Impact of CCL's proposed carbon fee and dividend policy:

A high-resolution analysis of the financial effect on U.S. households

Kevin Ummel †

Research Scholar, Energy Program

International Institute for Applied Systems Analysis (IIASA)

Prepared for Citizens' Climate Lobby (CCL)

April, 2016

Working Paper v1.4

I am grateful for comments, advice, and data provided by Kevin Perese, Chad Stone, Charles Komanoff, Robert Corea, Scott Curtin, Art Diem, Eric Wilson, Travis Johnson, James Crandall, Michael Mazerov, Danny Richter, Jerry Hinkle, and Tony Sirna. All remaining errors and omissions are mine.

† The analysis and opinions expressed here are those of the author alone and do not reflect the positions of CCL, IIASA, or any other organization. This document is released as a working paper subject to revision and improvement.

1 Executive summary

This study simulates a "carbon fee and dividend" policy similar to that proposed by the Citizens' Climate Lobby (CCL).[1] The policy consists of a $15 per ton of CO_2 "fee" (carbon tax) applied to domestic fossil fuel production and imports. Exports receive full tax rebates to maintain competitiveness of U.S. businesses. All remaining revenue is distributed to households as a taxable "dividend" (rebate) on a modified per-capita basis.

Assuming that firms pass the entire carbon fee on to consumers in the form of higher prices and there is no change in employment, technologies, or consumer behavior, the net financial effect of the policy for a given household is the difference between higher cost of goods and services and additional disposable income from the dividend.

Given these assumptions, the policy confers a positive net financial benefit on 53% of households nationwide (58% of individuals). An additional 19% of households incur a "minor loss", defined as a net financial loss that does not exceed 0.2% of pre-tax household income.

The distributional effects are highly progressive. Nearly 90% of households living below the Federal Poverty Level are benefited by the policy. The average net benefit in this group is $311 per household, equivalent to 2.8% of average pre-tax income. Overall, the primary distributional effect is to shift purchasing power from the top quintile to the bottom two quintiles of the income distribution (see figure on following page).

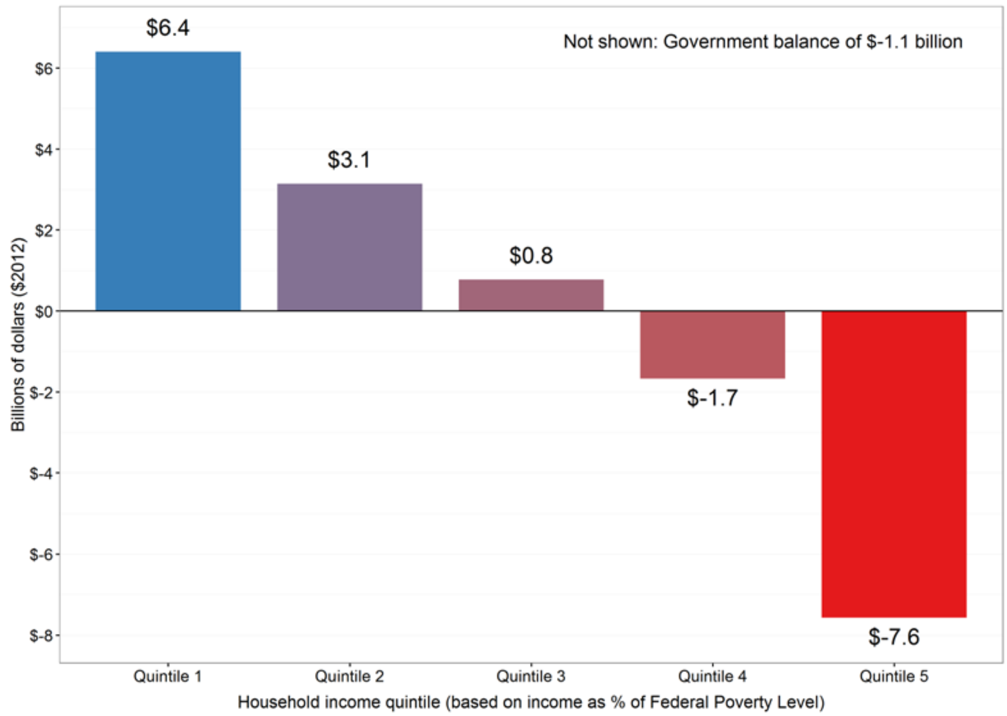
About two-thirds of younger households (age 18 to 35) and older households (age 80 and above) are benefited, compared to 44% of households age 50 to 65. Three-quarters of Latino households are benefited, compared to less than one-half of white households. The large household sample used here (5.8 million households) allows results to be generated for each of 30,000+ zip codes, revealing both regional and local spatial patterns (see figure on following page). Households in rural areas are not disproportionately harmed by the policy (54% benefited) and generally fare better than those living in suburbs (50% benefited).

Differential impacts across space and household type highlight the ways in which "geo-demographic" patterns combine with policy design to affect distributional outcomes. It is possible that a different dividend allotment formula with respect to household size and age, for example, could generate net positive benefits for a larger portion of the population.

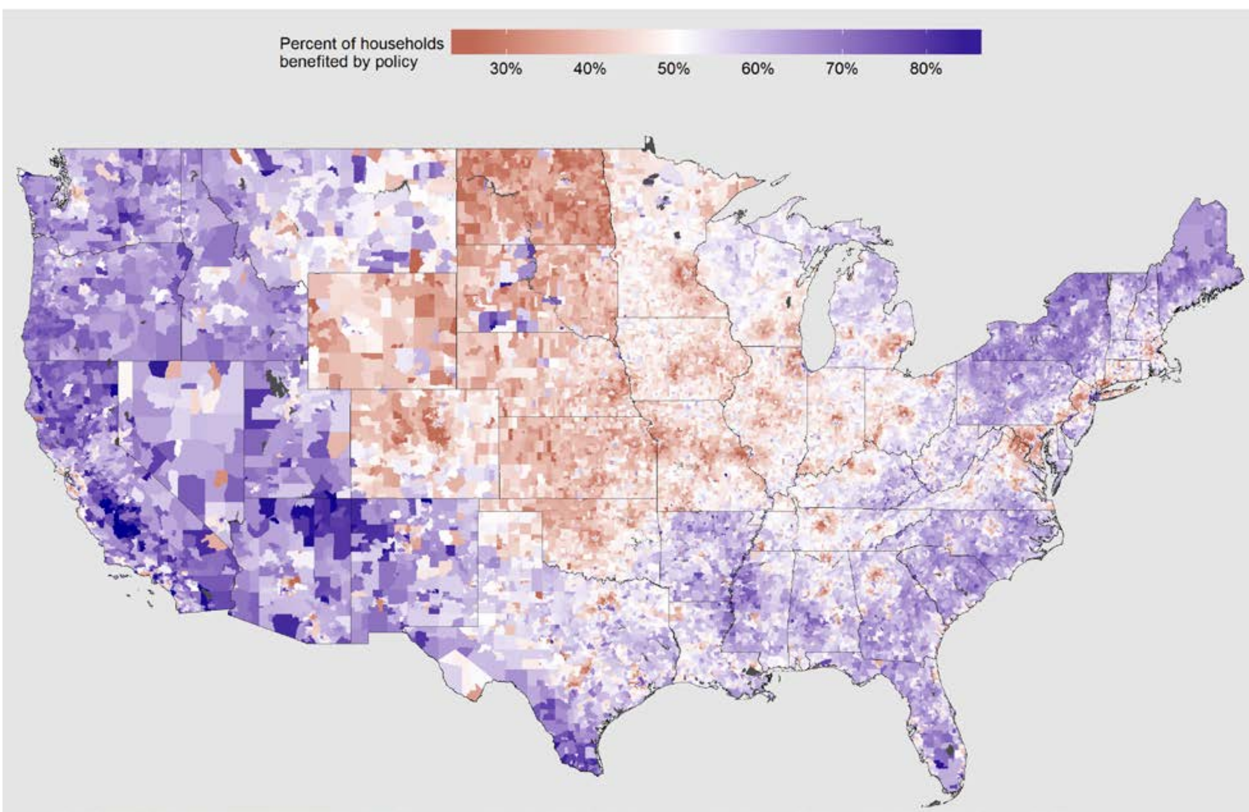
This study introduces a number of methodological advances relevant to both carbon footprinting and carbon tax analysis. These include adjustments for under-reporting of expenditures and variation in prices paid for goods and services across both space and household characteristics, as well as improvements to input-output modeling of carbon tax price impacts.

[1] https://citizensclimatelobby.org/carbon-fee-and-dividend/

Overall net financial effect of policy, by income quintile



Percent of households benefited by policy, by zip code



2 Table of contents

3 List of figures

4 Introduction

Governments often seek to discourage harmful behavior by making such activity costlier. Second-hand smoke causes harm to innocent bystanders, prompting federal, state, and local politicians to impose a tax on cigarettes. The tax increases the price of cigarettes – discouraging consumption and improving public health – while providing a source of revenue.

Unmitigated burning of coal, oil, and natural gas causes harm via local air pollution and global climate change. A "carbon fee" – a tax on fossil fuels – is analogous to a cigarette tax, discouraging the use of goods, services, and technologies that rely on fossil fuels and encouraging clean alternatives.[2]

A carbon fee increases the price of carbon-intensive products. This "price signal" is key to the policy's efficacy, as it incentivizes conservation and low-carbon choices among households and businesses. But the prospect of American families – especially low-income and elderly – facing higher costs is a central concern of carbon fee skeptics on both ends of the political spectrum.

Of course, a carbon fee also generates revenue that can be used to make households and/or businesses better off. Conservative economists have long argued that revenue from "environmental taxes" should be used to reduce other taxes – like income, capital, and corporate taxes – that hinder economic activity (Tullock 1967). Others argue that the revenue should be returned directly to households to help offset higher prices.

These differences reflect an inherent tradeoff between *efficiency* and *equity* when deciding how to "recycle" carbon fee revenue back into the economy. In general, reduction of capital and corporate taxes maximizes economy-wide efficiency (i.e. GDP growth), while the least-efficient recycling option is to return revenue directly to households. But the consequences for equity are reversed: reducing taxes on business disproportionately benefits the rich, while a rebate to consumers is more likely to benefit low-income households. Reducing taxes on labor generates effects somewhere in-between (Williams et al. 2014a).

While conceptually simple, carbon pricing can induce multiple and complex impacts on U.S. households. A reduction in economic efficiency might suppress employment and workers' wages in some industries more than others (Ho, Morgenstern, and Shih 2008). Improved local air quality or lower long-term climate risk might benefit households in particular places (Jerrett et al. 2005). Revenue returned to households through rebates or lower taxes might benefit certain demographic groups or regions of the country, depending on the policy design (Metcalf 2007).

This study simulates a "carbon fee and dividend" policy similar to that proposed by the Citizens' Climate Lobby (CCL).[3] The policy consists of a $15 per ton of CO_2 "fee" (carbon tax) applied to domestic fossil fuel production and imports. Exports receive full tax rebates to maintain competitiveness of U.S. businesses. All remaining revenue is distributed to households on a

[2] Readers are directed to Metcalf and Weisbach (2009), Marron et al. (2015), and Kennedy et al. (2015) for comprehensive reviews of the implementation and administrative details of such a policy.
[3] https://citizensclimatelobby.org/carbon-fee-and-dividend/

modified per-capita basis as a taxable “dividend” (rebate). Specifically, every adult receives a full dividend “share” and each child (up to two per household) receives a half share.

Importantly, this analysis is “static” and does not consider “dynamic” effects of a carbon tax on economic growth, employment, wages, trade, production processes, or consumption patterns over time.[4] Nor does it consider local or global environmental benefits. Instead, I calculate the short-term financial effect on families, assuming that the policy is implemented “overnight”, firms pass the entire carbon fee on to consumers in the form of higher prices, and there is no change in behavior, technologies, or emissions.

Under these assumptions, the net effect of the policy for a given household is the difference between additional costs due to higher prices and additional disposable income due to the dividend. The direct cost (tax burden) of the policy is related to a household’s “carbon footprint” – the amount of CO_2 emitted as a result of consumption. This includes emissions associated with direct consumption of energy (electricity, natural gas, gasoline, etc.) as well as indirect CO_2 that is emitted during the production of other goods and services (food, electronics, a visit to the doctor, etc.).

This basic technique is similar to those employed in prior research, including Metcalf (1999), Hassett, Mathur, and Metcalf (2007), Metcalf (2007), Burtraw, Sweeney, and Walls (2009), Hassett, Mathur, and Metcalf (2011), and Mathur and Morris (2014). This study differs in the level of socioeconomic, demographic, and spatial detail it provides. Household-level impacts can be assessed across almost any socioeconomic or demographic dimension, down to the level of individual zip codes. I also introduce a number of methodological improvements for estimating a household’s carbon footprint and, therefore, its tax burden due to higher consumer prices.

Section 5 describes how I estimate carbon footprints for each of 5.8 million households in a representative national sample covering the period from 2008 through 2012. This includes techniques to adjust for known under-reporting in household expenditure surveys and variation in prices paid for goods and services across households, as well as improvements to input-output modeling of carbon tax price impacts.

Section 6 explains how this information is used to simulate the specific carbon fee and dividend policy outlined above and determine the net financial gain or loss of each household. Section 7 presents results across the income distribution, space, and demographic groups. Section 8 concludes with a discussion of caveats, uncertainties, and policy design options.

[4] Addressing dynamic effects requires a computable general equilibrium (CGE) model of the economy. Examples include, among others, Rausch and Reilly (2012) and Williams et al. (2014a; 2014b).

5 Estimation of household carbon footprints

I use an expenditure-based approach to estimate a household's carbon footprint. This requires two pieces of information: 1) total expenditure for each kind of good or service; and 2) an estimate of the CO_2 emitted per dollar spent on those same goods and services. I refer to the latter as the "carbon intensity of expenditure" – denoted by *CIE* in subsequent formulae – and it has units of $kgCO_2$ per dollar.

A household's carbon footprint is simply expenditure multiplied by *CIE*, summed across *i* categories of goods and services:

$$Household\ CO_2\ footprint = \sum_i (Expenditure_i * CIE_i) \qquad (1)$$

Household-level expenditure by category is available from the U.S. Bureau of Labor Statistics (BLS) Consumer Expenditure Survey (CEX). This ongoing survey uses interviews and diaries to continually collect expenditure, income, housing, and demographic data for a representative sample of American households. It is the primary source of information on how expenditure patterns vary across types of goods and services, space, and household characteristics.

However, household expenditure totals in the CEX are consistently lower than those in the Personal Consumption Expenditures (PCE) component of the U.S. Bureau of Economic Analysis (BEA) national accounts (National Research Council 2013).[5] The latter provides aggregate household expenditure based on what businesses report to have *sold*, whereas the CEX provides what households report to have *purchased*.

When expenditure is summed across categories with comparable definitions, CEX totals are typically only 75% of PCE – and reporting rates vary widely across different kinds of goods and services. Discrepancies between expenditure surveys and national accounts are not uncommon. While there is no theoretical preference for one over the other, there are good practical reasons to prefer PCE as the accurate measure in rich countries (Deaton 2005).

This matters greatly for carbon footprinting, because the *CIE* term in Eq. 1 is calculated using data and techniques that assume national accounts provide the correct measure of expenditure and investment (see Section 5.2). Consequently, addressing the "under-reporting problem" is important for accurate analysis of carbon tax incidence.

Estimation of *CIE* also faces a number of methodological challenges. The standard approach (and the approach used here) relies on "input-output" (I-O) tables from the BEA that detail monetary flows of commodities to and from industries (Leontief 1953). These tables are used to estimate *CIE* for individual commodities.[6] The advantage of "I-O modeling" is that a single

[5] It is also likely that the CEX (like many surveys) underrepresents households at the upper end of the income distribution (Sabelhaus et al. 2013).

[6] I believe one of the earliest extensions of I-O modeling to the energy context – from which an extension to emissions can then be made – is Herendeen (1973). Kok, Benders, and Moll (2006) provide an excellent overview of methodological issues in this area.

analytical framework is used to measure all of the inputs (and, therefore, CO_2 emissions) required to produce a wide range of goods and services.

However, a national I-O model can only provide a *national average CIE* for each expenditure category. In reality, we know that *CIE* actually varies across households, and a primary reason for this is that *prices* vary across households.

Consider a household in Manhattan (New York City) that spends $2.00 for a 2-liter bottle of Coca-Cola. A household in Tulsa, Oklahoma spends only $1.33 for the same product. It is reasonable to assume that the real-world carbon footprints of each purchase are not significantly different. But using identical *CIE* for both transactions suggests that the household in Manhattan is responsible for 50% more carbon pollution. I refer to this complication – stemming from spatial variation in the price of *identical products* – as the "Manhattan effect".

