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Expected Returns to Crime and Crime Location†

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We provide first evidence that variations in the expected returns to crime affect the location of property crime. Our identification strategy relies on the widely held perception in the United Kingdom that South Asian households store gold jewelry at home. Price movements on the international market for gold exogenously affect the expected gains from burgling these households. Using a neighborhood-level panel on crime and difference-in-differences, we find that burglaries in South Asian neighborhoods are more sensitive to variations in the gold price than other neighborhoods in the same municipality. We conduct various tests on neighborhood and individual data to eliminate alternative explanations. (*JEL* D12, D91, J15, K42, R23)

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 labor market conditions as well as changes in the probability of arrest or sentencing.[1]

Less is known about the role played by changes in the returns to crime, mostly due to data limitations regarding the value of stolen goods and empirical issues such as difficulties in identifying counterfactual targets and the endogeneity of the returns to criminal activities on prices. 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 percent increase in the relative price of a good is associated with a 3.5 percent increase in the probability that this good is stolen. Their estimates are even stronger for a group of commodity-related goods—specifically fuel, jewelry, and metal—for which the elasticities are greater

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

than one. Kirchmaier et al. (2020) study metal theft in the United Kingdom with a particular focus on prices, policing initiatives, and regulation of secondhand buyers, specifically scrap metal dealers. Similar to Draca, Koutmeridis, and Machin (2019) but based on a time series analysis, they 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 on the extent to which changes to the expected returns of criminal activity affect criminals' choice of targets and, thus, the location of crime. 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]

In this paper, we assess, 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 finding of Draca, Koutmeridis, and Machin (2019) that jewelry theft is strongly correlated with variations in the price of gold, we rely on ethnic variations in the propensity to store gold jewelry and estimate whether exogenous variations in the price of gold affect the geographical pattern of crime in England and Wales. In particular, we exploit the long-standing cultural practices of families of South Asian descent (i.e., Bangladeshi, Indian, or Pakistani heritage) to store wealth in the form of gold jewelry (Lawrence 2003), especially of the highest (22-carat) quality (Fernandez, Veer, and Lastovicka 2011). As well as being a storage of wealth, it is a fundamental part of many rituals and religious or social festivities and signals a family's position in their local community (Fernandez, Veer, and Lastovicka 2011). These preferences have persisted outside of the Indian subcontinent and, through the various public displays as well as reports in the national media (e.g., Saner 2012; BBC 2019), are well known to the British population.

Compared to other goods that might be stolen, the secondary market for gold is large.[3] Prices are mostly determined via the global demand for gold on the international exchange and are unlikely to be affected by the selling of stolen gold jewelry in the United Kingdom. Indeed, international variation in the price of gold in the short run is mostly driven by change in the US price level, the behavior of central banks, and worldwide political uncertainty, especially concerning oil prices (Levin and Wright 2006). Gold prices are widely reported in the media and used to determine prices in the secondary gold market.

While not explicitly modeled, the decision on where to commit a crime fits within Becker's (1968) model of criminal behavior, whereby a potential criminal considers the expected costs and returns from committing a crime in two different locations. This behavior is also consistent with an influential theory in criminology that describes how offenders select potential targets. Based on models from behavioral

[2] There is also a large literature considering the effect of policing activities on crime; see Chalfin and McCrary (2017) for a review and Mastrobuoni (2019); McMillen, Sarmiento-Barbieri, and Singh (2019); Blanes i Vidal and Mastrobuoni (2018); Blattman et al. (2021); Weisburd (2021); and Braakmann (2022) for recent papers.

[3] d'Este (2020) highlights the importance of the secondary market for stolen good in the decisions of burglars.

ecology, where animals are understood to forage for food by maximizing the acquisition of resources while minimizing search effort and the risk of attack by a predator, optimal foraging theory posits that criminals aim to maximize the proceeds of crime and minimize the time spent searching for a suitable target, committing the crime, and risking being caught (Johnson and Bowers 2004; van Winden and Ash 2012). Empirically, we cannot distinguish between criminals being able to target South Asian households directly and their only being able to target South Asian neighborhoods without being able to identify whether a specific house belongs to a South Asian household—either of these mechanisms seems plausible and would lead to a larger number of burglaries in South Asian neighborhoods.

We collect data on individual crimes between 2011 and 2019 for all police forces in England and Wales and aggregate these to a monthly panel at the level of small neighborhoods. Using 2011 census data, we classify neighborhoods as having a high South Asian population density. We combine these data with monthly gold prices from the London Bullion Market Association (LBMA).

