The Effect of Adult Entertainment Establishments on Sex Crime: Evidence from New York City

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Abstract

This paper studies how the presence of adult entertainment establishments affects the incidence of sex crimes, including sexual abuse and rape. We build a daily panel that combines the exact location of not-self-reported sex crimes with the day of opening and exact location of adult entertainment establishments in New York City. We find that these businesses decrease daily sex crime by 13% per police precinct, and have no effect on other types of crimes. The results imply that the reduction is mostly driven by potential sex offenders frequenting these establishments rather than committing crimes. We also rule out the possibility that other mechanisms are driving our results, such as an increase in the number of police officers, a reduction in the number of street prostitutes and a possible reduction in the number of potential victims in areas where these businesses opened. The effects are robust to using alternative measures of sex crimes.

Keywords: Sex crimes, rape, adult entertainment establishments, substitute services

JEL codes: I18, J16, J47, K14, K42

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1 Introduction

Sex crimes, including sexual violence, are a major public health concern. Apart from the large psychological and physical burden, these crimes also lead to public health issues including unintended pregnancies, induced abortions and sexually transmitted infections.[1] However, little is known about how to prevent sex crimes, including sexual abuse and rape. Several have argued that rape is simply a substitute for consensual sex (Thornhill and Thornhill 1983; Thornhill and Palmer 2000a,b). Thus, having access to substitutes such as adult entertainment or paid-for sex (i.e. prostitution) may reduce the incidence of such crimes. Yet, little causal evidence has been produced to support this claim.

This paper examines whether the presence of adult entertainment establishments (strip clubs, gentlemen clubs and escort girl services) reduces sex crimes. Adult establishments may include prostitution, although it is generally illegal. While these clubs and services may reduce sex crimes if individuals use them instead of committing sex crimes (Posner 1992; Dever 1996), they may increase sex crimes if they reinforce the view of women as objects, leading to more violence against them (Brownmiller 1993).[2] One of the main challenges of evaluating whether adult entertainment is a substitute for sex-related crime is the difficulty of gathering data that allows for a causal interpretation of the effect of adult entertainment establishments on such crimes. Sex crimes are thought to be under-reported, and related data is often protected by privacy laws.

This paper exploits a unique data set with daily precinct-level crime information from New York City (NYC). We construct a new data set on adult entertainment establishments that includes the names and addresses of the establishments, providing precise geographic information. We complement this with information on establishment registration dates from the New York Department of State and Yellow Pages, which we use to define when an establishment opened. We categorize adult entertainment establishments by New York Police Department (NYPD) precincts to match crime data from the "Stop-and-Frisk" program. The crime data include hourly information on crimes observed by the police, including sex crimes. The data set covers the period from January 1, 2004 to June 30, 2012. Since these crimes are reported by the police, it minimizes the biases associated with self-reported data on sex crime. We check the robustness of the results using police complaint data.

[1] A 2007 national study of the Department of Justice estimated that 18% of American women experienced rape (or attempted rape) at least once in their life.

[2] In addition, assuming that sex crimes are an increasing function of the number of sex workers, adult entertainment businesses may rise this sort of crimes by increasing the number of sex workers.

Using variation in the date of registration of adult entertainment establishments, we show that opening these establishments in particular areas decreases the number of sex crimes committed nearby. We find that the presence of an adult entertainment establishment in a given precinct leads to a 13% daily reduction in sex crime in the precinct. This estimated coefficient comes from the preferred specification that includes fixed effects at the precinct, year, month, day-of-the-year, day-of-the-week and holiday level, and precinct-year time trends.[3] The results are robust to different regression models and to using police complaint data.

The main identification assumption is that the opening date of an adult entertainment establishment is exogenous to any other factor affecting sex crime. Since opening a business in NYC requires a long bureaucratic procedure, we can take the date of registration as a quasi-natural experiment to study the effect of these businesses on sex crime. In addition, we exploit cross-section daily variation in sex crimes across precincts within the city.[4] Therefore, since adult entertainment businesses were not opened in response to precinct-specific trends in reported sex crime, we can exploit the exogenous variation in openings at different time periods in different precincts to obtain the causal effects of adult businesses on sex crime.

The second focus of this paper is to understand the mechanism behind the effect of adult entertainment on sex crimes. One potential mechanism is that these establishments offer services that may substitute sex crimes, leading potential sex offenders to become adult customers of such businesses. Recently, scholars have argued that adult entertainment establishments might also offer prostitution services, they refer to them also as indoor prostitution. Adult entertainment establishments might provide a way for the whole transaction to occur behind closed doors (Farley (2003).[5] In addition, even if adult entertainment establishments do not offer paid sex they offer other services that can be considered as substitutes for sex crimes.

