Do Crime-Prone Areas Attract Gambling Shops? A Case of London Boroughs

Pradeep Kumar* and Hisayuki Yoshimoto†‡

The most recent version can be found at: `http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2801017`

July 10, 2016

Abstract

We investigate a causal effect of crime on the number of betting shops by using annual data from London boroughs (2007-2015). Using an instrumental variable strategy, we estimate a panel model accounting for omitted variables and borough-level heterogeneity. Our estimation results show that a 1% increase in crime rate causes a 1.2% increase in the number of betting shops (per capita). Put differently, a new betting shop opens in a borough for every 1.4% increase in the local crime rate, on average. The causal effect is robust across a variety of specifications, although the magnitude varies across models.

Keywords: Crime, Gambling Industry, Betting Shops, Causal Effect

JEL Classifications: J1 (Demographic Economics), L5 (Regulation and Industry Policy), L8 (Industry Studies: Services), R0 (Urban, Rural, and Regional Economics - General)

*University of Exeter Business School, Department of Economics, `P.Kumar@exeter.ac.uk`

†University of Glasgow, Business School, Economics Subject, `Hisayuki.Yoshimoto@glasgow.ac.uk`

‡The views expressed in this research do not reflect those of the institutions to which the authors belong, and any errors are our own.

1 Introduction

In February 2013, Newham council in east London rejected multinational bookmaker Paddy Power's application for a licence to open a new betting shop, arguing that it would attract crime and anti-social behaviour. Consequently, Paddy Power filed a lawsuit against the council. Newham happens to be one of the most economically deprived areas of Britain, with 82 gambling shops (6 betting shops per-square mile).[1] In June 2013, the Magistrate Court overturned the council's decision, allowing the bookmaker to open a new betting shop. The decision was based on the lack of strong evidence regarding the causal link between betting shops and crime. After this court decision, Mr Ian Corbett, council executive member, decried that '*Ministers fail to understand how the legislation is toothless in dealing with the clustering of betting shops.*'[2] Although this was the first case of its kind, the relationship between the number of betting shops and crime warrants a deeper investigation.

It is often suggested that gambling shops attract criminal behaviour in their vicinity. If this is indeed true, criminals may consume a non-negligible fraction of the gambling services. This leads to the question: do gambling firms consider crime-prone individuals as their consumers and open more shops in high-crime areas? The focus of this paper is to investigate this important question using annual borough-level data from London boroughs (2007-2015). To the best of our knowledge, this is the first study to highlight the effect of local crime on the supplied number of betting shops. This is particularly relevant to policy in the U.K. as one of the licensing objectives of the Gambling Act (2005) is to keep crime separate from gambling.[3]

Our econometric model is based upon explaining the number of betting shops using demand and supply drivers alongside local crime. Specifically, we add control variables such as unemployment, housing price, average age, gender distribution, borough, and time fixed effects. We correct the endogeneity bias by averaging the crime rate of the neighbourhood boroughs as an instrumental variable for the crime rate. The main identifying assumption is that criminals travel across boroughs, while gamblers do not.

The estimated parameters suggest that an increase in crime causes a rise in the number of betting shops. Specifically, an increase in crime rate of 1% causes the gambling shop count to increase by

[1] Regarding the geographic relationship, an anonymous official within the council commented '*We mapped out where crimes and disorder take place and compared that with where the betting shops are - and it lit up like a Christmas tree.*'

[2] See http://www.bbc.co.uk/news/uk-england-london-22934278 for the details of court decisions and official comments provided by Newham borough council and the bookmaker.

[3] Licensing objective: 'Preventing gambling from being a source of crime or disorder, being associated with crime or disorder or being used to support crime.' Source: http://www.legislation.gov.uk/ukpga/2005/19/section/1

1.2% per capita. We perform robustness checks by comparing parameter estimates across four models: (1) instrumental variable (IV) in a two-stage least squares model, (2) panel model (fixed and random effect), (3) instrumental variable in a panel model, and (4) lagged-dependent variable model. The empirical results indicate that borough heterogeneity and omitted variables play key roles and should be accounted for. Our key finding holds across the various models, however the magnitude of the effect varies.

Most of the literature focuses on the U.S. casino industry on which rigid zone restrictions are enforced.[4] However, these studies only examine the direction of causality opposite to our research. Gazel, Rickman, and Thompson (2001) investigate the changes in the number of crimes before and after the openings of casinos in Wisconsin counties between 1981-1994. They report an increase in local crime after the opening of casinos. Grinols and Mustard (2006) comprehensively examine county-level data across the U.S. between 1977-1996. They show that neighbourhood crime increases are relatively low over a short period, but become gradually larger in the long term.

Regarding the U.K., some studies report positive correlation between gambling activities and local crime. Brown (1987) uses data from Gamblers Anonymous in the U.K. and shows that the crime patterns of gamblers are similar to people with addiction to drugs. Based on survey data, Wardle et al. (2010) report that gamblers, on average, are from socio-economically deprived backgrounds. Furthermore, Astbury and Thurstain-Goodwin (2007) survey the local demographics around betting shops, reporting that they tend to be located in areas with high degrees of socio-economic deprivation. Economic studies exploring the gambling-crime causal link are rare for the United States, but they are virtually non-existent for the U.K.

The scope and limitation of this research should be mentioned. In this research, rather than conducting a comprehensive dual-causality investigation, we simply focus on studying the effect of local crime on the number of betting shops.

As a disclaimer, we mask the borough names throughout this research.[5] This is because the goal of this research is not to manifest the fact that some specific boroughs have high or low concentrations of crimes (and betting shops) but to investigate the causal effect.

This article is organised as follows. Section 2 describes the background of the U.K. betting industry and discusses the data. Section 3 illustrates the regression model, identification assumptions, and

[4] Eadington (1999) and Walker (2007) provide comprehensive surveys on the US casino industry and its economic effects.

[5] The exception is the City of London and Westminster.

Figure 1: London Boroughs

Figure 2: Total Number of Betting Shops in London Boroughs (excluding the City of London)