The analysis uses a differences-in-differences methodology where we interact the monthly gold price with an indicator for a South Asian neighborhood while controlling for various low-level geographical fixed effects and alternative time effects. Across all specifications, we consistently find that burglaries in South Asian neighborhoods are twice as sensitive to variations in the gold price as other neighborhoods. In our favored specification, a 1 percent rise in the price of gold increases burglaries in South Asian neighborhoods by 0.057 percent relative to other neighborhoods. For regularly observed increases in the gold price during our observation period—equal to about 25 percent over the course of a year—we find an increase in burglaries in South Asian neighborhoods of 2.6 percent, or an additional 0.4 burglaries per year and neighborhood. Relative to a mean of 15.24 burglaries per year, these estimates are not huge in absolute terms. However, given that jewelry theft occurs in only around 8 percent of burglaries (Braakmann, Chevalier, and Wilson 2022), this small increase in overall burglaries potentially translates to a 32 percent increase in burglaries involving the theft of jewelry in these areas.

We conduct several robustness checks—altering the definition of treated neighborhoods, the geographical fixed effect, or the treatment of time—and use a randomization inference procedure. Additionally, we consider effects on other crimes whose returns do not change with the gold price and conduct two falsification tests by considering other ethnic groups and poor neighborhoods as treated and considering alternative indicators of economic activity. All these confirm our main results. Only for variations in the gold price and South Asian neighborhoods do we observe relocations of burglaries.

Finally, we investigate spatial spillovers and displacement. We find evidence that the increases in burglaries only occur in urban areas and spillover into neighborhoods close to South Asian areas. Exploring drivers of these spillovers, we find that they can partially be explained by a higher South Asian population share in neighborhoods near treated areas. In a next step, we explore an alternative measure of distance based on connectedness of two neighborhoods via the road network. We find that they are largely insensitive to measuring physical or road distance, although using road distance leads to slightly larger estimates. 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 gold by relocating their efforts to areas with higher expected returns.

I. Data

We merge data from several sources[4] at the level of neighborhoods, specifically lower-layer super output areas (LSOAs). 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 and covering a homogenous population. They are designed for the publication of census data and have remained stable since their introduction in the 2001 census. LSOAs are nested within local authorities (LAs), the basic level of local government in the United Kingdom (roughly equivalent to US counties). LAs usually consist of a city or of amalgamations of smaller towns and rural areas. London as a special case is split into 32 boroughs, each designated as an LA. There are a total of 348 LAs in England and Wales, each containing on average 100 LSOAs, but with a large amount of variation, from 1 (Isles of Scilly) to 639 (Birmingham). Policing is organized into 43 territorial police forces in England and Wales, with each police force area (PFA) usually covering multiple LAs.

To define the ethnic composition of an LSOA, we rely on information from the 2011 census (Office for National Statistics 2011), which is the only source of information on population structure at the LSOA level. In 2011, 5.2 percent of the population in England and Wales self-identified as South Asian. For historical reasons, the South Asian population is geographically concentrated, as immigration was encouraged to address labor shortages in specific industries post–World War II. 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.

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 percent, and 1,988 LSOAs (around 6 percent of the total) do not contain a single person of South Asian descent. At the other extreme, the top 10 percent most concentrated LSOAs have a South Asian population share between 12 percent and 98 percent. If we were to define treated areas as having a high share of South Asians according to a national threshold measure, we would mainly pick neighborhoods in large urban conurbations and leave large swathes of the country in the control group. This would be unlikely to reflect the choice made by local burglars, who typically decide on targets in the vicinity of their own domicile (Vandeviver and Bernasco 2019; Kirchmaier, Langella, and Manning 2024). Our preferred definition of South Asian neighborhoods is that of an outlier within an LA—i.e., their share of South Asian population is in excess of the seventy-fifth percentile plus 1.5 times the interquartile range for that LA. Around 6.5 percent of

[4] Additional information on the data is contained in Section I of the online Appendix.

neighborhoods in our sample are classified as treated. This definition ensures there is at least one treated neighborhood in each LA, meaning that burglars always have a choice to target a "local" neighborhood. We also provide evidence of the robustness of our results to alternative definitions of treated neighborhoods, including using absolute population shares. Section II in the online Appendix discusses treatment area definitions in detail.

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 (grades 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.

The crime data were 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.[5] The data cover the period January 2011 to December 2019.[6] We do not include data from January 2020 onward as the COVID-19 pandemic possibly disrupted previous crime patterns. While the exact location of crimes is slightly anonymized, the LSOA of each offense is precisely recorded in the published data. For each neighborhood, we compute monthly counts of recorded offenses in several categories that are consistently defined: "burglary," "robbery," "violent crime," "vehicle crime," and "total crime (excluding burglary)."

