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Pay (for it) as you go: Prepaid energy meters and the heat-or-eat dilemma

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A R T I C L E I N F O

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A B S T R A C T

The "heat-or-eat" dilemma, a trade-off typically between food consumption and heating, may elevate public health concerns during the 2022 energy-price crisis. Our paper contributes to the literature by exploring the role of domestic energy prepayment meters (PPMs) in the heat-or-eat dilemma, focusing on the association between PPM use and fruit and vegetable consumption. Using a representative sample of 24,811 individuals residing in Great Britain (January 2019–May 2021), we find robust evidence of lower fruit and vegetable consumption amongst individuals using PPMs, compared to those using post-payment energy bill payment methods. On average, our point estimates suggest that individuals using a PPM consume 2.7 fewer portions of fruit and vegetables per week. Our findings hold when bounding analysis is employed to account for omitted variable bias. Using a suite of IV approaches to further alleviate endogeneity concerns we found that our ordinary least squares results are consistent as opposed to IV models. Further robustness analyses highlight the deleterious impact of PPMs on people's healthy eating habits relevant to the consumption of enough fruit and vegetables. Our results suggest that targeted support for PPM users may have beneficial effects on people's fruit and vegetable consumption patterns.

1. Introduction

The quality of a nation's diet is a key public health concern in many countries, including the United Kingdom (UK). According to the National Food Strategy only one quarter of the UK population meets the recommended consumption of fruit and vegetables (FVC hereafter) (Dimbleby, 2021), an important source of dietary fibre, minerals, and vitamins. This is evermore concerning amongst the lowest income decile who on average eat 42% fewer fruit and vegetables than recommended, compared to 13% amongst the wealthiest (Dimbleby, 2021). Increasing FVC up to "5-a-day", as recommended by the World Health Organisation's (WHO), reduces morbidity and mortality risks (Boeing et al., 2012; Wang et al., 2021). For example, inverse associations between FVC and several cancers (e.g., colon and lung) have long been established (Willet, 1994). Moreover, in the UK, diets low in fruit or vegetables are leading cardiovascular (CVD) and circulatory disease risk factors (Murray et al., 2013). CVD causes one in four deaths and costs the National Health Service £7.4 billion per year in England alone (Public Health England, 2019), highlighting the importance of the protective role of FVC for CVD risks (Wang et al., 2014). However, energy affordability may impact people's diet via the "heat-or-eat" dilemma, a trade-off between eating and heating, which has resurfaced throughout the 2022 energy-price crisis. This dilemma has the potential to worsen diet quality amongst the UK population if expenditure on healthy food is traded-off for energy consumption.

Indeed, price rises are likely to put households with a prepayment meter (PPM) – a type of energy bill payment method and meter that requires users to pay for energy before consuming it – at greater risk of cutting back on essentials. Around 20% of prepayment customers cut back on food and/or leisure to purchase credit for their PPM (Mummery and Reilly, 2010). Not least because "[…] unlike other customers, where prepayment customers pay too high a price, part of the detriment may be felt in abruptly curtailed consumption" (CMA, 2016: 58). Curtailing energy or the consumption of other goods and services (including food), often to avoid debt, is referred to as 'self-rationing'. One of the most extreme forms of rationing energy is 'self-disconnection' where the customer is cut off from supply because the PPM runs out of credit (O'Sullivan et al., 2011). Multiple strategies are employed by households to cut back on food at the expense of energy, e.g., skipping meals and eating out-of-date products (Koltai et al., 2021). There is an urgent

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need therefore for recent and rigorous evidence on the linkage between expensive energy bill payment methods, specifically PPMs which generally charge more as a payment arrangement and predominantly used by lower income and vulnerable households (as discussed below), and FVC – a gap the present paper addresses.

Early evidence of the heat-or-eat dilemma arose in response to the marked rise in fuel prices in the United States (US) during the winter months of 2000/1 (Cullen et al., 2004). Frank et al. (2006)'s study of the Low-Income Home Energy Assistance Program established that children living in households without this support for energy efficiency improvements were at a greater risk of malnutrition. Such findings coincided with Frank et al. (1996)'s seminal public health study which found higher rates of hunger amongst children living in US households under threat of disconnection by energy companies and/or households who forewent heating. Bhattacharya et al. (2003) drew upon the US Consumer Expenditure Survey (CEX) to illustrate how low-income households, during unusually cold weather spells, met their heating needs by decreasing expenditure on food, leading to lower caloric intake and potential long-term health consequences. In contrast, exploring the CEX between 1990 and 2002, Cullen et al. (2004) teased out that financially constrained households' non-energy spending (including food) is insensitive to *anticipated* changes in energy costs, yet sensitive to *unanticipated* energy spending. Common amongst these studies is the view that lower-income households are relatively more vulnerable to the heat-or-eat dilemma.

To the best of our knowledge, Beatty et al. (2014a) is the only study to empirically investigate the heat-or-eat dilemma in the UK, using a similar approach to the former two cited US studies. It found evidence that British households reduced their food spending to finance the additional cost of keeping warm during unseasonably cold weather events. However, little is known about the dietary implications of such reductions in food expenditure, especially about the role of energy payment methods in the heat-or-eat dilemma. This is crucial, not least because of the positive health effects attributed to fruit and vegetables in reducing CVD, cancer, and premature mortality risks (Aune et al., 2017). More closely aligned to the context of the present study, albeit earlier evidence, a representative survey of Great Britain (GB) suggested that of the 16 per cent of prepayment customers who reported running out of credit on the PPM, two fifths reduced spending on nutritious or hot meals in order to top up the PPM (Mummery and Reilly, 2010). More recently, Snell et al. (2018)'s qualitative arm of analysis painted a nuanced picture in which households' struggle to either top up a PPM or eat. Hence, in contrast to earlier qualitative evidence which suggested heating to be the priority over food amongst elderly people in the UK (O'Neill et al., 2006), Snell et al. (2018)'s mixed method approach also found food to be prioritised amongst a wider cross-section of low-income households. Furthermore, their study highlighted that a "clear gap in knowledge in existing evidence is the impact of energy bill payment methods on food consumption and/or expenditure" (Snell et al., 2018: 12).

