AN MPG FOR HOMES

ACCURACY AND APPLICATION OF AUTOMATED HOME ENERGY ESTIMATES

BY GREG HOPKINS AND JACOB CORVIDAE

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ABOUT US

ABOUT ROCKY MOUNTAIN INSTITUTE

Rocky Mountain Institute (RMI)—an independent nonprofit founded in 1982—transforms global energy use to create a clean, prosperous, and secure low-carbon future. It engages businesses, communities, institutions, and entrepreneurs to accelerate the adoption of market-based solutions that cost-effectively shift from fossil fuels to efficiency and renewables. In 2014, RMI merged with Carbon War Room (CWR), whose business-led market interventions advance a low-carbon economy. The combined organization has offices in Basalt and Boulder, Colorado; New York City; Washington, D.C.; and Beijing.

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EXECUTIVE SUMMARY

Automated home energy estimates can be a powerful tool for multiple stakeholder groups because they can provide transparency into residential energy performance at an unprecedented scale. Historically, energy performance information has been available only to the small fraction of US homeowners who have commissioned a professional on-site assessment—leaving most consumers unable to (1) estimate energy use and costs when comparing prospective homes, or (2) identify which energy upgrades could make their homes more comfortable, affordable, and valuable.

But the growing use and visibility of automated home energy estimates raises important questions about the trade-offs between customization and accuracy versus automation and scale. To better inform the stakeholders who stand to benefit from this data, Rocky Mountain Institute (RMI) set out to conduct an accuracy assessment of two algorithm-based data vendors, ClearlyEnergy and UtilityScore, by comparing their remotely generated home energy estimates against estimates produced by the US Department of Energy's Home Energy Score (HES) program, which leverages qualified on-site assessors.

FIGURE 1

SUBJECTS OF COMPARISON IN THIS REPORT

PARTICIPATING DATA VENDORS	
CLEARLYENERGY	ClearlyEnergy is an online platform designed to help consumers understand and simplify energy choices by providing algorithm-based energy cost and savings estimates as well as identifying relevant incentives, products, and contractors.
UtilityScore	UtilityScore is an online platform that estimates home energy and water bills, assigns a corresponding score, and provides savings estimates for solar, new windows, and heating/cooling upgrades along with free contractor quotes.
BASELINE FOR COMPARISON	
U.S. DEPARTMENT OF ENERGY Home Energy Score	Home Energy Score is a rating system and program launched by the DOE in 2012 to estimate a home's energy use and identify cost-saving upgrades using energy modeling software fed by a comprehensive set of data points collected on-site by a qualified assessor.

KEY FINDINGS

RMI's analysis of almost 8,000 homes across 27 states shows that remotely generated home energy estimates are just that—estimates—but they may be accurate enough to open up a variety of useful applications. The following results are based on a dataset for which the vendors were provided only property addresses (Set 1). A separate dataset including six key attributes for each home was also provided (Set 2), and the results improved slightly, as described later in the report. To preserve vendor confidentiality, ranges are provided instead of vendor-specific results (ranges do not indicate the highest and lowest differences but rather indicate limits within which both vendors' averages fell).

Throughout this report, differences between vendor and HES estimates are shown in **absolute value** (in green) and **nonabsolute value** (in blue) terms. Absolute figures are a better indicator of variance (i.e., vendor estimates are on average X percent different from the baseline) and are useful for applications concerning individual homes. Nonabsolute figures are a better measure of the directional bias (i.e., vendor estimates are over- or underpredicting by Y percent relative to the baseline) and are useful for applications based on aggregated sets of homes.

$\left| (10{,}000 \text{ kWh/yr}_{Vendor} - 11{,}000 \text{ kWh/yr}_{HES}) / 11{,}000 \text{ kWh/yr}_{HES} \right| =$ **10% absolute difference**

$(10{,}000 \text{ kWh/yr}_{Vendor} - 11{,}000 \text{ kWh/yr}_{HES}) / 11{,}000 \text{ kWh/yr}_{HES} =$ **(10%) nonabsolute difference**

TOTAL ENERGY USE:

- Estimates from both vendors showed a **20–30 percent** average absolute difference from HES estimates
  - Nearly three-quarters of all homes analyzed were less than 30 percent different
  - Nearly half of all homes analyzed were less than 20 percent different
  - More than one-quarter of all homes analyzed were less than 10 percent different
- Estimates from both vendors showed an overall average nonabsolute difference within **+/- 10 percent** of HES estimates

TOTAL ENERGY COSTS: Vendor algorithms can outperform on energy cost estimates given their ability to pull significantly more granular utility rate data (HES currently uses statewide average utility rates)

