Comparing the magnitude of simulated residential rebound effects from electric end-use efficiency across the US

Brinda A Thomas¹, Zeke Hausfather² and Inês L Azevedo¹,³

¹ Climate and Energy Decision-Making Center, Carnegie Mellon University, 5000 Forbes Ave., Pittsburgh, PA 15213, USA
² Berkeley Earth, Berkeley, CA, USA
³ Department of Engineering and Public Policy, Carnegie Mellon University, 5000 Forbes Ave., Pittsburgh, PA 15213, USA

E-mail: iazevedo@cmu.edu

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Abstract

Many US states rely on energy efficiency goals as a strategy to reduce CO₂e emissions and air pollution, to minimize investments in new power plants, and to create jobs. For those energy efficiency interventions that are cost-effective, i.e., saving money and reducing energy, consumers may increase their use of energy services, or re-spend cost savings on other carbon- and energy-intensive goods and services. In this paper, we simulate the magnitude of these ‘rebound effects’ in each of the 50 states in terms of CO₂e emissions, focusing on residential electric end-uses under plausible assumptions. We find that a 10% reduction in annual electricity use by a household results in an emissions’ reduction penalty ranging from 0.1 ton CO₂e in California to 0.3 ton CO₂e in Alabama (from potential emissions reductions of 0.3 ton CO₂e and 1.6 ton CO₂e, respectively, in the no rebound case). Rebound effects, percentage-wise, range from 6% in West Virginia (which has a high-carbon electricity and low electricity prices), to as high as 40% in California (which has low-carbon electricity and high electricity prices). The magnitude of rebound effects percentage-wise depends on the carbon intensity of the grid: in states with low emissions factors and higher electricity prices, such as California, the rebound effects are much larger percentage-wise than in states like Pennsylvania. Conversely, the states with larger per cent rebound effects are the ones where the implications in terms of absolute emissions changes are the smallest.

Keywords: energy efficiency, rebound effects, household consumption, carbon dioxide emissions

1. Introduction

Several states across the US rely on energy efficiency goals as a way to reduce CO₂e emissions, reduce air pollution, to minimize investments in new power plants, and to create green jobs. Twenty seven states have established Energy Efficiency Resource Standards or voluntary goals [1]. The ways states establish these goals vary widely in magnitude and format, ranging from annual goals to reduce electricity sales by a few percent to cumulative goals to reduce electricity sales by 22% in 2020 [1].

Bottom-up engineering-economics assessments show that end-use electric energy efficiency programs can save electricity at an average cost well below the cost of generation from new power plants, which makes energy efficiency one of the most cost-effective means to reduce emissions [2–5]. There is a large debate in the literature on whether utilities with extensive residential energy efficiency programs may...
experience diminishing returns from efficiency investments, i.e., seeing increased costs in energy efficiency measures and programs once the ‘low-hanging fruit’ is harvested. Simultaneously, energy efficiency technologies and energy efficiency measures may show technological progress, becoming more efficient and cheaper over time, and therefore increasing the supply of energy efficient strategies [6]. The direction of these and other underlying effects is not clear, and thus we opted to consider these aspects as outside of the scope of this paper.

Most bottom-up energy efficiency studies, however, assume constant energy service demand before and after the energy efficiency measure is implemented and do not account for consumer behavior. If households pursue cost-effective energy efficiency measures, i.e., measures that save money while also saving energy over their lifetime, then consumers may use more of these energy services. This is called a **direct rebound effect**. Consumers may also re-spend the cost savings on other goods or services that are also energy or carbon intensive. This is called an **indirect rebound effect**. The contribution (or lack thereof) of such behavioral adjustments in assessing the total energy and carbon savings from efficiency measures has gained some attention in recent years, and there a wide debate over its magnitude and even sign [7–9]. In order for utilities and state-level policymakers to know what level of effort and what costs will be imposed to meet energy efficiency goals after accounting for consumer behavior, estimates of rebound effects are needed. In this work, we use a neo-classical model of consumer behavior to simulate, under plausible assumptions, the magnitude of household indirect rebound effects in each of the 50 US states as a household invests in energy-efficient electric equipment.

Many papers determining the size of rebound effects from energy efficiency focus on energy rebound [10–19]. We argue that the focus ought to be on the negative effects associated with the use of energy services, not on energy consumption per se. Henceforth, in this paper, we represent the rebound effect in terms of carbon dioxide emissions.

