Analysis

Who rebounds most? Estimating direct and indirect rebound effects for different UK socioeconomic groups

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ABSTRACT

This study estimates the combined direct and indirect rebound effects from various types of energy efficiency improvement and behavioural change by UK households and explores how these effects vary with total expenditure. The methodology is based upon estimates of the expenditure elasticity and GHG intensity of 16 categories of goods and services, and allows for the capital cost and embodied emissions of the energy efficiency measures themselves. The study finds that rebound effects, in GHG terms, are modest (0–32%) for measures affecting domestic energy use, larger (25–65%) for measures affecting vehicle fuel use and very large (66–106%) for measures that reduce food waste. Furthermore, measures undertaken by low income households are associated with the largest rebound effects, with direct emissions forming a larger proportion of the total rebound effect for those households. Measures that are subsidised or affect highly taxed energy commodities may be less effective in reducing aggregate emissions. These findings highlight the importance of allowing for rebound effects within policy appraisals, as well as reinforcing the case for economy-wide carbon pricing.

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1. Introduction

'Rebound effects' is a widely used umbrella term for a variety of economic responses to improved energy efficiency and 'energy-saving' behavioural change. The net result of these effects is typically to increase energy consumption and greenhouse gas (GHG) emissions relative to a counterfactual baseline in which these responses do not occur. To the extent that rebound effects are neglected in policy appraisals, the energy and emissions 'saved' by such measures may be less than anticipated. For example, energy efficient light-bulbs will make lighting cheaper, thereby encouraging people to illuminate larger areas to higher levels over longer periods of time. Responses such as this will offset some of the potential energy and GHG savings.

This paper estimates the rebound effects following a number of energy efficiency improvements and behavioural changes by UK households. These effects are estimated in terms of GHG emissions, rather than energy consumption, and are averaged over a ten-year period. While there is a growing literature on rebound effects for households (Sorrell et al., 2009a), the majority of studies focus solely upon *direct* rebound effects and neglect the associated *indirect* rebound effects which may frequently be of comparable magnitude. There are also very few studies that investigate how these rebound effects vary

between different types of households. This study therefore seeks to estimate the magnitude of both direct and indirect rebound effects from the selected measures and to investigate how these vary between different income groups. The study builds upon earlier analyses by Druckman et al. (2011) and Chitnis et al. (2013).

2. Concepts and Previous Work

To aid understanding of rebound effects for households, we make the following distinctions:

- *Direct versus indirect rebound effects*: For households, *direct* rebound effects derive from increased consumption of energy services, such as heating or lighting, whose effective price has fallen as a result of improved energy efficiency. For example, the replacement of traditional light-bulbs with compact fluorescents will make lighting cheaper, so people may choose to use higher levels of illumination or not switch lights off in unoccupied rooms. In contrast, *indirect* rebound effects derive from increased consumption of other goods and services (e.g. leisure, clothing) that also require energy and GHG emissions to provide. For example, the cost savings from more energy efficient lighting may be put towards an overseas holiday.

- *Efficiency versus sufficiency rebound effects*: Rebound effects for households do not result solely from energy efficiency improvements, such as installing energy-efficient boilers, but also from behavioural changes, such as reducing average internal temperatures. This is

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Table 1
Previous estimates of combined direct and indirect rebound effects for households.

Author	Region	No. of commodity categories	Measure	Area	Metric	Energy/emissions	Estimated rebound effect (%)
Lenzen and Dey (2002)	Australia	150	Efficiency & sufficiency	Food; heating	GHGs	Direct and embodied	45–123%
Alfredsson (2004)	Sweden	300	Sufficiency	Food; travel; utilities	CO_2	Direct and embodied	7–300%
Brannlund et al. (2007)	Sweden	13	Efficiency	Transport; utilities	CO_2	Direct and embodied	120–175%
Mizobuchi (2008)	Japan	13	Efficiency	Transport; utilities	Energy	Direct and embodied	12–38%
Kratena and Wuger (2008)	Austria	6	Efficiency	Transport; heating; electricity	Energy	Direct only	37–86%
Druckman et al. (2011)	UK	16	Sufficiency	Transport; heating, food	GHGs	Direct and embodied	7–51%
Thomas and Azevedo (2013)	US	74	Efficiency	Transport, electricity	GHGs	Direct and embodied	7–25%
Murray (2013)	Australia	36	Efficiency & sufficiency	Transport; lighting	GHGs	Direct and embodied	4–24%
Chitnis et al. (2013)	UK	16	Efficiency	Heating, lighting	GHGs	Direct and embodied	5–15%

because the cost savings from these 'sufficiency measures' will either be spent on other goods and services or saved/invested, and both of these actions will necessarily be associated with energy use and GHG emissions. While efficiency improvements lead to both direct and indirect rebound effects, sufficiency measures only lead to indirect effects.

- *Energy versus emission rebound effects*: Both direct and indirect rebound effects may be estimated in terms of energy consumption, carbon dioxide (CO_2) emissions or GHG emissions, but the magnitude of those effects will differ in each case. As the carbon/GHG intensity of energy systems changes over time, the relative magnitude of these rebound effects will also change — and in some circumstances, rebound effects may be found to be small in energy terms but large in GHG terms, or vice versa.
- *Direct versus embodied energy use and emissions*: Households consume significant amounts of energy 'directly' in the form of electricity,[1] heating fuels and vehicle fuels, but they also consume energy 'indirectly', since energy is used at each stage of the supply chain for all goods and services. This life-cycle energy use is commonly termed *embodied energy* while the associated emissions are termed *embodied emissions*. While direct rebound effects typically relate to direct energy use and emissions, indirect rebound effects may derive from both direct and embodied energy use and emissions. For example, the savings from an energy-efficient heating or cooling system may be spent upon more heating or cooling (direct rebound, direct emissions), more lighting (indirect rebound, direct emissions) or more furniture (indirect rebound, embodied emissions).

Table 1 uses the above categories to classify the limited number of studies that estimate both direct and indirect rebound effects for households. These studies vary in the methodologies and economic models employed, the categories used for classifying household expenditures, the types of measure investigated, the rebound mechanisms captured and the quantitative results obtained. While most focus upon improved energy efficiency in electricity, heating or personal travel, others examine sufficiency measures, such as reducing car travel or food waste. Different studies estimate rebound effects in energy, CO_2 and GHG terms, but no study estimates and compares all three.

This diversity, combined with the methodological limitations of the various studies (see Sorrell, 2010), the limited use of sensitivity tests and the lack of systematic investigation make it difficult to draw firm conclusions. In particular, all but two of the studies estimate rebound effects for an 'average' household in the relevant countries and therefore provide no information on how rebound effects vary between different socio-economic groups. The exceptions are Murray (2013) who investigates rebound effects from both efficiency and sufficiency measures for different income groups in Australia, and Thomas and Azevedo (2013) who do the same for the US. Both find that rebound effects are inversely related to household income and that embodied

emissions form a larger proportion of the total rebound effect for higher income households. Murray further observes that higher income households have more scope for reducing the environmental impacts of their consumption patterns, as well as the lowest rebound effects from doing so.

This paper takes a similar approach to Murray (2013) for households in the UK. We estimate direct and indirect rebound effects in GHG terms following a range of efficiency and sufficiency measures by households in five income groups (quintiles). We also extend the existing literature by allowing for the capital cost of energy-efficient equipment, the emissions embodied in that equipment and the emissions associated with both household savings and government expenditure of product taxation revenues.

3. Methodology

3.1. Approach

This paper investigates ten widely advocated measures for reducing GHG emissions from UK households. Seven of these are efficiency measures that require the purchase and installation of equipment, while three are sufficiency measures that solely involve behavioural change (Table 2). We estimate that all of the efficiency measures were cost effective at normal market discount rates for an average UK household in 2009, although individual measures are not suitable for all households and the potential cost savings vary widely from one household to another. Four of the efficiency measures were eligible for investment subsidies under the UK Carbon Emissions Reduction Target (CERT) in 2009, with the size and availability of subsidies varying with the socio-economic circumstances of the household (DECC, 2010b).

All but one of the measures are aimed at reducing household consumption of electricity, heating fuels or vehicle fuels and hence are expected to reduce the *direct* GHG emissions associated with household consumption. The exception is eliminating food waste which primarily affects the *embodied* emissions associated with food consumption.

Both the measures themselves and the method for estimating rebound effects were previously described in Druckman et al. (2011) and Chitnis et al. (2013). This paper extends this analysis by exploring the variation in rebound effects between different income groups. The method relies upon four sources of information:

- Estimates of the savings in energy use and emissions from undertaking the efficiency measures in an 'average' UK dwelling, excluding any rebound effects. The estimates for the domestic energy measures (1–6 and 8) are derived from the *Community Domestic Energy Model* (CDEM), a detailed engineering model of the English housing stock (Firth et al., 2009). The corresponding estimates for the vehicle fuel (7 and 9) and food (10) measures are summarised in Annex B.
- Estimates of the embodied GHG emissions associated with the relevant energy efficiency equipment, such as insulation materials. These are derived from a number of Life Cycle Analyses (LCA), summarised in Chitnis et al. (2013).

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[1] Emissions from electricity consumption are commonly labelled as direct, although they occur at the power station.

Table 2
Selected measures.

Type	No.	Measure	Emissions targeted	Energy service	Subsidy available
Efficiency measures	1	Insulating previously un-insulated cavity walls	Direct	Heating	Yes
	2	Topping up loft insulation to 270 mm	Direct	Heating	Yes
	3	Replacing existing boilers with condensing boilers	Direct	Heating	No
	4	Insulating hot water tanks to best practice (75 mm jacket)	Direct	Heating	Yes
	5	Replacing existing incandescent bulbs with compact fluorescent bulbs (CFLs)	Direct	Lighting	No
	6	Replacing all existing lighting with LEDs	Direct	Lighting	Yes
	7	Replacing an existing car with an energy efficient model	Direct	Car transport	No
Sufficiency measures	8	Reducing average internal temperatures by one degree centigrade	Direct	Heating	–
	9	Eliminating all car journeys of less than two miles	Direct	Car transport	–
	10	Eliminating food waste	Embodied	Nutrition	–
Combined measures	11	1, 2, 3, 4, and 5 combined	Direct	Heating and lighting	Yes
	12	1, 2, 3, 4, and 6 combined	Direct	Heating and lighting	Yes
	13	8, 9 and 10 combined	Direct and embodied	Heating, car transport and nutrition	–

- Estimates of the direct and embodied GHG emissions associated with household consumption of different categories of goods and services. These are derived from the *Surrey Environmental Lifestyle Mapping Framework* (SELMA), a quasi-multi-regional, environmentally extended input–output model that provides estimates of the GHG intensity of UK household expenditure in each category (in tCO$_2$e/£) for 2004 (Druckman and Jackson, 2008; Druckman et al., 2008).[2]
- Estimates of the expenditure elasticities of the 16 categories of household goods and services for each of five income groups. These are derived from econometric analysis of the 2009 UK Living Costs and Food Survey (LCFS).

Section 3.2 summarises the method for estimating expenditure elasticities, while Section 3.3 summarises the method for estimating rebound effects.

3.2. Expenditure Model

To estimate rebound effects, it is necessary to estimate how the cost savings from the measures will be re-spent on different categories of goods and services. To model this we estimate the *expenditure elasticities* of 16 categories of goods and services (*i* − Table 3) for five different income groups, or quintiles (*j* − Table 4).

To calculate these elasticities, we estimate *Engel curves* for each category of goods and services. Engel curves describe how the expenditure on a particular category of goods or services varies with total expenditure. Our data source for household expenditure is the 2009 edition of the UK Living Costs and Food Survey (LCFS). This uses a stratified random sample of ~6000 households who are required to keep detailed records of their expenditure over a two-week period, as well as providing further information on their purchases of large items over the previous twelve months. Since income is not accurately recorded by the LCFS, we use total household expenditure as a proxy and adjust this with an *equivalence scale* so different households can be compared (Lewbel, 1997). We use the 'OECD modified equivalence scale' which calculates the *equivalised expenditure* (X_h) of a household (h) as follows:

$$X_h = \frac{Z_h}{n_h} \tag{1}$$

where Z_h is the expenditure of household h and n_h is the equivalised household size, given by:

$$n_h = 1 + 0.5A_h + 0.3C_h \tag{2}$$

where A_h is the number of additional household members who are over the age of 14 and C_h is the number of children below the age of 14. This scale implies, for example, that a household with two adults and two children needs more than twice the income ($n_h = 2.1$) of a single adult household ($n_h = 1.0$) to achieve a comparable standard of living. With these adjustments, the more accurate label for our 'income quintiles' is 'equivalised total expenditure quintiles'. Table 4 summarises the mean equivalised household size and equivalised annual expenditure in each quintile.

For simplicity we adopt the widely used *Working-Leser* (WL) form for the Engel curves (Leser, 1963)[3] and add the age of the 'household reference person'[4] as an additional explanatory variable. The WL function then takes the lin-log form:

$$W_i = \alpha_i + \beta_i \ln X + \gamma_i HRP + \upsilon_i \tag{3}$$

where:

$$W_i = \frac{X_i}{X}. \tag{4}$$

X_i is the equivalised expenditure on category i; X is equivalised total expenditure; W_i is the share of category i in total expenditure ($0 \leq W_i \leq 1$); HRP is the age of the household reference person; α_i, β_i and γ_i are the unknown parameters; and υ_i is the random error term.