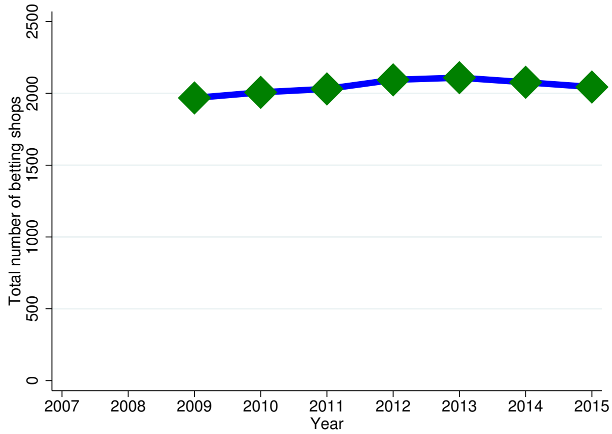


Figure 3: Per Capita Number of Betting Shops by Borough

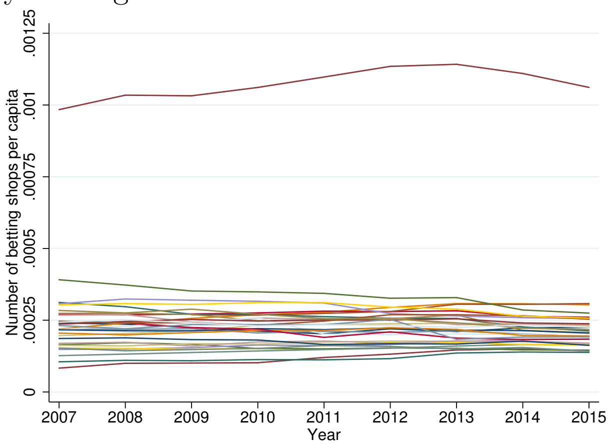
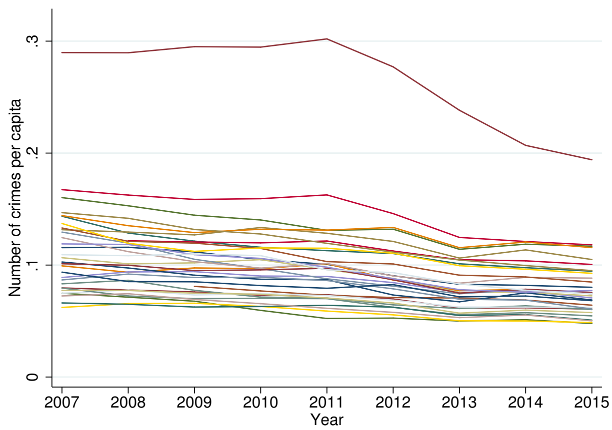


Figure 4: Per Capita Number of Crimes by Borough



economic insights behind the model. Section 4 discusses the estimation results and provides policy implications. Lastly, Section 5 concludes and provides potential directions for future extensions.

2 Indutsry and Data Description

This section describes the key features of the U.K. gambling industry, discusses the data used, and presents basic descriptive statistics.

Figure 5: Correlation between Number of Betting Shops and Crime for 2007-2015 (Outliers are from the City of Westminster)

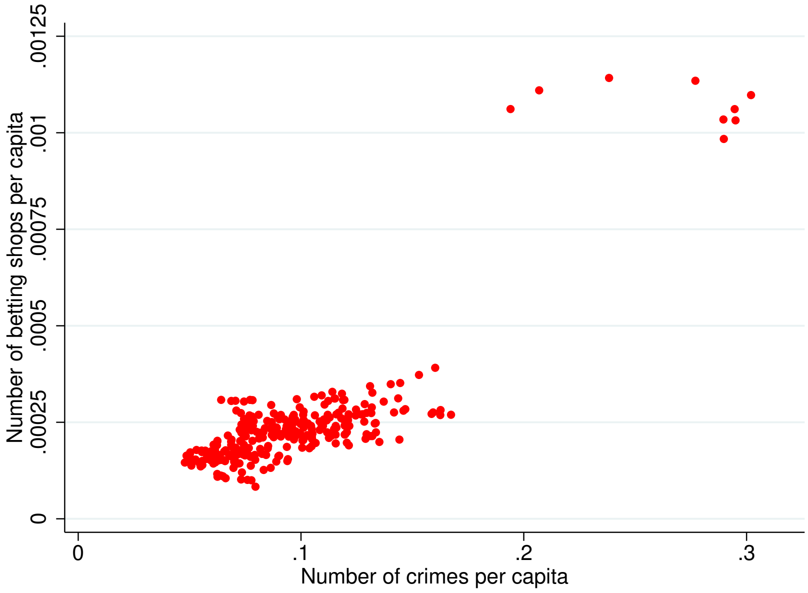


Table 1: Descriptive Statistics

Description	Num. of betting shops per capita	Num. of crimes per capita	Unemp-loyment rate	Average house price (in £10 million)	Average age (among 18+)	Gender ratio (males divided by females)	Average num. of (per capita) crimes in connected boroughs
Mean	0.00022	0.091	8.041	0.043	43.66	0.957	0.096
S.t.d.	0.00006	0.026	2.299	0.018	2.81	0.046	0.021
Min	0.00008	0.048	3.500	0.024	37.57	0.892	0.057
25th percentile	0.00017	0.071	6.200	0.032	41.56	0.919	0.080
Median	0.00022	0.088	7.800	0.038	43.63	0.953	0.093
75th percentile	0.00026	0.110	9.700	0.047	45.51	0.978	0.107
Max	0.00039	0.167	14.200	0.137	49.11	1.114	0.154

The sample size is 276. Observation unit is annual and borough-level (excluding the City of London and Westminster).

2.1 Gambling Industry in the U.K.

In the U.K., it is common to see a sizable number of betting shops in each modestly populated city due to the lax zone restrictions.[6] Common forms of gambling include bingo, casinos, lotteries, betting and arcades. According to the Association of the British Bookmakers, there are more than 8,700 betting shops in the U.K. as of 2013, which generate £3.2 billion GDP.[7] Betting has been the largest gambling sector with gross a yield of roughly £1.5 billion, and it accounts for the employment of 55,234 individuals

[6] In the U.K., the Gambling Act (2005) enacted to form the regulating authority, the Gambling Commission, which issues operating licences. The Act also authorised the local municipal councils to provide licences to gambling premises. Objections against new licences can be raised. According to the parliament document, '*Objections can be raised against an application for a new premises licence by interested parties (eg people living close by) and responsible authorities (eg the police).*'

[7] 'The Truth about Betting Shops and Gaming Machines' Source: `www.gov.uk/government/uploads/system/uploads/attachment_data/file/248922/Association_of_British_Bookmakers.pdf`

as of March 2013.[8] Betting sector consists of betting shops and online betting. Our focus of study is betting shops since it comprises of the majority of betting activity.[9]

Betting shops are premises in which a gambler can legally place bets in person with a licensed bookmaker. Bets can be placed on virtually anything, including a wide range of sports games, horse races, motor races, awards ceremonies (e.g. the Oscars), and election outcomes. In a typical betting shop, there is a counter where gamblers submit betting slips and numerous television screens that post betting odds for live events. In addition, a typical betting shop has some high-tech gambling machines that allow gamblers to bet on computerised games (e.g. poker games, black jack, slot machines, roulette, etc.). Importantly, upon winning, a gambler can immediately obtain cash at a betting shop. Instant gratification is one of the underlying commonalities between criminals and gamblers, a key modeling concept addressed in the next section.

Contrary to their popularity, betting shops are not free from social controversy. Local councils, which grant licences for betting shop premises, are concerned about the neighbourhood demographics. This is because betting shops could influence local demographics and their public policies, such as the treatment of addictive gamblers by social workers.[10] Education authorities may also be concerned if children regularly witness anti-social behaviour around gambling shops, which are often located on high streets (busy market places), and may perceive such problem gambling activities as common in society.[11] Thus, investigation into the relationship between local crimes and betting shops is particularly relevant to British society.

