010; Grubb, 2004). But it should be noted that not all innovation leads to energy savings and/or environmental progress. Both refrigerators and televisions provide examples of products that have had energy savings from efficiency gains partially offset by innovations that encourage, larger, more energy consuming attributes. As refrigerators have gotten more efficient per unit volume of cold storage, they have also in many parts of the world gotten larger. A similar phenomenon has been seen with televisions which have seen rapidly increasing screen area while the energy use per unit of screen area has dropped rapidly in recent years.

In addition to the evolution of features that can diminish energy savings from energy efficiency, there is also a rebound effect that has several different modes of operation that can decrease net energy savings (Borentstein, 2013; Herring, 2006). Some authors have introduced a concept of "sufficiency" to help create product energy performance policies that can more effectively lead to sustained energy savings (Princen, 2005). But whether policies are defined in terms of efficiency or sufficiency, satisfying policy objectives will require accelerated progress in energy efficiency technologies.

With respect to specific global objectives, the need for accelerated technological innovation has been recently codified into the goal of doubling the rate of energy efficiency improvement.[1] With this clarified technological progress target, the goal of a 2X acceleration of technology improvement rates is receiving wider adoption and acceptance in the international energy policy community as a concrete and measureable improvement target for long term energy efficiency (EE) improvement in markets. In particular, the Sustainable Energy for All initiative of the United Nations (SE4All) has explicitly set as one of its two key goals to: "double the global rate of improvement in energy efficiency".

Given the broad agreement in the international efficiency policy community on the goal of doubling the pace of progress on energy efficiency, the technical question that arises next is: How may such how such goals be achieved with the appropriate policy and program designs? Specifically we need to ask:

- What are possible technical factors that can drive long term efficiency improvement rates?
- How can policies and technologies be designed to move markets faster?
- How can policymakers translate the over-all long term goal of accelerated efficiency improvement into specific objectives, targets, and policy designs for different energy end uses in different markets?

Some recent empirical work on the impacts of different energy efficiency programs and policies in different product markets is beginning to shed some light on some possible answers to these questions.

For the solar PV industry, the policies necessary to help accelerate technological innovation have been studied and discussed for decades, and have been successfully applied to bring solar PV to maturity using a combination of R&D, policies that promote diffusion and adoption (Neij, 1997), and consumer and commercial incentive programs and/or mandates (Crago & Chernyakhovskiy 2014). But a key difference between solar PV and energy efficiency is that the policy goal for solar PV is a one-time switch from traditional electricity sources to a new, cleaner source. Whereas for EE, the long term need of policy is for a continuing improvement in technology over one to several decades. The mathematical and modelling characteristic of designing policies that can meet this type of improvement rate objective is therefore qualitatively different than the solar PV case.

One recent attempt of modelling continuous EE improvement created a set of model equations with rapid technological learning for the incremental cost of increased energy efficiency and applied this to data for refrigerators in the European market. This principal was used to develop a set of partial differential equations (PDEs) for dynamic price-efficiency forecasting (Van Buskirk, 2013) in a continuously dynamic market. But the complicated formulation of the mathematics of the model has made it difficult to use such modelling for practical policy analysis applications.

Simpler approaches have used the application of experience curves and empirical trend analysis to illuminate policy options, and potential costs and benefits of energy efficiency policies (Siderius, 2013; Siderius 2014, Desroches et.al.; 2013). These analyses have developed useful projections of potential policy benefits and costs, but do not yet provide predictions how underlying innovation rates might be changed by improvements in policy design.

A recent retrospective study of the long term impacts of EE standards and labelling policies (Van Buskirk, et.al., 2014) has demonstrated a strong association between the implementation of EE standards and labelling policies and an acceleration of the long term decline of total appliance life-cycle cost (LCC), and sometimes an acceleration of innovation in quality-adjusted appliance price. This innovation acceleration occurs relative to a pre-policy period with little or no market information regarding product efficiency and energy use. One implication of that study might be that increased transparency and information regarding efficiency and energy use accelerated innovation. The study also demonstrated that the incremental cost of energy efficiency for the examined appliances decreases at a rate that is substantially faster than the first cost of the base appliance when policies are active. The ability of the price-efficiency relationship to shift over time indicates that the price-efficiency relationship is highly dynamic and that such dynamics can potentially be influenced by elements of policy design.

Analogous results were found over a relatively short time period for clothes washers in the U.S. for standards implemented over the previous decade (Spurlock, 2014), where both an immediate level drop and as well as a downward break in in-model price trend was observed coincident with EE standards. It was also found in the study that a price discrimination model of a diversified oligopolistic product market (Mussa & Rosen, 1978) could potentially explain elements of the observed price dynamics.