We find considerable evidence that sex crime is reduced when potential sex offenders

[3]One potential concern is that the opening date might be different from the registration date. Yet, to the best of our knowledge there is no evidence in the literature, nor any reason to believe, that such difference might discredit our identification assumption. Furthermore, our results are robust to conducting the analysis at both weekly and monthly level. It is important our results are robust to such specifications since opening and registration dates occur close in time.

[4]A precinct is a geographical division of neighborhoods within a city. We follow the 77 precincts of the NYPD.

[5]Indoor prostitution is any kind of sex work that happens behind closed doors (as opposed to street prostitution). Indoor prostitution includes massage parlors and saunas, brothels, strip clubs, and escort prostitution (Urban Justice Center 2005; Shively et al. 2012). In the US, indoor prostitution is the major source of prostitution: according to the Urban Justice Center (2005) the indoor market constitutes roughly the 85% of all sex work activity.

frequent adult entertainment establishments. We find that at night, the effect of the establishments is negative and larger in absolute value than our benchmark. This suggests that these establishments are most effective at preventing sex crimes from being committed at night. Since the majority of adult entertainment establishments are only open at night, and the demand for their services is higher at that time of day, the results suggest that potential sex offenders prefer to use these services rather than commit sex crimes. Therefore, these results suggest that potential criminals consider sex crime and adult entertainment establishment services as substitute activities, as Farley et al. (2009) documents by interviewing men who purchase prostitution. Dahl and DellaVigna (2009) identify a similar mechanism in which violent movies have an incapacitation effect: they reduce the crime rate by keeping potential offenders off the streets and in the cinemas. The only difference is that potential sex offenders do not commit sex crimes simply due to incapacitation (i.e. time constraint), but because they substitute sex crimes with services offered in adult entertainment establishments.

We also use our data to rule out three other mechanisms. First, we find that opening adult establishments does not affect other types of crimes, which demonstrates that the results on sex crimes are not driven by an increased police presence on the streets. This also rules out the hypothesis that these businesses may attract other types of criminals such as drug dealers as well. Second, we find that sex crimes are not moving to other areas, which shows that there are no negative spillover effects on bordering precincts.[6] Third, we also check if there is a reduction in street prostitution.[7] The number of street sex workers would decline if they started working in adult entertainment establishments or if they moved to other precincts due to the increased competition. However, we find no effects on the number of street sex workers and no reallocation to bordering precincts. This suggests that the results are not driven by a reduction in potential victims who are now avoiding the area or by a reduction in sex crimes against sex workers.[8]

This is the first paper to study the casual impact of adult entertainment establishments on sex crimes. The study contributes to the economics of crime literature by focusing on one of the factors that lead to sex-related crimes. So far in the literature, there is little evidence on how to prevent sex-related crimes. While most of the literature has focused on theories of control, labor markets and the role of deterrence policies (Card and Dahl

[6] These results are consistent with previous studies that have shown that increasing the number of police officers on the street does not displace crime to other areas (Di Tella and Schargrodsky 2004; Draca et al. 2011).

[7] Scholars found that about 70% of (street) sex workers have been victims of sex crimes due to their job (Farley 2003).

[8] This is consistent with the fact that sex workers represent a small proportion of the total reported sex crimes, given the illegal nature of their work (Bridgett and Robinson 1999).

2011; Munyo and Rossi 2013; Bobonis et al. 2013; Aizer 2010; Amaral et al. 2018; Iyengar 2009; Kavanaugh et al. 2018; Miller and Segal 2016), this paper focuses on the role of services for men that may substitute for sex crimes. Moreover, while most of the focus has been on domestic violence, in this paper we analyze the effects of introducing adult entertainment options in an area on rape and sexual harassment in nearby public spaces, which may have other unexpected consequences such as reducing women's economic mobility. For example, Borker (2017) shows that women choose to attend lower-ranked schools than men in order to avoid sexual harassment from men on the street.

This paper is closely related to two recent studies of the effects of decriminalizing prostitution. Cunningham and Shah (2017) exploit an unperceived decriminalization of indoor prostitution in Rhode Island; their estimates are based on a year-state specification. Bisschop et al. (2017) study the effect of street prostitution in special red-light zones, also using annual estimates.[9] Both papers find that decriminalizing prostitution decreases sex crimes against sex workers.

