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Distributional Effects of the UK Carbon Price Floor

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Abstract

This paper empirically investigates the distributional effects of the UK carbon price floor (CPF) on households' electricity expenditure. I employ the difference-in-differences model to analyse the impact of the carbon price floor on vertical inequality. The main result finds that households in the poorest quintile are most impacted by the electricity price increase. I further explore the heterogenous effect on households within the bottom quintile by considering various household characteristics. This paper contributes to the existing literature on carbon pricing policies, in particular their impact on inequality both across income groups and within households in the poorest quintile.

Keywords: Carbon Pricing, Inequality, Expenditure Inequality, Carbon Price Floor (CPF)

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1. Introduction

Climate change and inequality are two mainstream issues among economists and politicians. Although the two issues are inextricably linked, few studies and policies are aimed at addressing both issues, particularly in the UK. In this paper, I investigate the distributional impact of the UK carbon price floor (CPF). The CPF is a carbon pricing policy introduced in 2013 consisting of the EU emissions trading system (ETS) and the carbon price support (CPS) which is a carbon tax on producers. The price floor sets a price on carbon of £9/tCO_2. Both components cover the electricity production sector which has consequences for households as the additional cost for producers is passed through to consumer prices. The consensus in the literature is that carbon pricing policies are inherently regressive as carbon- intensive goods such as electricity are necessity goods for which there are no substitutes (Parry, 2004; Nordhaus, 2006; Metcalf, 2009). Hence, this paper explores how the CPF affects electricity expenditure across households, focusing on two forms of inequality: vertical and horizontal inequality. Vertical inequality is defined as the inequality across the income distribution and horizontal inequality is the inequality within the same income range due to various household characteristics.

2. Vertical Inequality

To study the inequality effects of the cost pass-through from the Carbon Pricing Floor (CPF), the Difference-in-Differences (DiD) methodology is employed using data from the UK Living Costs and Food Survey (Oldfield, Banks, and Leicester, 2020). In this paper, the main treatment group is households in the 1st quintile and the control group is households in the 5th quintile.

2.1 Choice of Control Group

Since the carbon price floor is a nationwide policy, finding an adequate control group is challenging. I decided to use households in the 5th quintile (highest) as the control group since they are less affected by the CPF. The reason for this is that richer households have higher price elasticity as they see electricity as less of a necessity good, which makes them more immune to fluctuations in electricity expenditure (Chitnis et al., 2014; Schulte and Heindl, 2017). Furthermore, they have more energy efficient homes meaning they are less affected by electricity price rises (Ministry of Housing, Communities & Local Government, 2014). Thus, in theory, the CPF is expected to have a limited impact on the electricity bills of richer households. A graphical test for the parallel time trend assumption is provided in Figure 1, where it is shown that both the control and treatment groups have similar trends prior to 2013, thereby indicating that the highest quintile is an adequate control group. The lowest quintile is the main treatment group as the poorest households are most vulnerable to changes in electricity prices.