Our paper adds to the literature by providing evidence on the role of PPMs in the heat-or-eat dilemma. More specifically, whether PPMs represent a practical barrier to attaining the recommended level of FVC. We use the most recent and topical release of nationally representative data (January 2019–May 2021) in order to explore the potential role of PPMs on FVC for individuals residing in GB. In addition to the Ordinary Least Squares (OLS) regression models, we employ Oster's bounding approach and Instrumental Variable (IV) estimation methods to respectively test the robustness of our results to omitted variable biases and selection effects. Whilst the use of the exogenous changes in the energy price caps as our IV is a novel addition to the literature, establishing causal relationships with absolute certainty using survey data is always challenging and demanding. Nonetheless, our analysis provides some evidence towards a more causal interpretation of our results. As a sensitivity analysis, we further explore healthy eating using alternative outcomes relevant to the "5-a-day" target and the use of food banks.

Our paper finds the presence of the systematic and negative association between using PPMs for domestic energy bill payments and an individual's FVC. Moreover, our study addresses the urgent policy need for updated and rigorous evidence on the association between payment methods for energy, specifically PPMs, and the consumption of fruit and vegetables. This evidence should be used by policymakers to assess the potential health costs and benefits of their energy policy interventions.

1.1. Background on the energy-price crisis and prepayment meters

The unprecedented increase and volatility in wholesale energy prices since the onset of the pandemic have created concerns about the cost of living in the UK. For example, in GB, the focus of the present study, wholesale gas prices soared by 250% since early 2021 (Ofgem, 2022a), driven by a mix of high global demand following the end of COVID-19 lockdowns and supply bottlenecks exacerbated by the Russia-Ukraine conflict (IEA, 2021). Electricity and gas rates in GB rose by 54% in April 2022, resulting in increases of £693 and £708 in annual energy bills for *typical* dual-fuel customers paying by direct debit (DD) or PPMs respectively (Ofgem, 2022a). The energy crisis is expected to negatively influence food consumption patterns, particularly for the most vulnerable.

It should be noted here that households either purchase energy on credit, e.g., by DD or by cash/cheque on receipt of bill (i.e., post-payment methods), or purchase energy on a pay-as-you-go basis (i.e., prepayment methods). The prepayment segment is considered more vulnerable than post-payment customers by the energy market regulator – the Office for Gas and Electricity Markets (Ofgem, 2019) – partly due to the fact that this payment method is associated with pre-existing debt. This view is largely supported by the Competition and Markets Authority (CMA, 2016)'s energy market investigation which established that prepayment customers face greater detriment on both the demand-side (e.g., lower levels of engagement, perceived and actual barriers to switching tariff, payment method or supplier) and supply-side (e.g., fewer cheaper tariffs, weak competition).

Following the CMA's report, Ofgem introduced price caps in 2017 for prepayment customers. The aim of the caps was to protect roughly 4.5 million, often vulnerable, customers from the detriment associated with limited access to cheaper deals and weak competition in this segment of the retail energy market (CMA, 2016; Ofgem, 2019). Whilst the energy price caps dampened the longstanding price premium since its inception, the premium (around £300/year in 2016) remains with typical PPM customers paying on average more per year in 2019 (£2017) than DD customers (£1971) (CMA, 2016; Ofgem, 2020a).

2. Data

The data are obtained from the longitudinal survey of the UK, Understanding Society: the UK Household Longitudinal Study (UKHLS) (University of Essex, 2022). We rely on Wave 11 (January 2019–May 2021) of the General Population Sample of the UKHLS, a cross-sectional and representative sample of the adult residential UK population, consisting of 29,282 individuals. We focus on this cross-section of data for two key reasons: a) UKHLS introduced the 'food poverty' module for the first time in Wave 11, which allows for the exploration of an important alternative outcome – the use of food banks; and b) the data underpinning our IVs only vary across energy payment methods from 2019 onwards. As noted above, Ofgem introduced price caps in 2017 for prepayment customers, yet it was not until the 1st of January 2019 when separate price caps were implemented for the post-payment segment of the retail energy market (coinciding with the beginning of Wave 11 fieldwork). Additionally, as the data underpinning the main IVs are only available for England, Scotland, and Wales, our analysis is confined to individuals residing in GB. Our final sample for the main analysis contains 24,811 individuals, after adjusting for outliers and invalid responses in all variables used in our analysis.

All analyses are weighted using probability sample weights, ensuring that our sample is representative of the GB population. These sample weights were calculated using backward stepwise logistic regressions on observed predictors, adjusting the published UKHLS sample weights to account for item missingness and unit nonresponse for all variables used in our analysis. Our FVC measures and energy bill payment methods are discussed in detail in the next two sub-sections. Summary statistics and descriptions of explanatory variables used in our analysis can be found in the online Appendix A (Table A1). Overall, the mean values are comparable between the weighted and unweighted results (Table A2), with slightly higher weighted mean values for characteristics typically underrepresented in social science datasets, including individuals without formal education, who are of non-white ethnicity, unemployed, retired, living with a disability, and residing in rural areas.