Further, consider the purchase of shoes. A pair purchased at Walmart might cost $30, while a pair of Gucci luxury brand shoes might cost $600.[7] Both transactions are categorized as "Shoes and other footwear" for the purposes of Eq. 1. The Gucci shoes may, in fact, have a higher carbon footprint than those from Walmart – but probably not 20 times higher, which is what a uniform *CIE* implies. In practice, we expect *CIE* to vary with household income as wealthier households, on average, buy higher-priced versions of otherwise similar items. I refer to this complication – stemming from differences in price paid across households *within a given expenditure category* – as the "Gucci effect".[8]

Both the Manhattan and Gucci effects suggest that conventional approaches may overestimate the carbon footprints of rich households. On the other hand, it is possible that rich households are disproportionately responsible for under-reporting of expenditures in the CEX. These two factors push in opposite directions – with possibly important distributional consequences.

The following sections describe how I address the issues raised above, specifically 1) adjustment of household-level expenditures reported in the CEX to match associated PCE totals and 2) calculation and adjustment of national average *CIE* to account for both the Manhattan and Gucci effects.

5.1 Simulation and adjustment of household expenditures

The CEX sample size is not sufficient to allow an analysis of this kind at both high spatial and high demographic resolution. However, it is possible to use CEX data to *simulate* household expenditure for the U.S. Census Bureau's much larger American Community Survey (ACS), relying on the large overlap in household and geographic variables between the two surveys.

---

[7] For the record, I (proudly) have no idea what a pair of luxury-brand shoes actually cost.

[8] We can imagine a third effect that we might call the "Hawaii effect" or "Alaska effect", reflecting the fact that prices are higher in some places due to geographic considerations and transportation costs, independent of the Manhattan and Gucci effects. In theory, a spatial econometric approach could isolate this effect using the data described in Section 5.3, but I leave this for future analysis.

This type of survey integration is sometimes referred to as “micro data fusion” (Pisano and Tedeschi 2014).

The CEX-ACS fusion process was introduced and described by Ummel (2014). The technique relies on boosted quantile regression trees – a machine learning strategy – to estimate expenditure probability distributions conditional on observable household, climatic, and local economic characteristics (e.g. fuel prices). In conjunction with an algorithm to generate random uniform variates that exhibit observed correlation across spending categories (Schumann 2009), it is possible to simulate an expenditure dataset that preserves both micro and macro patterns in the original CEX data. Readers are directed to the original paper for details.[9]

This study takes the fused CEX-ACS dataset as its starting point. It contains inflation-adjusted expenditures (2012 dollars) for nearly 6 million households across 48 different expenditure categories over the period from 2008 through 2012, along with the complete set of household-level variables inherent to the ACS. The main extension in this paper is to adjust expenditures for the aforementioned discrepancy between CEX and PCE expenditure totals (i.e. under-reporting problem).

I rely on a comparison of CEX and PCE totals across comparable expenditure categories carried out by BLS and BEA staff.[10] It provides the ratio of CEX-to-PCE expenditure (“reporting ratio”) for each category. Expenditures for rent, utilities, vehicle purchase, gasoline, and communication services (e.g. phone service) are all reported quite accurately. Outside of these categories, the aggregate reporting ratio for 2014 was just 53%.

To understand why this is problematic, consider the example of expenditures for meals consumed outside the home (i.e. fast food and restaurants). The reporting ratio is about 60%. I-O analysis produces a *CIE* for restaurants (kgCO_2 per dollar of expenditure) based on total PCE expenditure for the category (see Section 5.2). If the *CIE* is applied to unadjusted CEX expenditure, it will underestimate total emissions from eating out by 40%.

To make matters worse, reported restaurant expenditure increases disproportionately with household income. Indeed, this is true of many of the categories with low reporting ratios. Without any adjustment, Eq. 1 will not only underestimate *total* restaurant emissions, it will disproportionately under-estimate emissions among rich households (assuming the rich report as accurately as the poor).

Clearly, it is necessary to adjust CEX expenditure upwards to match PCE totals and create compatibility with *CIE* derived from I-O tables. However, absent detailed survey data comparing household reported expenditure to *actual expenditure* (something that is very difficult to do), there is no way of knowing if the likelihood and/or magnitude of under-reporting is related to household demographics (e.g. income).

[9] http://www.cgdev.org/publication/who-pollutes-household-level-database-americas-greenhouse-gas-footprint-working-paper
[10] http://www.bls.gov/cex/cecomparison.htm

Consequently, I assume that under-reporting is uniform across the population. For each category, CEX expenditure for *all* households is divided by the category-specific reporting ratio. The net effect is to disproportionately increase expenditure among the rich – but only because the rich disproportionately consume those categories where BLS/BEA analysis suggests under-reporting is most significant.[11]

To check that the adjustment for under-reporting produces plausible total expenditure, I compare aggregate PCE with aggregate (adjusted) expenditure in the household sample. Since the two are not directly comparable as is, I subtract-out the following PCE components from the national accounts data:

- Imputed rental of owner-occupied nonfarm housing
- Rental value of farm dwellings
- Health care
- Health insurance
- Pharmaceutical and other medical products
- Final (net) consumption expenditures of nonprofit institutions serving households

For 2012, this leaves $7.2 trillion in the remaining PCE categories. I compare this figure with under-reporting-adjusted total expenditures in the household sample, excluding Health insurance, Drugs, Medical services, and Medical supplies, and Cash contributions. The resulting total expenditure is $7.17 trillion. Whether the adjustment procedure generates the correct *distribution* of expenditures remains an open question, but it does produce overall spending in agreement with the national accounts.

5.2 Input-output modeling of national *CIE*

The data and techniques used here to estimate national *CIE* across expenditure categories are similar to those employed by Fullerton (1996), Metcalf (1999), and others.[12] My approach is most similar that of Perese (2010), and readers are directed to that paper for technical and mathematical details.[13] This section describes where, why, and how I modify the conventional approach, and I assume the reader is familiar with the basics of I-O modeling.[14]

[11] Cross-country analysis shows that the ratio of total household survey expenditure to total national account expenditure declines with rising income (Deaton 2005). If this observed pattern between countries were to hold within the U.S. – implying that rich households disproportionately under-report expenditures – then my assumption of uniform under-reporting across households will underestimate spending among the rich.
[12] Strictly speaking, the analyses cited do not estimate *CIE* directly but, instead, estimate commodity relative price changes for a given carbon price. Mathematically, these are two sides of the same coin and analogous for our purposes.
[13] https://www.cbo.gov/sites/default/files/111th-congress-2009-2010/workingpaper/2010-04-io_model_paper_0.pdf
[14] In short, the I-O "framework" or model relies on "Use" and "Make" input tables that describe the monetary flow of commodities to and from industries. They report all inputs and outputs associated with the production of goods and services. The tables are consistent with one another and with the national account totals for consumption and investment across households and government, as well as imports and exports. See UN Statistics Division (1999).

Estimation of *CIE* requires the analyst to pass a "tax matrix" into the I-O framework such that, when solved, the system of equations returns a vector of price increases for each commodity. These price increases reveal the *CIE*, given the (static) state of the economy described in the I-O tables. Each cell of the tax matrix should contain the revenue to be raised from the use of a given commodity by a given industry.

The tax matrix is typically constructed to reflect revenue from energy-related CO_2 *emissions* for the year in question. However, this omits carbon embedded in fuel exports. Fossil fuel inputs (e.g. crude oil) used to produce fuel exports (e.g. fuel oil) are to be taxed at the well, mine mouth, or border, but the associated carbon is not reflected in energy-related *emissions* since it remains embedded in fuel sent abroad.

To correct for this, I remove fuel exports from the Make and Use tables. I adjust all intermediate inputs to the respective industries proportionally, reflecting the share of fuel exports in total industry output. This reduces total output of fossil fuel commodities in the I-O framework to account for emissions embedded in fuel exports.

In practice, earlier research probably did not suffer too much from this omission, because U.S. fuel exports were relatively small. But fuel exports in the post-2008 period are not negligible. This is most pronounced in the case of petroleum product exports containing almost 500 $MtCO_2$ of embedded carbon in 2012 (coal exports were also significant in CO_2 terms).

It is also necessary to distribute the revenue in the tax matrix across specific commodity-industry cells. Typically, revenue is allocated across industries in proportion to input value, assuming that *ad valorem* tax rates are constant for a given fossil fuel commodity. However, in practice input prices can vary considerably across industries.

I address this, in part, by integrating U.S. Energy Information Administration (EIA) data on the amount of CO_2 emitted, by fuel, in the "Electricity" and "Other" sectors. This allows me, for a given fossil fuel, to assign one *ad valorem* tax rate for the power sector and one rate for all other users. In the case of coal, for example, this leads to larger *ad valorem* rates in the electricity sector compared to industrial users, presumably reflecting lower input prices for the former.

Unlike Perese (2010), I do not *explicitly* include rebates for carbon sequestered through non-combustive use of fuel (asphalt, lubricants, etc.). Technically, the CCL proposal would provide such rebates. However, since the size of the tax passed into the I-O model purposefully excludes sequestered CO_2, the model captures the aggregate effect of such an adjustment but ignores differential effects across industries. Ideally, future work would include sequestered CO_2 in the tax matrix alongside explicit rebates in the I-O framework per Perese (2010).

I multiply commodity-specific *CIE* values from the I-O model across all final uses in the Use table to calculate the total carbon associated with each commodity and end use. This effectively assumes that nonfuel imports have the same carbon-intensity (and, therefore, face the same tax rate) as domestically-produced counterparts. This is a common assumption in such analyses and could well reflect real-world border tax adjustments under unilateral carbon pricing (Metcalf and Weisbach 2009).

In the case of fuel imports and exports, I calculate the associated carbon separately by integrating additional data on physical quantities of fossil fuel produced, imported, and exported in conjunction with CO_2 emission factors from the Environmental Protection Agency (EPA).[15] I find that the fuel import and export emissions implied by the I-O model do not consistently replicate the quantities calculated from physical fuel data. This may be due to differences in prices or other issues specific to the treatment of imports and exports in the BEA data. This is an area where additional work in needed. I assume that the fuel import and export emissions derived from physical fuel quantities are correct.

The remaining departure from previous research concerns the level of detail used in the I-O model itself.[16] The BEA provides "benchmark" I-O tables every five years that contain detailed data for almost 400 commodities and industries (most recently for 2007). Annual "summary" tables contain analogous data for an aggregated set of about 70 commodities and industries (currently through 2014). Typically, researchers face a tradeoff between detail and timeliness, and all previous research has relied on the comparatively coarse product detail of the summary-level tables.

It is possible, however, to use the 2007 benchmark data to "expand" each cell of a summary year table. This results in new Make and Use tables for non-benchmark years that have the product detail of the benchmark tables but retain cell values consistent with the summary-level tables. Since this process can result in discrepancies in commodity and industry total output across the Use and Make tables, I use an iterative proportional fitting procedure (i.e. "matrix raking" or "RAS algorithm") to adjust cell values and achieve identical margins across the two tables.[17] I employ an analogous process to create detail-level versions of the PCE bridge matrices.

Using the expanded I-O tables, I compute *CIE* for each BEA commodity and year from 2008 through 2012. The expanded PCE bridge matrices are used to calculate *CIE* for more than 200 PCE categories. Finally, *CIE* is calculated for 46 expenditure categories contained in the fused CEX-ACS dataset, using a cross-walk provided by BLS and BEA that links CEX expenditure line item codes to PCE categories. National CEX expenditure at the line-item level is used to weight the relative contribution of different PCE categories in the calculation of final *CIE* for each expenditure category.

---

[15] Both energy-related CO_2 emission and physical fuel quantity data come from EIA's Monthly Energy Review (http://www.eia.gov/totalenergy/data/monthly). Emission factors are from the EPA (http://www.epa.gov/energy/ghg-equivalencies-calculator-calculations-and-references).

[16] I utilize the BEA Make and Use tables, in producer prices and after redefinitions, at both the summary and benchmark level of detail along with the commodity-PCE bridge data. For an introduction to the BEA Industry Accounts, see Streitwieser (2009).

[17] Every carbon tax analysis using summary-level BEA I-O tables must take analogous steps to, at a minimum, disaggregate the "Coal mining" industry from the aggregated "Mining, except oil and gas" industry. The technique used here is simply a systematic extension of this process to the rest of the matrix.

5.3 Modeling spatial variation in prices

As indicated above, variation in consumer prices poses a challenge when computing household carbon footprints from expenditures alone. Previous analyses of CEX data in the context of carbon pricing and/or footprinting have ignored this fact. In order to account for both the Manhattan and Gucci effects, it is necessary to specify how prices for different kinds of goods vary across the country.

I rely on a proprietary dataset of consumer prices provided by the Council for Community and Economic Research (C2ER).[18] The C2ER data used here provides reported consumer prices for 53 individual goods and services (referred to here as "items") for the period 2008 through 2012 and for nearly 400 urban areas. These data indicate, for example, the retail price of a gallon of regular gasoline or a 2-liter bottle of Coca Cola.

The C2ER data generally report consumer prices *excluding* state and local sales tax. However, prices for gasoline, beer, and wine include federal and state excise taxes paid by producers, and gasoline additionally includes sales tax when applicable.

Reported retail prices for gasoline, beer, and wine are first stripped of their sales and excise tax components. Per-gallon excise and applicable sales taxes for gasoline come from the American Petroleum Institute's motor fuel tax reports.[19] Excise taxes for beer and wine come from the Tax Foundation.[20] This step removes spatial variation in prices due to differences in state tax policy. The resulting "tax-free" prices reflect the underlying cost of production, transport, and wholesale and retail trade margins for a given location.

For each item and year, I spatially interpolate observed prices using zip-code level data as regressors in a universal Kriging model. The zip-code level regressors include a measure of typical per-capita income created by combining information from multiple ACS five-year (2010 through 2014) estimate tables, along with population density and typical home value provided by Zillow Real Estate Research.[21]

Following spatial interpolation of tax-free prices, applicable sales and excise tax for each item is added to arrive at the tax-inclusive retail price in each zip code.[22] Combined state and local sales tax rates for each zip code come from Avalara.[23] Exclusion of certain items from the sales tax base is determined using guidance on state-specific exclusions of food and drugs from the Federation of Tax Administrators.[24]

---

[18] https://www.coli.org
[19] http://www.api.org/Oil-and-Natural-Gas-Overview/Industry-Economics/Fuel-Taxes
[20] http://taxfoundation.org/tax-topics/alcohol-taxes
[21] http://www.zillow.com/research/data/
[22] There is no dominant, large-scale spatial pattern underlying sales tax rates. While there is significant intra-state variation due to taxes imposed by local municipalities in addition to the statewide rate, there is effectively zero overall correlation (-0.024) between zip code sales tax rate and typical per-capita income. This suggests that explicit consideration of sales tax leads to place-specific (and somewhat random) adjustments to CIE rather than systematic adjustments along spatial or demographic lines.
[23] http://salestax.avalara.com
[24] http://www.taxadmin.org/assets/docs/Research/Rates/sales.pdf

The prevailing, tax-inclusive price in a given zip code (p_i) may differ from the *effective consumer price* – i.e. the average price *actually paid* by residents (P_i). This is most pronounced for locales and items where tax rates vary significantly across political borders (e.g. gasoline prices across state borders). I assume that the effective price in a given zip code resembles an average of local prices within some radius of residents' homes.

To capture this effect, I convert the polygon zip code data to a raster grid and, for each cell, item and year, calculate the effective consumer price as the weighted mean price within 40 km (25 miles) of each grid cell. For cell *k* with *j* cells at distance d_j and local population[25] y_j, the effective price P_k is the weighted mean of local prices p_j such that

$$P_k = \frac{\sum_j p_j w_j}{\sum_j w_j} \quad where \quad w_j = \frac{y_j}{1+d_j} \tag{2}$$

For each item and year, the effective price in zip code i is then simply the population-weighted mean of associated grid cells *k*:

$$P_i = \frac{\sum_k P_k y_k}{\sum_k y_k} \tag{3}$$

For each item and year, the effective price in zip code i is then divided by the population-weighted mean national price for the item in question ($\bar{P}$), giving a ratio R_i defined by:

$$R_i = \frac{P_i}{\bar{P}} = \frac{P_i \sum_i y_i}{\sum_i P_i y_i} \tag{4}$$

Each of the items are then assigned to a CEX Universal Classification Code (UCC; line-item code) and one of 11 categories: Alcohol, Apparel, Consumer goods, Dairy, Fast food, Fruits and vegetables, Gasoline, Health care, Meat and eggs, Other food, and Services. For each category, a weighted relative price index is calculated (V_i), where the n associated item weights are equal to total U.S. expenditure for the associated UCC code (E_n):

$$V_i = \frac{\sum_n R_i E_n}{\sum_n E_n} \tag{5}$$

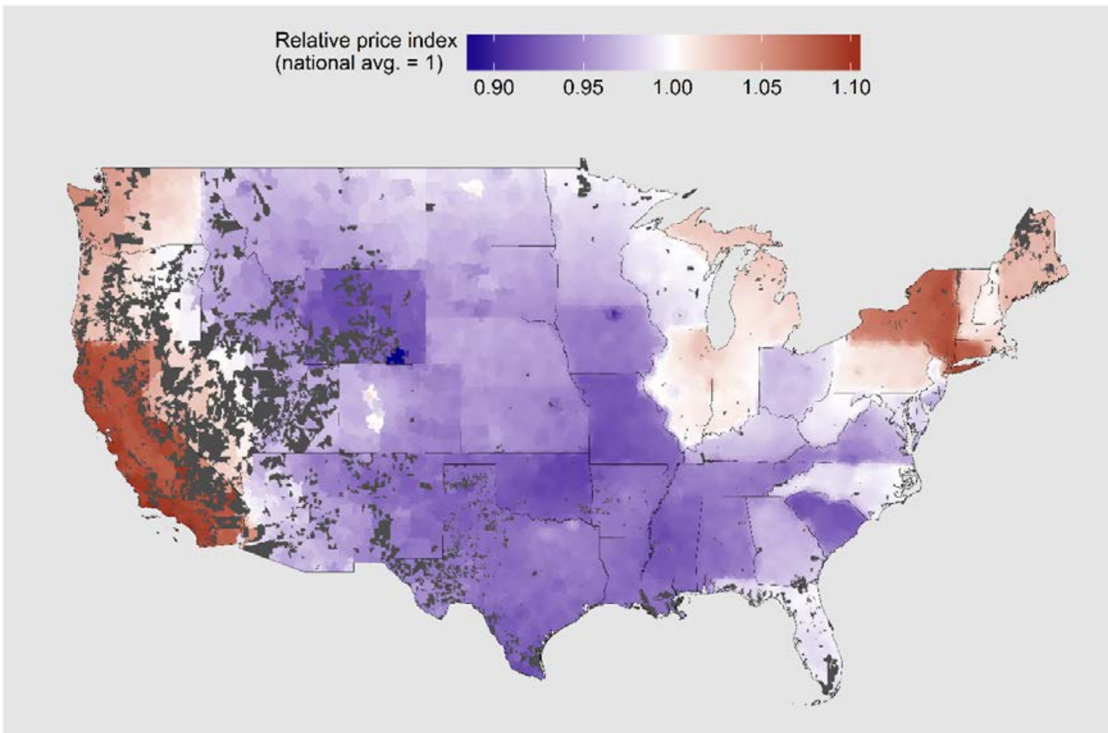
The variable V_i is computed for each year from 2008 through 2012 and measures relative differences in price levels across zip codes. A value of $V_i = 1$ indicates parity with national average prices for the category in question.