For the WL model, the adding-up restriction implies that:

$$\sum_i \alpha_i = 1 \quad \text{and} \quad \sum_i \beta_i = 0 \tag{5}$$

This is satisfied automatically when the model is estimated using OLS. The expenditure elasticity of category i is given by:

$$\varepsilon_i = \frac{\partial X_i}{\partial X} \frac{X}{X_i} = \frac{\partial \ln X_i}{\partial \ln X} \tag{6}$$

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[2] The GHG intensity of a category is estimated from the GHG emissions associated with that category in 2004 (obtained from SELMA) divided by 'real' expenditure on that category in 2004 — taking 2009 as the reference year for real expenditure. The exception is electricity where emissions are estimated from 2009 electricity consumption (in kWh) multiplied by an emission factor for 2009 (kg CO2e/kWh).

[3] Engel curves have been estimated using a wide range of functional forms which may be more or less consistent with the data in different circumstances (Haque, 2005; Prais and Houthakker, 1955). The chosen form should allow for saturation in demand for a category as expenditure increases, as well as satisfying the 'adding-up restriction' (i.e. the sum of expenditures on each category must equal the total expenditure) and providing the best statistical fit. But single functional forms rarely satisfy all three requirements simultaneously, with the fit frequently being poorer for extreme values of expenditure (Haque, 2005).

[4] Defined as the person who pays the mortgage or rent or, if this is paid jointly, the person with the highest income.

Table 3
Categories of goods and services.

Category (i)	COICOP category	Description
1	1	Food & non-alcoholic beverages
2	2	Alcoholic beverages, tobacco, narcotics
3	3	Clothing & footwear
4	4.5.1	Electricity
5	4.5.2	Gas
6	4.5.3 and 4.5.4	Other fuels
7	4.1 to 4.4	Other housing
8	5	Furnishings, household equipment & household maintenance
9	6	Health
10	7.2.2.2	Vehicle fuels and lubricants
11	Rest of 7	Other transport
12	8	Communication
13	9	Recreation & culture
14	10	Education
15	11	Restaurants & hotels
16	12	Miscellaneous goods & services

Notes: COICOP — Classification of Individual Consumption According to Purpose. Other housing includes rent, mortgage payments, maintenance, repair and water supply. Other transport includes public transport, aviation and non-fuel expenditure on private vehicles.

For the *WL* model, this leads to:

$$\varepsilon_i = \frac{\beta_i}{W_i} + 1 \tag{7}$$

When estimating elasticities for each quintile (ε_i^j), this expression is evaluated at the mean value of the expenditure share for that category within each quintile (W_i^j):

$$\varepsilon_i^j = \frac{\beta_i}{W_i^j} + 1 \tag{8}$$

3.3. Rebound Model

Following Chitnis et al. (2013), we model the impact of each measure on global GHG emissions as the net result of three different effects which we term the *engineering*, *embodied* and *income* effects respectively:

- *Engineering effect (ΔH):* Each efficiency measure is expected to reduce the amount of energy required to deliver a given energy service (e.g. heating, lighting, transport), while each sufficiency measure is expected to reduce consumption of the relevant energy service. The *engineering effect* represents the estimated reduction in GHG emissions assuming that consumption of the energy service remains unchanged for the efficiency measures and falls for the sufficiency measures.
- *Embodied effect (ΔM):* Efficiency measures require the manufacture and installation of equipment (e.g. insulation materials) which is necessarily associated with GHG emissions at different stages of the supply

Table 4
Mean equivalised household size and annual expenditure in each quintile.

	Annual household expenditure (Z^j)	Equivalised household size (n^j)	Equivalised annual household expenditure (X^j)
Quintile 1	£6.8 k	1.46	£4.7 k
Quintile 2	£12.4 k	1.59	£7.8 k
Quintile 3	£17.3 k	1.65	£10.5 k
Quintile 4	£23.2 k	1.64	£14.1 k
Quintile 5	£40.3 k	1.64	£24.6 k
Mean	**£19.7 k**	**1.60**	**£12.3 k**

Note: Based upon the 2009 Living Costs and Food Survey using the OECD modified equivalence scale.

chain. These emissions are conventionally treated as 'embodied' in the relevant equipment. The *embodied effect* represents the difference between the embodied emissions associated with the measure and those associated with the relevant alternative — which may be doing nothing (e.g. for loft insulation), continuing to use existing equipment or purchasing less energy efficient equipment. Sufficiency measures do not require additional equipment, so have no embodied effect.

- *Income effect (ΔG):* Both efficiency and sufficiency measures should lead to reduced expenditure on the relevant energy service. The resulting cost savings may be partly offset by the capital cost of the relevant measure, but the net savings will be positive if averaged over a period longer than the simple payback time. This 'avoided' expenditure may be treated as analogous to an increase in household income since it allows increased consumption of goods and services and/or increased savings. The *income effect* is an estimate of the impact on global GHG emissions of this increased consumption and savings. For efficiency measures the income effect includes increased consumption of the energy service, while for sufficiency measures it does not.[5]

The estimated total impact (ΔQ) of each measure on global GHG emissions is then given by:

$$\Delta Q = \Delta H + \Delta M + \Delta G \tag{9}$$

In percentage terms, we define the rebound effect (*RE*) from each measure as:

$$RE = 100 * \left[\frac{\Delta H - \Delta Q}{\Delta H}\right]. \tag{10}$$

Substituting for ΔQ from Eq. (9) gives

$$RE = -100 * \left[\frac{\Delta G + \Delta M}{\Delta H}\right]. \tag{11}$$

This definition treats the embodied effect as offsetting some of the anticipated GHG savings from the measure and thereby contributing to the rebound effect. An alternative approach, which is not used here, would be to subtract the embodied effect from the anticipated GHG savings (Chitnis et al., 2013).

In implementing this approach, we assume that each measure is undertaken by all *eligible*[6] UK households in 2009 ($t = 1$). We estimate the corresponding impact on global GHG emissions over a period of T years ($t = 1$ to T) where T is less than the economic lifetime of the energy efficiency measures. For simplicity, we present all our results for a ten-year period ($T = 10$) and hold the variables affecting GHG emissions fixed over this period. A different choice of time period would modify the results. We take 2009 as the reference year for all 'real' values and estimate each effect on an equivalised basis.

We estimate the engineering (ΔH_t^j), embodied (ΔM_t^j) and income (ΔG_t^j) effects for each quintile and year using the mean value of total equivalised expenditure (W^j) and household composition (n_j) within each quintile (assumed to be fixed over period T). We then estimate the rebound effect for households in each quintile averaged over a period of T years (RE^j) as follows:

$$RE^j = -100 \left[\frac{\sum_{t=1}^{T}\left[\Delta G_t^j + \Delta M_t^j\right]}{\sum_{t=1}^{T}\Delta H_t^j}\right]. \tag{12}$$

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[5] Murray (2013) criticises Druckman et al. (2011) for allowing re-spending on the categories that are the target of the sufficiency measure(s). But this is incorrect. Druckman *et al* do not allow this form of re-spending and we do not do so here.

[6] Not all households are eligible for each measure. For example a dwelling without cavity walls cannot have cavity wall insulation.

While factors such as variations in dwelling characteristics and average internal temperatures could lead to significant variations in the embodied and engineering effects between quintiles, we lack the data to model these explicitly. Instead, we model differences in the engineering effect by allowing for differences in the equivalised expenditure on energy commodities by each quintile.

Annex A describes the estimation of the engineering, embodied and income effects in detail.

4. Assumptions

In this section and in Annex B, we summarise some of the assumptions used when estimating these effects for each measure and quintile. Many of the relevant assumptions are summarised in Druckman et al. (2011) and Chitnis et al. (2013), so only the key points are highlighted here.

4.1. Assumptions for the Engineering Effect

We use the CDEM to estimate the percentage energy savings by fuel type from the domestic energy measures (1–6 and 8 in Table 2) (Chitnis et al., 2013). These relate to an 'average' UK household and allow for the fact that some measures (e.g. cavity wall insulation) are only suitable for a subset of households. The relevant assumptions for the other measures are summarised in Annex B.

To obtain estimates of the GHG savings from each measure for each quintile (ΔH_t^j) we use the above to *adjust* our estimates of the GHG emissions associated with the relevant expenditure categories for each quintile (H_{lt}^j where $l =$ electricity, gas, other fuels, vehicle fuels or food and non-alcoholic beverages). The latter in turn are estimated from the product of equivalised expenditures (X_{lt}^j — in £) and the GHG intensity of expenditure (u_{lt} — in tCO$_2$e/£) for each quintile and expenditure category. This approach ensures that our estimates of the engineering effect vary between quintiles and are consistent with our estimates of the income effect which are derived in a similar way (see Table A.1).

4.2. Assumptions for the Embodied Effect

Estimates of the incremental embodied emissions for each measure are summarised in Table A.2. These represent the difference between the embodied emissions of the measure and those associated with the relevant counterfactual. Sufficiency measures involve no equipment, so have no embodied emissions. The assumptions for the domestic energy measures (1–6) are taken from a number of LCA studies, summarised in Chitnis et al. (2013). For the lighting measures, we assume that the counterfactual involves the continued use of traditional, incandescent bulbs.

In the UK, the emissions embodied within an average new car typically account for 16–24% of its total life cycle emissions (Carbon Trust, 2011).[7] We assume that only cars at the end of their natural life are scrapped and that they are replaced by a fuel-efficient diesel rather than an average new car. Embodied emissions will form a greater proportion of total lifecycle emissions for the latter, but may be smaller in absolute terms and could therefore lead to a negative embodied effect. But in the absence of more accurate data, we assume that the embodied effect is zero for this measure.

4.3. Assumptions for the Income Effect

Estimates of the income effect require assumptions about the equivalised cost savings (ΔX_t^j) and capital cost (ΔK_t^j) associated with each measure for each quintile, the GHG intensity of expenditure in each category (u_{it}) and the expenditure elasticity of those categories for each quintile (ε_i^j).

Estimates of the cost savings from the domestic energy measures are derived using the CDEM and data on domestic energy prices in 2009 (Chitnis et al., 2013). Estimates for the other measures rely upon simpler calculations, described in Annex B. This Annex also summarises our assumptions for the capital cost of each measure both with and without the subsidies provided by the Carbon Emissions Reduction Target (CERT).

Estimates of the GHG intensity of household expenditure in 2009 (u_{it}) are derived from SELMA, with additional adjustments to allow for the emissions associated with household savings and for government expenditure of product taxation revenues. For the former, we assume the average household saves and invests 15% of their annual income, and that the GHG intensity of this investment is comparable to the UK average.[8] For the latter, we estimate the GHG emissions associated with spending the revenue from product taxes in each category and add these to the emissions provided by SELMA.[9]

Fig. 1 (top) shows that expenditure on electricity, gas, other fuels and vehicle fuels is approximately three times as GHG intensive as expenditure on the other categories and five times as intensive as the share-weighted mean (see also Table A.5). But for an average household, the high GHG intensity of energy commodities is offset by their small share of total expenditure (Fig. 1, middle), with the result that direct energy consumption only accounts for 41% of an average household's 'GHG footprint' (Fig. 1, bottom), split between 29% domestic energy (i.e. electricity, gas and other fuels) and 12% vehicle fuels. As discussed below, these proportions vary significantly between quintiles. The category providing the largest single contribution to total emissions for an average household is food and non-alcoholic beverages (14%).

Our estimates of GHG intensities allow for the variation of product taxation between categories: namely VAT exemption for food and non-alcoholic beverages, lower rate VAT for domestic energy and high taxation of vehicle fuels (~60% of retail price). The latter contributes to the comparatively low GHG intensity of vehicle fuels compared to domestic energy.

Table 5 summarises the estimated expenditure elasticities for each category and quintile (ε_i^j), while Table A.7 summarises the estimated Engel curves.[10] The coefficient of log equivalised total expenditure (β_i) was found to be significant at the 5% level for all categories, while that for the age of the household reference person (γ_i) was significant for all but one category. Despite the low adjusted R^2, the WL specification provided a better fit than alternative functional forms.[11]

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[7] As a consequence, scrapping an existing car before the end of its natural life and replacing it with a fuel-efficient model may lead to little or no emission reductions, even if driving patterns remain unchanged.

[8] An alternative approach would be to model household savings as deferred consumption. In either case, the purpose of including savings is to explicitly highlight their consequences for GHG emissions.

[9] Environmentally-Extended Input–Output (IO) models such as SELMA only include the GHG emissions associated with each expenditure category. But expenditures on different commodities include various taxes (such as Value Added Tax — VAT) which in turn are used to fund government expenditure. Since government spending is a separate category in the national accounts, the associated GHG emissions are normally excluded from the estimated GHG intensities of household expenditure. Exclusion of these emissions could bias estimates of the rebound effect, in particular because differing levels of product taxation are applied to different goods and services. For example, in the UK there is 20% VAT on most goods and services; 5% VAT on electricity, gas and other fuels; zero rate VAT on most food products; and around 65% taxation on vehicle fuels. To eliminate this potential bias we: first, estimate the GHG intensity of UK government expenditure in the base year; second, use this to estimate the GHG emissions associated with taxation in each category; and third, add these to the emissions provided by SELMA for each expenditure category. This in turn leads to an adjusted GHG intensity of expenditure for each category which is used in the calculation of rebound effects. As the GHG intensity of government expenditure is relatively low, this adjustment does not significantly change our estimates of rebound effects.

[10] White test showed that heteroskedasticity could not be rejected for all the estimated Engel curves. Hence, White heteroskedasticity-consistent estimator was used to correct the standard errors for heteroskedasticity.