2.1. Fruit and vegetable consumption

To measure annual FVC, we utilise two sets of survey questions. The first set asks: i) how many days in a usual week “do you eat fruit” (including tinned, frozen, dried, and fresh fruit); and, similarly, ii) how many days in a usual week “do you eat vegetables” (including tinned, frozen, and fresh vegetables, and excluding potatoes, crisps, or chips). The second set of follow up questions establish, on the days one eats iii) fruit or iv) vegetables, how many portions are eaten. Portions of fruit (*PFRU*), vegetables (*PVEG*) and both fruit and vegetables (*PFNV*) eaten in a typical week are calculated by multiplying the typical number of days individuals eat fruit or vegetables provided in i) and ii) with the respective values provided in iii) and iv). To ameliorate the potential impact of outliers, consumption levels above the 99th percentile are replaced with the 99th percentile value. The results are qualitatively identical despite this adjustment.

These outcomes not only capture FVC, but also represent healthy dietary choices (Carrieri et al., 2020). The sample statistics presented in Table 1 (Figure A1, Appendix A) show that the mean portions of fruit and vegetables eaten per week is 26.5; equivalent to 3.8 portions per day and consistent with the recent health survey of adults in England, that is, 3.7 portions per day (NHS, 2020).

Table 1
Definitions and summary statistics – portions of fruit and vegetables and payment method for gas and/or electricity.

Variables	Definition	Mean	Standard deviation
Portions of fruit and vegetables			
PFNV	Portions of fruit (including tinned, frozen, dried and fresh fruit) and/or vegetables (including tinned, frozen and fresh vegetables, excluding potatoes, crisps or chips) eaten per week.	11.560	10.072
PFRU	Portions of fruit (including tinned, frozen, dried and fresh fruit) eaten per week.	14.887	10.349
PVEG	Portions of vegetables (including tinned, frozen and fresh vegetables, excluding potatoes, crisps or chips) eaten per week.	26.447	16.714
Payment method for gas and/or electricity			
PPM	1 = Method of payment for gas and/or electricity is a prepayment (key/card or token); 0=Otherwise.	0.115	0.319
N		24811	

Notes: The first set of variables used to calculate the number of typical days in a week an individual eats portions of fruits and vegetables takes on four categories: Never, 1–3 days, 4–6 days, and every day. Zero is allocated to those who stated ‘never’. The mid-points (i.e., 2 days and 5 days) are used for the intermediate categories. All statistics are weighted using sample weights.

2.2. Energy bill payment methods

We define and focus on an indicator of energy bill payment methods (*PPM*), set equal to 1 if the individual pays for their gas and electricity using a PPM, and 0 otherwise. PPM customers pay for energy on a ‘pay-as-you-go’ basis by adding credit to a smartcard, key or token that can be topped up at local stores. We exclude those using prepayment for one energy source and post-payment for the other as well as those using atypical payment methods (such as paying for energy through government schemes); constituting to about 3% of our original sample in total. This sharpens the allocation of energy prices in our IV analysis; our main findings are qualitatively identical following their inclusion and available on request.

Close to the GB average of 14–15% (BEIS, 2022a), around 12% of our sample use PPMs (Table 1). Figure A1 (Appendix A) shows that, on average, 19.5 portions of fruit and vegetables are consumed per week by those using a PPM, compared to the sample mean of 27.4 portions consumed by post-payment customers – a difference of around one portion per day.

2.3. Covariates

Our analysis controls for a standard set of socio-economic and demographic covariates identified in the literature as being likely determinants of FVC (see, e.g., Devine et al., 2003; Dave and Kelly, 2012; Vinther et al., 2016; Cornelsen et al., 2019). We account for the UK’s monthly food consumer price index (*FOODCPI*) (ONS, 2022), the (log) of annual equivalised household income (*LNINCOME*) and its polynomial (*LNINCOME2*) and for a six-group categorical variable representing their situation in the labour market (*UNEMPLOYED, RETIRED, STUDENT, DISABILITY,* and *OTHER_JOBSTATUS*). These variables may affect individual’s budget constraints, time available for food preparation and cooking, as well as caloric need, within the constraints of employment statuses. We also include educational attainment (*ALEVEL_DEGREE* vs *NODEGREE*) as a further potential confounder on the association between PPM usage and FVC. Moreover, our analysis controls for a set of demographic indicators including age (*AGE*), gender (*MALE* vs *FEMALE*), ethnicity (*WHITE*, *MIXED*, *BLACK*, *OTHER_ETHNICITY*), marital status (*MARRIED, SEPARATED, WIDOW, SINGLE*) and housing tenure (*OWNER* vs *RENTING*). Household size (*HHSIZE*) and the proportion of children in the household (*HHCHILD*) capture different patterns of dietary needs. Nine government office regional indicators for England and indicators for Scotland and Wales, together with a dichotomous variable capturing urban and rural differences (*URBAN* vs *RURAL*), account for potential regional variations.

Table A3 (Appendix A) provides the mean values for the set of our covariates between the prepayment and post-payment groups. It seems that, in line with CMA (2016), the prepayment group have a systematically lower income, are more likely to be single and of non-white ethnicity, are less likely to have a university degree, and more likely to have a long-term illness/disability. Over and above OLS models that control for these covariates and our bounding models that assess the influence of omitted variable bias, we also employ a suite of IV models to account for potential selection effects given the differences in the observable characteristics across the two groups.

3. Methodology

3.1. Baseline econometric specification

Empirically the paper proceeds by regressing the fruit and vegetables variables on the *PPM* indicator using OLS, following the general linear specification:

$$PORTIONS_i = \alpha + PPM_i^{'}\beta + X_i^{'}\delta + \omega_t + \mu_r + \varepsilon_i \quad (1)$$

where, $PORTIONS_i$ represents the weekly consumption of fruit (*PFRU*), vegetables (*PVEG*) and fruit and vegetables (*PFNV*) by individual *i*. Separate regressions are estimated for each outcome. The energy bill payment method is represented by PPM_i. The vector X_i contains the socio-economic and demographic covariates discussed above and are understood to be related with FVC as well as with PPM use. The constant term is denoted by α, whilst β and δ are the regression coefficients to be estimated; ω_t is the vector of month and year indicators capturing seasonality in FVC. It should be mentioned here that these influences may be over and above any potential price effects that are accounted for in our analysis using the UK's monthly food consumer price index (*CPI*). μ_r accounts for regional fixed effects, whilst ε_i represents the error term.