We make four contributions to this literature. First, while previous studies have focused on how the decriminalization of prostitution affects sex crimes, we find evidence that adult entertainment establishments can reduce sex crimes even in a setting where prostitution is illegal.[10] While the decriminalization of prostitution is a contentious issue, adult entertainment establishments are generally legal around the world, although there are often strict regulations governing where they can be located.[11] The results in this paper imply that the regulation of adult entertainment establishments is one way to address sex crimes. Moreover, it is a viable alternative that is less ethically challenging than legalizing prostitution and can achieve similar effects. Second, we complement previous papers, that used year and state variation, by analyzing the short-term effects using daily precinct data within a city as well as non-self-reported data. Third, by shedding light on the mechanisms linking adult establishments and the incidence of sex crimes, the results have several policy implications. The fact that the effects are driven by potential

[9] In 1980 in Rhode Island prostitution law was amended and prostitution was degraded from a felony to a misdemeanor. The legislators removed the section that addressed committing the act of prostitution itself, yet street solicitation, running a brothel, and pimping remained illegal. Therefore, indoor prostitution was "de iure" decriminalized. However, Arditi (2009) argued that this decriminalization occurred by mistake, so probably neither legislators nor citizens realized that the amendment created a legal vacuum.

[10] Although in the United States (except Nevada) prostitution is illegal, there is a lack of agreement about how to legislate against it. European countries such as Germany, the Netherlands and Belgium legalized and regulate prostitution via licenses, while Sweden and Norway opted to criminalize the *purchase* of prostitutes rather than the supply of such services. In 2014 the European Parliament passed a resolution to follow the Swedish model.

[11] The legalization of prostitution is one of the most frequently discussed topics related to gender issues. For example, *The Economist* has published many articles on this debate. See, e.g., Basin and Farly, *Prostitution debate*, September 6, 2010); *A job like any other*, August 8, 2014; *A personal choice*, August 9, 2014.

customers and that there is no increase in other crimes suggests that these establishments can have positive effects on reducing sex crimes without the negative externalities often associated with decriminalizing prostitution (such as an increase in the use of drugs or violent crimes against sex workers).[12] However, it could be argued that adult entertainment establishments should be supervised since some of their customers are potential sex offenders. Finally, we complement the previous literature by showing direct evidence that opening adult entertainment businesses generates positive externalities on sex crime for the whole population: sex crimes are reduced for both sex workers and non-sex workers.[13]

The paper proceeds as follows. In the next section, we provide background information on adult entertainment establishments in NYC. Section 3 presents the data. Section 4 discusses the identification strategy and the possible threats. Section 5 shows the results of our specification. Section 6 discusses the possible mechanisms that could be driving the effect. The last section summarizes the findings and offers concluding remarks.

2 Background information on adult entertainment establishments

2.1 Adult entertainment establishments in NYC

The New York State Department of State classifies adult entertainment establishments as businesses that *regularly feature movies, photographs, or live performances that emphasize "specified anatomical areas" or "specified sexual activities" and excludes minors by reason of age*. We define such businesses more narrowly, only considering four types – strip clubs, gentleman's clubs, adult entertainers and escort girl services.

In the early 1990s the NYC Division of City Planning published a report on the nature and impact of adult entertainment establishments on the city

In October 1995, following this study, the New York City Council amended its zoning regulations to restrict the location and size of adult entertainment establishments and to disperse such businesses across different areas (i.e. decrease their concentration in certain

[12]In a theoretical model, Lee and Persson (2015) show that decriminalizing prostitution increases the size of the sex market by reducing the costs of entry. Using country cross-sectional data, Cho (2018); Cho et al. (2013) argue that legalized prostitution leads to an expansion of the prostitution market, and an increase in human trafficking.

[13]These results are in line with Cunningham and Shah (2017), who show that decriminalizing prostitution affects the health outcomes of both sex workers and non-sex workers.

neighborhoods).[14]

The New York City zoning amendment applies to all sorts of *adult establishments*, including adult bookstores and adult cinemas, that are not studied in this article. The amendment does not ban adult establishments; it simply requires that they: (1) must be located at least 500 feet from a school, house of worship, day care center, or residential district; (2) must be located at least 500 feet from any other adult establishment; (3) must be limited to one establishment per zoning lot; and (4) must not exceed 10,000 square feet of floor space. None of these features are related to the distribution of sex crimes.

2.2 Adult entertainment establishments and indoor prostitution

Recent literature has documented that most prostitution takes place indoors in massage parlors and saunas, brothels, strip clubs, and escort prostitution services (Farley 2005; Urban Justice Center 2005). Hence, the adult entertainment establishments considered in this article may represent a share of the prostitution market.

The US prostitution market is stratified into three segments.[15] The lowest rung of the ladder is formed by outdoor prostitution (i.e. street prostitutes), which is usually run by pimps. Hence, street prostitutes lack control about their choice of clients, earnings and health checks. They also tend to be younger and are more likely to be victims of violence, to be arrested or to be drug addicted. Strip clubs and gentlemen's clubs comprise the medium rung of the ladder. In this sector prostitution is run as a business; prostitutes might lack control over their clients but enjoy higher earnings, safer controls and more frequent health checks. Self-employed escort girls occupy the top rung. In this market segment, prostitution is professionalized: since prostitutes are not *pimped*, they have control over their customers, earnings, health status and "careers."