In an appendix at the end of this article, we provide a simplified rate equation for EE improvement rate under conditions of an idealized, dynamic market equilibrium. The assumptions of the dynamic equilibrium are that energy efficiency is improving at a constant, exponential rate over time, that quality-adjusted product prices are declining at a constant exponential rate, that the variance and correlation between log efficiency and log price is constant over time in the market, and that new more efficient products are constantly being adopted at the top

1. See: http://www.se4all.org/our-vision/our-objectives/energy-efficiency/. Accessed January 4, 2015.

of the market while older, less efficient technologies become obsolete and leave the market at a constant rate. We refer to this simplified rate equation derived from these assumptions as the adoption form of the "Moore's Law of Energy Efficiency" (MLEE). We describe it as a "Moore's Law" as an analogy to the famous Moore's Law for computer technologies. The Moore's Law for computers describes the consistent, continuous exponential improvement of the technical performance of computer chip technologies (Moore, 1965).

EQUATION FOR ENERGY EFFICIENCY IMPROVEMENT RATE

In the derivation of the equations describing the MLEE, the equations of steady, dynamic improvement and adoption of EE are used to relate a steady, exponential EE improvement rate to three key empirical product market parameters: (1) price variance with respect to EE, (2) adoption rate, and (3) elasticity of price with respect to EE. In this way, the MLEE in this form provides the following equation relating long term EE improvement rates to market parameters:

$$\alpha = \frac{\gamma q}{\varepsilon} \qquad (1)$$

In this equation, α is the steady, exponential rate of EE improvement, γ is the logistic distribution scale parameter for log price which is proportional to the variance of log price with respect to log EE, q is the logistic adoption rate (Bass, 1969) and ε is the elasticity of price with respect to EE. Key assumption of this version of the MLEE is that the adoption rate, q, is the same for all efficiency levels, that there is a power-law price-efficiency relationship, and that the elasticity of price with respect to efficiency is constant over time. This equation therefore represents a rather idealized quasi-steady set of conditions for the appliance market EE improvement dynamics.

The version of MLEE described in equation (1) provides the rate of improvement in terms of the dynamic distribution parameters of a product market. There is an alternative version of MLEE that assumes life-cycle cost minimization of a market that is written in terms of the economic cost parameters of the product market. This version of MLEE provides a relationship between the energy use of a product and the price of electricity, present worth factor, product price and price elasticity under cost-minimizing conditions. This variant of MLEE argues that if these economic parameters change, then the energy use and product EE must change to maintain cost minimization (Van Buskirk, et.al., 2014; Van Buskirk, 2015). Since in this study we wish to forecast the long term rate of EE improvement in terms of market price elasticities and adoption without forecasting product and electricity prices, we use the adoption form of MLEE provided by equation (1).

Equation (1) codifies a fairly common sense relationship between potential energy efficiency improvement rates and product market parameters under idealized conditions. The equation indicates that improvement rates can be large when one or more of the following three market conditions are met:

1. When some consumers are willing to pay a high price for efficiency relative to the market average price;
2. When the market adoption rate for new products is fast; and
3. When the elasticity of price with respect to EE is small.

This mathematical result is relatively intuitive. If some consumers are willing to pay a high price for efficiency and high efficiency appliances are adopted at a high rate, then of course one might expect the rate of efficiency improvement in a market to be high because manufacturers might be expected to compete to provide high efficiency appliances to customers willing to pay high appliance prices.

Similarly if the adoption rate for newly introduced energy efficient appliances is high (i.e. large q), then one might expect manufacturers to fairly rapidly introduce new, more efficient appliances to the market to take advantage of the potential market share growth that such efficient appliances might be able to garner.

Additionally, if the price barrier to adopting more efficient products is low (i.e. low price elasticity with respect to efficiency) it would be expected that the rate at which efficiency can be improved would be relatively high.

The rest of this paper describes six different policy measures or policy features that may help accelerate the long term rate of energy efficiency improvement consistent with equation (1). The six features and measures are:

1. Increasing market transparency.
2. Improving the accuracy and veracity of energy savings measurements.
3. Crowd-sourcing energy savings data to increase knowledge of actual in-field energy savings.
4. Correlating product consumer value (and desirable product attributes) with energy efficiency.
5. Promoting EE for off-grid applications.
6. Enhancing EE technology road mapping and research and development.

In Table 1, we provide a summary of the mechanisms by which different policy features or measures may accelerate EE innovation rates as inferred from the MLEE hypothesis as described by equation (1).