[11] We also estimated the Double Semi-Log (DSL) functional form: $X_i = \lambda_i + \theta_i X + \varphi_i \ln X + \rho_i HRP + \omega_i$ — where λ_i, θ_i, φ_i and ρ_i are parameters and ω_i is the error term (Haque, 2005). This gave comparable elasticities to the WL over the whole sample, but the differences were more pronounced for individual quintiles. Since the DSL estimation results were less satisfactory in terms of statistical significance and expected signs, we only report the WL results here.
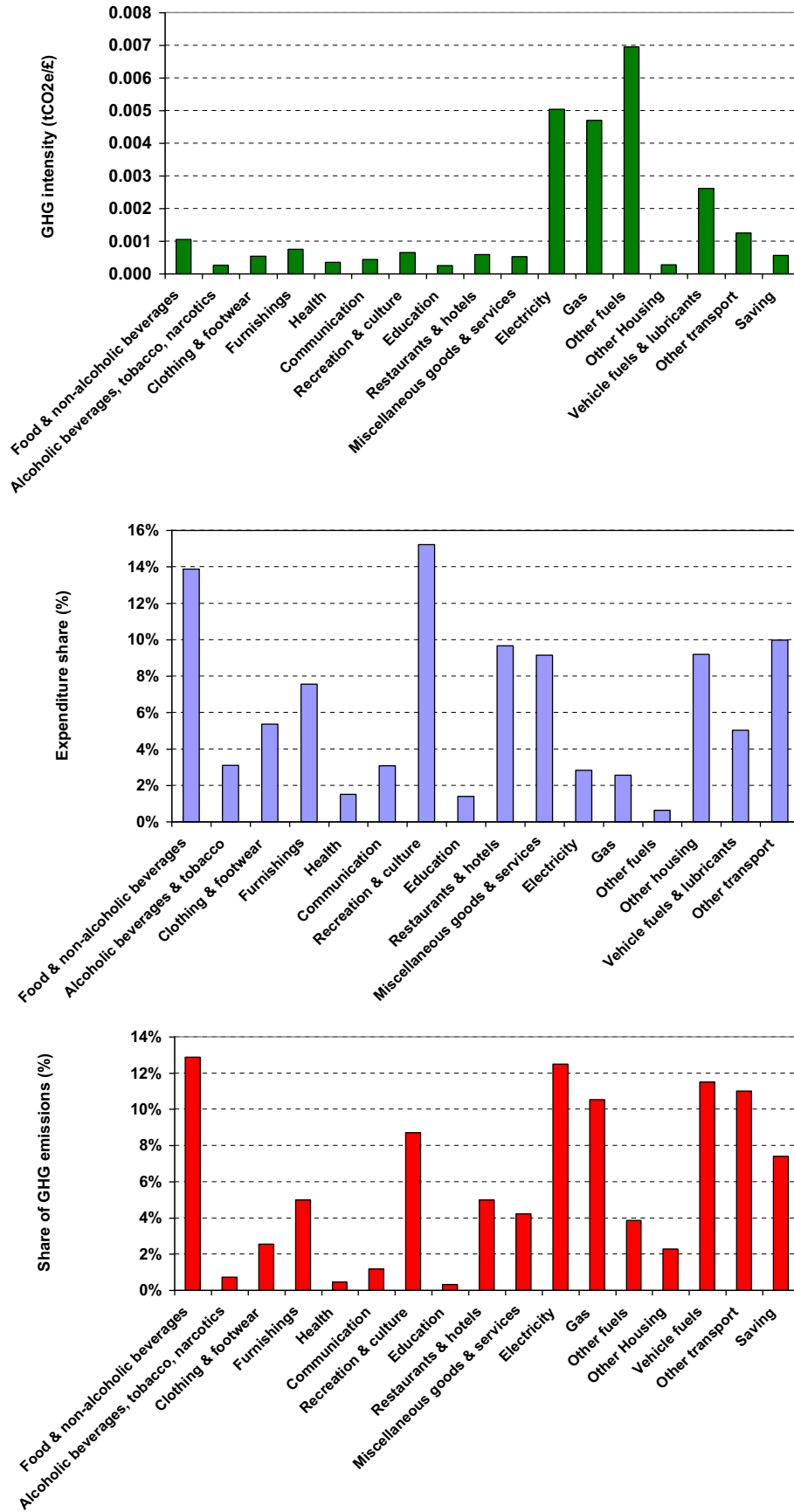
Fig. 1. GHG intensity of expenditure, share of total expenditure and share of total GHG emissions by category for an average household.

Table 5
Estimated expenditure elasticities by quintile in 2009.

Category	Quintile					Mean
	1	2	3	4	5	
Food & non-alcoholic beverages	0.65	0.57	0.48	0.38	0.06	0.39
Alcoholic beverages & tobacco	0.71	0.68	0.65	0.60	0.45	0.59
Clothing & footwear	1.51	1.34	1.32	1.27	1.28	1.30
Electricity	0.57	0.37	0.17	0.00	− 0.62	0.05
Gas	0.62	0.49	0.34	0.15	− 0.25	0.23
Other fuels	0.85	0.77	0.82	0.79	0.69	0.77
Other housing	0.73	0.73	0.68	0.68	0.56	0.66
Furnishings	1.60	1.56	1.44	1.40	1.30	1.38
Health	1.82	1.69	1.59	1.50	1.38	1.48
Vehicle fuels & lubricants	1.20	1.13	1.12	1.13	1.17	1.14
Other transport	2.31	1.80	1.61	1.52	1.40	1.52
Communication	0.63	0.54	0.47	0.39	0.06	0.38
Recreation & culture	1.39	1.37	1.31	1.30	1.23	1.28
Education	9.96	5.63	3.97	2.37	1.47	1.90
Restaurants & hotels	1.34	1.27	1.24	1.22	1.22	1.23
Miscellaneous goods & services	1.10	1.10	1.10	1.09	1.09	1.09

Food, drink and domestic energy were found to be expenditure inelastic for all quintiles, ($\varepsilon_i^j < 1$), as was communication and other housing (Table 5). All other categories were found to be expenditure elastic ($\varepsilon_i^j < 1$). The elasticity of most categories of expenditure fell as equivalised total expenditure increased, although to varying degrees and more steeply for necessities (defined here as $\varepsilon_i^j < 1$). The elasticities for electricity and gas were estimated to be negative for Q5 — suggesting, rather surprisingly, that energy is an inferior good for these households. However, the assumed values for these elasticities have only a small impact on the estimated rebound effects.

5. Results

This section presents our estimates of the rebound effects from the different measures for each quintile, averaged over a period of ten years. To illuminate the drivers of these results, we first discuss the magnitude of the engineering, embodied and income effects for an average household and then summarise how the quintiles differ in terms of equivalised expenditure, GHG emissions and average GHG intensity of expenditure. We then present the estimated rebound effects for each quintile in two stages, namely: a) income effects only, ignoring capital costs; and b) income and embodied effects, allowing for capital costs (with and without the CERT subsidies). Section 6 discusses the implications.

5.1. Estimated Effects for an Average Household

Fig. 2 and Table A.6 summarise our estimates of the engineering, embodied and income effects for each measure as a percentage of baseline emissions for an average UK household. The corresponding effects for each quintile may depart significantly from these values.

The results suggest that, ignoring rebound effects, the combined adoption of the efficiency measures could reduce the total 'GHG footprint' of an average UK household by ~3.8% while the combined adoption of the sufficiency measures could reduce emissions by a comparable amount.[12] The measures with the largest single impact (~1.5%) are reducing internal temperatures and reducing food waste, in part because these are available to all households and affect the categories with the largest share of total emissions. For those measures that are only

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[12] The emission savings from combining measures may not be additive — for example, installing insulation reduces the savings achievable from reducing internal temperatures, while installing energy-efficient lighting leads to an additional demand for heating fuels in order to compensate for the lost heat from traditional lightbulbs. We use the CDEM to model these effects.
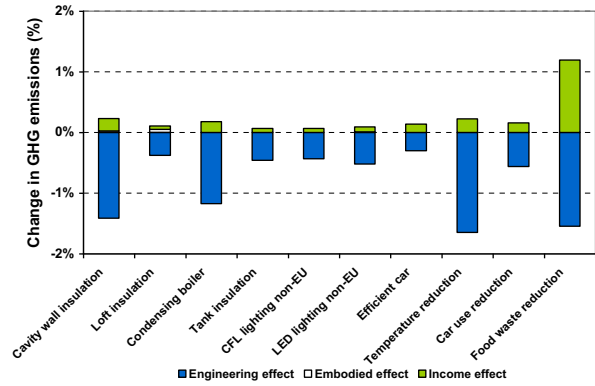

Fig. 2. Estimated engineering, embodied and income effects (ignoring capital cost) for an average household (percentage of baseline emissions).

suitable for a subset of households (e.g. cavity wall insulation), the percentage reductions for adopting households will be higher.

Fig. 2 compares the relative size of the income and embodied effects for the efficiency measures. Averaged across all measures, the embodied effect is only 13% of the income effect. However, the embodied effect is more important for loft insulation and LED lighting — which both have a lifetime that considerably exceeds the ten year period considered here.

Fig. 3 illustrates the estimated contribution of each category to the income effect for combined measures 1–4 and 6, ignoring capital costs. The relative share of each category depends upon the product of its GHG intensity, expenditure share and expenditure elasticity. So despite being GHG intensive, the three domestic energy categories provide only a small (7.1% total) contribution to the income effect owing to their small share of total expenditure and low expenditure elasticity for an average household (Fig. 2).

5.2. Variation of Expenditures and Emissions between Quintiles

Fig. 4 shows the split of equivalised expenditures by category and quintile. There is a fairly linear increase in total expenditure from Q1 to Q4, but with Q5 expenditures being disproportionately high, suggesting a long tail of very high spending households. Q1 households spend less than half as much on necessities[13] as Q5, but these form a much larger share of their total budget (57% versus 27%). For those necessities with a high GHG intensity (i.e. electricity, gas, other fuels, food & non-alcoholic beverages), the corresponding figures are 36% for Q1 and 13% for Q5. In contrast, Q1 households spend only 4% of their budget on other transport, while Q5 households spend 13% — or 17 times as much in absolute terms.

Fig. 5 plots GHG emissions against total expenditure, while Fig. 6 shows the breakdown of equivalised GHG emissions for each quintile. Emissions are correlated with expenditure, but the average GHG intensity of expenditure falls as total expenditure increases (Fig. 7). For example, spending by Q1 households is 16.3% more GHG intensive than spending by Q5 households. A similar pattern is observed with marginal expenditures which are ~19% less GHG intensive than average expenditures (Fig. 7). This pattern suggests that total GHG emissions may not increase at the same rate as incomes increase, but income redistribution may increase aggregate emissions.

Since necessities are comparatively GHG intensive, low-income households have disproportionately high emissions relative to expenditure. Fig. 8 shows that embodied emissions are more strongly correlated with total expenditure than direct emissions, with the correlation being

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[13] Defined here as those categories whose estimated expenditure elasticity is less than unity: i.e. electricity, gas, other fuels, food & non-alcoholic beverages, alcoholic beverages and tobacco, other housing and communications.
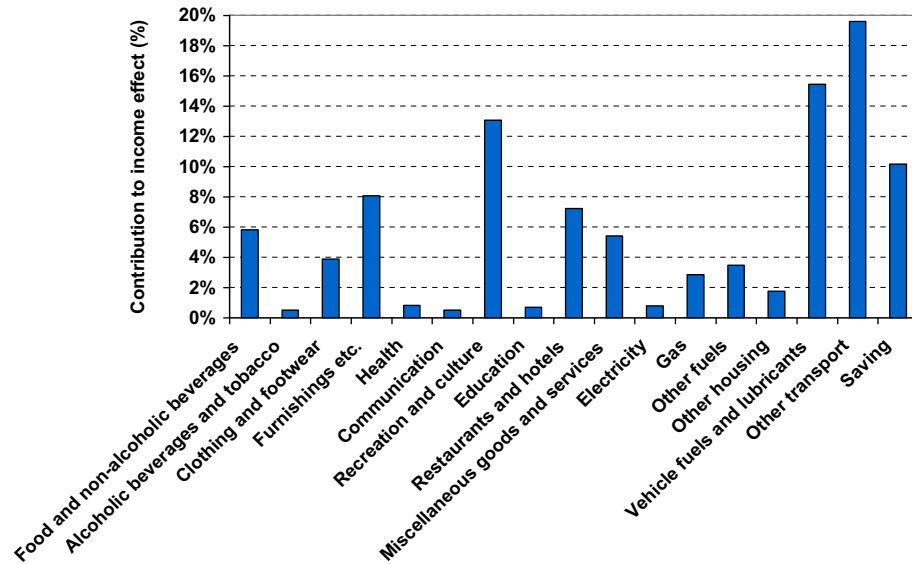
Fig. 3. Contribution of different categories to the income effect for an average household (measures 1–4 and 6 combined).

weakest for domestic energy emissions. Hence, while total emissions for Q5 households are four and half times larger than Q1 households, their domestic energy emissions are only 60% larger while their embodied emissions are more than six times larger. Saunders (2013) finds a similar distribution for US households.

