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Are you puffing your children's future away? Energy poverty and childhood exposure to passive smoking*

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Abstract

We examine whether having a parent who smoked during one's childhood or adolescence increases the probability of being in energy poverty in adulthood. We find that people who had a parent who smoked when they were young are 0.8 to 1.4 percentage points more likely to be in energy poverty later in life. Various checks suggest that this relationship can be regarded as being plausibly causal. We identify health, human capital, labour market outcomes and noncognitive traits as channels through which early life exposure to passive smoking increases the likelihood of being in energy poverty. Our results have important implications for early life interventions to address the deficits caused by exposure to passive smoking.

JEL classification: Q41, I32

Keywords: energy poverty, fuel poverty, smoking, early life shocks, Australia

1. Introduction

When parents engage in behaviours that are detrimental to their health, this frequently not only directly affects the parents, but has spillover effects to their children. There is growing recognition that these spillover effects can be persistent. We examine the long-term effects of the health behaviours of parents on outcomes in adulthood of their children, focusing on exposure to parental smoking. As we discuss in detail in Section 2, children have immature respiratory and immune systems that make them particularly susceptible to passive smoking. Exposure to passive smoking in childhood can cause asthma and chronic respiratory problems in the short-term, which persist and accumulate in the longer-term, leading to serious health risks, associated with a decline in vital organs and mental functioning. There is also evidence that exposure to smoking makes it more difficult to concentrate in school, reducing the accumulation of human capital. The combined education and health consequences of exposure to smoking are likely to be cumulative and lead to poorer outcomes later in life.

Previous studies have examined the effects of being exposed to parental smoking in childhood and adolescence on a range of outcomes later in life, such as cognitive function (Rovio et al., 2020), employment (Prakash & Kumar, 2021), health (Jaakkola et al., 2021; Juonala et al., 2019) and morbidity (Diver et al., 2018). Rovio et al (2020) find that exposure to passive smoking early in life is associated with having poorer memory and associated learning outcomes in mid-life. Prakash and Kumar (2021) find that exposure to passive smoking during one's childhood increases the likelihood of being unemployed later in life. Jaakkola et al (2001) and Juonala et al. (2019) find that exposure to passive smoking in childhood increases the risk of obesity and having associated heart disease later in life, while Diver et al (2018) find that exposure to passive smoking early in life increases the likelihood of premature death.

One gap in the extant literature is the effect of exposure to passive smoking in childhood on the likelihood of being in energy poverty in adulthood. We address this gap in the literature by extending existing studies to be the first to examine whether exposure to parental smoking in one's childhood or adolescence is associated with a higher likelihood of being in energy poverty later in life. To do so, we use nationally representative longitudinal data from the Household, Income and Labour Dynamics in Australia (HILDA) survey, covering the period from 2005 to 2019. Our identification strategy compares the effect of parental smoking on the likelihood of being in energy poverty in adulthood for those whose parents smoked with those whose parents did not smoke during one's childhood and adolescence. We control for observed characteristics of survey respondents in their childhood and adulthood as well as employing state and time fixed effects, which we use to account for permanent differences across states and territories and time-varying factors correlated with energy poverty.

We supplement the main analysis using a range of approaches – the bounding analysis proposed by Oster (2019); an identification strategy, proposed by Lewbel (2012) that does not rely on external instruments, but rather constructs an internal instrument based on the presence of heteroskedasticity in the data; and propensity score matching (PSM) – to show that our estimates can reasonably be attributed as being causal.

We examine health, human capital, labour market outcomes and Locus of Control (LoC) as potential channels through which exposure to passive smoking in the home could affect proclivity to be in energy poverty later in life. We find that exposure to passive smoking in childhood contributes to being in energy poverty later in life and that mental health, general health, educational attainment, labour market factors (the probability of being employed and income) and LoC are channels through which early life exposure to smoking affects the probability of being in energy poverty in adulthood. We show that early life exposure to smoking increases the probability of being in energy poverty through income poverty via poor health and education and labour market outcomes. We show that exposure to early life smoking nudges people to be more external on LoC, which previous research suggests is associated with paying higher energy prices and using home appliances in an inefficient way (Awaworyi Churchill & Smyth, 2021b). Thus, we show *why* exposure to second-hand smoking in childhood and adolescence contributes to one having low income and having high energy bills.

We make three main contributions to the literature. First, we contribute to the literature that has examined the effect of adverse early life experiences, and, in particular, being subject to passive smoking in childhood and adolescence, on outcomes later in life (Diver et al., 2018; Jaakkola et al., 2021; Juonala et al., 2019; Prakash & Kumar, 2021; Rovio et al., 2020).

Second, we contribute to the nascent literature on the behavioural and environmental reasons why some people exhibit a higher likelihood of being in energy poverty. Traditionally, most research on the causes of energy poverty has focused on the roles of high energy prices, low income, energy inefficient housing and energy inefficient home appliances (Best & Burke, 2019; Legendre & Ricci, 2015; Moore, 2012). While these studies have helped characterize whether people live in energy poverty, they do not tell us *why* one has low income and/or has high energy bills. As a result, a new strand of literature has emerged that seeks to understand the behavioural, environmental and social factors that explain why people are in energy poverty. While this "literature is still in its infancy" (Apergis et al., 2021), it has shown that characteristics, such as ethnic diversity and trust (Awaworyi Churchill & Smyth, 2020), home ownership status (Abbas et al., 2020), human capital accumulation (Apergis et al., 2021), problem gambling (Farrell & Fry, 2021) and financial inclusion and savings behavior (Dogan et al., 2021; Koomson & Danquah, 2021) are important determinants of energy poverty.

Third, we examine the channels through which our observed relationship occurs, which is important for thinking about appropriate social policies to address the effect of early life adversity on energy poverty. We find that health, labour market outcomes and LoC are all channels. Thus, exposure to passive smoking affects the likelihood of being in energy poverty through affecting the probability of having a low income, as well as people's likelihood to switch suppliers, negotiate a better energy plan with their existing supplier and reduce expenditure on energy through LoC as a non-cognitive trait. We explore the implications of these results for the formulation of appropriate social policies to address the early life deficit caused by spillovers from adverse health behaviours caused by exposure to passive smoking.

The study closest to ours is Cheng et al. (2021) who examined the role of an early life shock, defined as being a child or adolescent in China's 1959-1961 Great Famine, on the probability

of being in energy poverty in adulthood. They find that a one unit increase in the intensity of the Great Famine, measured by the number of excess deaths per 100 people, in the province in which one grew up, is associated with a 1.8-3.5 percentage points decline in the probability of being in energy poverty in adulthood. The authors attribute this result to the psychological effects of the Famine, which contributes to success in later life. Specifically, growing up in the Famine contribute to the development of adaptive and coping skills – what they term "psychological assets" – that help to make one more successful later in life.

Cheng et al. (2021) focus on the role of early life shocks; however, early life shocks due to catastrophic events, such as earthquakes, famines or wars, are fortunately infrequent. More generally, a large literature exists that attests to the importance of the home environment on children's socioeconomic development and outcomes later in life (see, e.g., Gennetian, 2005). What we do not know is how early life experiences in the home affect the likelihood of being in energy poverty later in life. One aspect of early life experiences in the home that is of particular interest to health professionals is whether children are exposed to passive smoking. Unlike events such as famines that few people will ever experience as children, exposure to second-hand smoke in the home is relatively common. It is estimated that about a quarter of children of children have been exposed to second-hand smoking at home in Canada, Cuba and the United States and that figure might be as high as 60 per cent in Europe (Öberg et al., 2011).