Figures 1-3 show the resulting zip-code level relative price indices for the Gasoline, Fruits and vegetables, and Services categories for the year 2012. In the case of gasoline, the differences largely reflect variation in state excise tax. But for Fruits and vegetables and Services, the patterns reflect other economic forces.

[25] Grid-cell population provided by: http://beta.sedac.ciesin.columbia.edu/data/set/gpw-v4-population-density

Finally, for the purposes of subsequent analysis that integrates price index data with the fused CEX-ACS dataset, it is necessary to aggregate the zip code level results to the level of Public Use Microdata Areas (PUMA's). This is accomplished using a linkage between zip codes and PUMA's provided by the Missouri Census Data Center's MABLE/Geocorr12 system and constructing a population-weighted mean index value for each PUMA.[26]

Figure 1 - Gasoline price index (2012)



[26] http://mcdc.missouri.edu/websas/geocorr12.html

Figure 2 - Fruits and vegetables price index (2012)

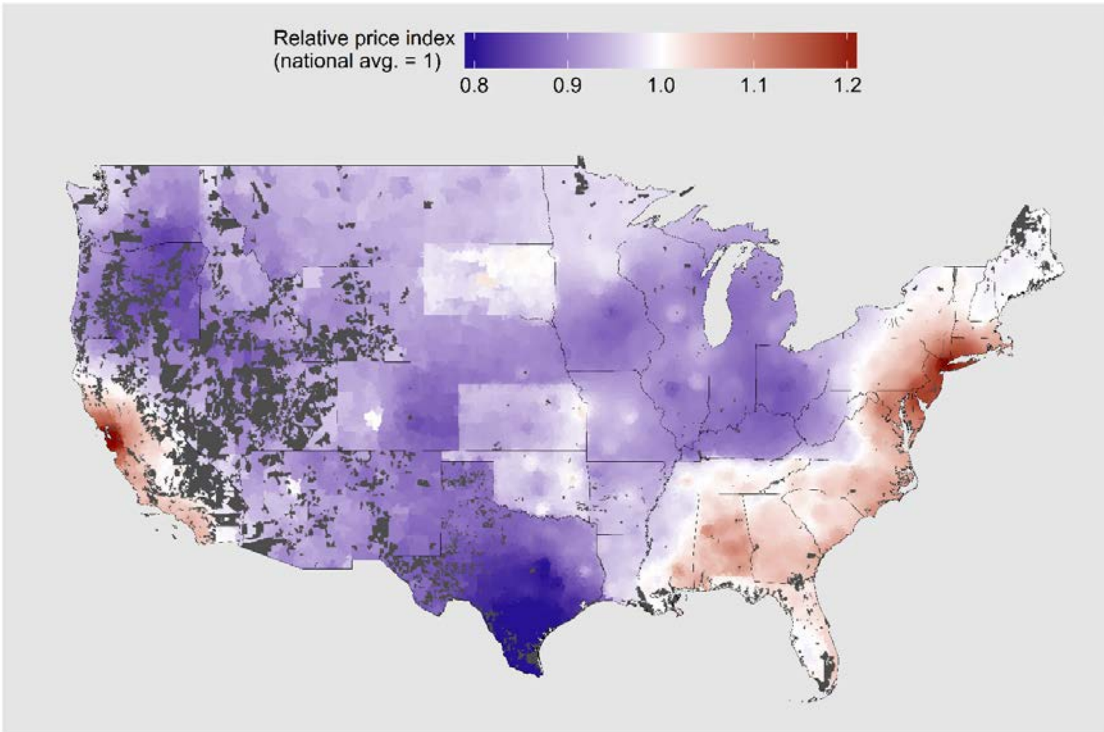
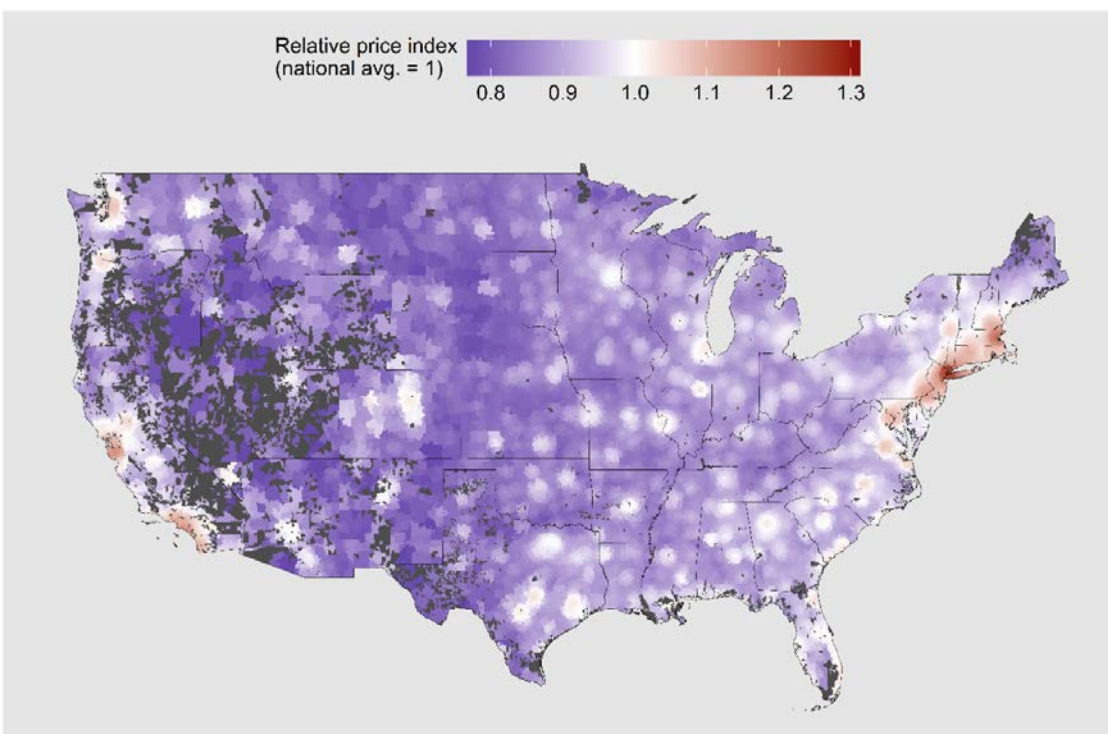


Figure 3 - Services price index (2012)



5.4 Adjusting CIE for Manhattan and Gucci effects

With the price index data developed above, adjusting *CIE* for the Manhattan effect is straightforward. For a given expenditure category, the local CIE in PUMA *m* is simply:

$$CIE_m = \frac{\overline{CIE}}{V_m} \qquad (6)$$

where $\overline{CIE}$ is the national average *CIE* derived from the I-O analysis in Section 5.2. That is, the local *CIE* results from adjusting national average *CIE* up (down) in places with below-average (above-average) prices.

However, adjusting for *both* the Manhattan and Gucci effects is more complicated. The Gucci effect implies that the average price paid for otherwise-similar products (i.e. products within a given expenditure category) varies with household characteristics – particularly income. To estimate the size of this effect, I analyze patterns in physical consumption and expenditure across different types of food.

The CEX contains no information on physical quantities consumed (for food or otherwise), but the National Health and Nutrition Examination Survey (NHANES) contains a dietary interview in which participants recall physical quantities of food eaten over a two-day period.[27] Physical quantities are categorized and converted to nutrient intake values (e.g. calories consumed) using the USDA's Food and Nutrient Database for Dietary Studies. Participants also provide demographic information (income, age, education, etc.) for both themselves and the head of household.

I pool the NHANES dietary component from the 2007-2008, 2009-2010, and 2011-2012 rounds, providing a total sample of 23,476 individuals. Individual foods and beverages are assigned to one of the ten food and drink categories created in the fused CEX-ACS dataset. This includes a category for food of all types consumed outside the home (i.e. fast food, restaurants), constructed from NHANES information on where individuals sourced their meals.

I model total calories consumed and the share of calories from each of the ten food categories as a function of respondent age, household income, household size, as well as the age, sex, education level, and race of the head of household. All of these independent variables are also observable in the CEX. The statistical procedure utilizes boosted (mean) regression tree models; 8-fold cross-validation is used to determine the optimal number of regression trees, as determined by minimizing the average root-mean-squared error across the folds.

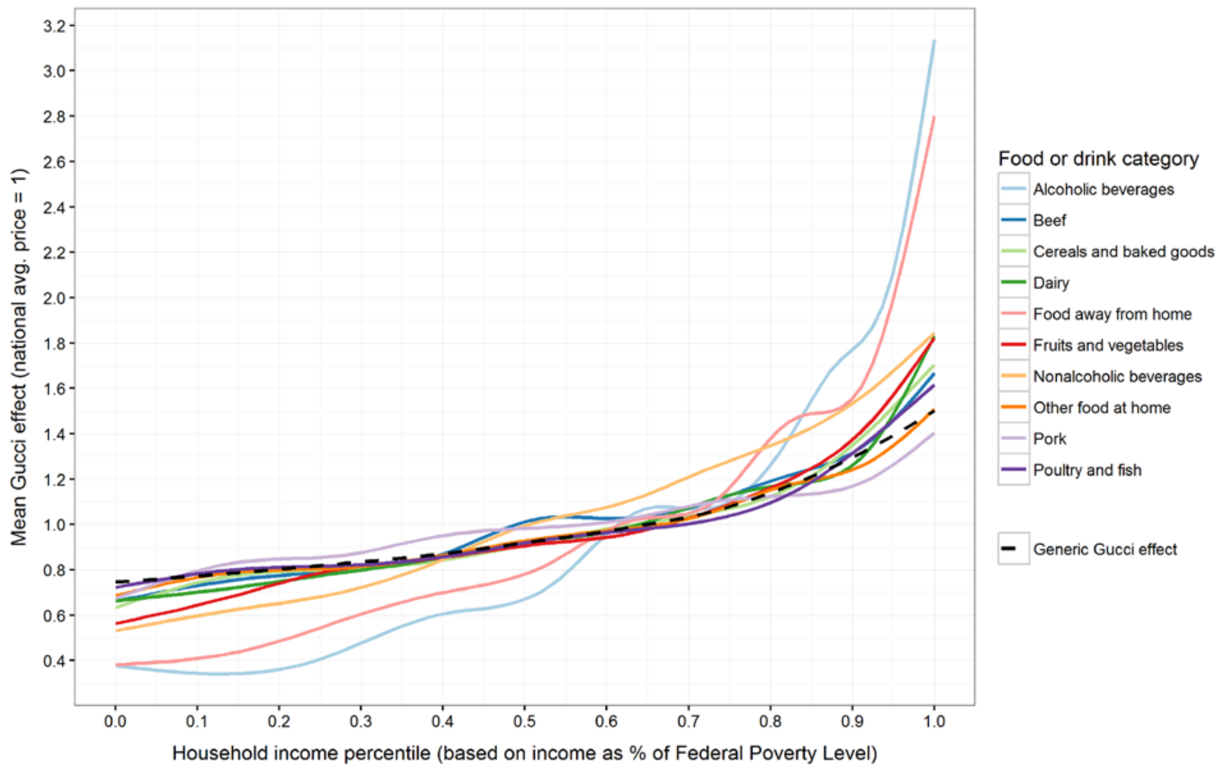
The fitted models are then used to predict expected (mean) calorie intake for each of the ten food categories for each household in the CEX sample. Since this sample also contains reported *expenditures* for the same categories, I am able to estimate cost-per-calorie at the household level. Importantly, I first adjust CEX food expenditures to account for spatial variation in prices using product-specific price indices from Section 5.3.

---

[27] http://www.cdc.gov/nchs/nhanes.htm

Figure 4 shows how the mean cost-per-calorie changes across the income distribution (relative to the national average) for each of the ten food categories. Three of the categories – Food away from home, Alcoholic beverages, and Nonalcoholic beverages – exhibit comparatively steep gradients with respect to income. This makes sense, to the extent that up-scale or luxury versions of these products are widely available (e.g. sit-down restaurants, high-end wine and coffee).

Figure 4 - Estimated Gucci effect for food and drink categories



The other categories exhibit more muted gradients, but the variation across the income distribution is still significant. These results suggest that for most classes of grocery items a household at the 90th percentile of the income distribution (measured relative to the Federal Poverty Level) spends, on average, ~40% more per calorie than the typical (median) household and ~75% more than a household at the 10th percentile – even after controlling for local price levels.

Part of this variation is explained by non-income factors like education that exert a strong influence on food choices. Using a boosted regression tree model, I isolate the marginal effect of income on cost-per-calorie, controlling for the education, age, and race of the household head and then average the marginal effect across all food categories that do not exhibit exceptionally steep gradients. The black dotted line in Figure 4 shows the resulting relationship.

This curve describes the generic relationship between household income and average cost-per-calorie relative to the national average *controlling for local price levels and non-income* *household characteristics*. In other words, it is a measure of the degree to which richer households buy more expensive versions of otherwise-similar calories. I refer to it here as the "generic Gucci effect", and I assume that this relationship holds across all applicable expenditure categories outside of food and drink.[28] Using the information in Figure 4, it is possible to estimate a Gucci effect ratio (*G*) for individual expenditure categories and households in the fused CEX-ACS sample.

I rely on food consumption and expenditure data to estimate the Gucci effect, because it is the only consumption class for which physical quantities are readily available using open-source data. Given that there are physical limits to the amount of food and drink that a person can consume, it may constitute a class of goods where richer households disproportionately opt for quality (i.e. higher-priced calories) over quantity. On the other hand, one can imagine other goods (e.g. vehicles, appliances, clothing) where demand for social status or conspicuous consumption might lead to even stronger Gucci effects than observed for food.

Recent research using detailed, proprietary consumer data suggests that the Gucci effect is comparatively muted (but still apparent) in the case of a low-cost, ubiquitous commodity like toilet paper (Orhun and Palazzolo 2016). The only other attempt I am aware of to account for variation in effective prices is a footprinting study by Girod and De Haan (2010) of Swiss households. They find that households in the upper-half of the income distribution do pay higher average price-per-unit for many types of goods compared to households in the lower half. Interestingly, the price premium for food is not exceptional – and actually smaller than that observed for things like vehicles and electronics.

The strength of the Gucci effect clearly varies across categories and is influenced by more than just household income, so the generic relationship assumed here is necessarily a rough approximation in the absence of more and better data. That said, ignoring the effect entirely – as almost every previous footprinting or carbon tax study has done – seems far less defensible.

A simple adjustment to *CIE* might consist of including *G* in the denominator of Eq. 6. However, as mentioned earlier, it is possible that higher-price products and services are, in fact, more carbon-intensive than lower-price alternatives.[29] Exactly *how much* more is unclear and probably not knowable outside of extremely detailed, item-specific expenditure surveys coupled to life-cycle analyses.

A practical (if simplistic) approach is to assume that variation in *G* is due entirely to differences in trade margins. That is, Gucci and Walmart shoes are effectively identical at the factory gate, and the difference in consumer price is due to (much) higher transport, wholesale, and retail margins in the case of the former.