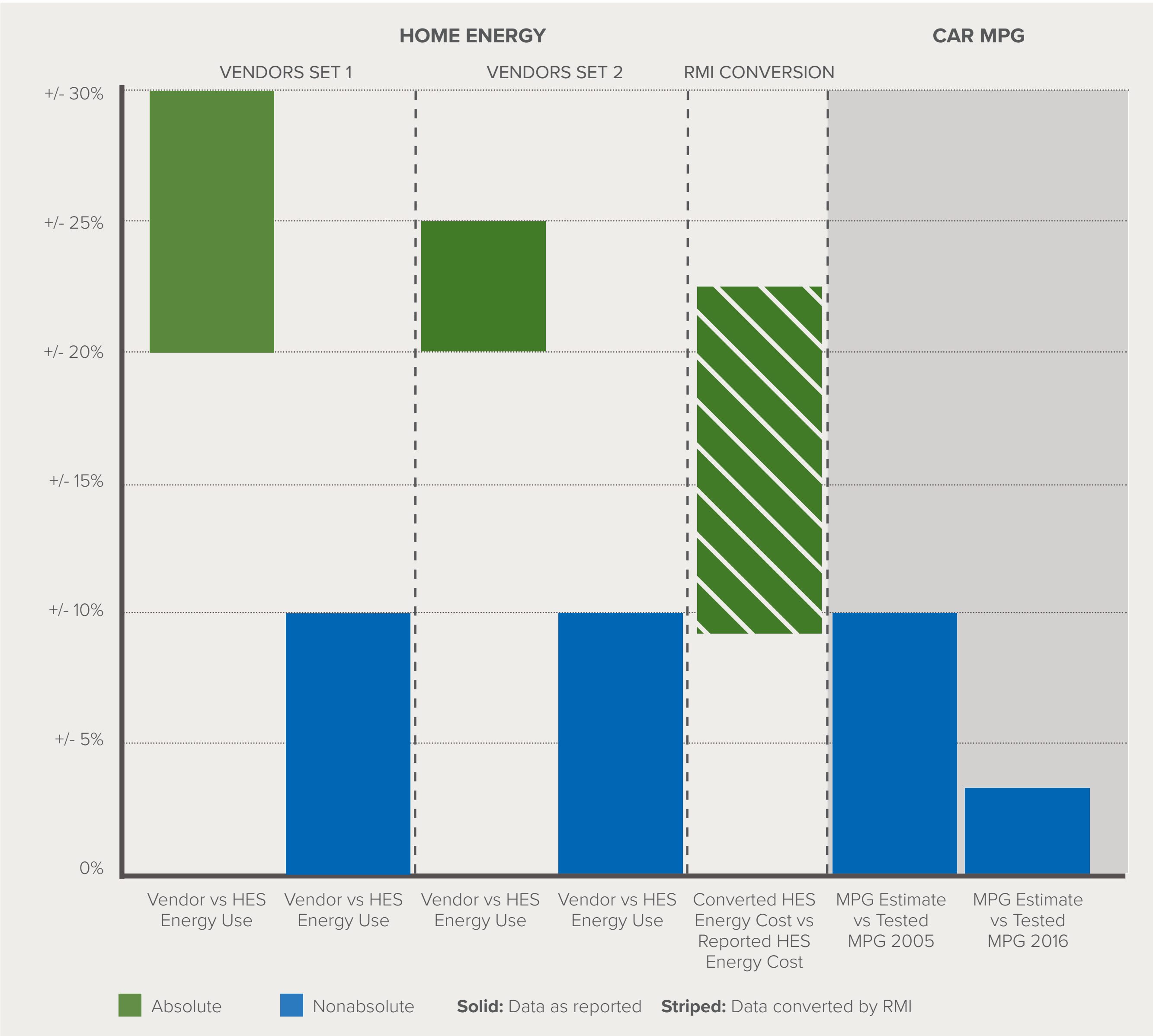
- Using the vendors' implied utility rates, converted HES energy cost estimates were **9–22 percent** different from reported HES cost estimates

AVERAGE DIFFERENCES

Figure 2 reflects the ranges for the overall average results of both vendors' energy use estimates as well as converted HES cost estimates as described above (and on page 23) along with a comparison to MPG estimates for cars as described on page 26:

FIGURE 2

DIFFERENCES BETWEEN VENDOR AND HES ESTIMATES COMPARED WITH RESULTS FOR CAR MPG



KEY USE CASES

While algorithm-based estimates offer a readily available first look that can inform several applications, they are not a replacement for comprehensive on-site assessments like HES that can provide homeowners with deeper insights into home energy performance and recommended energy- and cost-saving upgrades. Nonetheless, this report can help the market close the gap between information and action by showing that algorithm-based home energy estimates may be sufficiently accurate to support viable use cases for multiple stakeholder groups:

- **Homeowners and Homebuyers:** greater awareness of home energy performance, and more conservative budgeting for total homeownership costs (when buying a home with no energy assessment information)
- **Real Estate Portals:** higher customer retention on sites that provide more robust information (e.g., affordability calculators) and potential lead-generation revenue
- **Energy Service Contractors:** higher sales of products/services by leveraging personalized home energy profiles plus the ability to target marketing efforts
- **Government Sponsored Enterprises (GSEs) and Mortgage Lenders:** avenues to better address energy cost risks (correlated with loan default rates) at a local level and easier identification of good candidates for energy-related loan products
- **City and State Governments:** ability to better prioritize investment of public funds toward higher energy burden areas and refine residential policies/targets with broader baseline data

Since most of these use cases rely on energy costs—as opposed to energy use—as the relevant metric, it is important to consider how energy use estimates relate to energy cost estimates. The vendor algorithms currently use more granular utility rate information than HES does nationally, although HES has the ability to obtain and incorporate more localized utility rate data to produce better cost estimates in select markets (e.g., Portland, Oregon). Where available, better rate data can compensate for some of the variance found in energy use.

02

INTRODUCTION

INTRODUCTION

RMI recently released a report, **An MPG for Homes: Driving Visible Value for Home Energy Performance in Real Estate,** about the rise of automated home energy data and what it can offer to homeowners and key industry stakeholders. Until recently, residential energy performance information has only been available to the less than 3 percent of US single family homes that have undergone on-site assessments like **Home Energy Score** and **RESNET'S Home Energy Rating System (HERS)** (and even then, this information is typically not readily available to prospective buyers of those homes).[i] On-site assessments provide valuable home energy performance insights and actionable recommendations, but by nature they are more difficult to scale across the residential sector given the time, cost, and initiative required.

However, vendor algorithms are making home energy transparency more the rule than the exception by leveraging public data to provide fast and free energy estimates for all homes nationwide. Now all homeowners have the opportunity to more holistically understand the full operating costs of a new home before purchasing, and lower their energy bills and improve the comfort of their homes at any point after purchasing.

The widespread availability of home energy data can also be put to good use by real estate, energy service, and mortgage industry players to support their business models and generate value for customers, as well as by local governments to engage citizens, inform policy, and make measurable progress toward climate goals.