Nonetheless, even sex workers on the medium and high rungs might face many difficulties. A recent paper documents the close connection between strip clubs, gentleman's clubs and escort girls services to prostitution in NYC (Urban Justice Center 2005). The majority of indoor prostitutes studied in this report lived precarious lives, and encountered similar problems faced by street-based prostitutes, including violence, constant fear of police interference, and a lack of substantive support services.

[14] For further information see Department of State New York State (1998)

[15] For further information, see Church et al. (2001), Albert (2002), Shively et al. (2012) and Ciacci (2017).

3 Data

NYC is divided into five boroughs: the Bronx, Brooklyn, Queens, Manhattan and Staten Island. The data are organized in a panel of observations of 77 police precincts in NYC from January 1, 2004 to June 30, 2012. We combine two sets of data: police stops and adult entertainment establishment data. For robustness checks, we use police complaint data.

3.1 Sex crimes: "Stop-and-Frisk" data set

Sex crimes in the main specification are drawn from the NYPD "Stop-and-Frisk" data set which provides information on each "Stop-and-Frisk" encounter. This data set has three convenient features. First, it minimizes the problem of self-reporting of sex crimes, since the data comes directly from what the NYPD saw in the street. Previous studies have relied on self-reported measures, which most likely suffer from a high degree of non-random under-reporting. There are multiple reasons why respondents may under-report, including fear of the aggressor and the social stigma associated with victims of these crimes. Second, this data set can be easily used at the daily level since crimes are counted according to when the officers report it. Other data sets document information about crimes that happened during a given time period without documenting the number of occurrences. Thereby, it is difficult to compare them or to use them at the daily level. Third, the "Stop-and-Frisk" data have information on the exact position, hour and day of the crime, which is crucial for the analysis.

The "Stop-and-Frisk" data set contains 7,478 stops for sex crimes (sexual abuse and rape) in NYC.[16] Table 1 (Panel A) presents the summary statistics of sex crimes per day. We observe that on average only 0.0313 sex crimes were committed in each precinct per day. Sex crime data have substantial variation over years and precincts. Figure 1 shows that the number of sex crimes stayed roughly constant from 2004–2008, after which they peaked three times.

In addition, the total number of sex crimes presents considerable differences across boroughs. Table 1 (Panel B) shows that sex crimes are concentrated in the borough of Manhattan (3,844 during the 8.5-year study period). Brooklyn and Queens have roughly half as many sex crimes as Manhattan (1,464 and 1,646, respectively). These patterns motivate the inclusion of geographical fixed effects and time trends.

[16] Appendix Section A contains precise information on the categories used to count sex crime occurrences.

Since the total number of sex crimes also varies by season, we include month fixed effects in the analysis. Table 1 (Panel C) presents these results. The fewest sex crimes are committed in the winter. There is also substantial variation in the number of sex crimes committed across precincts within a given borough. For example, in Manhattan the highest proportion of sex crimes is concentrated in Precinct 14 (28%), followed by Precinct 13 (16%).[17]

Men commit 95% of sex crimes, and the percentage of such crimes committed by men on weekdays vs. weekends is relatively constant (Panel D of Table 1). Sex crimes are not concentrated on particular days of the week (Figure 2) or particular hours of the day.[18]

3.2 Adult entertainment establishments

The second data set was obtained from Reference USA and provides information on all registered adult entertainment establishments from 2004–2012 in NYC. It contains data about the year when each establishment was registered, the number of employees in each establishment and its geographic coordinates. Using businesses' records such as the Yellow Pages, Superpages, and the NY State Department of State records, we match almost every establishment with an opening and/or registration date, and sometimes also with a closing date.[19]

We use these two data sets to construct a panel counting the total number of establishments in each precinct for each day of the period of observation. We mainly used three sources to determine the opening date of the establishments. The first two are the Yellow Pages and Superpages, which are telephone directories of businesses organized by category. Advertising a business in these directories is free, and it takes at most five business days to get an establishment advertised after applying online. Since owners have to supply their name and phone number, the ads are likely to be accurate. The third source is the Department of the State of NY, which records every business in the state; for each business it provides detailed information including jurisdiction, address, current entity status, etc. In some cases the names of the establishments are different from those they used to register with the Department of the State of NY's database, so they cannot be

[17]Precincts 13 and 14 are both located in midtown Manhattan. The former is primarily a commercial and entertainment-oriented precinct. The latter is home to several residential complexes, insurance companies and major health care facilities. Further descriptions are available in the NYPD database.