Policy features and tools that can accelerate innovation

Next, we discuss in some detail, the six potential energy efficiency policy features and measures that can play a role in accelerating EE improvement rates. We describe how the policy feature or measure may quantitatively impact the parameters of the MLEE equation and therefore impact the EE improvement rate. We also review some of the articles and studies in the energy efficiency policy and economics literature that may provide some evidence for the potential impact of different policy features or measures on efficiency improvement and innovation.

MARKET TRANSPARENCY

Consumers, EE program managers, and policy-makers cannot buy or promote EE if they cannot see and understand how much EE is being purchased at what price and how much benefit the EE is providing.

A recent stated-preference consumer choice investigation of consumer willingness to pay for energy efficiency (Newell &

Table 1. Inferred mechanisms for EE innovation acceleration for different policy features and measures.

Policy Feature or Measure	*Principal Mechanisms for Accelerating Innovation Rate*
Market transparency	• Increase incremental price of EE, which increases γ • Increase adoption rate of more efficient products
Improved (in-field) savings estimation	• Decrease uncertainty, leading to greater willingness to pay for EE, which increases γ
Crowd-sourced data acquisition	• Improve savings estimates [see above] • Could yield increased range of savings estimates, increasing γ
Aligning/correlating energy savings with other dimensions of consumer value	• Increase adoption rate of more efficient products • May increase willingness to pay for EE, which increases γ • New feature(s) may cross-subsidize EE, decreasing the observed market price elasticity with respect to the EE attribute
Developing EE product markets for off-grid applications	• Increase willingness to pay for EE, which increases γ • Increase adoption rate of more efficient products overall, if off-grid product market grows quickly
Enhanced technology road-mapping and R&D	• Ensure continued availability of high-efficiency products, increasing (or at least maintaining) γ • Lower the incremental cost of EE products, decreasing the observed market price elasticity with respect to EE

Siikamaki, 2013) showed for that when consumers are given information regarding the energy efficiency of water heaters in a variety of formats, that they are willing to pay a higher price for more efficient water heaters that corresponds roughly to cost-minimizing behaviour (see Table 4 of the reference). Hence market transparency is potentially a very valuable tool for market conditions where product price is correlated with energy efficiency.

Potential impacts of market transparency on the MLEE equation

Market transparency is a policy feature that can impact the terms in the MLEE equation in several ways. The key impact of market transparency is that it should allow consumers to pay a higher incremental price for energy efficiency, hence increasing γ, the parameter that describes the variance in price with respect to EE. Enhance market transparency should also enable an increase in the adoption rate of more efficient appliances because more early adopters can now identify and purchase more efficient products. A recent long term empirical retrospective study (Van Buskirk, et.al, 2014), is perhaps the clearest demonstration of how an increase in market transparency (i.e. comparing a period with standards and labelling policies with a period before such policies) with respect to energy efficiency can have an associated change in product market innovation rates.

IMPROVED SAVINGS ESTIMATION

Errors and mismatches between the apparent energy savings of appliances and equipment and the actual energy savings of thee equipment can have the effect of de-correlating energy savings and energy use from efficiency ratings. When consumers have increased risk of not obtaining the expected savings this can also decrease their willingness to pay for energy efficiency.[2]

2. Alternatively it is possible that some consumers are in some sense "over-paying" for efficiency because they believe that the savings are actually larger than they are. In this case more accurate energy savings estimates could lead to decreased innovation willingness to pay and innovation rates.

A key consumer impact of the lack of correlation between actual energy savings and efficiency rating is to potentially increase the "efficiency gap" which is the difference between the apparent unwillingness of consumers to pay for energy efficiency and that efficiency that appears to be in their long economic self-interest (Gerarden, Newell & Stavins, 2015). The technical literature notes that a specific mechanism by which inaccurate energy savings estimates can increase the efficiency gap, namely: "Analytical assumptions can contribute to the EE gap, by overestimating projected energy savings or failing to account for consumer heterogeneity. Engineering-economic analyses … [can] … estimate energy savings that exceed savings observed in ex post energy consumption data" (Davis, Fuchs, & Gertler, 2014).

Potential impacts of improved savings estimation on the MLEE equation

Errors or inaccuracies in the actual energy savings compared to the apparent or rated energy savings of efficient products can adversely impact long term EE innovation in two ways. First, if relative incremental savings of energy are not as large as relative incremental changes in nominal efficiency, then the efficiency improvement rate, α, does not correspond to the energy savings rate. To the extent incremental energy efficiency can more closely correspond to incremental energy savings, then the climate impact effects of a nominal energy efficiency improvement rate can be larger.

The second way in which uncertainties in actual energy savings can diminish the long EE innovation rate is that if there are errors or uncertainties in the actual energy savings associated with a given efficiency improvement, then it is likely that this will lead to a lower willingness to pay for a given energy efficiency improvement. For a given range of nominal efficiencies in the market this will decrease the variance in the price with respect to efficiency, γ, in equation (1), leading to a corresponding decrease in the long term efficiency improvement rate.

