Impact of Rising Cost-of-Living on Crime in London

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October 2023

A Abstract

In the United Kingdom, one million crimes were recorded on an average each year in the 1960s, increasing to two million during the 1970s, and 3.5m in the 1980s. During the 20th century, there was a notable increase in crime rates compared to earlier decades.[1]. The earlier debates have tried to link the relationship between unemployment and crime from the standard Becker/Ehrlich model, in which an individual faces a choice between crime and work. Over the years, researchers in the field of crime and justice have repeatedly explored various factors, including the potential contentious relationship with socio-economic disadvantage. This work attempts to investigate one such identified factor which is economic hardship's impact on the crime rates, and audit of law and order in London at borough-level. The results suggest that a 10% increase in the cost of living in London is associated with a decrease of all crime reporting to London police by 2.4% with respect to their mean and a 0.5% decrease in violent crime calls with respect to the mean value. Further, evidence of an increase in burglaries, thefts, violence against the person, abandoned calls and, wanted-police/court order/bail is found. The cost of living has the highest effect on all three types of calls to London police in the inner-city student clusters. In these clusters, the effect is highest for all calls (β= 0.065) followed by crime-related calls (β= 0.04) and finally violent crime-related calls (β= 0.02). Moreover, the borough of Hillingdon (northeast of Greater London) remains one of the main affected areas by the rising cost of living.

[1] https://www.data.gov.uk/dataset/f79c8194-93b0-41eb-bba5-56a83fd32f10/historical-crime-data

B Introduction

B.1 Cost of living crisis: Overview

The cost-of-living crisis (COLC) refers to the recent increase in the price of essential goods faster than the average income of households in the United Kingdom. Prices have grown more than wages, resulting in a fall in real income and affecting the purchasing power of households. Institute for Government defines COLC as "the fall in real disposable income of the households (that is, adjusted for inflation and after taxes and benefits)."[2] The prices have been rising since late 2021 and inflation reached a peak in October 2022 at 11.1%. The growth in total pay in real terms fell by 1.2% from March to May 2023, making it hard to keep pace with inflation. While 82% of the adults blame electricity or gas for the cost-of-living crises, about 96% blame the more visible increase in food prices.The prices have increased in the UK fastest in the past four decades (see Figure 1). The latest measure indicates an increase in the Consumer Price Index of 7.9% in May 2023 from 7.8% in April 2023 for owner occupier's housing cost. Housing and household services (electricity and gas) including food remained the key contributors to the rising inflation rate.[3] Further, the doubling of average annual energy bills from 2021 to 2022 added to the increasing concerns of the public. 50% of the adults reported that they were worried about the cost of energy and food while more than 4 in 10 adults were finding it very difficult to afford rent or mortgage payments.[4]

Inflation impacts different types of households in different ways (see Figure 2). Not all households experience the same average rate of inflation because of the difference in their underlying consumption basket. For example, richer households experience a relatively lower impact of inflation while those at the bottom of the income ladder experience a relatively higher burden of inflation. The top panel of Figure 2 shows that the price index is about 0.02 pp higher for subsidized renters as compared to owner-occupiers towards the end of 2022. The situation is worse for low-income households as they spend a higher share of their income on energy and food, the prices of which spiked rampantly. The rising inflation is attributed to several underlying events ranging from national to global. Turbulence in the world due to the Covid-19 pandemic, energy crises, supply

[2] https://www.instituteforgovernment.org.uk/explainer/cost-living-crisis#footnoteref1_8llzp0y

[3] https://www.ons.gov.uk/economy/inflationandpriceindices/bulletins/consumerpriceinflation/may2023#notable-movements-in-prices

[4] https://www.ons.gov.uk/economy/inflationandpriceindices/articles/costofliving/latestinsights

Figure 1: Inflation: recent trends show inflation to be the highest in the past four decades, with peaks since late 2021. *Source: Office for National Statistics*

chain disruptions, and Russia's invasion of Ukraine severely affected the economy of the United Kingdom. While economic growth was restored in 2021 to some levels after the pandemic, depleted gas supplies from Europe and a shortage of semiconductor chips in Asia exacerbated the energy woes of the public. The UK market suffered not only due to the operation closure of multiple companies in Russia but was also affected by instability in the energy supply in the European Union. The recent announcement of the European Commission to phase out oil imports from Russia pushed the energy prices upward in the UK due to the integration of both markets. Domestic

