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Expected returns to crime and crime location

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Expected Returns to Crime and Crime Location

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Abstract

We provide first evidence that temporal variations in the expected returns to crime affect the location of property crime. Our identification strategy relies on the widely-held perception in the UK that households of South Asian descent store gold jewellery at home. Price movements on the international market for gold exogenously affect the expected gains from burgling these households, which become relatively more lucrative targets as the gold price increases. Using a neighbourhood-level panel on reported crime and difference-in-differences, we find that burglaries in South Asian neighbourhoods are more sensitive to variations in the gold price than other neighbourhoods in the same municipality, confirming that burglars react rationally to variations in the expected returns to their activities. We conduct a battery of tests on neighbourhood and individual data to eliminate alternative explanations.

JEL classification: K42; J19

Keywords: Crime; Gold prices; Returns to crime; Becker model; Optimal Foraging Theory; Criminal Behaviour; Crime Location

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1 Introduction

How do criminals adjust their choice of targets when the expected returns to crime vary? The seminal Becker-model (Becker, 1968) considers crime participation as an economic decision arising from a comparison of the expected risk-adjusted returns of legal and illegal activities, so that variations in their relative returns alter the decision to engage in crime. This theory has generated a vast empirical literature, with a focus on the influence of labour market conditions as well as changes in the probability of arrest or sentencing.[1]

Less attention has been given to the role played by changes in the returns to committing crime, mostly due to data limitations regarding the financial value of the stolen goods and empirical issues, primarily difficulties in identifying counterfactual targets and the endogeneity of the returns to criminal activities on prices. However, in the Becker-model of crime the returns to criminal activity are an important determinant of the decision to commit a crime, especially for property crime (burglary, robbery and various forms of theft) which represents the majority of crime. Indeed, in one of the few available studies Draca, Koutmeridis, and Machin (2019) – using a panel of stolen goods linked to data on product prices – estimate that a 10% increase in the price of a good, relative to the prices of other goods, is associated with a 3.5% increase in the probability that this good is stolen. Their estimates are even stronger for a group of commodity-related goods, specifically fuel, jewellery and metal, for which the elasticities are greater than one. Another recent paper by Kirchmaier, Machin, Sandi, and Witt (2020) studies metal theft in the UK with a particular focus on prices as well as the effects of policing initiatives and regulation of buyers, specifically scrap metal dealers. Similar to Draca et al. (2019), but based on a time-series analysis, they also report a price elasticity greater than unity in the case of metal theft.

While these papers provide evidence that price changes affect which goods are stolen, there is no evidence yet to what extent changes to the expected returns of criminal activity affect criminals' choice of targets and thus the location of crime. However, this question is arguably of great policy interest – knowing where crime will be committed allows for a better targeting of police resources and thus helps with crime prevention. Indeed police forces are increasingly making use of the predictability of criminal activities to allocate forces, with predictive policing found to have a positive effect on clearance rates (Mastrobuoni, 2020).[2]

[1] The findings of a number of studies point towards a significant relationship between labour market outcomes, policing and crime rates, but less robust effects of sentencing, see Chalfin and McCrary (2017); Draca and Machin (2015) for reviews, or Fu and Wolpin (2018) for a structural model.

[2] There is also a large literature considering the effect of policing activities on crime, see Chalfin and McCrary (2017) for a review. Examples include redeployment of police following terrorist attacks in Buenos Aires (Di Tella and Schargrodsky, 2004) and London (Draca, Machin, and Witt, 2011), police (or other guard) redeployments within cities due to specific events (e.g., Marie (2016); MacDonald, Klick, and Grunwald (2016); Cheng and Long (2018); Mastrobuoni (2019); McMillen, Sarmiento-Barbieri, and Singh (2019); Braakmann (2022)) or specific initiatives around police hiring or equipment (e.g., Bove and Gavrilova (2017); Mello (2019)). Evidence from both criminology and economics on the policing of crime hot spots, often based on randomised controlled trials, suggests such targeted policing as a viable policing strategy (see, e.g., Braga, Weisburd, Waring, Green Mazerolle, Spelman, and Grajewski (1999); Braga and Bond (2008); Weisburd, Morris, and Groff (2009); Ratcliffe, Taniguchi, Groff, and Wood (2011); Lazzati and Menichini (2016);Ariel, Sherman, and Newton (2020)). However, more limited redeployment of police forces and patrolling have been found to have either no effect (Blanes i Vidal and Mastrobuoni (2018); Blattman, Ortega, Green, and Tobon (2021)) or sometimes large negative effects on crime, e.g., using quasi experimental variations in police force deployment Weisburd (2021) find that a reduction of police force by 10% increases crime by 7%.

We expand this literature by assessing, for the first time, how variations in expected returns to crime alter not only the nature of crimes committed but also their location. Building on the findings of Draca et al. (2019) that jewellery crime is strongly correlated with variations in the price of gold, we consider the implications for targets selected by criminals. While their work concentrates on how variations in price affects the basket of stolen goods, we focus on its effect on the choice of victims, and thus where the crime is committed. When a commodity is more likely to be held by a specific demographic group, and the price of that commodity increases relative to other goods, we should also expect the relative victimisation rate of this demographic group to increase. Furthermore, when this group is geographically concentrated, we would then expect the location of crimes to vary with variations in the price of the underlying commodity.

To test this assertion we rely on ethnic variations in household preferences to store wealth in the form of gold jewellery, and estimate whether exogenous variations in the price of gold affects the geographical pattern of crime in England and Wales, as burglars target households with an expected greater preference for gold. In particular, we exploit the long-standing cultural practices of families of South Asian descent (i.e., those with Bangladeshi, Indian or Pakistani heritage) to have a high proclivity towards storing wealth in the form of gold jewellery (Lawrence, 2003), especially of the highest (22-carat) quality (Fernandez, Veer, and Lastovicka, 2011). Lawrence (2003) notes the importance of gold jewellery in Hindu and Muslim cultures. As well as being a storage of wealth, it is a fundamental part of many rituals, religious or social festivities and signals a family's position in their local community (Fernandez et al., 2011). These preferences have persisted outside of the Indian sub-continent and, through the various public displays as well as reports in the national media (e.g., The Guardian (2012); BBC (2019)), are well known to the British population.

Individuals from South Asian descent represent just over 5% of the population in England and Wales (Office for National Statistics, 2012), settling mostly in the 20 years following World War II. Since migration was mostly driven by labour force shortages in specific industries, South Asian communities tend to be regionally concentrated in the UK (see Appendix B, Figure 8). This national variation is not well suited to our purpose since it would imply that burglars travel large distances in order to target neighbourhoods with a high South Asian share. Instead our identification strategy uses the large level of segregation within local authorities[3] (see examples in Appendix B, Figures 9 and 10), so that adjacent neighbourhoods within a local authority have large variations in the share of the population originating from South Asia. We exploit this within-local authority variation in the share of South Asian households to estimate how fluctuations in the price of gold affect the distribution of burglaries within a local authority. We thus capture the location choices made by burglars concerning where to commit crimes within a local authority, and how those are affected by variations in the price of gold.

Compared to other goods that might be stolen, the secondary market for gold is large, with gold price changes widely reported in the media.[4] Prices are mostly determined via the global demand for gold on the international exchange and unlikely to be affected by the selling of stolen gold jewellery in the UK. Indeed international variation in the price of gold in the short-run is

[3]Local authorities are the basic level of local government in the UK, roughly equivalent to US counties.
[4]d'Este (2020) highlights the importance of the secondary market for stolen good in the decisions of burglars.

mostly driven by change in the US price level, the behaviour of central banks, and worldwide political uncertainty, especially concerning oil prices (Levin and Wright, 2006). Hence it seems safe to assume that variation in the gold price is exogenous to the quantity of gold stolen in burglaries in the UK.

While not explicitly modeled, the decision on where to commit a crime fits within Becker's model of criminal behaviour, whereby a potential criminal considers the expected costs and returns from committing a crime in two different locations. Since the expected returns to burgling a South Asian household increase relatively more when the price of gold is higher, it becomes a more valuable target. Burglars may not be able to perfectly identify an individual South Asian household, but will increase their expected returns by operating in neighbourhoods with a greater share of South Asian households. All else equal, the model predicts a relative shift of burglaries towards South Asian neighbourhoods when the price of gold increases. This behaviour is also consistent with an influential theory in criminology that describes how offenders select potential targets. Based on models from behavioural ecology, where animals are understood to forage for food by maximising the acquisition of resources whilst minimising search effort and the risk of attack by a predator, *optimal foraging theory* posits that criminals aim to maximise the proceeds of crime and minimise the time spent searching for a suitable target, committing the crime and the risk of being caught (Johnson and Bowers (2004); van Winden and Ash (2012)).

For our main analysis, we collect data on individual crime occurrences between 2011 and 2019 for all police forces in England and Wales and aggregate these to form a monthly panel at the level of small geographical neighbourhoods (lower-layer super output areas (LSOAs)). The neighbourhoods are classified as relative high density South Asian neighbourhood when their share of South Asians is an outlier in their local authority. We combine these data with monthly gold prices from the London Bullion Market Association (LBMA).

The analysis proceeds using a differences-in-differences methodology where we interact the monthly gold price with an indicator for a South Asian neighbourhood, while controlling for various low-level geographical fixed effects, as well as time effects and neighbourhood specific time-trends, i.e., the identifying variation comes from monthly variations in the price of gold in neighbourhoods identified as having a relatively high share of South Asian households in their local authority. Across all specifications, we consistently find that increases in the the price of gold lead to a surge in burglaries in neighbourhoods with a large share of South Asians relative to other neighbourhoods in the same local authority. In our favoured specification a 1% rise in the price of gold leads to a relative increase of burglary in South Asian neighbourhood by 0.056%. This elasticity is of the same order of magnitude as the main effect of the gold price on burglaries, i.e., burglaries in South Asian neighbourhoods are twice as sensitive to variations in the price of gold as in non-South Asian neighbourhoods. We conduct a battery of robustness checks, altering the definition of treated neighbourhood, the geographical fixed effect or the treatment of time to demonstrate the stability of this result.

In a next step we explore some heterogeneity related to the costs of searching neighbourhoods and the ease with which a burglar could acquire targets. LSOAs are constructed to have similar population figures, hence they are spatially smaller and thus easier to search in urban areas. In addition, the absolute share of South Asians tends to be larger in urban areas as well. Both of these factors suggest that our effects should be stronger in urban than in rural areas. We indeed find that this is case. We then explore this idea in a more direct way by looking at the absolute share of South Asian households. We find that the effect becomes stronger in treated neighbourhoods with more South Asian households, i.e., the effect is stronger the easier it is to identify a neighbourhood as having a high South Asian density. These findings strongly support our hypothesis that criminals respond to exogenous changes in the potential returns to a crime by selecting areas with potentially more lucrative targets, consistent with optimal foraging theory.

We then assess various threats to identification. First, we conduct two falsification tests by altering which neighbourhoods are defined as treated (other ethnic minority, poor) and considering alternative indicators of economic activity, which might affect crime but should not have any specific effects on the targeting of South Asians households. Our estimated effects are not mirrored in other neighbourhood types, nor for other indicators of economic activity. Second, we use a randomisation inference procedure where we randomly assign treated neighbourhoods and reestimate our main effects a 1,000 times. Both of these tests, confirm our main results and strongly support that the effect is likely to be driven by burglars targeting South Asians households when the price of gold is high.

Additionally, we explore whether the increase in burglaries in neighbourhoods with a high proportion of South Asian households induce displacement to other crimes in the neighbourhood or to burglaries in other part of the local authority. In both cases, we do not find evidence of displacement and instead find that burglaries in neighbourhoods surrounding areas with a higher concentration of South Asian households are also positively related to variations in the gold price, which is consistent with the idea that burglars cannot perfectly identify neighbourhood boundaries.

We also test whether police forces relocate resources to South Asian neighbourhoods in response to changes in the gold price, for example, because they are aware of changes in burglary behaviour. To test this we use data on the incidence of "stops and searches" conducted by the police in a neighbourhood. Specifically, a variety of laws allows the UK police to stop and search individuals if a police officer has a reasonable suspicion that a crime has been committed. We focus on all searches as well as searches for stolen items and articles used in theft conducted under the Police and Criminal Evidence Act 1984. Using these as outcomes in a regression analogous to our main specification, we find no evidence that South Asian neighbourhoods experience an increase in police activity when gold prices are high.

Finally, to complement the main analysis, we pool individual-level data from the Crime Survey for England and Wales. While this data does not include information on neighbourhoods, we can instead directly identify the ethnicity of the head of household. This allows us to test for possible alternatives to the optimal foraging hypothesis. First, we find that, conditional on being burgled, South Asian households are twice as likely to report the theft of jewellery, confirming the greater proclivity of South Asian households to store gold jewellery. Second, we provide evidence that only South Asian households report more burglaries when the price of gold increases. Hence both at the neighbourhood and at the household level, we find that South Asians are more at risk of burglaries when the price of gold increases. The survey also allows us to dismiss concerns that South Asian households differ in their propensity to report burglaries to the police or differ in the level of protections of their house.

Altogether, we find consistent evidence supporting optimal foraging theory as well as the mechanism underpinning the Becker model: Burglars respond to changes in the price of the goods they want to steal by relocating their efforts to areas of the local authority with a higher share of households likely to store this good. The effect is potentially large, doubling the risk of burglary associated with the price change in these neighbourhoods.