CROWD-SOURCED DATA

One possible measure that policy-makers can use to help improve the quality and accuracy of estimates of the energy savings from energy efficiency is the crowd-sourcing of actual energy savings data. One example of combined government and private sector efforts to promote greater access to high resolution energy data is the Green Button initiative in the U.S. (Sayogo & Pardo, 2013). With the advent of customer and third party access to high resolution energy use data, it then become theoretically possible to create a variety of energy analysis activities to utilize this data (see for example (Schmidt, 2012).

Another method of collecting crowd-sourced data is through the recruitment of energy use surveyors through the Internet (Yang, et al., 2015). This method has been used for example to collected energy use data in Northern California on miscellaneous electrical loads (Greenblatt, et al., 2013).

Potential impacts of crowd-sourced data on the MLEE equation

Crowd-sourced data can potentially have three different types of impact that could help accelerate long term EE improvement rates.

The first, most obvious impact is that the larger volumes of ex-post data that can be potentially acquired through crowd sourcing can lead to enhanced measurement of the actual energy savings at different efficiency levels of equipment, thus aiding innovation as described in the section above on improved energy savings measurement.

The second way that crowd-sourced data can aid in efficiency and energy savings innovation is that it creates the possibility of measuring in-field behavior-based energy saving measures and performance. By increasing the range and variety of energy savings opportunities through field-verified behaviour-related features, the MLEE equation is impacted in two ways: (1) First, because the range of energy savings possibilities has increased, there is the possibility that the range of efficiency-related price changes that consumers are willing to pay increases. An increased range of energy savings possibilities should increase the variance of efficiency-related price changes in the product market … increasing γ; (2) Secondly, an increased diversity of energy savings measures should allow for more energy savings at lower incremental product cost, thus decreasing the elasticity of product price with respect to efficiency and energy savings.

The third, and perhaps most subtle way that crowd-sourced data may be able to enhance EE innovation is by shedding light on meaningful variation on appliance operating costs between consumers with different use patterns and behaviours. Models of rational consumer behaviour in the face of uncertain costs indicate that "consumers will be less likely to undertake costly search [for information] when the variance of energy savings across models in a class is small, and when the variance of other attributes is large." (Sallee, 2013) Thus by illuminating when there can be large variances in energy savings and energy costs for appliances and equipment, savings analysis based on crowd-sourced data can help increase the likelihood that consumers will consider energy savings effects in their appliance and equipment purchases. This should both increase the variance of prices paid for efficiency (i.e. γ) and the potential rate of adoption of more efficient product models (i.e. q).

CORRELATING EFFICIENCY WITH CONSUMER VALUE

According to the model equations for MLEE, if other dimensions of product and equipment consumer value can be strongly correlated with the benefits of energy efficiency, then this can lead to a potentially strong acceleration of the long term efficiency improvement rate. The positive correlation between other dimensions of consumer value with EE as part of accelerating adoption and improvement in EE has been seen in several historical cases. A retrospective study of the 1990 and 1993 US refrigerator standards found that as the efficiency of refrigerators improved in that market, another desirable consumer feature – glass shelves – also became more prevalent (Greening, et al., 1996). In the case of the television EE, in recent years the desirable product feature of LED backlighting has been associated with increased EE relative to LCD screens with lower-efficiency fluorescent backlighting. In the case of efficient light bulbs, the desirable feature of increased light bulb lifetime has been associated with EE improvements.

Potential impacts of correlating efficiency with consumer value on the MLEE equation

There are perhaps three mechanisms by which correlating EE with other dimensions of consumer value may impact the MLEE equation.

The first mechanism is that by correlating EE with desirable product features, it may be possible to increase the adoption rate (q) of new, more efficient products.

The second mechanism is that if the new features allow consumers to pay a higher price for the more efficient products, this may allow for a greater willingness to pay for the more efficient products, increasing the price variance and therefore γ. This might be counter-acted by a similar increase in the elasticity of price with respect to energy efficiency (because the feature and efficiency are so closely correlated) so in some cases this may not increase the EE improvement rate.

The third mechanism is when consumers are adopting both efficiency and the complementary product attribute in tandem. If the new attribute can carry some of the cost of the EE improvement (essentially "cross-subsidizing EE") then this can decrease the observed market price elasticity with respect to the EE attribute, thus decreasing ε. Historically this appears to be what happened with glass shelves and EE in the 1990 and 1993 US refrigerator standards.