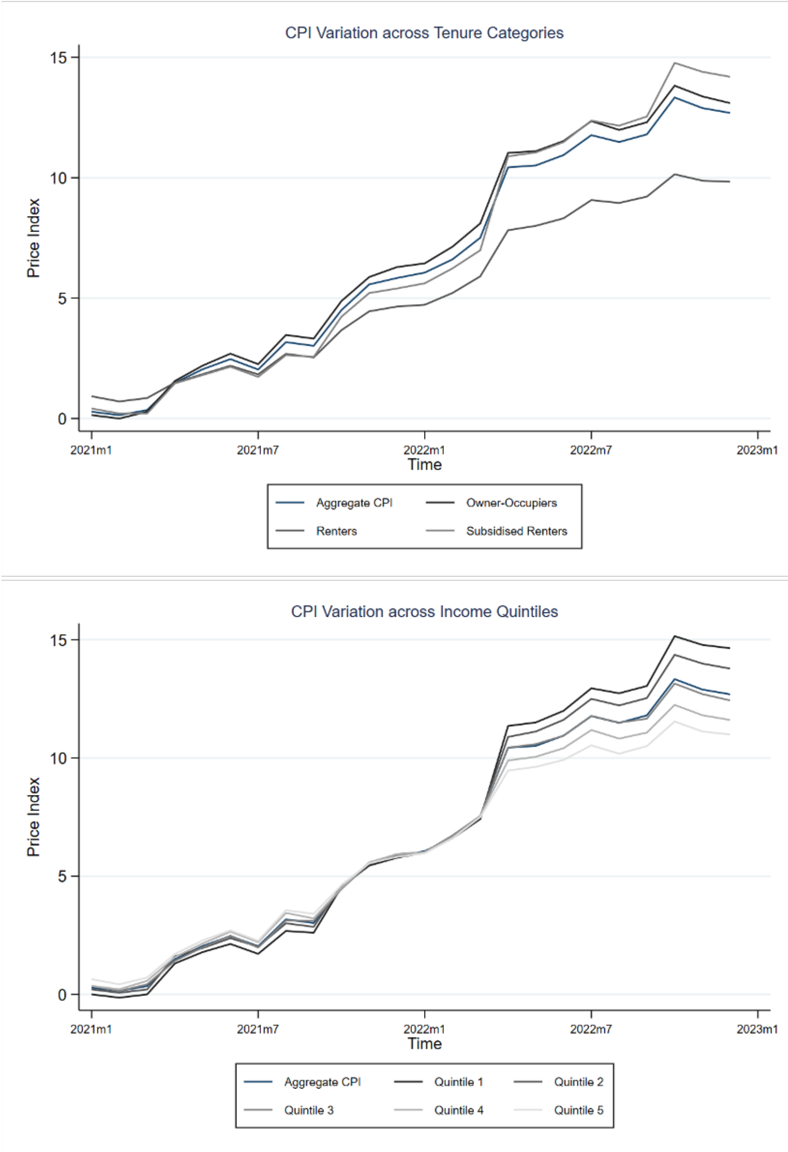

Figure 2: Inflation: differential levels and evolution depending on household income and housing tenure (underlying consumption basket). *Source: Office for National Statistics*

events in the UK such as the labour market shortage and higher food prices due to red tape policies on imports driven by Brexit have further worsened the situation.

B.2 Literature Review

In the United Kingdom, an average of over one million crimes were recorded each year in the 1960s, increasing to two million during the 1970s, and 3.5m in the 1980s. This slumped to the

20th century recording a sharper rise in crimes as compared to the earlier decades[5]. To probe into it, the literature on crime and justice is opening itself again and again to find a contentious relationship with numerous factors, one being socio-economic disadvantage. It is often accepted that the later does not directly cause the former; there is still evidence linking the two. The fundamental argument underlying the relation is that legal employment sources are failing to help the entire population meet the rising cost of living. This is driving a selective population to transition to illegal means of sustaining themselves. Additionally, a historical class divide and income divide are breeding acquisitive behavior in the have-not to obtain illegally what they do not have. What they do not have can be attributed to a better standard of living, social status, congenial relations in (local) society, psychic gains, etc.

The earlier debates have tried to link the relationship between unemployment and crime from the standard Becker/Ehrlich model, in which an individual faces a choice between crime and work. Unemployment is perceived as a complementary indicator of income opportunities in the legal labor market. However, the model needs to account for more crucial determinants of crime levels in an economy. Over the years, expanding research on crime has pinned its relations with education, local infrastructure development, the social fabric of communities, healthcare, etc. The linkage of crime with economic incentives has been very less explored particularly accounting for the change in wages of those who are at the bottom of the wage distribution in the United Kingdom. Machin and Meghir (2004) developed a structural model to test this relation between crime and the labor market using the police force areas of England and Wales between 1975 and 1976. The results find that a (relative) fall in wages of low-wage workers causes an increase in crime. A dynamic model of lagged dependent spatial crime-variation and conviction rate in the same study also reveals that crime rates are higher in initially high crime areas and where the probability of conviction is low.

Amidst the expanding research waves on crime, Draca and Machin (2015) explain how changing economic incentives also alter the participation of individuals in criminal activities using different kinds of evidence from the formal labor market and economic returns to illegal market activities. For instance, it is observed that changing values of goods affect the incentives for property-related crimes. The expansion and advancement of security technologies are also acknowledged to strengthen the deterrence effect for criminals by increasing the fixed costs of stealing particular goods. Apart from labor-market factors, Bell et al. (2018) use UK and US data to document the

[5] https://www.data.gov.uk/dataset/f79c8194-93b0-41eb-bba5-56a83fd32f10/historical-crime-data

persistent impact of macroeconomic disturbances like recessions on youth who are more likely to lead a life of crime because they left school during the recession and joined the labor market very early. Kawachi et al. (1999) used two sets of societal characteristics likely to impact the level of crime intensively: the degree of relative deprivation in society, and the degree of cohesiveness in social relations among citizens. They tested the hypothesis on different types of crimes and found that Violent crimes (homicide, assault, robbery, etc.) were consistently associated with relative deprivation (income inequality) and indicators of low social capital in the UK.