2 Data

To conduct the main analysis, we merge data from several sources. The measure of a neighbourhood is a lower-layer super output area (LSOA), which constitutes the unit of observations in our analysis. In England and Wales there are almost 35,000 LSOAs, these are relatively small spatial units with a minimum population of 1,000 (with a mean of 1,500), equal to approximately 650 households. They are designed for the publication of census data and have remained stable since their introduction in the 2001 census (see appendix A for further details). By design, they cover a homogenous population and can be interpreted as a neighbourhood. LSOAs are nested within local authorities (LA), the basic level of local government in the UK with responsibility for public service provision within their boundaries (roughly equivalent to US counties). Local authorities usually consist of a city or amalgamations of smaller towns and rural areas. London as a special case is split into 32 boroughs each designated as a Local Authority. There are a total of 348 LAs in England and Wales, each contains on average 100 LSOAs but with a large amount of variation, from 1 (Isles of Scilly) to 639 (Birmingham). LAs are responsible for various policies but not for policing. This is the remit of a Chief Constable who leads the police within a Police Force Area (PFA). There are 43 PFAs in England and Wales, each usually covering multiple local authorities.

To define the ethnic composition of an LSOA we rely on information from the 2011 census. In 2011, 5.2% of the population in England and Wales self-identified as South Asian, which we define as the proportion of the population identifying themselves as Bangladeshi, Indian and Pakistani, the largest ethnic group in the country. For historical reasons, the South Asian population is geographically concentrated, as immigration was encouraged to address labour shortages in specific industries post world war II.[5] Subsequent migration has predominantly been in the form of family reunification, which has tended to reinforce the concentration of migrants creating diasporic communities with strong cultural ties to their communities of origin. The census is the only source of information on ethnic composition at the neighbourhood level, we will thus define South Asian neighbourhoods on the basis of their 2011 population, and this will remain fixed over the period of analysis.

Figure 8 in appendix B displays the distribution of the South Asian population across the UK. It is clear that South Asians are highly concentrated in London and the urban areas of the Midlands and North West. The median share of the South Asian population is 1.15%, and 1,988

[5]Immigration from Commonwealth citizens remained restriction-free until the passing of the Commonwealth Immigrants Acts of 1962 and 1968. Migration flows from India peaked in 1968 (Naujoks, 2009).

LSOAs (around 6% of the total) do not contain any persons of South Asian descent. At the other extreme, the top 10% most concentrated LSOAs have a South Asian population share between 12% and 98%. If we were to define treated areas as having a high share of South Asians according to a national threshold measure, we would just be picking up neighbourhoods in large urban conurbations and leave large swathes of the country in the control group. This would be unlikely to pick up the choice made by a local burglar who typically decides on targets in the vicinity of their own domicile (Vandeviver and Bernasco, 2019). Moreover, it is unlikely that burglars can identify small variations in the share of South Asian households between target neighbourhoods, but instead could identify those that have a relatively high share. This means that their behaviour is unlikely to react in a linear manner to the neighbourhood-level share of South Asian. We thus rely on the heterogeneity in the distribution of South Asian neighbourhoods within a local authority, which is still substantial (the standard deviation of the South Asian share within local authorities is 8 percentage points) and define neighbourhoods as high share if their share of South Asian population is in excess of the 75th percentile plus 1.5 times the interquartile range for that local authority (which is a standard outlier definition). Around 6.5% of neighbourhoods in our sample are then classified as (relatively) high density South Asian areas. This definition of neighbourhoods with a relatively high share of South Asian population assures that there is at least one treated neighbourhood in each local authority, meaning that burglars always have a choice to target a "local" neighbourhood. We also provide evidence of the robustness of our results to alternative definitions of treated neighbourhoods.

We merge this data with LSOA-level characteristics based on the 2011 Census. This includes the share of the black population, the share of low skilled households (Category D and E from the social grade classification) and rural status. For the purpose of the analysis these characteristics are considered fixed over time and will mostly be used in robustness checks to define alternative definition of treated areas. As neighbourhoods are nested within local authorities, we also include LA specific information, in particular the local authority level unemployment rate, calculated by the ONS from the Labour Force Survey.

The crime data was extracted from www.police.uk, a website created and maintained by the British police that provides crime maps down to the street level for England, Wales and Northern Ireland.[6] The data covers the period January 2011 to December 2019.[7] Note, we do not include data from January 2020 onwards as the COVID-19 pandemic possibly disrupted previous crime patterns. In principle the location of a crime is recorded with exact coordinates, however, in the published data locations are slightly coarsened for anonymisation reasons (see appendix A for details). This potential measurement error is inconsequential in our case, since we aggregate the data at the LSOA level which is precisely recorded in the published data. For each neighbourhood, the reported outcomes are monthly counts of recorded offences in several categories. We mainly focus on burglary, which is consistently measured across the observation period. In addition, we also provide results for crimes in other categories that are consistently defined: "robbery", "violent crime", "vehicle crime" and "total crime (excluding burglary)". We

[6] As crime data is not reported identically in Scotland and Northern Ireland, our analysis includes England and Wales only.

[7] From July 2019 there is no data for the Greater Manchester Police Force after an inspection from Her Majesty's Inspectorate of Constabulary and Fire & Rescue Services revealed that more than 20% of crimes over the period July 2019 to June 2020 had not been recorded (HMICFRS (2020)).

also collect data on stop and search activities which we will use to approximate the deployment of police personnel within LSOAs, on a monthly basis.

Table 1: Summary Statistics

Variable	Total	Control	Oulier in LA
Demographic Characteristics			
Share of South Asian	0.050	0.042	0.162
	(0.108)	(0.095)	(0.193)
Outlier in LA	0.065	0	1
	(0.246)	(.)	(.)
Share of Black	0.031	0.031	0.036
	(0.065)	(0.066)	(0.054)
Share in class DE	0.253	0.249	0.309
	(0.131)	(0.128)	(0.150)
Rural	0.179	0.188	0.055
	(0.383)	(0.390)	(0.228)
Total population	1613.6	1607.9	1696.1
	(303.4)	(297.1)	(374.0)
Local unemployment rate	5.982	5.980	6.011
	(2.557)	(2.562)	(2.471)
Crime counts			
Burglaries reported	1.024	1.007	1.270
	(1.459)	(1.440)	(1.701)
Robberies recorded	0.157	0.153	0.220
	(0.643)	(0.642)	(0.653)
Vehicle crimes reported	0.956	0.944	1.119
	(1.485)	(1.477)	(1.587)
Violent crimes reported	0.414	0.395	0.684
	(1.623)	(1.543)	(2.504)
Total crime excluding burglary	13.32	12.76	21.34
	(19.89)	(19.05)	(28.38)
Time periods (months)	108	108	108
Neighbourhoods	34,753	32,506	2,247
Observations	3,743,286	3,501,636	241,650

Notes: The table displays summary statistics at the neighbourhood level (LSOA). The top panel is based on Census 2011 data, quarterly unemployment rate is provided by NOMIS. Monthly Crime data are aggregated at the LSOA level by the authors. Note, that there is no data available for the Greater Manchester Police Force between June and December 2019.

Table 1 provides summary statistics for the main variables of interest at the neighbourhood level, overall and separately by treatment status. Unsurprisingly, the treated areas have a higher share of South Asian households than control areas (16% vs. 3.6%) and are much less likely to be classified as rural (5.5% vs 19.3%). They also have a higher share of population in the lowest social class (25% vs 31%) but do not differ in the proportion of Black households, local-area unemployment or population size.

Crime counts are generally fairly small in absolute numbers, which is not surprising given the small neighbourhoods we consider in this paper and the monthly frequency of the data. On average there is 1 burglary per month per neighbourhood, but there is a relatively large amount of variation with a standard deviation of 1.459. Indeed, due to the small area sizes and short periodicity, a substantial proportion (47%) of neighbourhood-month cells are zero-valued for our main outcome burglaries. For the empirical analysis we therefore take an inverse hyperbolic sine transformation of the crime series, which approximates the natural logarithm but retains zero-valued observations.[8] Treated neighbourhoods have a 27% higher level of reported burglaries and tend to suffer from higher levels of total reported crime for all categories, especially violent crimes and overall crime (excluding burglaries); this is partly due to their greater propensity to be located in urban areas.

Finally, the identification involves variation in gold prices at which burglars can expect to sell their good, which we approximate by the monthly average of the over-the-counter transaction price of gold from the London Bullion Market Association (LBMA).[9] The headline Pound Sterling figure is regularly published in both traditional and digital media in the UK, and consequently is easily available to members of the public. In addition, while gold on the secondary "scrap" gold market is sold at a discount compared to the LBMA, traders update their prices immediately according to the LBMA spot market price.[10] There are important variations in the price of gold over the sample period, as shown in Figure 1. At the beginning of our observation period, January 2011, the price (expressed in 2015 values[11]) stood at £934.56 per troy ounce and reached a record high of £1154.97 in November of the same year. In April 2013 the price dropped sharply in the wake of the Cypriot financial crisis, reaching a nadir in around December 2013, stabilising at around £700-£800 for the following 24 months. Prices somewhat recovered at the beginning of 2016, holding around the same value in real terms as at the beginning of the period before climbing sharply in the latter half of 2019. Altogether, compared to baseline, gold price varies by +20% to -20% during the period of analysis.

Gold price broadly reflects the state of the world economy, as such we will conduct a series of robustness checks using other economic indicators. To this extent, we sourced the oil price from the World Bank's Commodity Price Data (Pink Sheet), where it is presented in nominal US dollars. These prices are converted into real UK (2015) prices using the Bank of England's monthly average spot exchange rate and the Current Price Index (CPI) from the Office of National Statistics. Over the period the price of oil was stable until summer 2014, it then slid by 50% and remained at this lower level until early 2016. It then recovered to about 80% of its original price, before sliding down again after 2019. While both gold and oil reflect economic and geopolitical uncertainty globally, we also focus on two indicators of the UK and local economy. The UK Economic Policy Uncertainty Index (Baker, Bloom, and Davis, 2016) is an index based on the monthly count of articles including terms describing the economic environment across 11 UK newspapers. The count of each term is summed across newspapers to produce and index which is normalised to 100 in 2011. A higher level of the index indicates greater level of economic

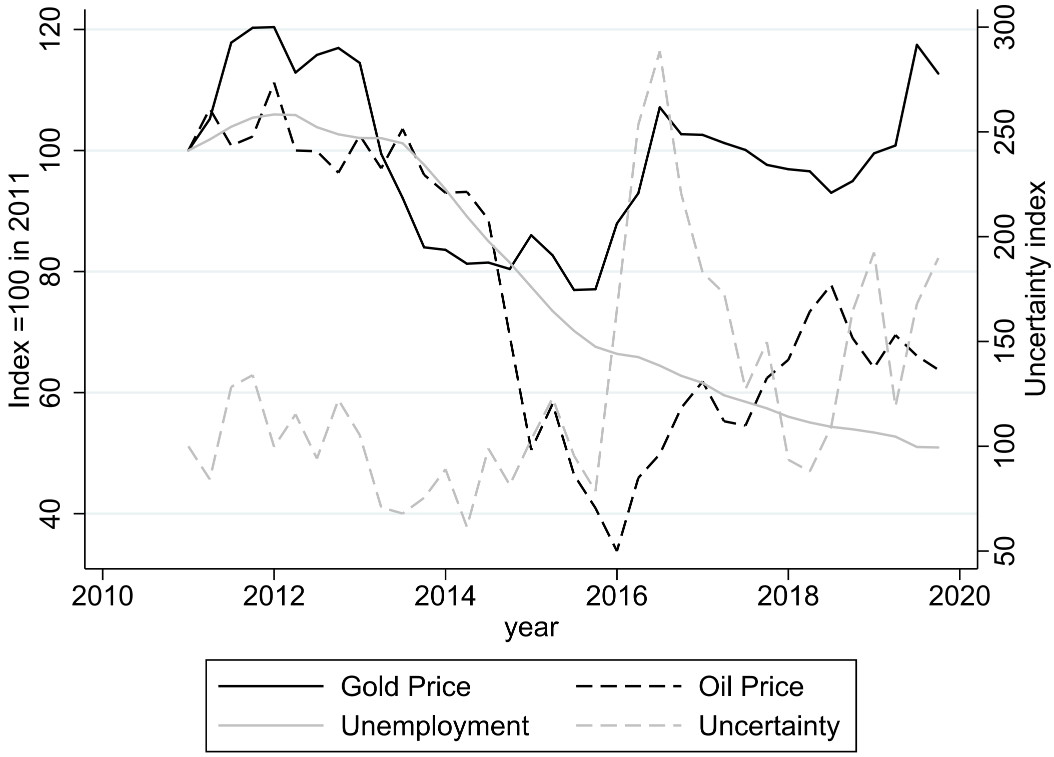
[8] The inverse hyperbolic sine transformation is given by $\sinh^{-1}(x) = \ln(x + \sqrt{(x^2+1)})$, which is defined over any real number and is therefore an attractive alternative to a logarithmic transformation when data contains zero-valued observations. Bellemare and Wichman (2019) show that $\hat{\xi}_{yx} \approx \hat{\beta}$ for large values of x and y.

[9] Although gold is traded in various markets worldwide, London is the largest trading centre accounting for 86% of the volume of trades in 2011 (Lucey, Larkin, and O'Connor, 2013). The currency of trading is the US dollars, but the LBMA announces the official gold price on its website in US dollars, Pound Sterling and Euros twice in a trading day (10.30am and 3.00pm local time).

[10] For example gold.co.uk states that "We buy scrap gold for up to 95% of its spot value, giving you excellent value and a great customer experience."

[11] We deflate the nominal price using the Current Price Index (CPI) from the Office of National Statistics

Figure 1: Gold Price and Alternative Measures of Economic Activity



The graph compares the evolution of the gold price, oil price, local unemployment and UK Uncertainty Index, each indexed to January 2011. Sources: Gold prices - London Bullion Market Association; Oil prices - World Bank; Local Authority Unemployment - ONS/Nomis; UK Uncertainty Index - www.policyuncertainty.com.

uncertainty. It hovered around 100 until 2016 and rose up to 300 around the "Brexit" referendum, and then hovered between 100 and 200 for the remaining of the period. The last measure of the economic environment, is the local unemployment rate. This is computed quarterly, by the Office for National Statistics, for each local authority.[12] Local unemployment was about 8% for the first two years before decreasing gradually to 4% by the end period.