PROMOTING EFFICIENCY FOR OFF-GRID APPLICATIONS

Most of off-grid and micro-grid electricity is supplied from either diesel generators or solar PV. As is discussed elsewhere (Van Buskirk, 2015), the cost of off-grid electricity can be very high. This means that for off-grid applications the relative cost that consumers may be willing to pay for efficiency can be correspondingly high. Also given recent advances in providing solar PV electricity systems and microgrids to developing country customers, the off-grid market is likely to be growing relatively fast over the next 1–2 decades.

Potential impacts of promoting off-grid applications on the MLEE equation

Promoting EE for off-grid market applications should help accelerate long term global EE improvement rates in two key ways.

First, because the cost of electricity in off-grid applications is so high, this should greatly increase willingness to pay for super-efficient products. Even at fairly low market shares, this is likely to more than double the variance of the log price with respect to EE in global markets and should lead to a corresponding increase in long term EE improvement rates.

The second way in which promoting off-grid applications should increase long term EE improvement rates is because adoption rates for new, high consumer-value-technologies in these markets are likely to be very high. For example the annual exponential growth rate of solar home system (SHS) installations in Bangladesh from 2000 to 2010 was 40 %–50 % (Van Buskirk, 2015), implying a relatively high adoption rate of 0.4 to 0.5. These high adoption rates are likely to lead to very large EE improvement rates if EE products for off-grid applications can become a significant portion of global product sales over the next decade.

An anecdotal observation that warrants detailed research and study is that markets for laptops, smart phones, and tablets utilize technologies that are often more energy efficiency than their grid connected counterparts. For example, laptops used LED backlight displays substantial earlier than their computer monitor counterparts. Similarly tablets routinely use very high efficiency OLED displays while these technologies have not yet gained substantial market share in monitor and television markets.

ENHANCED TECHNOLOGY ROAD-MAPPING AND R&D

In the well known example of Moore's Law, long term rates of computer technology improvement were sustained somewhat by foresight and planning that created a self-fulfilling prophesy. The creator of the law, Gordon Moore, was also a co-founder of Intel, a company that played a pivotal role in realizing Moore's law through its research, and product development of central processing unit chips. Gordon Moore held key positions at Intel for 30 years, spending 12 of those years as CEO. The chips that his company made drove the computer revolution that occurred from the 1970's and 1990's, and he was directly involved in managing their development. The historical example of Moore's Law indicates that there is the possibility of planning elements of the long term technology progress through a combination of foresight, road-mapping, research, and development (Mack, 2011).

Potential impacts of enhanced technology road-mapping on the MLEE equation

Enhanced technology road mapping and research and development can impact the MLEE in two key ways.

The first way that road mapping and research impacts the MLEE is in helping assure that as EE improves, there is always a supply of high efficiency products with a range of efficiencies available in the market. An extremely detailed example of energy efficiency research prioritization planning and road-mapping can be seen in a research investment prioritization tool that was developed by the U.S. Department of Energy in 2012 (Farese, 2012). By accelerating research and the creation of new, more efficient product designs and technologies, when consumers move from purchasing low efficiency to high efficiency products, new, even higher efficiency product are available for them to purchase and adopt. Without the creation of constantly improving designs through research, the loss of the low efficiency products without a corresponding increasing in the availability of even higher efficiency products will result in a decrease in the range of product efficiencies available in the market. This will decrease the price variance with respect to efficiency in the MLEE equation and can lead to a decrease of the EE improvement rate if other parameters in the equation do not change. Road mapping, research, and the introduction of new, more efficient products into the market is a key element of sustaining long term EE improvement rates.

The second way that road mapping and research impacts the MLEE is that it can lower the incremental cost of high efficiency products by accelerating learning processes (Weisenthal, et.al, 2012). This decreases the elasticity of product price with respect to EE and can have the corresponding impact on the long term EE improvement rate.

Summary and conclusion

In this paper, we introduced a new formulation of a long term EE improvement rate equation that we refer to as the "Moore's Law of Energy Efficiency." The MLEE equation relates the long term rate of EE improvement to key market parameters: (1) the price variance with respect to EE, (2) the EE product adoption (or diffusion) rate (Bass, 1969), and (3) elasticity of price with respect to EE.

A key limitation of the MLEE equation is that it is premised on a steady evolution of a product market where efficiency and price changes at a constant exponential rate over time, where the log variance of the price is constant over time, where the elasticity of price with respect to efficiency is constant over time, and where more efficient products are adopted by the market according to a logistic adoption curve with a constant Bass diffusion rate of q. In general markets are more complex than this, and all of these market parameters are likely to be changing over time. The extent to which efficiency appliance markets can be modelled by the quasi-steady mathematical description that underlies this formulation of the MLEE equation has not yet been thoroughly investigated but this may be a fruitful line of future research.

