CAGE

Did the policy response to the energy crisis cause crime? Evidence from England

CAGE working paper no. 662

May 2023

Thiemo Fetzer

Did the policy response to the energy crisis cause crime? Evidence from England

Thiemo Fetzer*

May 4, 2023

Abstract

The invasion of Ukraine has led to an unprecedented increase in energy prices in much of Western Europe with policy makers actively intervening in energy markets to cushion the shock. The UK's policy response stands out: the energy price guarantee (EPG) was entirely untargeted and is, in real terms, much less generous to those living in properties with low energy efficiency. Using granular data and following a documented research approach this paper documents that areas more exposed to the energy price shock saw a notable increase in burglaries and anti-social behaviour: the energy price shock is responsible for a 6 to 10 percent increase in burglaries and a 9 to 24 percent increase in police reported anti-social behaviour between October 2022 to March 2023 inclusive. A quantification of policy alternatives suggests that a more targeted energy support package and/or a more energy efficient housing stock could have resulted in a drastically less pronounced uptick in crime.

Keywords: CRIME, WELFARE, INSTABILITY, CLIMATE CRISIS, COST-OF-LIVING
JEL Classification: Q40, Q48, K42

1 Introduction

The Russian invasion of Ukraine has resulted in sharp increase in energy prices across much of the world – in particular in Europe. Governments subsequently

*The author is affiliated with the University of Warwick, CAGE, NIESR and CEPR. I would like to thank Peter Lambert, Jakob Schneebacher, Christina Palmou, Hector Rufrancos and everybody else who feel connected to the Climate Crisis political economy research group for comments and suggestions as this agenda evolves and more research output is made available over the coming months on `http://www.trfetzer.com/climate-crisis-research/`. This paper will further evolve as more outcome data becomes available as I describe in more detail on `https://osf.io/vhnjz/`.

scrambled to find different ways to cushion the economic blow to household and firms in the short term often by directly intervening in energy markets and interfering in price setting mechanisms. Bruegel (2021) estimate that since September 2021 nearly €758 billion have been pledged to protect consumers from rising energy costs. What may be surprising to many is that, despite the predictability of winter and the expected seasonally increasing demand for energy in winter and, despite the fact that governments had more than six months to prepare, much of the financial support to consumers was handed out in an entirely untargeted fashion.

The UK's policy response stands out: the energy price guarantee (EPG) capped unit costs that consumers face across the UK irrespective of a households level of energy consumption or the energy efficiency of their home. A reduction in the unit price of energy, owing to the energy inefficiency of the UK's housing stock, implies that this support mechanism provides notably less generous support to households living in energy inefficient properties compared to those living in more energy efficient ones (Fetzer et al., 2023). And: the UK's housing stock is among the least energy efficient in the Europe (see Grantham Institute, 2022). Further, unlike in other countries, the UK government would have had at its disposal quite granular data that could have been used to mak at least a serious attempt to provide more targeted support to households as was highlighted in Fetzer (2022).

In this paper I present some first research of the (un)intended consequences of this policy choice: the impact that the untargeted nature of the energy price support had *causing an increase in crime*. I exploit the timing of the energy price shock hitting households with the start of the heating season from October 2022 – together with the fact that the UK's existing housing stock is quite energy inefficient to set up a difference-in-difference estimation. The most affected demographic group is people who live in poorly insulated homes that are on relatively low income. To measure and model the exposure to the energy price shock, I developed a data framework *at the property level* in summer 2022. This was published in November 2022 as an interactive and visual storytelling piece in the *Financial Times*.[1] The underlying crime data is provided as an event-level dataset, roughly, at the street-by month-level. I aggregate this data into statistical census area geographies of

[1]The visual storytelling piece can be accessed here: `https://ig.ft.com/uk-energy-efficiency-gap/`.

different spatial granularities and construct, using the property-level modelled impact, an *intention-to-treat* exposure measure of the median household in any given area. This allows the estimation of a difference-in-differences model to document to what extent crime saw a differential increase in areas that were more exposed to the energy price shock, on average, after October 2022.

I estimate that, on average, the energy price shock caused an increase in police reported burglaries by between 6.5 to 9.7 percent between October 2022 and March 2023. Police reported events of anti-social behaviour – a less well-defined crime category – increased by 9.1 to 24.3 percent owing to the energy price shock. The results are robust to a broad range of checks. I estimate more and less saturated empirical specifications zooming in on the underlying identifying variation; I check for functional form sensitivity; I carry out the analysis across three different spatial granularities to document the robustness of the research design that is particularly relevant owing to the arbitrariness of the concept of space when working with aggregated event data; I control for a broad range of other confounding factors that may drive the results; I further carry out a range of placebo exercises shifting the empirical design to earlier years which highlight that the 2022/2023 period stands out.

A key finding and emphasis of this paper is that the increase in crime, to a large extent, could have been avoided, had the energy bills support been more targeted. I use the point estimates in this paper to quantify how much crime would have increased under alternative policy formulations. Without an intervention, the estimated increase in burglaries, at the median, would have been around 10 percent. The energy price guarantee resulted in a lower increase in burglaries of around 6 percent. Yet, an alternative policy proposal with a mild degree of targeting – a two-tier tariff – is estimated to increase burglaries only by 3 percent. Such a two-tier tariff was designed to be similarly costly in fiscal terms to the energy price guarantee; it would have preserved the signal function of (marginal) prices for most consumers and would have left an estimated 12 million lower and middle income households or nearly 50 percent of households notably better off compared to the implemented energy price guarantee and could have been technically implemented.[2] This highlights that there may be large tangible indirect economic and

[2]This two tier tariff was discussed in Fetzer (2022) and publicly presented in October 2022 and

social benefits to providing more targeted support to households in managing their energy bills. And public investment in the governments capacity to provide such targeted support may yield large indirect social- and economic benefits.

Further, I also provide a quantification for what the effect sizes would have been if the UK's building stock was at its highest attainable level of energy efficiency. It is estimated that without an intervention, burglaries would have increased by 7.5 percent. With the energy price guarantee in place, which would have naturally been fiscally less costly due to the lower primary energy consumption with a more energy efficient building stock, the estimated increase in burglaries would have been lower at just around 4 percent. With the two-tier tariff, the estimated increase would have been just around 1 percent. This quantification highlights that any trade-offs between providing financial assistance and other socio-economic outcomes, such as crime as in this paper, is much less severe when the underlying building stock is more energy efficient. This suggests that investment in retrofitting the housing stock can provide large indirect social and economic benefits. Taken together, it suggests that investments in public data infrastructure that enables the state to provide targeted financial assistance and public investment in energy efficiency are *complementary*.

The micro-level results are quite consistent in magnitude and timing with increased aggregate media reporting of both – anti-social behaviour and burglaries – and, in timing, with new announced government initiatives to tackle crime, specifically, the new "Anti-Social Behaviour Action Plan" (see Home Office, 2023) published on March 27. A news index for the UK – presented in Figure 2 – suggests that, relative to the past year, news articles that mention the keyword "anti-social behaviour" increased by up to 50%. News article that refer to burglaries increased by 25%. Aggregate police reported crime data is less sharp: while there appears a gentle increase in burglaries, the aggregated data does not suggest a sharp increase that is mirrored in the news index; similarly, police reported anti-social behavior even decreased yet, the governments anti-social behavior strategy suggests that this may be due to structural undereporting which is less likely to be the case for burglaries. This highlights the importance to study the underlying data through

discussed along with even better – albeit technically more complex and difficult to implement – policy proposals at an event in Westminster `https://www.niesr.ac.uk/events/beyond-energy-price-guarantee-what-next`.

micro-econometric techniques. The analysis presented in this paper suggests that a non-negligible share of the recent uptick in burglaries and anti-social behaviour may be attributable to the poorly targeted energy support – exacerbated by the poor energy efficiency of the housing stock.

This paper is part of a broader research agenda. Over the summer 2022, a measurement framework of the impact of the energy price shock – at the *property level* was developed and shared with the *Financial Times*, which, after much delay published it as a visual storytelling piece in November 2022. A broad range of research projects have been lodged that leverage this data such as household-level data; survey data; individual-level mortgage data; food bank use data; health outcomes along with many others.[3] The progress on this particular research piece, which only marks a part of this broader agenda, was documented in a public register.[4] A technical description that introduces this empirical evaluation framework – at the *property level* – has been published in technical form as Fetzer et al. (2022a) and in a more accessible form in Fetzer et al. (2023). The original ambition was wider: to document the impact that the untargeted energy price support had on crime, health outcomes and economic deprivation – leveraging data from the UK's National Health Service (see e.g. Fetzer and Rauh, 2022a,b), along with granular individual-level foodbank use data to study economic deprivation. Unfortunately, data on the latter has not been forthcoming yet and data on the former has not yet been released for the relevant time period. The paper will be refined over the coming months as more data becomes available with a much more specific focus on the underlying mechanisms at play.[5]

This paper is related to an old strand of literature that seems to come back every odd years on whether income shocks cause crime or even broader insecurity and social instability. Using historical data from France (Bignon et al., 2017) study economically motivated crimes in 19th century France, while Rufrancos and Power (2013) provide a meta-analysis of the relationship between inequality and crime. Khanna et al. (2021) stands out owing to the exceptional granularity of the data

[3] The output and narration around this research agenda and project is shared on `https://www.trfetzer.com/climate-crisis-research/`.

[4] See `https://osf.io/vhnjz/`. The repository provides a record of the underlying data that was used for the analysis along with a narration of the research process.

[5] I would like to mention Hector Rufrancos of Stirling University who has been helping me in the efforts to secure access to the foodbank network data.

they are able to work with: individual level data on the perpetrators. Exploiting mass-layoffs in Colombia they document a significant increase in crime in the wake of an income shock. Similarly, also exploiting individual level data in the case of Brasil, Britto et al. (2022) document that social insurance can reduce the effect that job loss has on increasing crime. Relatedly, in (Fetzer, 2019), I document that social insurance, in the form of a workfare program in India, has a significant cushioning effect on civil conflict, crime and social unrest more broadly suggesting that public investments in social insurance can yield notable economic as well as non-economic benefits. This highlights that the extent to which adverse economic shocks cause social instability, crime or even outright civil conflict is a societal choice. A rigorous cost- benefit analysis would study to what extent public investment in resilience may turn out to be more cost effective. Such a cost- and benefit analysis would look at the extent to which public investments in institutions for prevention – such as social insurance or the ability to provide targeted transfers – may be cheaper than the many private investments in security and guard labor, along with the often much more costly short-term interventions that politics is shaping in the wake of an increase in instability.[6]

The paper is also related to research literature studying crime with a specific focus on the UK. In this strand of work Facchetti (2023) documents that cuts to frontline services that were part of the UK's austerity drive has caused a notable uptick in violent crime, lower crime clearance rates and resulting in less deterrence. A side result in Fetzer et al. (2022b) documents that housing benefit cuts, which caused a notable uptick in (statutory) homelessness and evictions contributed to a temporary increase in crime in the UK. Draca et al. (2011) uses the increase in deployment of police forces across London in the wake of the 2005 terror attacks as a natural experiment to document the effectiveness of police patrolling. Focusing on the criminal opportunities channel, Draca et al. (2019) documents that commodity prices are an important driver of specific property crimes and thefts in the UK. Kirchmaier et al. (2020) document the cycles of criminal activity and policing counter activity. Disney et al. (2021) document that areas with increased home ownership in the wake of the UK's privatisation of the social housing stock had a

[6]In this line of work Besley et al. (2015) quantifies the welfare losses that arise from a breakdown of law-and-order documenting that the costs vastly outstrip the private gains accruing to small groups in society.

positive impact of reducing crime.