Table 1 provides summary statistics for the main variables of interest at the neighborhood level, overall and separately by treatment status. Unsurprisingly, the treated areas have a higher share of South Asian households than control areas (16 percent versus 4.2 percent) and are much less likely to be classified as rural (5.5 percent versis 18.8 percent). They also have a higher share of population in the lowest social class (25 percent versus 31 percent) but do not differ in the proportion of Black households.

Crime counts are generally fairly small in absolute numbers, and a substantial proportion (47 percent) of observations report 0 burglaries, which is not surprising given the small neighborhoods and the monthly frequency of the data. On average there is one burglary per month per neighborhood, but there is a relatively large amount of variation, with a standard deviation of 1.459. For the empirical analysis we take an inverse hyperbolic sine transformation of the crime series, which approximates the natural logarithm but retains zero-valued observations.[7] We also use absolute counts in a robustness check using fixed effects Poisson regressions.

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 (real) over-the-counter transaction price of gold from the LBMA (London Bullion Metals

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

[6] From July 2019, there are no data for the Greater Manchester Police Force after an inspection revealed that more than 20 percent of crimes over the period July 2019 to June 2020 had not been recorded (HMICFRS 2020).

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

Table 1—Summary Statistics

	Total	Control	Outlier in LA
South Asian population share	0.050	0.042	0.162
	(0.108)	(0.095)	(0.193)
Outlier in local authority	0.065	0.000	1.000
(1 = yes)	(0.246)	(0.000)	(0.000)
Black population share	0.031	0.031	0.036
	(0.065)	(0.066)	(0.054)
Share of low-skilled households	0.253	0.249	0.309
(social grades D and E)	(0.131)	(0.129)	(0.150)
Rural neighborhood	0.179	0.188	0.055
(1 = yes)	(0.383)	(0.390)	(0.228)
Total population	1613.606	1607.915	1696.054
	(303.431)	(297.103)	(373.991)
Reported crime (*counts per neighborhood and month*)			
Burglary	1.024	1.007	1.270
	(1.460)	(1.440)	(1.702)
Robbery	0.157	0.153	0.220
	(0.643)	(0.642)	(0.653)
Vehicle crime	0.956	0.944	1.119
	(1.485)	(1.477)	(1.587)
Violent crime	2.639	2.531	4.202
	(4.173)	(3.984)	(6.095)
Total crime (except burglary)	13.322	12.768	21.345
	(19.900)	(19.052)	(28.379)
Observations	3,742,962	3,501,312	241,650

Notes: The table displays summary statistics at the neighborhood level (LSOA). Socio-demographic information is based on 2011 census data. Monthly crime data are aggregated at the LSOA level by the authors. There are no data available for the Greater Manchester Police Force between June and December 2019. Grades D and E cover semiskilled and unskilled manual occupations, the unemployed, and lowest-grade occupations.

Authority 2020), which accounted for 86 percent of the volume of trades in 2011 (Lucey, Larkin, and O'Connor 2013). We convert this to real pound sterling using the the Current Price Index (CPI) from the Office of National Statistics (Office for National Statistics 2023a). The headline pound sterling figure is regularly published in media outlets in the United Kingdom and is thus easily available to the public. 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.[8] There are large variations in the price of gold over the sample period, as shown in Figure 1. Overall, gold prices vary by +20 percent to −20 percent during the period of analysis.

We also conduct a series of robustness checks using other economic indicators. We use the oil price from the World Bank's Commodity Price Data (World Bank 2023), converted into real pound sterling using the Bank of England's monthly average spot exchange rate (Bank of England 2023) and the CPI. As both gold and oil reflect economic and geopolitical uncertainty globally, we also focus on two indicators

[8] For example, gold.co.uk, a large online trader, states, "We buy scrap gold for up to 95 percent of its spot value, giving you excellent value and a great customer experience."

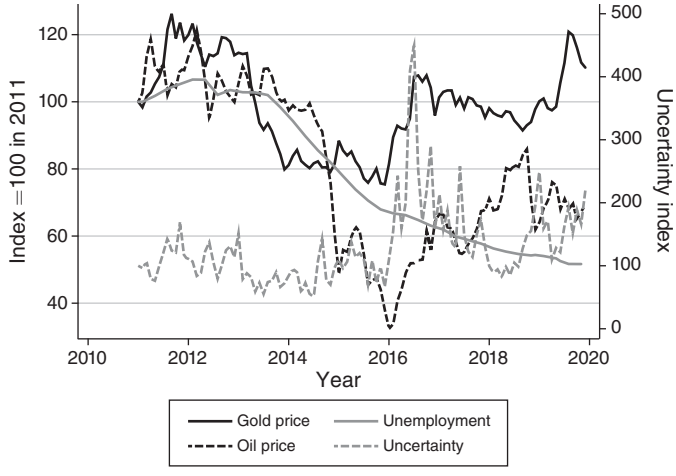

Figure 1. Gold Price and Alternative Measures of Economic Activity

Notes: 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 Metals Authority (2020). Oil prices: World Bank (2023). Local Authority Unemployment: Office for National Statistics (2023b). UK Uncertainty Index: Baker, Bloom, and Davis (2016). The figure uses the plotplain scheme developed by Bischof (2017).

of the United Kingdom 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 an index that is normalized to 100 in 2011, with higher values indicating greater economic uncertainty. The last measure is the local unemployment rate (Office for National Statistics 2023b). This is computed quarterly by the Office for National Statistics for each LA, except for the "City of London" and the "Isles of Scilly" due to their small population.