Under this assumption, for a given expenditure category and household located in PUMA *m*, the fully-adjusted *CIE* is a function of the predicted generic Gucci ratio *G* (based on the household's

[28] Utility, gasoline, air travel, and public transportation expenditure categories are excluded from the Gucci effect adjustment, because premium or luxury versions of these goods are limited (e.g. air travel generally offers only two classes; gasoline comes in a limited number of grades) or simply unavailable.

[29] A relevant exception here is organic food, which may have both a lower carbon footprint and higher price.

observed income), the local price index (V_m), the share of trade margins in total purchaser price (S_t) and the national average *CIE* for the production and trade margin components ($\overline{CIE_p}$ and $\overline{CIE_t}$, respectively).[30]

$$CIE_m = (V_m G)^{-1}\left[(1 - S_t)\overline{CIE_p} + (S_t + G - 1)\overline{CIE_t}\right] \qquad (7)$$

5.5 Calculation of fuel-specific CIE

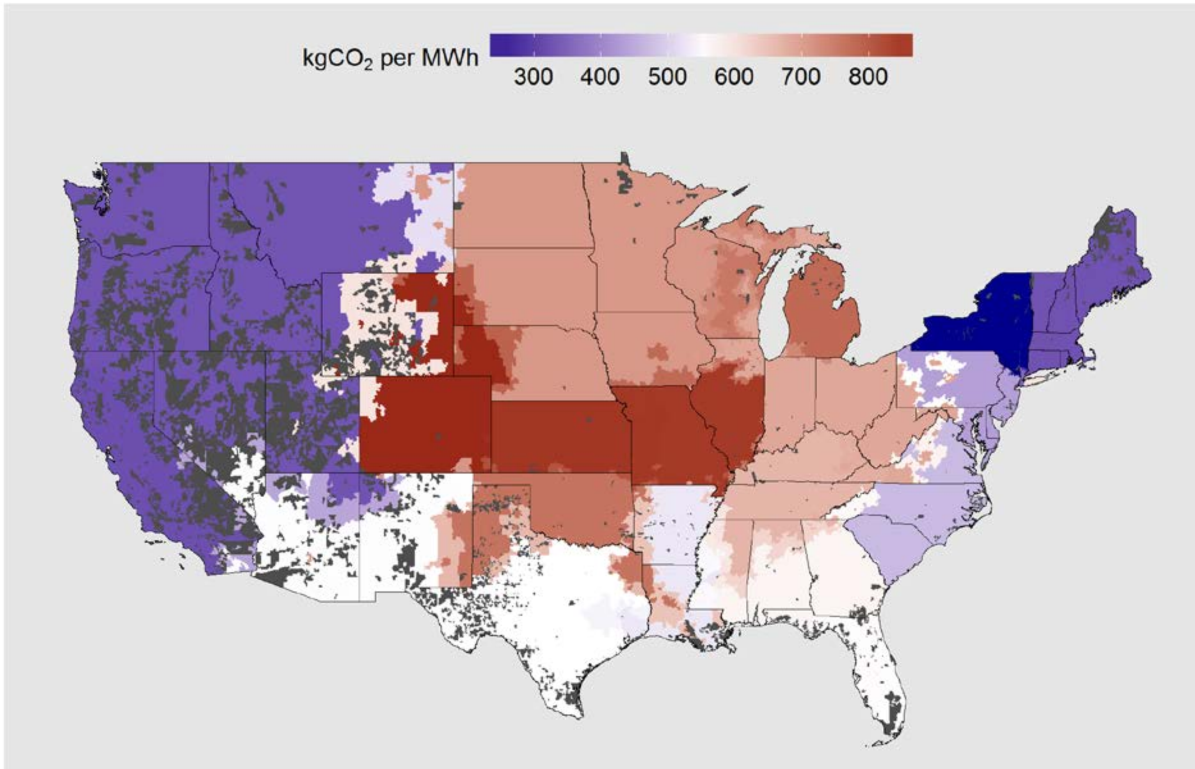
In the case of electricity, the EPA eGRID dataset provides total CO_2 emissions and electricity generation for 26 power grid sub-regions in year 2012.[31] I also include an adjustment for transmission and distribution losses between generators and consumers.[32] Using spatial data on the boundaries of the eGRID subregions, I am able to estimate the carbon intensity of electricity supply for each household in the fused CEX-ACS sample (Figure 5).

[30] In the case of services, the I-O accounting makes no formal distinction between production and trade margin components. However, the logic used for goods is, arguably, still applicable to services. For example, restaurants procure, refrigerate, and cook raw ingredients in basically similar ways regardless of the establishment type (akin to the "factory gate" in the case of goods), but they may differ widely in terms of rent, marketing, or staffing levels/salaries (trade margins). Consequently, for all services I assume that S_t is 33% and $\overline{CIE_t}$ is equal to 50% of the I-O overall *CIE*, consistent with values generally observed for goods.

[31] http://www.epa.gov/energy/egrid

[32] The eGRID-derived emission factors do not account for inter-regional electricity flows that could impact the true GHG-intensity of electricity consumed. Up to 30% of electricity consumed in some grid sub-regions originates elsewhere, but there is currently no simple way to account for these flows (Diem and Quiroz 2012).

Figure 5 - Carbon intensity of electricity supply (2012)



The EIA's State Energy Data System (SEDS) provides information on average residential retail energy prices, by state and year.[33] Combined with the eGRID emission factor data, this allows one to estimate local *CIE* assuming state average electricity prices. There is no need to rely on *CIE* from the I-O model in the case of electricity.

However, we know that a given household's actual *CIE* for electricity could be significantly lower or higher than the average. This is due to the fact that households face different effective price-per-kWh. A household that reports $100 of monthly electricity expenditure does not necessarily consume twice as much electricity as a household that reports $50 of expenditure (as implied by identical price-per-kWh). Both fixed monthly costs and tiered pricing impact the relationship between total expenditure and effective price – and, ultimately, *CIE*.

In an attempt to account for this, I utilize the most recent round (2009) of the EIA's Residential Energy Consumption Survey (RECS) to analyze how the effective price-per-kWh varies with the level of electricity expenditure in different parts of the country (*N* = 12,083 households).[34] The RECS is a unique data source for this kind of analysis, since it reports household energy expenditure and physical quantity consumed based on actual utility bills.

The location of each household in the RECS is disclosed at the level of 27 geographic regions. Larger states are assigned their own region; smaller states are grouped together. I calculate the

[33] http://www.eia.gov/state/seds/

[34] http://www.eia.gov/consumption/residential/

ratio of each household's actual price-per-kWh to the population-wide mean price in the same region. I then fit a boosted (mean) regression tree model to predict a household's "price ratio" as a function of electricity expenditure, region, household income, primary heating fuel, and poverty status.

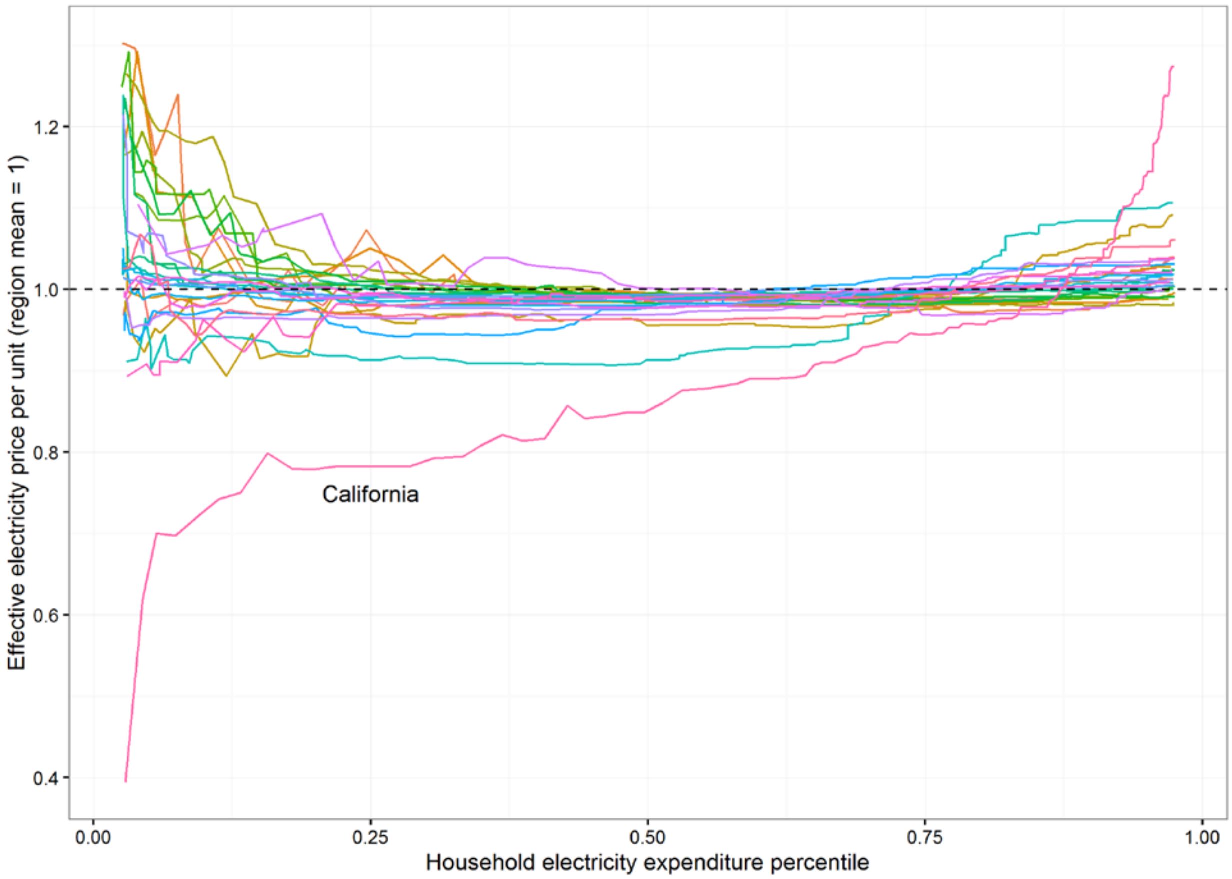
If all households in a region face identical electricity pricing structures, then we expect none of the independent variables other than electricity expenditure and region to help predict the price ratio. In practice, the other independent variables help control for intra-region variation in the price of electricity (i.e. on average, rich households live in places where electricity prices are higher) and low-income cost assistance programs (i.e. households in poverty that heat with electricity may receive government support).

Figure 6 shows the marginal average effect of electricity expenditure (reported as a region-specific percentile) on a household's electricity price ratio, for each of the 27 regions. This plot shows how the relative effective price-per-kWh changes depending on a household's position in the electricity expenditure distribution.

In general, low-expenditure households in a given region pay more per-kWh (reflecting fixed monthly costs), as do the highest-expenditure households (reflecting tiered rate structures with increasing marginal cost). The lowest price-per-kWh is often paid by households in the middle of the distribution. A notable exception is California, where public-owned utilities pair low fixed monthly costs with aggressive tiered pricing.[35] Consequently, the *average* price-per-kWh in California (as reported in SEDS, for example, and denoted by the dashed line in Figure 6) is considerably higher than the effective prices paid by most Californian households.

[35] https://energyathaas.wordpress.com/2014/11/03/whats-so-great-about-fixed-charges/

Figure 6 – Mean relative electricity price, by state/region (based on 2009 RECS)



The information in Figure 6 and the underlying models is critical for accurate adjustment of *CIE* to account for region-specific pricing structures. I use the fitted models to predict household-level electricity price ratio in the fused CEX-ACS dataset and then adjust the initial *CIE* estimate to reflect this information. A similar adjustment is made for natural gas, though I rely on the initial *CIE* estimate from the I-O model.

In the cases of heating oil and LPG, I use state-level residential prices from the EIA to adjust the national average *CIE*. Since this could lead to erroneous values (primarily because the I-O analysis *CIE* for these fuels will reflect all uses – not just residential), I include a further, final adjustment to ensure that total residential CO_2 emissions from these fuels match totals reported by the EIA.

6 Simulation of carbon fee and dividend policy

The simulated policy imposes a $15 per ton CO_2 carbon fee on all domestic fossil fuel extraction and imported fuels and goods. I calculate that the average annual carbon tax base – that is, the total amount of CO_2 assumed subject to taxation – was 7,810 $MtCO_2$ per year over the period from 2008 through 2012.[36] Assuming a static economy and no response to the tax, this yields annual gross revenue of $117 billion for simulation purposes.

About 20% of gross revenue is used to finance carbon tax rebates for businesses exporting goods abroad or using fossil fuel for non-combustive uses (see Section 6.1). The remaining ~80% is returned to households in the form of a taxable "dividend". The revenue is disbursed to households, assuming that each adult receives a full dividend "share" and each child (up to two per household) receives a half share.

A measure of "net financial benefit" (*NFB*) is calculated for each household in the sample. Given a pre-tax dividend (*D),* marginal income tax rate (*M*; see Section 6.2 below), effective CO_2 footprint (*Z),* and a nominal carbon tax rate of $15 per ton CO_2 (*T*=15), a household's *NFB* is given by:

$$NFB = D(1 - M) - ZT \qquad (8)$$

In the context of carbon pricing, revenue and CO_2 emissions are analogous. The tax burden for a given entity – assuming that the tax is passed entirely on to consumers and there is no macroeconomic response to the policy – is proportional to that entity's carbon footprint. Since a primary objective of this study is to assess the balance of costs (i.e. emissions or tax burden) and benefits (i.e. dividends) for individual households, it is important to ensure that the "sources and sinks" of these flows are fully accounted for.

6.1 Sources of gross revenue

Results from the I-O model show that 12.8% of CO_2 emissions (and, therefore 12.8% of gross revenue in the carbon tax simulation) is attributable to local, state, and federal governments. These entities face higher prices when providing public services. In addition, 44% of health care services – ostensibly household consumption in PCE accounting – are, in fact, paid by governments (primarily through Medicare and Medicaid).[37] I calculate that the government-financed portion of total health sector CO_2 emissions averaged 201 $MtCO_2$ per year from 2008 through 2012, equivalent to ~2.6% of gross revenue. All told, governments at all levels ultimately finance about 15% of gross revenue. See Table 1 for details.

[36] Note that the carbon tax base in this case is considerably larger than conventional production-related or "territorial" emissions reported by the EPA and other organizations. The latter reflects only the carbon content of fossil fuels combusted within the United States. The carbon tax base, however, also includes emissions associated with nonfuel imports, non-combustive use of fuel, and fossil fuel exports (all of which are effectively taxed at the point of entry or extraction). Section 5.2 provides additional information regarding measurement.

[37] https://kaiserhealthnews.files.wordpress.com/2014/04/highlights.pdf

Another 16.3% of gross revenue is derived from implicit taxation of fuel, goods, and services produced for export. This is higher than the result of ~10% reported by Perese (2010) using data from 2006. However, given the significant increase in U.S. fuel exports since that time, the higher figure seems reasonable. A policy with full border tax adjustments requires that exporters receive a rebate equal to the carbon tax embedded in their production costs.

Consequently, I assume that 16.3% of gross revenue is effectively a new cost (an export rebate) to be paid by the federal government.[38] In addition, I estimate that nearly 4% of gross revenue is derived from taxation of carbon sequestered by nonfuel uses of energy (asphalt, petrochemicals, etc.). This revenue would also need to be rebated. Together, about 20% of gross revenue is directed back to business in the form of tax rebates.

The remaining ~65% of revenue must be sourced from households. However, total emissions/costs that can be assigned to households on the basis of actual *expenditure* amount to only 54% of gross revenue. Part of the discrepancy is due to health care. Individuals rarely report (or know) the actual value of health care services received. Nor do most report (or know) the value of private health insurance premiums paid by employers. Based on the I-O model results, I estimate that private, nongovernment provision of health care is the source of ~3.3% of gross revenue.

I assume this cost is evenly distributed across the non-Medicare and non-Medicaid population. I make a rough estimate of participation in these programs on the basis of head-of-household age and household income relative to the Federal Poverty Level (133% being the general threshold for Medicaid eligibility). This effectively assumes that privately-insured individuals pay 3.3% of gross revenue through higher health insurance premiums, imposing an average cost of $19 per person.

Another 7.5% of gross revenue is attributable to taxation of fixed private investment – that is, construction of physical structures and purchase of durable equipment by both businesses and households.[39] There is no agreement on how (or even whether, in some cases) revenue derived from fixed capital formation should be allocated to households. In the absence of any preferable technique, I assume this cost is distributed across households in proportion to total expenditure.

[38] This is different from the border tax adjustment policy proposed by CCL. CCL proposes to make all exports eligible for a rebate *except* fossil fuel exports. I chose to simulate the more generic rebate policy since it is unclear how to assign the cost of the fossil fuel exemption across households (if at all). Additionally, CCL proposes the use of a separate government account where revenue from taxation of nonfuel imports is deposited and subsequently used to pay for rebates on nonfuel exports. Based on the I-O model output, I suspect that this account would generate a small positive balance.