Whilst UKHLS is comprehensive, the dataset is not without limitations. UKHLS does not contain objective information on food consumption patterns, and instead collects self-reported, subjective information about FVC. Such data may suffer from the typical limitations attributed to subjective reporting such as recall and social desirability biases. Exploring the link between energy payment methods and objective measures of FVC could be an interesting avenue for future research, though beyond the scope of this paper.

UKHLS also does not contain data on the energy efficiency of the property or relevant technologies within the home. Whilst our baseline specifications control for a wide array of covariates, including time and regional effects, concerns surrounding unobserved heterogeneity and selection into PPMs may remain. For example, whether individuals/households can pay for energy by drawing down precautionary savings (or can access credit) in order to buffer price or cold weather shocks (as well as cope with the related implications for food consumption patterns) and, thus, decide between pre- or post-payment energy methods (Cullen et al., 2004). Thus, we employ Oster's bounding approach to explore the robustness of our results to omitted variables bias related to unobservables, such as the presence of energy efficient (heating) technologies, which are correlated with the FVC outcome variables and the installation of PPMs.

PPMs are installed either at the request of households (accounting for the balance between the costs and benefits) or proposed, sometimes force-fitted under warrant, by the retail energy supplier and/or landlord. If the household cannot rely on savings or credit to cover energy debt, the installation of PPMs can be used, as a mechanism of last resort, by energy suppliers and/or landlords to collect problematic debt (CMA, 2016). As discussed in detail below, we rely on IV estimation to further address such selection effects.

3.2. The bounding approach

Oster (2019) developed the line of thought put forward by Altonji et al. (2005), arguing that the commonly held view that the stability of coefficients between uncontrolled models (i.e., without covariates) and controlled models (i.e., with covariates) is insufficient to claim that omitted variable bias plays a limited role in regression estimates. Not least because, coefficient stability could simply arise with covariates that have limited explanatory power. Oster (2019) developed the bounding approach, utilising the concomitant movements in coefficients and the coefficient of determination (R^2) between the uncontrolled baseline and the controlled regressions, in order to explore the influence of omitted variable bias on the sample estimate of β.

The importance of unobservables, compared to the variables included in models is captured by the relative degree of selection (δ) and is assumed to fall between 0 and 1. One would expect $0< \delta < 1$ if the covariates included in models are carefully selected based on the evidence established in relevant literature (Oster, 2019). Nonetheless, as suggested by Oster (2019) and Clark et al. (2021), we apply a more cautious degree of selection, $\delta = 1$, which implies that the observed and unobserved covariates are of equal importance.

Theoretically, the R^2 can take a value of 1; however, in practice, the maximum variation explained by empirical models (R^2_{MAX}) may fall below unity. Oster applied the bounding approach using the data published alongside peer-reviewed experimental literature to define a reasonable limit for the R^2. Oster (2019)'s approach considered the literature to be robust to omitted variables if the estimated bounds did not contain zero; in so doing, Oster established a reasonable R^2_{MAX} to be $\min\{1, 1.3\widehat{R}^2\}$, where $\widehat{R}^2$ represents the coefficient of determination in the controlled regression.

If $\beta > 0$, a lower (upper) bound $\beta*$ is estimated with respect to the controlled regression if the model exhibits upward (downward) bias; and the reverse is true if $\beta < 0$. Taking the above into consideration, the bounds are estimated as follows:

$$\beta* = \widehat{\beta} - \delta(\dot{\beta} - \widehat{\beta})\frac{R^2_{MAX} - \widehat{R}^2}{\widehat{R}^2 - \dot{R}^2} \tag{2}$$

where, $\widehat{\beta}$ represents the controlled coefficient of interest specified in Equation (1), $\dot{\beta}$ denotes the coefficient in the uncontrolled model (upon removal of all other covariates in Equation (1)). $\dot{R}^2$ is the coefficient of determination in the uncontrolled regression.

3.3. Instrumental variable (IV) estimations

We employ IV models to address potential remaining concerns about endogeneity associated with the selection into (or potentially endogenous decision to adopt) prepayment methods of payment.

Most customers decide on whether to use PPMs by weighing the costs and benefits. Prices and total energy costs are a key factor in the decision to install or remove PPMs. The PPM price premium largely reflects the lack of incentives to efficiently serve this segment of the market (Mummery and Reilly, 2010). Weak competition further compounds the higher associated cost of installing, maintaining, and servicing PPMs (Ofgem, 2020a). Additionally, other unobserved costs are a source of customer dissatisfaction, including informational gaps (e.g., lack of billing and debt repayment information) and the hassle of topping up the meter at local shops (Mummery and Reilly, 2010).

On the other hand, PPM customers are generally satisfied with the service (Mummery and Reilly, 2010). Only a small proportion (fewer than 5%) attempt to switch to a post-payment credit meter (Ofgem, 2019). An increase in post-payment energy prices raises the likelihood that debt accrues and may nudge (financially vulnerable) customers towards installing a PPM to prevent debt occurring in the future (Ofgem, 2019), especially if problematic debt remains to be paid. The additional flexibility to manage finances, whilst having full control of energy bills (O'Sullivan et al., 2011), appears to outweigh the costs for most prepayment customers (Boardman, 2010; Anderson et al., 2012). Despite the perceived benefits, the increased energy costs associated with PPMs are likely to cause financial hardship and distress, under-utilisation of energy and under-heated homes in low-income and vulnerable households (O'Sullivan et al., 2011).