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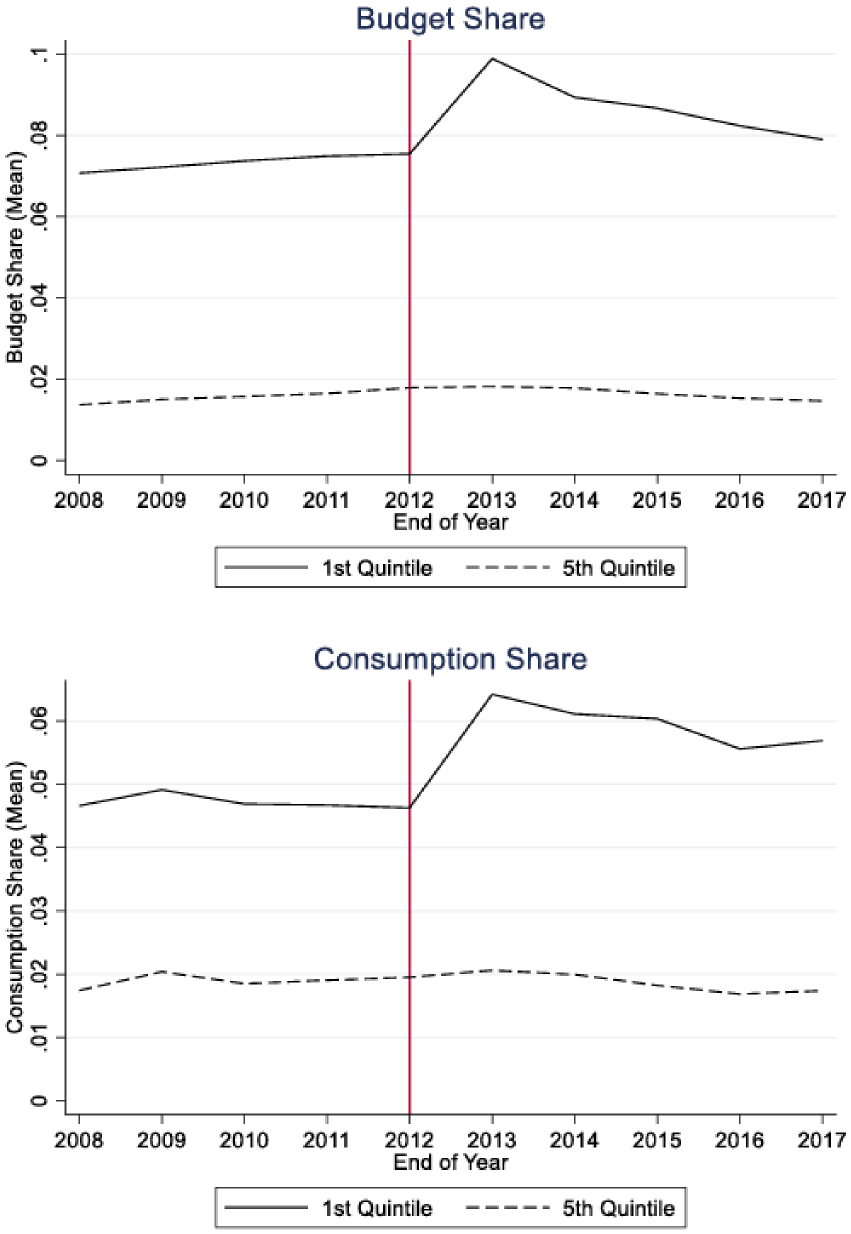

Figure 1: Budget Share and Composition Share

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2.2 Model Specification

The following regressions are estimated:

Budget Share

$$w_{it} = \frac{p_{it}q_{it}}{y_{it}} = \beta_0 + \beta_1 time_t + \beta_2 treated_i + \beta_3 did_{it} + \beta_n X_{it} + \varepsilon_{it} \tag{1}$$

Consumption Share

$$\phi_{it} = \frac{p_{it}q_{it}}{C_{it}} = \beta_0 + \beta_1 time_t + \beta_2 treated_i + \beta_3 did_{it} + \beta_n X_{it} + \varepsilon_{it} \tag{2}$$

where the variables $time_i$ and $treated_i$ are dummy variables and did_i is the interaction term of $time_i$ and $treated_i$. X_{it} represents a vector of control variables and ε_{it} is the error term. This model specification yields the average treatment effect of the carbon price floor.

Budget share and consumption share are chosen as the dependent variables as they reflect the proportion of income spent on electricity. I control for time-varying variables such as the age of the household reference person, household size, employment status, and the number of electrical appliances. I do not control for energy efficiency as this threatens to invalidate the choice of control group, since households in the highest quintile have more energy efficient homes. I also do not control for the geographical location as the Living Costs and Food survey randomises the selection of households chosen each year.

Since the CPF increased yearly from £9/tCO$_2$ in 2013 to £18/tCO$_2$ in 2015 (Hirst, 2018), it is also of interest to analyse the yearly effects. In order to decompose the yearly effects between 2013 and 2015, I adapt the staggered difference-in-differences from Abadie (2005) and Callaway and Sant'Anna (2021) which is shown below:

$$y_{it} = \beta_0 + \beta_1 treated_i + \sum_{j=2008}^{2016} \lambda_j year_{t=j} + \sum_{j=2013}^{2015} \delta_j (did_{i,t=j}) + \gamma_n X_{it} + \varepsilon_{it} \tag{3}$$

where $did_{i,t=j}$ is the interaction term of $treated_i$ and $year_{t=j}$. The coefficient δ_j thus represents the estimate of the j-th yearly treatment effect compared to the pre-intervention level. The variable $year_t$ is a dummy variable taking the value 1 if $t = j$ and zero otherwise.