Our study also differs from Cheng et al. (2021) with respect to its findings which have implications for social policy. While Cheng et al. (2021) find that early life adversity reduces the likelihood of being in energy poverty in adulthood, we find that adverse early life experience leads to poorer outcomes later in life. This finding is consistent with the literature on the long-term effects of passive smoking in childhood and with the vast majority of the literature that has examined how early life adversity affects outcomes later in life (see, e.g., Almond & Currie, 2011). In addition, while Cheng et al. (2021) identify income as the sole channel, we identify a broader set of mechanisms. Specifically, we identify early life education and social policies to build resilience additional avenues for addressing early life deficits due to passive smoking.

2. Why should exposure to parental smoking influence energy poverty?

Conceptually, health, human capital, labour market outcomes and LoC in adulthood represent potential channels through which exposure to parental smoking in childhood and adolescence could influence the likelihood of being in energy poverty in adulthood.

2.1. Health outcomes

Health is an important channel through which early exposure to parental smoking could influence the probability of being in energy poverty in adulthood. There is a well-established relationship between childhood exposure to smoke and health outcomes in the short- and long-terms (Ciaccio & Gentile, 2013). Children have relatively immature respiratory and immune systems that make them vulnerable to impaired functioning of the lungs and vascular systems (Chuang et al., 2011; Diver et al., 2018; Miller et al., 2002; Schwartz, 2004; West et al., 2015). In the short-term, exposure to parental smoking increases the risk of asthma and chronic

respiratory diseases (Fagerström, 2002; Marangu & Zar, 2019). Given that the effects of exposure to smoke are cumulative over time (Juonala et al., 2019), such short-term health effects can persist into adulthood when exposure to parental smoking causes a decline in important organs or systems. For instance, the effect of parental smoking on impairing lung function and causing developmental issues with the vascular system, have been linked to long-term adverse physical and general health outcomes in adulthood (Raghuveer et al., 2016).

The established correlation between physical and mental health lends support to the long-term effects of exposure to parental smoking on mental health in adulthood (Goodwin et al., 2014; Ohrnberger et al., 2017). Additionally, evidence suggests that the psychological effects of exposure to parental smoking in childhood can linger on into adulthood. Thus, early exposure to smoking has been linked to higher rates of depression, anxiety and other mental health disorders as an adult (Fluharty et al., 2016; Taha & Goodwin, 2014).

People who have poor physical or mental health as adults have a higher likelihood of being in energy poverty for several reasons. First, some health conditions require that minimum temperature requirements be met (Free et al., 2010). People with existing health conditions requiring specific thermal needs are likely to pay more to maintain thermal comfort, which could increase their expenditure on energy. Second, people in poor health may be less likely to leave the home, contributing to higher energy expenditure. Third, people with certain mental health problems may find it difficult to communicate payment problems to energy retailers or to negotiate a better plan with their supplier. It has been noted that people "with generalised anxiety disorder can struggle with complex financial tasks such as comparing different energy tariffs, and anxiety can be triggered by certain forms of communication, such as opening bills or talking on the phone" (VCOSS, 2018, p. 24). Fourth, poor health is linked to poor labour market outcomes and lower income, which contributes to energy poverty.

2.2. Human capital accumulation

Poor physical and mental health in childhood resulting from exposure to smoke reduces the rate of human capital accumulation. Specifically, poor health is negatively associated with school attendance and early cognitive development (Jackson et al., 2011; Sandeberg et al., 2008). Evidence suggests that poor health is associated with lower test scores and schooling attainment (Currie & Stabile, 2006; Fletcher & Wolfe, 2008). Beyond the indirect health effects of smoking on human capital accumulation, parents who smoke may have less money to spend money on their children's education, including additional support such as after school tutoring.

Poor educational attainment and cognitive functioning can be linked to outcomes such as fewer labour market opportunities, lower wages, and ultimately income poverty (Awaworyi Churchill & Mishra, 2018; Barrett, 2012; Kingdon & Unni, 2001; Lin et al., 2018), which is associated with energy poverty (Okushima, 2016). Poorer educated individuals may also be less likely to switch to another supplier or negotiate with their own supplier; hence, paying higher energy prices. Studies document that less well educated individuals have lower self-efficacy when it comes to negotiation (Sheehy-Skeffington & Rea, 2017), making them less able to cope with situational anxiety or stress associated with switching (Brooks & Schweitzer, 2011). Switching

can also be extremely complex. For example, the Thwaites et al. (2017) report into the energy sector in Victoria in Australia noted that energy bills tend to be complicated, making it hard for people with poor cognitive functioning to understand whether one is on the best plan.

2.3.Labour market outcomes

Individuals with lower educational attainment and impaired health, due to exposure to second-hand smoking in early life, are likely to have poorer labour market outcomes and lower income in adulthood. A large body of literature links good health with labour market opportunities and being productive (see, e.g., Böckerman & Maczulskij, 2018; Contoyannis & Dooley, 2010; García-Gómez, 2011; Goetzel et al., 2003). Studies suggest that people with existing health conditions are less productive and often work reduced hours (Bubonya et al., 2017; Meerding et al., 2005). Thus, poor labour market outcomes and low income, can be a channel through which exposure to parental smoking early in life can contribute to energy poverty in adulthood.

2.4.Locus of Control

LoC is a non-cognitive trait that is an important channel through which early exposure to parental smoking could influence energy poverty in adulthood. Individuals can be classified as either internal or external on LoC depending on the extent to which they believe that they have control over their lives. People who are external on LoC believe that events in their life result from factors that they are unable to control, such as fate, luck and the action of others, while people who are internal on LoC believe that actions have consequences and their own behaviour and actions are responsible for events they experience (Lekfuangfu et al., 2018).

LoC is formed during childhood and adolescence and is relatively stable among adults (Cobb-Clark & Schurer, 2013). Several studies suggest that exposure to parental smoking in childhood nudges one to be more external on LoC (Nowicki et al., 2018; Prakash & Kumar, 2021). This response could reflect several factors. It could, in part, be a physiological response to inhaling passive smoke. It could reflect an environmental response, given that children do not have any control over their home environment, leading to learned behavior. It could also reflect more distant parenting strategies of parents who are smokers (Nowicki et al., 2018).

Being external on LoC is associated with higher likelihood of being in energy poverty as an adult for several reasons. Those who are more external on LoC have poorer mental and physical health (Awaworyi Churchill et al., 2020a; Buddelmeyer & Powdthavee, 2016), lower educational attainment, worse labour market outcomes and lower savings (Caliendo et al., 2020; Caliendo et al., 2015; Cobb-Clark et al., 2016; Coleman & DeLeire, 2003). People who are more external on LoC are also more likely to be in energy poverty because they are less likely to take relevant steps to reduce their expenditures on energy. For instance, people who are more external on LoC are less likely to adopt energy saving appliances and lighting or switch off lights when leaving a room (Awaworyi Churchill & Smyth, 2021b). People who are more external on LoC are also less likely to switch suppliers or negotiate with their existing supplier because they are likely to feel less responsible for their expenditure on energy.

3. Data

We use Release 19 of the HILDA survey, which is an Australian longitudinal survey covering the period from 2001 to 2019. The HILDA survey reports on the health, labour market dynamics and socioeconomic outcomes of Australians aged 15 years and above. The HILDA survey was initiated, and is funded, by the Australian Government Department of Social Services. The survey, since its inception in 2001, has been managed by the Melbourne Institute: Applied Economic and Social Research at the University of Melbourne. The HILDA survey began with a large national probability sample of Australian households occupying private dwellings (Summerfield et al., 2019). All members of the household that provided at least one interview in the first wave formed the basis of the panel that was reinterviewed in each subsequent wave. The initial sample had 19,914 people in 7,682 households (Summerfield et al., 2019). The sample was replenished in wave 11 with an additional 5,462 people from 2,153 households. To ensure that the sample is nationally representative of the population HILDA makes two types of adjustments. First the data is weighted to overcome differences in the likelihood of various households and individuals being in the sample. Second, imputation of missing values where the data is incomplete. This process is described in Henstridge (2001).