[39] From BEA NIPA Handbook (https://www.bea.gov/national/pdf/NIPAhandbookch6.pdf): "Private fixed investment (PFI) measures spending by private businesses, nonprofit institutions, and households on fixed assets in the U.S. economy. Fixed assets consist of structures, equipment, and software that are used in the production of goods and services. PFI encompasses the creation of new productive assets, the improvement of existing assets, and the replacement of worn out or obsolete assets."

Table 1 - Sources of gross carbon tax revenue (based on avg. annual emissions 2008-2012)

		$MtCO_2$	**Revenue, $B ($15 per tCO_2)**	**Percent of total**
Households	Consumption expenditures	4,188	$62.8	53.6%
	Private health care	256	$3.8	3.3%
	Private fixed investment	582	$8.7	7.5%
Government (all levels)	Consumption and investment	1,003	$15.0	12.8%
	Medicare and Medicaid	201	$3.0	2.6%
Rebate-eligible activities	Export of fuel and goods	1,270	$19.0	16.3%
	Non-combustive use of fuel	310	$4.8	3.9%
	TOTAL	**7,810**	**$117.1**	**100%**

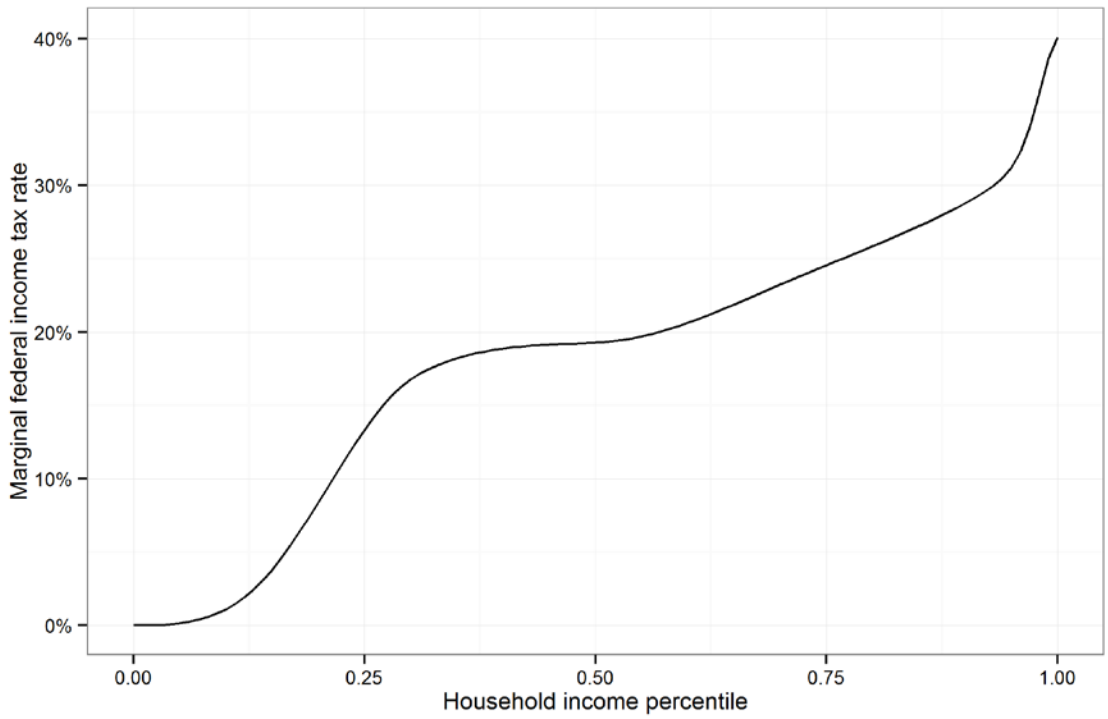
6.2 Dispersal and taxation of dividend

The dividend is treated as fully taxable income at the federal level, and I assume that all households in the fused dataset receive a dividend and pay federal income tax. The policy has no impact on state income taxes. In reality, details of the rebate mechanism(s) could have significant practical and distributional consequences, both for welfare and tax revenue. Dinan (2012) and Stone (2015) provide excellent overviews of the relevant issues and concerns. For the purposes of this study, details of the rebate mechanism itself are ignored.

Each household pays a portion of the rebate back to the federal government, reflecting the household's marginal income tax rate. I estimate the marginal rate of each household using results from the Urban-Brookings Tax Policy Center Microsimulation Model.[40] The assumed relationship between household income percentile and marginal tax rate is given in Figure 7. This assumption results in about 18% of the gross dividend returning to the federal government as income tax revenue.

[40] http://www.taxpolicycenter.org/numbers/displayatab.cfm?Docid=2503

Figure 7 - Assumed relationship between household income and marginal tax rate



6.3 Impact on government budget

The simulation results in a net cost to government of $1.1 billion. Given the allocation of the dividend across households and the assumed marginal tax rate relationship with income, about 18% of the gross dividend is recouped by the federal government as income tax revenue. This generates revenue of $17 billion, but the tax burden imposed on government through higher prices is $18.1 billion, leaving a $1.1 billion shortfall.[41] It should be noted (again) that this analysis does not consider any dynamic effects of the policy on macroeconomic outcomes.

This simulation suggests that the increase in government spending due to higher prices is equal to ~20% of the (net) revenue remaining after export and non-combustive fuel rebates are paid out ($18.1B / $93.3B = 19.4%). This is the portion of revenue that must be either retained or recouped in some way to maintain revenue neutrality across all levels of government. It also happens to be similar to the effective tax rate on the household dividend given CCL's rebate formula, resulting in a comparatively small overall budget impact.

It is worth noting how this budget calculation differs from that of the Congressional Budget Office (CBO) when "scoring" indirect tax legislation, including carbon pricing. For budgetary purposes, the CBO reduces the expected indirect tax revenue by a 25% "offset" to account for

[41] The simulated increase in public outlays reflects *all* levels of government (federal, state, and local), since the expenditures and carbon-intensity of each are captured in the underlying I-O tables. In practice, the federal government would need to return some of the recouped revenue to the states to cover increased local costs.

the loss of federal tax revenue from other sources (Stone, Horney, and Greenstein 2008). In effect, the offset assumes that the indirect tax is passed entirely "backward" onto capital and labor *and* that the effective tax rate on corporate and personal income is about 25%.[42]

If one instead assumes that the tax is passed entirely "forward" into consumer prices (as done here), a 25% offset is likely higher than needed to maintain budget neutrality. The CBO itself acknowledges this (CBO 2009; footnote 4), and the results here offer some confirmation.

But an implicit tradeoff is at work: If the tax is assumed to be borne by capital and labor (i.e. passed "backward"), then the gross tax burden on households is less regressive but only 75% of the revenue is ostensibly available to finance rebates or other politically-appealing projects. Conversely, if the tax is assumed to be passed "forward" into consumer prices, the offset required for budget neutrality is arguably lower (perhaps 20%) but the household tax burden is more regressive in the first place.

[42] The income-weighted effective tax rate implied by the curve in Figure 7 is, indeed, 25%. The lower effective tax rate of 18% in the case of the CCL proposal is due to the dividend allocation formula disproportionately benefitting poorer households with lower marginal tax rates.

7 Results

When assessing the results presented below, it is important to remember that this analysis is "static" and does not consider "dynamic" effects that a carbon tax would have on economic growth, employment, wages, trade, or consumption patterns over time. Nor does it consider local or global environmental benefits. Instead, I calculate the short-run financial effect on families, assuming that the policy is implemented "overnight" with 100% pass-through of the tax into consumer prices, no change in household behavior, and no change in production processes, technologies, or emissions.

Throughout this section, a household is said to be "benefited" by the policy if it experiences a positive net financial benefit (NFB) given the assumptions and limitations noted above. I also report results for those households that incur a "minor loss", defined as a net financial loss that does not exceed 0.2% of pre-tax household income.

The policy's $15 per ton CO_2 carbon fee generates annual revenue of $117 billion for the purposes of the simulation. About 20% of gross revenue is used to finance carbon tax rebates for businesses exporting goods abroad or using fossil fuel for non-combustive uses. The remaining 80% ($93 billion) is returned to households in the form of a taxable "dividend", assuming that every adult receives a full dividend "share" and each child (up to two per household) receives a half share.

This amounts to a pre-tax dividend of, on average, $811 per household ($323 per person) at current emission levels.[43] Given the assumed marginal tax rate relationship with income (Section 6.2), the average after-tax dividend – that is, the increase in disposable income due to the rebate – amounts to $664 per household ($264 per person).

7.1 Costs and benefits across the income distribution

Overall, 53% of U.S. households (58% of individuals) experience a positive NFB under the policy. Figure 8 shows the percentage of households benefited across income quintiles. Each quintile contains an equal number of people, ranked according to household income as a percentage of the Federal Poverty Level (FPL).[44] Figure 8 also reports the percentage of households that incur a minor loss relative to income.

Among households benefited, the typical (median) gain is $192 per household or 0.5% of income. Among the 47% of households with a negative NFB, the typical loss is $195 per household; since these households tend to have higher incomes, the typical loss as a percentage

[43] All "per-person" results include both adults and children equally in the denominator. Also, the ACS sample excludes people living in "group quarters", which includes correctional facilities, juvenile facilities, nursing homes, and health care facilities. Consequently, per-household and per-person results are slightly over-stated.

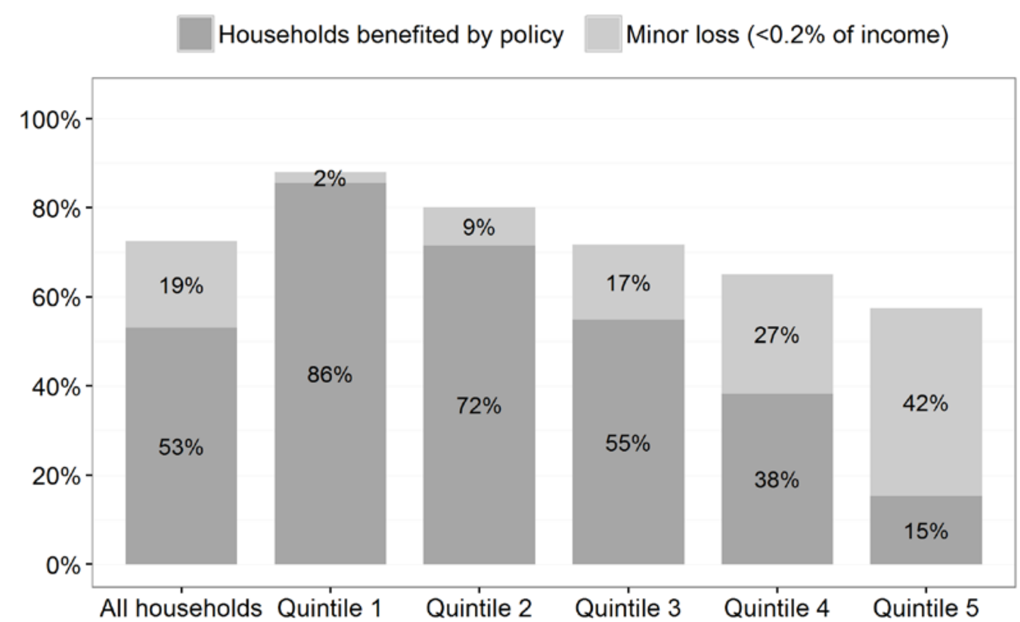
[44] I use household income as a percentage of FPL to rank households, because the latter incorporates an adjustment for household size that better reflects relative economic standing (https://aspe.hhs.gov/poverty-guidelines). Percentage of FPL is also often used to determine eligibility for government programs, so distributional effects along this dimension have practical policy relevance.

of income is less (0.25%). Across all households, the mean NFB is just slightly positive ($7), reflecting the fact that the policy, as simulated, results in a small net transfer from government to households (Section 6.3).

The policy is highly progressive overall. Eighty-six percent of households in the bottom quintile of the income distribution are benefited, compared to just 15% in the top quintile. Among households in the bottom quintile, mean net benefit is $280 per household or about 1.8% of average household income. Households in the top quintile, on average, experience losses of a similar absolute magnitude ($322) but less relative to income (-0.2%). Households in the middle of the income distribution (Quintile 3) see a small overall benefit (mean value of $27 per household).

Overall, 72% of households experience either a net financial benefit or a minor loss of no more than 0.2% of income. The share of households incurring only a minor loss increases rapidly with income, reflecting the fact that incomes increase faster than net policy costs as one moves up the income scale.

Figure 8 - Percentage of households benefited, by income quintile



	All households	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Mean net benefit (% of avg. income)	$7 (0.01%)	$280 (1.78%)	$133 (0.37%)	$27 (0.05%)	$-83 (-0.10%)	$-322 (-0.18%)
Median gain (% of HH income)	$192 (0.50%)	$279 (1.95%)	$202 (0.60%)	$161 (0.29%)	$128 (0.15%)	$93 (0.07%)
Median loss (% of HH income)	$-195 (-0.25%)	$-96 (-0.79%)	$-116 (-0.38%)	$-143 (-0.29%)	$-183 (-0.24%)	$-319 (-0.20%)
Median HH income % of FPL	326%	95%	204%	326%	489%	858%

Figure 9 shows overall financial effects across income deciles. The size of the after-tax dividend (additional disposable income) received by each decile does not vary significantly across the income distribution, though it does decline slightly with rising income and higher marginal tax rates. Conversely, the tax burden imposed through higher prices for goods and services increases with income. Overall, the *net* distributional consequences of the policy are largely (but not exclusively; see Section 7.3) driven by differences in the exposure of households to carbon pricing (i.e. their carbon footprint).

This pattern results in a net transfer of money from upper-income to lower-income households (Figure 10). Overall, households in Quintiles 3 and 4 exhibit comparatively small net gains and losses, respectively. The primary distributional effect is to shift purchasing power from the top quintile to the bottom two quintiles.