Over the years, law and welfare policies have also been held responsible for the increase in crime levels in certain sections of the population. Melander and Miotto (2023) use the New Poor Law reform of 1834 UK in a difference-in-differences instrumental variable strategy to investigate the impact of heterogeneous reductions in welfare spending across English and Welsh counties. The Act centralised the administration of welfare payments to the poor but then reduced the payment amounts enough to deter the poor from applying for further relief. The impact of such amendment is heterogeneous for authors to exploit the variation in the treatment. Their study documents a robust negative relation between such kind of welfare provision and criminal activity. Emerging research in the US also finds that persistent effects of inflation are associated with crime rates both within the US and outside. Crime is tied to economic conditions and is central to the tradition of criminological thought (Cloward and Ohlin, 2013).

Classical economic traditions construe that the economic participation of individuals in a society is crucial to constructing an optimal welfare function. However, with the soaring cost of living, active economic participation does not completely help guarantee citizens afford necessities, and their improve standard of living. Global prices have risen by more than 8% on average in 2022, sparked by the war in Ukraine and "zero-covid" restrictions in China. It is found that such geopolitical tensions and pandemics also impact the crime statistic. For instance, due to the rise in energy prices after the invasion of Ukraine, the Energy Price Guarantee (EPG) as per UK's policy response turned out to be very ineffective for those living in energy-inefficient properties (Fetzer, 2023) and that untargeted nature of energy price support is causing an increase in crime in the UK. Moreover, areas more exposed to the energy price shock saw a notable 6-10% increase in burglaries and a 9 to 24% increase in anti-social behaviour in the UK between October 2022 to March 2023 inclusive.

In recent years, academicians have also contended that the relationship between poverty and crime may flow in the reverse direction. They propound that it is the burgeoning unsafe community environment due to a selective troop of people involved in the crime that is hindering the process of economic development and collection of taxes. This further debars people of a given community from attaining a better welfare state. They also claim it to be the reason behind the remaining community members resort to illegal activities to fulfill their needs and get stuck in a vicious cycle of privation.

The Crime Lab of the University of Chicago is developing a workhorse model to understand the drivers behind evaluating police performance. The model aims to deploy officers in the busiest segments of the city where the existing capacity of the Police is struggling to respond to Computer-aided dispatch (CAD) calls. Ander (2022) They have developed the model focusing on a key metric: the amount of time officers spend responding to calls compared to the time they spend doing other work. "The Crime Lab developed the model to optimize patrol staffing across districts so that officers ideally spend not more than 60% of their time answering calls for service, freeing up 40% of their time to devote to other police work (administrative work, community policing, and proactive policing)".

What still goes overlooked while developing such devices is predicting the pattern of crime before such interventions are put to practice. The existing research is yet to account for a statistical relation between key indicators breeding crime. This further translates to allocating police department resources based on the estimated results/requirements rather than the intuitions of decision-making authorities right there. The existing research lacks the construction of a dynamic model that could simulate scenarios for even extreme measures of suspected determinants of crimes (especially violent crimes), predict crimes on that basis, and accordingly allocate the police workforce.

C Data

We obtain data on the cost of living crises by using publicly available information on inflation from the Office of National Statistics (ONS). The ONS aggregates the prices of consumer's basket i.e. goods and services to calculate the Consumer Price Index (CPI). This measure is representative of the inflation level in the economy at a time. In addition to the CPI, the ONS measures the consumer price index including owner-occupier's housing costs (CPIH). The CPIH allows us to determine the differential impact of inflation on different kinds of households depending on their principal consumption basket. Specifically, we can observe the consumer price index of households based on their housing tenure type. The information for the CPIH has been publicly available on the ONS website at the monthly level since January 2005.

The setting of our analysis is Greater London because it is one of the most affected areas in the United Kingdom by the cost of living crises. Our unit of analysis is an Output Areas-month pair. Output Areas (OAs) are the lowest level of geographical area for census statistics. OAs are usually between 40 and 250 households (with a median of 125) and a resident population between 100 and 625 persons. Over the years, substantial work by the Office for National Statistics (ONS) has led to defining of groups of socially homogeneous families for OAs. Thus, OAs are a small and homogeneous enough neighbourhood area for us to carry out a precise analysis. We restrict our period of study from January 2021 to May 2023 as the cost of living crises started spreading in late 2021.

$$\mathbf{COLC_{it}} = \sum_{\mathbf{g=1}}^{\mathbf{G}} (\mathbf{CPIH_{gt}}) \times \frac{\mathbf{n_{ig}}}{\mathbf{n_i}} \tag{1}$$

We construct the cost of living crises $COLC_{it}$ measure at the OA-month level. We construct this variable as the average change in Consumer Prices Index for different household groups including owner-occupiers' housing cost $CPIH_{gt}$ (subsidised renters, owner-occupiers, and renters) at month t, weighted by the share they represent in the output area (n_{ig}/n_i). In other words, the COLC measure is the average of the Consumer Price Index for different household groups weighted by their share in a given output area. For example, the COLC measure for OA E00000001 in January 2021 for owner-occupier would be calculated as [141.20 x (72/94)] where the CPIH for owner-occupier January 2021 is 141.20, 72 represents the number of owner-occupiers and 94 represents the total number of households in that Output Area. Simultaneously, we compute the COLC measure for subsidised renters and renter groups. Finally, we take the average of the three different household groups to compute the COLC tenure measure of an output area in a particular month. Data on household groups at the OA level is retrieved from the 2021 England and Wales Census.