The survey collected data on household energy expenditure needed to measure energy poverty from wave five onwards. Thus, our analysis is restricted to data covering the period 2005 to 2019. This gives us a final estimation sample of 94,869 observations on 15,662 individuals with non-missing information on all relevant control variables across our sample period.

3.1. Measuring energy poverty

At its broadest level, a household can be regarded as being energy poor when it cannot meet its energy needs (Bednar & Reames, 2020). The European Commission defines energy poverty as a distinct form of poverty "due to a combination of high energy expenditure, low household incomes, inefficient buildings and appliances, and specific household energy needs" (European Commission, 2021). Llorca et al. (2020) suggests that it is important to use both objective and subjective measures of energy poverty in the same study. This is important because, as Deller et al. (2021) finds, different measures do not always produce the same result. Our first measure of energy poverty (Pov1) is a subjective indicator. It is based on the HILDA survey question which asks respondents: "did any of the following happen to you because of a shortage of money?" To measure energy poverty using this indicator, we set a binary variable equal to one if, as a response to this question, the respondent selects "was unable to heat home".

Our second measure of energy poverty (Pov2) is our objective indicator, which is the low income-high cost (LIHC) measure proposed by Hills (2012). With this measure, one is in energy poverty if their "energy costs are above the median level and were they to spend that amount they would be left with a residual income below the official poverty line" (Hills, 2012, p. 9).

Our third measure is a composite measure which combines Pov1 and Pov2. We apply equal weights to Pov1 and Pov2 to derive household energy deprivation scores, which we calculate

as the weighted sum of the two energy poverty measures that lies between 0 and 1. We set a binary variable equal to one if the energy deprivation score of a household is 0.5 or above.

3.2.Measuring parental smoking

Our measure of potential smoking reflects whether an individual, during his or her childhood, lived in a home environment in which he or she was exposed to smoking either by their parents or guardians. Data on parental smoking in the HILDA survey was collected in waves 9, 13 and 17 as part of questions related to childhood experiences of adults.[1] The specific question asked: "Were any of your parents or guardians' smokers at any stage during your childhood". The period of childhood was defined as before one turned 15 years of age. Given the historical nature of this data, we use this data across all available waves of the survey for our analysis. In our sample, 64 per cent of respondents reported that at least one of their parents or their guardian smoked at some stage during their childhood or adolescence (see Table 1).

3.3. Measuring potential channels

3.3.1. Health outcomes

We examine the role of health outcomes using three variables that capture mental, physical and general health obtained from the SF-36 instrument included within the Self-Completion Questionnaire of the HILDA survey. The SF-36 Health Survey is an internationally recognised diagnostic tool for assessing functional health status and wellbeing (Summerfield et al., 2019). It contains 36 items which provide multi-item scales measuring distinct health concepts.

First, we use five items from the SF-36 questionnaire to obtain a Mental Health Inventory (MHI-5) scale used to assess mental health. These questions relate to respondents being asked on their feelings of being nervous, down, calm, peaceful and happy in the four weeks prior to the survey. Following previous studies, responses to these questions are transformed to a 0-100 mental health index with "worst possible mental health" represented as 0 and "best possible mental health" represented as 100. This measure of mental health from the HILDA survey has been widely validated and shown to be a good proxy for mental health (see, e.g., Awaworyi Churchill et al., 2020a; Buddelmeyer & Powdthavee, 2016; Prakash & Munyanyi, 2021).

Second, we use ten items relating to the physical functioning of individuals collected as part of the SF-36 questionnaire to measure individual physical health. This index which captures aspects of activities that one might do during a typical day, was transformed to a scale of 0-100 where 0 represents "worst physical health" and 100 represents "best physical health".

Third, to measure general health we use five items from the SF-36 questionnaire to assess respondents' general health status. This measure also includes the widely used single indicator of self-reported health, which has been used in various economics and health studies to measure general health status (see, e.g., Benjamins et al., 2004; Gravelle & Sutton, 2009; Pega et al.,

[1] This question was only asked once – in the earliest wave in which the respondent participated. For example, if a respondent participated in waves 9, 13 and 17, he or she was only asked this question in wave 9.

2013; Ronconi et al., 2012). The five-item measure is a broader measure of general health status. In addition to capturing self-assessed current health status, it also asks respondents to self-assess their future health and how it compares with others. This index is transformed to a scale of 0-100 where 0 represents "worst general health" status and 100 represents "best general health" status. This broad measure has been commonly used in recent studies using the HILDA survey (Awaworyi Churchill & Smyth, 2021a; Prakash & Munyanyi, 2021).

3.3.2 Education and labour market outcomes

We examine the role of labour market outcomes using individual employment status, income and educational attainment. To measure employment status, we use a dichotomous variable denoted by 1 if an individual is employed either in paid employment or is self-employed while zero denotes the respondent being unemployed. We measure income as annual household financial year disposable regular income. Educational attainment is measured using the highest education level achieved. We create a dichotomous variable where 1 represents if an individual has at least bachelor or honours level education while zero represents otherwise.

3.3.3 Locus of Control

We use the seven item Pearlin and Schooler (1978) Mastery Scale to measure LoC. The questions used to measure individual LoC are collected in waves 3, 4, 7, 11, 15 and 19. These questions are designed to capture the respondent's perception about things that happen in their life and the extent that they feel they can determine future outcomes in their life. Consistent with existing studies (see, e.g., Awaworyi Churchill et al., 2020a; Cobb-Clark & Schurer, 2013) that have used this measure from the HILDA survey, we take the average of the LoC scores over the waves in which it is available as a measure of LoC for each respondent. This gives us a LoC score that ranges from 1 (external LoC) to 7 (internal LoC).

3.4 Control variables

Consistent with the literature on energy poverty (see, e.g., Awaworyi Churchill et al., 2020b; Kahouli, 2020; Llorca et al., 2020; Prakash & Munyanyi, 2021) and the impact of childhood environment on adult outcomes (see, e.g. Juonala et al., 2019; Prakash & Kumar, 2021; Rovio et al., 2020) we use a rich set of control variables to minimize omitted variables bias. These covariates include controls for the respondent's socioeconomic circumstances, such as age, gender, marital status, number of dependents and family size, as well as controls for the respondent's childhood, such as the employment status of both parents, whether either parent was deceased and parents' marital status.[2] For a complete set of control variables see Table A1.

3.5 First look at the relationship

Table 1 contains data on the status of energy poverty by parental smoking status for each of the three measures of energy poverty. Of the 94,869 person-year observations, just under two-thirds (64.23 per cent) were exposed to parental smoking at some stage during their childhood or

[2] Given that energy poverty is a household outcome, our control variables focus on the household reference person.

adolescence. This figure suggests Australia is mid-range for childhood exposure to passive smoking between the United States and Europe (Öberg et al., 2011). Energy poverty rates differ across the three measures, consistent with findings in previous studies (see eg. Deller et al., 2021). Based on the subjective (Pov1) measure, 3.63 per cent observations experienced energy poverty over the sample period. The energy poverty rate using the LIHC (Pov2) and multidimensional (Pov3) measures was 7.74 per cent and 10.74 per cent, respectively. The average rate of energy poverty is higher for those with, than for those without, a parent who smoked during childhood and adolescence for all three energy poverty measures and the mean difference is significant.