The year dummy for 2017 is omitted to avoid the dummy variable trap. The variable y_{it} represents the dependent variable budget share and consumption share.

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2.3 Results

The electricity budget and consumption share increased for low-income households after the introduction of the carbon price floor in 2013, compared to high-income households as illustrated by Figure 1 and Table 1.

	(1)	(2)	(3)	(4)
	Average Treatment Effect		Yearly Treatment Effect	
VARIABLES	Budget Share	Consumption Share	Budget Share	Consumption Share
time	0.000526	-0.000692**		
	(0.00163)	(0.000330)		
treated	0.0581***	0.0257***	0.0604***	0.0286***
	(0.00128)	(0.000702)	(0.00222)	(0.00187)
did	0.0146***	0.0137***		
	(0.00230)	(0.00109)		
did_2013			0.0186***	0.0132***
			(0.00192)	(0.00198)
did_2014			0.0100***	0.0106***
			(0.00199)	(0.00192)
did_2015			0.0107***	0.0103***
			(0.00200)	(0.00188)
age	-0.000378***	0.000185***	-0.000380***	0.000183***
	(2.85e-05)	(1.98e-05)	(6.17e-05)	(4.04e-05)
unempl	0.0210***	0.0120***	0.0197**	0.0110**
	(0.00475)	(0.00199)	(0.00673)	(0.00403)
elec_app	2.24e-05	-4.82e-05***	2.12e-05	-4.85e-05***
	(1.50e-05)	(6.86e-06)	(1.45e-05)	(7.62e-06)
hhsize	0.00125**	-0.000547***	0.00127	-0.000530
	(0.000486)	(0.000206)	(0.00105)	(0.000520)
Constant	0.0298***	0.0114***	0.0276***	0.00867***
	(0.00189)	(0.00109)	(0.00429)	(0.00167)
Observations	19,741	19,797	19,741	19,797
R-squared	0.161	0.190	0.163	0.189

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 1: Results from the Difference-in-Differences Regressions

Post-intervention, the average budget share and consumption share increased by 1.46% and 1.37% respectively (Table 4). The carbon price floor incentivised a transition towards cleaner but more expensive electricity which in turn passed through to household energy bills (Castagneto-Gissey et al., 2019). The disproportionate increase in electricity bills for low- income households is consistent with the finding that carbon policies are inherently regressive as UK households in the poorest decile view energy as the second-most important commodity, only after food (Advani et al., 2013).

It is of note that the increase in the carbon price support from £9/tCO2 to £18/tCO2 in 2015 did not further increase the electricity budget share or consumption share for households in the lowest quintile. The treatment effect in 2014 and 2015 was in fact smaller than the effect in 2013 even though the tax component of the CPF had increased, indicating that the increase in carbon price did not pass through to consumers and did not further increase electricity expenditure shares for the lowest quintile. The further increase in the price of the CPS in 2014 and 2015 had smaller effects on household electricity expenditure since most of the production had already been shifted away from expensive coal-generated power plants.

3. Horizontal Inequality

I next explore the heterogeneity of electricity expenditure across households within the lowest quintile. As observed in the previous section, poorer households spend a large proportion of their income on electricity and the carbon price floor has widened this gap. Hence, any policy that aims to address the disproportionate budget share on low-income households also needs to take into account household characteristics such as age, employment status, and household size. In order to determine the relationship between electricity expenditure and various household characteristics, both before and after the intervention, I use an OLS model with year-fixed effects specified below:

$$Elec_i = \beta_0 + \beta_1 age_i + \beta_2 age_i^2 + \beta_3 hhsize_i + \beta_4 unempl_i + \sum_{j=2008}^{2016} \lambda_j year_{i,t=j} + \varepsilon_i \qquad (4)$$

where $Elec_i$ is the household electricity expenditure, $year_t$ is a year dummy, age_i is the age of the household reference person (HRP), $hhsize_i$ is the household size, and $unempl_i$ is a dummy variable taking a value of 1 if the HRP is unemployed and zero otherwise.