2.2 Data Sources

We obtain data from various sources. Betting shop data is obtained from publicly available data sources such as the UK Data Service and the Gambling Commission.[12] The crime data used is the total number of crimes observed in the Metropolitan Police Service's record system. Unemployment rates are collected from the Official Labour Market Statistics of Nomis. Average housing prices are obtained from

[8] The second largest gambling sector is casinos, which provided employment to 15,010 individuals. Source: http://www.gamblingcommission.gov.uk/Gambling-data-analysis/statistics/Industry-statistics.aspx

[9] Only 4% people participated in online betting according to a survey by Gambling Commission in 2010. Source: http://www.gamblingcommission.gov.uk/pdf/british%20gambling%20prevalence%20survey%202010.pdf

[10] The National Health Service (NHS) website states: 'There may be as many as 593,000 problem gamblers in Great Britain. The anticipation and thrill of gambling creates a natural high that can become addictive.'

[11] One of the licensing objectives of the Gambling Act (2005) is: protecting children and other vulnerable people from being harmed or exploited by gambling.

[12] Furthermore, this publicly available data is cleaned by matching it to the data provided by local councils via Freedom of Information requests.

the Price Paid Data of the Land Registry, which collects traded real-estate property prices. Average housing prices are inflation-adjusted using 2016 consumer price index. The data on population, adult gender ratio, and adult average age is obtained from the Round Demographic Projection collected by the Greater London Authority. As the legal age for gambling in the U.K. is 18 and above, the gender ratios and average ages are calculated for ages 18 and up.[13]

2.3 Data Description and Summary Statistics

We use annual data for the London boroughs from 2007-2015. There are 33 boroughs in the London Area, as illustrated in Figure 1. We exclude the City of London and the City of Westminster from our analysis. Our primary reason to exclude the City of London is the limited access to crime data from the City of London police.[14] Also, the City of London is generally recognised as a financial district for corporate offices with low residential population. This makes it different from the other boroughs in our analysis, which are mostly residential. We also exclude the City of Westminster because it is an outlier in terms of the patterns and magnitude of crime and number of betting shops. Figure 4 shows that the crime rate in the City of Westminster has persistently been much higher than in the other boroughs (close to 30% up until 2011).[15] In fact, the outliers observed in Figures 3 - 5 are all from the City of Westminster. After excluding these two boroughs, we have 276 annual borough-level observations for our study.[16]

There are approximately 2,000 betting shops in London and this number has remained fairy stable across the study period, as shown in Figure 2. In other words, there is one betting shop for approximately every 4,500 residents in London. Figure 3 plots the per capita number of betting shops and suggests heterogeneity among the boroughs. As some boroughs are more populated than others, the number of betting shops is normalised by population.[17] Betting shops per capita also change over time, depicting the presence of entry and exit in the gambling industry.

Figure 4 plots the numbers of crimes per capita by borough. In addition, following the tradition of precedent crime literature in Economics, we normalise the number of crimes by the residential

[13] Adult gender ratio is calculated as (18+ years old male population) divided by (18+ years old female population).

[14] The City of London Police is different from the London Metropolitan Police Service, which exercises jurisdiction over the other 32 boroughs.

[15] Due to its sightseeing nature and its associations with well-known historical sites, crime in the City of Westminster (mostly thefts and muggings involving tourists) could be considered different from other boroughs.

[16] The math is $276 = 9$ years $\times$ 31 boroughs $- 3$. There are 3 missing data points in our dataset. Specifically, one sample is missing from a borough in 2007, and the other two samples are missing from another borough in 2007-2008.

[17] Population un-adjusted figures are found in the Appendix.

population (Cornwell and Trumbull (1994), Levitt (1996), Draca, Machin, and Witt (2011)). Similar to the per capita numbers of betting shops, there is large heterogeneity among boroughs, indicating the fact that some boroughs are more crime-prone than others. In addition, there is a decreasing trend in crimes over our sampling period.

Figure 5 shows the relationship between the number of betting shops and the number of crimes per capita. The figure indicates a strong correlation between betting shops and crime, and the correlation coefficient is 0.844 (significant at $\alpha = 0.01$).

Table 1 reports the descriptive statistics, further confirming substantial demographic heterogeneity across boroughs. While unemployment rate ranges from 3.5% to 14.2%, average housing prices are spread from £240,000 to £1.37 million. The adult average age ranges from 37.6 to 49.1. The adult gender ratios are relatively less dispersed from 0.89 to 1.11. In summary, we observe substantial heterogeneity across boroughs and over time, hence we account for this in the empirical model.

3 Empirical Model

In this section, we explain the econometric model and discuss the identification assumptions needed for our model.

We use the following indices: $b \in \{1, 2, \cdots, 31\}$ stands for a borough index, and $t \in \{2007, 2008, \cdots, 2015\}$ represents an annual time index. We use the constant elasticity model,

$$\ln(BetShops_{b,t}) = \beta \ln(Crimes_{b,t}) + \mathbf{c}_{b,t}^{'}\gamma + \lambda_t + \alpha_b + u_{b,t}, \tag{1}$$

where $BetShops_{b,t}$ is the number of betting shops per capita, $Crimes_{b,t}$ is the per capita number of reported crimes, and $\mathbf{c}_{b,t}$ is a vector of control variables, which includes unemployment rate, average housing price, average age among adults, and the ratio of male to female population. Note that the β is the primary interest of our causal investigation, while γ is a vector of control variable coefficients.

The equation (1) could be seen as a reduced-form solution of a zero-profit condition in an entry model equilibrium, such as Dixit and Stiglitz (1977), Mankiw and Whinston (1986), and Bresnahan and Reiss (1991). Given local consumer characteristics, firms enter into (and remain in) a market until the additional profit from opening a new shop vanishes. The left-hand side of equation (1) captures the entry decisions of gambling firms, while the right-hand side captures the demand and supply drivers of the decision, such as local demographics, macro-economic environment, and tax structure.

In Equation (1), we propose two channels through which crime affects the demand for betting shops. First, crime and betting are both inherently 'risky' activities. Crime has a high opportunity cost if someone gets arrested, and in gambling one can quickly lose money. Crime and gambling are also instantly gratifying activities as the rewards are immediate in both. Hence, if the number of crimes in a borough increases, there is an increase in the population who could also have a demand for gambling. Second, money related crime (e.g. drug-dealing) could lead to extra cash which can be used to consume gambling services. Subsequently, the betting industry may respond by increasing the number of betting shops.[18]

The year-by-year time effect, λ_t, captures changes that affect all boroughs homogeneously. Such aggregate components include gambling-related taxes, popular betting events (e.g. the Olympics, elections, etc.), and London-wide activities (such as anti-gambling campaigns and social workers' treatment for addictive gamblers). The borough effect term, α_b, captures a borough-level heterogeneity not captured by the control variables that does not change over time, such as a borough-level gambling culture or time-invariant components of transportation access.