5.3. Rebound Effects from Income Effects Alone

Table 6 summarises our estimates of the rebound effect for each measure for an average household. These estimates relate to the income effect alone; in other words, ignoring the embodied effect and capital cost of the efficiency measures. As with our earlier work (Chitnis et al., 2013), the results show that rebound effects for the domestic energy measures are broadly comparable and relatively modest — with all estimates converging around 14–15%. The primary reason these effects are modest is that most of the re-spending is on goods and services with a much lower GHG intensity than domestic energy itself. The rebound effects for heating and lighting are comparable in size because, in our model, expenditure on electricity is approximately as GHG intensive as expenditure on heating fuels. However, this result is contingent upon the fuel mix in electricity generation in 2009. As Chitnis et al. (2013) observe, the transition towards a low carbon electricity system in the UK will increase the (GHG) rebound effect from electricity efficiency measures — with those effects potentially exceeding 100% by 2030.[14]

Again confirming our earlier work (Druckman et al., 2011), the rebound effects for the vehicle and food measures are found to be much larger: namely 46% for the efficient car, 28% for reducing car use and 77% for eliminating food waste. In these cases, reduced consumption of vehicle fuels and food leads to relatively modest GHG savings and relatively high cost savings. These cost savings are then spent

upon other goods and services that have a comparable GHG intensity, leading to a large income effect relative to the engineering effect and hence a high rebound effect.

For the efficient car, the cost savings on vehicle fuels are supplemented by the cost savings on vehicle excise duty which amplifies the rebound effect. This demonstrates how measures that achieve cost savings in more than one category, as well as measures that are subsidised in some way, may be associated with larger rebound effects. However, a full accounting of the GHG implications of subsidies would need to consider their source (e.g. taxation) and the corresponding implications for economic activity and emissions.

While reducing food waste has the largest technical potential to reduce emissions, it is also the measure with the largest rebound effect (77%). As a result, the net contribution to emission reductions from this measure is less than a quarter of its technical potential and only one tenth of the contribution from the domestic energy measures combined (Table A.6).

Table 6 also indicates the contribution of direct emissions to the estimated rebound effect for each measure. These numbers set an upper limit for the direct rebound effect for the efficiency measures, since a significant proportion of these emissions derive from increased consumption of the relevant energy service.[15] The results show that, on average, direct emissions contribute only ~19% of the rebound effect — in other words, the bulk of the rebound effects in our model derive from the emissions embodied in non-energy goods and services. Moreover, a large (~40%) and growing proportion of these occur outside the UK (Druckman and Jackson, 2009; Wiedmann et al., 2008).

Fig. 9 shows how the estimated rebound effects vary between quintiles. Two important observations may be made. First, rebound effects decline as total expenditures increase and are therefore significantly larger for low-income households. For example, the estimated rebound effect from measures 1–5 in combination is 20.1% for Q1 households but only 12.6% for Q5. This pattern also applies to the sufficiency measures, but is less pronounced when these measures are combined — largely

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[14] UK electricity generators are participating in the EU ETS and hence are covered by an EU wide carbon cap. In this context, any actions that reduce carbon emissions from UK electricity generators, including improvements in household electricity efficiency, will not reduce global carbon emissions at all. This is because such actions will simply free up allowances that could be used by other participants in the EU ETS to cover either increases in emissions or reduced emissions abatement (Sorrell and Sijm, 2003). Alternatively, the allowances may be banked and used in subsequent trading periods, but they will still ultimately be used to cover emissions. Hence, from this perspective, the engineering effect of electricity efficiency improvements is *zero* while the EU ETS cap is in place. As a result, improvements in electricity efficiency *already* increase aggregate GHG emissions as a consequence of the embodied and income effects.

[15] The direct rebound effect is zero for the sufficiency measures since re-spending in the relevant categories is disallowed. Also, our methodology does not permit the straightforward isolation of the direct rebound effect for the domestic energy measures owing to the way different energy carriers are treated. So for example, we model the income effect for electricity consumption following the installation of energy-efficient lighting, but we cannot easily distinguish between increased use of electricity for lighting and increased use of electricity for other purposes — including heating.
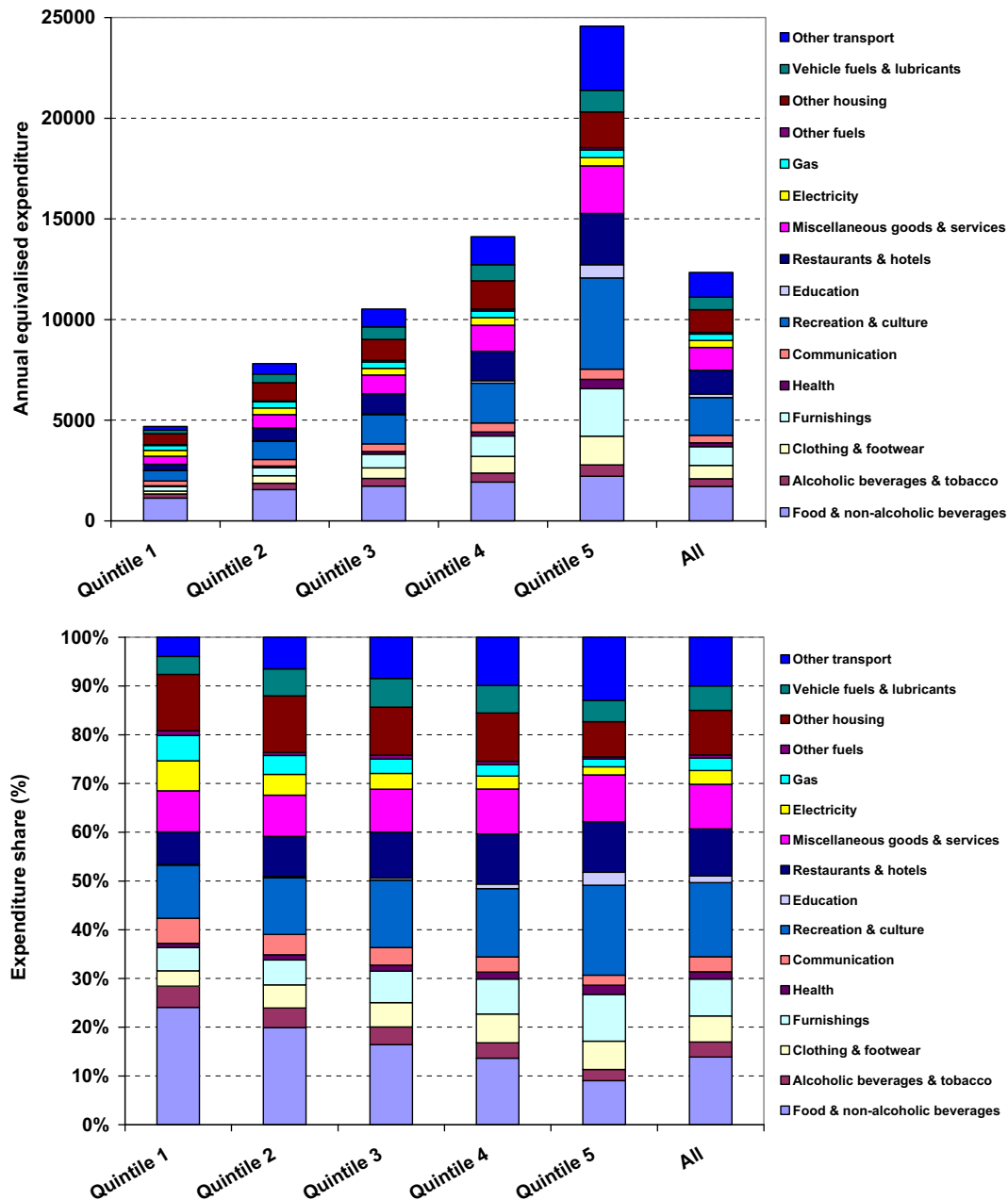
Fig. 4. Equivalised expenditure by category and quintile (2009).

because re-spending on food, domestic energy and vehicle fuels is disallowed.

Second, direct emissions form a much larger proportion of the total rebound effect for low-income households. For example, for measures 1–5 in combination, direct emissions form ~45.0% of the income effect for Q1 households but only ~7.2% for Q5. Since GHG-intensive necessities form a larger share of total expenditure for low-income households, as well as having a proportionately higher expenditure elasticity, they account for a larger proportion of total re-spending. The reverse is the case for high income households where almost all the rebound effect derives from embodied emissions. This indicates that confining attention to direct emissions would lead to an overestimate of emission savings, especially for high income households.

Low income households may be expected to have the strongest financial motivation to reduce food waste, but our results suggest that this measure could lead to a net increase in emissions ('backfire'). In

practice, the actual GHG savings will be sensitive to the particular commodity choices made. For example, vegetarian households would have lower GHG savings from reducing food waste since their diet is approximately 22% less GHG intensive (Berners-Lee et al., 2012). If such households were to achieve comparable cost savings from reducing food waste, then backfire would be a likely outcome. But since vegetarian food tends to be cheaper, the cost savings and hence the income effect is also likely to be lower.

5.4. Rebound Effects Taking into Account the Capital Cost and Embodied Emissions of the Efficiency Measures

Allowing for capital costs and the embodied effect modifies our estimates of the rebound effect for the efficiency measures, but in opposite ways. Allowing for capital costs reduces the estimated cost savings over a given time period and therefore *reduces* the estimated rebound effect,
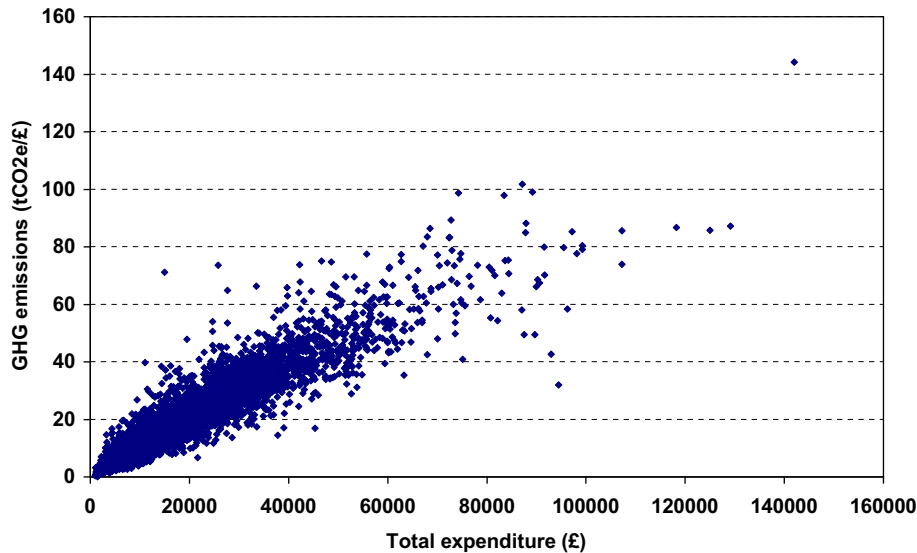
Fig. 5. GHG emissions versus total expenditure for the sample of households.

while allowing for the emissions embodied in the measures themselves *increases* the rebound effect (with our definition). The net effect varies between measures and quintiles and with the time period considered.

Table 7 summarises the net result for an average household over our ten year time period, with and without the CERT subsidies (DECC, 2010b). With subsidies (column 5), the estimated rebound effect is higher than that from the income effect alone for most of the measures. The exceptions are tank insulation and LED lighting where the capital cost of the measure erodes the rebound effect by more than the embodied effect increases it over the ten-year period — although a longer time period would generate a different result. When households face the full capital costs of each measure (column 4), the rebound effects are generally reduced.[16]

Fig. 10 shows how the estimated rebound effects for the efficiency measures vary between quintiles, both with and without allowing for subsidies (CFLs are not subsidised). The pattern is broadly similar to Fig. 9 except for unsubsidised loft insulation and LED lighting where rebound effects are found to increase with total expenditure. Both these measures are relatively costly and for low income households, whose expenditure on domestic energy is smaller in absolute terms than for high income households, the capital cost significantly offset the energy cost savings. This picture would change if the rebound effects were calculated over a longer time period. Also, the variance in emissions both within and between quintiles (Fig. 5) makes it likely that rebound effects will vary widely from one household to another.

6. Discussion

The main conclusions of the above analysis are as follows. First, rebound effects appear to be fairly modest (0–32%) for measures affecting domestic energy use, larger (25–65%) for measures affecting vehicle fuel use and very large (66–106%) for measures that reduce food waste. Second, indirect rebound effects contribute most to these results,

with the overall effect being dominated by the embodied emissions of non-energy goods and services. Third, rebound effects are generally larger for low-income households — mainly because they spend a greater proportion of their cost savings on GHG-intensive necessities such as food and drink. Fourth, direct emissions form a much larger proportion of the total rebound effect for low-income households. Finally, measures that achieve cost savings in more than one category, as well as measures that are subsidised in some way, may be associated with larger rebound effects (although the source of the subsidies must also be taken into account). We first discuss the robustness of these findings and then highlight some relevant implications.

6.1. Robustness of the Results

Some uncertainty is created by the poor coverage of some expenditure categories by the LCFS (e.g. durable goods) and our use of GHG intensities that date from 2004, but these should not bias our results. Also, we improve upon earlier studies by allowing for the emissions associated with government spending of product taxation revenues and the variation in that taxation between product categories.

Our use of only 16 categories of household expenditure obscures the variations in the price, quality and GHG intensity of goods *within* each expenditure category and implicitly assumes that all households purchase the same priced goods (Girod and de Haan, 2009). If, as seems likely, high income households purchase higher-priced goods (at least in some categories), our methodology could overestimate their expenditure elasticities. Similarly, if low-income households purchase lower-priced goods, our methodology could underestimate their expenditure elasticities. This in turn would bias our results.