Researchers in industrial ecology and in energy economics have studied the energy efficiency rebound effect using different methods and assumptions, which we reviewed and integrated in prior work [20–22] and briefly summarize here. Recent work on household carbon footprints (HCF) from industrial ecology literature that includes direct combustion emissions (or scope 1), purchased electricity emissions (or scope 2), and upstream supply chain emissions from the production of goods and services (or scope 3) is also relevant for our method and analysis [23–26].

### 1.1. The direct rebound effect

Describes an increase in households’ demand for energy services due to a decrease in the price of energy services (i.e. $/mile driven or $/lumen hour of lighting) with an efficiency investment. An example of this effect is leaving the lights on for longer periods of time after switching the lighting system in your living room from incandescent lamps to light emitting diodes. Energy economic studies of the direct rebound for energy efficiency measures for residential electricity end-uses find effects to be as low as 0% and as high as 30%, depending on household income [11, 27, 28], region [29–31], and end-use [10, 30, 32].

Industrial ecology studies tend to treat the direct rebound as an exogenous parameter in demand simulations of new technologies and emphasize the indirect rebound effects [33, 34]. **Indirect rebound effects** describe the consequences of households re-spending the operating cost savings from an efficiency investment on other goods and services. Studies find that indirect rebound effects range between 15% and 50% [35–40], when excluding consideration of the direct rebound effect.

Our approach is similar to some recent studies from the industrial ecology literature in that we jointly model direct and indirect rebound effects by considering marginal spending patterns and using life-cycle analysis by including scope 1–3 emissions [41–44]. These studies have found indirect rebound effects that range from 5% to 25% [13, 14, 21].

In contrast, studies in energy economics literature tend to include scope 1 and 2 emissions from energy end-uses, but largely ignore upstream supply chain emissions (scope 3). Furthermore, energy economics studies generally apply econometric methods to distinguish between average and marginal spending patterns, finding a wide range in indirect rebound results ranging from 10% to over 100% [12, 15, 17].

While the industrial and commercial sectors may exhibit similar direct and indirect rebound effects [10, 16, 45], in this paper we restrict our focus to residential direct and indirect rebound effects for electric end-uses. We also restrict our focus to rebound effects as defined in industrial ecology and economics, although the fields of psychology and sociology provide complementary definitions and perspectives on consumer behavior with efficiency investments that are also important when assessing the consequences of energy efficiency investment [22]. Also outside the scope of this paper is a third effect at a macro level, called the **economy-wide rebound effect**, in which widespread investments in energy efficiency lead to a decrease in the market price of energy, which triggers macroeconomic changes in economic structure and energy demand [18, 19, 46–48]. Rebound effects can also increase consumer welfare by allowing households to enjoy higher consumption, and that issue has been largely understudied in the rebound effect literature, but is also outside of the scope of our work.

In prior work [20], we developed a framework that merges a micro-economic model of household behavior with scope 1, 2, and 3 emissions to simulate the carbon dioxide emissions rebound effects from residential efficiency investments for electricity, natural gas, and gasoline [21]. We found that scope 3 emissions contribute to a substantial portion of the indirect rebound effect. We compared average and marginal spending patterns and found that under most conditions the two resulting simulations of rebound effects are similar in magnitude [21]. This paper is motivated by that previous work [21] as we found that the indirect rebound from efficiency in electric end-uses is highly sensitive to a number of regionally varying factors, such as grid emissions factors,
electricity and gasoline prices, transportation (gasoline) demand, and overall household consumption or expenditure patterns. Here, we simulate energy efficiency investments in electric end-uses made by typical households in the 50 US states using regional consumer expenditure data [49], regional grid emissions factors, and a national environmentally-extended input–output life-cycle assessment model [50, 51] to provide a novel regional assessment of indirect rebound effects. We provide the results in terms of percentage rebound effect, rebound in emissions, and net avoided CO₂e emissions for an average household in each state.

This paper is organized as follows: section 2 describes the methods and data sources used in the analysis. Section 3 provides the results and analysis, and section 4 concludes with a discussion of the application of rebound estimates for energy efficiency policy analysis.