After securing the spatial setup of London, we match the aforementioned with the information on the crime management system that the UK Police force uses in its Output Area respectively. It is referred to as the Computer Aided Dispatch system through which the police force operates in the UK. Under this mechanism, the residents in a given Output Area make a CAD call to report information on crime activities to the Police deployed in their Output Area in anticipation of support to deal with the crime. Every time a call comes in, a call handler at the back end records the details of the crime incident on CAD, and further flags it with appropriate required response. During the process, a sequential CAD or incident log number is automatically generated. This facilitates easy follow-up actions for either party to serve the interests. In this manner, the police manage the reporting of crimes and allocate resources accordingly.

For our study, we have obtained access to CAD calls from MOPAC [6] for the year 2019- 2022 in each Output Area against 71 categories. Moreover, the data obtained from MOPAC is a micro data, meaning we have each call and its geographical coordinates. We aggregate them at the Output Area month-level to keep it consistent with the CPIH data.

Figure 3 represents the average cost of living crises measure and the CAD calls distributed across output areas in Greater London in 2022.

The first dependent variable on which we attempt to study the impact of the cost of living is 'All calls'. This variable consists of all the 71 categories of CAD calls received by MOPAC for which its team prioritises policing and community safety in London. Table A1 lists the classification of all CAD calls in detail.

The second variable on which we attempt to study the impact of the cost of living is CAD calls received by MOPAC against criminal activities happening in London. Thus, a category of Crime calls is created by aggregating all the CAD calls MOPAC received against criminal activities reported. All the CAD identified as relating to Crime calls is listed in Table A2. Besides an aggregate count of All CAD calls, MOPAC groups the CAD call records into standard categories of transport, antisocial activities, public safety, administration, covid-related calls, etc. Approximately 10.3 M registries are accessed on request for our study. These are entries aggregated in each Output Area by month level from 2019-2022.

The third and last dependent variable of our interest constructed is 'Violent crime'. The CAD calls which are identified as relating to Violent crimes are listed in Table A3. This category is of

[6] MOPAC is set up in London under the Police Reform and Social Responsibility Act (2011). Its key responsibilities include setting the priorities for policing and community safety in London, agreeing on the policing budget, and holding the Met Commissioner to account for delivering a professional, efficient, and effective service to Londoners

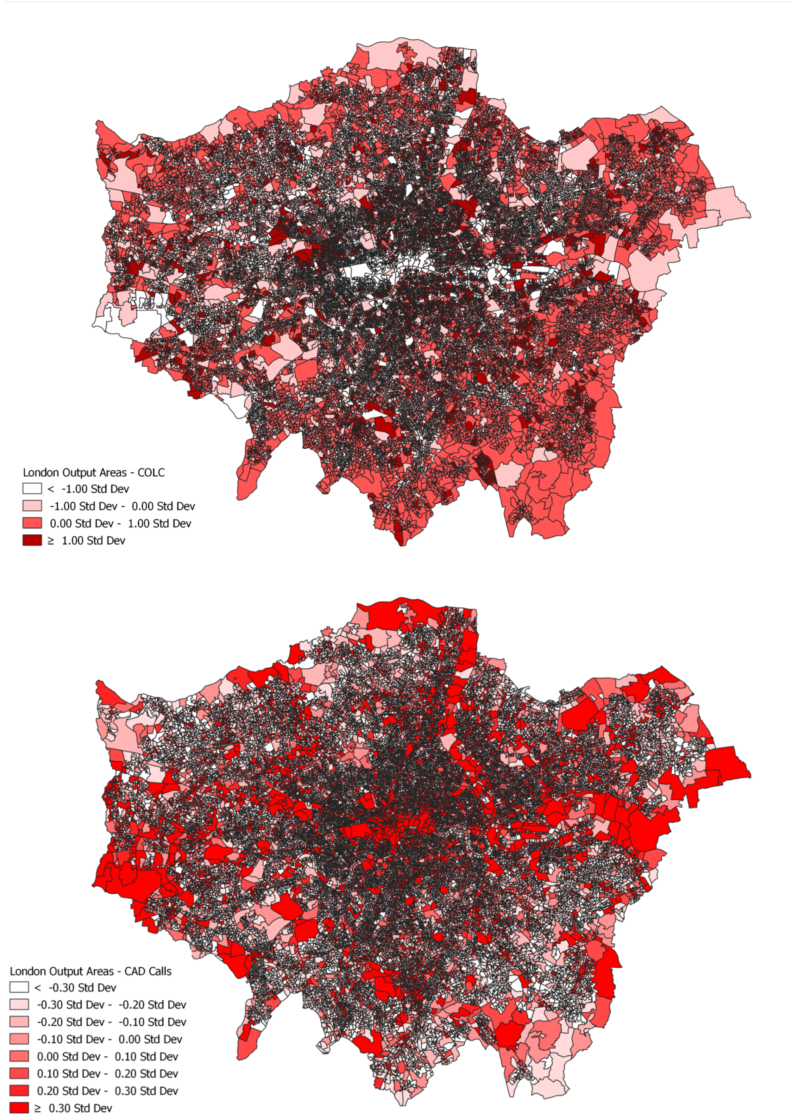

Figure 3: Average COLC measure (top) and CAD Calls (bottom) in 2022
Source: Office for National Statistics and MOPAC

interest to our current analysis, as violent crime CAD calls demand urgent attention and redressing. Therefore, we construct it to investigate its pattern on average in concerned Output Areas.