The work is also more broadly related to a broader research agenda in political economy. Poor public sector performance and poor political management of crisis or economic transitions can breed distrust (see e.g. Algan et al., 2017), undermine societal resilience and can further the rise of populism (see e.g. Guriev and Papaioannou, 2021 for a review). Populism, or populist policies that are based on narratives or (mis)perceptions rather than rigorous evidence can, in turn, exacerbate the underlying structural factors or grievances that enable populist campaigns. In this line of work, Funke et al. (2020) provides cross-country evidence on the cost of populism documenting how populist leaders tend to cause much economic harm and hollow out institutions. In the case of Brexit, my own work documents how Brexit has been enabled by austerity-policies that had was supported by rather thin empirical evidence (Fetzer, 2018). Brexit itself, in turn appears to notably exacerbate the same regional inequalities that were, at first, cushioned by the welfare state and subsequently amplified by austerity (Fetzer and Wang, 2020).

The paper suggests that more targeted interventions, in addition to having the potential to being fiscally cheaper, could further yield significant indirect societal benefits. Investment in technology and data integration across government departments may be vital to ensure this can happen. While much of the focus on the literature around state capacity and development has been on measuring state capacity via the tax collection (see Besley and Persson, 2009, 2010). The technological constraints on governments to provide targeted transfers may be an interesting alternative measure of state capacity that may shed light on other societal preferences – such as the demand for privacy.

The rest of the paper is organized as follows. Section 2 provides some background and introduces the data used in the paper. Section 3 presents the empirical approach and the family of estimating equations. Section 4 presents the results and discusses the robustness checks. The last section concludes.

2 Context and data

This section describes the context and the underlying data used.

2.1 Crime reporting and media attention

The micro-level results are quite consistent with increased aggregate media reporting of both – anti-social behaviour and burglaries – and reported government initiatives to tackle anti-social behaviour. A news index for the UK – presented in Figure 2 – suggests that, relative to the past year, news articles that mention the keyword "anti-social behaviour" increased by up to 50%. News article that refer to burglaries increased by 25%. This contrasts with aggregate reporting on anti-social behaviour. On March 27 launched an "Anti-Social Behaviour Action Plan" (see Home Office, 2023) to tackle the perceived growing issue of anti-social behaviour through a range of measures. The analysis presented in this paper suggests that a non-negligible share of the recent uptick in anti-social behaviour may be attributable to the poorly targeted energy support exacerbated by the poor energy efficiency of the housing stock.

2.2 Measuring the exposure to the energy crisis

This section describes the measures that will be used from the data described in more detail in Fetzer et al. (2022a). This paper described how, through a combination of energy performance certificate data, along with a moment matching approach using individual level meter micro data, along with spatially granular post-code level energy consumption data, an estimate of the property-level energy consumption for space, hot water and electricity consumption is arrived at. This estimate is used to construct a measure of the exposure of a property i to a shock in energy prices and it allows the modelling of different price scenarios. Let $E^{act}_{i,est}$ be the estimated energy consumption using e.g. the ensemble estimate from Fetzer et al. (2022a) at the property i level. Similarly, I have an estimate of the potential energy demand $E^{pot}_{i,est}$ that proxies for the energy consumption of said property i if all energy efficiency upgrades that are recommended for it were implemented.

For each of the two estimates I can construct an energy cost measure or spending measure under different energy price scenarios. Again, the details of this has been described in Fetzer et al. (2022a). The data is available down to the individual property level i. Depending on the geographic resolution of the data, a corresponding measure of the energy price shock can be constructed at higher level geographic units. For our property-level energy consumption estimates $\mathbf{E_{p,act}}$ and $\mathbf{E_{p,pot}}$, I produce a vector of spending estimates. For example, for the preferred ensemble average energy consumption estimate $E^{ensemble}_{p,act}$, I have estimates of spending estimates that capture different past and current price scenarios, for example, spending estimates October 2021 and October 2022, in addition to spending estimates that capture policy scenarios such as the implemented Energy Price Guarantee (EPG) or simulated alternative policies, such as a Two-tier tariff that has been designed to be fiscally similarly costly compared to the energy price guarantee:

$$\mathbf{C}^{ensemble}_{p,act} = (C^{ensemble}_{p,act,21}, C^{ensemble}_{p,act,22}, C^{ensemble}_{p,act,EPG}, C^{ensemble}_{p,act,Two-tier})$$

These estimates allow us to measure changes in energy bills under different price scenarios and policy interventions at the individual property p level. The energy price shock measure can be estimated, at the property level as a year-on-year shock is

$$\Delta C^{ensemble}_{p,act} = C^{ensemble}_{p,act,22} - C^{ensemble}_{p,act,21}$$

The price shock that is implemented politically would be measured as

$$\Delta C^{ensemble}_{p,act} = C^{ensemble}_{p,act,EPG} - C^{ensemble}_{p,act,21}$$

An important and exogenous driver of the extent to which the energy price shock is the *energy inefficiency* of the housing stock, in addition to the price shock. The energy inefficiency of properties, e.g. due to poor insulation is something that is hardly changing in the short term. In most instances, the outcome data that is available will require the measures to be aggregated to coarser geographic levels, such as, for example, the lower layer super output area (LSOA). Since every property p can be mapped to a higher order geography such as an LSOA indexed with $d(p)$, we compute the energy price shock that the median property faces in an area. In the estimation, this would exploit variation in the energy price shock across the median property between LSOAs. Given that the energy price shock is large and given the significant variability in the energy efficiency of properties across England, even the aggregated measures will produce a lot of variation.

I construct a measure of the exposure of the median property in each output area (OA), each LSOA and each middle layer super output area (MSOA) and use this for the main empirical analysis. It is important that these are nested geographies: MSOAs are consist of multiple LSOAs, while LSOAs in turn are the result of combinations of different OAs. Figure 1 provides an illustration of the distribution of the EPG mediated shock measure for the median property across LSOAs. This highlights that there is ample variation.

2.3 Crime data

I leverage crime data obtained from the Open Data platform `https://data.police.uk/`. This provides, for most police forces that operate in the UK, a monthly tabulation of police reported crime event data. The temporal granularity of the data is at the monthly level. Spatially, the data is provided with an LSOA identifier, along with latitude- and longitude information and the indication of the nearest street.

I have downloaded the March vintage in each calendar year from `https://data.police.uk/data/archive/` starting with the most recent release (March 2023). This implies a data overlap across the different year as each snapshot provides data pertaining to a 24 month window. I make the assumption that the most recent data for an overlapping window is more accurate and hence retain the data pertaining to the calendar year that is more recent in case of a data overlap. I have extended the data back to 2012. The focus for most of the analysis, however, will be on the 18 month window from October 2021 to March 2023. I keep the older data in the dataset to carry out robustness checks such as replicating the main estimating equation in earlier years as placebo tests.

The underlying data provides a file for stop-and-search, outcome data per crime event and street level crime reporting data – the latter is the most comprehensive dataset available. Every crime has a unique crime identifier and so duplicates can be removed. This identifier seems consistent across datasets and is not unique to each vintage. It also provides latitudes- and longitudes that match to the nearest street. Since I want to explore different spatial granularities for the estimation, I build a version that captures the counts, incidence and intensity of different types of crimes that occur in a given month and in a given location. I map the latitudeand longitude in addition to the census 2011 output area boundaries, along with the middle layer super output areas using the provided lower layer super output area definitions.

With this, I construct an empty panel data structure at the output area (OA), LSOA and MSOA level. Earlier years of the data do not have all crime categories that are subsequently used. I will focus on reported anti-social behaviour and burglaries. In the repository I discussed some of the challenges that arise when working with some other outcomes. The main concern is that the area-specific energy price shock measures are likely inadequate to capture non area-specific crime.

2.4 Additional data

I leverage a range of additional measures that are mostly used as control variables in discretized form allowing me to leverage them in an interactive fashion as time fixed effects. For example, I can account for non-linear time effects that are specific to an areas prevalence of a specific type of property. Most of these features are constructed as spatial aggregates to match the resolution of the outcome data being constructed from property-level data that was used as at the individual property level in Fetzer (2023).

Indices of Multiple Deprivation I leverage data from the English Indices of Multiple Deprivation from 2019. Specifically, I focus on the income deprivation score; the employment deprivation score; the education, training and skills score; the health deprivation and disability score; the barriers to housing and services score; as well as the living environment score. Each of these scores can be used to ranks each LSOA in England from least- to most deprived. For each of the scores I create categorical variable that capture the quintile of the empirical distribution that an area falls under in terms of the deprivation measure specific to each score. This allows the construction of deprivation-score dimension specific time fixed effects that, in turn, can be interacted with an area or region identifier. This allows me to absorb non-linear time trends in area-specific deprivation characteristics in a flexible fashion.

Property level characteristics Based on the population of EPC that are lodged, I construct a vector of capturing the construction age, a property's built form, the property type and the main heating fuel (gas or electricity). These variables are categorical. For each category, I compute the share of properties in an area that is in a specific category, e.g. the share of properties that are of property type "flat". I then discretise this measure capturing whether an area has an above- or below median share of flats. This is used to allow for non-linear time trends that are specific to an areas built-form and a range of other housing characteristics.

Council tax band For nearly the universe of properties, I observe the council tax band. Council tax is a tax levied to pay for local services provided by the local council, such as garbage collection. The liability is computed based on property valuations that originate in the 1990s. They are provided by different bands. As with the other measures, to allow for a more granular measure I compute the share of properties in each council tax band. I then compute the quintile of distribution of each of these shares and use this as control variable interacted with area-specific time effects.

Property price data I compute the average price paid per square meter for properties using the tax authorities price paid public data register. I compute the median of the price paid in an area per square meter along with the interquartile range as second estimate. For each, I then construct the quintile to capture whether an area is in each of the 1 to 5 quintiles in the median price paid distribution. Again, this is used to allow for non-linear time trends in an areas' specific property prices and the underlying distribution of property prices.

Higher order geographic boundaries I leverage data on a broad range of other geographic boundaries that have administrative meaning in the UK, for example, the police-force areas; administrative boundaries for health care (sub integrated care units); enterprise zones; political boundaries such as wards, parliamentary constituencies or local authority districts. I use these additional spatial divisions to saturate the empirical specification with time fixed effects that are specific to each of these successively more granular spatial divisions in one set of robustness checks.

In another set of robustness checks, I interact the boundaries to create unique group identifiers for each specific combination of said spatial boundaries, again, interacted with time fixed effects.