[18]Table A.1 in Appendix Section B shows the total number of sex crimes committed on weekends vs. weekdays and divides weekend days into four different parts: morning (6 A.M. to 12 P.M.), afternoon (12 P.M. to 6 P.M.), evening (6 P.M. to 12 A.M.) and night (12 A.M. to 6 A.M.).

[19]We were able to match 90% of the adult entertainment establishments found in Reference USA. In our data set we observe only a closure of such establishments.

matched. This problem does not apply to Yellow Pages and Superpages, since the name of the registered business is the same as that used to register with Reference USA.

The number of adult entertainment establishments increased significantly during the period of observation from 76 in 2004 to approximately 280 in 2012. Thus, the data include roughly 200 openings of adult entertainment establishments during the 8.5-year study period. We use this variation to identify the effect of adult entertainment establishments on sex crime. Figure 3 displays the evolution of adult entertainment establishments during the sample period. Appendix Section C analyses the geographic evolution of such establishments across precincts.[20]

Column (2) of Table 1 (Panel B and C) shows that adult entertainment establishments' openings are concentrated in Manhattan (75%, 150 out of 206) and in the summer (34%, 70 out of 206). Table A.2 shows that the openings are roughly equally distributed between weekends and weekdays (90 vs. 116, respectively). Figure 4 illustrates that openings are not more likely to take place on a particular day of the week. The distribution of sex crimes over days of the week looks balanced: sex crimes do not appear to happen more often on a given day. Given these findings, we conclude that openings do not take place more likely on any particular day of the week.

3.3 Sex crimes: complaint data set

To check the robustness of our results in Section 5.4 we also use data on sex crimes from two different versions of the NYPD Complaint Data Historic.

First, we use the disaggregated data set at the daily level. We refer to this data set as the Complaint Disaggregated data set. This data set contains all valid felony, misdemeanor, and violation crimes reported by legal complaint to the NYPD. In this data set crimes are recorded according to the time range in which they took place (i.e. for each crime a starting date and an ending date can be reported and in some cases one of the two is missing). While the information is recorded, the classification is carried out in this way since the NYPD is concerned with how long the crime lasted. Yet, for our purposes we need to quantify how many times that crime occurred in a certain number of days.

Second, we use the aggregate version at the yearly level of the NYPD Complaint Data Historic. We refer to this data set as the Complaint Aggregated data set. This data set also contains all valid felony, misdemeanor, and violation crimes reported by legal complaint

[20] In addition, Appendix Figure A.9 shows the estimated coefficients and corresponding standard errors at 90% level of computing our main specification interacting our treatment variable with borough fixed effects. It is encouraging to find no borough exhibits a statistically positive estimated coefficient, two out of five boroughs exhibit statistically negative estimated coefficients and Manhattan is one of the two.

to the NYPD. However, this data set accumulates total crimes occurred at the precinct and year levels. This allows us to precisely quantify the number of times a certain offense takes place. This data set will be useful to compare the distribution of sex crimes across the two data sources (i.e. ”Stop-and-Frisk” and Complaint). Unlike the former database, these two data sets do not include any information on the aggressor. Moreover, none of these two data sets geocodes the location of sex crimes, but includes the precinct of occurrence, which allows for precinct-by-precinct comparisons.

Both data sets only include valid complaints. Complaints judged unfounded due to reporter mistakes or misinformation (or invalid due to internal errors) are excluded, since they are not reflected in official figures and thus are not considered to have occurred in a criminal context.[21] Also, since *mala prohibita* crimes do not require a complaint report, they may not be represented accurately, or at least in the Complaint Disaggregated data set. Such incidents are usually recorded using other department forms, such as arrests and summonses. These offenses include (but are not limited to) certain drug, trespassing, theft of service, and prostitution charges.

Appendix Section D compares descriptive statistics between the complaint data set and the ”Stop-and-Frisk” data set. The distribution of sex crimes in the complaint data set is substantially similar to that of the ”Stop-and-Frisk” data set.[22]

Unlike the ”Stop-and-Frisk” data set, data from the NYPD Complaint Data Historic might include domestic violence cases as sex crimes. This seems plausible for two reasons. First, the domestic violence category does not exist in this data set. Second, since these crimes happen indoor and are self-reported the victim might report domestic violence cases as sex crime.

4 Identification strategy

Similar to Dahl and DellaVigna (2009), we estimate the following specification:

$$\log\left(Sex\,Crime_{pt}\right) = \beta Adult\,Enter_{pt} + \Gamma X_{pt} + \varepsilon_{pt} \tag{1}$$

The dependent variable is the logarithm of one plus the number of sex crimes committed in precinct p on a given day t.[23] $Adult\,Enter_{pt}$ denotes the total number of adult en-

[21] Investigation reports are not included either, in order to guarantee relevance and lessen extraneous material.