These stakeholders have questioned the reliability of home energy estimates generated remotely by proprietary vendor algorithms. **To address this market uncertainty, RMI conducted a third-party accuracy assessment of two data vendors active in this space**—ClearlyEnergy and UtilityScore—by comparing their estimates to those produced by Home Energy Score's on-site assessments, both with and without the help of key HES inputs.

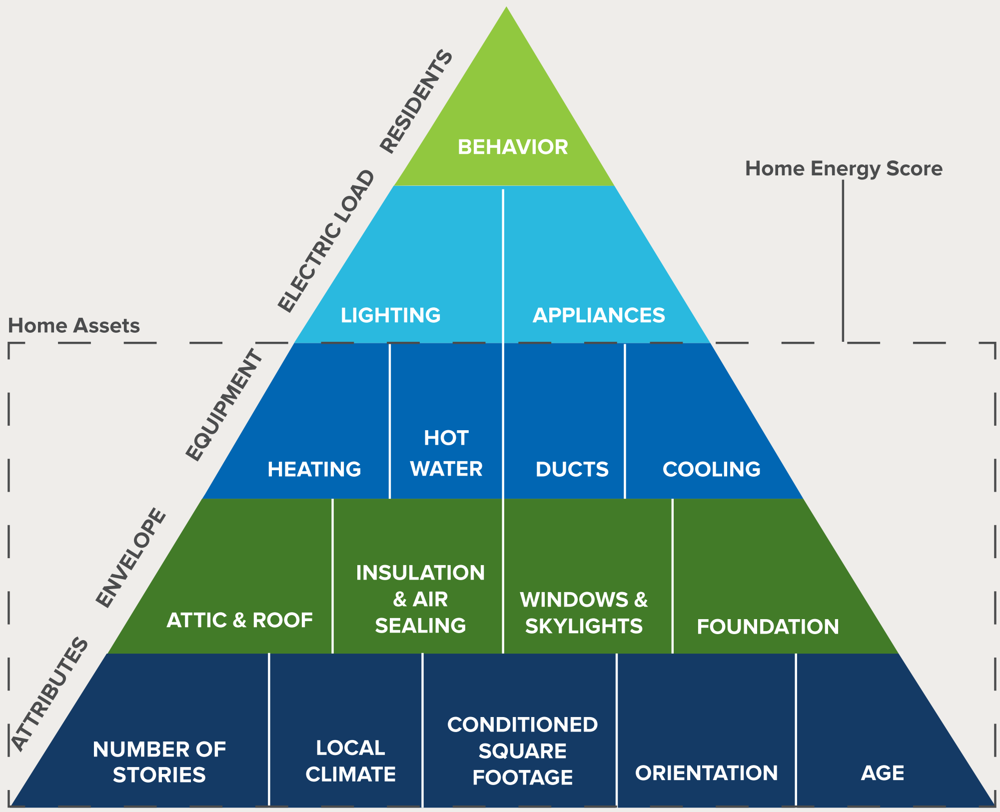
[i] As of January 2018, HERS had completed over **2 million** assessments since 2006 and HES had completed **81,300** assessments since 2012; together, they had assessed 2.6 percent of the **81 million** US single-family homes.

03 SETTING THE BASELINE

SETTING THE BASELINE

FIGURE 3

WHAT HES RATINGS DO AND DO NOT TAKE INTO ACCOUNT



Source: US Department of Energy Better Buildings

The US Department of Energy (DOE) launched the Home Energy Score (HES) program in 2012 as a nationwide "asset rating" system for homeowners and homebuyers to better understand their home's energy performance. Asset ratings evaluate the energy performance of a home based solely on its inherent physical components (e.g., equipment, envelope, size). They do not take into account operational considerations that can vary widely from one homeowner to the next (e.g., number of occupants, thermostat settings, schedules, appliance and plug loads). As a result, asset ratings allow different homes to be compared on an apples-to-apples basis, and are more useful in the real estate market because they analyze components that will stay with homes when their ownership transfers.

HES estimates are based on in-home assessments that can be completed in less than one hour, telling homeowners how efficient their home is, how it compares to other homes, and how much money they can save by installing certain cost-effective upgrades. HES predicts annual energy use and costs based on 50 different data points collected on-site by qualified assessors. More detail on the background and methodology of HES can be found on the DOE's Better Buildings website.

While comprehensive, HES and other asset ratings reflect *estimated* energy performance as opposed to actual utility billing data. Other analyses, including a previous study by the National Renewable Energy Laboratory (NREL), have looked at the accuracy of

HES outputs compared to actual utility billing data, as described below. RMI used HES as the baseline rather than HERS in part because, to RMI's knowledge, no publicly available accuracy analysis of HERS estimates has been performed and HERS is **more widely used for newly constructed (versus existing) homes**.

It should be noted that comparing asset ratings like HES to actual utility billing data presents inherent challenges for determining accuracy given high operational variability between households. Asset ratings assume a fixed set of standard operating conditions, but any individual home will likely deviate from these conditions (e.g., will have more or fewer occupants and appliances, set temperatures higher or lower, etc.). Therefore, on a home-by-home basis, comparing asset ratings to actual utility data to assess accuracy can be difficult without detailed operational information about how each home is being used, which is rarely available.

With these caveats in mind, NREL's study found that:

- In **nonabsolute** terms, HES on average overpredicted electricity use by **13 percent** and underpredicted natural gas use by **6 percent** versus actual usage
- In **absolute** terms, HES electricity-use estimates were on average **33 percent** different and natural gas use estimates were on average **28 percent** different from actual usage

HES and other on-site assessment programs can provide valuable home energy performance information to homeowners. Relative to remotely generated estimates, on-site energy assessments—which range from visual inspections to more involved diagnostic testing—can better identify the root causes of energy- or comfort-related issues in homes and prioritize performance improvements. While useful to engage at any time, on-site energy assessments can be **particularly beneficial** prior to purchasing a home (e.g., alongside a home inspection) to set expectations and potentially to negotiate the resolution of any major findings with the seller.