3 Empirical approach

Throughout, I will be estimating variants of the following difference-in-differences specification:

$$y_{d(p),t} = \xi_{d(p)} + \nu_{h(d)t} + \beta \times Post_t \times \Delta C^{ensemble}_{d(p)} + \eta \times X_{d(p),t} + \epsilon_{k(d(p))} \quad (1)$$

where

$$Post_t = \begin{cases} 1 & \text{after October 2022} \\ 0 & \text{before} \end{cases}$$

The specification is set up to be rather parsimonious. It includes area fixed effects ξ_d, which contorl for any time-invariant (un)observerable factors that may explain level differences in terms of the outcome variable $y_{d,t}$. The outcome variable is varying at the geographic unit d and time t level. The specification is set to include time fixed effects $\nu_{h(d)t}$ to control for common time-varying shocks. These could be specific to coarser geographic unit $h(d)$. For example, if the data is available at the mid-layer super output area (MSOA), it may make sense to control for local authority (LAD) by time fixed effects where $h(d)$ provides the mapping from MSOA to local authority since the geographies are nested. Lastly, there is additional control variables that are time varying $X_{d,t}$. These could be e.g. a set of other area characteristics or characteristics of the population in an area that are interacted with a set of time fixed effects to allow for non-linear trends in these. I discuss the main approach next.

As main estimating window for the difference-in-difference design I focus on the 12 month period from March 2022 to March 2023. Results are robust to larger estimating windows. The choice is mostly driven by three reasons: first, due to structural changes in reporting mechanisms for different types of crime (for example, data from prior to 2016 provided a categorisation of crime types that was much less granular); second, in light of such structural changes, area-specific fixed effects become distorted; third, the distorting effects that the pandemic had on the underlying data generating process is material for several crime categories – in particular, anti-social behavior reporting.

In the pre-registration that I publicly share on `https://osf.io/vhnjz/` along with several updates and intermediate and first results I estimated the difference-in-differences design using a much broader set of outcomes. The focus on a narrower set of outcomes is owing to the improved understanding of the underlying data generating process and the empirical relevance and accuracy of the measurement of the energy price shock: anti-social behaviour along with burglaries is widespread across all spatial units and time periods making it empirically relevant if we want to test the hypothesis that, in particular for burglaries, an income channel may be driving the results whereby lower real incomes – in the wake of the energy price shock – is causing an increase in crime out of economic need. For burglaries in particular, the location of the shock as well as the location of the crime may align rather well in the discussion of such a mechanism.

Saturation with other geographic time effects As indicated, I leverage a range of other geographic boundaries that have (some) administrative or political meaning and along which policy may be discretely different in a fashion that may be correlated within area but not between area over time. The easiest and most relevant one are police-force areas. There are around 40 different police forces in England that have dedicated areas that they are responsible for. For example, the Metropolitan Police is responsible for policing in Greater London (except the City of London). It is not unreasonable to expect that there may be notable differences in how the police force in one area responds to changes in crime activity compared to the police in other areas. As such, it may be prudent to control for police-force area specific time fixed effects that capture such police-force area specific changes in policing.

Similarly, administratively, local authorities may handle the energy crisis differently, e.g. providing other forms of financial or non-financial relief to households. Or, companies that are part of an enterprise zone may encourage firms in their area to provide targeted support or loans to households that may struggle in their area.

Again, each of these may create area-specific (un)observable policy changes that may vary over time that may be correlated with the treatment.

To account for these, I successively saturate the specification with additional time fixed effects that are specific to each of these different sets of area boundaries capturing different spatial concepts. I do so in two ways: adding each of these boundaries and area specific time fixed effects linearly but *separately* – that is, I add a set of Police-Force Area specific time fixed effects, in addition to Local Authority specific time fixed effects. But, going further, I also control for time-fixed effects that are specific to *each potential unique combination* of different spatial concepts as naturally, the spatial concepts are not all perfectly geographically nested.

For example: the Metropolitan Police may be responsible to police Greater London, but may adopt different approaches to different localities that make up Greater London. By accounting for each unique combination as I add more area-specific identifiers, I can in essence account for different approaches to policing that the same police force may implement in different areas within their same overall area of responsibility. Given my past work on community policing in Brasil (see e.g. Barbosa et al., 2021; Blair et al., 2021), this seems a relevant and prudent additional control variable to account for.

Saturation with area-specific socio-economic characteristics As indicated, I have a range of socio-economic characteristics or features that capture the building stock in an area. I have each converted these features capturing the quintile that each area is in vis-a-vis the full distribution. In total I consider 40 features that each have five categorical values indicating the quintile that an area is in with regard to each feature. Further, I allow each feature to have a different signature in each of the 41 areas in which different police forces have responsibility in England. That is, the most saturated specification will account for 40 x 5 x 41 = 8,200 feature specific time fixed effects allowing for non-linear time trends in a broad range of property- and area-specific socio-economic characteristics that are (likely) empirically relevant to the data generating process and may account for further unobservable factors or trends.

4 Results

4.1 Pooled estimation

Table 1 presents the difference-in-difference estimation results. Across columns, I add successively more granular time fixed effects that are specific to more granular area definitions that have administrative meaning. The most granular set of fixed effects are here at the ward level. There are nearly 8,000 different wards in England. The dependent variable has been normalized by the mean of the dependent variable. Similarly, the shock measure has been normalized by the standard deviation. This implies that we can interpret the point estimate on the reported coefficient as capturing the percent change in the dependent variable after October 2022 that is differentially occurring in an area that has a 1 SD higher exposure to the energy price shock. For reference, for the data resolution at the LSOA level, a 1 SD higher exposure to the energy price shock equates to £ 458.

The estimates suggest that a 1 SD higher exposure to the energy price shock is associated with an increase in reported anti-social behaviour of between 9 to 10 percent. On average, a representative household in a area is expected to experience an increase in their annual bills of nearly £ 1,200. This implies that the energy price shock may have increased anti-social behaviour, on average, by, on average, by 23%.

For burglaries, the effect sizes are smaller but not negligible. A one standard deviation higher exposure to the energy price shock as mediated via the EPG is associated with a 2 to 4 percent increase in burglaries. Combined, this suggests that the energy price shock may have caused an increase in burglaries, on average, by between 5 to 10 percent.

Varying data granularity The point estimates that are obtained here are very similar when carrying out the analysis at the coarser MSOA level as suggested in Appendix Table A1 or the (much) more granular output area as highlighted in Appendix Table A2. The effects are qualitatively and quantitatively very similar. Yet, given that the MSOA level data is much coarser, it is not surprising that the point estimates are a bit attenuated. This is owing to the fact that at the coarser level, the variation in the shock measure is much more compressed; at the same time, the same level of area-specific time fixed effects are absorbing much more of the variation in both the dependent variable as well as the shock measure. For the most part of the analysis I focus on the LSOA level data granularity which is also the granularity in terms of spatial identifiers that the crime data comes from via the original data source.

Functional form sensitivity etc. Appendix Tables A3 and A4 present a version of Table 1 estimated with transformed measure of the shock. The results are very similar. Appendix Tables A5 and A6 explore sensitivity of results to alternative transformations of the dependent variable. I consider the extensive margin capturing an *incidence* of an event and the transformation using a *log + 1*. All results are both qualitatively and quantitatively similar – the one exception is the fact that the sign flips for the anti-social behaviour outcome on the extensive margin. This, however, I do not consider to be too surprising or significant: most LSOAs report anti-social behaviour events regularly with more than half of the LSOA's having some police reported anti-social behaviour event in at least 75% of the months. This implies simply that there is not a lot of variation in the outcome measure when studying the extensive margin.[7]

4.2 Additional control variables

Table 2 presents the first analysis that saturates the specification with higher order interactions of the different area identifiers. That is, rather than e.g. by controlling separately for Police Force $\times$ Time fixed effects and Local Authority $\times$ Time fixed effects, I control for Police Force $\times$ Local Authority $\times$ Time fixed effects. Naturally this is a much more higher dimensional set of fixed effects as it implies a different group identifier for each combination of the two features that exist in the data. As explained, this may, for example, control for different area-specific policing strategies that may be adopted by the same police force in different areas. The comparison of the model statistic that indicates the number of estimated time fixed effects between Table 1 and Table 2 showcases how the number of estimated time

[7]In fact, as the pre-registered analysis of more granular outcome data at the output area, the sign flips back positive as for (much) more granular cut of the crime data the extensive margin becomes meaningful again. This can be read up on in the registration lodged on April 22, 2023 on `https://osf.io/vhnjz/`.

fixed effects increases drastically. The point estimates barely change.

Table 3 adds successively more discretized control variables interacted with police-force area identifiers and time fixed effects as *separate* sets of time effects. Across columns (1) to (4) I focus on features that are informative about the socio-economic characteristics of the residents in areas as proxied through the value of the housing stock as measured through the property price data; the various component scores that capture the resident populations varying degrees of relative deprivation; along with the indices capturing the council tax band of the property (historic property values). The estimated effects attenuate a bit when adding the property value controls, in particular, for the anti-social behaviour outcome.

What is more interesting and also, not surprising, is that the addition of area-specific non-linear time trends that are capturing the physical makeup of the housing stock, in particular, the built age of properties, we notice a further shrinking in the effect size and, for the most demanding specification that only uses three observation, on average, for each parameter estimated, the coefficient becomes insignificant at conventional levels.

This is not surprising. It is, in fact, very much expected. The primary driver for an areas differential exposure to the energy price shock as mediated via the energy price guarantee is due to the energy inefficiency of the housing stock. This was described in detail in Fetzer et al. (2022a). The prime driver of the energy (in)efficiency of housing in the UK is the period or age in which the property was build (see e.g. ONS, 2022). The energy price guarantee cushioned the energy price shock in an untargeted fashion, which means that, in real terms for residents with a poorly insulated homes, the energy price support was *less generous*, which is the prime source of identifying variation that this paper relies on. Naturally, this implies that when controlling, in a very granular fashion, for the age makeup of the housing stock in an area interacted with time fixed effects, invariably most of the identifying variation in the interaction term is absorbed in these fixed effects. Further, adding these fixed effects may lead to attenuation bias as invariably, the intention-to-treat measure is measured with error.

4.3 Common trend assumption

I next present evidence in support of the underlying common trends assumption visually in Figure 3. This estimates the plain difference-in-differences controlling just for LSOA-specific time fixed effects and time fixed effects without any other control variables. The omitted month is October 2022. A pattern that emerges is that there is a notable and consistent differential increase in police reported anti-social behaviour and burglaries in areas (expected to be) more exposed to the energy price shock from October 2022 onwards. The point estimates in the pre-treatment period are not entirely stable or centered around zero but there is no obvious visual queue that would suggest a concern in terms of identification. To some extent, it is important to flag up that the timing of the shock is not sharp.[8]

The energy price shock measure is computed as the property-level using the energy consumption as modelled in Fetzer et al. (2022a) together with the energy prices under the Ofgem October 2021 energy price cap vis-a-vis the October 2022 energy price cap that was set by the energy price guarantee. Yet, relative to the earlier years, spot market energy prices in October 2021 had already increased notably resulting in the Ofgem price cap for April 2022 to increase from £1,176 in April 2021 to £2,027 in April 2022 (see Appendix Figure A1 for the Ofgem energy price cap over time). Modelling over the summer would have suggested that bills would increase to £3,652 for the average UK household. The energy price guarantee capped the increase at £2,500. Yet, this implies that the energy price shock hit already earlier compared to what is modelled here hence, some spurious earlier effects are not surprising.

What is reassuring though is that the timing of the effects are very consistent with the expected timing. The energy price shock is most sharply felt economically in areas where the energy efficiency of the housing stock is low – that is – where the untargeted energy price guarantee implies different levels of support, in real terms, at a time when we expect the demand for energy to be particularly high – in the winter season. The patterns in the crime data are very consistent.