It is worth considering potential omitted variables in $u_{b,t}$ that could influence the demand for betting shops in a borough. We consider two candidates for such omitted variables (1) the expected future income of a representative resident ($\mathbb{EFI}_{b,t}$) and (2) the density of alternative entertainment venues ($Entertain_{b,t}$), such as movie theaters, night-clubs, bingo shops, and arcades.

$\mathbb{EFI}_{b,t}$ is part of the expected future income that is not explained by control variables in $\mathbf{c}_{b,t}$, such as average housing price and unemployment rates.[19] $\mathbb{EFI}_{b,t}$ is positively correlated to the gambling demand in at least two ways. First, when a gambler expects higher future income, his/her budget for gambling activities increases (potentially cutting current savings) due to a permanent income effect. Second, his/her chance of obtaining a financial loan improves, resulting in more money that can be spent on gambling.[20] Next, $Entertain_{b,t}$ measures the availability of alternative entertainment. Gambling is a

[18] Rather than using the narrowly defined crime categories (e.g. theft, violence, drug-dealing, and sexual offences), we use the 'total' number of reported crimes (per capita) throughout this investigation. This is because the demand for betting shops is likely to be affected not only by a specific type of crime but by any kind of crime. We base this argument on the hypothesis that a risk-loving and instantaneous (yet myopic) gratifying nature is shared by betting activities and all kinds of crime. Econometrically, we could focus on the causal investigation between a specific type of crime (e.g. thefts) and betting shops in Equation (1). However, such a focus is expected to exacerbate the omitted variable problem in our empirical investigation (e.g. if we only use theft crime data in Equation (1), the model fails to include the relation with other types of crimes (such as violence and drug-dealing-related crimes) on betting shops).

[19] For example, if there is an unexpected announcement of local construction projects for the future, it will change the income expectations among local construction workers.

[20] Similar to their popularity in the U.S., pay-day loan shops are popular in the U.K. where a

form of entertainment which must compete with other entertainment services. In this sense, gambling and other entertainment avenues are substitutes.

For the sake of simple interpretation, we split $u_{b,t}$ into

$$u_{b,t} = \delta \mathbb{EFI}_{b,t} + \theta Entertain_{b,t} + \varepsilon_{b,t}, \tag{2}$$

where δ and θ are constant coefficients. We assume $\varepsilon_{b,t}$ as i.i.d. idiosyncratic shocks across boroughs, yet they can be serially correlated within a borough. Among other factors, this could include local-level advertisement expenditures, consistency of performance of local sports teams, and measurement error. For this reason, robust standard errors clustered within a borough are used in the empirical section.

Lastly, we have to omit variables related to online betting due to lack of data. However, this omission is unlikely to be a serious problem in our empirical analysis for the following three reasons. First, according to the to the 'British Gambling Prevalence Survey 2010' only 4% of people bet online.[21] Thus, the influence of online betting on offline betting is expected to be small. Second, the usage of online betting can be reasonably assumed to be correlated with the average age of a borough resident, as younger people are more familiar with using the internet. Our empirical model contains age and age squared as control variables, hence it does not create an omitted variable bias. Third, Equation (1) consists of borough fixed-effects and year-fixed effect dummies. These dummy variables are able to capture borough-level heterogeneity and the London-wide time-trend of online betting.

3.1 An Instrumental Variable and Identifying Assumptions

Regarding Equation (1), it is natural to be concerned with reverse causality and endogeneity problems. A reverse causality is based on the plausible possibility that some gamblers who lose money may attempt to recover losses thorough criminal activities. Also, the model will suffer from endogeneity bias if any of the omitted variables are correlated with crime. We reduce such econometric problems by using the instrumental variable approach to isolate the variation in $\ln(Crimes_{b,t})$ which is uncorrelated with $u_{b,t}$. The instrument we use here is in the spirit of Hausman (2008). The instrument, $z_{b,t}$, is constructed by

borrower can immediately borrow money on the agreement of paying it back on pay-day. News media articulates the high correlation of pay-day loan shops and betting shops. For example: `www.theguardian.com/money/datablog/2014/mar/12/payday-lending-shops-boom-in-uk-the-full-data`.

[21] See Table 2.1 of Wardle et al. (2010) for details.

taking the log of averaged per capita crime in nearby connected boroughs,

$$z_{b,t} = \ln\left(\frac{1}{\text{NNCB}(b)} \sum_{a \in \text{SNCB}(b)} Crimes_{a,t}\right), \tag{3}$$

where SNCB(b) is the set of nearby connected boroughs, and NNCB(b) is the number of nearby connected boroughs. For example, the log of crime rate in Harrow will be instrumented by the log of averaged crime rates in Hillingdon, Ealing, Brent and Barnet.[22]

The identification assumptions (exclusion restrictions) are based on travelling patterns. Specifically, we assume that a criminal may travel across boroughs to commit crimes, but a gambler does not travel across boroughs to gamble. This is a reasonable assumption since betting shops are widespread (60 shops per borough on average) and provide nearly homogeneous gambling services and products (i.e. betting events and odds have little variation across betting shops to prevent arbitrage). Thus, there is not much incentive for a gambler to sacrifice his travel cost for visiting a distant betting shop in a neighbouring borough. Empirically, this means that a change in the instrument does have negligible influence on the omitted determinants of betting shop demand, but it is correlated with crime in a borough. We expand on this idea in the rest of the section.

Our model and instrument are compatible with two well-known theories in criminology. The first theory states that criminals conduct crimes near to where they live, because they have informational advantages for successfully completing crimes (Wiles and Costello (2000)). The second is called 'hot spot' theory, which describes that criminals travel to commit crimes in hot spots that have more crime opportunities (Brantingham and Brantingham (1999)). The first theory is compatible with our model of Equation (1) in which individuals commit crimes in their resident boroughs, where they also visit local betting shops. The second theory is compatible with the construction of the instrument in Equation (3) in which criminals travel across boroughs to get to the hot spots.

Regarding the exogeneity condition of the instrument, it should be emphasised that committing a crime in an area where an individual is not a resident requires substantial information.[23] We argue that such advanced information is available mostly among organised crime-group members who share

[22]Refer to Figure 1 for details of nearby connected boroughs.

[23]Such required information includes: knowledge of crime hot spot locations; knowledge of CCTV locations and their covering angles; the deployments of local police officers and their shift and patrol patterns; knowledge of safe escaping routes after a crime without the usage of a public transportation (as buses, tubes, and their stations are equipped with CCTVs). It is worth noting that, based on advanced vision-analysing-computer programs, the cutting-edge technologies of CCTVs allow police officers and security guards to automatically detect suspicious movements that criminals typically make.

information (e.g. locations of hot spots). Without such professional information, a person who commits a crime in a remote borough has to bear a high risk of arrest. We base our instrument exogeneity on these informational requirements among criminals. The detailed descriptions of the instrument exogeneity are further developed in the Appendix.