In Figure 1, we report the co-evolution of the four series of economic environment. For ease of comparison, we index them to have a value of 100 at the beginning of the period. Note that due to its greater volatility, the economic index is reported on a different scale. Although there is a degree of co-movement between the measures, especially at the beginning of the period, they vary mostly independently thereafter. Indeed, the correlations between the gold price and the other three measures range from 0.23 to 0.42, the latter being for oil price. The low correlations between gold price and specific indicators of economic activity in the UK goes some way to reassure us that variations in the gold price are unlikely to reflect fluctuations in the UK economy, which by themselves could have a direct effect on crime propensity.

Finally, we present corroborating analysis using the Crime Survey for England and Wales (CSEW - previously known as the British Crime Survey). This is a national survey conducted annually

[12] The local unemployment rate is not computed for the "City of London" and the "Isles of Scilly" due to the small populations in these local authorities.

on behalf of the Office for National Statistics and covering topics such as victimisation and attitudes towards crime. The survey has been conducted continuously since 2001, and samples a representative set of households about their victimisation experiences in the previous 12 months. Each annual survey includes between 30,000 and 50,000 respondents. We pool data from the 2001 to 2018 releases, and we re-weight to account for differential survey non-response. This leaves us with a sample of almost 800,000 observations. The CSEW does not include any geo-coding what would allow us to identify the neighbourhood in which respondent live but crucially head of households self-report their ethnicity, with 4.7% identifying as South Asian. This will provide corroborative evidence on whether South Asians households are more likely than other ethnic groups to be victims of burglaries in period of higher gold price.

Table 2 reports summary statistics on the CSEW for the main variables of interest for the full population and separately for South Asian and non-South Asian respondents. While South Asians are about 10% more likely to report having been a victim of crime in the 12 months preceding the interview, conditional on having been burgled they are more than 2.5 times more likely to report that jewellery was stolen. This is consistent with our assumption that South Asian households are more likely to store jewellery at home. Conditional on having been a victim of crime, respondents are asked to rate how serious they evaluate this crime. This is coded on a scale from 1 (theft of a bottle of milk) to 20 (murder). South Asian respondents rate their crime experience as worse than non-South Asians (7.4 vs 5.4). Our main data refers to police records, which could be biased if different ethnic groups differentially report crime to the police. According to the CSEW, 40% of crimes are reported to the police, and this proportion is the same for the two ethnic groups of interest. Finally, some respondents are asked to evaluate the security features of their house. This is important as the ethnic differences in burglaries could be driven by differences in the ease of successfully burgling one type of household. We note, that there are very little differences in the anti-burglary features by ethnicity, so this is unlikely to drive the outcomes from our main analysis.

3 Empirical Strategy

Our aim is to evaluate the extent to which criminals react to changes in the financial returns to their activities when deciding on a target. Intuitively, our identification strategy relies on the common perception in the UK that families of South Asian descent keep a substantial amount of gold in their houses. The expected gains from targeting these households for burglaries consequently change with the gold price. If gold prices are high, burglars should become more likely to shift their efforts towards neighbourhoods containing a large number of South Asian households, i.e., areas with a large number of potential targets. Note that traditionally for these families, gold is an insurance rather than an investment. For example, the jewellery gifted to the bride (*stridhan* or women's property) is particularly important as an insurance mechanism since traditionally women have no other recourse to financial assets. The *stridhan* remains her property in case the marriage breaks down (Halder and Jaishankar, 2008). As such, it is unlikely that variations in the price of gold affect the selling of gold jewellery among South Asian households. Also, since the jewellery is regularly displayed, households are likely to store it at home rather than in a bank safe.

Table 2: Summary Statistics: British Crime Survey

Variable	Total	Non-South Asian	South Asian
Crime	0.331	0.330	0.351
	(0.471)	(0.470)	(0.477)
burglary	0.038	0.038	0.042
	(0.191)	(0.191)	(0.200)
jewell / burglary	0.088	0.082	0.198
	(0.283)	(0.273)	(0.399)
How serious / crime	5.540	5.444	7.414
	(4.297)	(4.241)	(4.910)
Police informed / crime	0.392	0.392	0.395
	(0.488)	(0.488)	(0.489)
Asian	0.047	0	1
	(0.211)	(.)	(.)
Rural	0.194	0.202	0.031
	(0.395)	(0.401)	(0.174)
Burglar alarm	0.300	0.298	0.359
	(0.458)	(0.457)	(0.480)
Double locks	0.820	0.819	0.825
	(0.394)	(0.385)	(0.380)
Window locks	0.873	0.874	0.855
	(0.333)	(0.332)	(0.352)
Observations	798,057	768,485	29,572

Notes: The table displays summary statistics at the household level extracted from the Crime Survey for England and Wales 2001 to 2018/19. Each observation is re-weighted to account for survey non-response according to the CSEW user guide.

Our analysis links the gold price in a month to burglaries in the same month. This contemporaneous link requires that burglars cannot separate the stealing and the selling activities over time, i.e., they do not store stolen goods until their prices reach a certain level. There are several reasons to think this is indeed the case. First, storing loot is an illegal activity by itself and could identify the burglar, in particular when the stolen goods are jewellery, which is usually more distinct than cash or electronic goods. Qualitative evidence indeed suggest that burglars trade stolen goods rapidly (Stevenson, Forsythe, and Weatherburn, 2001). Second, burglars are unlikely to have large savings that could sustain their consumption while waiting for the price of the loot to increase. Third, it has been documented that criminals have a greater preference for the present, which suggests that they would be unlikely to delay cashing in their work (Åkerlund, Golsteyn, Grönqvist, and Lindahl (2016) find that time discounting in childhood correlates with future criminal activities). Due to this inability to maximise income by waiting for higher prices, it is likely that gold price variations affects contemporaneous criminal burglary activities. However, even if burglars were able to wait to sell at higher prices, this would likely introduce measurement error towards zero as it would lead to a conflation of periods with high and low prices.

3.1 Main Empirical Strategy

The main analysis relies on a difference-in-differences-style framework where the variation in the share of South Asian households across neighbourhoods creates cross-sectional variation, while changes in the gold-price lead to longitudinal variation in the intensity of treatment.[13] Importantly, this variation is exogenous to the behaviour of burglars since the gold price is determined on international market.

Specifically, we estimate regressions of the type

$$y_{ict} = \beta_0 + \beta_1 SA_{ic} + \beta_2 GP_t + \tau(SA_{ic} * GP_t) + \alpha_c + \gamma TREND_{it} + \epsilon_{ict} \tag{1}$$

where i indexes neighbourhoods (LSOA) nested within local authorities c and t indexes time. The outcomes y_{ict} are measures of the prevalence of various types of crime (principally burglary) for the respective neighbourhood in a given month, GP_t is the average monthly gold price, and SA indicates a treatment area - i.e., a neighbourhood with a relatively high proportion of South Asian households compared to the rest of the local authority. To ease the interpretation, the measure of crime and the gold price are expressed in inverse hyperbolic sine, so that τ can be interpreted as an elasticity.

This specification includes local authority (LA) fixed effects α_c, which capture time-invariant influences which are common to all neighbourhoods within a local authority such as public service provision, as well as neighbourhood specific quadratic time trends $TREND_{it}$, which capture time-varying influences at the local level, such as neighbourhood policing strategies. Our effect of interest τ is identified using a combination of the indicator of high South Asian

[13] Note that we do not have differential timing as the gold price increases are identical across all neighbourhoods, hence the problems documented in the recent literature on differences-in-differences with staggered designs (e.g., de Chaisemartin and D'Haultfoeuille (2020); Goodman-Bacon (2021); Callaway and Sant'Anna (2021)) do not apply in our case.

share, SA_{ic}, which is determined at the beginning of the period, and the average gold price in a month GP_t; i.e. τ measures the differential impact of changes in the price of gold on crime across areas with different shares of South Asian households within a local authority. Note that the share of South Asians that we use to define treated areas is fixed at the beginning of the observation period and thus not endogenous to the number of crimes taking place in the neighbourhood, i.e. we do not allow for a change in treated and control neighbourhoods caused by a flight of some demographic group to a "safer" neighbourhood. In our favoured model, the standard errors are clustered at the level of the neighbourhood, but we also provide evidence of the robustness of our inference to alternative clustering levels.

Subsequently, we address potential threats to our identification strategies in turn. Firstly, we assess the robustness of our effect to (a) different specifications of the area fixed effects and (b) the functional form of time. For example, the share of South Asian households may be correlated with other factors such as local deprivation, or housing type which by themselves might influence crime rates. While those are not observed, we can control for them – to the extent that they are fixed over the period of time considered – by including neighbourhood fixed effects. In this specification, we can only identify the interaction effect between the South Asian share and the gold price. Alternatively, since policing is the remit of Police Force, PFA fixed effects are used instead. This also relaxes the implicit assumption that burglars only consider targets within their local authority.

We also assess the robustness of the main results to different functional forms of time. Including neighbourhood specific trends might account for part of the variation we want to capture. We thus replicate the analysis but include trends that are specific to larger geographical entities (National, PFA or LA) and might thus better capture the municipal labour market, or policing strategies, and their evolution over time. Additionally, rather than using quadratic trends we also replicate the analysis by including time-area fixed effects that are either common to all neighbourhoods, or specific either to the police force or to the local authority. For example, d'Este (2020) shows that the number of pawnbrokers in a county affects the elasticity of burglary to gold price variations.[14] One concern would thus be that the greater proclivity of South Asian households for gold is correlated with a greater number of pawnbrokers, and that the effect that we capture is driven by the number of pawnbrokers in the area and not by the greater elasticity of burgling a South Asian household. To rule out this possible confounder, we include local authority-specific monthly time effects which capture the impact that gold price variations would have on burglary in the local authority overall, including via its effects on the number of pawnbrokers.[15]

Secondly, we assess the sensitivity of the results to the definition of a high South Asian population neighbourhood. First, we define a treated neighbourhood as having a share of South Asian in the top 90% of the local authority rather than being an outlier, which increases the number of treated neighbourhoods by about 40%. Second, while burglars have a preference for operating locally (Vandeviver and Bernasco, 2019) imposing that their search is limited to the local authority

[14] A greater density of pawnbroker makes the resale market more competitive and easier to dispose of stolen goods

[15] We believe that the local authority rather than the neighbourhood is the relevant geography here. Stolen gold is often in the form of jewellery, which could easily be identified. Hence, we assume that burglars sell their goods within the municipalities but not necessarily within the neighbourhoods in which they stole it.

might be overly restrictive. As an alternative, we redefine neighbourhoods as being outliers within their police force area (PFA). Third, we tackle inference issues in two ways, either by varying the level of clustering from our preferred specification, where we cluster at the neighbourhood level, or by undertaking a falsification exercise, where we randomly assign high-density South Asian status to neighbourhoods in a randomisation inference procedure to assess whether the results could occur by chance.

Thirdly, we conduct a series of robustness checks inspired by "optimal foraging", and assess the sensitivity of our main results to the ease/costs of identifying a high South Asian population neighbourhood. It seems reasonable that it is easier for burglars to identify an area as having a relatively high share of South Asian the larger the proportion of South Asian households is. We thus re-estimate the main equation for different samples, progressively excluding treated neighbourhoods with a low absolute share of South Asian households. Similarly, we split the analysis between rural and urban local authorities, as it should be less costly for a criminal to shift their activities in a more densely populated area. In both cases, we expect that the response of burglars to variations in the gold price should be greater the easier it is to identify a neighbourhood as having a high share of South Asian households and the lower the costs of operating in a different neighbourhood. We also investigate whether the effect is driven by the extensive or intensive margin by (a) redefining the burglary variable as an indicator equal to one if at least one burglary was committed in a given month, and zero otherwise (extensive) and (b) use the count variable but condition on having experienced at least one burglary (intensive).

Fourthly, another threat to the identification would come from changes over time that are correlated (a) with the evolution of gold prices and (b) with the probability of neighbourhood with a high share of South Asians being targeted by burglars. To assess those, we conduct a series of robustness tests. Since gold prices might reflect the general economic outlook, welfare policies disproportionately affecting ethnic minorities or possibly poor neighbourhoods could potentially invalidate our identification. To test for this possibility we conduct two types of falsification tests. First, we estimate equation (1) with alternative definitions of the treated neighbourhoods, namely using the share of the population with Black ethnicity and the share of households in the two lowest social groups of the British social structure classification. These are defined by the head of household being in semi-skilled and unskilled manual occupations, unemployed and lowest grade occupations (see Appendix A for details). As with our main regressions, we define binary indicators for neighbourhoods that have a relatively high share in these categories compared to their local authority. Importantly, these groups are not known for storing large quantities of jewellery and should not become more attractive targets to burglars when the price of gold increases. Secondly, we re-run the analysis for other indicators of economic activity, which are not known to specifically affect South Asian neighbourhoods, using variations in the oil price, an economic uncertainty index and local unemployment respectively instead of the gold price. The point of these falsification exercises is to test whether our results are specific to variation in the price of gold affecting burglaries in South Asian neighbourhood or could also be observed for other type of neighbourhoods or indicators of economic activity.

Finally, an important policy consideration is whether criminals relocate their activities to different neighbourhoods only or engage in different types of crime when burglars become more likely to target a given neighbourhood. To assess displacement to other crimes, we simply rerun equation (1) for different types of crimes that can be consistently identified during our observation period; two that might have financial motives but whose returns should be unaffected by the price of gold: robbery and motor theft, and one with no financial motive: violent crime. We also assess the effect on overall crime excluding burglary. This test also provide support for our main mechanism that the effect of gold price on the probability of burglaries in South Asian neighbourhood is driven by changes in the relative returns to crime driven by variations in the price of gold. For other crimes, variations in the price of gold should not affect the relative returns to South Asian households.