None-the-less, assuming that efficient appliance markets can attain the quasi-steady state of continuous improvement described above, this paper examines the potential policy implications of the resultant MLEE equation. Specifically, the paper reviews in some detail the potential impacts that six different types of EE policy measures and features can have based on the EE improvement rate as described by the MLEE equation. We find that all six policy measures and features – (1) market transparency (2) improved (in-field) savings estimation, (3) crowd-sourced data acquisition, (4) aligning/correlating energy savings with other dimensions of consumer value, (5) developing EE product markets for off-grid applications, and (6) enhanced technology road-mapping and R&D – can make important contributions to policies and programs that can likely accelerate long term EE improvement rates in global markets.

Yet several of these measures and features also have their practical and political challenges. For example full market transparency according to standard economic theory will create conditions where it is very difficult for manufacturers to make or sustain profits. Improved in-field savings estimation could discourage some consumers from investing in efficiency in those cases when they find out that actual energy savings are less than expectations. With respect to crowd-sourced data, many households and businesses might be hesitant to volunteer data to governments or policy analysts for impact monitoring. Meanwhile aligning efficiency with other dimensions of consumer value can lead to decreasing energy savings when high value product attributes (like screen size in TVs, or automatic ice makers for refrigerators) consume extra energy compared to products with fewer or older attributes.

Yet, in spite of these challenges, the MLEE hypothesis – if validated by future research – provides the possibility of quantitatively estimating and forecasting the potential improvement contribution that different policy features and measures can provide in the effort to accelerate global EE improvement rates. Further research into the dynamics of energy efficiency improvement rates in different markets and their relationship to features of policy design and other policy measures is recommended. Such research should help clarify to what extent policies can be explicitly designed to accelerate EE technology improvement rates thus assisting global climate mitigation efforts over the next 1–3 decades.

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Appendix: Derivation of MLEE equation

In this appendix, we derive equations that describe the continuous, steady adoption of increasingly efficient appliances where the market share of appliances at or above a particular efficiency follows a logistic adoption curve.

CONTINUOUS ADOPTION OF IMPROVED EFFICIENCY

If $F_j(t)$ is the fraction of appliance sales at or above (cumulative market share) a particular efficiency level Eff_j, then a simple logistic (S-curve) model of the high-efficiency market fraction can be written in the following form:

$$F_j(t) = \frac{1}{1+e^{-q(t-t_j)}} \quad \text{(A1)}$$

where t_j is the time at which the cumulative market share is 50% for the j-th efficiency level Eff_j. Higher levels of efficiency attain cumulative market share of 50% at times later than lower levels of efficiency in a continuously improving market. If a market consists of distinct efficiency levels, then the market share of the *j*-th efficiency level, $MS_j(t)$, is given by the difference between the *j*-th and *(j+1)*-th cumulative efficiency:

$$MS_j(t) = F_j(t) - F_{j+1}(t) = \frac{e^{-q(t-t_{j+1})} - e^{-q(t-t_j)}}{(1+e^{-q(t-t_j)})(1+e^{-q(t-t_{j+1})})} \quad \text{(A2)}$$

These equations model the market shares of a distribution of efficiencies as a family of logistic curves. If we assume that the efficiency for the whole distribution is improving exponentially over time and that q is constant and the same for all market share curves, then we can write the time of median (50%) market share as a function of efficiency:

$$Eff_j(F_j = 50\%) = Eff_0 \cdot e^{\alpha(t_j - t_0)} \quad \text{(A3)}$$

where α is the exponential rate at which efficiency is increasing over time, Eff_0 is the median efficiency of the the market at $t=t_0$, and Eff_j is the median market efficiency at time t_j. We can write equations (A1) and (A3) in the following alternative forms:

$$\ln\left(\frac{1-F_j(t)}{F_j(t)}\right) = -q(t-t_j) \quad \text{(A4)}$$

$$\ln\left(\frac{Eff_j}{Eff_0}\right) = \alpha(t_j - t_0) \quad \text{(A5)}$$

Combining equations (A4) and (A5), can create the following equation:

$$\ln\left(\frac{Eff_j(t)}{Eff_0}\right) = \alpha(t-t_0) - \frac{\alpha}{q}\ln\left(\frac{1-F_j(t)}{F_j(t)}\right) \quad \text{(A6)}$$

If we now take equation (A6) and exponentiate both sides, this allows us to write the following equation describing efficiency as function of both cumulative market share and time:

$$\frac{Eff(F_j,t)}{Eff_0} = e^{\alpha(t-t_0)} \cdot \left(\frac{F_j}{1-F_j}\right)^{\frac{\alpha}{q}} \quad \text{(A7)}$$

This is the equation for a logistic market distribution of efficiency where the efficiency adoption curves have a constant adoption rate, q, and the median efficiency is increasing at an exponential rate α.