4 Estimation Results and Policy Implications

This section discusses the estimation results, their economic interpretations, and policy implications. Our main results, summarised in Table 2, report that a rise in crime increases the number of betting shops in an area. Our explanations are threefold. First, we explain the importance of accounting for borough-level heterogeneity and the bias caused by ignoring it. Second, we discuss the effect of omitted variables and the role of the instrumental variable in mitigating the bias. Third, we discuss the effect of accounting for both borough-level heterogeneity and omitted variables using a panel model with an instrumental variable. Here, we also describe our main estimation result.

Finally, we briefly discuss the policy implications of our analysis. The Appendix contains the regression results with the City of Westminster borough included and various robustness checks regarding control variables.

4.1 Estimation Results

We compare the estimation results of (i) the OLS model and (iii) the panel fixed effect model as reported in Table 2, to examine the effect of borough-level heterogeneity. In model (iii), F-statistics of no borough effect has nearly zero p-value. This is naturally expected as we observe substantial heterogeneity in Figures 3 and 4. Subsequently, we investigate whether the regressors are correlated with the borough effects (α_b) using the Hausman test (Hausman (1978)). The second column of Table 3 reports that the null hypothesis is rejected, indicating that our regressors are correlated with borough effects. This correlation is demonstrated by the large difference between the fixed-effect and random effect panel models in (iii) and (iv). The estimated crime parameter shows that the omission of borough effects creates an upward bias, as crime elasticity in the OLS model is 0.77, compared to the fixed-effect panel model in which elasticity is 0.28. This suggests that crime and α_b (such as gambling culture) are positively correlated. This positive correlation is intuitive, as crime and gambling share the same risk-loving and instantly-gratifying preferences.

Table 2: Regression Results

Variable	(i) OLS	(ii) IV	(iii) Panel F.E.	(iv) Panel R.E.	(v) Panel F.E. IV	(vi) Panel R.E. IV	(vii) Lagged dependent
ln(*Crimes*)	0.769***	1.852***	0.280*	0.631***	1.098*	1.236***	0.0462*
	(0.0806)	(0.648)	(0.163)	(0.149)	(0.660)	(0.480)	(0.0279)
Unemployment rate	0.0280***	-0.0306	0.00770	0.0147*	0.00433	0.00473	0.0018
	(0.00905)	(0.0384)	(0.00723)	(0.00883)	(0.00963)	(0.0100)	(0.0026)
Avg. housing price	-3.834***	-11.93**	-7.468**	-4.579**	-9.190***	-9.033***	-0.3176
	(0.727)	(4.910)	(2.721)	(1.788)	(3.155)	(3.217)	(0.2554)
Adult avg. age	0.0208	-0.0541	-1.609**	-0.455*	-1.658***	-1.458***	0.0489
	(0.0924)	(0.134)	(0.653)	(0.272)	(0.630)	(0.562)	(0.0326)
(Adult avg. age)^2	-0.000185	0.00117	0.0201**	0.00533*	0.0200***	0.0175***	-0.00051
	(0.00108)	(0.00167)	(0.00743)	(0.00308)	(0.00715)	(0.00633)	(0.00038)
Gender ratio	0.514	0.959**	0.442	1.327*	1.633	1.919	0.2147**
(among adults)	(0.327)	(0.461)	(0.975)	(0.753)	(1.469)	(1.187)	(0.0877)
Lag of ln(*Betshops*)							0.9082***
							(0.0272)
Constant	-7.520***	-3.694	23.78	1.660	27.23*	23.54*	-2.0557***
	(2.043)	(3.649)	(14.73)	(6.202)	(14.26)	(12.64)	(0.7896)
Observations	276	276	276	276	276	276	245
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borough effect	No	No	Yes	Yes	Yes	Yes	No
Instrument	No	Yes	No	No	Yes	Yes	No
R-squared	0.634	0.398					0.964

The dependent variable is the log of number of betting shops per capita ($ln(BetShops)$).
Data includes all boroughs except the City of London and Westminster.
For panel regressions the standard errors are clustered at the borough level.
Robust standard errors in parentheses, *** significant at 1%, ** significant at 5%, * significant at 10%

Table 3: Hausman Test Results

	Panels: between model (iii) and (iv)	Panel-IVs: between model (v) and (vi)
χ^2 statistic	64.61	1.65
(p-value)	(0.0000)	(0.9999)

Null hypothesis is that (instrumented) regressors are uncorrelated with a borough effect.

Next, we investigate the influence of omitted variables (primarily $\mathbb{EFI}_{b,t}$ and $Entertain_{b,t}$) and the effectiveness of our instrument by comparing the parameters of IV and non-IV models. First, we compare the estimates of (i) the OLS model and (ii) the IV model are reported in Table 2.[24] The elasticity of crime in the IV model (1.85) is more than double that of the OLS model (0.77) at the point estimate. This implies that it is important to account for omitted variables.

Consequently, we examine the estimation results of (v) the panel fixed effect IV model and (vi) the panel random effect IV model, which are reported in the last two columns of Table 2.[25] The result of the Hausman test, which examines whether instrumented regressors are correlated with borough effects (α_bs), is listed in the last column of Table 3. The Hausman test fails to reject the null hypothesis of no correlation. This result is not surprising, as we construct our instrument by using the different boroughs' crime rates, while a borough effect captures gambling culture in a borough. Similar to the OLS model and its IV-counterpart, we see a large difference between the crime elasticity in the random effect IV model (1.24) and its non-IV counterpart, random effect model (0.63). This reaffirms the importance of correcting the omitted variable bias.

The downward bias in the crime parameter of the non-IV models implies that crime in a borough is negatively correlated with the unobserved betting shop demand shifters. It is important to understand the economic arguments behind this downward bias, which suggests the following convariance structure,

$$\text{Cov}(\ln(Crimes_{b,t}), \mathbb{OV}_{b,t}) < 0, \tag{4}$$

where omitted variable $\mathbb{OV}_{b,t}$ can be $\mathbb{EFI}_{b,t}$ or $Entertain_{b,t}$. If a person expects a high future income and improved access to financial loans (high $\mathbb{EFI}_{b,t}$), the propensity to commit a crime diminishes due to the increased opportunity costs. This seems intuitive and in-line with classic crime studies such as Becker (1968) and Ehrlich (1996). For the entertainment omitted variable, $Entertain_{b,t}$, if potential gamblers are budget-constrained, which is likely to happen as gamblers tend to live in more economically deprived areas, they cannot afford to consume both gambling and other entertainment services. Therefore, the prevalence of substitutable entertainment in a borough may prevent potential gamblers from visiting betting shops. Moreover, even when a potential gambler is not budget constrained, as his/her demand for excitement may be fulfilled by other entertainment avenues, he has less incentive to visit a betting

[24] In addition, the first stage regression results are reported in Table 4.

[25] We investigate the possibility of weak instrument by using Cragg-Donald F-statistic, suggested by Stock and Yogo (2005), and could not find any significant evidence of weak instrument at reasonable maximum test sizes. See the Appendix for the details.

shop. As a result, there is less necessity for a person to commit a crime to recover lost money through betting.[26] Thus, the direction of omitted variable bias observed in the regression results seems to be in-line with previous studies and economic intuition.