[22] Figures similar to those explored for the ”Stop-and-Frisk” data set are available upon request.

[23] We use $\log\left(1+y\right)$ since our dependent variable takes a value of 0 on days that no sex crimes were committed. In Section 5 we test the robustness of this functional form.

tertainment establishments in precinct p for day t. This variable accumulates the opened businesses up until day t. X_{pt} represents a set of seasonal and geographic control variables: indicators for precinct, year, month, day of the week, day of the year and holidays, and geographic (precinct level) year trends. All standard errors are clustered at the precinct level.

The identification strategy relies on the exogeneity of variation in the time of openings and registration of adult entertainment establishments across precincts in NYC. The main assumption is that opening and registration dates are exogenous in a model of daily crime. Given that opening a business in NYC requires a long bureaucratic procedure we can take the day as random. Since our specification is daily, this amounts to the opening date of a business being exogenous to any other factor affecting sex crime. The comparability of the treatment and control groups boils down to the comparability of NYC police precincts over time. Thus, our specification captures any confounding factor that varies at the precinct or day level. The inclusion of precinct time trends ensures that $\hat{\beta}$ is not capturing any effect simply due to temporal changes in trends by precinct.[24]

One potential threat could be measurement error in the dependent variable and/or the explanatory variable. On the one hand, measurement error in the former could easily arise if we do not observe all the sex crimes committed in NYC (i.e. if sex crimes are committed but are not seen by the officers). However, assuming that the measurement error is random, this problem would produce larger standard errors, suggesting that the level of statistical significance of the coefficient is smaller than what we found. Measurement error is an issue in every crime data set, and even more in data related to sex crimes. Measurement error in the crime economics literature is mostly due to victims choosing not to report the crime (especially sex crimes). Nonetheless, we believe using the "Stop-and-Frisk" data set minimizes this concern since victims do not decide whether or not to report the crime. Therefore it seems reasonable to assume that there is less measurement error than in data sets based on complaints. On the other hand, measurement error in the explanatory variable might arise if these businesses are not registered in the Reference USA database. In this case, assuming that this measurement error is random would lead to attenuation bias, suggesting that the population regression function's coefficient is negative but larger in absolute value than our estimates.[25]

[24] A critique of this specification could be that the stable unit treatment value assumption is not satisfied, since the number of adult entertainment establishments in a precinct could affect the number of sex crimes in bordering precincts. We address this issue in the mechanism analysis (when we explore the *potential victims channel*).

[25] There is no reason to believe that some adult entertainment establishments would prefer not to appear in Reference USA since their activity is totally legal. Yet even if this were the case, there is no evidence to suggest that such mismeasurement would not be random.

5 Results

This section shows that adult entertainment businesses can reduce sex crimes by 13% per day per precinct. This result is robust to different specifications and to using different data sets to measure sex crimes. Moreover, effects are persistent over time and there is no evidence of the existence of pre-trends. Future openings of adult entertainment establishments have no effect on sex crimes.

5.1 The effect of adult entertainment establishments on sex crime

Table 2 presents the results. Column (1) presents the correlation between the opening of an adult entertainment establishment and sex crimes including precinct fixed effects. Columns (2) and (3) add month and year fixed effects. In all the specifications the coefficient is statistically significant and negative, indicating that having an adult entertainment establishment in a certain precinct is negatively associated with the number of sex crimes.

Since it is plausible that crime patterns may differ throughout the week, during the year and in holidays, Columns (4)–(6) present the results based on the day-of-the-week, day-of-the-year and holiday indicators, respectively. The results do not change.

Column (7) presents the results with the inclusion of precinct specific year trends, which increases the absolute value of the coefficient. This pattern suggests that omitted variables were attenuating the estimated coefficient. This is the preferred specification, it shows that having an adult entertainment establishment decreases the number of sex crimes by roughly 13% per day in a particular precinct .[26]

Since once taking into account precinct-year trends the estimated coefficient approximately doubles there could be the concern that the model oversaturates. This is not the case since we have about 238,000 observations and the inclusion of the trends simply implies we have a different trend for each of the 77 precincts in each of the 9 years of our sample period (i.e. 693 variables=77*9). Yet, to double check that our results are not driven by the inclusion of the precinct-year trends, we use Double LASSO techniques. This technique gets more ”parsimonious” trends by selecting the trends given an optimization problem that penalizes high coefficients and converges the irrelevant ones to