To assess the geographical displacement of crime, we compute for each control neighbourhood the minimum distance between its centroid and the centroid of the nearest treated neighbourhood, and add indicators of distances (500 metres bins) and their interactions with the gold price, so that we estimate the following model, splitting the control neighbourhoods into 10 equidistant bins (C_d).

$$\begin{aligned} y_{ict} &= \beta_0 + \beta_1 SA_{ic} + \sum_{d=1}^{10} \beta_1^d C_{cd} \\ &+ \beta_2 GP_t + \beta_3 (SA_{ic} * GP_t) + \sum_{d=1}^{10} \tau^d (C_{cd} * GP_t) \\ &+ \alpha_c + \gamma TREND_{it} + \epsilon_{ict} \end{aligned} \tag{2}$$

Assuming that the costs of finding an alternative location to commit a burglary are increasing with distance, we would expect that areas located closer to a South Asian neighbourhood are negatively affected by a rise in the price of gold (i.e., $\tau^d < 0$ for areas closer to a treated area), as local burglars switch their effort to the neighbouring South Asian neighbourhood. We would expect the displacement to decrease with distance so that burglaries in neighbourhood situated further away from a South Asian neighbourhood are less affected by this displacement. Alternatively, burglars might not be able to identify the treated neighbourhoods very precisely, especially when communities adjacent to a high-share South Asian neighbourhood also have a substantial share of South Asians. In this case, we would expect some positive spillover to communities in the vicinity of treated neighbourhoods.

While we have so far assumed that the estimated effects reflect the behaviour of criminals, it might also be an indicator of police allocation. Our main estimates could, for example, be biased if police forces use predictive models or local knowledge which include gold prices and their link to burglaries in some neighbourhoods in their policing strategies to allocate forces. We approximate police force allocation at the neighbourhood level by the number of "stops and searches" conducted, data on which is available from the same source as the crime data. As that the data contains information on the legislation allowing the stop and search as well as the object searched for and the location of the search, we can consider both the total number of stops and searches as well as searches for articles used to commit theft or for stolen goods, conducted under the Police and Criminal Evidence Act 1984 (section 1). Using (1), we then test whether gold price affects policing differently in neighbourhoods with a greater share of South Asians.

3.2 Corroborative Empirical Strategy

Finally, while the main analysis relies on neighbourhood level data, we use the CSEW – an annual cross sectional survey of households – to provide evidence that South Asian households are indeed more likely to have jewellery stolen, but also to assess some potential mechanisms consistent with the main analysis.

The main analysis hypothesises that South Asian households become more attractive targets to burglars when the gold price increases because these households hold larger amounts of gold and that this is known to potential burglars. The CSEW does not include information on wealth or assets but for victims of burglaries it includes a list of goods that may have been stolen which includes jewellery. To test our assumptions, we can estimate whether conditional on having been burgled, South Asian households are more likely to report having had jewellery stolen.

Additionally we corroborate our main analysis at the neighbourhood level using this household level data. One difficulty is that while for households victim of a crime, we know in which month the crime took place, and thus what the average gold price was in that month, for non-victims we cannot directly observe a gold price. Instead we randomly allocate a date at which these household could have been a victim of crime in the previous 12 months and use the monthly gold price in that month to estimate the following OLS model:

$$y_i = \gamma_0 + \sum_{d=1}^{3} \gamma_1^d Ethnic_i + \gamma_2 GP_t + \sum_{d=1}^{3} \gamma_3^d (Ethnic_i * GP_t) + \gamma_4 X_i + \gamma_t + \epsilon_{it} \tag{3}$$

where *Ethnic* is a self-reported measure of the ethnicity of the head of household. Ethnicity is categorised into South Asian, Black, White and Others. The survey does not contain information on the local authority but only 10 governmental regions. We also control for urban location since ethnic minority and crimes are more concentrated in the urban environment. To capture time effects we include a set of dummies for year and month the survey took place. We repeat the randomisation of GP_t for "non-victim" households and estimate (3) one thousand times. We report the average estimated effect and its standard error across the 1,000 replications. In first instance the outcomes of interest are different indicators of having been a victim of crime, or specifically a burglary in the previous 12 months, or whether jewellery was stolen.

The CSEW does not include information on the financial value of the basket of goods that was stolen but respondents are asked to score how serious a crime it was. While not directly measuring prices, when conditioning on being a burglary victim, this measure can be seen as an indicator of the loss, both financial and emotional, associated with the stolen goods. We use this score to test whether ethnicity and its interaction with the gold price affects the perceived seriousness of the crime.

One remaining concern is that the neighbourhood level analysis is based on crimes reported to the police. This is usually seen as an underestimate of the amount of crime committed, especially for ethnic minorities who might be loathe to be in contact with the police. While burglaries are likely to be reported to the police so that an insurance claim can be made, one could worry that the effects identified in equation (1) are driven by differences in reporting between ethnic groups, and that this reporting gap is itself affected by variations in the price of gold. For example, South Asians could become more likely to report burglaries to the police when the price of gold is higher if the crime was then perceived as having a greater effect on the family wealth, and an insurance claim was more likely to be filled. If this was the case, the effect identified in equation (1) would stem from a greater probability of victims to report crimes rather than a change in the behaviour of criminals. To assuage this concern we run equation (3) on indicators of having reported a burglary to the police, and test whether these differ for South Asian households depending on the price of gold; i.e. $\gamma_3^d > 0$.

Finally, we investigate to what extent South Asian households differ from other households on protective measures, such as having burglary alarms. While base level differences in protective measures would not invalidate our main strategy, they could matter for the interpretation of our results.

4 Results

4.1 Main Estimates

In our main specification we test how variations in the price of gold affect the location choice of burglars, in particular, whether burglaries in neighbourhoods with a greater share of South Asian households are more sensitive to variation in the price of gold than other neighbourhoods within the same local authority. As previously detailed, the identification strategy assumes that criminals can approximate the share of South Asians in a neighbourhood, and thus reallocate their criminal effort when the pay-off from burgling a South Asian household increases. Note that we do not need to assume that criminals know whether a given dwelling hosts a South Asian family, only that criminals are able to identify a neighbourhood with a relatively high share of South Asian households, so that in expectations the financial returns to burgling in one particular neighbourhood rather than in another neighbourhood is higher.

Table 3 reports estimates of the main result for different specifications of the geographical fixed effect. It includes a quadratic neighbourhood-specific time trend, which effectively relaxes the common trends assumption necessary for identification (the sensitivity of our results to this specification of time effects is tested below). The simple specification in column (1), which omits any geographical fixed effects, indicate that burglaries are more prevalent in high density South Asian neighbourhoods, but this likely reflects other characteristics of these neighbourhoods – such as their urban status – rather than a greater prevalence of crime. The *LBMA* gold price is an indicator of the resale value of gold jewellery. As far as a potential burglar is concerned, this price is exogenously given and not affected by the local preference for gold in the LSOA or the amount of gold that is being sold on second hand markets in the area. This – descriptive – estimate reveals that the number of burglaries increase as the gold price rises, with a crime elasticity with respect to price of 0.10. This is consistent in sign but somewhat smaller in magnitude than the crime-price elasticity in Draca et al. (2019). However, it should be noted that these estimates are not directly comparable: Draca et al. (2019) consider the sum of burglaries and robberies as

Table 3: Impact of Gold Price on Burglaries

	(1)	(2)	(3)	(4)	(5)
High South Asian neighbourhood	0.140***	0.148	-0.291*	-0.283*	.
	(0.011)	(0.126)	(0.129)	(0.129)	(.)
Gold Price	0.104***	0.104***	0.047***	0.047***	0.047***
	(0.000)	(0.000)	(0.004)	(0.004)	(0.004)
High South Asian neighbourhood ×		-0.001	0.056***	0.056***	0.056***
Gold Price		(0.016)	(0.017)	(0.017)	(0.017)
Fixed Effect	None	None	PFA	LA	LSOA
Quadratic Time Trend	LSOA	LSOA	LSOA	LSOA	LSOA
# time periods			108		
# LSOAs			34,753		
Obs ($N \times T$)			3,743,286		

*Notes: The table displays estimates of the impact on burglaries estimated using Eq.1. Regressions also control for seasonality via monthly dummies. Standard errors adjusted for clustering at the LSOA level in parentheses. */**/*** denote statistical significance on the 10%, 5% and 1% level respectively.*

the outcome variable, as compared to our analysis for burglaries only. We also consider the sum of burglaries by neighbourhood rather than individual crimes, and account for neighbourhood trends which partially captures the relationship between gold price and burglary.

In Column (2) we add the interaction term between the South Asian neighbourhood and the gold price, our parameter of interest. The interaction between the gold price and the indicator of a high South Asian density captures the change in behaviour of criminals, and in particular, whether they relocate their efforts towards areas with higher expected pay-offs when prices for the expected stolen goods increase. As such the estimate can be interpreted as the causal effect of gold price on the additional risk of suffering a burglary in a neighbourhood with a high density of South Asians. In this basic specification, the estimated coefficient on this interaction term is not statistically significant, and the main terms remain unchanged. However, as discussed previously, South Asian neighbourhoods are not randomly allocated within the country or even within municipality - as seen in column (1) burglaries are more common in high South Asian neighbourhoods - and this estimated coefficient might be biased if unobserved characteristics of South Asian neighbourhoods affect the reaction of criminals to variations in the gold price. It is thus important to control for area-specific fixed effects.

This choice of the granularity of area affects to include is *a priori* ambiguous as it imposes some restrictions on the variation in crime that we identify. In Column (3) to (5) we thus consider three levels of geography, differing in their size, from the large Police Force Area (PFA), to the Local Authority (LA), to the smallest neighbourhoods - Lower-layer Super Output Areas (LSOA). Adding area-specific fixed effects substantially affects the estimates, but importantly they are robust to whichever fixed effect is used. The indicator for a high South Asian neighbourhood flips signs and become marginally significant, high density South Asian neighbourhoods are in fact less likely to experience burglaries than other neighbourhoods in their region. The elasticity of burglary with respect to the price of gold drops to 0.047, i.e., in neighbourhoods without a relatively high share of South Asian households, an increase in the price of gold of 10% increases the number of burglaries by around 0.5%. Our parameter of interest, the interaction term, which captures the additional effect of an increase in the gold price in South Asian neighbourhood, jumps to 0.056. Taking the results in (4) as our favoured specification, this indicates that compared to neighbourhoods in the same local authority, neighbourhoods with a relatively high share of South Asian households have an elasticity of burglaries with respect to the price of gold that is more than double of control neighbourhoods. These conclusions are identical regardless of whether the included geographical fixed effect define a police force (3), a local authority (4) or even a neighbourhood (5). These estimates strongly support that burglaries become more common when the price of gold increases but importantly burglars focus their effort on neighbourhoods that have, in expectations a higher pay-off.

We now discuss the robustness of our main results to alternative treatment of time effects. While the estimates appear very robust to different specifications of the geographical fixed effects, we now assess how they differ when specifying time effects differently. The main regression controlled for neighbourhood specific quadratic trends, we now explore the robustness of our results to controlling for quadratic trends specific to larger geographical levels (National, Police Force or Local Authority) which may better capture variations over time in welfare policies, policing strategies and labour market opportunities, which could affect crime. In a second set of tests, we use monthly fixed effects that are specific to these larger geographical areas. This allows us to capture the monthly variations in burglaries that are common across the area, even those that are driven by variations in the price of gold. While this latter approach may be over-controlling, it allows us to capture region specific effects that might be triggered by variations in the price of gold but that are not specific to South Asian neighbourhoods. For example, d'Este (2020) shows that the density of pawnbrokers in a U.S. county, by affecting the ease to resell stolen goods, affects the elasticity of burglaries with respect to the gold price. Including local authority specific time fixed effects would allow us to capture this effect, as long as we assume that burglars resell their loot in the local authority rather than the particular neighbourhood in which they commit their crime.

Table 4 reports the main estimates for various specifications of the time dimensions. In Column (1) we do not control for time, leading to an estimate for our parameter of interest of only 0.04. Essentially the same result is obtained when including national quadratic trends (column (2)) or time-period fixed effects (column (5)). Adding a Police Force Area specific quadratic trend (column (3)), a local authority-specific quadratic trend (column (4)) or a LSOA-specific quadratic trend (column (5)) increases this estimate to between 0.051 to 0.056. Note that the more specific to the area the time trend is, the larger the relative increase in burglaries in South Asian neighbourhoods.

In the final two columns, we display the estimates when controlling for month fixed effects, defined at either the police force or local authority level. Those obviously capture the monthly variation in the price of gold and only the interactions with the indicator of high density South Asian neighbourhood can be identified. When interacted with PFA or LA, these time fixed effects capture all the variations in burglaries activities in the region that is not specific to neighbourhoods. Even in this very stringent specifications the price elasticities in South Asian neighbourhoods remain precisely estimated at around 0.05.

Table 4: Impact of Gold Price on Burglaries - Alternative Time Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High South Asian area	-0.1613	-0.155	-0.2447*	-0.2737**	-0.2825*	-0.1497	-0.2465*	-0.2583**
	(0.105)	(0.105)	(0.102)	(0.100)	(0.129)	(0.105)	(0.102)	(0.100)
Gold Price	0.1526***	0.048***	0.0473***	0.0470***	0.0469***	.	.	.
	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(.)	(.)	(.)
High South Asian area ×	0.040***	0.0396**	0.0507***	0.0546***	0.0559***	0.0380**	0.0509***	0.0525***
Gold Price	(0.014)	(0.014)	(0.014)	(0.013)	(0.017)	(0.014)	(0.014)	(0.013)
Fixed Effect	LA	LA	LA	LA	LA	LA	LA	LA
Time Control		National	PFA	LA	LSOA	National	PFA	LA
		trend	trend	trend	trend	fixed	fixed	fixed

*Notes: The table displays estimates of the impact on burglaries using Eq.1. Standard errors adjusted for clustering at the LSOA level in parentheses. */**/*** denote statistical significance on the 10%, 5% and 1% level respectively.*

Altogether, these two sets of results provide us with confidence that the specific effect on burglary in South Asian neighbourhoods is driven by variations in the price of gold and that this effect is very stable to alternative specifications of the geographic or time effect.