In practice, however, the potential size and direction of this bias is difficult to assess. For example, low income households in the UK typically pay *higher* prices for domestic energy, since they are more likely to use prepayment meters and less likely to either pay by direct debit or to switch suppliers. As a result, our methodology may overestimate energy-related emissions for those households and hence overestimate the engineering savings from efficiency improvements. At the same time, it may underestimate the cost savings from such measures and hence underestimate the income effect. In combination, this implies that we may be underestimating the rebound effect for low-income households. More generally the GHG intensity of different goods within each category may vary widely and these variations may or may not be correlated with the prices of those goods. This in turn could contribute to wide variations in the GHG emissions of households with comparable

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[16] In practice, only a portion of households benefit from subsidies and these are funded through higher energy bills for all household consumers (Sorrell et al., 2009b). For example, DECC (2010a) estimates that CERT raised household gas prices by 2.8% in 2010 and household electricity prices by 3.3%. These energy price increases will reduce real household incomes and expenditures and hence reduce both energy-related and total GHG emissions. As a result, the positive income effect from the energy efficiency improvements will be offset by a negative income effect from the energy price rises — for both participants and non-participants in CERT (Sorrell et al., 2009b). To properly account for this, it would be necessary to estimate the proportional contribution of each measure to the overall increase in energy prices.
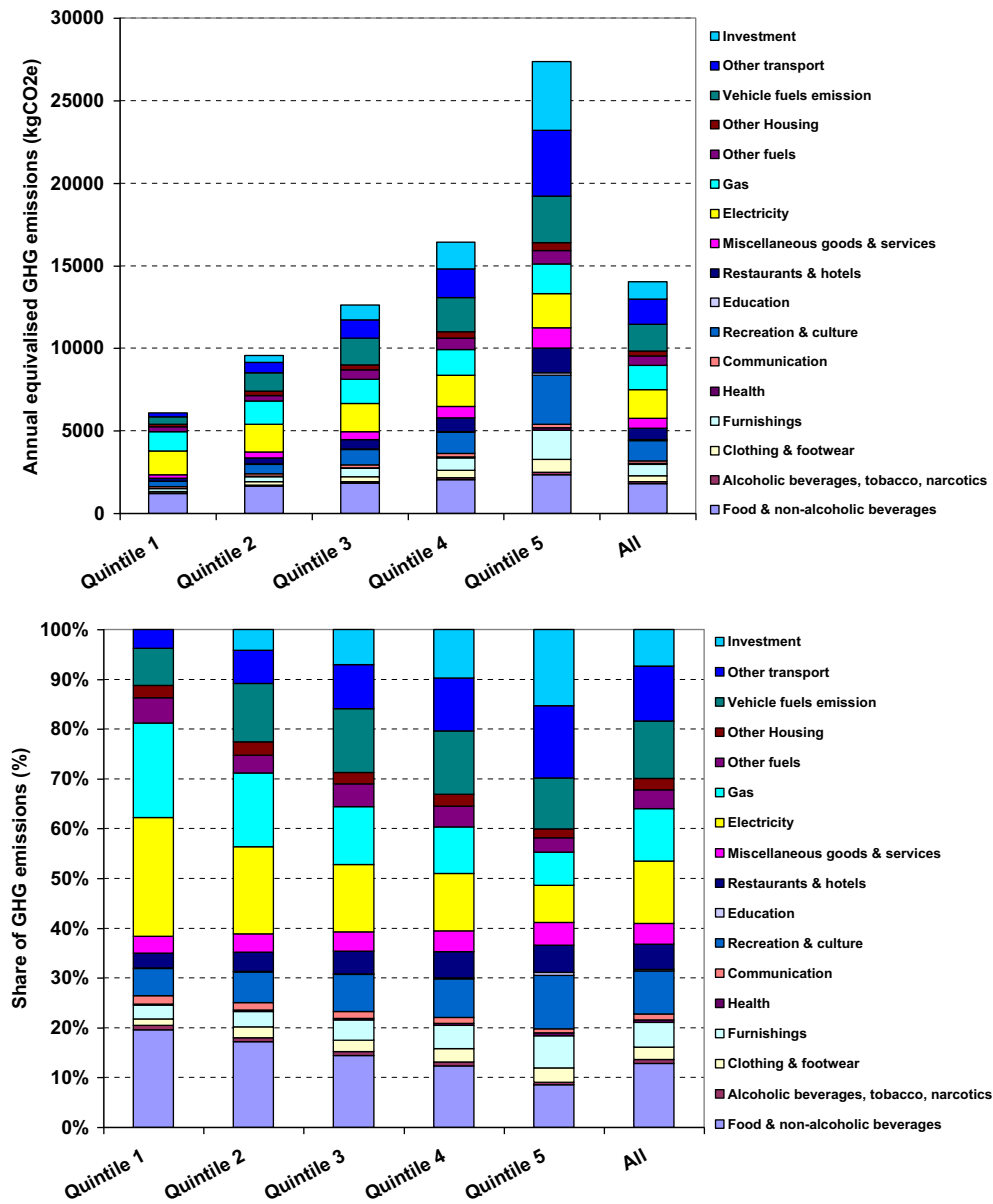
Fig. 6. Equivalised GHG emissions by category and quintile (2009).

levels of expenditure. The manner in which such factors affect rebound effects deserves further exploration.

A key limitation of this study is that we only capture the *income* effects of energy efficiency improvements and not the *substitution* effects. To appreciate this distinction, consider a household that installs loft insulation and recovers the capital costs over ten years through lower heating bills. The income effect is zero over this period, since the bill savings exactly offset the capital costs. Assuming, for illustration, that the embodied effect is zero as well, our methodology would estimate a zero rebound effect over this period (and a negative rebound effect for periods less than 10 years). But since the unit cost of heating has fallen relative to that of other goods and services, the household is likely to consume more heating and fewer goods and services that are 'substitutes' to heating. At the same time, the household may consume more of other goods and services that are 'complements' to heating. The net result will be a shift in consumption patterns and hence a change in the household's total GHG emissions. In practice, we would expect substitution *towards* heating and *away* from other goods and services and since the former is more GHG intensive than the latter, the net result

is likely to be an increase in GHG emissions and hence a positive rebound effect. More generally, the rebound effect will be given by the sum of income and substitution effects for all commodities and is likely to be greater than that from income effects alone. Hence, by neglecting substitution effects, we suspect our methodology may be systematically *underestimating* rebound effects.[17]

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[17] This potential source of bias may help explain the differences between our results and several studies of direct rebound effects from improved insulation (Boardman and Milne, 2000; Guertin et al., 2003; Nesbakken, 2001; Sanders and Philipson, 2006). These often find that low-income households have larger rebound effects since they are further from satiation in their consumption of heating services (Hong et al., 2006; Madlener and Hauertmann, 2011; Sorrell, 2007). In particular, many UK households live in excessively cold conditions and take much of the benefit of such improvements in the form of increased comfort rather than lower bills (Sanders and Philipson, 2006). While our study confirms the general finding of higher direct rebound effects for such groups, our estimates appear relatively low — indeed, our estimates of the *total* rebound effect from these measures are lower than some estimates of the *direct* rebound effect alone. This may be because our methodology only captures a subset of the relevant mechanisms.
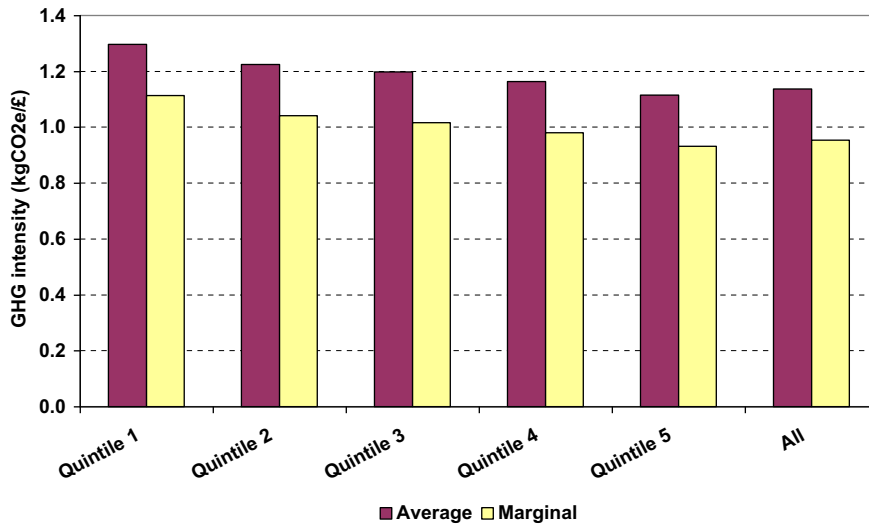
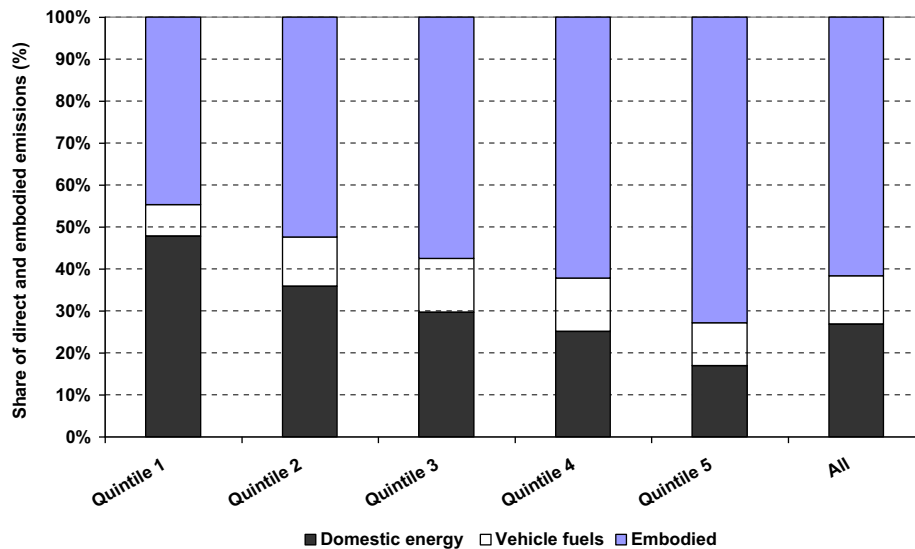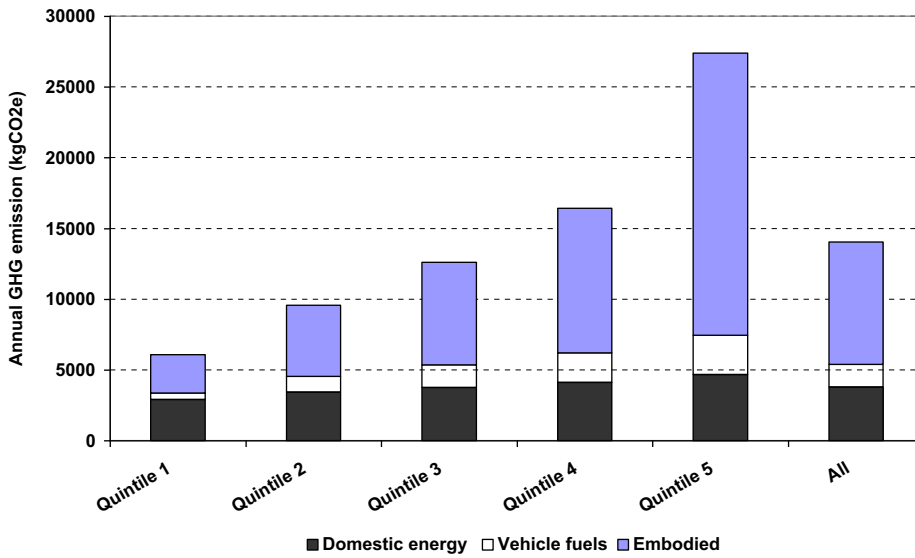**Fig. 7.** Average and marginal GHG intensity of expenditure by quintile (2009).

Fig. 8. Equivalised direct and embodied emissions by quintile.

Table 6
Estimated rebound effects for an average household — income effects alone, ignoring capital costs.

No.	Measure	Rebound effect (%)	Contribution of direct emissions to the rebound effect (% of total)
1	Cavity wall insulation	14.5	20.4
2	Loft insulation	14.5	20.4
3	Condensing boiler	15.2	20.4
4	Tank insulation	14.6	20.4
5	CFLs	15.3	29.0
6	LEDs	15.2	20.4
7	Efficient car	46.4	20.4
8	Temperature reduction	13.7	16.6
9	Car use reduction	28.1	8.5
10	Food waste reduction	77.4	24.1
11	1, 2, 3, 4 and 5	14.8	20.4
12	1, 2, 3, 4 and 6	14.8	20.4
13	8, 9 and 10	35.5	2.7

A second limitation derives from our use of a static input–output model that neglects price changes and relies upon numerous simplifying assumptions such as constant returns to scale and Leontief (fixed proportions) production functions. As a consequence, we cannot capture any supply-side responses to improved energy efficiency which may modify the size of the estimated effects. For example, reduced energy demand may lower energy prices, thereby triggering increased consumption and larger rebound effects. Alternatively, such reductions may lead to 'disinvestment' in the upstream energy industry which may contribute to smaller rebound effects (Anson and Turner, 2009). The use of CGE models to more fully capture such mechanisms should be a priority for future research. However, input–output models have the advantage of simplicity and transparency and can still deliver useful insights — particularly when the use of a multiregional framework permits accurate estimation of the emissions embodied in traded goods.

Related to this, there has been some debate in the literature regarding the appropriate measure of the 'engineering effect' in this type of study (Turner, 2013). Specifically, Guerra and Sancho (2010) argue that this should include both direct emissions and the emissions embodied in the intermediate inputs to the energy supply sectors. As described in Annex 1, our approach is consistent with Guerra and Sancho's recommendations since both engineering and income effects are estimated on a consistent basis using our input output model.