In Figure 1, we report the coevolution of the four measures of the 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 comovement 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 the gold price and specific indicators of economic activity in the United Kingdom suggest 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.

II. Empirical Strategy and Baseline Estimates

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 United Kingdom 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 toward neighborhoods containing a large number of South Asian households. Traditionally, gold is an insurance rather than an investment for these households, which makes it unlikely that the gold price affects the selling of gold.[9] Also, since the jewelry is regularly displayed, households are likely to store it at home rather than in a bank safe.

Our analysis links the gold price in a month to burglaries in the same month. This contemporaneous link requires that burglars cannot simply 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 jewelry, which is usually more distinct than cash or electronic goods. Qualitative evidence indeed suggests 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 et al. 2016 find that time discounting in childhood correlates with future criminal activities). However, even if burglars were able to wait to sell at higher prices, this would likely bias our estimates toward zero as it would lead to a conflation of periods with high and low prices.

The analysis relies on a difference-in-differences-style framework where the variation in the share of South Asian households across neighborhoods creates cross-sectional variation, while changes in the gold-price lead to longitudinal variation in the intensity of treatment.[10] Specifically, we estimate regressions of the type

$$(1) \quad y_{ict} = \beta_0 + \beta_1 SA_{ic} + \beta_2 GP_t + \tau\left(SA_{ic} \times GP_t\right) + \alpha_c + \theta_t + \gamma TREND_{it} + \epsilon_{ict},$$

where i indexes neighborhoods nested within LAs c, and t indexes time. The outcomes y_{ict} are measures of the prevalence of various types of crime (principally, burglary) for the respective neighborhood in a given month, GP_t is the average monthly gold price, and SA indicates a treatment area—i.e., a neighborhood with a relatively high proportion of South Asian households compared to the rest of the LA. 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 LA fixed effects α_c and month effects θ_t, as well as neighborhood-specific quadratic time trends $TREND_{it}$. τ measures the differential impact of changes in the price of gold on crime across areas with different shares of South Asian households within an LA. Note that the share of South Asians that

[9] For example, the jewelry 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).

[10] Note that we do not have differential timing as the gold price increases are identical across all neighborhoods.

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 neighborhood; i.e., we do not allow for a change in treated and control neighborhoods caused by a flight of some demographic group to a "safer" neighborhood. In our favored model, the standard errors are clustered at the level of the neighborhood. However, estimates remain statistically significant using alternative clustering levels (see Table 1 in the online Appendix for details).

Table 2 reports estimates for different specifications and treated area definitions. Panel A presents results for the former. Column 1 contains our base specification with LA fixed effects and neighborhood time trends. Column 2 replaces the LA fixed effects with neighborhood fixed effects, and column 3 the neighborhood quadratic trends with LA-by-month-by-year fixed effects. The latter capture region-specific effects that might be triggered by variations in the price of gold but that are not specific to South Asian neighborhoods. For example, d'Este (2020) shows that the density of pawnbrokers in a US county, by affecting the ease to resell stolen goods, affects the elasticity of burglaries with respect to the gold price. Including LA-specific time fixed effects would allow us to capture this effect, as long as we assume that burglars resell their loot in the LA rather than the particular neighborhood in which they commit their crime. The interaction term across columns 1 to 3 is essentially identical at 0.053 to 0.057. These estimates strongly support that burglars focus their effort on neighborhoods that have, in expectation, a higher payoff. In columns 1 and 2, the elasticity of burglary with respect to the price of gold is 0.047; i.e., in control neighborhoods, an increase in the price of gold of 10 percent increases the number of burglaries by around 0.5 percent. Comparing the size of these effects indicates that neighborhoods 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 neighborhoods.

Table 2, columns 4 and 5 deal with potential concerns around the inverse hyberbolic sine transformation of the outcome given the large number of zeroes. In column 4 we instead estimate a Poisson fixed effects model for count data on the untransformed outcome, while column 5 uses a dummy outcome for any burglaries in a neighborhood and month. We again find very similar estimates for the interaction term.