Nonetheless, with their current rates of adoption (and given the time, expense, and energy required from both homeowners and service providers), it will likely take significant time for on-site solutions alone to bring about the energy transformation needed across the residential sector. It is worth noting that this timeline could accelerate rapidly if more citywide programs like in **Portland, Oregon's** and statewide programs like **Massachusetts' proposed plan** to start requiring home energy information be made available at point of listing were to take effect. As an increasing number of consumers are seeing similar data being generated by algorithms and featured on real estate listings, RMI set out to understand how accurate these estimates are and, in turn, how they can be utilized by various stakeholder groups.

04 ANALYSIS SCOPE & METHODOLOGY

ANALYSIS SCOPE & METHODOLOGY

RMI partnered with the DOE to obtain a dataset for several thousand homes across 27 states and multiple climate zones that underwent an HES assessment during 2017. RMI asked the participating data vendors, ClearlyEnergy and UtilityScore, to generate their own estimates for electricity use and heating fuel use,[ii] and corresponding estimates of costs for two different subsets of the data:

- **Set 1:** Vendors were given **property addresses only**
- **Set 2:** Vendors were given **six key inputs** from HES in-home assessment data: zip code, year built, conditioned floor area, number of bedrooms, heating/ cooling system types, and fuel types.
    - These inputs were intended to represent a minimum set of property attributes required to generate an estimate. However, the availability and reliability of these types of inputs via real estate portals, multiple listing services (MLSs), and/or public tax assessor databases was not evaluated.

For **Set 1,** RMI's objective was to evaluate how vendor algorithms can estimate home energy use and costs remotely with no assistance. For **Set 2,** RMI's objective was to evaluate how much these estimates can improve when only these six key inputs are provided, relative to the 50 data points that HES assessors collect on-site—which, for this number of homes, would require the equivalent of two years of a full-time assessor's work to collect.[iii]

While outside the scope of this report, RMI believes that the market would benefit from additional research and analysis of:

- The difference between the inputs that vendors are able to pull from public sources and data collected manually by qualified on-site assessors
- The accuracy of the vendors' energy cost estimates relative to a reliable cost baseline
- The accuracy of the vendors' energy upgrade recommendations relative to HES or other on-site assessment sources

Vendor outputs were sent to RMI for both Set 1 and Set 2 and reconciled against reported HES estimates from the original dataset. Differences between vendor and HES estimates were calculated in **absolute** and **nonabsolute** terms. **Absolute** figures are a better indicator of the variance (i.e., vendor estimates are on average X percent different from the baseline) and are useful for applications concerning individual homes. **Nonabsolute** figures are a better measure of the directional bias (i.e., vendor estimates are over- or under-predicting by Y percent relative to the baseline) and are useful for applications based on aggregated sets of homes.

RMI's analysis compares asset rating estimates between the vendors and HES, focusing on homes' underlying energy-related assets and mitigating some of the operational uncertainty introduced by actual utility billing data, as mentioned above. While electricity and natural gas *use* estimates were evaluated in this way using HES as the baseline, energy *cost* estimates were evaluated differently given accuracy concerns built into the HES baseline, as described below.

Informed by the results, RMI then considered potential use cases for key stakeholder groups that stand to benefit from automated home energy data.

[ii] Heating fuel results reflect only natural gas, which was the least common denominator between vendors (one of the vendors can estimate other fuel types, including oil and propane).

[iii] Assuming one hour per on-site audit yields 4,100 audit hours divided by 2,080 full-time work hours in a year.

05 KEY FINDINGS

KEY FINDINGS

Compared to HES estimates, vendor algorithms remotely generated site energy consumption estimates for nearly 8,000 homes in 27 states with the following results. To preserve vendor confidentiality, ranges are provided instead of vendor-specific results (ranges do not indicate the highest and lowest differences but rather indicate limits within which both vendors' averages fell). Negative numbers are shown in parentheses.

Set 1 (Providing No External Inputs):

- **Absolute differences** indicate typical differences to be expected for any **individual** home
  - **Total Energy Use:** Estimates from both vendors were, on average, **20–30 percent** different from corresponding HES estimates
    - Nearly *three-quarters* of all homes analyzed were less than 30 percent different
    - Nearly *half* of all homes analyzed were less than 20 percent different
    - More than *one-quarter* of all homes analyzed were less than 10 percent different
  - **Electricity Use:** Estimates from both vendors were, on average, **25–30 percent** different from corresponding HES estimates
  - **Natural Gas Use:** Estimates from both vendors were, on average, **30–35 percent** different from corresponding HES estimates
- **Nonabsolute differences** indicate general trends across an **aggregated** set of homes
  - **Total Energy Use:** Estimates from both vendors were, on average, within **+/- 10 percent** of corresponding HES estimates across the dataset, with one vendor slightly underpredicting and the other slightly overpredicting
  - **Combined Total Energy Use:** Using a combined average of the vendors' estimates for each home (similar to how credit scores combine scores from multiple sources) resulted in an overall average difference of less than **1 percent** versus HES

TABLE 1. SET 1 RESULTS SUMMARY: VENDOR ESTIMATES VS HES ESTIMATES

	ELECTRICITY USE	NATURAL GAS USE	TOTAL ENERGY USE
Given Inputs	Property addresses only		
# Properties Analyzed	2,777 to 3,962[iv]		
Median Absolute Difference	20% to 25%	20% to 30%	**15% to 25%**
Mean Absolute Difference	25% to 30%	30% to 35%	**20% to 30%**
Standard Deviation	—	—	15% to 30%
% of Homes <30% Different	—	—	*65% to 75%*
% of Homes <20% Different	—	—	*45% to 50%*
% of Homes <10% Different	—	—	*25% to 30%*
Median Nonabsolute Difference	(15%) to 10%	(25%) to 0%	(15%) to 0%
Mean Nonabsolute Difference	(10%) to 10%	(20%) to 5%	(10%) to 5%
Combined Nonabsolute Difference	—	—	*(1%)*

[iv] Ranges of properties analyzed for both Set 1 and Set 2 varied between vendors based on the number of property addresses that matched records in their reference databases and the availability of fuel and cooling types and systems.