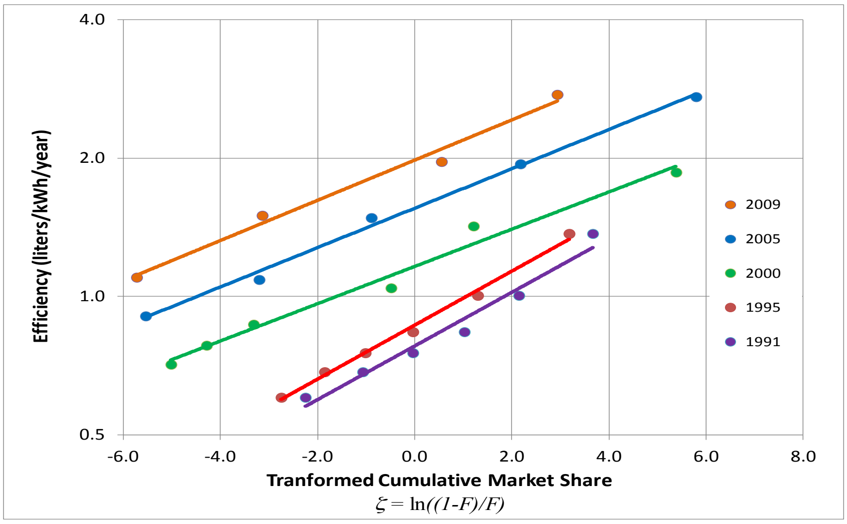

Figure A1. Illustration of equation (A6) with data from the EU refrigerator market. Vertical axis is log scale. Note that categoral labels were adopted in 1995. Also, after categorical labels appeared, parameters in (A6) changed: both α and q increased.

CONTINUOUS ADOPTION OF PRODUCTS WITH A PRICE PREMIUM

Next, we go through a similar derivation as in the last section, but this time, modeling the price of efficiency. If we repeat equation (A1):

$$F_j(t) = \frac{1}{1+e^{-q(t-t_j)}} \quad \text{(A8)}$$

where t_j is the time at which the cumulative market share is 50% for the j-th efficiency level Eff_j which has an average price at the efficiency level that is written as $P(Eff_j(t))=P_j(t)$.

If we assume that the price of the at each fixed efficiency level in the distribution is declining exponentially over time and that the exponential rate of price decline is constant and the same for all market share curves, then we can write the price of median (50 %) median efficiency appliance over time as:

$$P(Eff_j(F_j = 50\%)) = P(Eff_0, t_0)\cdot e^{-\beta(t_j - t_0)} \quad \text{(A9)}$$

Where β is the rate at which price is declining over time, Eff_0 is the median efficiency of the the market at $t=t_0$, and Eff_j is the median market efficiency at time t_j.

We now assume a constant variance in the changes in log-price with respect to efficiency:

$$\ln\left(\frac{P(F_j,t_j)}{P_{50\%}(t_j)}\right) = -\gamma\cdot\ln\left(\frac{1-F_j}{F_j}\right) \quad \text{(A10)}$$

When equation (A10) is true, then equation (A6) can be re-written as:

$$\ln\left(\frac{Eff_j}{Eff_0}\right) = \alpha(t-t_0) + \frac{\alpha}{\gamma\cdot q}\cdot\ln\left(\frac{P_j(t_j)}{P_{50\%}(t_j)}\right)$$

$$= \alpha(t-t_0) + \frac{\alpha\cdot\beta}{\gamma\cdot q}\cdot(t_j - t_0) + \frac{\alpha}{\gamma\cdot q}\cdot\ln\left(\frac{P_j(t_j)}{P_0}\right) \quad \text{(A11)}$$

Note that if we assume that the relationship between price and efficiency is a power law with a power law exponent that is constant over time, then the ratio of prices at two efficiency levels is constant over time. Also if the log variance of the price distribution over time is constant, then price is decreasing at the same exponential rate in on each efficiency level[3] and then this provides:

$$\frac{P(Eff_j(t))}{P(Eff_j(t_j))} = e^{-\beta(t-t_j)} \quad \text{(A12)}$$

Then equation (A11) implies the following equation:

$$\frac{Eff_j}{Eff_0} = e^{\alpha(t-t_0)}\cdot\left(\frac{P_j(t_j)}{P_{50\%}(t_j)}\right)^{\frac{\alpha}{\gamma q}}$$

$$= e^{\alpha\cdot(t-t_0)+\left(\frac{\alpha\beta}{\gamma q}\right)(t_j - t_0)}\cdot\left(\frac{P_j(t_j)}{P_0}\right)^{\frac{\alpha}{\gamma q}}$$

$$= e^{\alpha\cdot(t-t_0)+\left(\frac{\alpha\beta}{\gamma q}\right)(t - t_0)}\cdot\left(\frac{P_j(t)}{P_0}\right)^{\frac{\alpha}{\gamma q}} \quad \text{(A13)}$$