Figure 9 - Total financial cost and benefit, by income decile

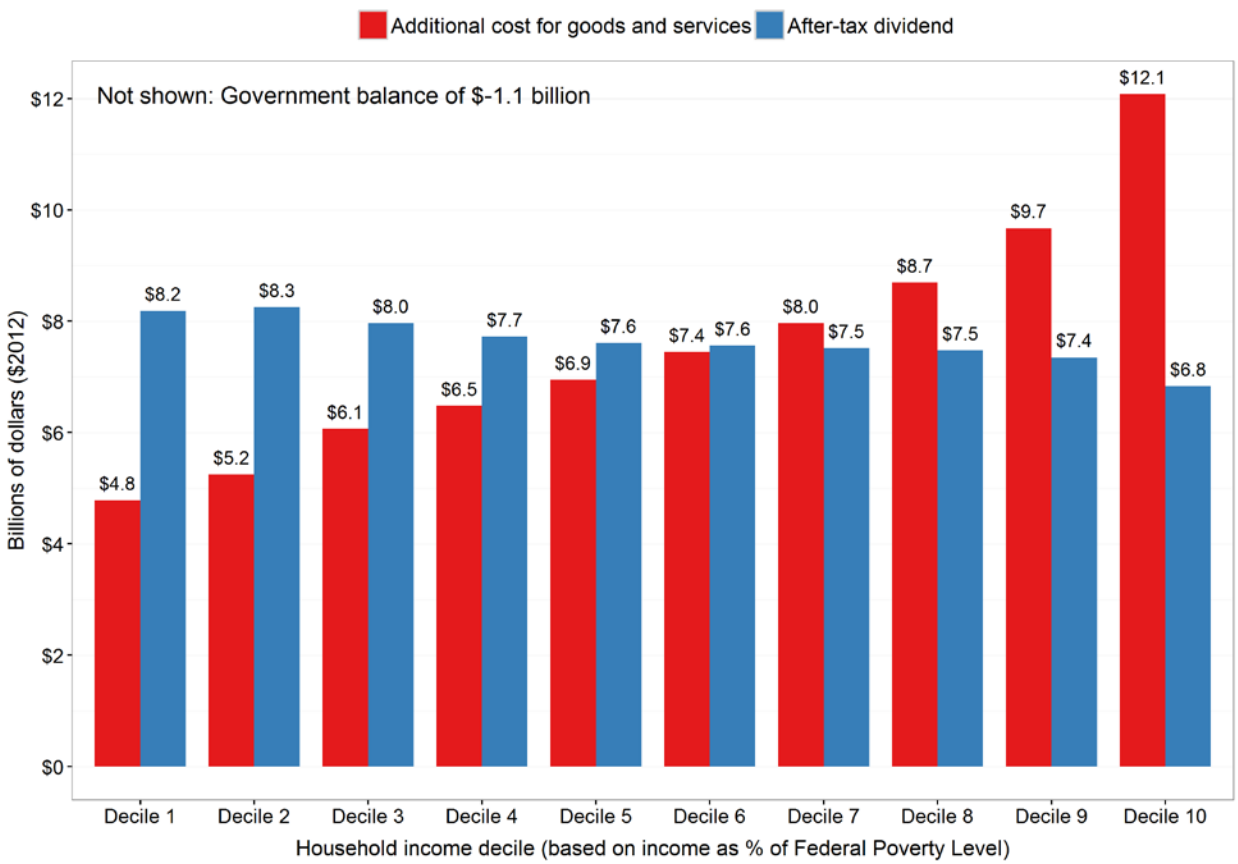
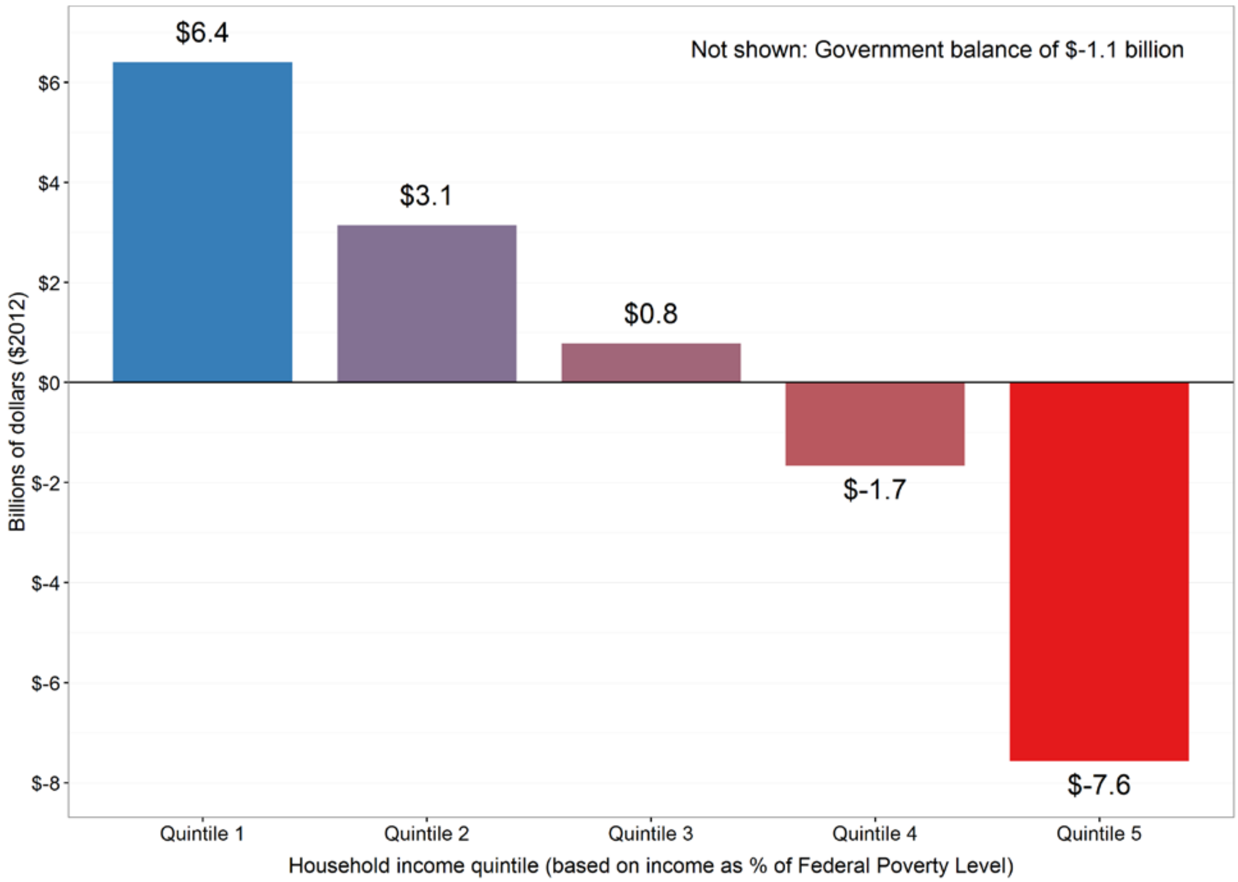


Figure 10 - Overall net financial effect of policy, by income quintile



7.2 Spatial variation in net benefit

Figure 11 shows the percentage of households benefited for each of 30,000+ zip codes. A value of 50% is represented by white shading in the map. Blue (red) areas are those with higher (lower) values.[45] Figure 12 reports results across three major community types: rural, suburb or town, and urban.[46]

[45] Readers should consult Ummel (2014) for details regarding derivation of zip code-level results from the fused CEX-ACS dataset. From that paper: "In order to calculate statistics for alternative geographic regions (e.g. zip codes or congressional districts), it is necessary to compute new sample weights that reflect the likelihood of a given household being located in a given region. A sample weight 'raking' algorithm is employed to assign and re-weight households for any given geographic region, using region-specific marginal household counts from ACS and 2010 Census summary files. This technique ensures that the subsample of households assigned to a given zip code or congressional district, for example, reflects the *actual* distribution of households across income, age, race, housing tenure, and household size."

[46] Results for community types are derived by estimating the dominant type (rural, suburb/town, or urban) for each of the 30,000+ zip codes using the "locale codes" spatial dataset developed by the National Center for Education Statistics (https://nces.ed.gov/ccd/rural_locales.asp).

Figure 11 - Percentage of households benefited, by zip code

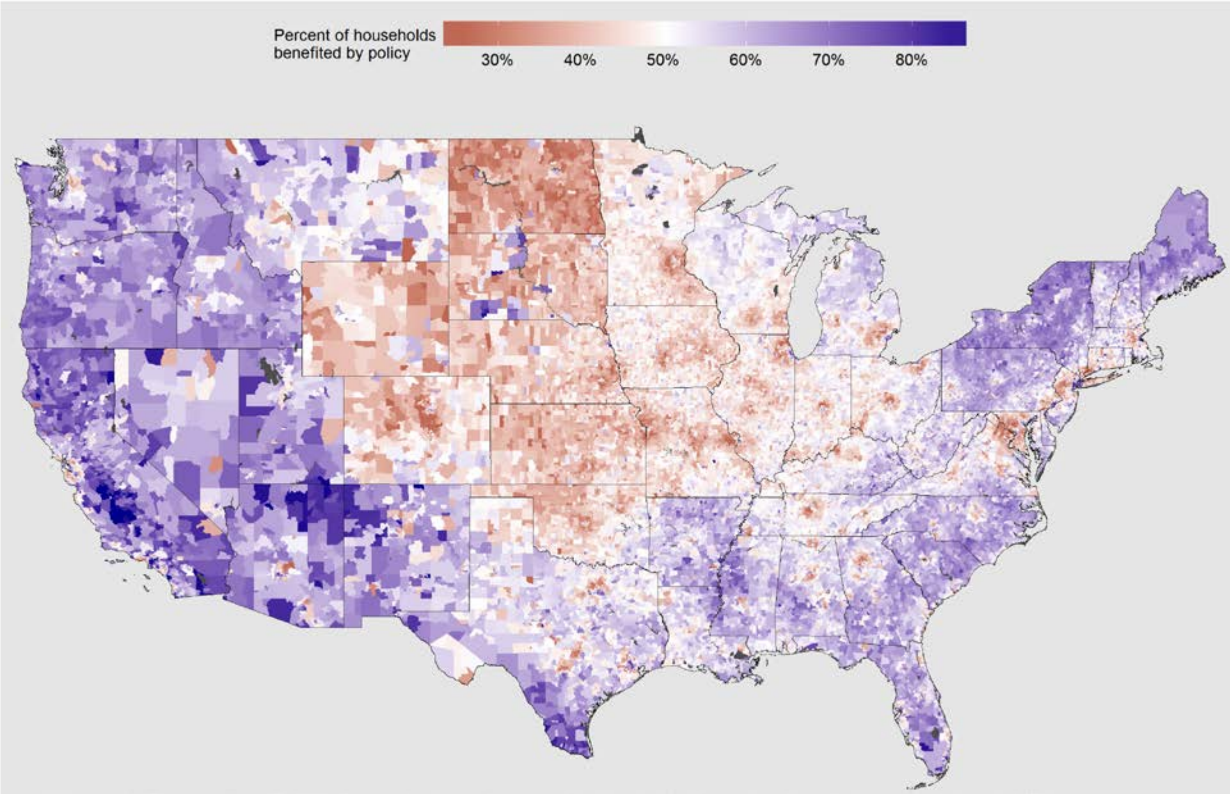
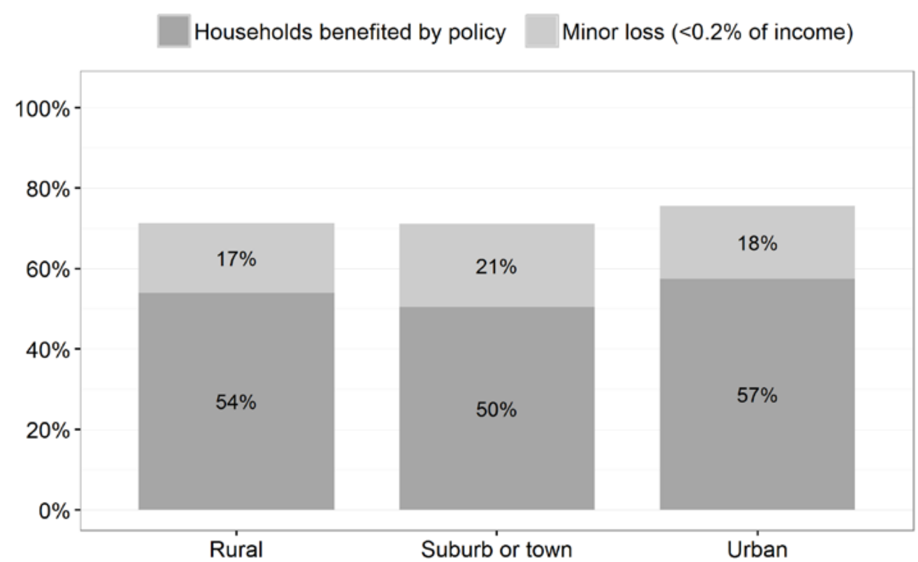


Figure 12 - Percentage of households benefited, by community type



	Rural	Suburb or town	Urban
Mean net benefit (% of avg. income)	$13 (0.02%)	$-18 (-0.02%)	$49 (0.07%)
Median gain (% of HH income)	$186 (0.52%)	$184 (0.44%)	$209 (0.62%)
Median loss (% of HH income)	$-185 (-0.28%)	$-203 (-0.24%)	$-185 (-0.24%)
Median HH income % of FPL	286%	355%	302%

I do not provide a formal analysis of the drivers of these spatial patterns. However, it is possible to surmise three factors that explain at least some of the variation. First, areas with comparatively low-carbon electricity tend to fare better (compare with Figure 5 in Section 5.5). Second, households in suburban areas tend to fare worse, reflecting higher incomes/consumption and carbon footprints (red "hotspots" around urban cores). Third, areas with comparatively mild climates tend to do better.

The zip-code level results generally bear out trends hinted at in the state-level CGE modeling of Williams et al. (2014b) – namely, that small-scale variation in the distribution of benefits *within* geographic regions or states may well be more important than differences *across* regions. This is consistent with the finding of Ummel (2014) that household carbon footprints rise and then fall as one moves outward from urban cores (i.e. a suburban effect).

7.3 Net benefit across demographic groups

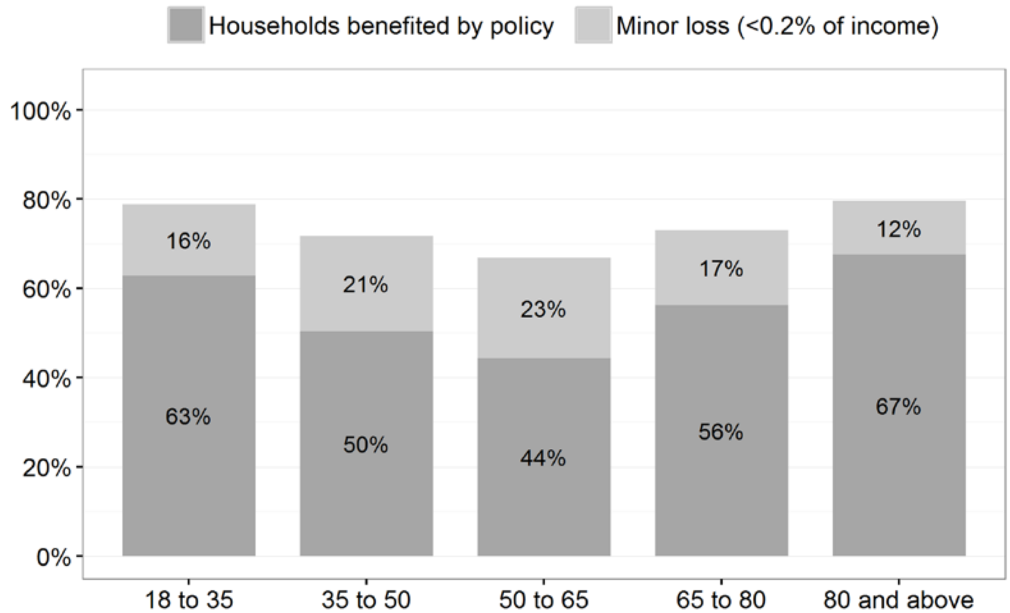
This section presents results by age group, household type, and race.

Figure 13 reports net effects across five age groups, based on age of the household head. Roughly two-thirds of younger households (age 18 to 35) and older households (age 80 and above) households are benefited, compared to 44% of households age 50 to 65.

The pattern of benefits across groups makes sense given the impact of age on both carbon footprints and dividend received. Older households tend to have smaller footprints, reflecting reduced mobility and less consumption as a result of low fixed incomes. Younger households tend to be larger – and therefore benefited by the dividend formula – in addition to having less income/consumption in early career.

Households in the "35 to 50" and "50 to 65" groups, on the other hand, have higher incomes/consumption and, as children age and move out, smaller and less efficient households (from a carbon footprint perspective).

Figure 13 - Percentage of households benefited, by age group



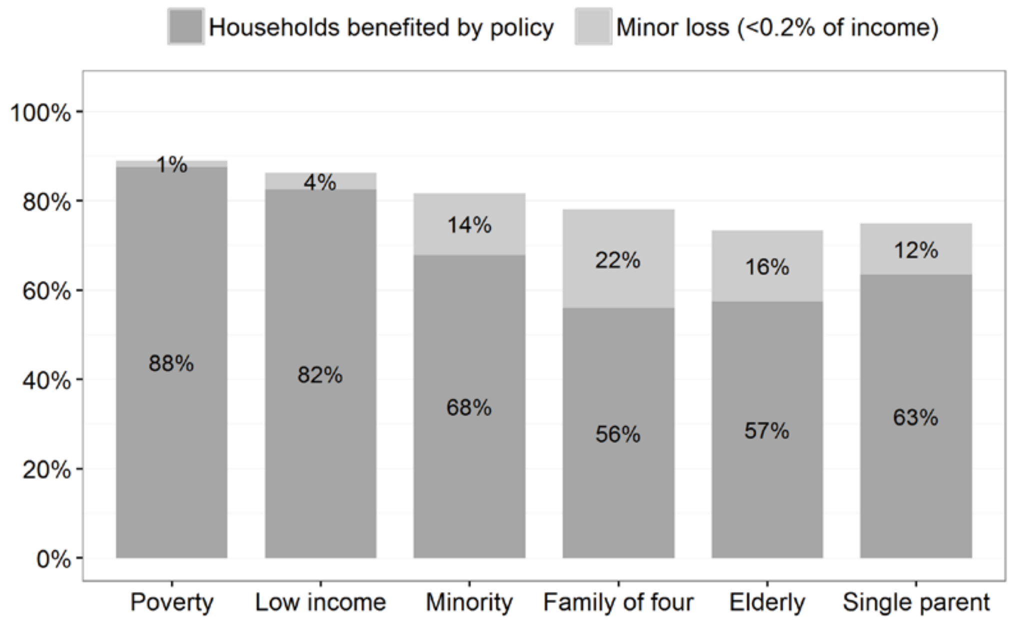
	18 to 35	35 to 50	50 to 65	65 to 80	80 and above
Mean net benefit (% of avg. income)	$104 (0.18%)	$-7 (-0.01%)	$-64 (-0.07%)	$11 (0.02%)	$69 (0.17%)
Median gain (% of HH income)	$233 (0.64%)	$215 (0.44%)	$170 (0.40%)	$163 (0.53%)	$161 (0.70%)
Median loss (% of HH income)	$-160 (-0.24%)	$-218 (-0.24%)	$-218 (-0.25%)	$-167 (-0.28%)	$-129 (-0.30%)
Median HH income % of FPL	266%	357%	411%	282%	203%

Figure 14 reports net effects across different household types. “Elderly” households are those with a household head age 65 or older, no more than two adults, and no children present. “Poverty” and “Low income” refer to households with income below 100% and 200% of FPL, respectively.

Reflecting the strong progressivity seen earlier, 88% of households living below the poverty line are benefited by the policy. Among households in poverty, the average net benefit is $311 per household or about 2.8% of average household income.

Household income is not the sole determinant of policy effects. This is evidenced by comparing results for the “Minority” and “Elderly” groups. Household income as a percentage of FPL is similar for the two groups, but minority households see significantly larger positive effects: mean NFB of $148 versus just $2 for elderly households. This is likely due to differences in household composition and resulting dividend allotment.