Our empirical investigation through (i) to (vi) in Table 2 relies primarily on static panel models. We also examine a lagged-dependent variable model for testing dynamic causality in the simplest possible manner. Here, the lagged dependent variable acts as a proxy for borough effects and omitted variables. The estimation result in the model (vii) in Table 2 shows that, given last year's betting shops and other control variables, an increase in per capita crime of 1% leads to an 0.0462% increase in the number of betting shops per capita. This further supports our claim.

Lastly, regarding the estimated coefficients of the control variables, boroughs with higher unemployment, cheaper housing, and a larger fraction of adult males are associated with having more betting shops. A natural concern here is of multi-collinearity, since crime is usually associated with unemployment and cheap housing. We find a correlation coefficient of less than 0.5 in all cases, which mitigates these worries. However, we exclude income as an explanatory variable due to its strong correlation with unemployment and price of housing. Age has a parabolic relationship, decreasing until around 42 years old and increasing afterward. We understand that the control variables do not have a causal interpretation, but having an intuitive sign on the parameter increases confidence in our model.

Given the above estimation results, we base our main empirical finding on the elasticity estimate of 1.2 in (vi) the random effect panel IV model in Table 2. The estimate is most reliable because: borough effects and omitted variable bias are both accounted for; the result of first-stage regression rejects the possibility of weak instrument with a conservative criteria; Hausman test fails to reject the consistency of the estimator; and the estimator is asymptotically efficient.[27]

4.2 Policy Implications

We report that a 1% increase in per capita crime leads to a 1.2% increase in the number of betting shops per capita. This implies that for every 1.4% increase in per capita crime a new betting shop

[26] A seminal study by Dahl and DellaVigna (2009) investigates the direct link between violent movies and local crimes in the US from 1995 to 2004. They report that premieres of violent movies actually *decrease* local violent crimes, due to (1) an incapacitation effect (i.e. a person cannot conduct violent activities while watching a violent movie) and (2) a substitution effect (a person substitutes violence with watching a violent movie). In addition, Cunningham, Engelstätter, and Ward (2011) find a *decrease* of violent crimes after blockbuster sales of violent video games in the US between 2005-2008. Our reasoning behind Equation (4) is compatible with these findings.

[27] Note that the standard deviation of the causal parameter in model (vi) is smaller than that in model (v).

opens up in a London borough, on average.[28] This study is particularly relevant to U.K. policy as one of the licensing objectives of the Gambling Act (2005) was to keep gambling crime-free. This paper shows evidence to the contrary.

Moreover, if we accept that gambling shops also attract crime, the findings of our paper point to a spiral-effect which can have serious consequences for the social environment.[29]

5 Conclusion

We investigate the causal effect of local crime on the number of betting shops in London boroughs between 2007-2015. Using a novel instrument, average crime rates in neighbourhood boroughs, we empirically find that a 1% increase in the crime rate causes a 1.2% increase in the number of betting shops (per capita). Expressed in a different way, a new betting shop is opened in a borough for every 1.4% increase in local crime rate, on average. Our finding is significant and robust across a variety of econometric specifications.

This study is a stepping stone for more work in this economically and socially important area. A natural extension of our research is the long-term impact of betting shops on crime. In other words, what happens to the crime rate when a new betting shop opens? More research in this area is needed to derive comprehensive policy recommendations.

References

Astbury, Gaynor and Mark Thurstain-Goodwin (2007), *Contextualising machine gambling characteristics by location - final report - A spatial investigation of machines in bookmakers using industry data.* Prepared by Geofutures for The Responsible Gambling Trust.

Becker, Gary S (1968), "Crime and punishment: An economic approach." In *The Economic Dimensions of Crime*, 13–68, Springer.

[28]The calculation is based on: a unit change in # of shops ≈ mean shops per capita (=0.00022) × avg. population in a borough (=256,858) × 1.24% × 1.4.

[29]Even though the evidence of gambling shops attracting crime does not exist in the U.K., it is well documented for the U.S. data, hence it is not far fetched. Statistical evidence of the causal effect of gambling activities on local crime is reported in the U.S. casino literature, such as Friedman, Hakim, and Weinblatt (1989), Gazel, Rickman, and Thompson (2001), Evans and Topoleski (2002), and Grinols and Mustard (2006).

Brantingham, Patricia L and Paul J Brantingham (1999), "A theoretical model of crime hot spot generation." *Studies on Crime & Crime Prevention.*

Bresnahan, Timothy F and Peter C Reiss (1991), "Entry and competition in concentrated markets." *Journal of Political Economy*, 977–1009.

Brown, R.I.F. (1987), "Pathological gambling and associated patterns of crime: Comparisons with alcohol and other drug addictions." *Journal of Gambling Behavior*, 3.

Cornwell, Christopher and William N Trumbull (1994), "Estimating the economic model of crime with panel data." *The Review of economics and Statistics*, 360–366.

Cunningham, Scott, Benjamin Engelstätter, and Michael R Ward (2011), "Understanding the effects of violent video games on violent crime." *ZEW-Centre for European Economic Research Discussion Paper.*

Dahl, Gordon and Stefano DellaVigna (2009), "Does movie violence increase violent crime?" *The Quarterly Journal of Economics*, 677–734.

Dixit, Avinash K and Joseph E Stiglitz (1977), "Monopolistic competition and optimum product diversity." *The American Economic Review*, 67, 297–308.

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

Eadington, William R (1999), "The economics of casino gambling." *The Journal of Economic Perspectives*, 173–192.

Ehrlich, Isaac (1996), "Crime, punishment, and the market for offenses." *The Journal of Economic Perspectives*, 10, 43–67.

Evans, William N and Julie H Topoleski (2002), "The social and economic impact of native american casinos." Technical report, National Bureau of Economic Research.

Friedman, Joseph, Simon Hakim, and J Weinblatt (1989), "Casino gambling as a "growth pole" strategy and its effect on crime." *Journal of Regional Science*, 29, 615–623.

Gazel, Ricardo C, Dan S Rickman, and William N Thompson (2001), "Casino gambling and crime: A panel study of wisconsin counties." *Managerial and Decision Economics*, 22, 65–75.

Grinols, Earl L and David B Mustard (2006), "Casinos, crime, and community costs." *Review of Economics and Statistics*, 88, 28–45.

Hausman, Jerry A (1978), "Specification tests in econometrics." *Econometrica: Journal of the Econometric Society*, 1251–1271.

Hausman, Jerry A (2008), "Valuation of new goods under perfect and imperfect competition." *The Economics of New Goods*, 58, 209.

Levitt, Steven D (1996), "The effect of prison population size on crime rates: Evidence from prison overcrowding litigation." *The Quarterly Journal of Economics*, 111, 319–351.

Mankiw, N Gregory and Michael D Whinston (1986), "Free entry and social inefficiency." *The RAND Journal of Economics*, 48–58.