4.2 Robustness of Main Estimates

We now discuss the robustness of the results to alternative definitions of the treatment and approaches to statistical inference.

Our hypothesis is that burglars are able to identify neighbourhood with a relatively high share of South Asian households. In the main specification, this is defined as neighbourhood whose share is an outlier in their local authority. We provide now evidence for alternative measures of high share South Asian neighbourhoods. The first alternative is to define the treated area as having a share of South Asian households above the 90^{th} percentile for the LA. This definition leads to more neighbourhoods being considered as treated compared to using only outliers. The second alternative is to define the neighbourhood as an outlier within the Police Force Area rather than a local authority. Remember that PFAs are substantially larger entities than LAs, for example London contains 32 LAs but is policed by a single police force, the Metropolitan Police. This alternative definition expands the number of neighbourhoods that we assume burglars consider when choosing targets, but it reduces the number of treated neighbourhoods.

In Table 5, we report estimate using these alternative definitions. The estimates remain consistent with those presented in the main analysis. Extending the number of treated neighbourhoods by including the top 90% by share of South Asian households in the LA results in a smaller (0.038) but still statistically significant price elasticity of burglaries in South Asian neighbourhood. The drop in the effect is likely due to the additional treated areas having on average a lower proportion of South Asian households, making them more difficult to identify for potential burglars, which would bias the estimates towards zero. Nonetheless, even with this definition, South Asian neighbourhoods are found to have an elasticity of burglary with respect to the price of gold 80% larger than other neighbourhoods in their local authority.

Alternatively, we define treated neighbourhoods as outliers in their share of South Asians compared to their PFA, and include PFA-level fixed effect. Using this alternative definition, the elasticity of gold price rises to 0.043 and the additional effect on high South Asian neighbourhood now stands at 0.073, or 170% greater than in the rest of the PFA. Overall, the results are very consistent to alternative definitions of the treatment, and confirms our main result that burglars shift their activities to South Asian neighbourhoods depending on variations in the gold price, i.e., they reallocate their effort according to the expected returns to their crime.

Going back to our main estimates, since the unit of observation is at the neighbourhood level, it might appear natural to cluster the error terms at this level, as we have reported currently. In Appendix section C we also provide evidence of the robustness our our inference to different clustering strategies. We begin by assuming i.i.d. error terms and subsequently consider clustering at larger geographical levels, local authority and Police Force Area, to account for the possible correlations between neighbourhoods that are subject to common policies. As this reduces the number of clusters, some precision is lost but the estimates remain significant at

Table 5: Impact of Gold Price on Burglaries

	Top 90% in LA	Outlier in PFA
High South Asian area	-0.193	-0.343**
	(0.102)	(0.106)
Gold Price	0.047***	0.043***
	(0.004)	(0.004)
High South Asian area × Gold Price	0.038**	0.073***
	(0.013)	(0.014)
Fixed Effect	LA	PFA
Time Trend	LSOA	LSOA
# time periods	108	
# LSOAs	34,753	
Obs ($N \times T$)	3,743,286	

*Notes: The table displays estimates of the impact on burglaries estimated using Eq.1 for two alternative definitions of the treatment. Regressions also control for seasonality via monthly dummies. Standard errors adjusted for clustering at the LSOA level in parentheses. */**/*** denote statistical significance on the 10%, 5% and 1% level respectively.*

the 5% level. An alternative is to cluster along two dimensions, geographical and time. Doing so, has also a minimal effect on the precision of the estimates, the standard errors vary from 0.017 in our favoured specification to 0.023 when clustering on PFA only, and in all cases the estimate remains significant at the 5% level. Overall, our conclusions that gold price variations have a specific effect in South Asian neighbourhoods remain unaffected by the choice of inference correction.

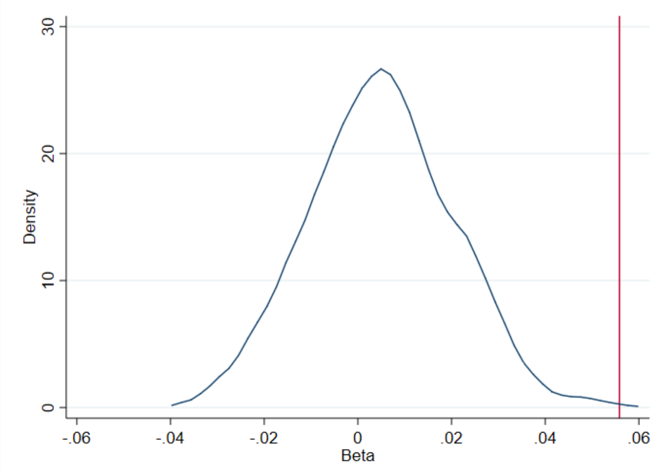
We further investigate possible inference issues and in Figure 2 we use randomisation inference as a falsification exercise whereby the indicator for a high South Asian neighbourhood is randomly allocated within a local authority. We then estimate the base model with this placebo indicator and replicate the analysis a 1,000 times. If some unknown characteristics of neighbourhoods drive our results, we would expect that when randomly allocating treatment, we should observe a substantial fraction of estimates to be larger than the one we report in our main analysis. However, as we can see in Figure 2, only 1 of the 1,000 estimates is larger than the one reported in the main analysis (vertical line), leading to an empirical p-value below 0.01. This confirms that our results are unlikely to be driven by other counfounding attributes of neighbourhoods.

4.3 Alternatives & Mechanisms

Our results so far are consistent with the hypothesis, both of the optimal foraging hypothesis and the Becker-model of crime that offenders are sensitive to variation in the return to crime and target areas most likely to offer higher returns, and thus change their target areas with variations in the price of gold. In this section we conduct a series of checks to assess alternative mechanisms by which gold price variations might disproportionately affect burglaries in South Asian neighbourhoods.

First, optimal foraging suggests a trade-off between the returns and the costs of operating in a new target area. Those are going to be a function of the ease in identifying a new area as potentially

Figure 2: Distribution of Placebo Estimates



Notes: The Figure displays the empirical distribution of placebo estimates for the definition of treated neighbourhoods within local authorities. The cummlative distribution functions are based on 1,000 replications of Equation 1. The vertical lines pertains to the value of the original estimate.

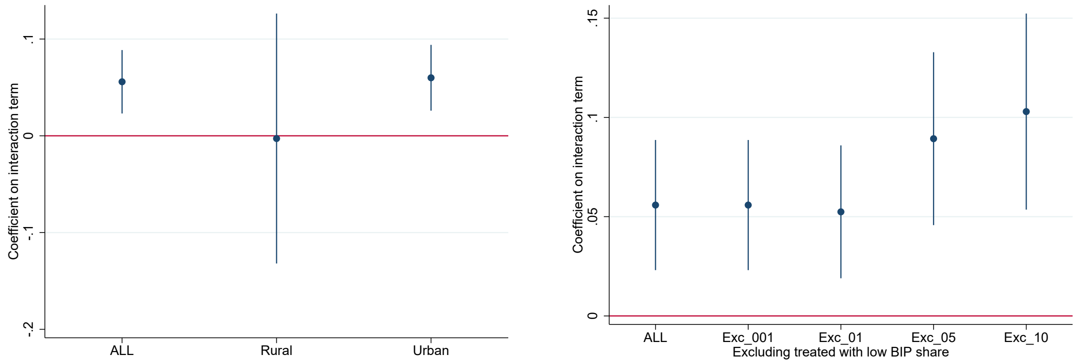
rich in targets. For example, a lower *absolute* density of South Asian households increases the costs in identifying the area as having a *relative* high South Asian density. Additionally, if burglars cannot identify for sure a given house as belonging to a South Asian family, a greater density of South Asian households means that the expected returns of burgling a house are higher in areas that have a greater concentration of South Asian families. As such, the absolute level of the South Asian share also matters in the burglars decision to reallocate their efforts towards specific neighbourhoods.

Since South Asian neighbourhoods are disproportionally located in urban areas (the shares of South Asian are 5.9% and 0.5% in urban and rural neighbourhood respectively), it seems likely that the costs of identifying such an area as target rich are lower in urban areas. Additionally, urban neighbourhoods are smaller, which, since all LSOAs contain approximately the same number of households, also reduce the costs of searching them for targets. We thus expect that the elasticity of burglaries in South Asian neighbourhoods with respect to the price of gold is greater in urban than in rural areas. To test this conjecture we split the sample between urban and rural neighbourhoods, and conduct the analysis for each subgroup separately, using the model presented in Table 3, column (4). The estimates on the interaction terms between a South Asian Neighbourhood and the price of gold are reported in Figure 3, panel (a). The estimated elasticity in rural areas is zero, confirming the presumption that in a rural environment is might be more difficult to identify South Asians neighbourhoods. Indeed, the main effect is entirely driven by urban areas.

To further test the assumption that the ease of identifying a neighbourhood as having a relatively large South Asian population matters we repeat the main analysis but exclude treated areas that have a low *absolute* share of South Asians. We progressively eliminate treated areas whose population share of South Asian household is less than 0.1%, less than 1%, less than 5% and less than 10%. The estimates on the gold price elasticity are reported for each sub-sample in Figure

3, panel (b). While the point estimates are not significantly different from each other across sub-samples, there is a significant gradient. When the treated area include neighbourhoods with a share of South Asian below 1%, the estimated elasticity is between 5% and 6%. However, when treated neighbourhoods with a low absolute share of South Asian households are excluded, the estimated elasticity jumps to between 9% and 10%, i.e., burglaries in these neighbourhoods are three times as sensitive to variations in the price of gold than in non-treated neighbourhoods. These results are fully consistent with optimal foraging as a plausible mechanism – the easier it is to identify a neighbourhood as having a high share of South Asian households, the greater the sensitivity of burglaries to gold price variations.

Figure 3: Elasticity of Burglaries in South Asian Neighbourhoods to Gold Price Variations



(a) Elasticity by Urban Status

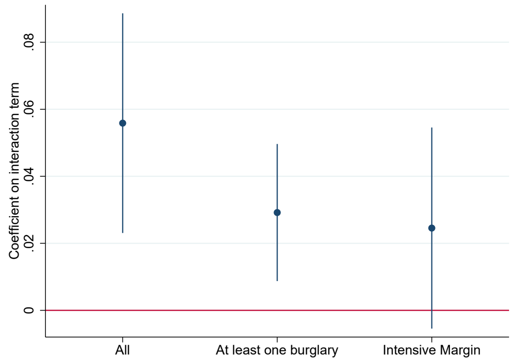
(b) Elasticity excluding Treated Neighbourhoods with Low S.A. Share

Notes: The figure displays the estimates, along with their 95% confidence interval, of the interaction term in Eq.1 estimated separately for a] Urban and Rural neighbourhoods, b] subsample excluding treated neighbourhoods with low absolute share of South Asians. Regressions control for seasonality via monthly dummies, municipality fixed effects and neighbourhood time trends.

The previous analysis suggest that criminals are sensitive to the costs of identifying neighbourhoods as having a relatively high concentration of South Asian households. To further investigate this point we assess whether our effects are driven by increases at the intensive or extensive margins, i.e., the number of burglaries in a given neighbourhood and whether a neighbourhood experiences at least one burglary. If current criminals just exercise more effort in their usual area of activity, the marginal costs of identifying a target when the price of gold increases is low. If on the contrary, criminals operate in different areas depending on the price of gold, the marginal costs of identifying new targets area would be higher. To better understand the mechanisms behind our main effect it is thus important to assess which margins drive our results.

In Figure 4 we report estimates, based on our main model, for the extensive (at least one burglary recorded) and intensive (number of burglaries if at least one) margins. When the price of gold increases by 10%, South Asian neighbourhoods become 0.3 percentage points more likely than other neighbourhoods in the local authority to experience at least one burglary in that month. The point estimate for the effect at the intensive margin is essentially identical to this, although imprecisely estimated. This pattern is consistent with both local burglars becoming more active, as well as burglars operating in new locations. At both margins we observe that burglaries in South Asian neighbourhoods are more sensitive to variations in the price of gold.

Figure 4: Intensive vs Extensive Margin



Notes: The figure displays the estimates, along with their 95% confidence interval, of the interaction term in Eq.1 estimated separately for having experienced at least one burglary in the last month and the number of burglaries conditional on having experienced at least one. Regressions control for seasonality via monthly dummies, municipality fixed effects and neighbourhood time trends.

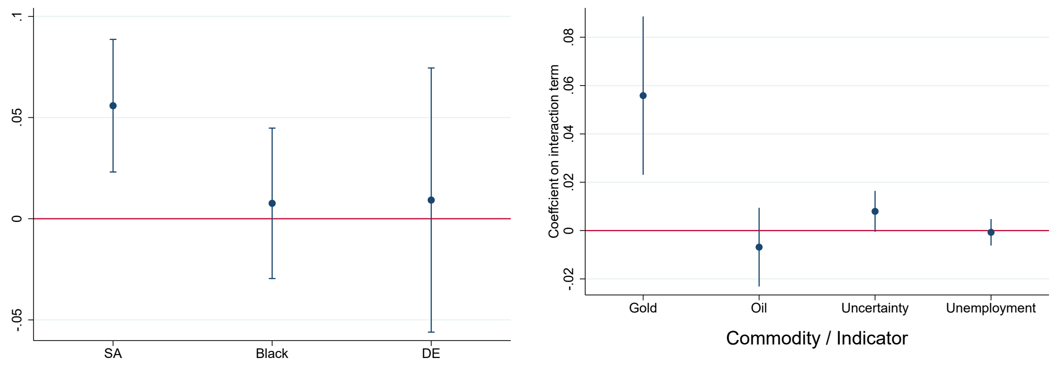
Second, a concern with our analysis is that areas with a large population of South Asians could simply be poorer or be particularly ethnically diverse neighbourhoods and that our results simply represent changes in burglary rates in areas with these characteristics and not the specific targeting of South Asian neighbourhoods by burglars. The identification strategy goes some ways to alleviate these concerns due to the inclusion of low-level spatial fixed effects. Moreover, as the parameter of interest is the interaction between neighbourhood and gold price, confounding unobserved characteristics would have to specifically alter the behaviour of burglars when the gold price varies.