Set 2 (Providing Six Key External Inputs):

- **Absolute differences** indicate typical differences to be expected for any **individual** home
  - **Total Energy Use:** Estimates from both vendors averaged **20–25 percent** different from corresponding HES estimates
    - Nearly *three-quarters* of all homes analyzed were less than 30 percent different
    - More than *half* of all homes analyzed were less than 20 percent different
    - More than *one-quarter* of all homes analyzed were less than 10 percent different
  - **Electricity Use:** Estimates from both vendors were, on average, **15–20 percent** different from corresponding HES estimates
  - **Natural Gas Use:** Estimates from both vendors were, on average, **20–25 percent** different from corresponding HES estimates
- **Nonabsolute differences** indicate general trends across an **aggregated** set of homes
  - **Total Energy Use:** Estimates from both vendors were, on average, within **+/- 10 percent** of corresponding HES estimates across the dataset, with one vendor slightly underpredicting and the other slightly overpredicting
  - **Combined Total Energy Use:** Using a combined average of the vendors' estimates for each home (similar to how credit scores combine scores from multiple sources) resulted in an overall average difference of less than **0.5 percent** versus HES

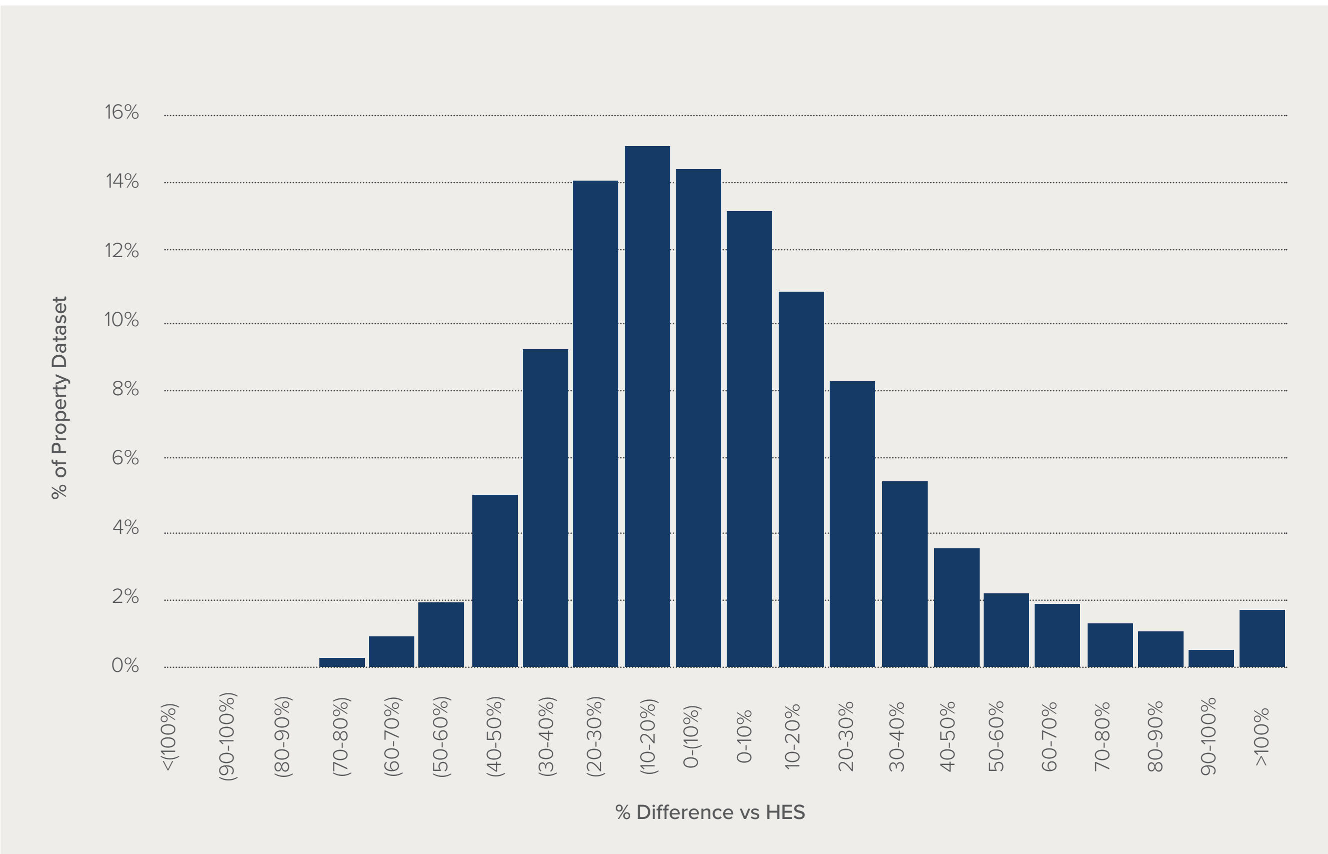
TABLE 2. SET 2 RESULTS SUMMARY: VENDOR ESTIMATES VS HES ESTIMATES

	ELECTRICITY USE	NATURAL GAS USE	TOTAL ENERGY USE
Given Inputs	Zip code, conditioned floor area, number of bedrooms, year built, heating/cooling system type, heating fuel		
# Properties Analyzed	4,105 to 4,114		
Median Absolute Difference	10% to 15%	15% to 20%	**15% to 20%**
Mean Absolute Difference	15% to 20%	20% to 25%	**20% to 25%**
Standard Deviation	—	—	15% to 20%
% of Homes <30% Different	—	—	*70% to 75%*
% of Homes <20% Different	—	—	*50% to 55%*
% of Homes <10% Different	—	—	*25% to 30%*
Median Nonabsolute Difference	(10%) to 15%	0%	(10%) to 5%
Mean Nonabsolute Difference	(15%) to 10%	0% to 15%	(10%) to 10%
Combined Nonabsolute Difference	—	—	*0%*