[8] For example, consumers can hedge against changes in energy prices by signing a fixed rate tariff that provides a fixed energy price for a specific period of typically a year. While many households may have entered into such fixed tariffs as energy prices started to shoot up in fall 2021 though most large energy suppliers pulled such tariffs early in 2022 as they were becoming financially unsustainable for them.

4.4 Placebo difference-in-difference in earlier years

I estimate a range of placebo difference-in-differences. In essence, what I do is simply shift the estimating time window to earlier years. The main estimation focuses on the time window from March 2022 to March 2023 estimating a specification as provided in 1 where the parameter of interest is the point estimate on the interaction term between the $Post_t$ indicator that is equal to 1 for the months after October 2022. I can replicate the same specification to earlier time windows: I estimate the same difference-in-difference focusing on the time window from March 2021 to March 2022 considering a post indicator as =1 for the months after October 2021 etc.

That is, I am shifting the full research design to earlier years and then compare the estimated coefficients that are obtained. The point estimates that are obtained from this exercise are provided in Figure 4. What is noteworthy is that the estimated effect for anti-social behaviour always has some spurious positive effect size – the pattern is quite evident and stark: anti-social behavior is only markedly and strongly increasing in areas more exposed to the energy price shock in the reserach design that focuses on the "correct" time window; the same is true for the burglary outcome. This provides further evidence that the results are robust.

I next turn to a counterfactual or quantification exercise.

4.5 Quantification of effects with different counterfactuals

Given the observed impact of the energy price shock causing a differential increase in anti-social behaviour and burglaries across England a natural question is – what would have happened had the government not intervened capping energy prices? What could have happened if energy price support was (more) targeted? And, to what extent would have a more energy efficient housing stock made a difference?

To tackle these questions I carry out a simple quantification using the point estimates and projecting them with different alternative simulated shock measures obtained under two different energy efficiency scenarios. The distribution of estimated effects across LSOAs is presented in Figure 5. In the left side I present the distribution of point estimates capturing the projected effect on anti-social behaviour (panel A) and burglaries (panel B) with the current energy inefficient housing stock.

The purple colored boxplot presents the distribution of projected effects across LSOAs. This maps directly into the main point estimates that were discussed. The median LSOA is estimated to have experienced an increase in anti-social behaviour of 17% and a 7% increase in burglaries. Without an intervention, the increase would have been much more pronounced had energy prices settled at the level that Ofgem projected for October 2022. Focusing on the two-tier tariff policy alternative, which would have left 12 million, predominantly lower to middle income households indifferent or, financially better off compared to the energy price guarantee, the increase in crime would have been much less pronounced. On average, burglaries and anti-social behavior would have increased only half as much.

The right panel performs the same quantification for the hypothetical levels of energy consumption with a building stock that has no more energy efficiency upgrade potential vis-a-vis its potential EPC rating as modelled in Fetzer et al. (2022a). This highlights very nicely that, with a more energy efficient housing stock, the increase in crime under any price scenario would have been much lower and, in the case of the two-tier tariff, it would have almost fully neutralised the shock owing to the fact that the vast majority of households would have been better off.

This highlights that more or better targeted energy bill support could provide large scale indirect societal benefits – captured here via less pronounced increase in crime. Alternatively, if social policy preferences are such that increases in crime similar to what is documented under the EPG is tolerated, it could suggest nevertheless that a cheaper alternative two-tier tariff could have been implemented that would have produced a similar level of crime as this paper suggests is associated with the untargeted transfer implemented via the energy price guarantee.

This highlights that there may be a large societal value to building an effective (digital) infrastructure that enables the state to provide targeted transfers. The lack of such a technical ability in many countries came into sharp relief during the pandemic in which stimulus payments had to be sent out in an untargeted fashion contributing to already growing economic inequality that is seen as a source of societal instability undermining cohesion – a mechanism that has been long studied in developing countries (see e.g. Alesina et al., 2016; Hodler and Raschky, 2014).

Further, this quantification suggests that energy efficiency investments may yield wider dividends in the form of higher resilience, making any trade-off between how one should target energy subsidies in the wake of a shock less pronounced. Cost and benefit considerations that merely consider the direct financial cost- and benefit of energy efficiency upgrades to the individual property owner will invariably underestimate these other indirect societal benefits.

5 Conclusion

This paper presents some first results on the wider socio-economic impact of the energy price shock in the UK. It focuses, for the time being, on crime. The paper documents that areas more exposed to the energy price shock saw a much more notable increase in burglaries and anti-social behavior. The paper exploits the fact that the energy price shock was cushioned through the energy price guarantee in an untargeted fashion – implying that the support is less generous in real terms for identical households who live in properties that differ in their degree of energy efficiency.

The quantification suggests that more targeted interventions could have resulted in much less pronounced increase in crime in the wake of the shock. Further, the data suggests that a more energy efficient housing stock may offer wider societal benefits in the form of less crime going beyond the direct economic and environmental benefits.

References

Alesina, Alberto, Stelios Michalopoulos, and Elias Papaioannou, "Ethnic Inequality," *Journal of Political Economy*, 2016, *124* (2), 428–488.

Algan, Yann, Sergei Guriev, Elias Papaioannou, and Evgenia Passari, "The European Trust Crisis and the Rise of Populism," *Brookings Papers on Economic Activity*, 2017, *2017* (2), 309–400.

Barbosa, Daniel AC, Thiemo Fetzer, Caterina Soto, and Pedro CL Souza, "De-escalation technology: the impact of body-worn cameras on citizen-police interactions," *CAGE Working Paper*, 2021, (581).

Besley, Timothy and Torsten Persson, "The origins of state capacity: Property rights, taxation, and politics," *American Economic Review*, 2009, *99* (4), 1218–1244.

_ **and** _ , "State Capacity, Conflict, and Development," *Econometrica*, 2010, *78* (1), 1–34.

_ **, Thiemo Fetzer, and Hannes Mueller**, "The Welfare Cost of Lawlessness: Evidence from Somali Piracy," *Journal of the European Economic Association*, apr 2015, *13* (2), 203–239.

Bignon, Vincent, Eve Caroli, and Roberto Galbiati, "Stealing to Survive? Crime and Income Shocks in Nineteenth Century France," *The Economic Journal*, feb 2017, *127* (599), 19–49.

Blair, Graeme, Darin Christensen, and Aaron Rudkin, "Do Commodity Price Shocks Cause Armed Conflict? A Meta-Analysis of Natural Experiments," *American Political Science Review*, 2021, (21).

Britto, Diogo G. C., Paolo Pinotti, and Breno Sampaio, "The Effect of Job Loss and Unemployment Insurance on Crime in Brazil," *Econometrica*, 2022, *90* (4), 1393–1423.

Bruegel, "National fiscal policy responses to the energy crisis," *Bruegel*, 2021, pp. 1–12.

Disney, Richard F., John Gathergood, Stephen J. Machin, and Matteo Sandi, "Does Homeownership Reduce Crime? A Radical Housing Reform from the UK," *SSRN Electronic Journal*, 2021, (December).

Draca, Mirko, Stephen Machin, and Robert Witt, "Panic on the streets of London: Police, crime, and the july 2005 terror attacks," *American Economic Review*, 2011, *101* (5), 2157–2181.

_ **, Theodore Koutmeridis, and Stephen Machin**, "The changing returns to crime: Do criminals respond to prices?," *Review of Economic Studies*, 2019, *86* (3), 1228–1257.

Facchetti, Elisa, "Police Infrastructure, Police Performance , and Crime: Evidence from Austerity Cuts," *mimeo*, 2023.

Fetzer, Thiemo, "Did Austerity Cause Brexit ?," *CAGE Working Paper*, 2018.

_ , "Can Workfare Programs Moderate Conflict? Evidence from India," *Journal of the European Economics Association*, 2019.

—, "The Energy Price Guarantee: what next?," *CAGE Policy Briefing*, 2022, pp. 1–24.

—, "Regulatory barriers to climate action: Evidence from Conservation Areas in England," *CAGE Working Paper*, 2023.

— **and Christopher Rauh**, "Pandemic Pressures and Public Health Care: Evidence from England," *CAGE Working Paper*, 2022, (607).

— **and** —, "Quantifying excess mortality among non COVID-19 patients in healthcare settings," *CAGE Working Paper*, 2022.

— **and Shizhuo Wang**, "Measuring the Regional Economic Cost of Brexit: Evidence up to 2019," *CAGE Working Paper*, 2020, (486).

—**, Ludovica Gazze, and Menna Bishop**, "How large is the energy savings potential in the UK?," *CAGE Working Paper*, 2022.

—**,** —**, and** —, "Distributional and climate implications of policy responses to the energy crisis: Lessons from the UK," *CAGE Working Paper*, 2023, (February).

—**, Srinjoy Sen, and Pedro C L Souza**, "Housing Insecurity and Homelessness: Evidence from the United Kingdom," *Journal of the European Economic Association*, nov 2022.

Funke, Manuel, Moritz Schularick, and Christoph Trebesch, "Populist Leaders and the Economy," 2020, (036).

Grantham Institute, "Decarbonising Buildings : Insights From Across Europe," 2022, pp. 1–20.

Guriev, Sergei and Elias Papaioannou, "The Political Economy of Populism," *forthcoming, Journal of Economic Literature*, 2021.

Hodler, Roland and Paul A Raschky, "Regional Favoritism," *The Quarterly Journal of Economics*, mar 2014, *129* (2), 995–1033.

Home Office, "Anti-Social Behaviour Action Plan," 2023, pp. 1–39.

Khanna, Gaurav, Carlos Medina, Anant Nyshadham, Christian Posso, and Jorge Tamayo, "Job Loss, Credit, and Crime in Colombia," *American Economic Review: Insights*, 2021, *3* (1), 97–114.