We produce a series of falsification checks to assess that our results are driven by the share of South Asian population in a neighbourhood and not other characteristics. To this extent, we repeat the main analysis using the model presented in Table 3, column 4, but define the treated neighbourhoods based on their share of Black households or based on the share of households belonging to the two lowest social classes in the UK. While variations in the price of gold, by reflecting economic activities might have a direct effect on crime, they should not have a specific effect on Black or poorer neighbourhoods, since those households are (in a UK context) not known to have a strong preference for holding gold jewellery.[16] As in the main analysis, the treatment is defined as the neighbourhood having an outlier share compared to the rest of the local authority. Figure 5, panel (a) depicts the estimates on interaction term for these different treatments. While the standard errors are sufficiently large so that we cannot rule out the possibility that the coefficients are statistically identical, there is a clear visual pattern that suggests that only in South Asian neighbourhoods are burglaries more sensitive than in the rest of the local authority to variations in the price of gold. The coefficients on the interactions between gold price and Black or lower social class areas are close to zero, indicating that changes in the gold price do not exert an additional impact on burglaries in these neighbourhoods.

Third, a remaining concern with our identification strategy is that the price of gold captures

[16]This is different from the US where some evidence such as Charles, Hurst, and Roussanov (2009) indicate that Black and Hispanic spend significant amounts on visible goods, such as jewellery.

Figure 5: Falsification Exercise



(a) Elasticity by Neighbourhood Type (b) Elasticity for Alternative Economic Indicators

Notes: The figure displays the estimates, along with their 95% confidence interval, of the interaction term in Eq.1 estimated separately for a) Black and poor neighbourhoods, b) oil price, uncertainty index and LA unemployment rate. Regressions control for seasonality via monthly dummies, municipality fixed effects and neighbourhood time trends.

economic uncertainty which could either directly or indirectly – via policies implemented to remediate it – alter the behaviour of criminals. To alleviate this concern, we consider alternative economic indicators, variations in which do not increase the return to burgling a South Asian household. In particular, we consider the oil price, which similarly to gold is set on world markets and is therefore exogenously given for a potential burglar. Like gold, oil pricing reacts to global uncertainty (the correlation between gold and oil prices is 0.48 for this period), but crucially there is no reason to believe that variations in oil price affect the returns to burgling in a South Asian neighbourhood. We also consider two alternative measures of economic activity which are not prices and should also not directly affect the returns to targeting South Asian households. These are the local unemployment, computed for each local authority on a quarterly basis, and the UK Policy Uncertainty Index, a measure of economic uncertainty based on newspaper articles. Note that the unemployment rate is the only of these indicators that vary locally, and could be thus potentially be considered endogenous, for example if criminal activities drive businesses away.

For each measure of the economic environment, we estimate the main model as previously defined, but replace the price of gold, by the value of one of the alternative economic activity measures. As previously, we transform these in hyperbolic sine, so that the estimate can be understood as an elasticity and easily compared to our main estimate. We estimate all these models separately and report the estimates on the interaction between a high share South Asian neighbourhood and the economic environment measure in Figure 5, panel (b). The results reveal that the additional impact on burglaries in South Asian neighbourhoods observed for variations in the gold price is not observed for variations in the oil price, local unemployment or economic uncertainty. The effects are precisely estimated and close to zero.

In summary, the response in burglaries to movements in the international price of gold we observe in high density South Asian neighbourhoods is not mirrored when we consider other type of neighbourhoods or alternative measures often used to proxy national macroeconomic influences. This supports the mechanisms that we had in mind when interpretring our main results: variations in the price of gold affect the attractiveness of South Asian neighbourhoods as potential targets of burglars.

4.4 Displacement Effects

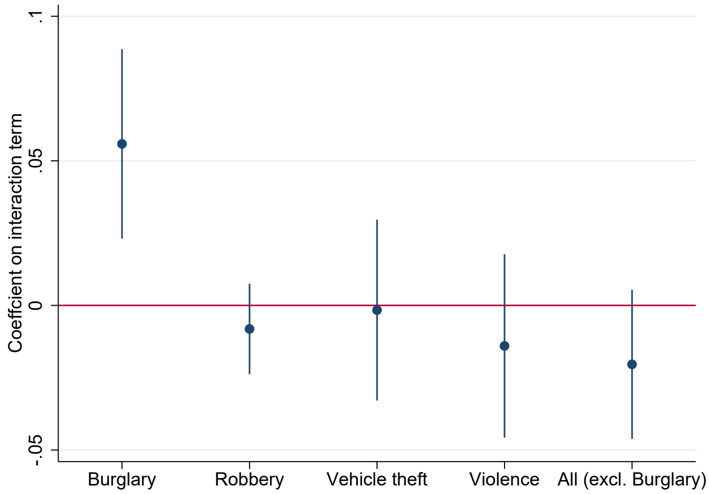
Having established that criminals revise their potential targets when the price of gold varies, the relevant policy questions is to assess whether this increase in burglaries in high density South Asian neighbourhoods induces displacement from or to other crime types or geographic areas.

First, the price of gold should have no direct effect on the propensity to commit crimes whose returns are not dependent on selling gold, unless criminals substitute their efforts between crimes. In particular, we might observe that crimes that offer a financial return are negatively affected by an increase in the price of gold, as criminal reallocate their effort from these crimes towards burglaries. To assess the extent of displacement between crimes we consider the effect of gold price variation on two crimes: robbery – taking or attempting to take anything of value by force, threat of force, or by use of fear – and vehicle theft. Additionally, if policing strategies are influenced by the price of gold or a resulting increase in burglaries, the reallocation of police forces could generate externalities to all crimes, including those that do not have a financial motive. We thus consider the effect of gold price variation on violent crime and the total crime count excluding burglary. To this extent, we run the base model on these crimes and report the estimates of the gold price elasticity in neighbourhoods with a relatively high share of South Asian households in Figure 6.

We find little support for displacement to other crimes in high South Asian neighbourhoods. When considering crimes with a financial motive, we estimate elasticities that are close to zero for robbery and vehicle theft; which does not support that criminals reallocate efforts away from these crimes towards burglaries. For violent crime, and crime overall, the estimated elasticities are negative, but small and not significantly different from zero. The relative increase in crime when the gold price increases in South Asian neighbourhoods compared to the remaining neighbourhoods in the local authority is observed only for burglary, which supports the hypothesis that offenders reallocate their efforts specifically toward crimes whose returns have increased and not just towards neighbourhoods with a high proportion of South Asian households. We find little evidence to support the notion that the increase in burglaries in high density South Asian neighbourhoods displaces other types of crime occurring in these neighbourhoods.

Second, the literature on location of crime is concerned with geographical displacement effects, whereby policies or other changes to the local environment only lead to a reallocation of crime between areas, but have no effect on the overall number of crimes. In Table 3, column (1) we have reported that the elasticity of burglaries with respect to gold price is 0.10, which supports – albeit descriptively – that increases in the gold price are associated with an overall increase in burglaries, as well as an additional effect in South Asian neighbourhoods. Nonetheless if burglars reallocate their activities towards South Asian neighbourhoods, some neighbourhoods might experience a drop in burglaries when the price of gold rises. This might principally affect neighbourhoods in the vicinity of South Asian areas, if we assume that the costs to a burglar to

Figure 6: Impact of Gold Price on different crime categories



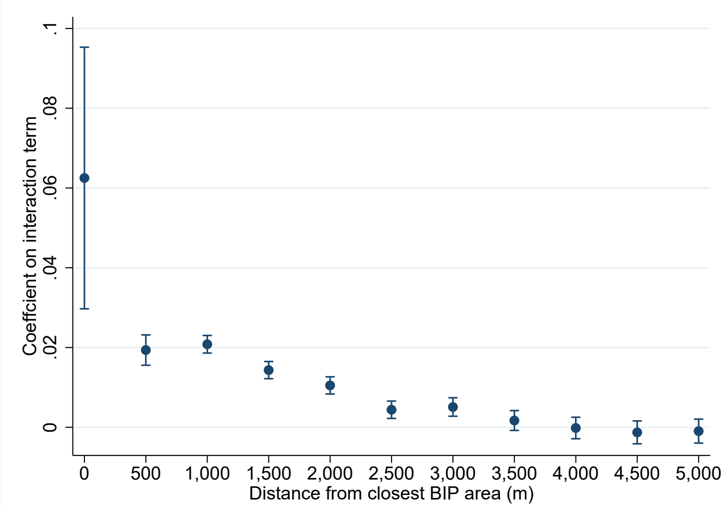
Notes: The figure displays the estimate, along with the 95% confidence interval, of the interaction term in Eq.1 described in Section 3 for respectively burglaries, robberies, violent crimes and the total crime count excluding burglary. Regressions control for seasonality via monthly dummies, municipality fixed effects and neighbourhood time trends.

operate in a new neighbourhood are correlated with distance. Alternatively, while LSOAs are defined in a cohesive way, neighbourhood boundaries can blur into each other. It is hence possible that burglars consider a street just outside a treated LSOA to be part of the neighbourhood they are searching for targets, which could lead to an increase in burglaries in neighbourhoods close to South Asian areas.

To test these possibilities, we estimate equation (2) where we allocate non-treated neighbourhoods to bins according to their distance to a treated neighbourhood. We define the distance between one non-treatment area and its closest treatment area as the euclidean distance between their relative centroids. Indicator variables are assigned for non-treatment areas grouped in distance intervals of 500 metres. We create 10 dummies to classify neighbourhoods ranging in distance from 500m to 5,000m from a treated neighbourhood. The omitted category represents a neighbourhood that is further than 5km from a high South Asian density neighbourhood. We also interact these distance indicators with (hyperbolic) gold price to estimate the elasticity of burglaries with respect to gold price for neighbourhoods that are more or less distant from a treated neighbourhood.

In Figure 7 we plot the estimates on these interaction terms, along with their 95% confidence intervals. Our results indicate that, rather than observing displacement of crime from the surrounding neighbours, there are marginal but significant positive spillover effects. Areas closest to treatment areas also experience with rising gold prices an increase in burglaries relative to the remaining neighbourhoods, but of a smaller magnitude than in the treated neighbourhoods. This positive externality declines with distance and the effect disappears for areas further than 3 kilometres from a high South Asian density neighbourhood. The positive elasticity in areas closest to treated neighbourhood reflect that these neighbourhoods also have a relatively higher share of South Asians than those further away[17]. In all cases, we do not find evidence of negative displacement of crime between neighbourhoods. An increase in the price of gold increases burglaries in all neighbourhoods. This effect is twice as large in South Asian neighbourhoods, and diffuses to neighbourhoods in their vicinity.

Figure 7: Spillover effects



Notes: The figure displays the estimates, along with their 95% confidence interval, of the interaction term in Eq.1 described in Section 3 and interacted indicator variables for 500m intervals from the closest South Asian neighbourhood. Regressions control for seasonality via monthly dummies, municipality fixed effects and neighbourhood time trends.

Overall, we do not find evidence of displacements from other crimes or neighbourhoods, an increase in the price of gold increases the number of burglaries, without reducing any other crimes. This is an important policy conclusion.

4.5 Policing Activities

Police forces might be aware of the relationship between gold price and displacement of crime to Asian neighbourhoods, highlighted above, and may relocate police officers accordingly. While this does not invalidate our identification strategy, the estimates reported in our main analysis would then be under-estimates. While we do not have information on the deployment of police officer at the neighbourhood level we approximate their activity by the location of "stop and search" activities on a monthly basis. In particular, the Police and Criminal Evidence Act 1984 allows officers to stop and search on suspicion of carrying objects for use in theft or stolen goods. This is the second most popular legislation used to conduct searches (15% of all searches) and variations in this type of search could indicate that police officers focus changes, and thus affect displacement to other crimes.

Using equation (1) we estimate whether variations in gold price relate to the (inverse hyperbolic sine) total number of "stops and searches" and to the "stops and searches" related to theft and stolen goods. Results are reported in Table 6. Within a local authority, high South Asian

[17]Neighbourhoods within 4km of a treated area have a significant higher share of South Asian than the national average for non-treated neighbourhoods

Table 6: Impact of Gold Price on Stop and Search Activities

	All searches		Theft-related searches	
High South Asian neighbourhood	0.676**	0.000	0.204*	0.000
	(0.229)	(.)	(0.098)	(.)
Gold Price	0.279***	0.278***	-0.035***	-0.035***
	(0.008)	(0.008)	(0.003)	(0.003)
High South Asian neighbourhood × Gold Price	-0.022	-0.008	0.010	0.016
	(0.031)	(0.032)	(0.013)	(0.013)
Fixed Effect	LA	LSOA	LA	LSOA
Quadratic Time Trend	LSOA	LSOA	LSOA	LSOA
# time periods	59			
# LSOAs	34,753			
Obs ($N \times T$)	1,977,873			

*Notes: The table displays estimates of the impact on "stop and search" conducted by the police estimated using Eq.1. Regressions also control for seasonality via monthly dummies. Standard errors adjusted for clustering at the LSOA level in parentheses. */**/*** denote statistical significance on the 10%, 5% and 1% level respectively.*

neighbourhoods appear to have a greater police presence - as approximated by total stop and search. Stops and searches appear to be positively correlated with variations in gold price, but this may not be related to redeployment of police officers to prevent burglaries since theft related stop and search are negatively correlated with gold price. Finally, neither for total search or theft-related search do we observe a change in search specifically in South Asian neighbourhoods. The point estimates are close to 0, and not statistically significant. Altogether, using stop and search to approximate police officer allocation and focus, we do not find any evidence that the police react to variations in gold price differentially in South Asian and other neighbourhoods. Our main estimates are thus likely to represent changes in the behaviour of criminals rather than changes in the allocation or behaviour of the police.