2. Scenarios, method and data

We simulate indirect rebound effects and resulting changes in expenditures and carbon footprints as consumers invest in energy efficient strategies that would reduce their electricity expenditures by 10%. In this work, we make several key assumptions: we assume a 10% direct rebound effect; we assume that retail electricity rates purely reflect the variable cost of electricity; and we only consider the subset of energy efficiency measures that have zero or less incremental annualized costs (thus, we assume, as in most of the rebound effects literature, that the cost of energy service effectively is reduced with the energy efficiency measure). Furthermore, we assume two scenarios: one where consumers re-spend all the monetary savings in the same proportion of expenditure categories as they were doing originally, and the second where we account for changes in this proportion by accounting for price and income elasticity. We do not account for substitution effects since in previous work we have shown that accounting for those effects has little consequence on the overall indirect rebound effect. This approach is similar to what we used in the theoretical derivation shown in Thomas and Azevedo [20].

It may be the case that an energy efficiency measure has an increased upfront capital cost when compared to the baseline technology being used. Borenstein [52] shows that in that case, the overall direct and indirect rebound effects will depend on whether the upgrade associated with the energy efficiency measure ‘is more energy intensive (per dollar) than purchases from new income.’ Borenstein [52] also states that in any case, ‘as a first cut analysis […], ignoring the embodied energy in the efficiency upgrade may not be a large source of error as long as one also ignores the cost of the efficiency upgrade when calculating income-effect rebound’.

We consider the following scenarios for an average household in each of the 50 US states, while considering the total scope 1, 2, and 3 carbon footprint in terms CO₂e emissions:

(i) A baseline case, i.e., the average household carbon footprint from all expenditure categories (baseline carbon footprint, or CFB) prior to an energy efficiency measure.

(ii) A no rebound case, i.e., the average household carbon footprint after an investment in electric energy efficiency measure that results in a 10% reduction in annual electricity consumption (scenario CFB₂), assuming none of the monetary savings are spent on other goods and services.

(iii) A proportional re-spending case, i.e., the average household carbon footprint after an investment in an electrical energy efficiency measure that results in a 10% reduction in electricity consumption is implemented, again for each of the 50 US states, but now accounting for direct and indirect rebound effects, and assuming that the household will spend the cost savings from the energy efficiency measure in the same proportion for each good and service that they were using prior to the energy efficiency intervention (scenario CFBRA).

(iv) A micro-economic model case, i.e., we simulate the average household carbon footprint after an investment in electrical energy efficiency measure that results in a 10% reduction in annual electricity consumption is implemented but now accounting for the fact that the household will spend the economic saving from the energy efficiency measure, and will do so according to a neo-classical standard model that uses price and income elasticities when assessing the new proportion of income allocated to each good and service in the household bundle of goods. We use a low and a high case for income elasticities, which we describe in more detail below, and thus this scenario includes two sub-scenarios, CFRB₁ and CFRB₂.

Figure 1 highlights the different scenarios, data and assumptions, and outputs. Our model does not apply to efficiency investments that have a positive incremental levelized cost for the household. Mizobuchi (2008), Chitnis et al (2012), and Borenstein (2013) show that capital costs will reduce the extent of the rebound effect for positive-cost efficiency measures [15, 40, 52]. For simplicity, we also assume that the household re-spends all of their energy cost savings and does not increase their savings. By considering only strategies with zero or negative incremental annualized costs, we in fact overestimate the indirect rebound effect, i.e., our results serve as an upper bound for indirect rebound effects.

The energy efficiency rebound effect, R, can be defined as the difference between the simulated carbon savings when assuming that the amount and quality energy services are held constant before and after an energy efficiency measure is implemented (i.e., (CFB₂−CFB₁)), and the actual emissions savings, i.e., the savings that occur after accounting for consumers’ re-spending (CFB₂−CFB₁). The rebound effect is generally expressed as a percentage, where $R = 1 - \frac{(CFB₂−CFB₁)}{(CFB₁−CFB₁)}$, and can be measured with respect to primary energy or pollutant emissions (for example, CO₂e,
NO\textsubscript{x}, or SO\textsubscript{2} or another environmental impact. Here we focus solely on a CO\textsubscript{2}e metric.