4. Empirical Model

To examine the effect of parental smoking in childhood and adolescence on the probability of being in energy poverty in adulthood, we estimate the following reduced form regression:

$$Pov_{it} = \alpha_0 + \beta_1 PSmoke_i + \sum_n \gamma_n \boldsymbol{X}'_{n,it} + \sum_n \delta_n \boldsymbol{H}'_n + \sigma_s + \tau_t + \varepsilon_{it} \qquad (1)$$

where Pov_{it} is the measure of energy poverty for household i at time t, which corresponds with the relevant HILDA survey wave. $PSmoke_i$ is a dummy variable capturing whether the respondent was exposed to a home environment in which either their parents or their guardian smoked in their childhood and β_1 is the coefficient of interest that captures the effect of parental smoking on energy poverty. Individual attributes of respondents in adulthood are captured in vector $\boldsymbol{X}$ while vector $\boldsymbol{H}$ captures household characteristics during respondents' childhood. These effects of these controls are captured in parameters γ_n and δ_n , respectively. To account for permanent differences across states and time-varying determinants of energy poverty, we control for state fixed effects, σ_s and include year dummies, τ_t. The constant and error term are captured in the model by a_0 and ε_{it}, respectively. Given that we use 15 waves of the HILDA survey, we pool our observations and cluster standard errors at the household level.

To examine health, human capital, labour market outcomes and LoC as potential channels between exposure to parental smoking and energy poverty, we adopt a multi-stage approach consistent with the literature (see, e.g., Alesina & Zhuravskaya, 2011). First, for health, human capital, labour market outcomes or LoC to qualify as a channel, in addition to being correlated with exposure to parental smoking in childhood, the variable should also be correlated with energy poverty. Second, the inclusion of the variable as an additional covariate in the regression linking exposure to parental smoking to energy poverty should decrease the magnitude of the coefficient on the parental smoking variable or render it statistically insignificant. We consider the role of health, human capital, labour market outcomes and LoC in alternating models.

5. Results

5.1. Main results

We present our main results in Table 2. In panel A of Table 2, we present a model with only state and time fixed effects. The coefficient of parental smoking in childhood is consistently positive and significant across the three measures of energy poverty. In panel B of Table 2 we

include individual attributes of respondents at the time of the survey. Our preferred estimate is presented in panel C of Table 2 where we extend the model to include respondents' household attributes in their childhood. These are our preferred results because they contain the fullest possible set of controls, which minimizes potential endogeneity due to omitted variables or unobserved heterogeneity. The relationship between parental smoking in childhood and being in energy poverty is positive and significant in all cases. For individuals whose parents or guardians smoked during their childhood, the likelihood of being in energy poverty measured by the subjective indicator (Pov1) increases by 0.8 percentage points. Using the objective LIHC measure (Pov2), parental smoking increases the probability of being in energy poverty by 0.6 percentage points and, with the composite measure (Pov3), parental smoking increases the probability of being in energy poverty by 1.4 percentage points. In appendix Table A2, we present results for our preferred specification (panel C in Table 2) with a full set of controls.

5.2.Robustness and plausibility

5.2.1. Can our results be interpreted as causal?

In this section we examine if our results can be regarded as being plausibly causal. There are three potential sources of endogeneity; namely, reverse causality, measurement error and omitted variable bias. We contend that reverse causality is unlikely to be a problem as potential exposure to passive smoking in the home occurred many years prior to observing whether the respondent is in energy poverty. Measurement error might bias the estimates upwards or downwards. We only observe whether either parent ever smoked. We do not observe whether the respondent was actually exposed to their parents' smoking. If the parent(s) that smoked never smoked indoors – in the car or at home – the estimates are potentially biased upwards. However, it is worth noting that while there has been a moderate decline in smoking indoors in Australia over time, estimates suggest that more than half of households with a smoker, regularly smoke within the home, exposing their children to second-hand smoke (Longman & Passey, 2013). The estimates might be biased downwards if (a) both parents smoked, which seems likely given evidence of assortative matching in smoking (Clark & Etilé, 2006); and (b) were regular smokers through the duration of the respondent's childhood and adolescence.

We have controlled for a wide range of observed characteristics of respondents in their childhood and adulthood. Yet, the determinants of energy poverty outcomes may also be correlated with those of parental smoking in ways that are not fully captured in the controls. For example, unobserved family circumstances, such as a stressful or violent home environment, could contribute to parents being more likely to smoke and, at the same time, adversely affect the cognitive development of survey respondents in their youth, making them more likely to be in energy poverty later in life (Srivastava & Trinh, 2021). A large literature exists on the intergenerational transmission of parental traits and socioeconomic status (see, e.g., Björklund et al., 2007). Factors correlated with parental smoking, such as low intelligence, low self-efficacy and poor motivation, may transmit to their children, making their children more likely to be in energy poverty as adults.

To address measurement error and omitted variable bias as sources of endogeneity, ideally, we would prefer to use a valid external instrument. One such potential instrument is cross-state and temporal variation in tobacco prices, which has been used in previous studies to instrument for smoking (see, e.g., Beenstock & Rahav, 2002; Srivastava & Trinh, 2021). We tried instrumenting for parental smoking using the average tobacco price for the period that the respondent was aged 0-14. However, state-level tobacco prices proved to be a weak instrument in our case with the first stage F statistic consistently lower than 10. While tobacco prices are routinely used to address endogeneity of smoking, one problem is that tobacco prices may be affected by consumption and, hence, not be truly exogenous (Srivastava & Trinh, 2021). Another potential problem is that state-level instruments, such as tobacco prices, have less predictive power than individual-level instruments, contributing to them being weak instruments (French & Popovici, 2011). Relatedly, Farrell and Fry (2021) find that state-level gambling expenditure was a weak instrument for an individual-level problem gambling severity index in their study of the relationship between problem gambling and energy poverty.

In the absence of a valid external instrument, we employ the bounding analysis approach, proposed by Oster (2019); an identification approach suggested by Lewbel (2012) that employs an internal instrument based on the presence of heteroskedasticity in the data; and PSM to examine the extent to which our estimates can be regarded as being causal.

5.2.2. Bias adjustment

Oster's (2019) bounding approach to assess whether results are robust to omitted variables bias has been employed as the main check on endogeneity in recent studies using household datasets when an external instrument is not available (see, e.g., Clark et al., 2021; Davillas et al., 2021). In their study on energy poverty and health, Davillas et al. (2021, p. 4) suggest that the "bounding approach is particularly suitable when an instrument cannot be relied upon".

Bounding analysis exploits information on coefficient and R-squared movements to calculate the bounding values for the treatment effect. Since observable covariates are assumed to be a random subset of all covariates that are relevant, the assumption is that the selection of the observable and unobservable covariates is the same and a lower bound estimate can be computed from movement in the coefficients following the inclusion of additional observable covariates. One needs to select bounds for δ – the relative degree of selection on observables and unobservables, which can theoretically lie between zero and 1, and R_{max}. We use the suggested bounds for δ and R_{max} in Oster (2019). We select δ =1, as it is unlikely that the unobservables have a greater impact than that of observables included in the model. This also follows the approach in other studies that have employed this approach (Clark et al., 2021; Davillas et al., 2021; Pan et al, 2021). While theoretically R_{max} could be unity, because of measurement error it is likely to be less than 1. Based on the survival rate of experimental publications in leading journals, Oster (2019) suggests a bound for R_{max}, given by $R_{max} = min\{1.3\tilde{R}, 1\}c$ where $\tilde{R}$ is estimated using the full specification in Table 2.

The results are reported in Table 3. Column (1) reports the estimated effects for the baseline uncontrolled model. Column (2) presents the estimates from the controlled model that includes

the full set of observed covariates. Standard errors and R-squared are given in parentheses and in brackets, respectively. Column (3) shows the identified set for the relationship between parents smoking in childhood and adolescence and the likelihood of being in energy poverty in adulthood, $[\tilde{\beta}, \beta^{*}(\min\{1.3\tilde{R}, 1\}, 1)]$, 1)] and column (4) shows the ratio of the unobserved covariates, relative to the observed control variables, which are denoted as $\bar{\delta}$, which would be required to drive the coefficient on parents smoking to zero.