Stock, James H, Jonathan H Wright, and Motohiro Yogo (2012), "A survey of weak instruments and weak identification in generalized method of moments." *Journal of Business & Economic Statistics*.

Stock, James H and Motohiro Yogo (2005), "Testing for weak instruments in linear iv regression." *Identification and inference for econometric models: Essays in honor of Thomas Rothenberg*.

Walker, Douglas M (2007), *The economics of casino gambling*. Springer Science & Business Media.

Wardle, Heather, Alison Moody, Suzanne Spence, Jim Orford, Rachel Volberg, Dhriti Jotangia, Mark Griffiths, David Hussey, and Fiona Dobbie (2010), "British gambling prevalence survey 2010."

Wiles, Paul and Andrew Costello (2000), *The road to nowhere: the evidence for travelling criminals*, volume 207. Research, Development and Statistics Directorate, Home Office London.

6 Appendix

This appendix reports the results of the first stage estimations, weak instrument tests, the estimation results with the City of Westminster included, robustness checks with the omission of control variables, and the figures of the population un-adjusted variables.

6.1 First Stage Regression Results and Test of Weak Instrument

Table 4 summarises the first-stage regression results used for the estimation methods reported in models (ii), (v), and (vi) in Table 2. Regarding the possibility of a weak instrument, we calculate the Cragg-Donald F-test statistic, which are examined by Stock and Yogo (2005) and Stock et al. (2012). Following their method, we use the maximum test size criterion, as we test the existence of causality between crime and betting shops. According to Table 5.2 of Stock and Yogo (2005), the critical value of the Cragg-Donald F-test statistic is 8.96 (with a maximum test size of 0.15) and 16.38 (with a maximum test size of 0.10) at $\alpha = 0.05$. These statistics are listed on the bottom row of Table 4. Our instrument used in (ii) the IV model does not satisfy any of these criterions. However, the F-statistic of (v) the panel fixed effect IV model exceeds the critical value of 8.96 (maximum test size 0.15), and the F-statistic in (vi) the panel random effect model further excels the critical value of 16.38 (maximum test size 0.10). Accordingly, we can safely ignore the concern of a weak instrument in the model (vi), on which we base our main empirical finding.

Table 4: First Stage IV Regression Results

Variable	(ii) IV	(v) Panel F.E. IV	(vi) Panel R.E. IV
Log of geographically connected borough crimes ($z_{b,t}$)	0.1827*** (0.0653)	0.5112*** (0.1673)	0.6232*** (0.1507)
Other control variables	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes
Observations	276	276	276
R-squared	0.8180		
t-statistic	2.798	3.056	4.135
Cragg-Donald F-test statistic	7.828	9.337	17.101

Dependent variable is the log of crime rate ($\ln(Crimes_{b,t})$).
Data includes all boroughs except the City of London and Westminster.
Robust standard errors in parentheses
*** significant at 1%, ** significant at 5%, * significant at 10%

6.2 Detailed Descriptions for Instrument Exogeneity

Regarding the validity of our instrument, the instrument exogeneity condition $\mathrm{E}[z_{b,t}u_{b,t}] = 0$ is satisfied if $\mathrm{Cov}(z_{b,t}, \mathbb{EFI}_{b,t}) = 0$ and $\mathrm{Cov}\,(z_{b,t}, Entertain_{b,t}) = 0$ hold. We now illustrate these two conditions.

First, if the condition of $\mathrm{Cov}(z_{b,t}, \mathbb{EFI}_{b,t}) = 0$ is violated, it means that connected boroughs' crime conditions affect the future employability among residents in a borough b, even after adjusted by control variables (or vice versa). This correlation story basically means (1) crime activities in connected boroughs create a macro economic change that affects the future income prospects of a resident in a different borough b, or (2) a variation in $\mathbb{EFI}_{b,t}$ changes crime activities that happen in connected boroughs. We claim neither (1) nor (2) is plausible for the following reasons. Criminal activities are generally not considered to have macro effects in a developed country. Furthermore, a person, whose $\mathbb{EFI}_{b,t}$ may change, has a legitimate job (or has the ability to have a legitimate job in the future) is less likely to be a crime-group member who can make his living through crimes. This is because someone with a legitimate job (or prospect to have a legitimate job) may lose future employability upon an arrest.

Second, the validity of $\mathrm{Cov}(z_{b,t}, Entertain_{b,t}) = 0$ is summarised by the following points. When connected boroughs experience changes in their crime rates (i.e. a change in $z_{b,t}$), such as the new emergence of crime 'hot spots', some criminals who live in borough b travel to these new spots in connected boroughs. However, the availability of entertainment ($Entertain_{b,t}$) in borough b is unlikely to be affected, as new crime hot spots are emerging in geographically-separate boroughs. Next, a change in $Entertain_{b,t}$ in a borough is unlikely to affect crimes in connected boroughs for the following reasons. Any change in $Entertain_{b,t}$ affects the demand for betting shops among potential gamblers who substitute betting with other entertainment activities. These people are considered to be non-serious and non-addict gamblers (as they may give up betting if other entertainments are available) and are less likely to lose large amounts of money, which may result in serious criminal behaviour. Furthermore, it is even more unlikely that this group of people has strong risk-seeking preferences, which can motivate them to travel and commit a crime in a remote borough where they do not have the advantage of local information. Thus, the likelihood of committing crimes in a connected borough could reasonably be considered negligibly small for these substituting gamblers.

6.3 Robustness Checks - Including the City of Westminster

Table 5 reports the regression results with the City of Westminster included. The estimates of the causal parameter are similar to those in Table 2, except for the following two major points. First, the OLS estimate of the crime coefficient in model (i) in Table 2 and that of (i) the OLS model in Table 5 are largely different. This difference is considered to be created by the large borough-effect term of Westminster ($\alpha_{b=\text{Westminster}}$) which is captured in an OLS error term and causes an upward bias. Second, the estimate in model (iii) in Table 5 loses significance. This is not a serious problem as the panel fixed effect model is not instrumented, and the parameter is downwardly biased towards zero. Overall, these estimates in Table 5 are further supporting our empirical finding on the causality.