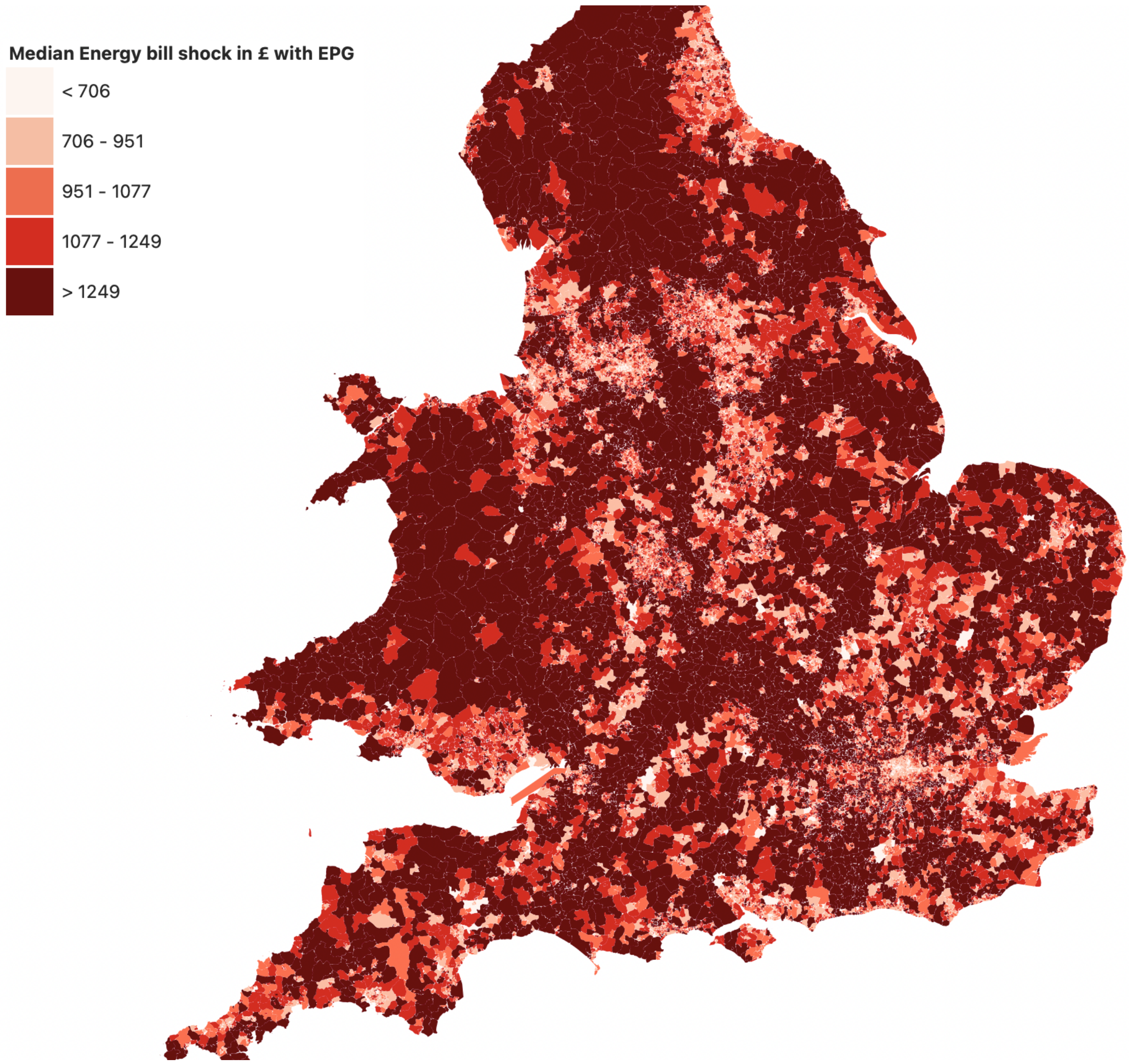
Kirchmaier, Tom, Stephen Machin, Matteo Sandi, and Robert Witt, "Prices, Policing and Policy: The Dynamics of Crime Booms and Busts," *Journal of the European Economic Association*, apr 2020, *18* (2), 1040–1077.

ONS, "Age of the property is the biggest single factor in energy efficiency of homes

- Office for National Statistics," *Office of National Statistics*, 2022, (January 2022), 1–20.

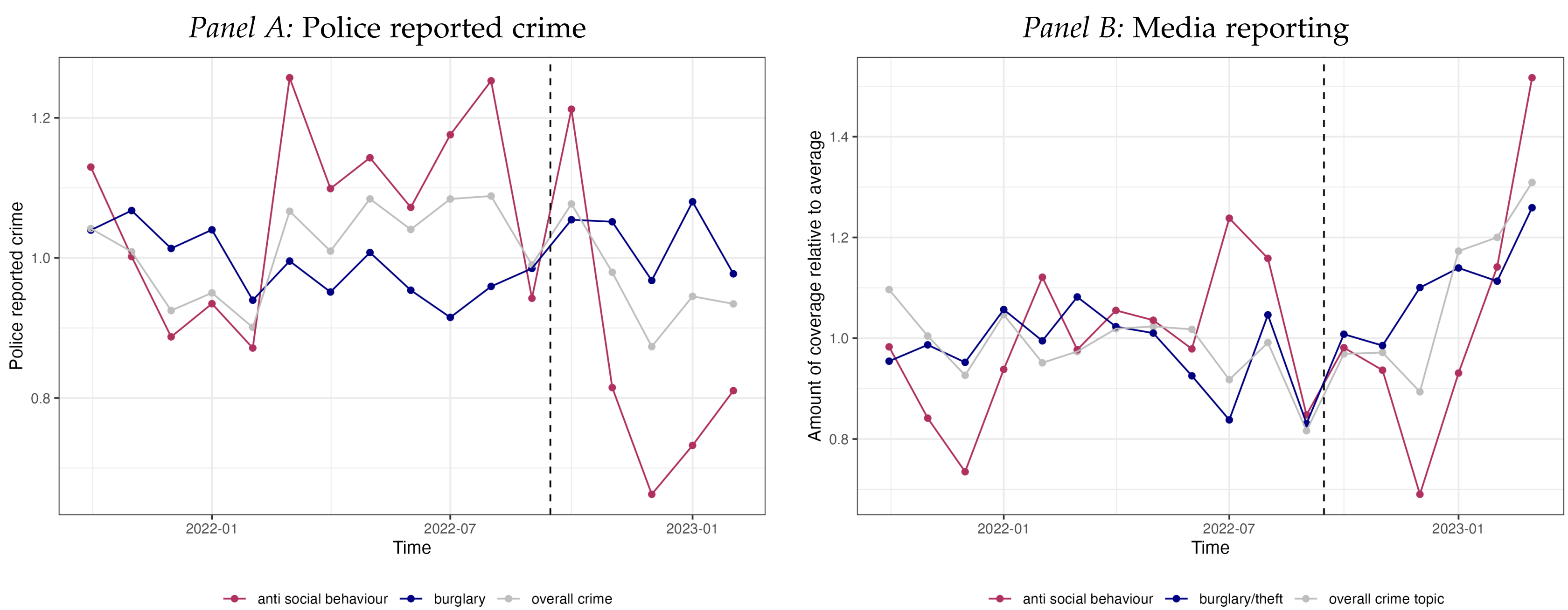
Rufrancos, Hector and Madeleine Power, "Income Inequality and Crime: A Review and Explanation of the Time?series Evidence," *Sociology and Criminology*, 2013, *01* (01), 1034172–1000103.

Figure 1: Map of simulated energy price shock for median property across LSOAs in England and Wales



Notes: Figure displays the projected impact of the energy price shock as mediated with the energy pice guarantee for the median property within each LSOA.

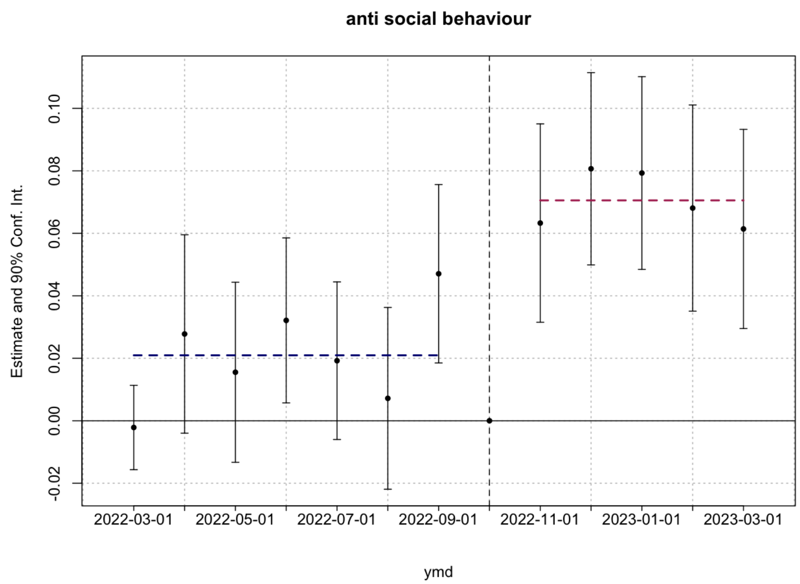
Figure 2: Disconnect between police reported crime data and media coverage in the UK



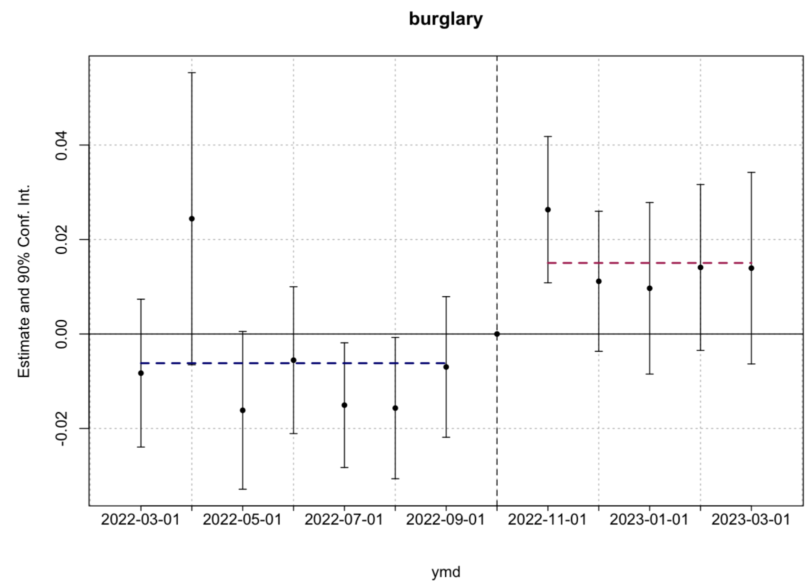
Notes: Figure displays police reported crime aggregates normalized by the average number o monthly police reported crimes over the time series focusing on burglaries, cases of anti-social behavior and the count of all police reported crime categories combined. Panel B presents the equivalent measures pertaining to media reported crime. This represents a news index covering the number of news articles published in UK news sources indexed on the Factiva news wires index. For burglary and theft and the overall crime topic, the index displays the amount of coverage normalized by the mean monthly coverage over the time window. Here Factiva uses topic modeling to classify articles. The anti-social behaviour time series measures the number of articles that mention these keywords. We note a sharp increase from early 2023 on.