The identified sets for each energy poverty measure in column (3), exclude zero, which suggests that the estimates from the controlled regressions are robust to omitted variable bias. The estimated values for the three energy poverty measures in column 4 range between 2.2 and 10.4, depending on how energy poverty is measured. This suggests that the impact of the omitted variables has to be twice as large (LIHC measure), four times as large (composite measure) or 10 times as large (subjective measure) as the impact of the observed explanatory variables. It would be unlikely for the impact of the omitted variables to be twice as large as the observed explanatory variables. For the impact of omitted variables to be tenfold those of the observed explanatory variables is highly improbable. Taken together, the results from the bounding analysis suggest that our main results in Table 2 are robust to omitted variables bias.

5.2.3. Internal instrument

The approach in Oster (2019) addresses endogeneity resulting from potential omitted variables bias, but it does not account for other sources of endogeneity, such as error associated with measuring the effects of parental smoking. In the absence of having a valid external instrument, we employ the identification strategy proposed by Lewbel (2012), which utilizes a heteroskedastic covariance restriction to construct an internal instrument. The main advantage of the Lewbel (2012) method is that it can be employed in cases when a conventional instrument is not available or weak (Mishra & Smyth, 2015). It has been widely employed as an identification strategy in the literature on energy poverty (see, e.g., Ampofo & Mabefam, 2021; Awaworyi Churchill et al., 2020b; Farrell & Fry, 2021; Zhang et al., 2021). The Lewbel (2012) approach does not require one to satisfy the exclusion restriction. While the Lewbel (2012) approach relies on some assumptions, the only non-standard one is that there be heteroskedasticity, which can be readily tested for using the Breusch-Pagan test. Lewbel (2012, p. 67) notes that because "the method is based on higher moments …. it is likely to produce less reliable estimates than identification based on standard exclusion restrictions". Yet, evidence provided in Lewbel (2012) and elsewhere (see, e.g., Mishra & Smyth, 2015) suggests that estimates based on the Lewbel (2012) method tend to be reasonably close to those obtained with valid external instruments when valid external instruments are available.

Table 4 presents the results instrumenting for whether parents smoked using the Lewbel (2012) method. The Breusch-Pagan test confirms the existence of heteroskedasticity in the first stage residuals. The point estimates using Lewbel (2012) are considerably higher in magnitude than those reported in panel C of Table 2, suggesting that the estimates from our main results are biased downwards. Consistent with the main results reported in Table 2, parents smoking has

the largest effect on the likelihood of being in energy poverty when energy poverty is measured using the composite indicator and has the smallest effect using the LIHC measure.

5.2.4. PSM

As a final check on whether our estimates in Table 2 are plausibly causal we employ PSM, which is often used as a check on endogeneity in the literature on determinants of energy poverty (see, e.g., Alvarez & Tol, 2021; Koomson & Danquah, 2021). To help draw causal inferences about the effect of having a parent who smoked on energy poverty using PSM, we ask the question: what is the outcome (in terms of propensity to be in energy poverty) for respondent i who is treated (i.e. had a parent who smoked growing up), relative to the hypothetical outcome that would have prevailed if the same respondent had a parent who did not smoke when they were growing up? We estimate the average treatment effect as follows:

$$\begin{aligned}\tau &\equiv E\{O_1 - O_0 | B = 1\} \\ &= E\{E\{O_1 - O_0 | B = 1, p(W)\}\} \\ &= E\{E\{O_1 | B = 1, p(W) - E\{O_0 | B = 0, p(W)\} | B = 1\}\end{aligned}$$

Where τ is the average effect of the treatment, B is a dummy variable equal to one if the respondent had a parent who smoked growing up and zero if otherwise. O represents our outcome variable – likelihood of being in energy poverty. W is a vector of pre-treatment characteristics represented by the covariates. The propensity score, $p(W)$, is the probability of being more likely to be in energy poverty, given pre-treatment characteristics (W). We report results using Nearest Neighbour Matching, Radius and Kernel, consistent with the standard approach in the existing literature that encourages the use of multiple matching algorithms to ensure robustness. The results, which are reported in Table 5, are consistent with the fixed effects estimates reported in Table 2 and the Lewbel (2012) estimates in Table 4.

5.2.5. Other robustness checks

In Table A3, instead of using a linear model, we employ logit and probit models. We find that the relationship between parents smoking and energy poverty later in life is positive and significant across the two models for the three measures of energy poverty, consistent with the main estimates.

We use LIHC (Pov2) as our preferred measure because of the criticisms that have been made of other objective indicators, such as the share of household income spent on energy or threshold measures, such as if the proportion of household income spent on energy exceeds 5 per cent or 10 per cent. Specifically, the share of household income spent on energy fails to account for differences between actual energy expenditure made by households and the energy expenditure that they would need to make, in order to realize an ambient temperature (Awaworyi Churchill et al., 2020b). Threshold indicators result in different rates of incidence that tend to either understate or overstate true rates of energy poverty (Herrero, 2017). As Hills (2012, 30) notes with respect to the 10 per cent cut-off, it is "possible for households with quite

high incomes to be classed as being in fuel poverty. Equally some households with relatively low required energy spending living in highly energy-efficient homes may also be counted as fuel poor if they report very low incomes to the survey". Hills (2012) designed the LIHC measure to address these limitations. This said, the share of household income spent on energy and threshold indicators are still regularly employed in studies of energy poverty, including studies that have used HILDA (see eg Awaworyi Churchill et al., 2020b; Farrell & Fry, 2020).

Another subjective measure of energy poverty, available in HILDA, asks respondents if they could not pay electricity, gas or telephone bills on time at any point since the beginning of the survey year (Yes=1). This is a noisier measure of energy poverty than our preferred subjective indicator (Pov1), because it includes subjective ability to pay the telephone bill, which is unrelated to energy poverty. Nevertheless, this alternative subjective measure is employed by Farrell and Fry (2020) and in sensitivity checks by Awaworyi Churchill & Smyth, (2021b).

In Table A4, we present results using (a) the share of household income spent on energy; (b) if the proportion of household income spent on energy exceeds 10 per cent; (c) if the proportion of household income spent on energy exceeds 5 per cent; and (d) if respondents answered that they could not pay electricity, gas or telephone bills on time at any point since the beginning of the survey year. With the exception of the 10 per cent threshold, which is insignificant, the results for the other measures are consistent with the main results reported in Table 2. Overall, given that the threshold measures are particularly sensitive to the cut-off (Hills, 2012) and different measures of energy poverty tend to give different results (Deller et al., 2021), our results are generally robust to a wide range of objective and subjective measures.

A final concern might be that our results could depend on whether respondents' recall of whether their parent/guardian smoked is accurate. Studies in psychology suggest that recall of childhood events start to falter once the respondent is in their mid-seventies (see, e.g., Lindsay et al., 2004). We re-estimate Table 2, excluding respondents aged 75 and older. In so doing, we lose about 9 per cent of total observations. The results, which are reported in Table A5, are consistent with the main results, although the point estimates are slightly lower. The lower point estimates could reflect that the proportion of parents who smoked is higher among older respondents, given that the proportion of people who smoke has declined over time.[3]

5.3.Channels

Section 2 discusses health, human capital, labour market outcomes and LoC as potential channels through which exposure to parental smoking might influence energy poverty. We adopt the approach described in Section 4 to examine whether these variables are mediators.