A supplier or landlord should only encourage the installation of a PPM as a mechanism of last resort to collect problematic debt accrued by individuals struggling to make payments (CMA, 2016). In fact, around 30% of all PPMs are installed because of debt recovery or related reasons (Ofgem, 2019). Breaking down the decision to install a PPM further, Mummery and Reilly (2010) similarly established that the energy supplier requested (4%) or insisted (2%) on the installation, and 28% were installed by landlords. The remaining two thirds of PPM installations were reported as requested by the customer (26%), inherited (35%) or unsure of the origin.

To summarise, households weigh the benefits of PPMs (e.g., budgeting and managing bills) against the costs of utilising PPM services (e.g., higher prices, fewer energy tariffs) – a decision-making process that also underpins whether to choose a property with a PPM installed. The decision to install PPMs is multifaceted and influenced by several agents, if left uncontrolled such factors could potentially introduce endogeneity in our baseline estimates. Our IV models aim to circumvent remaining endogeneity related to the decision to install PPMs.

The IVs rely on the variation in energy price caps, specifically on the standing charge caps – that is, on the fixed elements of the two-part energy tariff paid (£) per annum – which limit the rates suppliers can charge prepayment and post-payment customers. Ofgem introduced the price caps in 2017 for prepayment customers, and separate caps were rolled out for the post-payment segment from 1st January 2019. Ofgem announces revised levels of the price caps each year in February and August, reflecting changes in the cost of supplying energy over the preceding 6 months. The revised price caps are then implemented in April and October, respectively. The data on price caps are publicly available (Ofgem, 2022b) and matched to the UKHLS by month, year, region, and payment method. The matching process is detailed in the online Appendix B.

We expect the standing charge price caps to influence the process underpinning the decision to install a PPM, as captured by our first stage-IV regression as follows:

$$PPM_i^* = \alpha + PRICECAPS_i^{'}\gamma + X_i^{'}\varphi + \omega_t + \mu_r + u_i \tag{3}$$

where, PPM_i^* represents the latent indicator variable, $PRICECAPS_i$ is the vector of gas and electricity standing charge price caps (F_G, F_E). The first-stage error term is represented by u_i. In practice, the decision to install a PPM is estimated using a linear probability model (LPM), conditioning on the covariates (X_i) included in Equation (1).

The PPM price premium can be observed in the variation of the standing charge over time (Appendix B, Figure B1). The premium is prominent in comparison with the most frequently used post-payment method (i.e., DD), and evident in 2019 for electricity payments on receipt of bill and similarly for gas payments until 2021. We note that we utilise the DD price caps for the reference group (see Appendix B), since most post-payment customers (83%) use this method of payment (Ofgem, 2019). Nonetheless, the results remain consistent if the standard credit (i.e., receipt on bill) price caps are applied to the post-payment reference group and are available upon request.

Within the PPM price cap, crucially, Ofgem includes allowances – the payment method uplift and earnings before interest – and additional headroom, compared to post-payment, reflecting the difference in service and maintenance costs (Ofgem, 2020a). Hence, if the standing charge caps are employed as IVs, it may be assumed that they further influence the potentially endogenous regressor (*PPM*) via the allowances and headroom allocated to the prepayment price caps by Ofgem, which further vary by time and fuel type (Appendix B and Figure B1). Through such channels, the standing charge price caps are anticipated to be strongly associated (in the causal pathway) with the decision to install a PPM, and thus satisfying the relevance condition of an IV analysis.

Yet, the IVs are only valid insomuch as they are correlated with the endogenous variable and exogenous to the error term of the second stage equation. This indicates that our instruments can only affect the outcome (fruit and/or vegetable consumption) indirectly through the payment method (*PPM*). An advantage of using the price caps as an IV for our analysis relates to the fact that the levels set by Ofgem are based on the cost of supplying energy over the six (eight) months prior to its announcement (implementation):

> "[…] allowing the cap to change over time according to movements in exogenous cost indices, including wholesale costs, network costs, policy costs and inflation."
>
> - (CMA, 2016: 58)

Hence movements in the price caps are unlikely to directly affect the individual's current FVC. Utilising standing charges further ensures that we bypass potential direct links between energy prices and FVC, since, unlike prices charged per unit of consumption (the other element of the two-part tariff), standing charges are by definition independent of energy consumption. This may indicate that standing charge price caps are a strong contender to satisfy the exclusion restriction condition. Table 2 presents summary statistics for the standing charge price caps used in our main IV analysis.

Table 2
Definitions and summary statistics – Energy price caps.

Variables	Price caps	Mean	Standard deviation
F_G	Fixed gas standing charge (£/year)	93.840	10.202
F_E	Fixed electricity standing charge (£/year)	84.646	7.885
N		24811	

A potential limitation of our IVs relates to the aggregate, rather than individual-specific, nature of the price caps. On the one hand, the price caps may only be indirectly relevant for individuals who have secured discounted, fixed energy tariffs since the price caps represent the cost of switching to a variable tariff. On the other hand, whilst the price caps closely follow the market average for variable tariffs, the values are a proxy for prices allocated by retail energy suppliers. Given the challenges surrounding credible individual-specific instruments, several studies have relied upon aggregate data including grocery retail prices (Allcott et al., 2018) and energy retail prices (e.g., Awaworyi Churchill et al., 2020; Burlinson et al., 2021). Such instruments are considered credible in satisfying the exclusion restriction yet vary in their relevance. In some cases, the IVs appear relatively weakly correlated with the endogenous variable, perhaps due to the aggregate rather than individual-specific data structure. Like Allcott et al. (2018), for example, our instruments perform very well in the first stage regressions.

Notwithstanding, we employ the Lewbel IV estimator (2012) as additional instrumental analyses to address the preceding limitation; this estimator uses heteroskedasticity to *internally* generate IVs as functions of the model's data in the first stage regression. Baum and Lewbel (2019: 765) argue that heteroskedasticity-based identification is best implemented to "check robustness of results to alternative identifying assumptions and to increase estimation efficiency". Specifically, we estimate the Lewbel IV models using internal and both internal and external IVs. Comparisons of the results between the external IV models and the Lewbel estimates serve as a robustness test of our results and increase confidence in our findings when assessing the potential limitation in our IVs outlined above.