6.2. Implications of the Results

Our results demonstrate the importance of accounting for rebound effects within policy appraisals. This applies across the board, but is particularly important for low income groups for whom rebound effects are generally larger. Our results also demonstrate that both direct and indirect rebound effects need to be accounted for. This is especially important for high income groups who have a higher proportion of rebound as embodied emissions, much of which occurs beyond national borders. Failure to take account of these effects in policy appraisals will lead to an overestimate of energy and emission savings, in some cases by a significant amount. Also, the variation in the nature and scale of rebound effects between income groups should be considered when policies are targeted.

Our results also have implications for the design of carbon pricing schemes. Such schemes need to incentivise efficiency improvements and behavioural change, while at the same time mitigating any associated rebound effects and protecting low-income groups. This is best achieved by economy-wide schemes with revenue recycling that incorporate border carbon adjustments to capture the emissions embodied in traded goods (Monjon and Quirion, 2010; van Asselt and Brewer,

2010). Our results demonstrate that expenditure by low-income households is comparatively GHG intensive while their total GHG emissions are dominated by domestic energy (Fig. 8). This suggests that carbon pricing confined to domestic energy could be regressive without carefully targeted compensation. Such a scheme would also fail to capture the bulk of emissions from high-income households, the majority of which are embodied in the goods and services they consume.

The case for economy-wide carbon pricing is reinforced by the observation that taxing energy commodities leads to larger rebound effects. Specifically, we found that measures affecting vehicle fuels led to larger rebound effects than measures affecting domestic energy, primarily because the former were more heavily taxed. High taxation means that a unit reduction in consumption leads to greater cost savings and re-spending of those cost savings leads to a larger rebound effect. The paradox is that higher taxation also provides a stronger incentive to reduce consumption of energy commodities and hence to reduce the associated direct emissions. The net impact will depend upon a number of variables including the own price elasticity of the relevant energy commodities, the GHG intensity of expenditure on that commodity relative to other goods and services and any supply-side responses.

This problem may be reduced if the carbon taxation was economy-wide. This would raise the price of all goods and services in proportion to their carbon intensity, and thereby lower the GHG intensity of expenditure (in tCO$_2$e/£) of those goods and services. It would also provide incentives to reduce both household emissions *and* the GHG emissions associated with manufactured goods. The net result should be to reduce the size of the indirect rebound effect — although the precise implications require investigation with a macroeconomic model. But to be fully effective such a scheme would also need to capture the emissions embodied in imported goods. While mechanisms such as border carbon adjustments are feasible, they present considerable legal and practical challenges and may capture only small proportion of the relevant emissions. Ultimately, this form of 'carbon leakage' can only be adequately addressed through the development of international climate agreements that cover a significant proportion of global emissions.

Carbon pricing is not the only means to mitigate rebound effects however. The wide variation in GHG emissions between households with comparable levels of expenditure (Fig. 5) indicates the potential for voluntarily shifting consumption patterns towards lower carbon options — such as reducing air travel or putting savings towards low carbon investments. While all the measures considered here are necessarily associated with rebound effects, the magnitude of these effects may vary widely from one household to another depending upon their particular pattern of re-spending. Hence, existing policy approaches that target barriers to energy efficiency could usefully be complemented by parallel measures that incentivise and facilitate households in making lower carbon choices in all areas of consumption.

Finally, it is essential to recognise that all of the measures considered here will improve consumer welfare and (except in particular cases) reduce aggregate emissions. Hence, such measures should continue to be encouraged. What needs to change are our estimates of the emission reductions that such measures will achieve.

7. Summary

This study adds to a small but growing volume of evidence that estimates combined direct and indirect rebound effects for households. Our modelling indicates that such effects are modest (0–32%) for measures affecting domestic energy use by UK households, larger (25–65%) for measures affecting vehicle fuel use and very large (66–106%) for measures that reduce food waste. Our approach only captures a subset of the relevant mechanisms and may underestimate the total effect. We also find that measures undertaken by low income households are

associated with larger rebound effects and measures that are subsidised or affect highly taxed energy commodities may be less effective in reducing aggregate emissions. While the results do not undermine the rationale for energy efficiency policy, they do highlight the importance of allowing for rebound effects within policy appraisals, as well as reinforcing the case for economy-wide carbon pricing.
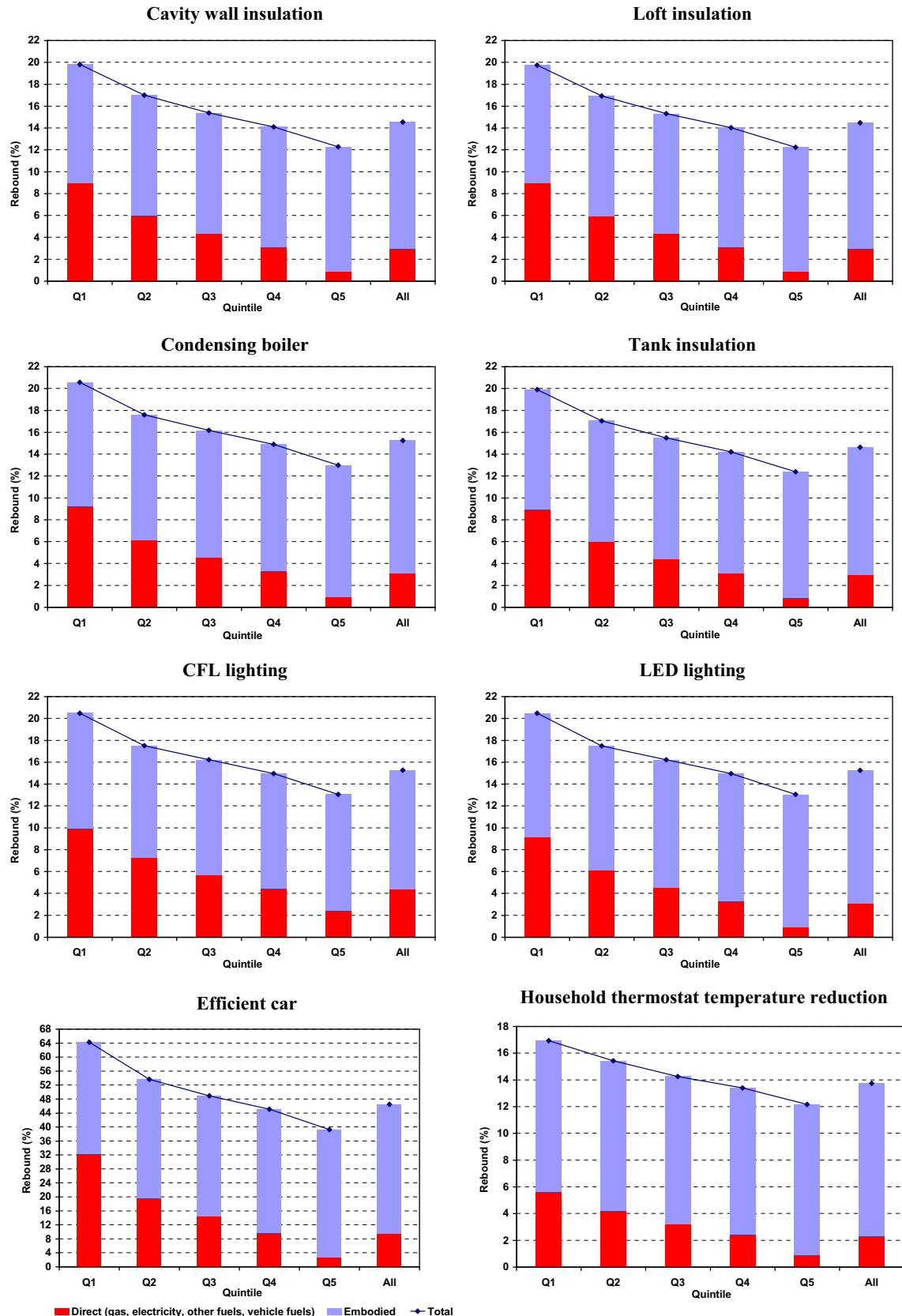

Fig. 9. Estimated rebound effects by quintile — income effects alone, ignoring capital costs.
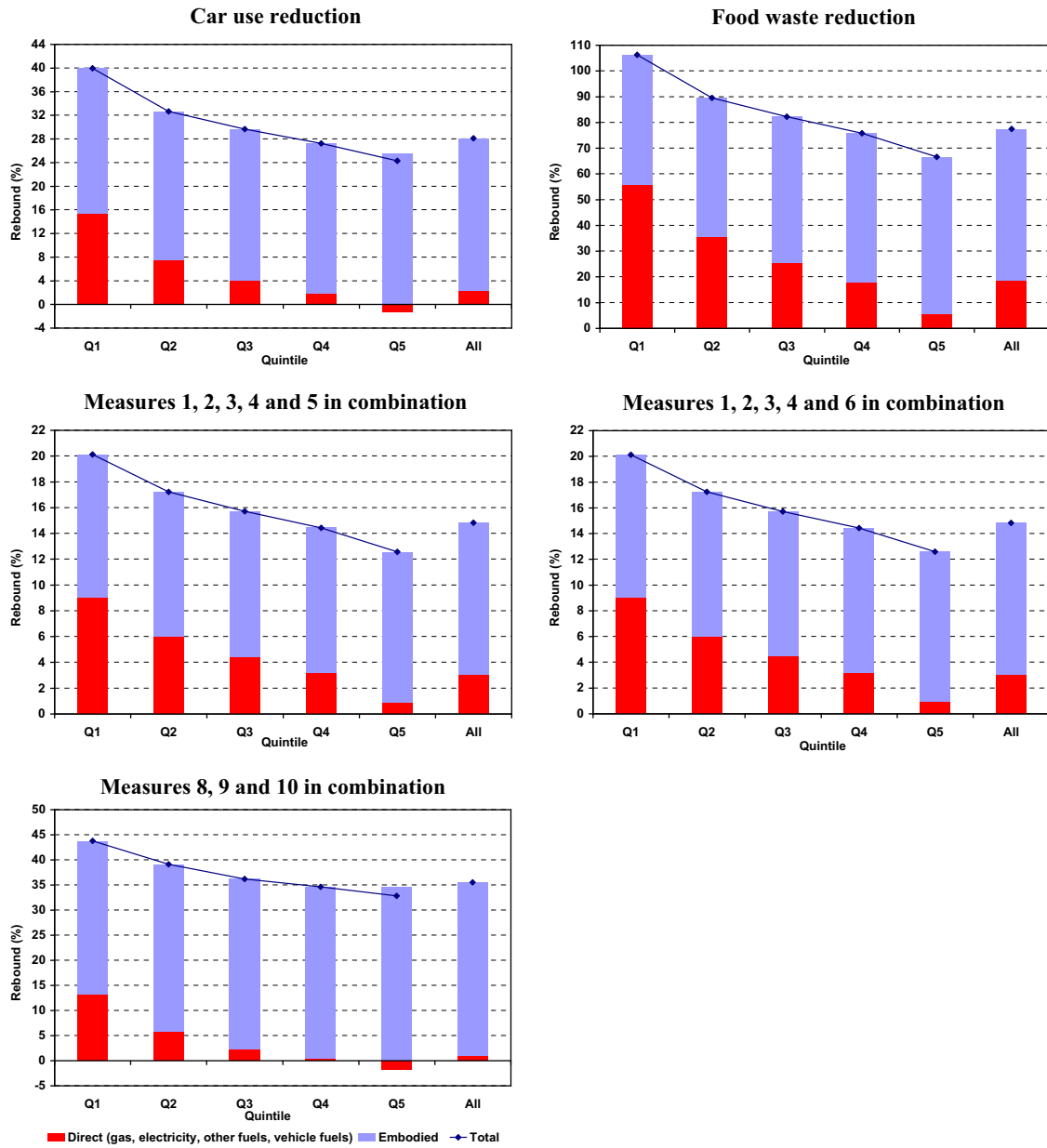
Car use reduction

Food waste reduction

Measures 1, 2, 3, 4 and 5 in combination

Measures 1, 2, 3, 4 and 6 in combination

Measures 8, 9 and 10 in combination

■ Direct (gas, electricity, other fuels, vehicle fuels) ■ Embodied ◆ Total

Fig. 9 (*continued*).

Table 7
Estimated rebound effects for an average household.