Each Output Area's CAD Calls are then matched with the Cost-of-living measure constructed for each Output Area in each month from 2019-2022. The Output Areas are also uniquely coded to get identified as geographically different entities. London is spatially divided based on three different spatial granularity- super-groups, groups, and sub-groups. Accordingly, the 2011 area classification is taken from the Office of National Statistics [7]. Henceforth, the Output Areas are

[7] https://www.ons.gov.uk/methodology/geography/geographicalproducts/areaclassifications/

Table 1: Summary Statistics for Call Data

CAD Call Category	**Average per OA-Month**	**% Total**
All Calls	8.29	100
Public Safety	2.41	29
Crime	2	24
Anti Social Behaviour	0.95	11
Administration	2.35	28

Source: CAD Automated records maintained by the London Metropolitan Police.

assigned their respective spatial category. Later, this setup is exploited to document the robustness of the research design across space.

D Methodology

We estimate the effect of the cost of living crises with the help of a panel data set. For this purpose, we use pooled OLS with clustered standard errors on the OA-month level. This model provides a general guide to the relationship between the Cost-of-Living Crises measure (COLC) and crime at the OA-month level. Equation 1 is the mathematical representation of the panel model.

$$\mathbf{Calls_{it}} = \beta \ \mathbf{COLC_{it}} + \lambda_i + \mu_t + \epsilon_{it} \tag{2}$$

Our left-hand side or dependent variable reflects the registered CAD call data for each OA-month pair. We first consider a measure of overall calls made. Yet, we also consider specific models for overall crime and violent crimes. We have constructed our left-hand side (LHS) variable from data provided by MOPAC as detailed in Section 2. Standard errors are clustered at the OA level, ϵ_{it}, to account for heteroskedasticity. The OAs across London substantially vary in several aspects. In this regard, the fixed effect for Output Areas (λ_i) is introduced in the model to control for such differences completely. To account for time-varying effects we include the fixed effect for month-year (μ_t). The coefficient measure for β will provide evidence of the degree of association between the cost of living and CAD calls.

It is claimed that the level of different types of crime in London may witness spatial dependencies

`2011areaclassifications/abouttheareaclassifications#toc` or spatial auto correlation. In other words, data points may tend to be endogenous of the geographical locations which is important to be considered while conducting regression analysis in this study. Hence, we attempt to explore how this relationship between cost-of-living and crime varies across space. This model will allow us to understand differential relationships by characteristics (such as socio-demographic composition) of the OAS. In this way, the model can indicate where the impacts of the crisis may be more strong. We estimate the effect of cost of living crisis measures over space using the following regression specification:

$$\mathbf{Calls_{it}} = \beta_c \ \mathbf{COLC_{it}} \times \mathbf{Group_c} + \lambda_i + \mu_t + \epsilon_{it} \tag{3}$$

where $Group_c$ includes 26 sub-divided groups of Output Areas. The main coefficient of interest is β_c. The interaction term allows us to estimate the effect of COLC on crime over space (here groups). The remaining specification is the same as Equation 2.

The level of crimes is also suspected to change continuously, hence inter temporally dependent. There could be variations in the cost of living across months in a particular year. A given Output Area which has already high cost of living may have lagged impact on the dependent variables. Thus a time regression model is constructed to analyse the temporal patterns and trends present in the data. This allows us to explore the similar relationship (causally) across time, which is valuable for forecasting future behavior and understanding underlying patterns. We estimate the effect of cost of living crisis measures over time using the following regression specification:

$$\mathbf{Calls_{it}} = \beta_t \ \mathbf{COLC_{it}} \times \mathbf{Time_t} + \lambda_i + \mu_t + \epsilon_{it} \tag{4}$$

where, $Time_t$ ranges from Jan 2019 to Nov 2022, with Dec 2022 as a base. β_t allows us to estimate the effect of COLC on crime over time. The remaining specification is the same as Equation 2.

E Results

The coefficients obtained from Equation 2 are presented in Table 2. The estimates from our regression exercise explain the degree of association between the cost of living crises and different types of crime reported through CAD calls. Our current findings indicate a significant correlation between the cost of living and CAD calls. As indicated in column (1) of Table 2, a 10% increase in the cost of living is associated with a decrease of all calls by 2.4% with respect to their mean. On the other hand, the COLC measure is associated with an increase in crime and public safety calls (approx. 8% for both) as highlighted in the next two columns. Columns (4) and (5) indicate that COLC is associated with a decrease in anti-social behaviour (ASB) and administration calls (approx. 27% and 13% respectively). Finally, column (6) indicates a 0.5% decrease in violent crime calls with respect to the mean value. We find further evidence of an increase in burglaries, thefts, violence against the person, abandoned calls and, wanted-police/court order/bail.[8] These findings indicate differential effects of the COLC measure for different types of crime calls made to MOPAC. While we find evidence of some degree of association between these two variables our findings do not imply causation (e.g. an increase in cost of living causes a change in CAD calls). There is a difference between causation and correlation, the former implies an association between X and Y whereas the latter implies X causing Y. Currently, our estimated results may be affected by omitted variable bias i.e. there can be a correlation between the cost-of-living crises measure and some unobservable or observable characteristic that may prevent us from capturing the causal effect of the COLC measure on the police-reported crime. To pin a causal channel, it is necessary to capture and control such variables. Thus, our current results need to be interpreted with caution.