As our study is based on secondary analysis of UKHLS data, we should mention that all UKHLS participants gave their informed oral consent to take part in each wave of the study; participants were enrolled only after consent was provided. The UKHLS has been approved by the University of Essex Ethics Committee. More details on ethical approval of the UKHLS dataset is available at University of Essex (2021).

4. Results

4.1. OLS estimations of fruit and vegetable consumption on PPM usage

Table 3 presents the OLS estimations of the consumption of fruit (*PFRU*), vegetables (*PVEG*) and fruit and vegetables (*PFNV*) on the utilisation of PPMs. The table shows the separate regression coefficients for each outcome in columns 1 to 3, respectively. Across all models there is a strong negative association, which is statistically significant at the 1% level. For example, all else constant, individuals using a PPM to pay for their energy consume almost 3 fewer portions (2.74) of fruit and vegetables on average per week than individuals with a post-payment credit meter (Table 3, Column 3).

Table 3
Baseline OLS regressions of portions of fruit (PFRU), vegetables (PVEG) or fruit and vegetables (PFNV) on prepayment meter (PPM) use.

Specifications	PFRU (1)	PVEG (2)	PFNV (3)
PPM	−1.242***	−1.499***	−2.740***
	(0.347)	(0.373)	(0.591)
Controls	Y	Y	Y
Observations	24811	24811	24811
R^2	0.059	0.061	0.081

Notes: *p < 0.1, **p < 0.05, ***p < 0.01. Robust standard errors in parentheses. Controls include socio-economic, demographic characteristics, food CPI and regional/time fixed effects.

Table 4
OLS and bounding regressions for portions of fruit (PFRU), vegetables (PVEG) or fruit and vegetables (PFNV) on prepayment meter (PPM) use.

Specifications	(1)	(2)	(3)
Dependent variable	$\beta^*(\min\{1, 1.3\widehat{R}^2\}, \delta = 1)$	$\delta(\min\{1, 1.3\widehat{R}^2\}, \beta^* = 0)$	Bounds
PFRU	−0.010	1.007	[-1.242, −0.010]
PVEG	−0.222	1.153	[-1.499, −0.222]
PFNV	−0.152	1.052	[-2.740, −0.152]

Notes: *p < 0.1, **p < 0.05, ***p < 0.01. Controls include economic and socio-economic, demographic characteristics, food CPI, and regional/time fixed effects.

4.2. Bounding estimates

In this sub-section we explore the potential influence of omitted variable bias in our models using Oster (2019)'s approach. Column 1 (Table 4) shows the estimates using Oster's approach, assuming unobservables are equally important as the observable controls (i.e., $\delta = 1$). Column 2 contains the estimated relative degree of selection (δ) that would render the main result (β^*) statistically and insignificantly different from zero. Column 3 presents the bounds, collating the results contained in column 1 (i.e., $\delta = 1$) and the OLS estimates shown in Table 3 (i.e., $\delta = 0$).

The bounding estimates presented in column 1 (Table 4) fall below zero, supporting the preceding findings of a negative association between PPM usage and FVC. The estimated relative degree of selection is greater than one. Hence, the unobservables would have to satisfy the unlikely assumption of being more important than the observed controls to render the associations of interest statistically insignificant. Ratios exceeding a value of one may be considered robust, since few studies survive the conservative assumption of equal selection as in column 1 (Altonji et al., 2005; Oster, 2019). Overall, the association between PPM usage and FVC appears robust to potential omitted variable bias as the bounds (column 3) do not contain zero.

4.3. Instrumental variable (IV) estimations

To address further potential endogeneity concerns surrounding selection into PPMs, we utilise IV regression and a set of plausible instruments relying on the variation in the standing charge price caps.

Table 5 presents the IV estimates using gas and electricity standing charge price caps (F_G, F_E) as instruments for the relationship between PPM use and the consumption of portions of fruit (column 1), vegetables (column 2), and fruit and vegetables (column 3); panels A and B include the second and first stage regression results, respectively. The second stage coefficients support our preceding findings of a systematic negative association between PPM use and FVC (Table 5, Columns 1–3), with

Table 5
Instrumental variable (IV) regressions of portions of fruit (PFRU), vegetables (PVEG) or fruit and vegetables (PFNV) on prepayment meter (PPM) use.

Specifications	PVEG-IV (1)	PFRU-IV (2)	PFNV-IV (3)
Panel A. Second stage results			
PPM	−1.320***	−1.464***	−2.784***
	(0.351)	(0.380)	(0.601)
Panel B. First stage results			
F_G	0.049***	0.049***	0.049***
	(0.000)	(0.000)	(0.000)
F_E	0.085***	0.085***	0.085***
	(0.001)	(0.001)	(0.001)
Controls	Y	Y	Y
Observations	24811	24811	24811
F statistic	84232.327	84232.327	84232.327
J statistic (p-value)	0.516	0.980	0.694
Robust Durbin-Wu-Hausman (p-value)	0.238	0.583	0.724

Notes: *p < 0.1, **p < 0.05, ***p < 0.01. Robust standard errors in parentheses. Controls include socio-economic, demographic characteristics, food CPI, and regional/time fixed effects.

the corresponding IV estimates being very close to the OLS regression coefficients (Table 3).

We note the high correlation between the IVs and the potentially endogenous regressor (*PPM*), with the corresponding F-statistic (=84232) consistently exceeding Staiger and Stock (1997)'s rule-of-thumb (i.e., F > 10). The F-statistic remains greater than 104.7, hence the standard errors do not need to be corrected as suggested by Lee et al. (2021). Moreover, the IVs appear valid, considering the J test statistics fail to reject the null hypothesis of instrument validity.