Figure 14 - Percentage of households benefited, by household type



	Poverty	Low income	Minority	Family of four	Elderly	Single parent
Mean net benefit (% of avg. income)	$311 (2.81%)	$243 (1.19%)	$148 (0.25%)	$17 (0.02%)	$2 (0.00%)	$61 (0.17%)
Median gain (% of HH income)	$300 (2.90%)	$257 (1.42%)	$261 (0.76%)	$259 (0.44%)	$148 (0.56%)	$211 (1.18%)
Median loss (% of HH income)	$-92 (-1.17%)	$-102 (-0.59%)	$-164 (-0.24%)	$-254 (-0.20%)	$-156 (-0.29%)	$-165 (-0.33%)
Median HH income % of FPL	69%	120%	240%	345%	252%	147%

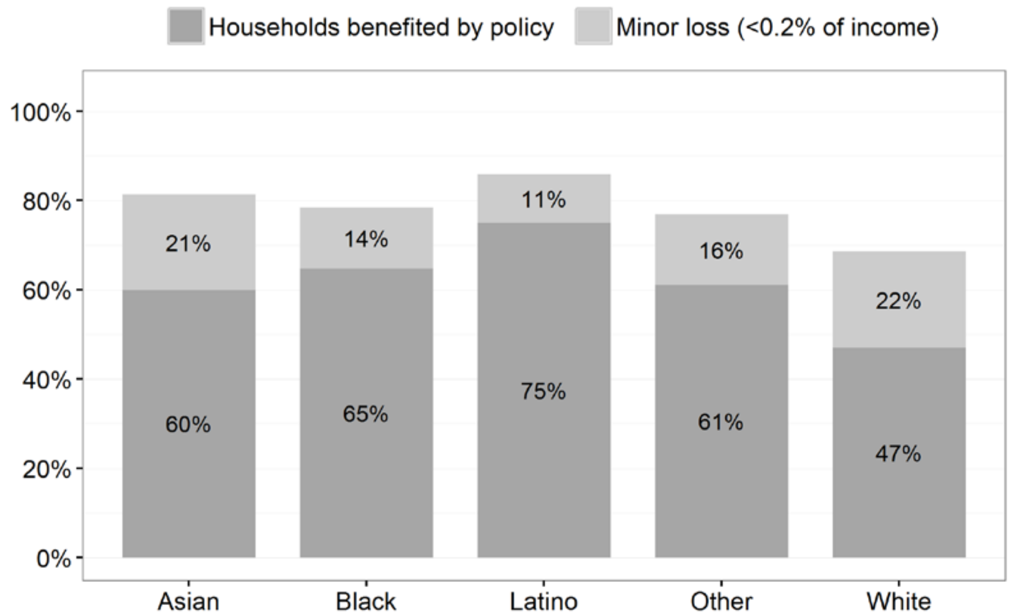
Figure 15 reports net effects by race, based on the self-identified race of the household head.

Most noticeable is the fact that three-quarters of Latino households are benefited by the policy, compared to less than one-half of white households. On average, Latino households are not only poorer than white households (generally associated with a lower footprint) but also significantly larger in size. Since the dividend formula benefits larger households (and especially households with multiple adults), this leads to both higher pre-tax dividend and NFB.[47]

Overall, the results highlight the ways in which geographic and social differences can combine with the design of the policy to produce important – and sometimes unforeseen – distributional outcomes.

[47] It is also possible that Latino households (and perhaps Asian households), on average, benefit from geographic concentration in parts of the country with comparatively mild climates, though this is not explicitly tested.

Figure 15 - Percentage of households benefited, by race



	Asian	Black	Latino	Other	White
Mean net benefit (% of avg. income)	$78 (0.08%)	$104 (0.20%)	$228 (0.41%)	$82 (0.13%)	$-52 (-0.06%)
Median gain (% of HH income)	$255 (0.47%)	$215 (0.75%)	$322 (0.89%)	$223 (0.65%)	$162 (0.40%)
Median loss (% of HH income)	$-202 (-0.18%)	$-153 (-0.27%)	$-160 (-0.23%)	$-175 (-0.26%)	$-203 (-0.25%)
Median HH income % of FPL	405%	230%	214%	267%	364%

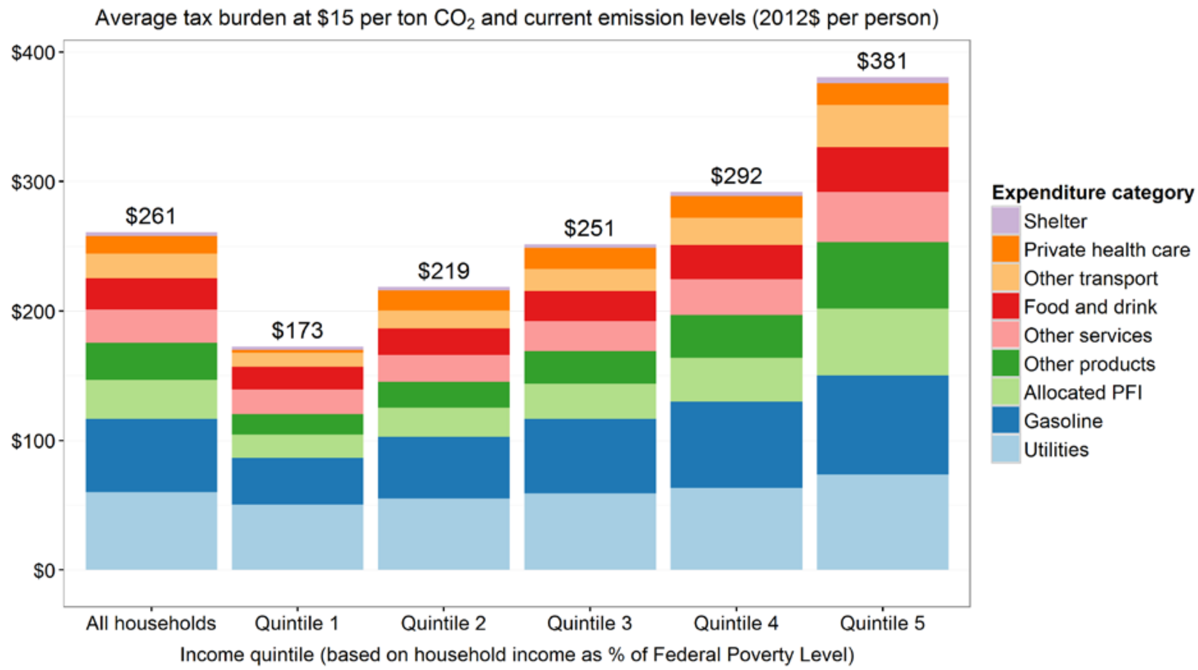
7.4 Gross tax burden across consumption categories

Figure 16 shows the mean per-person gross tax burden across income quintiles, broken down by consumption category. The results show how the burden of higher costs (pre-dividend) are allocated across different types of consumption, assuming complete pass-through of the tax into consumer prices. The categories are aggregates of more detailed categories used in the modeling itself. Table 2 in Section 10 provides the mapping from detailed to aggregate categories.

The "Shelter" category is noticeably small for all quintiles and included separately to make explicit the limited effect of carbon pricing on actual housing costs. While housing is a major component of household expenditure, carbon pricing is expected to have no effect on monthly outlays for households that *already* own property either outright (zero cost) or via a fixed-rate mortgage (fixed cost). The effect on renters and would-be buyers due to higher costs for new home construction will vary with local housing market conditions and not considered here.

The Shelter component reflects only emissions associated with insurance, maintenance, and management of existing properties (including vacation homes and operation of hotels), not new construction. That said, the "Allocated PFI" (Private Fixed Investment) component effectively includes the tax burden associated with new residential construction (among other things) but is simply assumed to be proportional to total household expenditure as explained in Section 6.1.

Figure 16 - Gross tax burden by income quintile and consumption category



The "Private health care" category reflects an assumption regarding increases in premiums for private health insurance plans (described in Section 6.1). Since low-income and elderly households are assumed to be covered by public health insurance (Medicaid and Medicare, respectively), the private insurance tax burden is negligible among households in the first quintile.

The "Gasoline" and "Utilities" categories reflect higher costs for *direct* energy purchases. All other categories reflect *indirect* tax burden due to higher prices for other goods and services. Across all households, the direct tax burden is 45% of the total. This figure varies from 40% for households in the top quintile to 50% for those in the first.

8 Conclusion

This study simulates a "carbon fee and dividend" policy similar to that proposed by the Citizens' Climate Lobby (CCL), assuming a "static" economy in which the policy is implemented "overnight" with 100% pass-through of the tax into consumer prices, no change in household behavior, and no change in production processes, technologies, or macroeconomic conditions.

I find that the policy confers a positive net financial benefit on 53% of households nationwide (58% of individuals). The overall distributional effects are highly progressive. Nearly 90% of households living below the federal poverty line are benefited by the policy. The average net benefit in this group is $311 per household, equivalent to 2.8% of average pre-tax income.

The typical size of the after-tax dividend (additional disposable income) does not vary considerably across the income distribution. As expected, the tax burden imposed through higher prices for goods and services increases with income. Overall, the policy's primary distributional effect is to shift purchasing power from the top quintile to the bottom two quintiles of the income distribution.

Differential impacts across space and population subgroups highlight the ways in which "geo-demographic" patterns (Singleton and Spielman 2014) combine with policy design to affect distributional outcomes. The results suggest that details of the dividend allotment formula with respect to household size and age, for example, could meaningfully impact the distribution of benefits. A different dividend design could prove equally simple to administer and explain while generating net positive benefits for a larger portion of the population.

Indeed, once the distribution of carbon tax *burdens* across households is accurately specified (and Section 5 makes significant progress here), a principle task – from a policy perspective – is to identify revenue distribution schemes that lead to micro and macro effects amenable to both sides of the political spectrum. Certainly, this task has not been ignored (e.g. Metcalf 2007; Williams et al. 2014a; Kaufman and Krause 2016), but "high-resolution" data and analysis – whether used to simulate household rebates, more complex changes to the tax code, or simply "downscale" output from other models – may help communicate policy options in ways that are more meaningful to politicians and the broader public.

Further, the challenge of creating "fair" or "equitable" carbon tax policy – for example, policy that does not unduly harm vulnerable populations – requires not only being able to identify critical populations in modeling output (ideally along richer dimensions than income groups alone) but also going beyond simple mean effects. I focused in Section 7 on the presentation of "percent benefited" results, because I believe this metric is closer to what we should care about most: not leaving some people (literally) out in the cold. For those interested in the full detail that large-sample micro-simulations can provide, I include additional distributional results in Section 10.

Among the real-world complications ignored here is the effect of higher consumer prices on government transfer programs and spending. This is most notable in the case of Social Security benefits, which are indexed to inflation through existing law. In the event of higher consumer prices due to carbon pricing, Social Security benefits will maintain purchasing power even in the absence of a dividend or rebate program (albeit with an important temporal lag). Strictly speaking, the CCL proposal would confer a dividend upon seniors *in addition* to the mandated benefit increase. I explicitly ignore the mandated increase in benefits and simulate only the effect of the modified per-capita dividend.[48]

The central assumption that consumers bear the full cost of the tax should probably be viewed as a worst-case scenario with respect to distributional outcomes. Should the tax be borne in part by owners of capital and, to a lesser extent, labor – thereby impacting households through reduced income rather than higher prices – the gross tax burden will be less regressive than assumed here (Rausch, Metcalf, and Reilly 2011).

Whatever the *aggregate* size and direction of effects on employment and wages, it will not fall uniformly across industries (Ho, Morgenstern, and Shih 2008). Certain types of workers (e.g. coal miners) and their families and communities will be impacted more than others. It is not immediately clear how inclusion of largely place- and industry-specific employment effects would alter distributional outcomes.[49] Since it is possible to observe the occupation of each worker in the fused CEX-ACS household sample, however, there is the possibility of gaining some clarity on this question in the future.

The static analysis also assumes no change in household consumption patterns in response to higher prices. While this approach approximates the formal welfare loss under carbon pricing (Metcalf 1999), it is effectively a worst-case scenario from a household *financial* perspective. In practice, some households could reduce their tax burden through changes that impose little or no inconvenience – for example, turning off lights in an unoccupied room. But others face taxation of activities that are not easily avoided or substituted for – for example, long commutes in places with no public transportation. As in the case of employment, the real-world financial effects are likely to vary considerably from one household to another.

[48] Social Security cost-of-living adjustments (COLA's) introduced in January are based on the year-on-year change in the BLS Consumer Price Index observed for the preceding third quarter. Consequently, there is a lag of up to 15 months between real-world price changes and adjustment of benefits. The effect would be most pronounced at the onset of a carbon pricing program. The simulation here is a fair representation of how policymakers might choose to address the problem of "lagging COLA's" in the initial year (via a dividend). If maintained beyond the initial year, however, extending dividends to seniors in addition to mandated COLA's would have significant distributional and budgetary consequences.

[49] For example, if those households most exposed to negative employment effects *already* experience net losses for unrelated reasons, then employment effects could make *some* households even worse off without significantly changing the *overall* proportion of households benefited.

9 References

Burtraw, Dallas, Richard Sweeney, and Margaret Walls. 2009. "The Incidence of U.S. Climate Policy." Discussion Paper, Resources for the Future.

CBO. 2009. "The Role of the 25 Percent Revenue Offset in Estimating Budgetary Effects of Legislation." Congressional Budget Office. http://www.cbo.gov/sites/default/files/cbofiles/ftpdocs/96xx/doc9618/01-13-25percentoffset.pdf.

Deaton, Angus. 2005. "Measuring Poverty in a Growing World (or Measuring Growth in a Poor World)." *Review of Economics and Statistics* 87 (1): 1–19.

Diem, Art, and Cristina Quiroz. 2012. "How to Use eGRID for Carbon Footprinting Electricity Purchases in Greenhouse Gas Emission Inventories." Environmental Protection Agency. https://www.epa.gov/sites/production/files/2015-01/documents/adiem.pdf.

Dinan, Terry. 2012. "Offsetting a Carbon Tax's Costs on Low-Income Households." Working Paper 2012-16, Microeconomic Studies Division, Congressional Budget Office.

Girod, Bastien, and Peter De Haan. 2010. "More or Better? A Model for Changes in Household Greenhouse Gas Emissions due to Higher Income." *Journal of Industrial Ecology* 14 (1): 31–49. doi:10.1111/j.1530-9290.2009.00202.x.

Hassett, Kevin A., Aparna Mathur, and Gilbert E. Metcalf. 2007. "The Incidence of a US Carbon Tax: A Lifetime and Regional Analysis." National Bureau of Economic Research. http://www.nber.org/papers/w13554.

———. 2011. "The Consumer Burden of a Carbon Tax on Gasoline." *Fuel Taxes and the Poor: The Distributional Effects of Gasoline Taxation and Their Implications for Climate Policy, Thomas Sterner, Ed., Resources for the Future Press*. http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2212939.

Herendeen, R.A. 1973. "An Energy Input–Output Matrix for the United States, 1963: User's Guide. Doc. No. 69." Center for Advanced Computation, University of Illinois at Urbana-Champaign, Urbana.

Ho, Mun S., Richard Morgenstern, and Jhih-Shyang Shih. 2008. "Impact of Carbon Price Policies on U.S. Industry." Discussion Paper, Resources for the Future.

Jerrett, Michael, Richard T. Burnett, Renjun Ma, C Arden Pope, Daniel Krewski, K Bruce Newbold, George Thurston, et al. 2005. "Spatial Analysis of Air Pollution and Mortality in Los Angeles:" *Epidemiology* 16 (6): 727–36. doi:10.1097/01.ede.0000181630.15826.7d.

Kaufman, Noah, and Eleanor Krause. 2016. "Putting a Price on Carbon: Ensuring Equity." World Resources Institute. http://www.wri.org/sites/default/files/Putting_a_Price_on_Carbon_Ensuring_Equity.pdf.

Kok, Rixt, René M.J. Benders, and Henri C. Moll. 2006. "Measuring the Environmental Load of Household Consumption Using Some Methods Based on Input–output Energy Analysis:

A Comparison of Methods and a Discussion of Results.” *Energy Policy* 34 (17): 2744–61. doi:10.1016/j.enpol.2005.04.006.

Leontief, Wasily. 1953. *Studies in the Structure of the American Economy; Theoretical and Empirical Explorations in Input-Output Analysis*. New York: Oxford University Press.

Mathur, Aparna, and Adele C. Morris. 2014. “Distributional Effects of a Carbon Tax in Broader U.S. Fiscal Reform.” *Energy Policy* 66 (March): 326–34. doi:10.1016/j.enpol.2013.11.047.

Metcalf, Gilbert. 2007. “A Proposal for a U.S. Carbon Tax Swap.” Discussion Paper, The Hamilton Project.

Metcalf, Gilbert E. 1999. “A Distributional Analysis of Green Tax Reforms.” *National Tax Journal*, 655–81.

Metcalf, Gilbert E., and David Weisbach. 2009. “Design of a Carbon Tax, The.” *Harv. Envtl. L. Rev.* 33: 499.

National Research Council. 2013. “Measuring What We Spend: Toward a New Consumer Expenditure Survey.” Edited by Don A. Dillman and Carol C. House. Committee on National Statistics, Division of Behavioral and Social Sciences and Education.