[26] Taking into account the transformation of the dependent variable, the effect can be computed using the following formula:

$$\frac{\partial \log(y)}{\partial x} = \frac{\partial \log(1+y)}{\partial x}\frac{\partial \log(y)}{\partial \log(1+y)} = \beta\frac{1+y}{y} \simeq \hat{\beta}\frac{1+\bar{y}}{\bar{y}} = -0.4\%\frac{1+0.0313}{0.0313} = -13.18\%$$

zero.[27] Appendix Section E presents our main findings using this methodology. Results do not change.[28]

5.2 Sensitivity to model specification changes and the definition of the dependent variable

This section explores the robustness of the results to different specifications. First, we replace the day-of-the-year and holiday indicators with exact-day indicators so that each day in the study period has its own fixed effect that captures any day-to-day differences. Second, we include precinct-month trends instead of precinct-year trends. Third, we include different precinct trends based on every month of each year and drop the precinct-year trends. The main difference is that precinct-year trends were varying in each precinct across years, while these are varying across each month of the year. For example, in this specification January 2004 has a different trend than both February 2004 and January 2005. Appendix Section F presents the results of running these specifications. In particular, Columns (1) to (3) in Appendix Table A.8 report the results of these three specifications. All estimates are negative and statistically significant in each of the three specifications, and the magnitude of the effect does not change.

Column (4) presents the estimates of specification (1), but only for sex crimes committed by male offenders. As before, we include all the fixed effects and precinct time trends in the specification. The results do not change, which is consistent with the fact that male offenders commit the large majority of sex crimes. In line with these results, Column (5) displays the outcomes of running this regression using the inverse hyperbolic sine (IHS) transformation of the dependent variable.

Appendix Table A.9 presents the results of using different transformations of the dependent variable. First, we apply the IHS transformation. In our main specification the dependent variable is $\log(1+y)$, while in this specification using the IHS it becomes $\log\left(y+(y^2+1)^{\frac{1}{2}}\right)$. The IHS is commonly used where there are fat tails (Pence 2006). Column (1) of Appendix Table A.9 shows the results of running such a regression. In line with our main findings, the estimated coefficient is statistically negative but larger in absolute value.

Another concern could be that the effect is driven by extreme values of the dependent variable. To address this issue, Columns (2) and (3) of Appendix Table A.9 correspond, respectively, to a probit and a linear probability model (LPM) using a dummy variable

[27]For further details this methodology is developed in Belloni et al. (2014).

[28]Further tables/figures using this methodology are available upon request.

that takes a value of 0 when no sex crimes are committed, and 1 otherwise. The coefficient of interest is negative and statistically significant at standard levels in the LPM. Finally, we estimate the model in levels form and find a negative, statistically significant coefficient in this case as well (Column(4) of Appendix Table A.9). In this specification, an extra establishment decreases sex crimes by 0.0076 units. This is equivalent to a 23% reduction.[29]

Our findings are also robust to changes in the time unit of the regression. Appendix Table A.10 shows the estimated coefficient if we run our main specification at weekly frequency. In the next section, we show the estimated coefficient at the monthly level as well, and the results do not change.

5.3 Falsification test

In this section we investigate whether the decrease in sex crimes is caused by a contemporaneous increase in adult entertainment establishments or by its leads or lags. This exercise serves as a falsification test since, if the identification assumption holds, future values of adult entertainment establishments should have no effect on sex crimes. In addition, it allows us to explore the timing of the effect, in other words, how long it takes for the effect to happen.

Our setting has two features that should be taken into account. On the one hand, the identification relies on the exogeneity of the variation in the timing of the openings and registration of adult entertainment establishments across precincts in NYC. On the other hand, the regressor of interest accumulates the number of adult entertainment establishments in a certain precinct. As Table 1 shows, there were 206 openings in the sample period. Hence, even collapsing the data set at the monthly level, the correlation of adjacent changes is extremely high (0.9983).

We break down this exercise in two different analysis. First, we check whether in our daily specification we find evidence that the effect of the establishments occurs after the registration day. We do so using a time window spanning from 1 day prior/posterior to 6 days (i.e. a week) prior/posterior. We refer to this analysis as *short run falsification test*. Second, we collapse our data at monthly level and check how long it takes for the effect to take place. We refer to this analysis as *long run falsification test*.

[29]This last specification is the most sensitive to extreme values, which is probably why the estimated coefficient is the largest (in absolute value) of all the specifications considered. Appendix Section H presents all the main results in levels. Such results are larger in absolute value but do not change.