Figure 3: Difference-in-difference plots across crime categories

Panel A: Anti Social Behavior



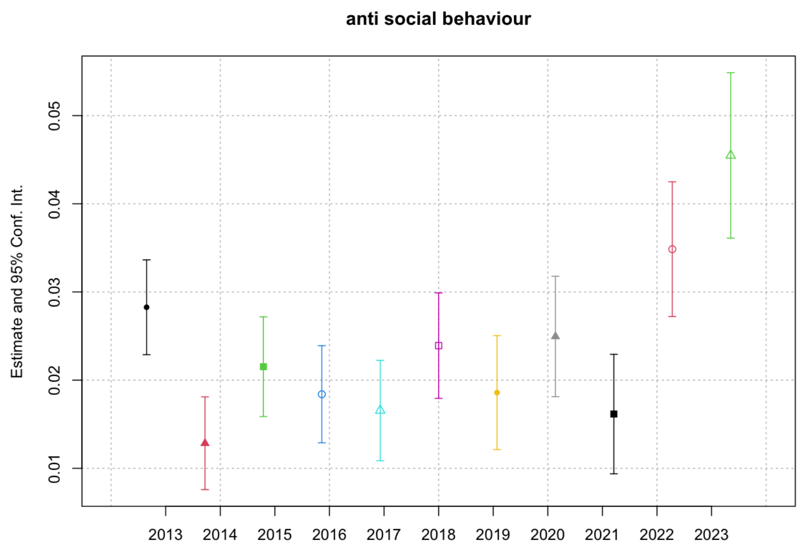
Panel B: Burglary



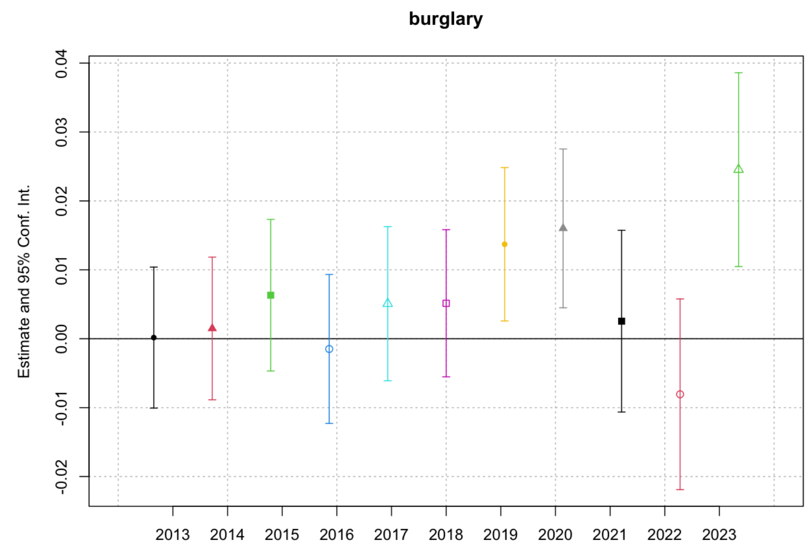
Notes: Figures present difference-in-difference estimation results. The dependent variable is the count of the number of crime events in a specific category indicated in the figure head in an LSOA and in a given month. The regressions control for LSOA level fixed effects and local authority district specific time fixed-effects. Coefficient plotted is the interaction between the average energy price shock exposure of an LSOA and month in which crime is reported. Standard errors are clustered at the local authority level with 95% confidence bands indicated.

Figure 4: Placebo difference-in-difference estimates replication of research design in earlier years

Panel A: Anti Social Behavior



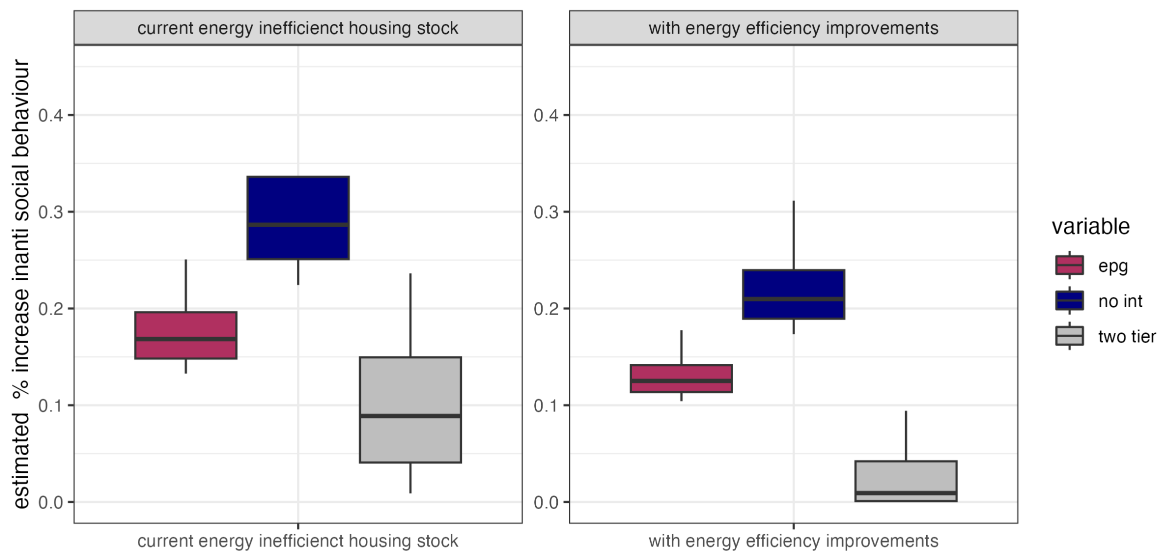
Panel B: Burglary



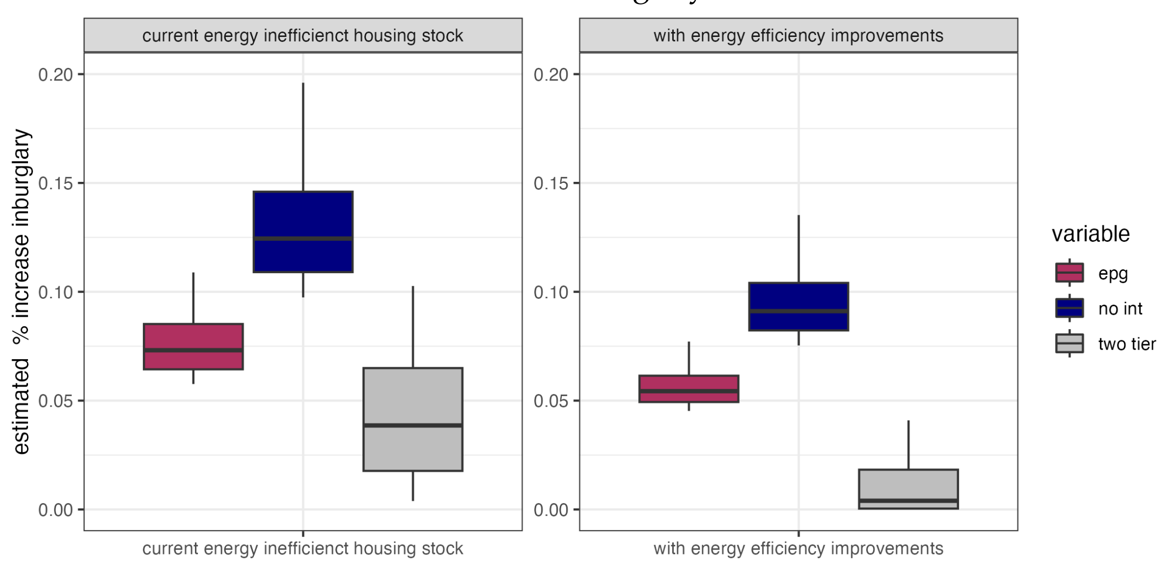
Notes: Figures present difference-in-difference estimation results. Each coefficient represents the result of a difference-in-differerence estimation with LSOA fixed effects and time fixed effects. The coefficient plotted is the interaction between the median 2022 energy price shock exposure of an LSOA and month in which crime is reported. Each year indicates the time window over which the regression is estimated. The main specification labeled 2023 in the paper is estimated covering the March 2022 to March 2023 period; the 2022 model replicates the same specification just covering the period March 2021 to March 2022 etc. Standard errors are clustered at the local authority level with 95% confidence intervals indicated.

Figure 5: Projecting estimated impact of energy price shock on crime across different policy scenarios and with different level of energy efficiency of housing stock

Panel A: Anti Social Behavior



Panel B: Burglary



Notes: Figures presents the distribution of the estimated effects taking the point estimates from a preferred specification and multiplying it with different energy bill intention-to-treat shock measures that were obtained under different policy scenarios and with different baseline energy demand owing to better energy efficiency of the housing stock. The figure plots distribution of the point estimates for the 25th to the 75th percentile as well as the median in a box-plot style figure. "EPG" is the scenario that was implemented as a cap on energy prices via the energy price guarantee; "No int" stands for a scenario in which there would have been no intervention and the energy price cap as modelled by Ofgem for October 2022 would have been implemented; "Two Tier" presents the effects under a two-tier tariff structure as introduced in Fetzer (2022).

Table 1: Impact of energy price shock on anti-social behavior and burglaries – pooled difference-in-differences results across output areas

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Anti-social behaviour				
post × EPG mediated shock	0.089***	0.091***	0.095***	0.097***	0.100***	0.087***	0.081***	0.095***
	(0.019)	(0.017)	(0.020)	(0.018)	(0.019)	(0.012)	(0.012)	(0.011)
R^2	0.721	0.724	0.724	0.728	0.724	0.733	0.736	0.795
No. of estimated FE	32,873	33,289	33,250	34,134	34,771	36,773	39,685	124,172
No. of area FE	32,756	32,756	32,756	32,756	32,756	32,756	32,756	32,756
No. of time FE	117	533	494	1,378	2,015	4,017	6,929	91,416
Observations	425,828	425,828	425,828	425,828	425,828	425,828	425,828	425,828
				Burglaries				
post × EPG mediated shock	0.026***	0.025***	0.025***	0.025***	0.023**	0.028***	0.027***	0.034***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.011)
R^2	0.373	0.375	0.375	0.377	0.378	0.383	0.390	0.524
No. of estimated FE	32,873	33,289	33,250	34,134	34,771	36,773	39,685	124,172
No. of area FE	32,756	32,756	32,756	32,756	32,756	32,756	32,756	32,756
No. of time FE	117	533	494	1,378	2,015	4,017	6,929	91,416
Observations	425,828	425,828	425,828	425,828	425,828	425,828	425,828	425,828
Time FE are specific by	Region	Police	Enterprise zones	Health	Commuting zones	Local authority	Parliamentary Constituency	Ward

Notes: Table presents estimated effects with differentially saturated two-way fixed effect specifications. The dependent variable is a count measure of the number instances of police reported crime in an area. The data granularity is at the LSOA level and the specification includes an LSOA level fixed effect throughout. Appendix Tables A2 and A1 report results at granular and coarser level. Time fixed effects are added at different spatial granularities across columns. The model statistic provides the number of estimated fixed effects in each specification. The shock measure is standardized with effect sizes capturing the impact of a 1 SD increase in exposure to the shock on the average levels of reported crime in a category. Stars indicate statistical significance obtained from estimating clustered standard errors at the district level with stars indicating *** p <0.01, ** p <0.05, and * p <0.1.

Table 2: Impact of energy price shock on anti-social behavior and burglaries – pooled difference-in-differences results across output areas

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Anti-social behaviour							
post × EPG mediated shock	0.089***	0.096***	0.099***	0.097***	0.103***	0.092***	0.089***	0.099***
	(0.019)	(0.019)	(0.019)	(0.018)	(0.018)	(0.012)	(0.012)	(0.010)
R^2	0.721	0.726	0.726	0.728	0.730	0.734	0.739	0.799
No. of estimated FE	32,873	33,627	33,926	36,435	39,568	42,688	50,098	137,198
No. of area FE	32,756	32,756	32,756	32,756	32,756	32,756	32,756	32,756
No. of time FE	117	871	1,170	3,679	6,812	9,932	17,342	104,442
Observations	425,828	425,828	425,828	425,828	425,828	425,828	425,828	425,828
	Burglaries							
post × EPG mediated shock	0.026***	0.024***	0.025***	0.025***	0.024***	0.031***	0.030***	0.036***
	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.010)	(0.009)
R^2	0.373	0.375	0.376	0.378	0.383	0.394	0.404	0.535
No. of estimated FE	32,873	33,627	33,926	36,435	39,568	42,688	50,098	137,198
No. of area FE	32,756	32,756	32,756	32,756	32,756	32,756	32,756	32,756
No. of time FE	117	871	1,170	3,679	6,812	9,932	17,342	104,442
Observations	425,828	425,828	425,828	425,828	425,828	425,828	425,828	425,828
Time FE involve more higher order combination by	Region	Police	Enterprise zones	Health boards	Commuting zones	Local authority	Parliamentary Constituency	Ward

Notes: Table presents estimated effects with differentially saturated two-way fixed effect specifications. The dependent variable is a count measure of the number instances of police reported crime in an area. The data granularity is at the Output Area level and the specification includes an Output Area level fixed effect throughout. Appendix Tables 1 and A1 report results at granular and coarser level. Time fixed effects are added at different spatial granularities across columns. The model statistic provides the number of estimated fixed effects in each specification. The shock measure is standardized with effect sizes capturing the impact of a 1 SD increase in exposure to the shock on the average levels of reported crime in a category. Stars indicate statistical significance obtained from estimating clustered standard errors at the district level with stars indicating *** p <0.01, ** p <0.05, and * p <0.1.