If we assume that households re-spent any reductions in their electric bills from electric end-use efficiency in proportion to their average spending patterns (scenario CF\textsubscript{RA}), the percentage rebound effect, in terms of CO\textsubscript{2}e emissions, is provided by equation (1). This equation provides a first order ratio comparison of the carbon emissions from re-spending relative to the electricity emissions, which were displaced by efficiency:

\[ R_{\text{RA}} \% = R_D + R_I = \left( w_s + \sum_{n=1,\ldots,o} w_n \frac{E_n}{E_s} \right) \times 100. \]  

\( R_{\text{RA}} \) is the rebound effect (in percent) assuming that all economic savings from the energy efficiency measure are re-spent across different spending categories in the same proportion the household was using prior to the energy efficiency investment. For example, if the household was spending 30\% of its budget on food, 30\% of the economic savings from energy efficiency will be allocated to food. \( R_D \) is the direct rebound effect and \( R_I \) is the indirect rebound effect. \( E_s \) and \( E_o \) represent the emissions per dollar of expenditure on the electricity service, \( s \), and \( n \) other goods and services, \( o \). The budget shares for the household’s spending on electricity services and other goods and services are reflected in \( w_s \) and \( w_o \). Note that under the proportional spending scenario, the direct rebound is constrained to be equal to the household’s budget share for electric end-uses, \( w_s \), which is between 1\% and 5\% for the average household in various US states. A full derivation of this equation can be found in Thomas and Azevedo [20]. We use this scenario to represent small changes in energy efficiency (such as a couple of CFLs, for example) where it is plausible to assume that consumers are simply re-spending their income in the same proportion as they did before the implementation of an energy efficient strategy. However, this scenario does not account for consumer reactions to changes in the price of the energy service, i.e., it ignores incomes and substitution effects. Therefore, we also account for a more realistic consumer behavior model, in which consumers will not re-spent these monetary savings proportionally. Instead, re-spending will depend on the own-price elasticity of the demand for that energy service and income elasticities defined as the percent change in demand for good \( a \) with respect to a percent change in net income, \( Y \) [53]. Based on the properties of price and income elasticities, in prior work [20] we derived a general model of the direct and indirect rebound effects which results in equation (2) for this scenario (RB):

\[ R_{\text{RB}} \% = R_D + R_I = \left( -\eta_{p,s} + \sum_{n=1,\ldots,o} \eta_{p,n} \frac{E_n}{E_s} \right) \times 100, \]  

where \( \eta_{p,s} \) is the own-price elasticity for an electricity service.
s; \eta_{ij} is the income elasticity for the electricity end-use s; \eta_{ij} is the income elasticity for good i; w_i is the share of household budget for electricity end-use s; w_i is the share of household budget for good i; E_i are the scope 2 and 3 emissions intensities per dollar of expenditure for an electricity end-use [e.g. kgCO₂e/$] and E_i are the scope 1, 2, and 3 emissions per dollar of expenditure on a non-electricity good.

We use equations (1) and (2) in two scenarios that simulate the magnitude of rebound effects across the 50 US states. We have assumed a constant 10% direct rebound effect across all 50 states. While there may be some regional variation in the direct rebound effect due to differences in climate, preferences, the rate of fixed cost versus marginal cost recovery through retail electricity rates [52], and other factors, there are limited direct rebound studies for electric end-uses ([32, 54] are rare examples). In Azevedo et al [54], we estimated residential price elasticity for electricity (which is sometimes used as a proxy for direct rebound effects) for each of the US North American Electric Reliability Corporation (NERC) regions and found long-term price elasticity ranging from −0.20 to −0.32. In this paper, instead of assuming different direct rebound effects by state, we use sensitivity analysis on the direct rebound, adapted from prior work [20]. In addition, we show the extent of variation in rebound effects due to different assumptions about spending patterns.

Next, we describe the key data and assumptions used to compute the simulations for the base-case and to populate equations (1) and (2) above. For reasons explained below, we use 2004 as the base-year of analysis to limit sources of uncertainty in rebound simulations due to structural change in the US economy. We assess the implications of changes in the key inputs that better reflect present and likely future conditions for our rebound simulations through the sensitivity analysis.

2.1. Consumer expenditures on different goods and services

To establish the baseline carbon footprint for households in each state, we follow the same procedure as Jones and Kammen [44], i.e., we multiply the expenditure from households for good i, by the carbon dioxide emission factor for good i, in tonCO₂e/ton (which includes scope 1, 2, and 3 emissions). We use two data sources for the household expenditures: State Energy Data System (SEDS) [56] from the Energy Information Administration (EIA) for year 2004 to obtain residential electricity and gasoline expenditures by state. Household consumer expenditures other than goods are assumed to follow the average household in the Census region in which the state is located, using the 674-category regional pre-publication tables of the 2004 Consumer Expenditure Survey (CES) [49]. These data sources are used to derive budget shares by spending category (w_i and w_o in equations (1) and (2) above), which we linearly adjust to sum to unity, given EIA state-level data on household budget shares for electricity and gasoline [56].