Figures 4 and 5 show the combined average of both vendors' total energy use estimates versus HES, showing a more normal distribution in Set 2 versus Set 1:

FIGURE 4

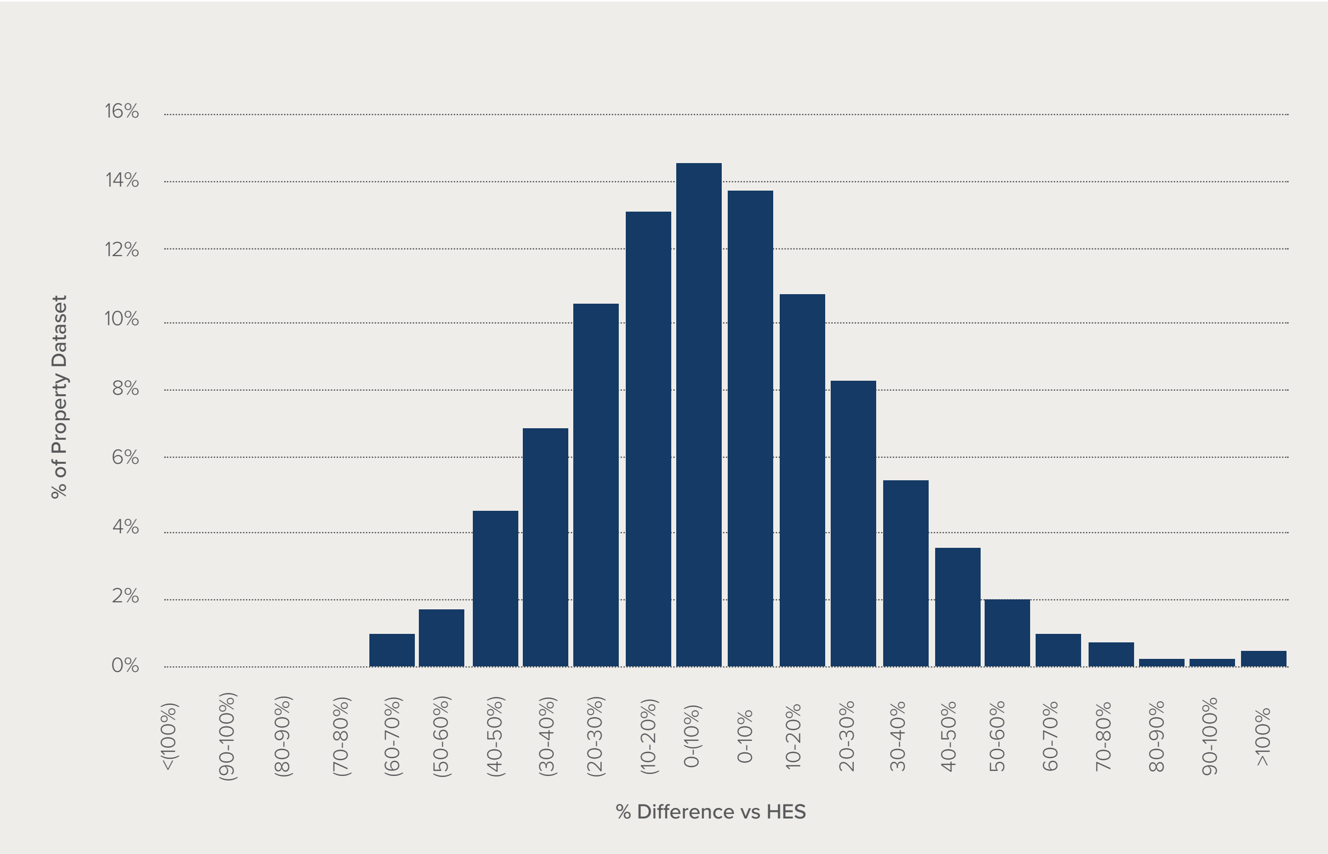
SET 1 TOTAL ENERGY USE VS HES (COMBINED AVERAGE OF VENDOR RESULTS)



As shown in Figures 4 and 5, the vendor results did improve from Set 1 to Set 2, particularly when looking at the isolated results for electricity and natural gas (versus total energy) use. In both cases, the range of absolute differences improved by roughly 10 percent. Unsurprisingly, this indicates that, when fed by reliable data inputs such as those collected on-site by qualified HES assessors and subject to a quality control process, vendor algorithms generate results more in line with HES.

FIGURE 5

SET 2 TOTAL ENERGY USE VS HES (COMBINED AVERAGE OF VENDOR RESULTS)



RMI also looked at how the vendor algorithms compared with HES at different levels of home performance. RMI divided both datasets into even quartiles based on properties' HES scores (1–2 at the low-performing end, 3–4, 5–6, and 7–10 at the high-performing end) and recalculated average nonabsolute energy use differences for each quartile. The results suggest that, given the inputs provided, both vendors tend to underpredict the most for the highest energy consuming homes, and overpredict the most for the lowest energy consuming homes, erring towards the norm at either extreme. While ideally this exercise would have shown a similar variance across all quartiles, RMI believes that (1) further study is required to evaluate whether additional home parameters available via MLS records or tax assessor databases would reduce the discrepancy; (2) because this is an emerging tool, it may be better to err on the conservative side at the extremes rather than risk overpredicting extremely high or low performance; and (3) the highest- and lowest-performing homes are better served by on-site assessments to validate their performance and prioritize their upgrades, respectively.