Table 3: Impact of energy price shock on anti-social behavior and burglaries – adding successively higher order discretized area-specific control variables interacted with time fixed effects

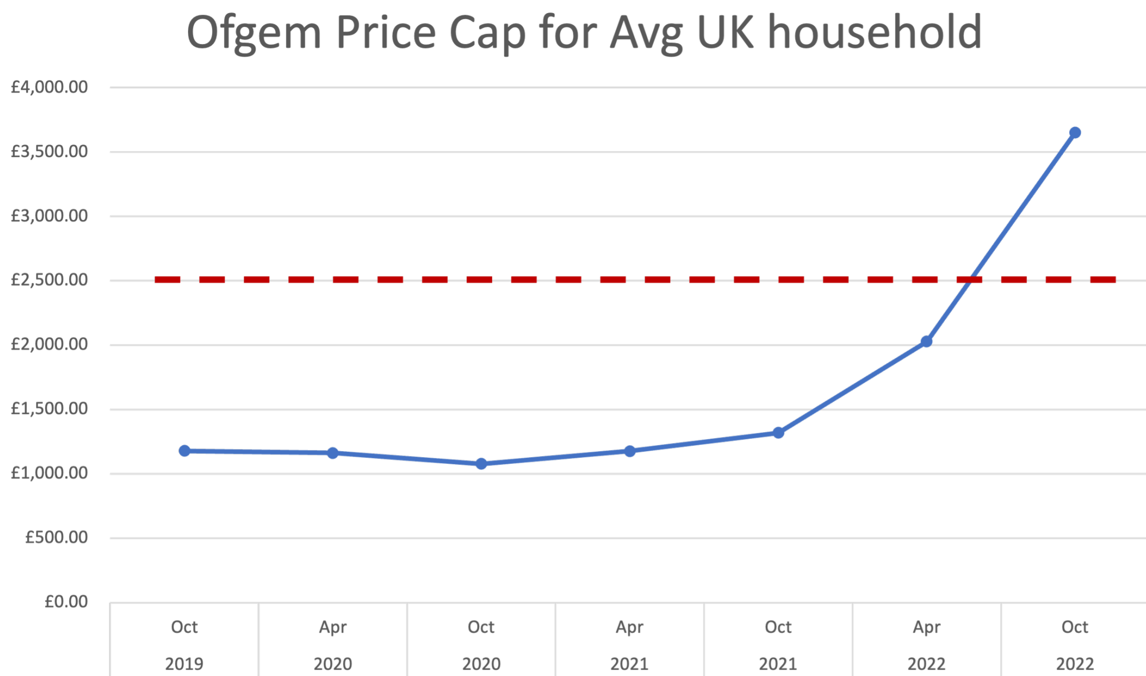
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Anti-social behaviour							
post × EPG mediated shock	0.087***	0.043***	0.046***	0.040***	0.037***	0.028***	0.023***	0.022***
	(0.012)	(0.010)	(0.010)	(0.008)	(0.006)	(0.007)	(0.007)	(0.008)
R^2	0.733	0.741	0.743	0.753	0.755	0.768	0.774	0.779
No. of estimated FE	37,644	50,631	55,818	80,921	83,677	114,292	130,646	143,321
No. of area FE	32,756	32,756	32,756	32,756	32,756	32,756	32,756	32,756
No. of time FE	4,888	17,875	23,062	48,165	50,921	81,536	97,890	110,565
Observations	425,828	425,828	425,828	425,828	425,828	425,828	425,828	425,828
	Burglaries							
post × EPG mediated shock	0.028***	0.024***	0.025***	0.023***	0.023***	0.016**	0.012	0.011
	(0.009)	(0.009)	(0.008)	(0.008)	(0.007)	(0.008)	(0.007)	(0.007)
R^2	0.383	0.398	0.404	0.427	0.430	0.461	0.478	0.490
No. of estimated FE	37,644	50,631	55,818	80,921	83,677	114,292	130,646	143,321
No. of area FE	32,756	32,756	32,756	32,756	32,756	32,756	32,756	32,756
No. of time FE	4,888	17,875	23,062	48,165	50,921	81,536	97,890	110,565
Observations	425,828	425,828	425,828	425,828	425,828	425,828	425,828	425,828
Time FE involve higher order interactions by	Local Authority	Property prices	Deprivation indices	Council tax band	Main heating fuel	Built age of properties	Built form	Property type

Notes: Table presents estimated effects with differentially saturated two-way fixed effect specifications. The dependent variable is a count measure of the number instances of police reported crime in an area. The data granularity is at the Output Area level and the specification includes an Output Area level fixed effect throughout. Appendix Tables 1 and A1 report results at granular and coarser level. Time fixed effects are added at different spatial granularities across columns. The model statistic provides the number of estimated fixed effects in each specification. The shock measure is standardized with effect sizes capturing the impact of a 1 SD increase in exposure to the shock on the average levels of reported crime in a category. Stars indicate statistical significance obtained from estimating clustered standard errors at the district level with stars indicating *** p <0.01, ** p <0.05, and * p <0.1.

Appendix to "Did the policy response to the energy crisis cause crime? Real time evidence from England"

For Online Publication

Figure A1: Ofgem energy price cap and energy price guarantee



Notes: Figures provides the estimated energy bill for the average UK household as modelled under the Ofgem model that is used to regulate and cap energy prices. The energy price guarantee cap is illustrated.

Table A1: Impact of energy price shock on anti-social behavior and burglaries – pooled difference-in-differences results across MSOAs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Anti-social behaviour							
post × EPG mediated shock	0.071***	0.073***	0.076***	0.078***	0.082***	0.067***	0.058***	0.054*
	(0.017)	(0.015)	(0.018)	(0.016)	(0.017)	(0.010)	(0.009)	(0.027)
R^2	0.840	0.847	0.846	0.854	0.846	0.865	0.871	0.969
No. of estimated FE	6,888	7,304	7,265	8,149	8,786	10,788	13,700	74,085
No. of area FE	6,771	6,771	6,771	6,771	6,771	6,771	6,771	6,771
No. of time FE	117	533	494	1,378	2,015	4,017	6,929	67,314
Observations	92,547	92,547	92,547	92,547	92,547	92,547	92,547	92,547
	Burglaries							
post × EPG mediated shock	0.019**	0.017**	0.018**	0.016*	0.013	0.021**	0.018*	0.034*
	(0.009)	(0.008)	(0.008)	(0.009)	(0.010)	(0.009)	(0.009)	(0.020)
R^2	0.581	0.586	0.585	0.592	0.594	0.611	0.629	0.906
No. of estimated FE	6,888	7,304	7,265	8,149	8,786	10,788	13,700	74,085
No. of area FE	6,771	6,771	6,771	6,771	6,771	6,771	6,771	6,771
No. of time FE	117	533	494	1,378	2,015	4,017	6,929	67,314
Observations	92,547	92,547	92,547	92,547	92,547	92,547	92,547	92,547
Time FE are specific by	Region	Police	Enterprise zones	Health	Commuting zones	Local authority	Parliamentary Constituency	Ward

Notes: Table presents estimated effects with differentially saturated two-way fixed effect specifications. The dependent variable is a count measure of the number instances of police reported crime in an area. The data granularity is at the MSOA level and the specification includes an MSOA level fixed effect throughout. Appendix Tables A2 and 1 report results at more granular level. Time fixed effects are added at different spatial granularities across columns. The model statistic provides the number of estimated fixed effects in each specification. The shock measure is standardized with effect sizes capturing the impact of a 1 SD increase in exposure to the shock on the average levels of reported crime in a category. Stars indicate statistical significance obtained from estimating clustered standard errors at the district level with stars indicating *** p <0.01, ** p <0.05, and * p <0.1.

Table A2: Impact of energy price shock on anti-social behavior and burglaries – pooled difference-in-differences results across output areas

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Anti-social behaviour							
post × EPG mediated shock	0.081***	0.082***	0.085***	0.086***	0.089***	0.078***	0.071***	0.064***
	(0.017)	(0.015)	(0.017)	(0.016)	(0.017)	(0.012)	(0.011)	(0.011)
R^2	0.567	0.568	0.568	0.569	0.568	0.571	0.572	0.592
No. of estimated FE	170,810	171,226	171,187	172,071	172,708	174,710	177,622	262,447
No. of area FE	170,693	170,693	170,693	170,693	170,693	170,693	170,693	170,693
No. of time FE	117	533	494	1,378	2,015	4,017	6,929	91,754
Observations	2,219,009	2,219,009	2,219,009	2,219,009	2,219,009	2,219,009	2,219,009	2,219,009
	Burglaries							
post × EPG mediated shock	0.026**	0.025**	0.025**	0.025**	0.024**	0.028**	0.026**	0.028*
	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)	(0.015)
R^2	0.228	0.228	0.228	0.229	0.229	0.230	0.232	0.266
No. of estimated FE	170,810	171,226	171,187	172,071	172,708	174,710	177,622	262,447
No. of area FE	170,693	170,693	170,693	170,693	170,693	170,693	170,693	170,693
No. of time FE	117	533	494	1,378	2,015	4,017	6,929	91,754
Observations	2,219,009	2,219,009	2,219,009	2,219,009	2,219,009	2,219,009	2,219,009	2,219,009
Time FE are specific by	Region	Police	Enterprise zones	Health	Commuting zones	Local authority	Parliamentary Constituency	Ward

Notes: Table presents estimated effects with differentially saturated two-way fixed effect specifications. The dependent variable is a count measure of the number instances of police reported crime in an area. The data granularity is at the output area level and the specification includes an output-area level fixed effect throughout. Table 1 and Table A1 report results at coarser level. Time fixed effects are added at different spatial granularities across columns. The model statistic provides the number of estimated fixed effects in each specification. The shock measure is standardized with effect sizes capturing the impact of a 1 SD increase in exposure to the shock on the average levels of reported crime in a category. Stars indicate statistical significance obtained from estimating clustered standard errors at the district level with stars indicating *** p <0.01, ** p <0.05, and * p <0.1.