2.2. Emissions factors for electricity

Given that most of the policy goals for energy efficiency are set at the state level, we use the state as our unit of analysis for rebound assessments. However, for the electricity carbon intensity (tonCO₂e kWh⁻¹), we use grid emissions factors for the 26 regions from the Environmental Protection Agency emissions and generation resource integrated database (eGRID) [57]. We used year 2004 data to correspond to the timeframe of the consumer expenditure data. When a state’s boundaries contained more than one eGRID region, emissions factors were weighted by the population contained in each region, using estimates from the 2005 American Community Survey [58]. Transmission loss data [57] from 2005 at a state level are used to further refine the emissions factors. We choose to use eGRID grid emissions factors rather than state-level grid emissions factors since Weber et al [59] argue that state-level grid emissions factors ignore inter-state electricity flows and the topology of the electric grid. Since the rebound results were similar with grid emissions factors using eGRID and other regional boundaries, such as NERC regions, we will only present results using grid emissions factors based on eGRID delineations. Marginal emissions factors, i.e. characterizing which generator and associated emissions are being displaced as one pursues interventions in the grid, are also important for assessing the carbon emissions effects of energy efficiency interventions. Understanding the marginal emissions avoided is relevant because energy efficiency will displace a different set of generation technologies than baseload demand [60, 61]. Siler-Evans, Azevedo, and Morgan [60] measure marginal grid emissions factors for CO₂e, NOₓ, and SO₂ emissions for NERC regions and show that average emissions factors can misestimate emissions impacts of efficiency, but not a lesser extent for CO₂e emissions. In our results, since we focus mostly on CO₂e emissions, we use average emissions factors.

2.3. Emissions factors for gasoline and natural gas

To compute the HCF, we also need to include the emissions from energy consumption from non-electric end-uses, namely from the combustion of gasoline and natural gas. For gasoline, we use 0.071 tonCO₂e/MMBTU and for natural gas 0.053 ton CO₂e/MMBTU.

2.4. Supply-chain emissions factors

For the supply-chain scope 3 emissions associated with the manufacture of goods and provision of services, we use the Environmental Input–Output Life Cycle Analysis model (EIO-LCA) from Carnegie Mellon University, for which 2002 is the most recent year of data [51]. These emissions factors are obtained by multiplying emissions per dollar of expenditure by the expenditure amount for each consumption category. Such strategy required a matching of the expenditure categories in EIO-LCA with the expenditure categories in the CES data mentioned above. We assume that goods are produced nationally and transported to the various regions of the US, so that national supply chain emissions per dollar of...
3. Results and analysis

3.1. HCF

Figures 2(A) and (B) show the carbon footprints for each of the 50 US states in the baseline case, sorted by highest to lowest carbon footprint and highlighting the different categories of consumption that correspond to such emissions. The largest contributions to the household’s carbon footprint are scope 1 and 2 emissions from electricity, scope 1 emissions from gasoline combustion, and the scope 1 to 3 emissions from other (non-fuel) consumption. While scope 3 emissions from electricity, natural gas, and gasoline are small, scope 3 emissions are important to consider for energy assessments given that roughly half of households’ carbon footprint comes from goods and services other than these fuels and energy carriers.

3.2. Rebound in emissions, actual emissions savings, and percent rebound

Figures 3(A) and (B) show the main results from the simulations for scenario RB-1. RB-1 represents the scenario where the Indirect Addilog elasticities from Houtakker and Taylor are used (see table 1). The height of the bars from the x-axis to the up-most part of the dashed bars corresponds to the potential annual reductions in the carbon footprint by a household in each of the states if there were no rebound effects. The sum of the colored bars corresponds to the penalty in emissions savings due to rebound effects under scenario RB-1. The colored bars show rebound effects in CO2e emissions from various types of spending. The dashed bars therefore correspond to the actual or net emissions savings after accounting for rebound effects for scenario RB-1. In the same plot, we also show the overall results from using a different set of elasticities (RB-2) and a proportional re-spending scenario (RA). Since these results represent different scenarios, rather than uncertainty, we choose to present them with different markers in figures 3 and 4, instead of using error bars. RB-2 scenario is shown with gray squares, representing an upper-bound rebound due to high transport re-spending. RB-1 and RB-2 use two sets of income elasticities from Taylor and Houthakker [61]. The proportional re-spending scenario, RA (represented by the black triangles), provides a lower bound for indirect rebound, representing households that exhibit proportional spending patterns for energy efficiency investments made by the average household in each state, ranked by the rebound in emissions (i.e. the same ranking in figures 3(A) and (B)). Again, the bars display scenario RB-1. The gray squares show scenario RB-2, and the black triangles represent scenario RA. While the rebound effect varies between 6% and 40%, smaller