In Table 6, we examine the role of three health-related outcomes. Panels A, B and C report results for mental health, physical health and general health, respectively. The results from Column (1) across all three panels suggest that exposure to parental smoking in childhood is associated with a decline in mental, physical and general health. Columns (2) to (4) of each

[3] In 1945, 72 per cent of men and 26 per cent of women in Australia smoked cigarettes. By 2019, the corresponding percentages were 12.8 per cent and 10.4 per cent (Cancer Council, 2019).

panel examine the impact of health on Pov1, Pov2 and Pov3, respectively. Consistently, we find evidence of a negative relationship between health and energy poverty. Specifically, an increase in mental, physical and general health is associated with a decline in all three indicators of energy poverty. Additionally, the inclusion of each health indicator as an additional covariate reduces the magnitude of the coefficient on the parental smoking variable or renders it insignificant. This suggests that mental health, physical health and general health are channels through which exposure to parental smoking in childhood influences energy poverty.

We examine the role of employment, income and education in Table 7. The results from Column (1) across Panels A, B and C suggest that exposure to parental smoking in childhood is associated with a decline in: 1) the probability of being employed, 2) income, and 3) the probability of having a least a bachelor's degree, respectively. The results from Columns (2) to (4) show that being employed, having higher income and having at least a bachelor's degree reduces the probability of being in energy poverty. We also find that the inclusion of each labour market related indicator as an additional covariate reduces the magnitude of the coefficient on the parental smoking variable or renders it statistically insignificant. Thus, income, employment status and educational attainment are each channels through which exposure to parental smoking in childhood and adolescence influences the probability of being in energy poverty.

Table 8 reports results for our potential channel analysis focused on LoC. In Column 1, consistent with the literature, we find that exposure to parental smoking in childhood is negatively associated with being more external on LoC. From Columns (2) to (4), we find that being more internal on LoC is associated with a decline in energy poverty. Further, the inclusion of LoC as an additional covariate reduces the magnitude of the coefficient on the parental smoking variable, which confirms that LoC is also a channel through which exposure to parental smoking in childhood and adolescence influences energy poverty.

6. Conclusions and Implications for Social Policy

We have examined whether exposure to parental smoking in childhood and adolescence increases the likelihood of being in energy poverty later in life. Our preferred estimates suggest that exposure to passive smoking in childhood and adolescence increases the likelihood of being in energy poverty in adulthood by 0.8-1.4 percentage points. Various checks suggest that this finding is plausibly causal and that allowing for error in measuring parental smoking, if anything, these estimates should be interpreted as a lower bound. We find that health, human capital, labour market outcomes and LoC mediate the observed relationship.

Our findings have important implications for social policy to address the long-term implications of harmful health behaviours due to exposure to passive smoking. First, they add to the growing body of literature that has identified long-term adverse implications from being exposed to passive smoking in childhood and adolescence. This reinforces the need for further investment in policies and additional strategies warn parents of the long-term dangers to their children of smoking indoors. Several websites, such as the Kids Health website, warn parents of the dangers of smoking.[4] More funding could be directed into advertising campaigns designed to

[4] https://kidshealth.org/en/parents/smoking.html

encourage smokers to quit. These campaigns have often focused on the adverse health implications for the smoker. More focus could be given to the implications for their children.

Second, the channel analysis suggests the potential for at least a couple of early life interventions to redress deficits created by exposure to passive smoking. We find that one channel through which exposure to passive smoking increases the likelihood of being in energy poverty is through education. Education also indirectly affects other channels such as labour market outcomes and income. Heckman (2006), for example, argues that deficits resulting from early-life adversity can be mitigated by investing in quality early childhood education. While it would be difficult from a practical perspective to single out the children of smokers for such targeted assistance, smoking rates are higher among low socioeconomic households; hence promoting social policies that entailed investing in early childhood education in low-income areas would *de facto* help to redress the early life disadvantage for many children of smokers.

We also find that LoC is a channel through which exposure to passive smoking early in life increases the likelihood of being in energy poverty. Awaworyi Churchill and Smyth (2021b) find that, more generally, being more external on LoC increases the likelihood of being in energy poverty and outline a number of strategies to nudge children and adolescents to become more internal on LoC, before LoC is stabilized in late adolescence. This includes redesigning school curricula to teach children greater resilience, to challenge negative beliefs and encourage children to be more assertive. Globally, a number of such programs already exist (see Schurer, 2017), such as the Penn Resilience Program (Bastounis et al., 2016).

In concluding, it is important to note the limitations of the study. One set of limitations relates to how our key independent variable is measured. We are only able to observe parental smoking at the extensive margin, not the intensive margin. We also only know if any of the respondent's parents (or guardian) smoked during his or her childhood or adolescence. We do not know if just one or both parents smoked. Finally, we do not know whether parents who did smoke, smoked indoors and, hence, the degree of exposure that respondents had to passive smoking. All of this is likely to result in measurement error, which the Lewbel (2012) estimates suggest is biasing the estimates downwards. Another limitation is that we do not have a valid external instrument for parents' smoking. Overall, though, the methods we do use to examine whether endogeneity is confounding our results – Oster (2019), Lewbel (2012) and PSM – are consistent and suggestive that our results are plausibly causal. Future research could examine the long-term implications of parental smoking and other experiences in the home in one's early life on the likelihood of being in energy poverty using alternative datasets with better measures of parental smoking and in a setting in which an external instrument is valid.

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Table 1 Parental smoking and energy poverty

Poverty status measured by:		Parents smoked		
		Yes	**No**	**Total**
Pov1	**Yes**	2.56% [N = 2,429]	1.07% [N = 1,016]	3.63% [N = 3,445]
	No	61.67% [N = 58,508]	34.70% [N = 32,916]	96.37% [N = 90,424]
	Total	64.23% [N = 60,937]	35.77% [N = 33,932]	100% [N = 94,869]
				Difference in means:
	Share in Pov1	0.040 (0.001)	0.030 (0.001)	0.010*** (0.001)
		Yes	**No**	**Total**
Pov2	**Yes**	5.31% [N = 5,042]	2.43% [N = 2,304]	7.74% [N = 7,346]
	No	58.92% [N = 55,895]	33.34% [N = 31,628]	92.26% [N = 87,523]
	Total	64.23% [N = 60,937]	35.77% [N = 33,932]	100% [N = 94,869]
				Difference in means:
	Share in Pov2	0.083 (0.001)	0.068 (0.001)	0.015*** (0.002)
		Yes	**No**	**Total**
Pov3	**Yes**	7.43% [N = 7,051]	3.31% [N = 3,137]	10.74% [N = 10,188]
	No	56.80% [N = 53,886]	32.46% [N = 30,795]	89.26% [N = 84,681]
	Total	64.23% [N = 60,937]	35.77% [N = 33,932]	100% [N = 94,869]
				Difference in means:
	Share in Pov3	0.116 (0.002)	0.092 (0.001)	0.024*** (0.002)

Notes: Difference in means in calculated as the difference between the average energy poverty status of those whose parents smoked and those whose parents did not smoke in childhood. Number of observations are in brackets. Standard errors are in parentheses. *** p<0.01.