Table A3: Impact of energy price shock on anti-social behavior – alternative measurement of shock – pooled difference-in-differences results across output areas

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Anti-social behaviour							
Panel A:								
post × EPG mediated shock	0.081***	0.088***	0.091***	0.089***	0.095***	0.084***	0.080***	0.090***
	(0.017)	(0.017)	(0.017)	(0.016)	(0.017)	(0.011)	(0.011)	(0.009)
R^2	0.719	0.724	0.725	0.726	0.728	0.732	0.737	0.799
No. of estimated FE	34,701	35,507	35,806	38,354	41,812	45,179	52,927	148,919
No. of area FE	34,571	34,571	34,571	34,571	34,571	34,571	34,571	34,571
No. of time FE	130	936	1,235	3,783	7,241	10,608	18,356	114,348
Observations	449,423	449,423	449,423	449,423	449,423	449,423	449,423	449,423
Panel B:								
post × $1(EPG mediated shock > median)	0.205***	0.215***	0.221***	0.221***	0.221***	0.197***	0.182***	0.137***
	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)	(0.027)	(0.025)	(0.020)
R^2	0.719	0.724	0.725	0.727	0.728	0.733	0.737	0.799
No. of estimated FE	34,701	35,507	35,806	38,354	41,812	45,179	52,927	148,919
No. of area FE	34,571	34,571	34,571	34,571	34,571	34,571	34,571	34,571
No. of time FE	130	936	1,235	3,783	7,241	10,608	18,356	114,348
Observations	449,423	449,423	449,423	449,423	449,423	449,423	449,423	449,423
Panel C:								
post × log(EPG mediated shock)	0.345***	0.376***	0.387***	0.385***	0.404***	0.362***	0.348***	0.351***
	(0.066)	(0.065)	(0.063)	(0.061)	(0.060)	(0.040)	(0.040)	(0.031)
R^2	0.719	0.724	0.725	0.727	0.728	0.733	0.737	0.799
No. of estimated FE	34,701	35,507	35,806	38,354	41,812	45,179	52,927	148,919
No. of area FE	34,571	34,571	34,571	34,571	34,571	34,571	34,571	34,571
No. of time FE	130	936	1,235	3,783	7,241	10,608	18,356	114,348
Observations	449,423	449,423	449,423	449,423	449,423	449,423	449,423	449,423
Time FE are specific by	Region	Police	Enterprise zones	Health	Commuting zones	Local authority	Parliamentary Constituency	Ward

Notes: The dependent variable measures the number of police reported events of anti-social behaviour in an LSOA. Table presents estimated effects with differentially saturated two-way fixed effect specifications. The dependent variable is a count measure of the number instances of police reported crime in an area. The data granularity is at the LSOA level and the specification includes an LSOA level fixed effect throughout. Time fixed effects are added at different spatial granularities across columns. Across panels the way that the shock is measuerd is varied. Stars indicate statistical significance obtained from estimating clustered standard errors at the district level with stars indicating *** p <0.01, ** p <0.05, and * p <0.1.

Table A4: Impact of energy price shock on burglaries – alternative measurement of shock – pooled difference-in-differences results across output areas

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Anti-social behaviour							
Panel A:								
post × EPG mediated shock	0.026***	0.024***	0.025***	0.026***	0.026***	0.032***	0.032***	0.039***
	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.010)	(0.009)
R^2	0.373	0.375	0.376	0.378	0.383	0.394	0.404	0.538
No. of estimated FE	34,701	35,507	35,806	38,354	41,812	45,179	52,927	148,919
No. of area FE	34,571	34,571	34,571	34,571	34,571	34,571	34,571	34,571
No. of time FE	130	936	1,235	3,783	7,241	10,608	18,356	114,348
Observations	449,423	449,423	449,423	449,423	449,423	449,423	449,423	449,423
Panel B:								
post × $1(EPG mediated shock > median)	0.035***	0.031**	0.032**	0.036***	0.033**	0.039***	0.036**	0.030**
	(0.013)	(0.013)	(0.013)	(0.013)	(0.012)	(0.013)	(0.014)	(0.014)
R^2	0.373	0.375	0.376	0.378	0.383	0.394	0.404	0.538
No. of estimated FE	34,701	35,507	35,806	38,354	41,812	45,179	52,927	148,919
No. of area FE	34,571	34,571	34,571	34,571	34,571	34,571	34,571	34,571
No. of time FE	130	936	1,235	3,783	7,241	10,608	18,356	114,348
Observations	449,423	449,423	449,423	449,423	449,423	449,423	449,423	449,423
Panel C:								
post × log(EPG mediated shock)	0.092***	0.084***	0.088***	0.093***	0.091***	0.115***	0.114***	0.132***
	(0.025)	(0.024)	(0.024)	(0.026)	(0.025)	(0.028)	(0.031)	(0.028)
R^2	0.373	0.375	0.376	0.378	0.383	0.394	0.404	0.538
No. of estimated FE	34,701	35,507	35,806	38,354	41,812	45,179	52,927	148,919
No. of area FE	34,571	34,571	34,571	34,571	34,571	34,571	34,571	34,571
No. of time FE	130	936	1,235	3,783	7,241	10,608	18,356	114,348
Observations	449,423	449,423	449,423	449,423	449,423	449,423	449,423	449,423
Time FE are specific by	Region	Police	Enterprise zones	Health	Commuting zones	Local authority	Parliamentary Constituency	Ward

Notes: The dependent variable measures the number of police reported burglaries in an LSOA. Table presents estimated effects with differentially saturated two-way fixed effect specifications. The dependent variable is a count measure of the number instances of police reported crime in an area. The data granularity is at the LSOA level and the specification includes an LSOA level fixed effect throughout. Time fixed effects are added at different spatial granularities across columns. Across panels the way that the shock is measuerd is varied. Stars indicate statistical significance obtained from estimating clustered standard errors at the district level with stars indicating *** p <0.01, ** p <0.05, and * p <0.1.

Table A5: Impact of energy price shock on anti-social behavior – alternative measurement of outcome variable – pooled difference-in-differences results across output areas

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Anti-social behaviour							
Panel A:								
post × EPG mediated shock	0.081***	0.088***	0.091***	0.089***	0.095***	0.084***	0.080***	0.090***
	(0.017)	(0.017)	(0.017)	(0.016)	(0.017)	(0.011)	(0.011)	(0.009)
R^2	0.719	0.724	0.725	0.726	0.728	0.732	0.737	0.799
No. of estimated FE	34,701	35,507	35,806	38,354	41,812	45,179	52,927	148,919
No. of area FE	34,571	34,571	34,571	34,571	34,571	34,571	34,571	34,571
No. of time FE	130	936	1,235	3,783	7,241	10,608	18,356	114,348
Observations	449,423	449,423	449,423	449,423	449,423	449,423	449,423	449,423
Panel B:								
post × EPG mediated shock	-0.006***	-0.006***	-0.007***	-0.007***	-0.007***	-0.007***	-0.008***	-0.009***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
R^2	0.420	0.429	0.429	0.431	0.436	0.442	0.451	0.577
No. of estimated FE	34,701	35,507	35,806	38,354	41,812	45,179	52,927	148,919
No. of area FE	34,571	34,571	34,571	34,571	34,571	34,571	34,571	34,571
No. of time FE	130	936	1,235	3,783	7,241	10,608	18,356	114,348
Observations	449,423	449,423	449,423	449,423	449,423	449,423	449,423	449,423
Panel C:								
post × EPG mediated shock	0.019***	0.021***	0.022***	0.021***	0.023***	0.021***	0.019***	0.022***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)
R^2	0.625	0.635	0.635	0.637	0.640	0.644	0.650	0.730
No. of estimated FE	34,701	35,507	35,806	38,354	41,812	45,179	52,927	148,919
No. of area FE	34,571	34,571	34,571	34,571	34,571	34,571	34,571	34,571
No. of time FE	130	936	1,235	3,783	7,241	10,608	18,356	114,348
Observations	449,423	449,423	449,423	449,423	449,423	449,423	449,423	449,423
Time FE are specific by	Region	Police	Enterprise zones	Health	Commuting zones	Local authority	Parliamentary Constituency	Ward

Notes: Table presents estimated effects with differentially saturated two-way fixed effect specifications. The dependent variable in Panel A is a count measure of the number instances of police reported anti-social behavior; in Panel B it measures whether any given month sees an event involving anti-social behavior; in Panel C its the log(count +1) of anti-social behavior events reported to the police in an area and a given month. The data granularity is at the LSOA level and the specification includes an LSOA level fixed effect throughout. Time fixed effects are added at different spatial granularities across columns. Stars indicate statistical significance obtained from estimating clustered standard errors at the district level with stars indicating *** p <0.01, ** p <0.05, and * p <0.1.

Table A6: Impact of energy price shock on burglaries – alternative measurement of outcome variable – pooled difference-in-differences results across output areas

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Burglary							
Panel A:								
post × EPG mediated shock	0.026***	0.024***	0.025***	0.026***	0.026***	0.032***	0.032***	0.039***
	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.010)	(0.009)
R^2	0.373	0.375	0.376	0.378	0.383	0.394	0.404	0.538
No. of estimated FE	34,701	35,507	35,806	38,354	41,812	45,179	52,927	148,919
No. of area FE	34,571	34,571	34,571	34,571	34,571	34,571	34,571	34,571
No. of time FE	130	936	1,235	3,783	7,241	10,608	18,356	114,348
Observations	449,423	449,423	449,423	449,423	449,423	449,423	449,423	449,423
Panel B:								
post × EPG mediated shock	0.005**	0.005**	0.005**	0.006**	0.006***	0.006***	0.006**	0.006**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
R^2	0.264	0.266	0.267	0.269	0.276	0.282	0.294	0.452
No. of estimated FE	34,701	35,507	35,806	38,354	41,812	45,179	52,927	148,919
No. of area FE	34,571	34,571	34,571	34,571	34,571	34,571	34,571	34,571
No. of time FE	130	936	1,235	3,783	7,241	10,608	18,356	114,348
Observations	449,423	449,423	449,423	449,423	449,423	449,423	449,423	449,423
Panel C:								
post × EPG mediated shock	0.007***	0.007***	0.007***	0.007***	0.007***	0.008***	0.008***	0.009***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
R^2	0.336	0.338	0.338	0.341	0.347	0.353	0.365	0.507
No. of estimated FE	34,701	35,507	35,806	38,354	41,812	45,179	52,927	148,919
No. of area FE	34,571	34,571	34,571	34,571	34,571	34,571	34,571	34,571
No. of time FE	130	936	1,235	3,783	7,241	10,608	18,356	114,348
Observations	449,423	449,423	449,423	449,423	449,423	449,423	449,423	449,423
Time FE are specific by	Region	Police	Enterprise zones	Health	Commuting zones	Local authority	Parliamentary Constituency	Ward

Notes: Table presents estimated effects with differentially saturated two-way fixed effect specifications. The dependent variable in Panel A is a count measure of the number instances of police reported anti-social behavior; in Panel B it measures whether any given month sees an event involving anti-social behavior; in Panel C its the log(count +1) of anti-social behavior events reported to the police in an area and a given month. The data granularity is at the LSOA level and the specification includes an LSOA level fixed effect throughout. Time fixed effects are added at different spatial granularities across columns. Stars indicate statistical significance obtained from estimating clustered standard errors at the district level with stars indicating *** p <0.01, ** p <0.05, and * p <0.1.