### Table 1. Assumptions for expenditure (income) elasticities.

| Category       | Expenditure elasticity for RB-1 (indirect addilog) | Expenditure elasticity for RB-2 (linear expenditure system) |
|----------------|-----------------------------------------------------|-----------------------------------------------------------|
| Food           | 0.36                                                | 0.12                                                      |
| Shelter        | 0.87                                                | 0.54                                                      |
| Appliances     | 0.87                                                | 0.54                                                      |
| Electricity    | 0.40                                                | 0.14                                                      |
| Natural gas    | 0.40                                                | 0.14                                                      |
| Other utilities| 0.40                                                | 0.14                                                      |
| Gasoline       | 1.3                                                 | 2.3                                                       |
| Transportation | 1.3                                                 | 2.3                                                       |
| Public transit | 1.3                                                 | 2.3                                                       |
| Air travel     | 1.3                                                 | 2.3                                                       |
| Health care    | 0.52                                                | 0.27                                                      |
| Financial      | 1.3                                                 | 0.27                                                      |
| Misc.          | 1.2                                                 | 1.1                                                       |

Notes: expenditure elasticities using the indirect addilog and linear expenditure system functional forms for consumer utility functions from Houthakker and Taylor’s [63] historical studies of the US Consumer Expenditure Survey.
Percentage rebound effects tend to be associated with higher net or actual CO$_2$e emissions savings and higher rebound effects in emissions, both of which are arguably more relevant for assessing the impacts of an energy efficiency measure for climate mitigation goals.

3.3. Sensitivity analysis

In the previous section, we assumed a 10% direct rebound effect. However, the direct rebound effect is, in itself, very uncertain. The magnitude of the direct rebound effect will determine the size of the indirect rebound effect. Thus, figure 5 provides a sensitivity analysis for the total (direct and indirect) rebound effect from residential electric end-use efficiency for an average household in California and Alabama. These two states have the highest and lowest percent rebound effects (and lowest and highest rebound effects in emissions), respectively. We vary parametrically the direct rebound effect between 0% and 50%, which correspond to the

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Figure 2. (A) Top 25 and (B) Bottom 25 carbon footprints for the average household in each state in 2004 (i.e., our baseline scenario). Sources/Notes: carbon footprint calculation uses the 4-census region 2004 Consumer Expenditure Survey data for non-energy goods and EIA SEDS data for electricity and gasoline expenditures and prices, all converted to 2002S by the CPI method, with an environmentally-extended input–output life-cycle assessment model (www.eiolca.net) using 2002 US data. S1, S2, and S3 mean scope 1, 2, or 3 emissions.
Figure A shows the rebound in emissions & net emissions savings from electric end-use efficiency in 2004 (ton CO₂/year) for various states. The graph compares actual emissions savings and rebound effects.

Figure B illustrates similar data for different states, highlighting the savings and rebound from electric end-use efficiency in 2004 (ton CO₂/year). The graph includes various categories such as actual emissions savings, other savings (S1-3), natural gas (S2-3), natural gas (S1), gasoline (S2-3), gasoline (S1), direct rebound (electricity, S1-3), direct + indirect rebound with proportional spending (RA), and 10% direct + indirect rebound with high transport spending (RB-2).
ranges found in the literature. The resulting total percent rebound effect could vary between 20% and 60% in California and between 7% and 50% in Alabama. However, this translates to a much smaller (<0.2 ton CO2e per household per year) effect in terms of a penalty on absolute emissions savings in California compared to Alabama (1 ton CO2e per household per year). Alabama has a much larger potential for emissions savings with efficiency because of its higher carbon electricity grid-mix and the larger fraction of household incomes devoted to spending on electricity compared to households in California.