No.	Measure	Rebound effect (income effect alone)	Rebound effect (income and embodied effects, full capital costs)	Rebound effect (income and embodied effects, subsidised capital costs)
1	Cavity wall insulation	14.5	11.6	15.2
2	Loft insulation	14.5	5.6	23.2
3	Condensing boiler	15.2	15.2	15.2
4	Tank insulation	14.6	13.4	14.4
5	CFLs	15.3	17.4	17.4
6	LEDs	15.2	5.0	13.4
11	1, 2, 3, 4 and 5	14.8	12.9	16.2
12	1, 2, 3, 4 and 6	14.8	11.3	15.7
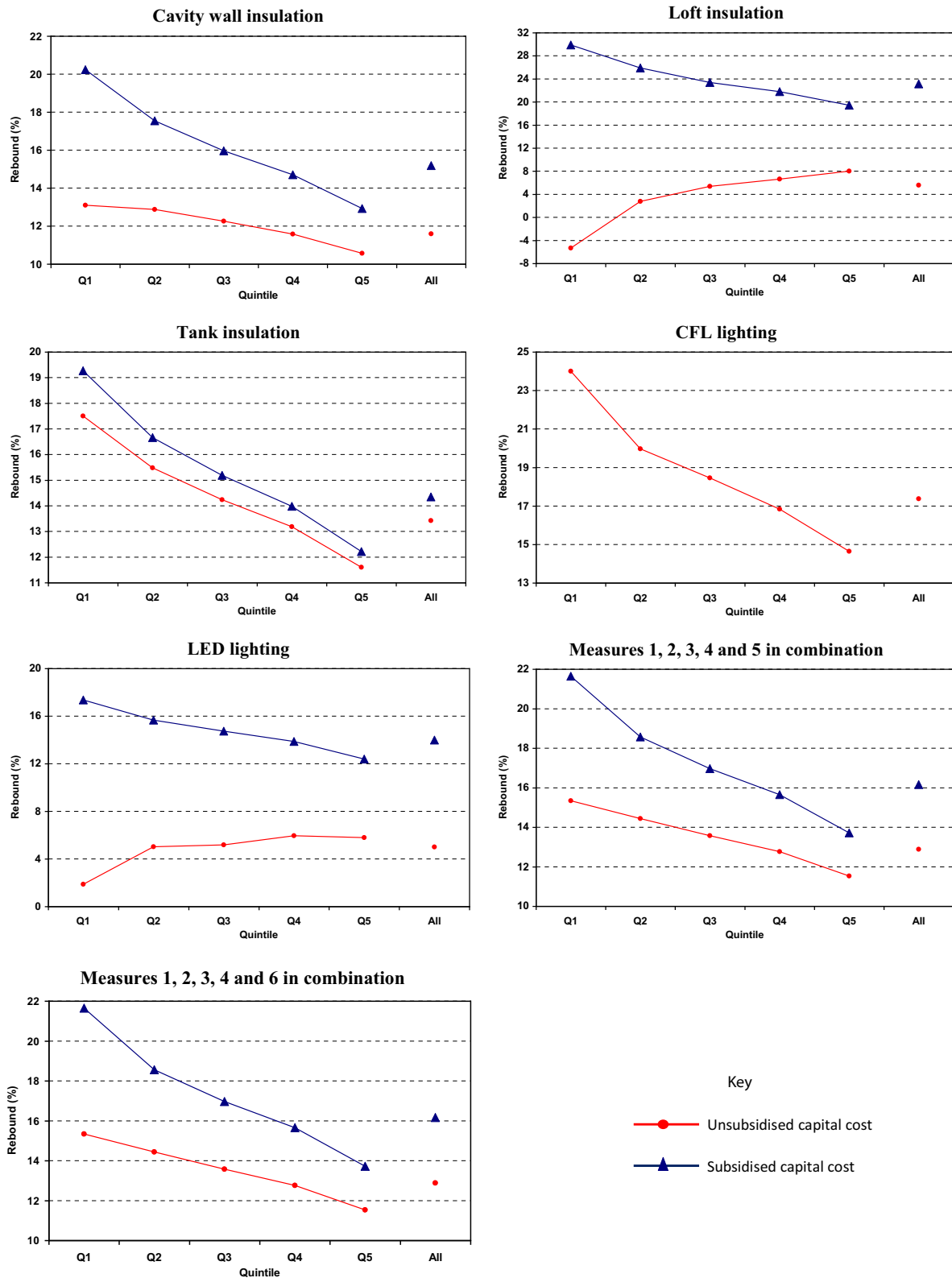
Fig. 10. Estimated rebound effects for the efficiency measures by quintile.

Annex A. Details of Methodology

A.1. Estimating the Engineering Effect

We estimate the engineering effect of the domestic energy measures (1–6 and 8) with the help of the CDEM. This simulates the energy

consumption of the English dwelling stock through modelling the behaviour of 47 different dwelling types. We first used the model to estimate the annual energy consumption of English households by year ($t = 1$ to T) and energy carrier (f — gas, heating oil, solid fuels, electricity) and then divide by the total number of households to give the average annual household consumption of each energy carrier (E_{ft}). We then model the adoption of the relevant measure by all *eligible* households (which may be a subset of the total) and re-estimate the average household consumption of each energy carrier (E_{ft}') — assuming that consumption of the relevant energy service remains unchanged in the case measures 1–6 and falls in the case of measure 8. The estimated fractional change in the average annual household consumption of energy carrier f as a result of the measure is then:

$$\frac{\Delta E_{ft}}{E_{ft}} = \frac{E_{ft}' - E_{ft}}{E_{ft}}. \tag{13}$$

With this approach, the estimated energy savings are averaged over all households but only a portion may be eligible for and hence benefiting from the relevant measure (e.g. not all dwellings have cavity walls). This means that, in percentage terms, the estimated average energy savings may be less than would be obtained for an individual household undertaking the measure, but are representative of the percentage energy savings achievable from the measure by English households as a whole. Similarly, while individual households may only use a single energy carrier (f) for heating, the energy savings are averaged over the mix of all energy carriers used in English households. We take these figures as representative of UK households.

We then use these estimates to *adjust* our estimates of the GHG emissions associated with expenditure on gas, other fuels and electricity (l) by households within each quintile (H_{lt}^j). We derive the latter as follows:

$$H_{lt}^j = u_{lt} X_{lt}^j \tag{14}$$

where l = gas, electricity and other fuels; X_{lt}^j (in £) is the mean equivalised expenditure on category l in year t by households in quintile j; and u_{lt} (in tCO$_{2e}$/£) is an estimate of the GHG intensity of this expenditure in 2004, derived from SELMA. This process involves translating estimates for the four energy carriers (f) used by the CDEM into estimates for the three relevant expenditure categories (l) used by SELMA.

By proceeding in this way, we ensure that our estimates of the engineering effect are consistent with our estimates of the income effect which rely upon the same data sources. In addition, this allows both saved expenditure and the engineering effect to vary between quintiles. The use of equivalised expenditures in Eq. (14) means that H_{lt}^j represents *equivalised* emissions rather than actual emissions, but this does not affect our estimates of rebound effects since we adjust all other variables in the same way (see below).

For households in each quintile, the estimated change in equivalised GHG emissions associated with consumption of gas, electricity and other fuels (ΔH_t^j) is given by:

$$\Delta H_t^j = \sum_l \frac{\Delta E_{lt}}{E_{lt}} H_{lt}^j. \tag{15}$$

The other three measures (7, 9 and 10) only affect a single expenditure category (m), namely vehicle fuels in the case of measures 7 and 9 and food and non-alcoholic beverages in the case of measure 10. For these measures, we use a simpler approach to estimate the fractional savings in GHG emissions from the relevant category for an average UK household (p_{mt}) and then use this to estimate the change in equivalised GHG emissions for households in each quintile as follows:

$$\Delta H_t^j = p_{mt} H_{mt}^j \tag{16}$$

where ($0 \le p_{mt} \le 1$). We term ΔH_t^j the **engineering effect** of the measure for quintile j in year t.

A.2. Estimating the Embodied Effect

For the efficiency measures, we use the results of a number of LCA studies to estimate the GHG emissions incurred in manufacturing and supplying the relevant equipment (Chitnis et al., 2013). We assign these embodied emissions to the year in which the measure is installed and divide by the total number of dwellings to give the average household embodied emissions for the relevant measure (M'_t). We assume that the economic lifetime of each measure is greater than T, so the embodied emissions are only relevant for the base year (i.e. $M'_t = 0$ for $t > 1$).

Following Chitnis et al. (2013), we also estimate the average embodied emissions of the relevant alternative for each household (M_t). If this alternative has an economic lifetime that is less than T, the measure will avoid the purchase of equipment in subsequent years, with the result that the embodied emissions associated with those purchases are also avoided (i.e. $M_t > 0$ for some $t > 1$). This is the case, for example, with conventional lighting which has a shorter lifetime than energy efficient lighting.

The difference between these two estimates represents the *incremental* embodied emissions associated with the measure in each year. To estimate these emissions on an equivalised basis for each quintile, we adjust by the mean household composition in that quintile (n^j):

$$\Delta M_t^j = \frac{(M'_t - M_t)}{n^j}. \tag{17}$$

We term ΔM_t^j the **embodied effect** of the measure for quintile j in year t.

A.3. Estimating the Income Effect

In the UK, household electricity and fuel bills normally include a fixed annual charge (a_{ft} in £/dwelling/year) and a charge per unit of energy used (k_{ft} in £/kWh). Efficiency and sufficiency improvements only affect the latter. Following Chitnis et al. (2013), we use data on energy consumption by fuel type for an average English household in 2009 (E_{ft} in kWh) to estimate the percentage change in mean annual energy expenditures following the adoption of each of the domestic energy measures (1–6 and 8):

$$\frac{\Delta C_{ft}}{C_{ft}} = \frac{k_{ft} \Delta E_{ft}}{\left(a_{ft} + k_{ft} E_{ft}\right)}. \tag{18}$$

We then map these estimates onto the corresponding expenditure categories (l = gas, electricity, other fuels) and estimate the change in mean annual equivalised energy expenditures for households in each quintile (ΔX_t^j) as follows:

$$\Delta X_t^j = \sum_l \frac{\Delta C_{lt}}{C_{lt}} X_{lt}^j. \tag{19}$$

For efficiency measures, we also estimate the capital cost associated with installing the measure in all eligible dwellings and divide by the total number of dwellings to give the average capital cost per household (K'_t). We do the same for the relevant alternative (K_t), with the difference between the two representing the *incremental* capital cost of each measure in each year (ΔK_t). The equivalised incremental capital cost for households in each quintile is then given by:

$$\Delta K_t^j = \frac{(K'_t - K_t)}{n^j}. \tag{20}$$

We assume that the full capital costs are incurred in the year in which the measure is installed (i.e. $K'_t = 0$ for $t > 1$). Again, if the

relevant alternative has an economic lifetime that is less than T, the measure avoids equipment purchases in subsequent years (i.e. $K_t > 0$ for some $t > 1$). For simplicity, we do not discount these avoided capital costs. Incremental capital costs are zero for the sufficiency measures (8–10) and we assume they are also zero for the fuel-efficient car (measure 7).

We treat the sum of the change in expenditures in the relevant categories and the net capital payments in a given year as analogous to a change in equivalised income for each quintile (ΔY_t^j):

$$\Delta Y_t^j = -\left(\Delta C_t^j + \Delta K_t^j\right). \tag{21}$$

We assume that households divide their annual disposable income between their expenditure on goods and services (X_t^j) and savings ($S_t^j = r^j Y_t^j$), where r^j is the fractional savings rate of quintile j:

$$Y_t^j = X_t^j + r^j Y_t^j. \tag{22}$$

We use estimates of savings rates by quintile derived from the LCFS and constrain them to be non-negative (Crossley and O'Dea, 2010).[18] While uncertain, this approach allows the environmental impact of savings to be incorporated within the analysis. The change in savings for each quintile is then given by:

$$\Delta S_t^j = r^j \Delta Y_t^j. \tag{23}$$

The change in mean equivalised total expenditure by households in each quintile (ΔX_t^j) is then given by:

$$\Delta X_t^j = \sum_{i=1}^{I} \Delta X_{it}^j = \left(1 - r^j\right)\Delta Y_t^j \tag{24}$$

where ΔX_t^j represents the change in equivalised expenditure on category i by quintile j. From consumer demand theory, the 'adding up restriction' leads to the so-called 'Engel aggregation condition', as follows (Deaton and Muelbauer, 1980):

$$\sum_{i=1}^{I} \varepsilon_i^j X_{it}^j = \left(1 - r^j\right)Y_t^j \tag{25}$$

where ε_i^j represents the expenditure elasticity of category i for households in quintile j. For sufficiency measures, we do not allow re-spending in the commodity categories that are directly affected by the relevant measure (e.g. food and non-alcoholic beverages in the case of eliminating food waste). Similarly, when the sufficiency measures are combined, we do not allow any re-spending between the relevant categories (e.g. savings from eliminating food waste are not re-spent on increased driving).

Letting u_{st} represent the GHG intensity of UK investment (in tCO$_2$e/£), the mean change in equivalised GHG emissions for households in quintile j as a consequence of the change in disposable income is then given by:

$$\Delta G_t^j = \sum_{i=1}^{I}\left[u_{it}\Delta X_{it}^j\right] + u_{st}r^j \Delta Y_t^j. \tag{26}$$

Using the definition of expenditure elasticity, the mean change in equivalised expenditure on category i in year t by households in quintile j can be written as:

$$\Delta X_{it}^j = \varepsilon_i^j \frac{\Delta Y_t^j}{Y_t^j} X_{it}^j. \tag{27}$$

Substituting ΔX_{it}^j from Eq. (27) into Eq. (26):

$$\Delta G_t^j = \left[\frac{\Delta Y_t^j}{Y_t^j}\right]\sum_{i=1}^{I}\left[u_{it}\varepsilon_i^j X_{it}^j\right] + u_{st}r^j \Delta Y_t^j. \tag{28}$$

Substituting for Y_t^j from Eq. (25), this can also be written as:

$$\Delta G_t^j = \Delta Y_t^j \left[\frac{(1-r_t)}{\sum_{i=1}^{I}\varepsilon_i^j X_{it}^j}\sum_{i=1}^{I}\left[u_{it}\varepsilon_i^j X_{it}^j\right] + u_{st}r^j\right]. \tag{29}$$

We term ΔG_t^j the **income effect** of the energy efficiency improvement for quintile j in year t.