Or conversely:

$$\frac{P_j(t)}{P_{50\%}(t_j)} = \left(\frac{Eff_j}{Eff_0\cdot e^{\alpha\cdot(t-t_0)}}\right)^{\frac{\gamma q}{\alpha}} \quad \text{(A14)}$$

Or:

$$\frac{P_j(t)}{P_0} = e^{(\beta-\gamma q)\cdot(t-t_0))}\cdot\left(\frac{Eff_j}{Eff_0}\right)^{\frac{\gamma q}{\alpha}} \quad \text{(A15)}$$

Note that in this equation the elasticity is $\varepsilon = \gamma\, q/\alpha$.

Figure A2, illustrates the observation of moving power-law price-efficiency relationships in the European efficient refrigerator market between 1995 to 2009 in both the data (symbols) and a partial differential equation (PDE) model (curves) of efficient refrigerator adoption with technological learning in

3. See supplemental information of (Van Buskirk, et.al., 2014), equation S19 and table S10 to see to what degree is this is a can be a good approximation to empirical market data for the EU refrigerator market.

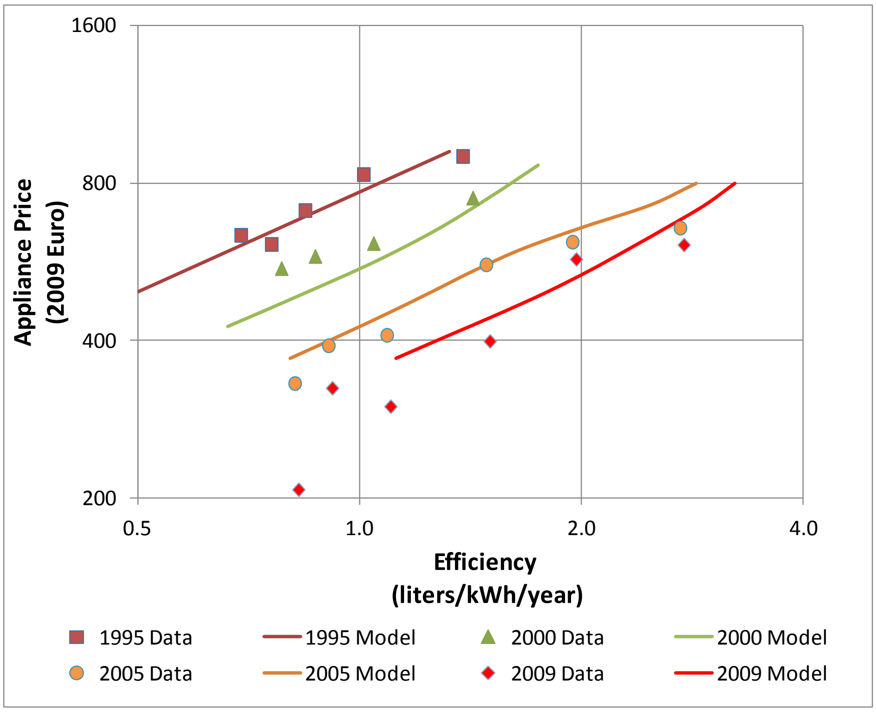

Figure A2. Appliance price vs. efficiency over time for the European refrigerator market illustrating the nearly constant progression of a power law curve from left to right, that is approximated by equations (A15) and (A11).

incremental energy efficiency technologies provied in (Van Buskirk, 2013). In essence the model equation (A15) is a set of model equations that appoximate the PDE model solution used in this previous study. The simpler model equation approximates a dynamic price-efficiency relationship as an exponentially decreasing power-law curve, where the parameters are related to the adoption curve dynamics.

Rearranging the relationship between price elasticity and other parameters in equation (A15), we get:

$$\alpha = \frac{\gamma \cdot q}{\varepsilon} \qquad \text{(A16)}$$

And this is the equation for the "Moore's Law of Energy Efficiency" (MLEE) discussed in the main paper. This equation says that the rate of improvement of the median efficiency is the adoption rate for more efficient products, times the logistic scale term for the price vs. efficiency distribution function, divided by the price elasticity with respect to efficiency.