Figure 6 shows a detailed sensitivity analysis, reproduced from prior work [21], of the key factors that influence the indirect rebound in percent. States with low grid emission factors (in kg CO2e kWh⁻¹) and higher than average electricity prices are expected to have higher rebound effects. Gasoline prices, budget shares, and income elasticities are also important factors affecting the indirect rebound simulation. Figure 6 suggests that regions with higher automobile use, such as rural areas and areas with limited public transportation, are expected to have higher indirect rebound effects, since gasoline-based transportation is an emissions-intensive activity compared to other goods and services.

As the US electric grid becomes less carbon-intensive, the indirect rebound effect will increase in percentage terms. However, the rebound in CO2e emissions may decline as all goods and services, including electricity, decline in carbon intensity. This highlights the relevance of providing rebound related results both in terms of percentage and absolute emissions, as reporting the rebound effects only percentage-wise may lead to erroneous environmental decision-making.

4. Discussion and conclusions

The results presented here, based on simulated electrical efficiency investments, national income elasticities based on historical data, and a direct rebound parameter, provide first order simulations of the magnitude of the indirect rebound effect by state. We have shown how rebound effects vary across states largely due to variation in the grid emissions factors, electricity prices, and gasoline budget shares. Based on our simulations, we find that the direct and indirect rebound effects for efficiency enhancement in the residential sector that include scope 1, 2, and 3 emissions from a electrical efficiency investments will be modest to moderate, ranging from a low as 6% in West Virginia (which has a high-carbon electricity and low electricity prices), to as high as 40% in California (which has low-carbon electricity and high electricity prices).

This work has some caveats and limitations. First, we use a national-scope Input–Output model, which provides limited characterization for regional or state-level variations in industrial structure, which in turn affects the embodied carbon of household spending in each state. Second, structural changes in the US economy and price dynamics for electricity, fuels, and other goods since the early 2000s may limit the validity of these rebound simulations for current economic conditions.

Third, as Borenstein (2013) recently noted, for electricity and other utilities, it is generally the case that the retail prices seen by consumer do not reflect the long-run marginal cost. This means that some of the rates seen by the consumer will include fixed charges, for example, and only part of the energy savings will result in new net income, while the rest is ‘a transfer of income from is a transfer of income from the ratepayers (or shareholders) who must cover the utility’s lost quasi-rents to the consumer investing in energy efficiency’ [52]. We are also considering only energy efficiency investment where the levelized costs of the efficient technology are lower than the levelized cost of a baseline technology. Thus, the rebound effects simulated here are likely to be upper bound estimates.

Fourth, there is a fundamental mismatch between the economy-wide mechanisms that influence the indirect rebound effect and the limited jurisdiction of state policymakers. Under the current state-by-state framework for Energy Efficiency Resource Standards in the US, state policymakers have no incentive to consider indirect rebound effects, which occur through household spending on tradable goods and services produced outside state borders. Thus, the indirect rebound from residential sector energy efficiency in a particular state may not be visible within that state’s energy statistics, although the direct rebound effect may be. In any case, we find the indirect rebound effects to be small, so including these effects in state level policies need not to be a priority.

Fundamentally, the more important question is whether the indirect (as well as direct) rebound effect should be considered a benefit or a cost of energy efficiency measures. If CO2e and other air pollutants are priced at their social cost, this should ensure that any rebound effects—as well as energy consumption in general—unambiguously increase social welfare. In other words, under carbon or pollutant pricing policies, the rebound effect should be framed as an additional benefit from an energy efficiency measure. The regions with the highest rebound effects in percent, namely California and the Northeast states, also have carbon...
Figure 4. Percent rebound effect in CO₂e emissions from residential electric end-use efficiency, for (A) top 25 states and (B) bottom 25 states, ranked by rebound in emissions (see figure 3) in 2004. Sources/Notes: the figure shows CO₂e rebound effects in percent for different scenarios. The bars represent RB-1, a scenario with moderate re-spending in transportation. RB-2, the gray squares, is the upper bound representing high transport re-spending. Both RB-1 and RB-2 use income elasticities from Taylor and Houthakker [61]. The proportional re-spending scenario, RA, provides a lower bound and represents a proportional spending patterns for energy efficiency cost savings [49]. S1, S2, and S3 mean scope 1, 2, or 3 emissions.
markets. If regulators in these states seek to enhance social welfare from energy efficiency policies, they should ensure that carbon prices are set to the social cost of carbon. The presence of rebound effects highlights the importance of complementing the ‘carrot’ of energy efficiency policy, which enable greater household consumption with cost-effective measures, with the necessary ‘sticks’ to price carbon and other emissions.

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