Orhun, A. Yesim, and Mike Palazzolo. 2016. “Frugality Is Hard to Afford.” Ross School of Business, Paper No. 1309. http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2742431.

Pisano, Elena, and Simone Tedeschi. 2014. “Micro Data Fusion of Italian Expenditures and Incomes Surveys.” *Working Paper No. 164, Sapienza University of Rome, Italy*. http://www.dipecodir.it/upload/wp/pdf/wp164.pdf.

Rausch, Sebastian, Gilbert E. Metcalf, and John M. Reilly. 2011. “Distributional Impacts of Carbon Pricing: A General Equilibrium Approach with Micro-Data for Households.” *Energy Economics* 33 (December): S20–33. doi:10.1016/j.eneco.2011.07.023.

Rausch, Sebastian, and John Reilly. 2012. “Carbon Tax Revenue and the Budget Deficit: A Win-Win-Win Solution?” MIT Joint Program on the Science and Policy of Global Change. http://18.7.29.232/handle/1721.1/72548.

Sabelhaus, John, David Johnson, Stephen Ash, David Swanson, Thesia Garner, John Greenlees, and Steve Henderson. 2013. “Is the Consumer Expenditure Survey Representative by Income?” National Bureau of Economic Research. http://www.nber.org/papers/w19589.

Schumann, Enrico. 2009. “Generating Correlated Uniform Variates.” COMISEF. http://comisef.wikidot.com/tutorial:correlateduniformvariates/.

Singleton, Alexander D., and Seth E. Spielman. 2014. “The Past, Present, and Future of Geodemographic Research in the United States and United Kingdom.” *The Professional Geographer* 66 (4): 558–67.

Stone, Chad. 2015. “Design and Implementation of Policies to Protect Low-Income Households under a Carbon Tax.” Issue brief, Resources for the Future.

Stone, Chad, James Horney, and Robert Greenstein. 2008. “How CBO Estimates the Cost of Climate-Change Legislation.” Center on Budget and Policy Priorities. http://www.cbpp.org/sites/default/files/atoms/files/5-13-08climate.pdf.

Streitwieser, Mary L. 2009. *A Primer on BEA's Industry Accounts*. Bureau of Economic Analysis.

Tullock, Gordon. 1967. "Excess Benefit." *Water Resources Research* 3 (2).

Ummel, Kevin. 2014. "Who Pollutes? A Household-Level Database of America's Greenhouse Gas Footprint." Working Paper No. 381, Center for Global Development. http://www.cgdev.org/sites/default/files/who_pollutes_greenhouse_gas_footprint_0.pdf.

UN Statistics Division. 1999. "Handbook of Input-Output Table Compilation and Analysis." Department of Economic and Social Affairs, United Nations. http://unstats.un.org/unsd/publication/SeriesF/SeriesF_74E.pdf.

Williams, Roberton C., Hal G. Gordon, Dallas Burtraw, Jared C. Carbone, and Richard D. Morgenstern. 2014a. "The Initial Incidence of a Carbon Tax across Income Groups." *Resources for the Future Discussion Paper*, no. 14-24. http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2537839.

———. 2014b. "The Initial Incidence of a Carbon Tax across US States." *Resources for the Future Discussion Paper*, no. 14-25. http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2537847.

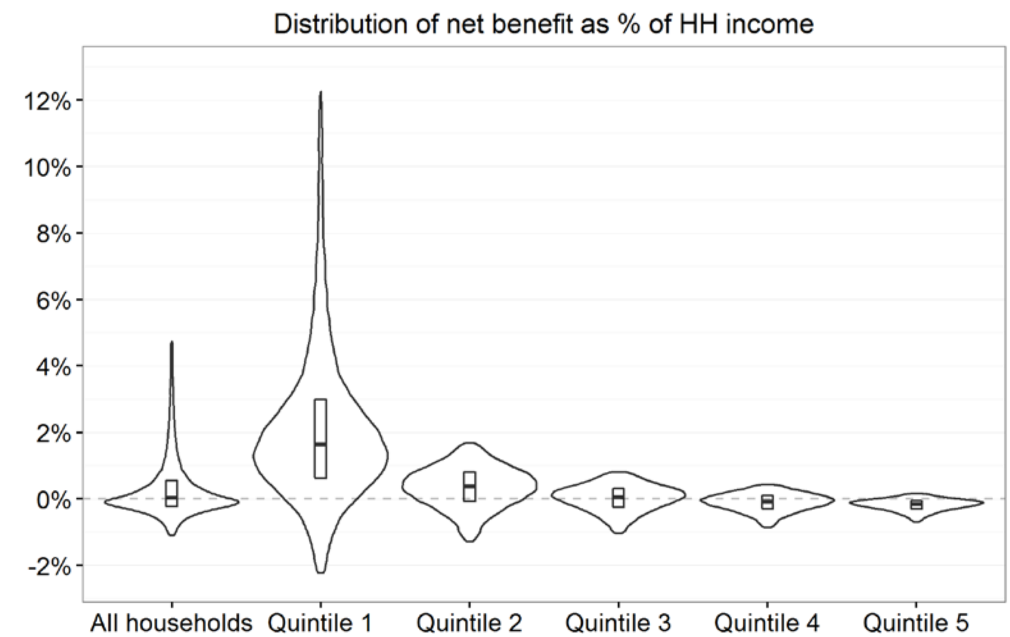
10 Additional tables and figures

Table 2 - Mapping of detailed consumption categories to aggregates

Detailed category	Aggregate category
Alcoholic beverages	Food and drink
Beef	Food and drink
Cereals and baked goods	Food and drink
Dairy	Food and drink
Food away from home	Food and drink
Fruits and vegetables	Food and drink
Nonalcoholic beverages	Food and drink
Other food at home	Food and drink
Pork	Food and drink
Poultry and fish	Food and drink
Gasoline	Gasoline
Apparel	Other products
Furniture	Other products
Household textiles	Other products
Laundry and cleaning supplies	Other products
Major appliances	Other products
Miscellaneous household equipment	Other products
Other entertainment supplies, equipment, and services	Other products
Personal care products and services	Other products
Pets, toys, and playground equipment	Other products
Small appliances, miscellaneous house wares	Other products
Television, radios, sound equipment	Other products
Tobacco products and smoking supplies	Other products
Education	Other services
Fees and admissions	Other services
Other household expenses	Other services
Personal insurance and pensions	Other services
Personal services	Other services
Telephone services	Other services
Water and other public services	Other services
Air travel	Other transport
New car and truck net outlay	Other transport
Other vehicle net outlay	Other transport
Public transportation	Other transport
Used car and truck net outlay	Other transport
Vehicle maintenance and repairs	Other transport

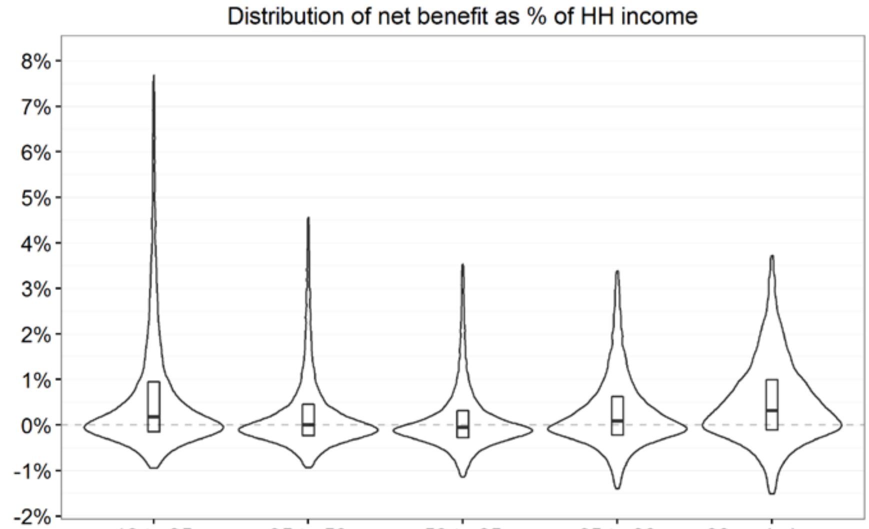
Vehicle rental, leases, licenses, other charges	Other transport
Private health insurance premiums	Private health care
Home insurance	Shelter
Home maintenance and repairs	Shelter
Other shelter	Shelter
Rent	Shelter
Electricity	Utilities
Heating oil	Utilities
LPG	Utilities
Natural gas	Utilities
Other fuels	Utilities
Private fixed investment (PFI) Allocated proportional to household total expenditure	Allocated PFI

Figure 17 - Distribution of net financial benefit, by income quintile



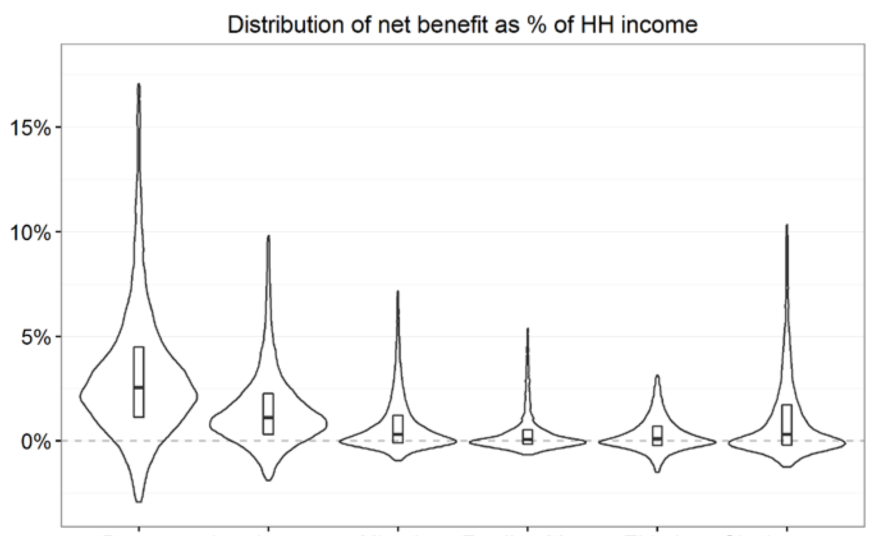
	All households	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
HH's benefited by policy	53%	86%	72%	55%	38%	15%
HH's incurring minor loss	19%	2%	9%	17%	27%	42%
Mean net benefit (% of avg. income)	$7 (0.01%)	$280 (1.78%)	$133 (0.37%)	$27 (0.05%)	$-83 (-0.10%)	$-322 (-0.18%)
Median gain (% of HH income)	$192 (0.50%)	$279 (1.95%)	$202 (0.60%)	$161 (0.29%)	$128 (0.15%)	$93 (0.07%)
Median loss (% of HH income)	$-195 (-0.25%)	$-96 (-0.79%)	$-116 (-0.38%)	$-143 (-0.29%)	$-183 (-0.24%)	$-319 (-0.20%)
Median HH income % of FPL	326%	95%	204%	326%	489%	858%

Figure 18 - Distribution of net financial benefit, by age group



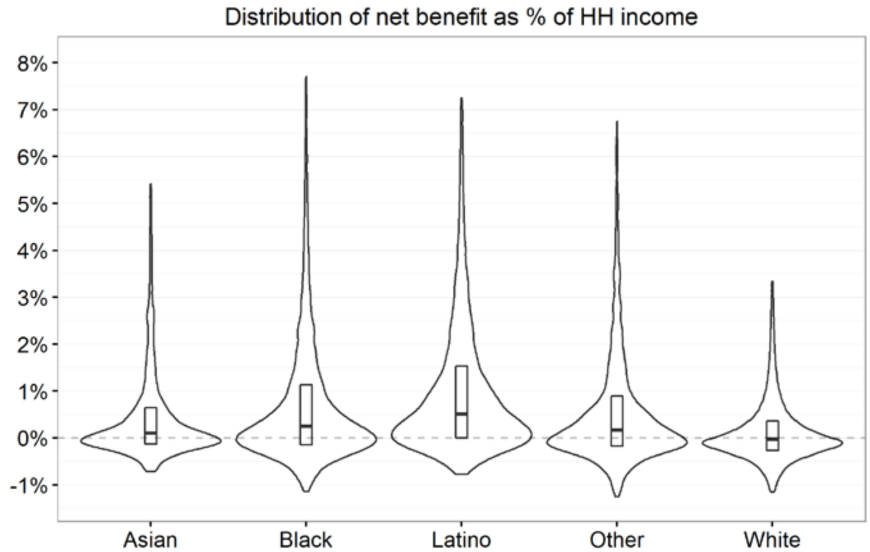
	18 to 35	35 to 50	50 to 65	65 to 80	80 and above
HH's benefited by policy	63%	50%	44%	56%	67%
HH's incurring minor loss	16%	21%	23%	17%	12%
Mean net benefit (% of avg. income)	$104 (0.18%)	$-7 (-0.01%)	$-64 (-0.07%)	$11 (0.02%)	$69 (0.17%)
Median gain (% of HH income)	$233 (0.64%)	$215 (0.44%)	$170 (0.40%)	$163 (0.53%)	$161 (0.70%)
Median loss (% of HH income)	$-160 (-0.24%)	$-218 (-0.24%)	$-218 (-0.25%)	$-167 (-0.28%)	$-129 (-0.30%)
Median HH income % of FPL	266%	357%	411%	282%	203%

Figure 19 - Distribution of net financial benefit, by household type



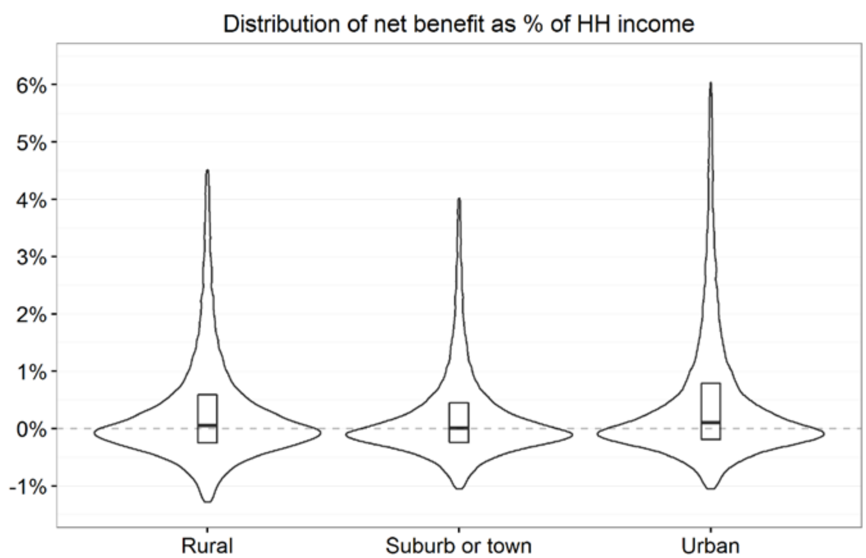
	Poverty	Low income	Minority	Family of four	Elderly	Single parent
HH's benefited by policy	88%	82%	68%	56%	57%	63%
HH's incurring minor loss	1%	4%	14%	22%	16%	12%
Mean net benefit (% of avg. income)	$311 (2.81%)	$243 (1.19%)	$148 (0.25%)	$17 (0.02%)	$2 (0.00%)	$61 (0.17%)
Median gain (% of HH income)	$300 (2.90%)	$257 (1.42%)	$261 (0.76%)	$259 (0.44%)	$148 (0.56%)	$211 (1.18%)
Median loss (% of HH income)	$-92 (-1.17%)	$-102 (-0.59%)	$-164 (-0.24%)	$-254 (-0.20%)	$-156 (-0.29%)	$-165 (-0.33%)
Median HH income % of FPL	69%	120%	240%	345%	252%	147%

Figure 20 - Distribution of net financial benefit, by race



	Asian	Black	Latino	Other	White
HH's benefited by policy	60%	65%	75%	61%	47%
HH's incurring minor loss	21%	14%	11%	16%	22%
Mean net benefit (% of avg. income)	$78 (0.08%)	$104 (0.20%)	$228 (0.41%)	$82 (0.13%)	$-52 (-0.06%)
Median gain (% of HH income)	$255 (0.47%)	$215 (0.75%)	$322 (0.89%)	$223 (0.65%)	$162 (0.40%)
Median loss (% of HH income)	$-202 (-0.18%)	$-153 (-0.27%)	$-160 (-0.23%)	$-175 (-0.26%)	$-203 (-0.25%)
Median HH income % of FPL	405%	230%	214%	267%	364%

Figure 21 - Distribution of net financial benefit, by community type



	Rural	Suburb or town	Urban
HH's benefited by policy	54%	50%	57%
HH's incurring minor loss	17%	21%	18%
Mean net benefit (% of avg. income)	$13 (0.02%)	$-18 (-0.02%)	$49 (0.07%)
Median gain (% of HH income)	$186 (0.52%)	$184 (0.44%)	$209 (0.62%)
Median loss (% of HH income)	$-185 (-0.28%)	$-203 (-0.24%)	$-185 (-0.24%)
Median HH income % of FPL	286%	355%	302%