Table 2 Parental smoking and energy poverty

VARIABLES	(1) Pov1	(2) Pov2	(3) Pov3
Panel A: No controls			
Parents smoked	0.010***	0.015***	0.024***
	(0.002)	(0.003)	(0.004)
Observations	94,869	94,869	94,869
R-squared	0.004	0.010	0.010
Individual level controls	No	No	No
Childhood related controls	No	No	No
State fixed effects	Yes	Yes	Yes
Time fixed Effects	Yes	Yes	Yes
Panel B: With individual level controls			
Parents smoked	0.009***	0.006**	0.015***
	(0.002)	(0.003)	(0.004)
Observations	94,869	94,869	94,869
R-squared	0.024	0.060	0.059
Individual level controls	Yes	Yes	Yes
Childhood related controls	No	No	No
State fixed effects	Yes	Yes	Yes
Time fixed Effects	Yes	Yes	Yes
Panel C: With individual and childhood related controls			
Parents smoked	0.008***	0.006**	0.014***
	(0.002)	(0.003)	(0.004)
Observations	94,869	94,869	94,869
R-squared	0.026	0.061	0.061
Individual level controls	Yes	Yes	Yes
Childhood related controls	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes
Time fixed Effects	Yes	Yes	Yes

Notes: Individual level control variables include gender, age, age-squared, number of dependent children aged 24 years and below and marital status. Childhood related variables are family characteristics that include employment status of both parents, whether any parent was deceased, whether both parents were living together in the same household or whether living with any of the stepparents or other family members when the individual was 14 years old. Robust standard errors at individual level are in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table 3 Bounds estimates for coefficient stability and robustness to omitted variable bias

Treatment variable	(1) Baseline coeff. $\dot{\beta}$ (S.E.), [$R^2{}_u$]	(2) Controlled coeff. $\hat{\beta}$ (S.E.), [$R^2{}_c$]	(3) Identified set $[\hat{\beta}, \beta^*(\min\{1, 1.3R^2{}_c\}, \delta = 1)]$	(4) $\bar{\delta}$ for $\beta = 0$ given $R^2{}_{max}$
Pov1	0.010*** (0.002) [0.001]	0.008*** (0.002) [0.026]	[0.008, 0.010]	10.402
Pov2	0.015*** (0.003) [0.001]	0.006** (0.003) [0.061]	[0.003, 0.006]	2.202
Pov3	0.023*** (0.004) [0.001]	0.014*** (0.004) [0.061]	[0.010, 0.013]	3.987

Notes: The results in column (1) are model specification without controls while the results in column (2) are from model specification with full set of control variables, state and year effects as in Table 1. Robust standard errors clustered at individual level are in parentheses. Significance: *** 1%, ** 5%, * 10%.

Table 4 Parental smoking and energy poverty (IV results using Lewbel [2012] method)

VARIABLES	(1) Pov1	(2) Pov2	(3) Pov3
Parents smoked	0.102***	0.059**	0.127***
	(0.029)	(0.026)	(0.036)
Observations	94,869	94,869	94,869
Breusch-Pagan test for heteroskedasticity in first stage regression residuals (p-value)	0.000	0.000	0.000

Notes: All model specifications include individual-level and childhood related control variables and fixed effects at state and year levels. The rejection of the null of constant variance at 5% level of confidence meets the precondition for the implementation of the Lewbel method suggesting the existence of heteroskedasticity in the data. Robust standard errors at individual level are in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table 5 Parental smoking and energy poverty, PSM results

Matching methods	Average Treatment effect on the Treated		
	Pov1	**Pov2**	**Pov3**
Nearest Neighbour Matching	0.005*** (0.001)	0.002* (0.001)	0.006** (0.003)
Radius	0.005*** (0.001)	0.002* (0.001)	0.008** (0.004)
Kernel	0.006*** (0.001)	0.003** (0.001)	0.008** (0.004)

Notes: *** p<0.01, ** p<0.05, * p<0.10. The control variables used in generating propensity scores with common support are as per Table 1. Bootstrap standard errors are reported in parenthesis. *** p<0.01, ** p<0.05, * p<0.10.

Table 6 Mediation analysis on health-related outcomes

VARIABLES	(1) Channel	(2) Pov1	(3) Pov2	(4) Pov3
Panel A: Mediating effects of mental health				
Parents smoked	-1.375***	0.006**	0.005*	0.011***
	(0.270)	(0.002)	(0.003)	(0.004)
Mental health		-0.002***	-0.001***	-0.002***
		(0.000)	(0.000)	(0.000)
Observations	94,399	94,399	94,399	94,399
R-squared	0.048	0.049	0.063	0.073
Comparison with same sub-sample				
Parents smoked		0.008***	0.006**	0.013***
		(0.002)	(0.003)	(0.004)
Panel B: Mediating effects of physical health				
Parents smoked	-1.886***	0.006***	0.005	0.010***
	(0.320)	(0.002)	(0.003)	(0.004)
Physical health		-0.001***	-0.001***	-0.002***
		(0.000)	(0.000)	(0.000)
Observations	93,784	93,784	93,784	93,784
R-squared	0.244	0.042	0.067	0.075
Comparison with same sub-sample				
Parents smoked		0.008***	0.006**	0.014***
		(0.002)	(0.003)	(0.004)
Panel C: Mediating effects of general health				
Parents smoked	-2.203***	0.005**	0.004	0.009***
	(0.353)	(0.002)	(0.003)	(0.004)
General health		-0.001***	-0.001***	-0.002***
		(0.000)	(0.000)	(0.000)
Observations	93,689	93,689	93,689	93,689
R-squared	0.055	0.043	0.066	0.076
Comparison with same sub-sample				
Parents smoked		0.008***	0.006**	0.013***
		(0.002)	(0.003)	(0.004)

Notes: The results in column (1) report the effects of parental smoking on the potential mediating variable. The coefficient of "Parents smoked" variable is also provided for comparison as the observation on mediating variable is less than the observations in Table 2. All the regressions include relevant covariates consistent with those included in panel C of Table 2. Robust standard errors clustered at individual level are in parentheses. Significance: *** 1%, ** 5%, * 10%.

Table 7 Mediation analysis on labour market and education outcomes

VARIABLES	(1) Channel	(2) Pov1	(3) Pov2	(4) Pov3
Panel A: Mediating effects of being employed				
Parents smoked	-0.032***	0.006***	0.003	0.009**
	(0.005)	(0.002)	(0.003)	(0.004)
Employed		-0.064***	-0.093***	-0.141***
		(0.004)	(0.004)	(0.005)
Observations	94,869	94,869	94,869	94,869
R-squared	0.426	0.040	0.076	0.087
Panel B: Mediating effects of income				
Parents smoked	-0.035***	0.007***	0.002	0.008**
	(0.009)	(0.002)	(0.003)	(0.003)
Income		-0.036***	-0.114***	-0.140***
		(0.002)	(0.003)	(0.003)
Observations	94,396	94,396	94,396	94,396
R-squared	0.424	0.039	0.129	0.136
Comparison with same sub-sample				
Parents smoked		0.008***	0.006**	0.013***
		(0.002)	(0.003)	(0.004)
Panel C: Mediating effects of having at least bachelor level education				
Parents smoked	-0.091***	0.006***	0.002	0.008**
	(0.009)	(0.002)	(0.003)	(0.004)
Above bachelor education		-0.022***	-0.042***	-0.058***
		(0.002)	(0.003)	(0.003)
Observations	94,869	94,869	94,869	94,869
R-squared	0.073	0.028	0.065	0.067

Notes: The results in column (1) report the effects of parental smoking on the potential mediating variable. The coefficient of "Parents smoked" variable is also provided for panel B as the observation on income variable is less than the observations in Table 2. All the regressions include relevant covariates consistent with those included in panel C of Table 2. Robust standard errors clustered at individual level are in parentheses. Significance: *** 1%, ** 5%, * 10%.

Table 8 Mediation analysis on Locus of control

VARIABLES	(1) Channel	(2) Pov1	(3) Pov2	(4) Pov3
Parents smoked	-0.039**	0.007***	0.005*	0.012***
	(0.018)	(0.002)	(0.003)	(0.004)
LoC		-0.031***	-0.016***	-0.041***
		(0.002)	(0.002)	(0.002)
Observations	93,964	93,964	93,964	93,964
R-squared	0.038	0.048	0.064	0.075
Comparison with same sub-sample				
Parents smoked		0.008***	0.006*	0.013***
		(0.002)	(0.003)	(0.004)

Notes: The results in column (1) report the effects of parental smoking on the potential mediating variable. The coefficient of "Parents smoked" variable is also provided for comparison as the observation on mediating variable is less than the observations in Table 2. All the regressions include relevant covariates consistent with those included in panel C of Table 2. Robust standard errors clustered at individual level are in parentheses. Significance: *** 1%, ** 5%, * 10%.