5 Corroborating evidence from individual data

We now turn to household level data, using the Crime Survey for England and Wales (CSEW) to confirm the interpretation of our main results. We begin by investigating whether South Asian households differ from other ethnic households in the probability of victimisation from any crime or burglaries as well as in the probability to have jewellery stolen in a burglary. We use the reporting of jewellery as an item that was stolen from the household during a burglary as a proxy for the storage of jewellery at home. Moreover, victims of crime self-assess how serious a crime this was, on a scale from 1 to 20. We also test whether the loss of jewellery is perceived as a more serious crime by Asian household as a crude proxy for the value attached to the lost goods. We address also a concern that the main results my reflect differences by ethnicity in the reporting of burglaries to the police and assess whether monthly variations in the price of gold affect these relationship. Finally, we investigate whether South Asian households differ from other households in protective measures against burglaries.

5.1 Victimisation of South Asian households

The CSEW contains self-reported information on the ethnicity of the head of the household which we use to determine whether a household is South Asian, Black, Hispanic, White or other ethnicity. While we do not expect burglars to accurately identify the ethnicity of households, we should nonetheless expect that South Asian household become more likely to report having been victim of burglary when the price of gold increases. But, first, we assess whether there are any differences in having been a victim of any crime by ethnicity. Controlling for year and month of interview, governmental region and whether the household is located in an urban area or not, we estimate that Asian households are no more likely than white households to have been a victim of crime or suffered a burglary in the last 12 months (Table 7, column (1) and (2)). Additionally, the CSEW allows us to provide indirect evidence on the greater proclivity for (gold) jewellery of South Asian household since conditional on a burglary having occurred, the questionnaire includes a detailed list of what was stolen. We use the reporting of jewellery as an item that was stolen from the household during a burglary as a proxy for the storage of jewellery at home, and test our assumption that Asian households are more likely to store jewellery. Indeed, conditional on having been burgled, Asian households are 130% more likely to have had jewellery stolen (column (3)). This is very different from other ethnic minorities (F-test = 23), whom on average do not report a rate of stolen jewellery different from white households. This is in line with the assumption that in the UK, South Asians but no other ethnic group has a strong preference for storing gold jewelery at home. We have no information on the value of the loot, but as an approximation we rely on the answer to the question regarding how serious a crime the victim thinks it was, which in case of burglary might refers to the value attached to the loot. All ethnic minority assess burglaries worse than white respondents, but this effect is the strongest for South Asians. Finally, South Asian households are 5% more likely than white respondents to report burglaries to the police. Overall, these results strongly supports our stated assumption that South Asian households are more likely to store jewellery at home than any other ethnic type.

5.2 Gold prices and the victimisation of South Asian households

We now investigate whether these relationships are affected by variations in the price of gold, which could lead to biases in our main estimates, for example, if Asian households become more likely to report a crime to police when the gold price is high. First, we replicate our main analysis, but at the household level and assess whether South Asian households' victimisation outcomes are disproportionally more affected than that of other ethnic groups from variations in the price of gold. As stated previously, only for victims do we know when the burglary happened and thus can we link it to gold price in that month. For non-victims, we randomly allocate a month, in the last 12 months prior to interview, when a burglary could have been committed. For all respondents, we match monthly average gold price to the observed or placebo period, and estimate the model presented in equation (3). We replicate this process 1,000 times and present the estimated mean effects and the associated standard errors in Table 8.

Table 7: Ethnicity and victimisation

	Crime	Burglary	Jewellery /Burglary	Serious /Burglary	Reported /Burglary
Asian	0.006	0.002	0.105***	2.472***	0.054**
	(0.021)	(0.003)	(0.013)	(0.340)	(0.019)
Black	-0.021	-0.000	0.000	1.986***	-0.017
	(0.020)	(0.003)	(0.011)	(0.383)	(0.027)
Other Ethnic	0.026	0.007	0.011	1.144**	-0.039
	(0.017)	(0.004)	(0.013)	(0.287)	(0.023)
Obs	773,249	773,249	28,524	28,335	28,400
Mean	0.330	0.038	0.082	6.925	0.595

Notes: Estimates based on the Crime Survey for England and Wales, 2001 to 2018. Regressions control for survey year, month of interview, governmental region, and indicators of urban, inner city or rural area. Each column reports the estimates for specific outcomes defined as (1) victim of crime in the last 12 months, (2) victim of burglary in the last 12 months, whether, conditional on burglary having taken place, (3) jewellery was stollen, (4) how serious the crime was, (5) whether the burglary was reported to the police. The observations are reweighted to account for differential non-response. Standard errors adjusted for clustering at the year level and governmental regions in parentheses. */**/*** denote statistical significance on the 10%, 5% and 1% level respectively. The reported mean value of each outcome refers to the mean for "white households".

In Table 8 we report estimates on ethnicity and their interactions with the log gold price, separately for the four outcomes of interest. The results reported in Column (1) provide direct evidence that South Asian households burglary victimisation relates to the price of gold. For Black there is no additional effect of gold price variation on the risk of burglary, and for other non-white gold price is negatively correlated with burglary rate. Note that in this dataset, we find a small, marginally negative effect of gold price on the overall burglary risk. This individual level data confirms our main analysis that burglars successfully target South Asian households when the price of gold is higher.

However, conditional on having been burgled, the probability of having jewellery stolen does not appear to depend on the gold price for households of any ethnicity with the possible exception of black households (Column (2)). Viewed together, the results in Columns (1) to (2) suggest that burglars act rationally in optimising the expected value of loot when choosing where to commit their crime, but also opportunistically in the sense that once they have committed the burglary they steal whatever valuables are available. Conditional on being burgled, the crime is perceived as significantly worse when the price of gold is high by South Asian households but no other ethnic groups, which is consistent with Asian households holding a greater quantity of gold or gold of higher quality than other households (Column (3)).

A remaining concern regarding the main analysis is that the effect that we capture is not driven by an increase of crime but an increase in the reporting of burglaries when the price of gold goes up. This would be the case if, for example, the gold price affects the perception of burglaries and the decision to make an insurance claim. To alleviate this concern, we test whether the reporting of burglaries to the police differ with the price of gold for the different ethnic groups. In Column (4) we report estimates on whether the crime was reported to the police. We find no evidence

Table 8: Ethnicity, Gold Price and victimisation

	Burglary	Jewellery stollen /Burglary	Perception of crime /Burglary	Reported to police /Burglary
Asian	-0.019**	0.093**	0.981**	-0.069
	(0.008)	(0.035)	(0.453)	(0.082)
Asian × Gold Price	0.011***	0.006	0.758***	0.063
	(0.003)	(0.017)	(0.245)	(0.043)
Black	-0.000	0.040	3.179***	0.049
	(0.013)	(0.022)	(0.500)	(0.068)
Black × Gold Price	-0.000	-0.021*	-0.634***	-0.035
	(0.006)	(0.010)	(0.224)	(0.028)
Other Ethnic	0.029**	0.034	2.172**	0.047
	(0.014)	(0.051)	(1.012)	(0.071)
Other Ethnic × Gold Price	-0.023 ***	-0.012	0.248	-0.046
	(0.007)	(0.030)	(0.366)	(0.032)
Gold Price	-0.011*	0.009	-0.558	-0.046
	(0.006)	(0.009)	(0.491)	(0.040)
Obs	773,249	28,524	28,335	28,400
Mean	0.038	0.088	6.925	0.595

Notes: Estimates based on the Crime Survey for England and Wales, 2001 to 2018. Regressions control for survey year, month of interview, governmental region, and indicators of urban, inner city or rural area. Month of reported crime is randomly allocated for non-burglary victims. The regressions are estimated 1,000 times, and the mean estimates are reported in the Table. */**/*** denote statistical significance on the 10%, 5% and 1% level respectively. The reported mean value of each outcome refers to the mean for "white households".

that the price of gold affects the reporting of burglaries to the police, either for white households or any of the ethnic group considered. Altogether, there is no evidence that the main effects previously reported could be driven by differences in reporting between ethnic groups.

5.3 Ethnicity and protection measures

Finally, the targeting of South Asian households might have to do with them being easier to successfully burglar. If variations in the pricing of gold increase burgling activities in all neighbourhoods but attempts in South Asian households are more likely to be successfully, this could be driving our main effects. We address this issue further using a sub-sample of the CSEW for which information on crime prevention and home security is available.[18] In particular, this includes the fitting of burglar alarms, door chains and locked windows. Using equation (3) we assess whether there are some ethical differences in the fitting of these security devices; these estimates are reported in Table 9. South Asian households are not significantly different from White households in terms of having security features. They are 6 percentage points more likely to have a burglar alarm; this is 22% more than the average "white" household, but only statis-

[18]Every year a random sub-sample of respondents are provided with a longer form of the questionnaire which addresses these and other specific points.

tically significant at the 10% level. They are 2 percentage points less likely to have door chains, and not significantly different in terms of window locks, so that the overall effect is that they have as many security features as white households. Note that this is not the case for other ethnic minority households, that feature significantly fewer security devices. Overall, we do not find any supporting evidence for a differential in ease of burgling as a potential mechanism to explain our main results.

Table 9: Ethnicity and protection measures

	Burglar Alarm	Door Chain	Window lock	Any of those
Asian	0.064*	-0.021**	-0.015	-0.005
	(0.020)	(0.006)	(0.010)	(0.004)
Black	-0.068**	-0.085***	-0.078***	-0.046***
	(0.015)	(0.011)	(0.012)	(0.009)
Other Ethnic	-0.016	-0.061**	-0.052**	-0.023*
	(0.014)	(0.015)	(0.015)	(0.010)
Obs	137,479	136,887	137,908	137,913
Mean	0.297	0.820	0.875	0.954

Notes: Estimates based on the Crime Survey for England and Wales, 2001 to 2018. Regressions control for survey year, month of interview, governmental region, and indicators of urban, inner city or rural area. Standard errors adjusted for clustering at the year level and governmental regions in parentheses. */**/*** denote statistical significance on the 10%, 5% and 1% level respectively. The reported mean value of each outcome refers to the mean for "white households".

6 Conclusion

A key insight of Becker's model of crime is that rational criminals are driven by the (financial) returns to their activities, so that changes in these returns affect their propensity to commit crime. We extent this logic to investigate how geographical differences in the expected returns to crime driven by well-established ethnic variation in household preferences affects the location of crimes. This hypothesis also aligns with a well-established criminological theory, optimal foraging theory. This paper provides quasi-experimental evidence using plausible exogenous variations in the expected returns to burglaries in different locations. In particular, the identification strategy relies on South Asian greater preferences for gold jewellery and variations in the price of gold over time, which we consider exogenous to the behaviour of UK burglars. The expected relative gains for a burglar from targeting neighbourhoods with a high share of South Asian households consequently change with the gold price.

Using detailed police records, our analysis indicates that areas with a large share of South Asians face a disproportionate increase in property crime relative to other neighbourhoods in the same local authority when the price of gold increases. This result suggests that criminals respond to exogenous changes in the potential returns to a crime by selecting areas with potentially more lucrative targets; a behaviour consistent with Becker's model and with optimal foraging theory. We then provide a raft of additional evidence, also using household level data on crime, which substantiate our findings and dismiss alternative explanatory mechanisms. The estimates are very stable and suggests that a 10% increase in the price of gold increases burglaries in South Asian neighbourhoods by 1%, twice as much as in other neighbourhoods in the same local authority. Over the period of interest, gold price varied by up to 40% resulting in South Asian households being at a substantial higher risk of burglaries.

From a policy perspective our findings may be useful in the design of policing strategies to deter crime, especially since we do not observe any displacement to other crimes or locations. When prices of specific goods are high, overtly visible police patrols specifically around areas rich in potential targets may prove a successful deterrent. In neighbourhoods with a high concentration of South Asian households, a model of police allocation should thus include the price of gold. Indeed, approximating police deployment by the location of "stop and search" activities, we do not find support that this is currently the case. However, the evidence on the effectiveness of patrolling on reducing crime are ambiguous (Blanes i Vidal and Mastrobuoni (2018), Blattman et al. (2021) or Weisburd (2021)). Using the estimates from Weisburd (2021), a reallocation of about 1% of police patrols towards South Asian neighbourhoods would compensate for a 10% increase in the price of gold.

More effective might be to increase regulations in the market for second-hand jewellery or gold; d'Este (2020) highlights the importance of the reselling opportunities on the behaviour of burglars. Indeed Kirchmaier et al. (2020) estimate that the introduction of tougher regulations on the trading of second-hand metals (Scrap Metal Dealers Act of 2013) and targeted policing both can substantially reduce theft. Stricter regulations on the selling of second hand gold and jewellery might thus be an effective way to limit the attractiveness for burglars of targeting South Asians.

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A Online Appendix: Data

A.1 Street-level crime data

The street-level crime data is available from https://data.police.uk/ for England and Wales (and Northern Ireland). Since December 2010, the available data contains details of each reported crime by month and police force area. Importantly, the data includes a measure of the location of each crime. To minimise privacy risks, the publicly available data adds noise to the location; i.e. the exact location of crime is approximated to the nearest "map point".[19] In the vast majority of cases in urban areas, this largely moves the crime from the exact address where it was committed to the centre of the respective street or from the exact location within a park to the centre of the park. If the nearest map point is more than 20km away, which can occur in rural areas, the co-ordinates are zeroed out. Importantly, the anonymisation process preserves information about the Lower Layer Super Output Area (LSOA) where the crime was committed, which we use as the location of crime.

The data distinguishes between the following crimes: "anti-social behaviour", "burglary", "criminal damage and arson", "drugs", "other theft", "other crime", "public disorder and weapons", "robbery", "shoplifting", "vehicle crime" and "violent crime". Not all of the categories are measured consistently over the observation period. "Criminal damage and arson", "drugs", "other theft" and "shoplifting" have been separate categories only since mid-2011 and were part of "other crime" before. "Public disorder and weapons" also underwent several changes - until mid-2011 it was part of "other crime" and since mid 2013 it has been split up into two separate categories "public disorder" and "possession of weapons". Theft also undergoes several changes with "bicycle theft" and "theft from the person" being split from "other theft" towards the end of 2013. For burglary, robbery, vehicle crime and violent crime, we aggregate at the LSOA level the number of reported crimes per month.