Table 2: Association between Cost of Living Crises and Crime

	(1)	(2)	(3)	(4)	(5)	(6)
DV	All Calls	Public Safety	Crime	ASB	Admin	Violent
COLC	-0.013***	0.011***	0.010***	-0.015***	-0.019***	0.006***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)
Obs.	1,242,816	1,242,816	1,242,816	1,242,816	1,242,816	1,265,712
R-squared	0.895	0.738	0.752	0.516	0.908	0.681

'***','**','*' indicate significance at the 1%, 5% and 10% respectively

[8]See Table A7, Table A6, Table A5, Table A4 and Table A8 for further detail

Using Equation 3, we estimate the effect of COLC measure on crime distributed across space (here Output Areas). Specifically, the coefficient estimates obtained from this exercise allow us to identify the Output Areas where the cost of living crises had a higher impact on different crime types. This can be traced from the CAD calls that are made to MOPAC for each type of those crimes. Using the map of Greater London, we highlight these Output Areas for our three main outcomes. Panel A of Figure 4 represents the spatial variation for all calls, panel B represents the spatial variation for crime-related calls and panel C represents the spatial variation for violent-crime-related calls. In all three cases, we observe that the effect of the COLC measure increases as we move from outer zones toward central London. Further, the cost of living has the highest effect on all three types of calls in the inner-city student clusters. In these clusters, the effect is highest for all calls (β= 0.065) followed by crime-related calls (β= 0.04) and finally violent crime-related calls (β= 0.02).[9] The borough of Hillingdon (northeast of Greater London) remains one of the main affected areas by the rising cost of living as indicated by Output Areas that appear in all three panels of the map.

In the setting of our analysis, we have variables like COLC and MOPAC CAD calls that also depend on themselves and determine themselves inter temporally. An Output Area which has an already high(low) cost of living is likely to maintain the high(low) cost of living in the next period too. Similarly, an Output Area which is already witnessing high(low) CAD calls for a given CAD call category is likely to receive high(low) calls even in the future. Thus it confirms that observations are dependent on time, and may exhibit patterns like trend, seasonality, or auto-correlation. Using Equation 4, we attempt to estimate how all the CAD calls, CAD calls related to crime, and CAD calls related to violent crimes are varying over time in response to the changing cost of living across London. We find that the estimates for all calls become close to zero over time. Panel A of Figure 5 highlights the same. Moreover, in the case of all CAD calls, the confidence intervals for the estimated coefficients are larger throughout the month of the year 2021 as compared to the year 2022. In that sense, there could be reasons on account of which MOPAC received a disproportionate number of CAD calls in broader categories. The year 2021 also clashed with emerging waves of the Covid-19 pandemic, which we reckon to be a precursor to such an outcome. Meanwhile, we observe a significant and increasingly negative effect of the COLC measure on CAD calls related to crime and violent crime on average. Panel B and

[9] The magnitude of the coefficient of all calls is larger as multiple categories are grouped in it. Any further decomposition into separate crime types reduces the magnitude.

C of Figure 5 confirm the same. The magnitude of the estimates is relatively strong in 2021 as compared to 2022. There could be an external event/shock in this case which is instrumenting the records of CAD calls in a particular period.

Overall, the findings present a convincing narrative to conclude that the rising cost of living may have toughened conditions for certain classes of inhabitants in several parts of London. To deal with the situation of rising crimes as a result of this, they may have resorted to seeking support from MOPAC by using their CAD call service. We are continuously working on developing a (quasi)-experimental research design to be able to establish causal claims.

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Figure 4: Spatial Estimation: Effect of COLC measure on crimes over space. Panel a, b, and c represent variation using Equation 3 for all calls, crime-related calls, and violent crime-related calls respectively. The effect of the COLC measure increases as we move from outer to central London. The spatial estimates indicate a higher number of all calls, crime-related and violent crime-related calls coming from the inner-city student region (central London).