Table 2, panel B presents results using alternative plausible definitions of treated areas. Column 1 replicates our main result. In column 2 we consider areas as treated if they are an outlier in the LA but also have an absolute South Asian population share of at least 5 percent. Columns 3 and 4 define neighborhoods as treated if their South Asian population share is in the top 10 percent within the LA (column 3) or nationally (column 4). The magnitude of the interaction terms varies between 0.038 in column 3 and 0.090 in column 2. Not unexpectedly, area definitions that result in a higher South Asian population share in treated areas correspond to larger values of the interaction. Finally, we estimate a dose-response DiD in column 5 where we use a neighborhood's South Asian population instead of the treated neighborhood. While the magnitude is not directly comparable, this linear specification again aligns with our other estimates.

How large are these effects? Figure 1 shows several periods during which the gold price increased for several months—in 2011, 2016, and 2019. During these

Table 2—Impact of Gold Price on Burglaries

	Main treated area definition: Outlier in Local Authority				
	(1)	(2)	(3)	(4)	(5)
Panel A. Different specifications					
Treated neighborhood	0.057	0.057	0.053	0.082	0.029
× Gold price	(0.017)	(0.017)	(0.013)	(0.029)	(0.010)
Treated neighborhood	−0.297	0.000	−0.266	−0.402	−0.158
	(0.130)	(.)	(0.100)	(0.223)	(0.081)
Gold Price	0.047	0.047	0.000	0.140	0.027
	(0.004)	(0.004)	(.)	(0.008)	(0.003)
Burglary measured as:	IHS	IHS	IHS	Count	Any
Estimator	OLS	OLS	OLS	Poisson	OLS
Area fixed effect	LA	LSOA	LA	LA	LA
LA-by-month-by-year FE	No	No	Yes	No	No
Calendar month FE	Yes	Yes	No	Yes	Yes
Quadratic time trend	LSOA	LSOA	None	LSOA	LSOA
Observations	3,742,962	3,742,962	3,742,854	3,742,962	3,742,962

	Main area def.	Alternative treated area definitions			
	Outlier in LA	Outlier in LA & SA share ≥5%	90th percentile in LA	90th percentile National	SA pop. share (dose response)
Panel B. Different treated area definitions					
Treated neighborhood	0.057	0.090	0.038	0.077	0.195
× Gold Price	(0.017)	(0.022)	(0.013)	(0.014)	(0.038)
Treated neighborhood	−0.297	−0.537	−0.193	−0.466	−1.263
	(0.130)	(0.173)	(0.103)	(0.110)	(0.300)
Gold Price	0.047	0.047	0.047	0.043	0.041
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Burglary measured as:	IHS	IHS	IHS	IHS	IHS
Estimator	OLS	OLS	OLS	OLS	OLS
Area fixed effect	LA	LA	LA	LA	LA
LA-by-month-by-year FE	No	No	No	No	No
Calendar month FE	Yes	Yes	Yes	Yes	Yes
Quadratic time trend	LSOA	LSOA	LSOA	LSOA	LSOA
Observations	3,742,962	3,742,962	3,742,962	3,742,962	3,742,962

Notes: Standard errors adjusted for clustering at the LSOA level in parentheses. Columns 1 to 5 in panel A and column 1 in panel B define a treated area as having a South Asian population share in excess of the seventy-fifth percentile plus 1.5 times the interquartile range for that local authority. Panel B, column 2 additionally imposes a minimum South Asian share of 5. Columns 3 and 4 in Panel B use areas with a South Asian population share above the ninetieth percentile in the local authority (3) and nationally (4). Panel B, column 5 uses the South Asian population share in a continuous dose response regression. Outcomes are burglaries in inverse hyberbolic sine, except for columns 4 and 5 in panel A that use counts and a dummy variable for any burglaries, respectively. LA denotes local authorities, and LSOA lower-layer super output areas ("neighborhoods"). Observations are effective observations numbers excluding any singleton combinations of fixed effects. The difference in observations between column 3 and other columns is due to the Isles of Scilly, which are a local authority with one LSOA. Columns 1–3 and 5 in panel A and columns 1–5 in panel B are estimated using reghdfe (Correia 2017), Panel A, column 4 is estimated using ppmlhdfe (Correia, Guimaraes and Zylkin 2020). Tables were created using the commands by Jann (2005, 2007).

periods, gold prices rose by around 25 percentage points over the course of a year. Using these periods as a benchmark, our estimates imply an increase in burglaries in control neighborhoods by around 1.2 percent and by an additional 1.4 percent in South Asian neighborhoods (for a total of 2.6 percent). An average South Asian neighborhood has a population of 1,696 and experiences 1.27 burglaries a month,

or 15.24 per year (about 9 per 1,000 population). Our estimates imply that the increased gold price would add another 0.4 burglaries per year to each of these neighborhoods (about 0.24 per 1,000 population). While these increases are not huge in absolute terms, they should be understood in the context of the proportion of burglaries where jewelry is targeted. Evidence from the Crime Survey of England and Wales indicates that jewelry is stolen in only 8.2 percent of all burglaries (Braakmann, Chevalier, and Wilson 2022). In South Asian neighborhoods this translates to 1.25 burglaries per year involving the theft of jewelry. Thus, an increase in burglaries of 0.4 due to a 25 percent rise in the price in gold would potentially translate to a 32 percent increase in burglaries involving the theft of jewelry in these areas.