Annex B. Key Assumptions

B.1. GHG Savings

Our assumptions for the GHG savings from the domestic energy measures are derived from the CDEM and described in Chitnis et al. (2013). For the vehicle and food measures, we assume the following:

- *Efficient car*: Fuel efficient diesel cars such as the Audi A3 1.6 can achieve ~100 g CO$_2$/km in test cycles, corresponding to ~115 g CO$_2$/km in real world conditions (DEFRA, 2012). This compares to a UK new car average in 2009 of ~172 g CO$_2$/km[19] and a fleet average of ~177 g CO$_2$/km. Hence, with no change in driving patterns, households that replaced a typical car with an average new car should reduce their vehicle fuel emissions by ~3%, while households that purchased a fuel-efficient diesel should instead reduce their emissions by ~35%. We take the difference between these two estimates (32%) as the incremental emission reductions from purchasing the latter instead of the former and further assume that this measure applies to the ~7% of cars that are scrapped and replaced in the base year. Since the average UK household owns 1.14 cars (DfT, 2012b), this corresponds to a ~2.6% reduction in vehicle-related GHG emissions for an average household. We use this to adjust our estimates of the emissions associated with vehicle fuel consumption for each quintile — which in turn reflect differing levels of car ownership and use within each quintile.
- *Reducing car use*: Some 22% of UK car trips are of less than two miles and these are estimated to account for ~3% of total car mileage and ~4.9% of total car emissions (DfT, 2012a).[20] We use the latter figure to adjust our estimates of the emissions associated with vehicle fuel consumption for each quintile.
- *Eliminating food waste*: Quested and Parry (2011) estimate that the average UK household throws away 18% of its food and drink purchases, and that 12% of this waste is avoidable. To a first approximation, eliminating this avoidable waste should reduce the embodied emissions associated with food consumption by 12% as well.[21] We use this figure to

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[18] Our assumptions are based on Crossley and O'Dea (2010) as follows: Q1 = 0%; Q2 = 9%; Q3 = 15%; Q4 = 20%; Q5 = 30%. Saving is calculated as income minus expenditure, and the saving rate as saving divided by income. However, this calculation is inaccurate because LCF income excludes key categories such as withdrawal of savings, loans, receipts from maturing insurance policies and proceeds from the sale of assets. Since recorded expenditure reflects these items, there is no reason why income and expenditure should balance. In practice, measured expenditure exceeds measured income at the bottom end of the income distribution.

[19] Test cycle emissions for new diesel cars averaged 149.9 g CO$_2$/km in 2009, while those for new petrol cars averaged 149.5 g CO$_2$/km. We apply an uplift factor of 15% to estimate emissions under 'real-world' driving conditions (DEFRA, 2012) and assume UK averages are the same as GB.
[20] This allows for the slower average speeds and cold start penalty associated with short journeys (DfT, 2008).
[21] In practice, the GHG intensity of the food most commonly thrown away may be higher or lower than the average GHG intensity of the food and non-alcoholic beverages category (WRAP, 2009, 2010).

adjust our estimates of the emissions associated with food and non-alcoholic beverages consumption by each quintile.

The results are summarised in Table A.1.

Table A.1
Estimated percentage change in GHG emissions by category following the adoption of each measure by an 'average' UK household over a period of 10 years.

No.	Measure	Gas	Electricity	Other fuels	Vehicle fuels	Food
1	Cavity wall insulation	−8.8	−1.7	−7.2	–	–
2	Loft insulation	−2.2	−0.5	−2.3	–	–
3	Condensing boiler	−11.8	0.6	−0.1	–	–
4	Tank insulation	−1.8	−1.6	−1.9	–	–
5	CFL lighting	0.9	−4.5	0.9	–	–
6	LED lighting	1.1	−5.4	1.0	–	–
7	Efficient car	–	–	–	−2.6	–
8	Temperature reduction	−9.4	−2.0	−10.5	–	–
9	Car use reduction	–	–	–	−4.9	–
10	Food waste reduction	–	–	–	–	−12.0
11	1, 2, 3, 4 and 5	−22.4	−7.6	−10.6	–	–
12	1, 2, 3, 4 and 6	−22.2	−8.5	−10.4	–	–
13	8, 9 and 10	−9.4	−2.0	−10.5	−4.9	−12.0

Note: Estimates refer to an average household with a mean level of equivalised total expenditure.

B.2. Embodied Emissions

Table A.2
Estimated incremental embodied emissions associated with implementing each measure in an average household over a period of 10 years.

No.	Measure	Embodied emissions (kg CO_2e)
1	Cavity wall insulation	55.2
2	Loft insulation	118.3
3	Condensing boiler	–
4	Tank insulation	2.3
5	CFLs	2.6
6	LEDs	24.5
7	Efficient car	0
8	Temperature reduction	0
9	Car use reduction	0
10	Food waste reduction	0
11	1, 2, 3, 4 and 5	178.4
12	1, 2, 3, 4 and 6	200.3
13	8, 9 and 10	0

Note: Estimates for an average household are derived by estimating the incremental embodied emissions associated with all eligible households adopting the measure, dividing by the total number of households and then dividing by the mean equivalised size of UK households (Table 4).

B.3. Cost Savings

Our assumptions for the cost savings from measures 1–6 are derived from the CDEM and described in Chitnis et al. (2013). For the other measures, we assume that reducing food waste will reduce food-related expenditure by 12%, reducing car use will reduce expenditure on vehicle fuels by ~4.9% and purchasing a fuel-efficient car will reduce expenditure on vehicle fuels by ~35% relative to purchasing an average new car.[22] Since we assume that only 7% of the car stock is replaced, this leads to a ~2.8% reduction in expenditure on vehicle fuels for an average

[22] Assuming: a) average fuel efficiencies of 6.5 l/100 km, 5.7 l/100 km and 4 l/100 km for new petrol, diesel and fuel-efficient diesel cars respectively; b) a 50:50 split between petrol and diesel in new car purchases; c) average 2009 fuel prices of £1.29/litre for petrol and £1.26/litre for diesel; d) an average of 1.14 cars per household; and e) replacement of 7% of the current vehicle stock. Households purchasing a new fuel-efficient diesel would reduce expenditure on vehicle fuels by ~37.5% compared to an average existing vehicle and by ~35% compared to an average new vehicle. We scale the latter figure to reflect our assumption that only 7% of the stock is replaced.

household. There will also be additional savings on vehicle excise duty, since low emission vehicles (<100 g CO_2/km) are exempt. Allowing for this increases the total annual cost savings by some 36%. The resulting assumptions are summarised in Table A.2.

Table A.3
Estimated percentage change in annual expenditure by category following the adoption of each measure by an average UK household over a period of 10 years.

No.	Measure	Gas	Electricity	Other fuels	Vehicle fuels	Food
1	Cavity wall insulation	−7.7	−1.5	−7.1	–	–
2	Loft insulation	−1.9	−0.4	−2.3	–	–
3	Condensing boiler	−10.3	0.6	−0.1	–	–
4	Tank insulation	−1.5	−1.5	−1.8	–	–
5	CFLs	0.8	−4.1	0.8	–	–
6	LEDs	1.0	−5.0	1.0	–	–
7	Efficient car				−2.8	
8	Temperature reduction	−8.2	−1.9	−10.5	–	–
9	Car use reduction				−4.9	
10	Food waste reduction					−12
11	1, 2, 3, 4 and 5	−19.4	−7.0	−10.5	–	–
12	1, 2, 3, 4 and 6	−19.3	−7.8	−10.4	–	–
13	8, 9 and 10	−8.2	−1.9	−10.5	−4.9	−12

Note: Estimates refer to an average household and are derived by estimating the emission reductions associated with all eligible households adopting the measure and dividing by the total number of households.

B.4. Capital Costs

Estimates of the incremental capital cost of each measure, with and without subsidies, are summarised in Table A.3. These represent the difference between the capital cost of the measure and the capital cost (if any) of the relevant counterfactual, such as continuing to use existing lightbulbs. The estimates for the domestic energy measures are based upon information provided by DECC (2010b) and described in Chitnis et al. (2013). For simplicity, we assume that the incremental capital cost of a fuel-efficient diesel car is zero, although since such cars tend to be smaller, lighter and have fewer features, the incremental cost could be negative. As a result, our estimate of the rebound effect for this measure may be conservative.

(See Table A.4.)

Table A.4
Estimated incremental capital cost associated with implementing each measure in an average UK household over a period of ten years.

No.	Measure	Capital cost without subsidy	Capital cost with subsidy
1	Cavity wall insulation	179	41
2	Loft insulation	235	54
3	Condensing boiler	0	0
4	Tank insulation	18	6
5	CFLs	58	58
6	LEDs	253	127
7	Efficient car	0	0
8	Temperature reduction	0	0
9	Car use reduction	0	0
10	Food waste reduction	0	0
11	1, 2, 3, 4 and 5	409	80
12	1, 2, 3, 4 and 6	605	149
13	8, 9 and 10		

Note: Estimates for an average household are derived by estimating the capital costs associated with all eligible households adopting the measure, dividing by the total number of households and then dividing by mean equivalised size of UK households (Table 4). The with-subsidies estimates take into account the level of CERT subsidies available for different socio-economic groups, as well as the proportion of installations expected within each.

B.5. GHG Intensities, Expenditure Shares and Share of GHG Emissions

Table A.5
GHG intensities, expenditure shares and share of GHG emissions by category for an average household.

No.	Description	GHG intensity (kg CO$_2$e/£) (u_{it})	GHG intensity as % of gas	Expenditure share in 2009 (%) (X_i / X)	GHG emissions as % of total (i / H)
1	Food & non-alcoholic beverages	1.05	22.4	13.9	12.9
2	Alcohol and tobacco	0.26	5.6	3.1	0.7
3	Clothing & footwear	0.54	11.5	5.4	2.6
4	Electricity	5.04	107.1	2.8	12.5
5	Gas	4.70	100.0	2.5	10.5
6	Other fuels	6.95	147.8	0.6	3.9
7	Other housing	0.28	6.0	9.2	2.3
9	Furnishings etc.	0.75	16.0	7.6	5.0
9	Health	0.35	7.4	1.5	0.5
10	Vehicle fuels and lubricants	2.61	55.5	5.0	11.5
11	Other transport	1.25	26.7	10.0	11.0
12	Communication	0.43	9.2	3.1	1.2
13	Recreation & culture	0.65	13.8	15.2	8.7
14	Education	0.25	5.4	1.4	0.3
15	Restaurants & hotels	0.59	12.5	9.7	5.0
16	Miscellaneous	0.52	11.1	9.1	4.2
	Saving	0.57	12.1	–	7.4

B.6. Estimated Effects

Table A.6
Estimated engineering, embodied, income and total effects (ignoring capital cost) for an average household (percentage of baseline GHG emissions).

No.	Measure	Engineering effect	Embodied effect	Income effect	*Net effect*
1	Cavity wall insulation	−1.4%	0.025%	0.2%	−1.18%
2	Loft insulation	−0.4%	0.053%	0.1%	−0.27%
3	Condensing boiler	−1.2%	–	0.2%	−1.00%
4	Tank insulation	−0.5%	0.001%	0.1%	−0.39%
5	CFL lighting	−0.4%	0.001%	0.1%	−0.37%
6	LED lighting	−0.5%	0.011%	0.1%	−0.43%
7	Efficient car	−0.3%	–	0.1%	−0.16%
8	Temperature reduction	−1.6%	–	0.2%	−1.42%
9	Car use reduction	−0.6%	–	0.2%	−0.41%
10	Food waste reduction	−1.5%	–	1.2%	−0.35%
11	1–5	−3.7%	0.080%	0.6%	−3.08%
12	1–4 and 6	−3.8%	0.090%	0.6%	−3.15%
13	8, 9 and 10	−3.8%	–	1.3%	−2.42%

B.7. Engel Curves

Table A.7
Estimated Working Leser Engel curves for whole sample in 2009.

Category	α_i	β_i	γ_i	$\bar{R}^2$
Food & non-alcoholic beverages	0.57 (41.84)*	−0.09 (−36.78)*	0.0009 (13.89)*	0.32
Alcoholic beverages & tobacco	0.11 (12.33)*	−0.01 (−8.64)*	−0.0001 (−3.10)*	0.02
Clothing & footwear	−0.01 (−1.58)	0.02 (11.47)*	−0.0004 (−7.72)*	0.04
Electricity	0.16 (24.66)*	−0.03 (−23.45)*	0.0003 (10.57)*	0.23
Gas	0.12 (18.61)*	−0.02 (−17.60)*	0.0004 (10.77)*	0.13
Other fuels	0.01 (1.52)	−0.001 (−1.95)*	0.0002 (5.97)*	0.01
Other housing	0.33 (17.64)*	−0.03 (−10.43)*	−0.001 (−9.83)*	0.03
Furnishings	−0.12 (−8.07)*	0.03 (11.39)*	0.0006 (7.15)*	0.04
Health	−0.04 (−6.23)*	0.01 (6.47)*	0.0003 (7.68)*	0.02
Vehicle fuels & lubricants	0.02 (2.97)	0.01 (6.39)*	−0.0002 (−3.88)*	0.01
Other transport	−0.17 (−11.16)*	0.05 (19.90)*	−0.0005 (−5.50)*	0.09
Communication	0.14 (25.24)*	−0.02 (−20.98)*	−0.0001 (−2.15)*	0.12
Recreation & culture	−0.12 (−6.31)*	0.04 (12.91)*	0.0005 (5.82)*	0.04
Education	−0.05 (−7.09)*	0.01 (8.61)*	−0.0002 (−5.12)*	0.03
Restaurants and hotels	−0.003 (−0.21)	0.02 (10.79)*	−0.0005 (−7.42)*	0.04
Miscellaneous goods & services	0.04 (3.68)*	0.01 (3.91)*	−0.00001 (−0.11)	0.004

Notes: Estimated with OLS over the full sample of households using 'White heteroskedasticity-consistent standard errors & covariance' to correct for heteroskedasticity. The *t*-statistics for each parameter are shown in parenthesis, with single asterisk indicating the estimate is significant at the 5% probability level.

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