Income is controlled for as the sample size is restricted to the 1st quintile. I also estimate the model before the policy (2008-2012) and after (2013-2017) to observe any changes caused by the CPF.

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VARIABLES	(1) Electricity Expenditure (2008-2017)	(2) Electricity Expenditure (2008-2012)	(3) Electricity Expenditure (2013-2017)
age	0.165***	0.160***	0.176***
	(0.0334)	(0.0432)	(0.0514)
age2	-0.00217***	-0.00193***	-0.00258***
	(0.000323)	(0.000418)	(0.000500)
hhsize	0.332***	0.499***	0.155
	(0.0626)	(0.0820)	(0.0950)
unempl	-0.888**	-0.897***	-0.327
	(0.280)	(0.325)	(0.484)
Constant	8.728***	8.121***	10.02***
	(0.842)	(1.067)	(1.273)
Observations	7,910	3,973	3,937
R-squared	0.361	0.434	0.331

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 2: Horizontal Inequality Regression Output for Households in the 1st Quantile

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3.1 Results

Table 2 reports that electricity expenditure increases with household size and is higher for unemployed households. This makes sense as larger households and households where people spend more time at home consume more electricity. Moreover, there is a concave relationship between age and electricity expenditure, meaning electricity expenditure increases with age until a certain point where expenditure starts to decrease. This relationship is consistent both before and after the introduction of the CPF in 2013 indicating that the policy had no discriminating effect on age. Figure 2 illustrates that younger and older households consume less electricity compared to households within the age range of 30-49 which have the highest expenditure on electricity which is somewhat surprising as one would expect older people and retirees to spend more time at home thereby consuming more electricity.

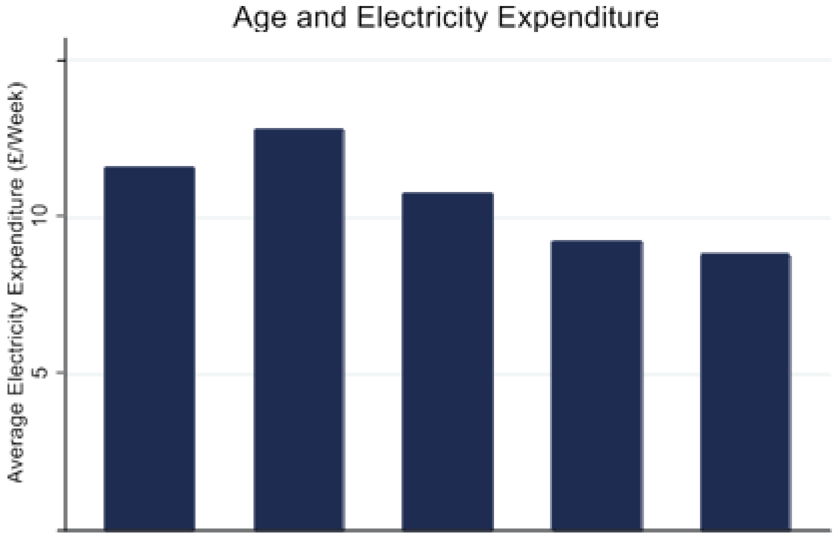

Figure 2: Electricity Expenditure across Age Groups

A possible explanation for this is the permanent income hypothesis, which states that households who expect to earn a higher income in the future will consume more in the present in order to smooth consumption, provided that they are not credit-constrained (Hall, 1978). Households in the lowest quintile can be categorised as either temporarily poor or permanently poor. Thus, households between 30-49 can be thought of as temporarily poor as they expect to maintain an income in the future and hence can consume more electricity.

Older households are permanently poor as they have lower expected lifetime income and hence consume less electricity. Younger households have a high expected lifetime income but may be credit-constrained and hence cannot smooth their consumption (Ortalo-Magné and Rady, 2006). Thus, young households can only afford entry-level homes resulting in lower electricity expenditures.

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4. Conclusion

In this paper, I explore the impact of the UK carbon pricing floor on both vertical and horizontal inequality. The main result from this paper is that households in the lowest quintile are most impacted by the electricity price rise, thereby exacerbating vertical inequality, and households between the age range of 30-64 have the highest electricity expenditure. The findings from this paper help inform policymakers on the distributional impacts of carbon pricing policies, which is especially relevant given the current cost of living crisis.

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