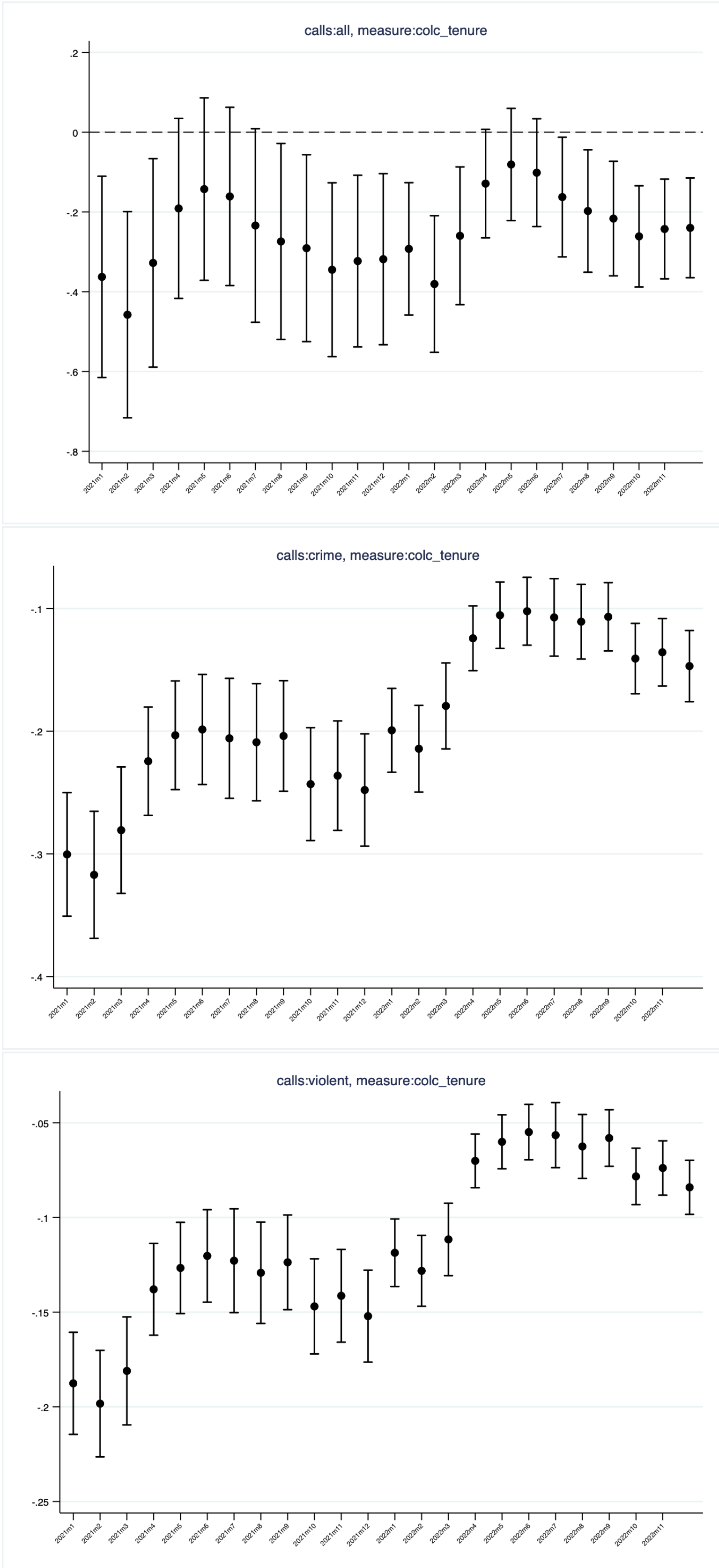

Figure 5: Temporal Estimation: Effect of COLC measure on crimes over time. Panel a, b, and c represent coefficient and confidence intervals estimated using Equation 4 for all calls, crime-related calls, and violent crime-related calls respectively.

Table A1: Sub-Classification of all CAD calls

All Calls			
Call code	Call type	Call code	Call type
code_1	ViolenceAgainstThePerson	code_308	CollapseIllnessInjTrapped
code_2	SexualOffences	code_309	ConcernForSafety
code_3	BurglaryDwelling	code_310	AbscondersAWOL
code_4	BurglaryOtherThanADwelling	code_311	MissingPerson
code_5	Robbery	code_312	WantedPolCrtOrderBail
code_6	TheftOfMotorVeh	code_313	SuddenDeath
code_7	TheftFromMotorVeh	code_314	SuspiciousCircumstances
code_8	TheftOther	code_315	InsecurePremisesvehs
code_9	FraudAndForgery	code_316	AlarmPoliceInstalled
code_10	CriminalDamage	code_317	AlarmCentralStation
code_11	DrugsOffence	code_319	AlarmPremisesAudibleOnly
code_12	BombThreat	code_320	Firearms
code_13	TheftShoplifting	code_321	Immigration
code_14	HarassmentActOffences	code_322	ProtestDemonstration
code_15	AbductionKidnap	code_323	Truancy
code_16	UnlistedCrime	code_324	Wildlife
code_17	MaliciousCommunications	code_325	HoaxCallToEmergencyServices
code_18	SexualOffencesRape	code_326	Absent
code_100	RTCIncidentDamageOnly	code_327	Pandemic
code_101	RTCIncidentInjury	code_400	SuspectsChasedOnFoot
code_102	HighwayDisruption	code_401	VehPursuit
code_103	RoadRelatedOffence	code_402	CBuFduplicatedrecord
code_104	RailAirMarineIncident	code_404	UrgentAssistance
code_105	RTCIncidentDeath	code_500	ComplaintsAgainstPolice
code_212	BeggingVagrancy	code_501	LostFoundPropertyPerson
code_214	ASBPersonal	code_502	Messages
code_215	ASBNuisance	code_503	PoliceGeneratedResourceActivity
code_216	ASBEnvironmental	code_504	PrePlannedEvents
code_300	AbandonedCall	code_505	Error
code_301	Licensing	code_506	Duplicate
code_302	NaturalDisasterIncidentWarn	code_507	ContactRecord
code_303	IndustrialIncidentAccident	code_508	SwitchboardCall
code_304	DomesticIncident	code_509	TestTraining
code_305	CivilDisputes	code_665	AbandonedCallNotToOperator
code_306	SuspiciousPackageObject	code_701	AssistanceRequestedRendered
code_307	AnimalsPetsDomesticated		

Source: CAD Automated records maintained by the London Metropolitan Police.