06 THE DATA BEHIND THE DOLLAR SIGNS

THE DATA BEHIND THE DOLLAR SIGNS

While, so far, this analysis has focused primarily on energy *use* estimates, a key area where algorithm-based vendors can outperform is in estimating energy *costs*, which are perhaps the more critical and tangible data points considered by homeowners/buyers and other stakeholders. Whereas HES uses statewide average utility rates (the latest available from the DOE's Energy Information Administration) in determining its energy costs and savings estimates, algorithm-based vendors pull significantly more granular utility rate data—down to the utility level and mapped by zip code.

For example, one vendor currently pulls from 956 electricity rate schedules and 732 natural gas rate schedules across the country, including thresholds for rate tiers where applicable (e.g., California). This level of granularity matters, particularly in states where rates can vary widely between cities (e.g., Pennsylvania, New Mexico, New York) as depicted on **NREL's residential electricity rate map**.

To gauge the implications of this, RMI analyzed energy cost estimates differently than energy use estimates as laid out above. RMI backed into each vendor's implied electricity and natural gas rates on a home-by-home basis, then applied these rates to the reported HES electricity and natural gas consumption estimates. These converted HES energy cost estimates were then compared against the reported HES energy cost estimates:

- In **absolute** terms, the converted HES cost estimates were found to be **9–22 percent** different on average from reported HES cost estimates using the implied vendor rates

The resulting range is likely due in part to the fact that one vendor uses rolling 12-month average rates while the other uses the latest month's rates. Both approaches are viable, but have different implications for how the data is understood and used.

This shows that more granular utility rate data can meaningfully improve HES energy cost (and savings) estimates, and that when energy costs are the metric in focus, algorithms may have improved estimation accuracy, depending on location. It is feasible for HES to obtain more locally accurate utility rate data to generate better cost estimates if another software tool is used with its API (as can be done in the City of Portland's HES program) although challenges can arise when multiple rates are available for the same address and when rate databases become out of date.

07 VIABLE USE CASES FOR AUTOMATED HOME ENERGY DATA

Photo © Green Energy Futures, courtesy of Dave Spencer and Debbie Whiltshire

VIABLE USE CASES FOR AUTOMATED HOME ENERGY DATA

Based on these results, RMI believes that automated home energy estimates may be sufficiently accurate for several use cases, including those laid out in Table 3, in light of accuracy standards acceptable in other industries. Colors correspond to the use of **individual** household estimates versus **aggregated** household data, although certain uses could leverage both. It should be noted that all proposed uses are based on the untested assumption that the algorithms can access key property attributes (as were provided to the vendors for this analysis) via real estate portals, MLSs, and/or public tax assessor databases to refine their estimates.

TABLE 3. POTENTIAL USE CASES FOR AUTOMATED HOME ENERGY DATA

STAKEHOLDER	USE CASE
Homeowners/Homebuyers	• **Greater awareness** of overall home energy performance relative to local context • **More conservative budgeting** for total homeownership costs when purchasing a home with no assessment information (RMI recommends incorporating a buffer of roughly 20 to 30 percent)
Real Estate Portals	• **Competitive advantage** from higher customer retention on sites that provide more robust information (e.g., in affordability calculators) • **Lead generation revenue** from energy service providers/contractors
Energy Service Providers & Contractors	• **Increased sales** of products/services from leveraging personalized home energy profiles • **Lead generation for more in-depth on-site energy assessments** due to raised awareness from owners of more inefficient homes • **Enhanced marketing and lead generation** with data that can show which customers stand to benefit the most from energy upgrades
Mortgage Lenders & GSEs (e.g., Fannie Mae, Freddie Mac)	• **Mechanisms to better assess loan performance risks** (versus standard underwriting procedures) arising from energy costs, which are **correlated with loan default rates,** at a local level • **Easier identification of good candidates** for energy-focused loan products and flexibilities
City & State Governments	• **Higher awareness/engagement** from citizens around home energy to prompt private investment • **Prioritized investment** of limited funds (e.g., HUD Community Development Block Grants) to neighborhoods with **higher energy burdens** • **Refined policies and target-setting** leveraging broader community-wide baseline residential energy performance data

The **aggregated** applications can be well served by algorithm-based data given the low overall nonabsolute difference from HES (+/-10 percent overall), especially when the vendor estimates are combined. The **individual** household applications are proposed on the basis that rough estimates that are, on average, 20–30 percent different, and less than 30 percent different nearly three-quarters of the time, are close enough to be useful. Undoubtedly, different stakeholders will have different opinions about what level of accuracy is acceptable for what applications, or how best to account for potential variances. RMI believes that level of debate and dialogue is healthy for an emerging tool.

For a comparison to other industries, consider the market impact of the following services. As a long-running standard for fuel economy in gas-powered vehicles, the US Environmental Protection Agency's miles-per-gallon (MPG) estimates were found to be 10.3 percent higher on average (nonabsolute) than the actual tested results of a **2005 analysis by Consumer Reports**; a 2016 update to this analysis found that EPA testing procedures improved over time to generate an average nonabsolute difference of only 3.1 percent (where 72 percent of vehicles tested were within +/- 15 percent). Note that the 10.3 percent nonabsolute average difference that was considered acceptably accurate for the auto industry is higher than the nonabsolute average difference RMI found for automated home energy estimates.

A **study by SSRS** found Zillow's home-value predictions to be less than 20 percent different from actual sale prices 83 percent of the time. In an industry where greater transparency is a critical market service, the **US Food and Drug Administration requires nutrition labels** to be less than 20 percent different from actual ingredient content in order to be in compliance. While these are higher levels of accuracy than what automated home energy estimates currently achieve, they provide useful points of reference.