The findings using the Lewbel IV estimator are presented in Table 6, based on the sole use of internally generated IVs (columns 1–3) and the dual use of internal and external (F_G, F_E) instrumental variables (columns 4–6). The findings based on internally generated instruments (Table 6, Columns 1–3) are remarkably similar to those presented above. Like our results from the standard IV models (Table 5), the internal instruments lead to coefficients close to the OLS estimates– as one would expect with instruments that are highly correlated (F = 620) with the endogenous regressor (Baum and Lewbel, 2019). The J-test statistics suggest that the internal instruments are valid.

It is important to note that the robust Durbin-Wu-Hausman (DWH) test in all IV results presented thus far fail to reject the null hypothesis of no endogeneity (Tables 5 and 6). In other words, any potential endogeneity in *PPM* does not appear to affect our OLS estimates. Hence our baseline OLS estimates are preferred over the IV results, since they not only appear consistent (i.e., unbiased) but are also the most efficient (i.e., smallest variance).

4.4. Further robustness checks and alternative outcomes

The price caps currently protect around 22 million consumers in GB on PPMs and (default or standard) variable tariffs. One potential caveat of the price-based IVs relates to the fact that the price caps only *directly* apply to customers if they pay for energy on a tariff that allows prices to vary for an indefinite amount of time. However, UKHLS does not distinguish between individuals who pay for energy on a fixed tariff (i.e., prices that do not vary over the term of a contact, typically 12–18 months) or variable tariffs. Nonetheless, this issue is tempered since nearly all (98%) PPM customers and over 60% of post-payment customers are on a variable tariff (Ofgem, 2020a). In addition, for a typical customer, the price caps closely follow the market average variable energy bill of the "Big 6" suppliers (Appendix A, Figure A2), which supply the majority of prepayment (98%) and post-payment (70%) customers (Ofgem, 2020b; Ofgem, 2022c). Hence, the price caps not only directly affect those on a variable tariff, but also are *indirectly* relevant to those on a fixed tariff since the price caps represent the cost

Table 6
Lewbel instrumental variable (IV) regressions of portions of fruit (PFRU), vegetables (PVEG) or fruit and vegetables (PFNV) on prepayment meter (PPM) use.

Specifications	PVEG-IV (1)	PFRU-IV (2)	PFNV-IV (3)	PVEG-IV (4)	PFRU-IV (5)	PFNV-IV (6)
	Internal IVs			Internal and external IVs		
Second stage results						
PPM	−0.985**	−1.481***	−2.466***	−1.298***	−1.495***	−2.793***
	(0.425)	(0.443)	(0.723)	(0.354)	(0.382)	(0.607)
Controls	Y	Y	Y	Y	Y	Y
Observations	24811	24811	24811	24811	24811	24811
F-statistic	619.490	619.490	619.490	5140.555	5140.555	5140.555
J-statistic (p-value)	0.057	0.613	0.282	0.051	0.646	0.233
Robust Durbin-Wu-Hausman (p-value)	0.330	0.321	0.214	0.170	0.737	0.479

Notes: *p < 0.1, **p < 0.05, ***p < 0.01. Robust standard errors in parentheses. Controls include socio-economic, demographic characteristics, food CPI, and regional/time fixed effects.

faced by customers upon leaving fixed contracts.

To further alleviate concerns surrounding the ability to precisely match the price cap information to those on fixed or variable tariffs, we employ an alternative set of price-based instruments. We utilise the market average gas and electricity standing charges ($\overline{F}_G$, $\overline{F}_E$) published by BEIS (2021a; 2021b), since this set of IVs represents a more general basket of tariffs than the price caps. Following the methodology outlined in Section 3 and Appendix B (Table B2), we match BEIS's PPM prices to prepayment customers and DD prices to post-payment customers by region and by year. Table A4 presents the standard IV estimates using BEIS′ average gas and electricity standing charges ($\overline{F}_G$, $\overline{F}_E$; columns 1–3) and the dual use of the internal and external Lewbel's IV analysis (columns 4–6). Overall, these findings are broadly in line with, and further reinforce, our results presented earlier.

As the main outcomes are count data, we show the findings to be robust using Poisson and Poisson-IV estimation. Poisson IV is conducted by the general methods of moments (GMM) control-function estimator under multiplicative errors (Wooldridge, 2010). As in our main analysis, PPM_i is instrumented by the vector of standing charge price caps ($PRICECAP_i$), augmenting the multiplicative Poisson model as follows:

$$PORTIONS_i = exp\left(PPM_i^{'}\beta + X_i^{'}\varphi + \omega_t + \mu_r + \left(PPM_i - \widehat{\varphi}PRICECAPS_i^{'}\right)\rho\right) \tag{4}$$

where, the inner brackets ($PPM_i - \widehat{\varphi}PRICECAPS_i^{'}$) represent the residuals (v_i) estimated from a linear regression of PPM_i on the instruments ($PRICECAP_i$), and $\widehat{\varphi}$ denotes the coefficients to be estimated. v_i controls for endogeneity in the model, hence the endogeneity of PPM_i can be tested under the null hypothesis that $\rho = 0$, where ρ is the coefficient vector on v_i in the augmented multiplicative Poisson model. Table A5 (Appendix A) presents the relevant results using the Poisson (columns 1–3) and the Poisson-IV estimator (columns 4–6); overall, these results align with the corresponding linear regression models in Tables 3 and 5

We extend our analysis exploring the potential heterogeneous association between PPMs and PFNV by socio-economic groups (Table A6, Appendix A). Overall, we found limited evidence of the presence of systematic differences in the association between PPMs and consumption patterns by age (at least 65 years old versus younger), poverty levels, house tenure (rented versus non-rented accommodation) and household composition. Gender, however, is an exception. Females who prepay for energy (compared to those who post-pay) are associated with a systematically lower FVC compared to males, with the relevant differences in the estimated coefficients for PPM by gender being statistically significant at the 5% level (t-statistic = −2.225).