III. Robustness

We now discuss our main robustness checks in detail. In addition, the online Appendix contains further robustness checks—specifically, robustness to various forms of clustering of the standard errors, randomization inference, and additional estimates on changes to police deployment. The discussion paper version of this paper (Braakmann, Chevalier, and Wilson 2022) contains additional individual-level results using the Crime Survey for England and Wales.

Firstly, 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. Changes to these crimes either could reflect criminals engaging in burglaries instead of other criminal activities or could be indicative of other unobserved trends at the neighborhood level that influence both burglaries and other crime. To assess the extent of displacement between crimes, we consider two crimes: robbery 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. The results in panel A of Figure 2 show little evidence that crimes other than burglaries see an increase in high South Asian neighborhoods when the gold price is high: 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 toward burglaries, and small and insignificant effects on violent crime and crime overall. This pattern supports the hypothesis that offenders reallocate their efforts specifically toward crimes whose returns have increased and not just toward neighborhoods with a high proportion of South Asian households.

Secondly, a concern with our identification strategy is that the price of gold captures economic uncertainty that could either directly or indirectly—via policies implemented to remediate it—alter the behavior of criminals. In Figure 2, panel B, we report estimates where we replace the gold price with three alternative economic indicators (namely, the oil price, which is also set on world markets) and two alternative measures of economic activity (namely, the local unemployment rate and the UK Policy Uncertainty Index, a measure of economic uncertainty based on newspaper

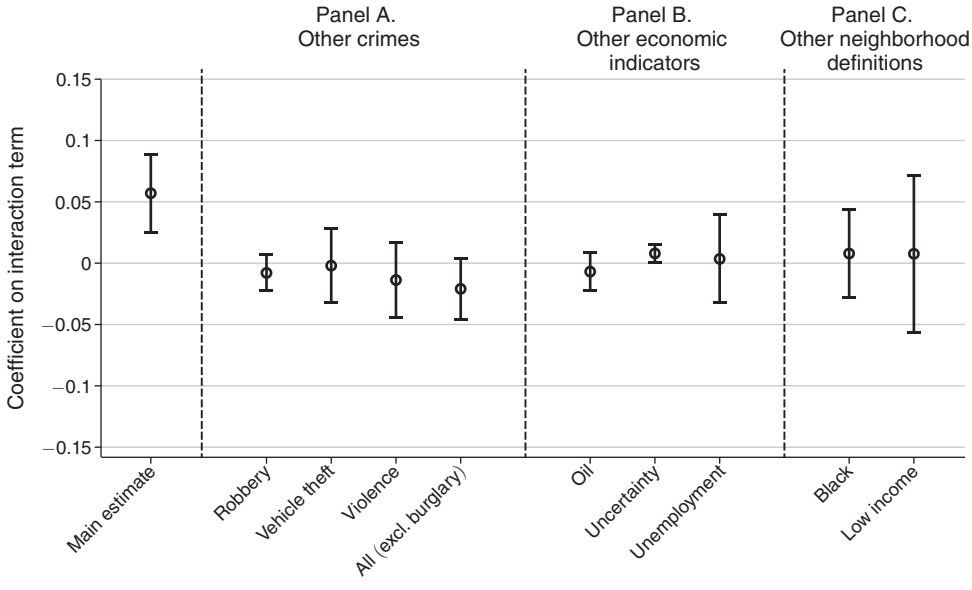

FIGURE 2. ROBUSTNESS

Notes: Main estimate uses burglaries as the outcome. Displayed is the estimate, along with the 95 percent confidence interval, of the interaction term between treated neighborhoods and the price of gold in equation (1) as described in Section I. Panel A displays the estimate for other crimes as outcomes—specifically, robberies, violent crimes, and the total crime count excluding burglary. Panels B and C display corresponding estimates using the the oil price, the uncertainty index, and the local authority unemployment rate instead of the price of gold (panel B) or with treated areas defined by either the Black population share or the share of low-skilled households (panel C). Regressions control for seasonality via monthly dummies, municipality fixed effects, and neighborhood time trends. The figure uses the plotplain scheme developed by Bischof (2017).

articles). The results show that the observed increase in burglaries in South Asian neighborhoods due to variations in the gold price is not found for variations in the other indicators. The effects are precisely estimated and close to zero.