It is important to note that the participating vendors' websites and certain forward-thinking real estate portals that already incorporate their algorithms (i.e., **Estately.com** and **RealEstate.com**) allow homeowners to "claim" their home and update the algorithms with actual information—asset and operational—to generate more accurate estimates and more actionable recommendations. This ability to override default modeling assumptions with actuals can substantially mitigate accuracy concerns for individual-household use cases.

In sum, RMI believes the vendor accuracy ranges are sufficient for the use cases highlighted above, especially given that many of them focus on energy costs, where algorithm-based estimates can readily outperform other estimates by leveraging more granular utility rate data. Looking ahead, RMI expects that further market penetration, more claiming by homeowners, scalable new data sources, and machine learning can all support a positive reinforcing loop that improves algorithm accuracy over time—just as MPG accuracy for cars improved over time.

08

CONCLUSION

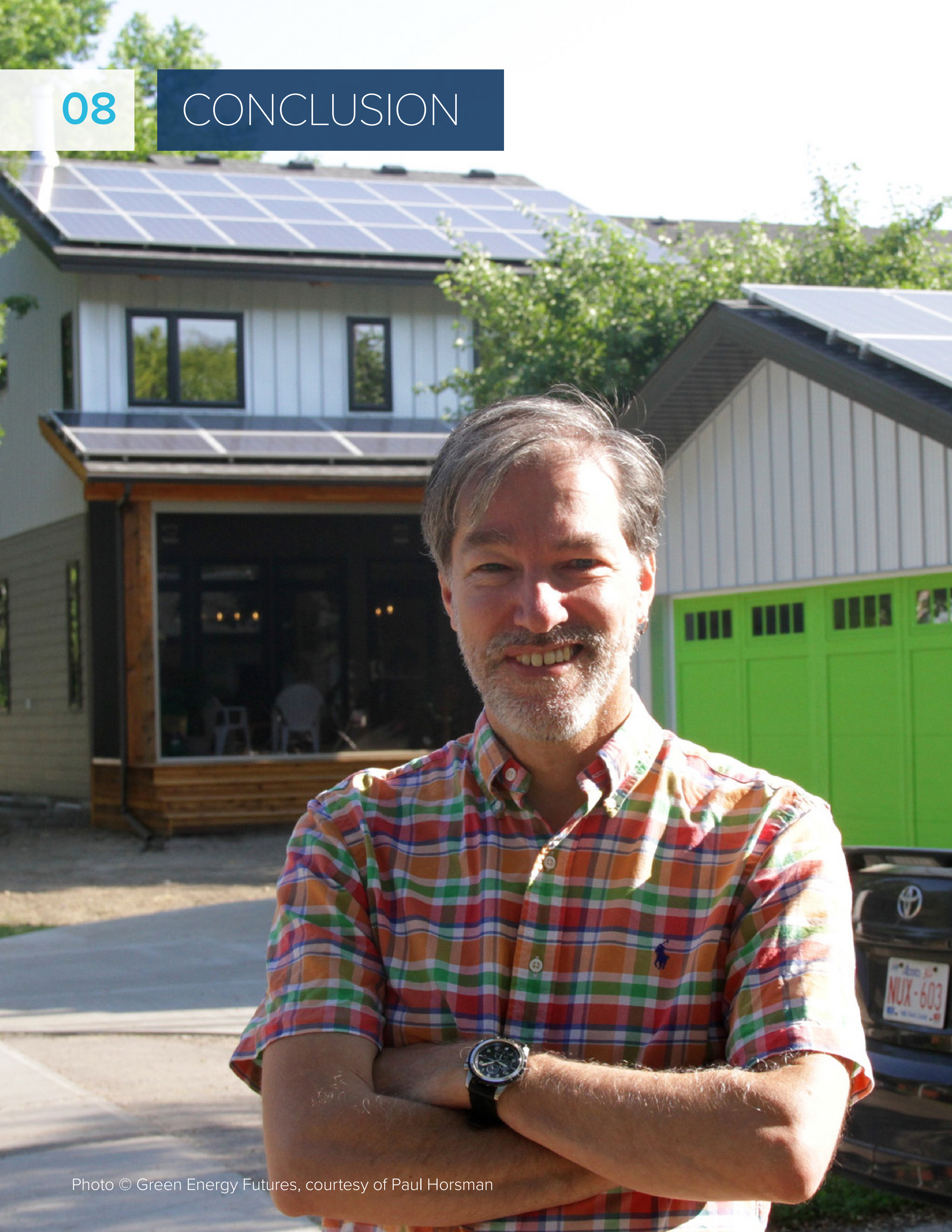


Photo © Green Energy Futures, courtesy of Paul Horsman

CONCLUSION

The existence of reasonably accurate "first look" energy performance estimates for all homes in the US can not only start the conversation for more homeowners, but can also motivate them to take the next step—whether that means pursuing a more comprehensive on-site assessment like HES or HERS, purchasing that more efficient home, or installing valuable energy upgrades themselves.

While RMI believes additional research into the accuracy of the algorithms' inputs and upgrade recommendations would advance the conversation and further benefit the market, the results of this analysis suggest that automated home energy estimates may be sufficiently accurate for multiple stakeholders to start reaping their benefits. A much larger population of homeowners has the ability to make better purchasing, renovating, and selling decisions than ever before. Real estate portals and energy service contractors can bolster their sales and stay ahead of the competition. Mortgage lenders and the GSEs can more appropriately account for risks and provide differentiated product offerings to more customers. And local governments can more efficiently invest public funds and better inform policy decisions while also engaging their communities in climate action.

While their accuracy can and should improve with time, these algorithms are ultimately making significant strides in closing the information gap and creating visible value across the residential energy performance market.

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