Separate files also contain information on stop and search activities, on a monthly basis and for each police force. This data is available from January 2015, but not all police forces reported stop and search activities by then. When available the data contains exact location of the stop and search, characteristics of the "searched person", ethnicity of the searching officer, legislation under which the search was conducted, and outcome of the search. Altogether, we have information for 1,771,935 searches, but after excluding searches conducted by the British Transport Police (essentially stops and seaches conducted on trains and train stations) and those for which no location information is available, we are left with 1,265,032, or 71% of the total. The location is the exact longitude and latitude, which is then mapped to postcodes based on the nearest distance. To achieve this, we use data from National Statistics Postcode Lookup (https://geoportal.statistics.gov.uk/datasets/1951e70c3cc3483c9e643902d858355b) and the command *geonear* in Stata (Pickard, 2019). Postcode information is then used to identify the LSOAs in which the search took place. 99% of locations are matched to a postcode centroid located less than 300 metres away. This process identifies 31,738 LSOAs with at least one stop and search activity recorded, or 91% of the LSOAs used in the main analysis. Over the period, almost 1.8 search and stop activities were recorded, but there is a large amount of variations over time and

[19] Map points are located over the centre point of a street, or "features" such as commercial premises. Map points must contains at least eight postal addresses or no postal addresses at all.

between police forces. The median LSOA has 0 stops and searches in a given month but some have more than hundred.

A.2 Lower Layer Super Output Area

LSOAs are an aggregation of adjacent Census Output Areas (OA) with similar social characteristics that align with local authority district boundaries. These OAs were built following the 2001 Census outputs from clusters of adjacent postcode units, and designed to be socially homogeneous (in terms of dwelling types and housing tenure) and of similar population sizes. The OAs tend to follow natural boundaries, such as roads. The OAs target size is 125 households, and cannot be lower than 40, with an average population of 297. The total numbers of OAs in England and Wales in 2011 were 171,372 and 10,036 respectively.

Following the 2001 census, LSOA were created by aggregating four to six OAs so that they have a population between 1,000 and 3,000, and are as homogenous as possible. In 2011, after some minor changes, there were 32,844 LSOAs in England and 1,909 in Wales.

A.3 2011 Census

The 2011 census was conducted in April. Aggregated data at the level of various geographies is available from NOMIS (https://www.nomisweb.co.uk/census/2011). We extract information at the LSOA level on population size, and population by ethnicity, so that we compute the share of the population for each ethnic group. We define South Asian as individuals reporting their ethnicity as Indian, Pakistani or Bangladeshi. Similarly the Black population aggregates the share of individuals identifying as Caribbean black, African black or other black. The social status classification is derived from census data by the Office for National Statistics and splits the UK population into 6 groups based on the employment of the household head : A “Higher managerial, administrative or professional” (often labelled “upper middle class”), B “Intermediate managerial, administrative or professional” (“middle class”), C1 “Supervisory or clerical and junior managerial, administrative or professional” (“lower middle class”) and C2 “Skilled manual workers” (“skilled working class”), D “Semi-skilled and unskilled manual workers”, also often labelled “working class”, and E “Casual or lowest grade workers, pensioners, and others who depend on the welfare state for their income”. The model uses occupation, employment status, qualification, tenure, full-time or part-time status to define social grade.

A.4 Other data

The quarterly unemployment rate at the local authority level is based on a model developed by the Office of National Statistics and is available from NOMIS (https://www.nomisweb.co.uk/datasets/umb). For details about the methodology see ONS (2006). The Economic Policy Uncertainty Index is available for the UK from https://www.policyuncertainty.com/. The index was developed by Baker, Bloom and Davis (2016). The index is based on the count of newspaper articles including the terms ’policy’, ’tax’, ’spending’, ’regulation’, ’Bank of England’, ’budget’, and ’deficit’. The index is based on 11 British newspapers and updated monthly.

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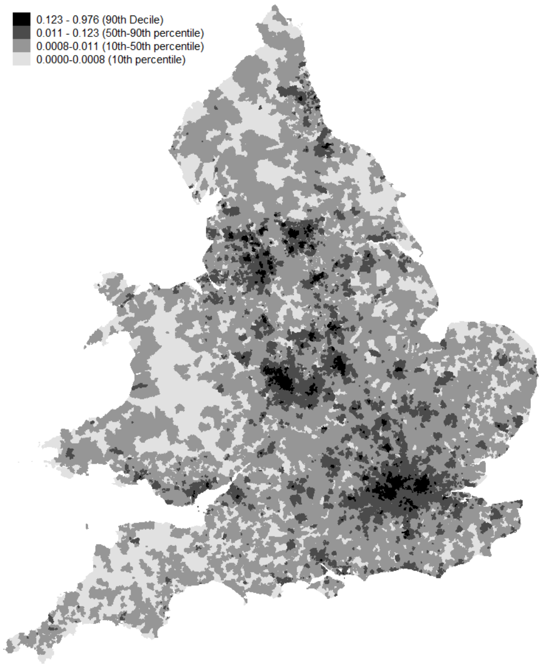
B Online Appendix: Definition of Treatment Areas

B.1 Definition of Treatment Areas

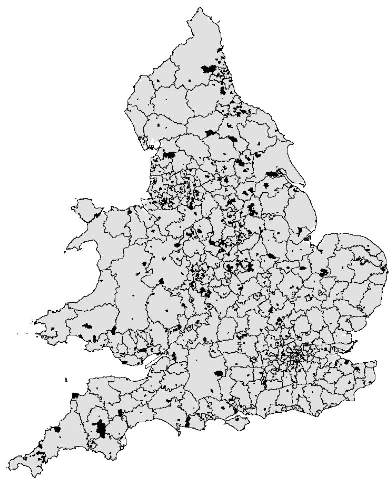
We use the 2011 census to determine the share of South Asian households per neighbourhood. Most neighbourhoods have a very low share of South Asian, the median is 1.1% but there is substantial heterogeneity with London, the Midlands and North West have neighbourhoods with high concentrations - see Figure 8, Panel (a). It is clear that defining treatment areas according to a simple national threshold, e.g., a neighbourhood with a South Asian share of household above the 90th percentile for England and Wales would mainly just pick up large urban conurbation effects, as these neighbourhoods are mainly concentrated in the large cities such as London, Birmingham and Manchester. Instead we define treatment areas as neighbourhoods (LSOA) with a high proportion of South Asian households relative to the share of South Asians in their local authority. The advantage of this approach which ensures a geographic spread of treatment areas across England and Wales.

Our prime definition of a treatment area is a neighbourhood with a share that is an outlier for the Local Authority, i.e., a South Asian share of households in excess of the 75th percentile plus 1.5 times the interquartile range of all neighbourhoods within a local authority. This defines 2,247 treatment areas which by definitions are spread throughout the country (see Panel b). These neighbourhoods have between 0.5% and 97.6% share of South Asian households, with a mean of 16.2% and comprise 6.5% of neighbourhoods in our sample.

Figure 8: Area definitions across England and Wales



(a) Share of South Asian Households



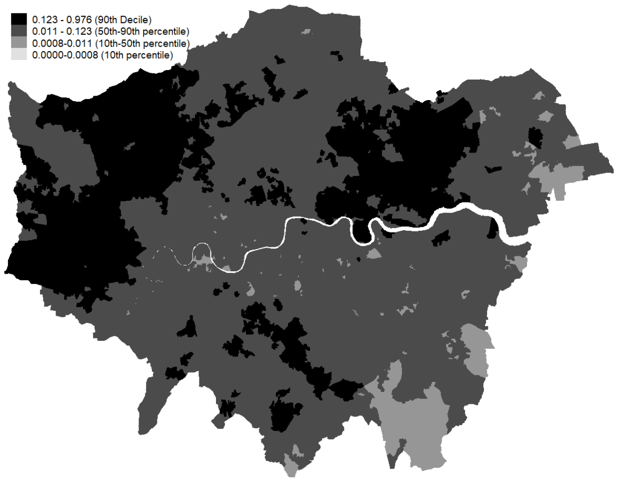
(b) LA Outlier areas

Notes: The maps display the share of South Asian households in each LSOA in England and Wales as enumerated in the 2011 census, and the treatment areas using our main definition of the treatment.

We also define treated neighbourhoods in two alternative ways. Defining treated neighbourhoods as having a South Asian share of population in excess of the 90th percentile of neighbourhoods within their local authority leads to around 10% (3,627) of neighbourhoods being defined as treated. These have a share of South Asian households between 0.2% and 97.6% and mean of 15.9%. We also define treated neighbourhoods as having an outlier South Asian share relative to the Police Force Area, not the local authority. Note that since PFA are larger than LA, this does not guarantee that there is at least one treated neighbourhoods per local authority.

The rationale behind our approach to defining treatment areas becomes even clearer when we consider individual police force areas, and the distribution of South Asian households within each areas as compared with the national distribution. Consider first the Metropolitan Police Force Area, which serves the multiple boroughs of London. As illustrated in Figure 9 panel (a), each neighbourhood and local authority in the Metropolitan police has a relatively high density of South Asian households as compared to the average density across England and Wales. The median share of South Asian households in a neighbourhood across England and Wales is 1.15%. Almost every neighbourhood in London is above this level. Therefore defining treatment areas relative to a nationwide measure would identify almost all neighbourhoods in London as treatment areas. In contrast the outlier definition (panel b) highlight the few neighbourhoods per local authortiy (London borough) that have a relatively high concentration of South Asian households.

Figure 9: Area definitions across London



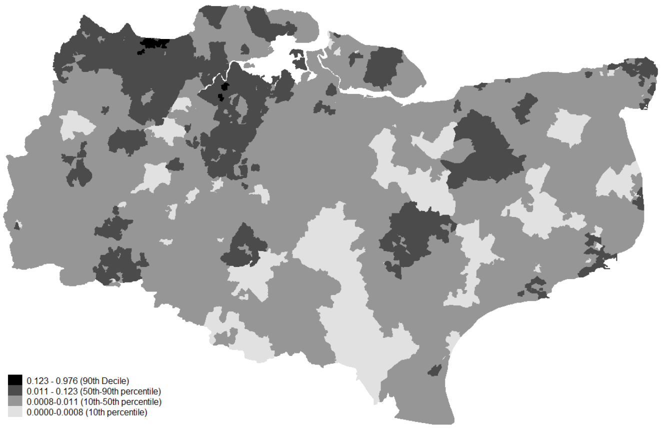
(a) Share of South Asian Households

(b) OUT areas

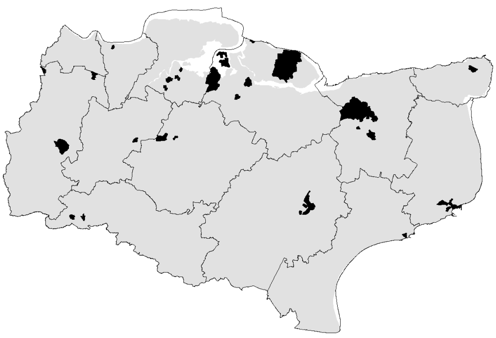
Notes: The maps display the share of South Asian households in each LSOA within the Metropolitan Police Force Area as enumerated in the 2011 census, and the treatment areas used in the analysis.

In contrast, when we consider the Kent Constabulary as an example of a rural PFA, as displayed in Figure 10, Panel (a) only a few neighbourhoods have a high density of South Asian households relative to a national threshold, and therefore defining treatment areas according to a nationwide measure would ignore the lower variation in rural areas. Our preferred definition in Panel (b) identifies some neighbourhoods as having a high South Asian relative to the other neighbourhoods in Kent.

Figure 10: Area definitions across Kent



(a) Share of South Asian Households



(b) OUT areas

Notes: The maps display the share of South Asian households in each LSOA within the Kent Constabulary Police Force Area as enumerated in the 2011 census, and the treatment areas used in the analysis.

C Online Appendix: Robustness of Main Estimates to Clustering

We explore the robustness of our results to different clustering levels in Table D1. As our panel is formed from observations at the neighbourhood (LSOA) level repeatedly over time, in our main analysis we report estimates clustered at the LSOA level (indicated in bold). This involves clustering using the 34,753 LSOAs.

As alternatives we consider clustering at the local authority level or the police force area. Al-

Table 10: Impact of Gold Price on Burglaries

	(1) Top 90% inLA	(2) Outlier in LA
Interaction term	0.0384	0.0559
No Clustering	(0.011)***	(0.014)***
Clustering on LSOA	**(0.013)****	**(0.017)*****
Clustering on LSOA by Time	(0.015)**	(0.018)***
Clustering on LA	(0.016)**	(0.020)**
Clustering on LA by Time	(0.016)**	(0.020)***
Clustering on PFA	(0.015)**	(0.023)**
Clustering on PFA by Time	(0.013)**	(0.021)**
Fixed Effect	LA	LA
Time Trend	LSOA	LSOA
# time periods	108	
# LSOAs	34,753	
Obs ($N \times T$)	3,743,286	

*Notes: The table displays the estimate on the interaction term of the impact on burglaries estimated using Eq.1 for two alternative definitions of the treatment: Share of South Asian in the top 90% within the local autority, and share is an outlier within the local authority. Regressions also control for seasonality via monthly dummies. Standard errors adjusted for clustering at each designated level in parentheses. */**/*** denote statistical significance on the 10%, 5% and 1% level respectively.*

though the estimates lose some precision when larger clusters are considered (clustering at local authority (police force area) level involves 348 (42) clusters), our estimates do not fall below the 5% level of significance. Additionally, we also consider that the errors terms might be correlated over time (108 clusters) and cluster both at the geographical and time level. Again this is found to have little effect on the statistical inference.