Table A2: Sub-classification of crime calls

Crime Calls	
Call code	Call type
code_1	ViolenceAgainstThePerson
code_2	SexualOffences
code_3	BurglaryDwelling
code_4	BurglaryOtherThanADwelling
code_5	Robbery
code_6	TheftOfMotorVeh
code_7	TheftFromMotorVeh
code_8	TheftOther
code_9	FraudAndForgery
code_10	CriminalDamage
code_11	DrugsOffence
code_12	BombThreat
code_13	TheftShoplifting
code_14	HarassmentActOffences
code_15	AbductionKidnap
code_16	UnlistedCrime
code_17	MaliciousCommunications
code_18	SexualOffencesRape

Source: CAD Automated records maintained by the London Metropolitan Police.

Table A3: Sub-classification of violent crime-related calls

Violent Crimes	
Call code	Call type
code_1	ViolenceAgainstThePerson
code_2	SexualOffences
code_3	BurglaryDwelling
code_4	BurglaryOtherThanADwelling
code_5	Robbery
code_12	BombThreat
code_15	AbductionKidnap
code_18	SexualOffencesRape

Source: CAD Automated records maintained by the London Metropolitan Police.

Table A4: Association between COLC and Public Safety & Welfare

Sub-Categories for Public Safety						
	(1)	(2)	(3)	(4)	(5)	(6)
DV	AbandonedCall	AbscondersAWOL	AlarmPoliceInstalled	AlarmCentralStation	AlarmPremisesAudibleOnly	AnimalsPetsDomesticated
COLC	0.007***	0.000	0.000	0.001***	0.000**	0.000**
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
DV	CivilDisputes	CollapseIllnessInjTrapped	ConcernForSafety	DomesticIncident	Firearms	HoaxCallToEmergencyServices
COLC	0.000***	0.001***	-0.001	-0.001***	0.000	0.001***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
DV	Immigration	IndustrialIncidentAccident	InsecurePremisesvehs	Licensing	MissingPerson	NaturalDisasterIncidentWarn
COLC	0.001***	-0.000**	0.000	-0.000***	0.001	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
DV	ProtestDemonstration	SuddenDeath	SuspiciousCircumstances	SuspiciousPackageObject	Truancy	WantedPolCrtOrderBail
COLC	-0.000**	0.000***	-0.001***	0.000***	0.000***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

'***','**','*' indicate significance at the 1%, 5% and 10% respectively

Table A5: Association between COLC and crime types

Sub-Categories for Crime						
	(1)	(2)	(3)	(4)	(5)	(6)
DV	AbductionKidnap	BombThreat	BurglaryDwelling	BurglaryOtherThanADwelling	CriminalDamage	DrugsOffence
COLC	-0.000	0.000**	0.002***	0.001***	0.000	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
DV	FraudAndForgery	HarassmentActOffences	MaliciousCommunications	Robbery	SexualOffences	SexualOffencesRape
COLC	-0.001***	-0.000*	-0.001***	0.000**	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
DV	TheftShoplifting	TheftOfMotorVeh	TheftFromMotorVeh	TheftOther	UnlistedCrime	ViolenceAgainstThePerson
COLC	0.001***	0.001***	0.001***	0.001***	-0.000	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

'***','**','*' indicate significance at the 1%, 5% and 10% respectively

Table A6: Association between COLC and anti-social behaviour

Sub-Categories for ASB				
DV	BeggingVagrancy	ASBPersonal	ASBNuisance	ASBEnvironmental
COLC	0.000	0.000	-0.015***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)

'***','**','*' indicate significance at the 1%, 5% and 10% respectively

Table A7: Association between COLC and administrative crime

	Sub-Categories for Admin				
DV	ComplaintsAgainstPolice	ContactRecord	Duplicate	Error	LostFoundPropertyPerson
COLC	-0.001***	-0.003***	-0.000	-0.000	0.000**
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
DV	Messages	PoliceGeneratedResourceActivity	PrePlannedEvents	TestTraining	
COLC	0.000***	-0.015***	-0.000	-0.000	
	(0.000)	(0.001)	(0.000)	(0.000)	

'***','**','*' indicate significance at the 1%, 5% and 10% respectively

Table A8: Association between COLC and Violent Crime

	Sub-Categories for Violent Crime			
DV	ViolenceAgainstThePerson	SexualOffences	BurglaryDwelling	BurglaryOtherThanADwelling
COLC	0.003***	-0.000	0.002***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
DV	Robbery	BombThreat	AbductionKidnap	SexualOffencesRape
COLC	0.000**	0.000**	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)

'***','**','*' indicate significance at the 1%, 5% and 10% respectively