Table 5: Regression Results: Including the City of Westminster Data

Variables	(i) OLS	(ii) IV	(iii) Panel F.E.	(v) Panel R.E.	(v) Panel F.E. IV	(vi) Panel R.E. IV	(vii) Lagged dependent
ln(*Crimes*)	1.325***	1.758**	0.221	0.744***	1.063*	1.085*	0.0765***
	(0.0830)	(0.684)	(0.145)	(0.150)	(0.594)	(0.576)	(0.0291)
Unemployment rate	0.000378	-0.0229	0.00802	0.0155*	0.00795	0.00806	-0.00168
	(0.00983)	(0.0402)	(0.00703)	(0.00895)	(0.00871)	(0.00882)	(0.00243)
Avg. housing price	-6.011***	-10.54	-6.121**	-2.791	-7.066**	-7.001**	-0.457*
	(0.965)	(7.263)	(2.720)	(2.425)	(3.459)	(3.497)	(0.264)
Adult avg. age	0.0698	-0.0216	-1.509**	-0.394	-1.485**	-1.476**	0.0525
	(0.105)	(0.194)	(0.701)	(0.321)	(0.746)	(0.740)	(0.0337)
(Adult avg. age)^2	-0.000352	0.000806	0.0191**	0.00479	0.0183**	0.0181**	-0.000512
	(0.00120)	(0.00234)	(0.00796)	(0.00360)	(0.00850)	(0.00843)	(0.000389)
Adult gender ratio	1.551***	1.121	0.298	1.845**	1.259	1.308	0.290***
	(0.362)	(0.783)	(0.970)	(0.823)	(1.265)	(1.242)	(0.0895)
Lag of ln(*Betshops*)							0.938***
							(0.0208)
Constant	-8.599***	-4.916	21.31	-0.239	23.20	23.10	-1.9141
	(2.335)	(6.606)	(15.78)	(7.322)	(16.46)	(16.32)	(0.7934)
Observations	285	285	285	285	285	285	253
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borough effect	No	No	Yes	Yes	Yes	Yes	No
Instrument	No	Yes	No	No	Yes	Yes	No
R-squared	0.760	0.723					0.983

The dependent variable is the log of number of betting shops per capita (ln(*Betshops*)).
Data includes all boroughs except the City of London.
For panel regressions the standard errors are clustered at the borough level.
Robust standard errors in parentheses, *** significant at 1%, ** significant at 5%, * significant at 10%

6.4 Robustness Checks - Control Variables

Robustness checks are implemented to understand the effect of control variables on the crime elasticity (causal parameter). The results of robustness checks are listed in Table 6. As our main empirical results are based on (vi) the panel random effect IV model in Table 2, we primarily analyse estimation model (vi-1), (vi-2), and (vi-3) in Table 6.[30]

The model (vi-1) in Table 6 omits the time fixed effect (λ_t). This leads to a decrease in magnitude of the crime parameter, and the significance is lost. This happens because we omit time fixed effects which is now absorbed by the error term in Equation (1) and the decreasing trend in crime (Figure 4).

The model (vi-2) in Table 6 reports the estimation results with the omission of unemployment and average housing price. By omitting these control variables, we fail to account for the unobserved heterogeneity related to present income (and part of the future income). Accordingly, we observe a downward bias in the crime parameter due to the negative correlation between crime and income.

The model (vi-3) in Table 6 reports the results with the omission of age and gender-ratio variables.

[30] The results of panel fixed effect IV models (v-1), (v-2), and (v-3) are quite similar.

Table 6: Control Variables - Robustness Check

Variable	(v-1) Panel F.E. IV	(v-2) Panel F.E. IV	(v-3) Panel F.E. IV	(vi-1) Panel R.E. IV	(vi-2) Panel R.E. IV	(vi-3) Panel R.E. IV
ln(*Crimes*)	0.162	1.095	1.267**	0.138	0.769***	1.213***
	(0.112)	(0.707)	(0.560)	(0.110)	(0.266)	(0.355)
Unemployment rate	0.000277		0.00754	0.00824		0.00670
	(0.00471)		(0.0118)	(0.00548)		(0.0122)
Avg. housing price	-5.296***		-8.631***	-1.320		-8.378***
	(1.842)		(2.957)	(1.298)		(2.613)
Adult avg. age	-1.795***	-2.462***		-0.969**	-0.663**	
	(0.681)	(0.705)		(0.424)	(0.307)	
(Adult avg. age)^2	0.0223***	0.0283***		0.0112**	0.00774**	
	(0.00774)	(0.00816)		(0.00476)	(0.00344)	
Gender ratio	0.424	1.710		1.588*	1.270	
(among adults)	(1.078)	(1.432)		(0.888)	(0.896)	
Constant	27.50*	45.96***	-4.804***	11.20	6.433	-4.951***
	(15.38)	(15.86)	(1.561)	(9.678)	(7.084)	(1.050)
Observations	276	276	276	276	276	276
Year F.E.	No	Yes	Yes	No	Yes	Yes
Borough effect	Yes	Yes	Yes	Yes	Yes	Yes
Instrument	Yes	Yes	Yes	Yes	Yes	Yes
R-squared						

The dependent variable here in the log of number of betting shops per capita (ln(*Betshops*)).
Data includes all boroughs except the City of London and Westminster.
For panel regressions the standard errors are clustered at the borough level.
Robust standard errors in parentheses
*** significant at 1%, ** significant at 5%, * significant at 10%

The estimates of model (vi) and (vi-3) are close, indicating that these two variables have little effect for controlling unobserved variables.

6.5 Figures of Population Un-Adjusted Variables

Figures 6 - 8 report the population un-adjusted numbers of betting shops and crimes. Similar to the population-adjusted equivalents in Figures 3 - 5, outliers in these figures are all from the City of Westminster. Compared to the population adjusted variables, we find similar patterns; there is substantial heterogeneity across boroughs, and the numbers of betting shops and crimes are strongly correlated. The correlation coefficient in Figure 8 is 0.823 (significant at $\alpha = 0.01$).

Figure 6: Number of Betting Shops by Borough

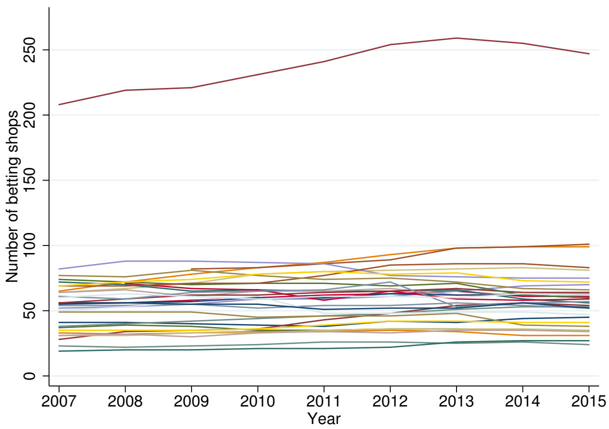


Figure 7: Number of Crimes by Borough

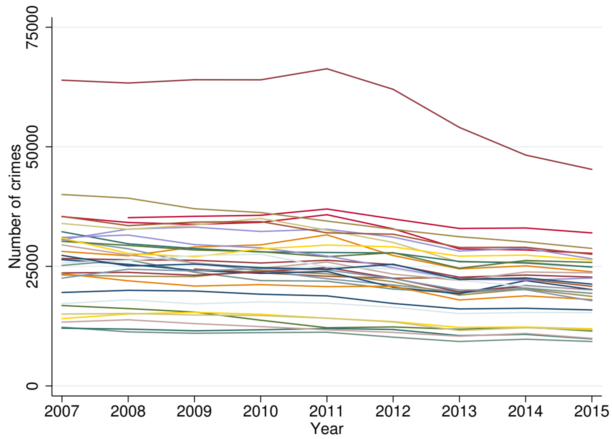


Figure 8: Annual Borough-Level Number of Betting Shops and Crimes for 2007-2015