Appendices

Table A1 Descriptive statistics

Variables	Descriptions	Mean	Std. Dev.
Pov1	Dummy variable equals 1 if household was unable to heat their home because of money shortage	0.04	0.19
Pov2	Dummy variable equals 1 if household has energy costs above the median level and a residual income after fuel expenditure below the poverty line	0.08	0.27
Pov3	Dummy variable if household is energy poor based on index combining POV1 and POV2.	0.11	0.31
Parents smoked	Dummy variable if respondent's parent(s) smoked at any stage during their childhood	0.64	0.48
Female	Dummy variable if respondent is female	0.43	0.49
Age	Age of the respondent	50.09	17.45
Age-squared	Square of age/100	28.13	18.36
Dependents	Number of dependents in household aged 0-24	0.60	1.02
Separated	Respondent is separated	0.04	0.20
Divorced	Respondent is divorced	0.10	0.30
Widowed	Respondent is widowed	0.08	0.27
Single	Respondent is single	0.18	0.38
Married/de-facto	Respondent is legally married or in a de-facto relationship	0.60	0.49
Family size	Number of family members in the household	2.40	1.35
Father employed	Dummy variable if father was employed in the respondent's childhood	0.91	0.29
Father unemployed	Dummy variable if father was unemployed in the respondent's childhood	0.03	0.18
Father dead	Dummy variable if father was dead in the respondent's childhood	0.03	0.18
Father separate	Dummy variable if the father was not living together in the respondent's childhood	0.02	0.16
Mother employed	Dummy variable if mother was employed in the respondent's childhood	0.51	0.50
Mother unemployed	Dummy variable if mother was unemployed in the respondent's childhood	0.47	0.50
Mother dead	Dummy variable if mother was dead in the respondent's childhood	0.01	0.12
Mother separate	Dummy variable if the mother was not living together in the respondent's childhood	0.01	0.08
Live mother-father	Dummy variable if the respondent was living with biological mother and father in their childhood	0.80	0.40
Live father step-mother	Dummy variable if the respondent was living with biological father and step-mother in childhood	0.01	0.10
Live mother step-father	Dummy variable if the respondent was living with biological mother and step-father in childhood	0.04	0.20
Live father only	Dummy variable if the respondent was living with biological father only in childhood	0.02	0.15

Live mother only	Dummy variable if the respondent was living with biological mother only in childhood	0.10	0.30
Live others	Dummy variable if the respondent was living with other family members in childhood	0.03	0.16
Mental health	Measure of mental health status on a scale of 0-100	74.52	17.25
Physical health	Measure of physical functioning on a scale of 0-100	82.15	23.80
General health	Measure of general health status on a scale of 0-100	67.15	20.85
Employed	Dummy variable if respondent is employed either as an employee or is self-employed (ref: unemployed and not in labour force)	0.68	0.47
Income	Log of real household financial year disposable regular income measured in Australian dollars	10.96	0.79
Above bachelor education	Dummy variable if respondent has at least bachelor level of education	0.28	0.45
LoC	Locus of control index on a 1-7 scale	5.41	0.92

Table A2 Parental smoking and energy poverty

VARIABLES	(1) Pov1	(2) Pov2	(3) Pov3
Parents smoked	0.008***	0.006**	0.013***
	(0.002)	(0.003)	(0.004)
Female	0.012***	0.028***	0.038***
	(0.002)	(0.003)	(0.004)
Age	0.001***	-0.002***	-0.001
	(0.000)	(0.001)	(0.001)
Age-squared	-0.002***	0.004***	0.002***
	(0.000)	(0.001)	(0.001)
Dependants	0.004**	0.021***	0.023***
	(0.002)	(0.001)	(0.002)
Separated	0.053***	0.012*	0.059***
	(0.007)	(0.007)	(0.010)
Divorced	0.065***	0.020***	0.074***
	(0.006)	(0.006)	(0.008)
Widowed	0.031***	0.027***	0.052***
	(0.006)	(0.010)	(0.011)
Single	0.036***	0.023***	0.051***
	(0.004)	(0.004)	(0.005)
Family size	-0.001	-0.031***	-0.029***
	(0.002)	(0.001)	(0.002)
Father employed	-0.015	-0.004	-0.018
	(0.011)	(0.010)	(0.013)
Father unemployed	-0.009	-0.006	-0.016
	(0.012)	(0.012)	(0.016)
Father dead	-0.016	0.012	-0.004
	(0.011)	(0.013)	(0.017)
Mother employed	-0.033	-0.018	-0.034
	(0.025)	(0.022)	(0.028)
Mother unemployed	-0.026	-0.008	-0.018
	(0.025)	(0.022)	(0.028)
Mother dead	-0.045*	-0.040*	-0.066**
	(0.027)	(0.024)	(0.030)
Live mother-father	-0.018***	-0.009	-0.024***
	(0.005)	(0.005)	(0.007)
Live father only	0.000	0.004	-0.002
	(0.010)	(0.011)	(0.015)
Live mother only	-0.006	-0.010	-0.016*
	(0.007)	(0.007)	(0.009)
Constant	0.035	0.125***	0.151***
	(0.027)	(0.026)	(0.033)
Observations	94,869	94,869	94,869
R-squared	0.026	0.061	0.061
State fixed effects	Yes	Yes	Yes
Time fixed Effects	Yes	Yes	Yes

Notes: Robust standard errors at individual level are in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table A3 Robustness checks: (Probit and Logit model results)

Variables	Pov1	Pov2	Pov3
Panel A: Logit model			
Parents smoked	0.006***	0.006**	0.013***
	(0.002)	(0.002)	(0.003)
Controls?	Yes	Yes	Yes
Observations	94,869	94,869	94,869
Panel B: Probit model			
Parents smoked	0.007***	0.006**	0.014***
	(0.002)	(0.003)	(0.003)
Controls?	Yes	Yes	Yes
Observations	94,869	94,869	94,869

Notes: The coefficients presented are the marginal effect at the mean in both logit and probit model specification. The control variables used in all the specifications are as per panel C of Table 2. Robust standard errors clustered at household level are in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table A4 Robustness checks: alternative measures of energy poverty

VARIABLES	(1) **Energy cost to income share**	(2) **Dummy variable "if energy cost to income share exceeds 10%"**	(3) **Dummy variable "if energy cost to income share exceeds 5%"**	(4) **Dummy variable "if unable to pay bills on time"**
Parents smoked	0.093**	0.001	0.010***	0.039***
	(0.043)	(0.002)	(0.004)	(0.004)
Observations	94,832	94,869	94,869	94,760
R-squared	0.047	0.023	0.069	0.062

Notes: Outcome variable in column (1) is "household energy related expenditure as a share of household disposable income"; column (2) is a dummy variable if "the energy cost to income share of the household exceeds 10%"; column (3) is a dummy variable if "the energy cost to income share of the household exceeds 5%"; column (4) is a dummy variable if "a household is unable to pay electricity, gas or telephone bills on time". All model specifications include individual-level and childhood related control variables and fixed effects at state and year levels. Robust standard errors at individual level are in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table A5 Robustness checks: excluding those aged over 75 years

VARIABLES	Pov1	Pov2	Pov3
Parents smoked	0.009***	0.005*	0.012***
	(0.002)	(0.003)	(0.004)
Observations	86,554	86,554	86,554
R-squared	0.026	0.062	0.063

Notes: All model specifications include individual-level and childhood related control variables and fixed effects at state and year levels. Robust standard errors at individual level are in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

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