Finally, Figure 2, panel C presents results from a falsification exercise where we define the treated neighborhoods based on their share of Black households or based on the share of households belonging to the two lowest social classes in the United Kingdom. The latter are defined by the head of household being in semiskilled or unskilled manual occupations and being unemployed or in lowest-grade occupations. These estimates address concerns that areas with a large population of South Asians could simply be poorer or be particularly ethnically diverse neighborhoods and that our results simply represent changes in burglary rates in areas with these characteristics rather than the specific targeting of South Asian neighborhoods by burglars. Variations in the price of gold should not have a direct effect on Black or poorer neighborhoods, since those households are (in a UK context) not known to have a strong preference for holding gold jewelry.[11] Panel C of Figure 2 displays the estimates for the interaction term for these different treatments. While the standard

[11] This is different from the United States, where some evidence such as Charles, Hurst, and Roussanov (2009) indicates that Black and Hispanic households spend significant amounts on visible goods, such as jewelry.

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 we observe the increase in burglaries only for South Asian neighborhoods.

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

IV. Spatial Spillovers

Finally, we investigate the extent to which there are geographical spillovers and their potential drivers. To assess the geographical displacement of crime, we compute for each control neighborhood the minimum distance between its centroid and the centroid of the nearest treated neighborhood, and add indicators of distances (500-meter bins) and their interactions with the gold price, so that we estimate versions of the following model, splitting the control neighborhoods into 10 equidistant bins (C_d):

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

In panel A of Figure 3, we plot estimates based on equation (2) where we allow the treatment effect to vary with the (ellipsoidal) distance from a treated area. We also provide separate estimates for urban and rural areas. South Asian neighborhoods are disproportionally located in urban areas (the shares of South Asian are 5.9 percent and 0.5 percent in urban and rural neighborhoods, respectively). Additionally, urban neighborhoods are smaller, which, since all LSOAs contain approximately the same number of households, also reduces the costs of searching them for targets. We thus expect effects to be larger in urban areas. This is indeed the case: the estimated effects in rural areas are zero, and all effects are entirely driven by urban areas.

There are three plausible mechanisms underpinning possible spillovers. First, burglars might relocate to treated neighborhoods from nearby areas, which would lead to drops in crime in surrounding neighborhoods. Recent evidence (Kirchmaier, Langella, and Manning 2024) suggests that crime in the United Kingdom is often committed close to an offender's residence and that the propensity to commit crimes declines rapidly with commuting time. Second, burglaries might spill over into neighboring areas if, for example, these areas also have a comparatively high share of South Asian households or if burglars cannot observe neighborhood boundaries perfectly. Third, if burglars relocate to South Asian areas, they might also discover new targets in neighborhoods along their commute. Figure 3, panel A suggests that there indeed