To further explore the impact of PPMs, we carry out additional sensitivity analysis using alternative outcomes related to healthy eating, specifically dichotomous variables set equal to one: i) if an individual (at least) eats the ascribed five portions of fruit and/or vegetables a day (*5ADAY*), and zero otherwise; and, ii) if the individual or another member of the household stated that they used a food bank or similar service over the past year, and zero otherwise (*FOODBANK*). Whilst the UK has witnessed rapid growth in demand for food banks, providing a lifeline to households unable to access food otherwise, the latter outcome recognises that food parcels are generally energy-dense, nutrient-poor, and often lacking in fruit, vegetables, and dairy (Oldroyd et al., 2022). The variable definitions and summary statistics are presented in Table A7 (Appendix A). These alternatives sequentially replace the outcome in Equation (1) and are estimated using LPMs. The IV estimates, using either external (price-based instruments) and/or the Lewbel internally generated instruments, are consistent with OLS and available upon request.

Table A8 reveals that PPM use is associated with a lower probability (6.2 percentage points) of consuming at least five portions of fruit and/or vegetables a day than post-payment users (column 1). Hence, on average, *ceteris paribus*, PPM use is not only associated with lower FVC, but also associated with a reduction in the probability of meeting the WHO's recommended "5-a-day". In addition, Column 2 shows that prepayment, compared to post-payment, is associated with a higher probability (1 percentage point) of using a food bank or a similar service. These findings are statistically significant at the 1% and 5% level, respectively.

5. Conclusions

Our paper contributes to the literature by exploring the role of PPMs in the heat-or-eat dilemma. Using a representative sample of GB, we find robust evidence of lower FVC amongst individuals using PPMs, compared to those using post-payment methods. On average, our point estimates suggest that individuals using a PPM consume 2.7 fewer potions of fruit and vegetables per week – a roughly even split between fruit (1.2) and vegetables (1.5). Our findings hold when utilising Oster's bounding approach, and therefore can be viewed as robust to omitted variable bias. We further alleviate endogeneity concerns related to the decision to adopt PPMs, through IV estimation. In so doing, we contribute to the literature by using the exogenous variation in the standing charge price caps as an IV. Our OLS results are preferred since the estimates appear consistent and the most efficient as opposed to the IV analyses. Further specification checks highlight the deleterious impact PPMs has on one's FVC, including the use of food banks and not eating the recommended "5-a-day", which comes with a greater associated risk of morbidity and mortality (Boeing et al., 2012; Wang et al., 2021).

Our results offer important insights for policymakers – with clear public health policy implications. The financial support aimed at reducing heating or eating self-rationing during the cost-of-living crisis is particularly relevant. Despite the UK governments' "cost-of-living payments" being labelled in a way that could encourage households to spread cash transfers more evenly across food and energy (Beatty et al., 2014b), the support could be absorbed by the latter due to the sheer scale of the energy-price crisis. Therefore, in light of our evidence, a public health policy message may be to allocate additional financial support to PPM users, which improves access to healthy food during the cost-of-living crisis. For example, public health initiatives such as the Healthy Start Scheme (Best Start Foods) in England and Wales (Scotland) may be expanded to include vulnerable PPM users in order to increase FVC and promote the beneficial health effects of the latter (Murray et al., 2013).

Second, the UK government potentially overlooked an opportunity to target support in April 2022 to those most in need by allocating energy bill rebates universally or by council tax bands – rather than to households with PPMs, for example. In response to the lack of targeted support, the Welsh government issued £4 million in fuel vouchers to support those with PPMs or without mains gas connections (Welsh Government, 2022). UK-wide support could not only be targeted towards PPM users, but also fine-tuned to increase in line with price rises and account for the "postcode lottery" in standing charges which have increased more in some areas (e.g., North Wales and Merseyside, 102%) than others (e.g., London, 38%) (BBC, 2022). Based on our findings, these targeted support measures may increase healthy food choices (in particular fruit and vegetables) for those more vulnerable; this may be viewed as a preventable measure from a public health perspective as healthier food has the potential to reduce CVD, cancer, and premature mortality risks (Aune et al., 2017).

Third, with the cost-of-living biting, short-term relief is necessary but not sufficient to protect households from future energy price shocks. To tackle the ongoing risks associated with unbalanced diets arising from the heat-or-eat trade-off, the UK government should develop strategies that could make a lasting difference to households. The government has not heeded calls for a social tariff (BEIS, 2022b), which *first* targets low-income and vulnerable households using PPMs (NEA, 2022). The social tariff could eliminate the PPM price premium, bringing prices in-line with DD customers – paid for in the short-term by a windfall tax on oil and gas companies and general taxation in the longer-term. Our study shows that supporting households who bear this premium (as opposed to those on other domestic fuel payment methods) could be more effective for protecting women's health, given the observed and more pronounced association between FVC with PPMs, compared to men's.

Finally, over the medium and long term, governments should scale up the installation of energy efficiency and low-carbon technologies in the residential sector, including insulation and solar panels. Policy instruments aimed at reducing energy demand, whilst ensuring energy services are affordable, may not only help vulnerable households (including PPM users) achieve adequate levels of energy, but also could increase their resilience to future energy price volatility, reduce carbon emissions, and have the potential to improve the quality of diets and population health as a result.

Credit author statement

Andrew Burlinson: Conceptualisation; investigation; formal analysis; methodology; validation; writing (original draft); writing (review and editing); software. Apostolos Davillas: Conceptualisation; investigation; formal analysis; methodology; validation; writing (original draft); writing (review and editing); software. Cherry Law: Conceptualisation; investigation; formal analysis; methodology; validation; writing (original draft); writing (review and editing); software.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

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