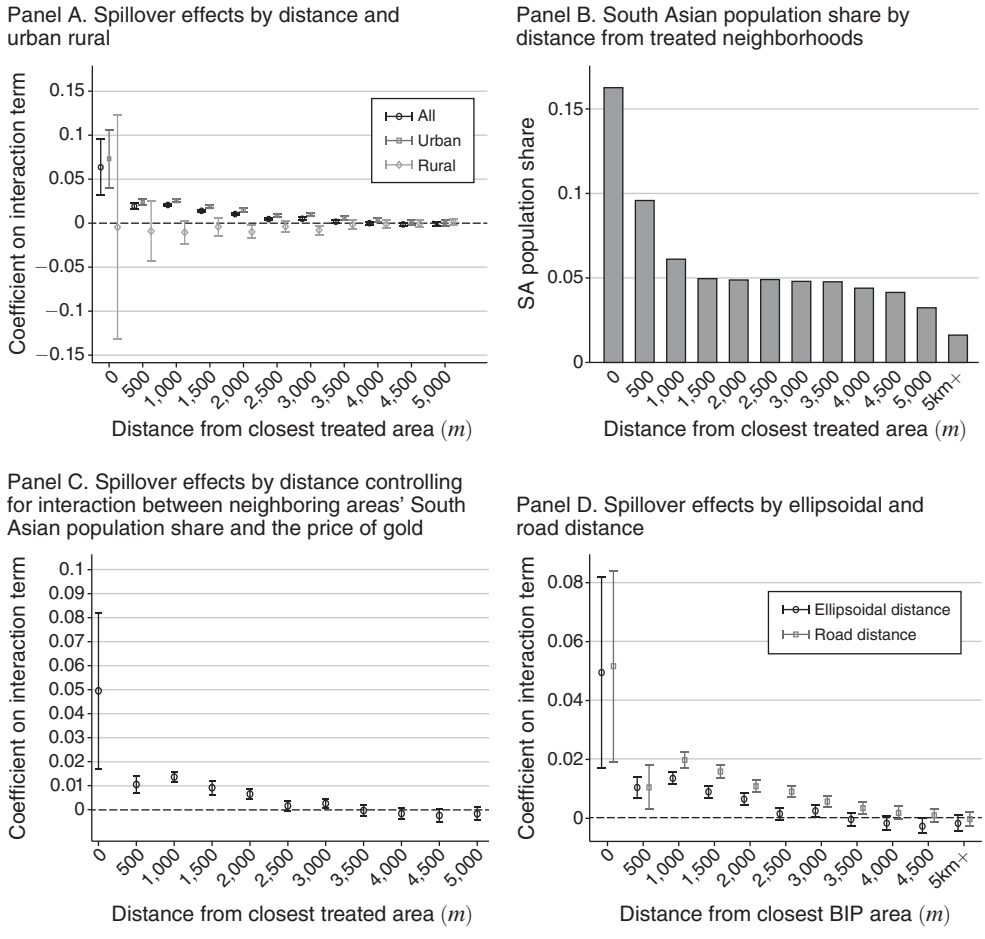

FIGURE 3: SPATIAL SPILLOVERS

Notes: Estimates in panels A and C–D are based on variations of equation (4) and display coefficients and 95 percent confidence intervals. Panels A and D display sets of coefficients from separate regressions. Ellipsodial distance is calcualted using geodist (Picard 2010). The figure uses the plotplain scheme developed by Bischof (2017).

were positive spillovers into neighboring areas: while the largest increases in burglaries are observed in treated areas, neighboring areas also experience an increase in burglaries, although of a smaller magnitude. This effect declines with distance and disappears for areas farther than three kilometers (km) from a treated neighborhood.

Figure 3, panel B presents a potential explanation for these effects: the population share of South Asian households is comparatively high near treated areas and also declines with distance. To test whether this fact is driving our results, we augment equation (2) with controls for an area's South Asian population, measured by dummies for each decile, and their interaction with the gold price. In this specification, τ^d measures the effect of distance to a treated area while controlling for changes in each neighboring area's attractiveness to burglars. Results can be found in panel C of Figure 3. Estimates show the same pattern, but a decrease in

magnitude relative to Figure 3, panel A. This suggests that the spillovers in panel A are partially but not fully driven by a higher South Asian share in neighboring areas.

An alternative way to think about distance is based on the connectedness of two areas. For example, two areas might be close to each other based on their ellipsoidal distance but might be separated by a river or a motorway. To consider this possibility, we first recalculate distances based on the road network (Ordnance Survey 2023)—specifically, the driving distance between two centroids. Results of this exercise can be found in Figure 3, panel D, where we compare the distance interactions from separate regressions using either the ellipsoidal or the road network distance. We find a similar pattern for both distance measures, although driving distance leads to larger interaction terms for neighborhoods at least 1 km from a treated area. The results suggest that spillovers are driven by connectedness via the road network rather than physical closeness, which is consistent with burglars traveling through these areas to treated areas.

V. Conclusion

A key insight of Becker's (1968) 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 extend this logic to investigate how geographical differences in the expected returns to crime affect 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 jewelry and variations in the price of gold over time. The expected relative gains for a burglar from targeting neighborhoods 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 an increase in property crime relative to other neighborhoods in the same LA when the price of gold goes up. 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 behavior consistent with Becker's (1968) model and with optimal foraging theory.

From a policy perspective, our findings may be useful in the design of policing strategies to deter crime. When prices of specific goods are high, overtly visible police patrols—specifically, around areas rich in potential targets—may prove a successful deterrent. In neighborhoods with a high concentration of South Asian households, a model of police allocation should thus include the price of gold. However, the evidence on the effectiveness of patrolling on reducing crime is ambiguous (Blanes i Vidal and Mastrobuoni 2018; Blattman et al. 2021; Weisburd 2021). Using the estimates from Weisburd (2021), a reallocation of about 1 percent of police patrols toward South Asian neighborhoods would compensate for a 10 percent increase in the price of gold.

More effective might be to increase regulations in the market for secondhand jewelry or gold; d'Este (2020) highlights the importance of the reselling opportunities on the behavior of burglars. Indeed, Kirchmaier et al. (2020) estimate that

the introduction of tougher regulations on the trading of secondhand metals (Scrap Metal Dealers Act of 2013) and targeted policing both can substantially reduce theft. Stricter regulations on the selling of secondhand gold and jewelry might thus be an effective way to limit the attractiveness for burglars of targeting South Asians.

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