5.3.1 Short run falsification test

We estimate the following specification:

$$\log\,(Sex\,Crime_{pt}) = \sum_{j=-J}^{J} \beta_j Adult\,Enter_{p,t+j} + \Gamma X_{pt} + \varepsilon_{pt} \tag{2}$$

where X_{pt} includes the same controls of our main regression model (i.e. specification (1)). J ranges from 1 to 6 to analyse different time windows. Note that each lag (lead) takes the value of the main regressor exactly $-j$ (j) days away from the opening. Similar to Autor (2003), the last lag takes the value of the main regressor $-J$ days away and forward. Column (1) of Table 3 presents the results for $J = 6$. Despite the high autocorrelation the pattern is clear: there is no effect till 6 days (or later) after the opening of the establishment. This evidence supports our identification strategy at daily level.

Columns (2) to (6) of Table 3 respectively display the results from $J = 5$ to $J = 1$. Such results show that in each of these regressions we find the very same pattern than in Column (1): it is always the final lag the largest one in absolute value and the only one statistically negative. These findings show further support for our identification strategy at daily level.[30]

5.3.2 Long run falsification test

Given that in the previous section we find support in favour of the identification strategy, the ensuing question is: how long does this effect take to happen? In this section we answer this question using a methodology similar to Dustmann and Fasani (2016). We collapse our data set at monthly level to span a longer time window. We consider the following regression model:

$$\log\,(Sex\,Crime_{pt}) = \sum_{j=-3}^{3} \beta_j Adult\,Enter_{p,t+j} + \Gamma X_{pt} + \varepsilon_{pt} \tag{3}$$

where X_{pt} includes month fixed effects, year fixed effects, precinct fixed effects and precinct-year time trends. $j = -3$ and $j = 3$ stand for a time window of three years prior and posterior to the year in which the establishment was opened. Columns (1), (2) and (3) of Table 4 respectively present the results of running regression model (3) using either only $Adult\,Enter_{p,t+3}$, $Adult\,Enter_{p,t+2}$ or $Adult\,Enter_{p,t+1}$. In these three regressions the

[30] Appenidix Table A.20 shows the results of replicating this falsification test using IHS transformation of the dependent variables. Results are robust to this specification.

estimated coefficient associated to any of these regressors is low in absolute value and statistically insignificant.

Columns (4) to (7) of Table 4 repeat the same analysis but only including either the contemporaneous (i.e. $j = 0$) number of adult entertainment establishments or its lag values. In these four regressions, the estimated coefficient associated to any of these regressors is at least about three times larger than any of the lead values and in all regressions, except the one with $Adult\,Enter_{p,t-3}$ (i.e. column (7)), statistically different from zero.

Column (8) shows the results of running regression model (3). Results of this regression are in line with columns (1) to (7) of Table 4. Estimated coefficients of lead values are positive and statistically equal to zero. While, estimated coefficients of lag values are negative. In addition, the one associated with $Adult\,Enter_{p,t-3}$ is about three times larger than the other estimated coefficients and statistically negative. Figure 5 shows the estimated coefficient with the respective 90% level confidence intervals of the regression model associated with Column (8).[31] In addition, Figure 6 presents the same graph but with Double LASSO selected precinct trends.[32] In both graphs we find evidence that the effect takes place in the long run and it is permanent (i.e. it lasts beyond the third year).

5.4 Representability of ”Stop-and-Frisk” data set

Sex crimes drawn from the ”Stop-and-Frisk” data represent only a share of all the sex crimes in NYC. If such data were not representative of all the sex crimes occurring in NYC, our findings would not be either.

In this section we address this issue in two different ways. First, we use high-frequency data drawn from the NYPD's historical complaints data set that fit into our specification. Second, we use aggregate (low-frequency) data to determine whether the ”Stop-and-Frisk” data set is representative of the patterns of all sex crimes recorded by the NYPD.

5.4.1 Disaggregated complaint data at high frequency

We build a database that includes complaint sex crimes and perform the same analysis as for our main specification. Columns (1) and (2) of Appendix Table A.22 present the results of this regression using the logarithmic transformation or the IHS, respectively.[33] In

[31] In Appendix Section I, Appendix Table A.21 and Figure A.10 show the results of replicating this falsification test using IHS transformation of the dependent variables.

[32] Appendix subsection E.2 presents the tables with Double LASSO selected precinct trends for both falsification tests. Results do not change.

[33] Table A.12 in Appendix Section H shows the results of running such regressions in levels.

both cases, the coefficient of interest is statistically negative at standard levels and larger in absolute value than the estimated coefficient of the main specification, indicating that indoor sex crimes decrease as well. We find that the opening of an adult entertainment business decreases sex crimes by approximately 7%.[34]

5.4.2 Aggregated complaint data at low frequency

This section explores whether sex crimes in the ″Stop-and-Frisk″ data set are representative of all sex crimes recorded in NYC. Using the complaints data set with our specification is problematic, since the occurrence of such crimes is not recorded on a daily basis. To solve this problem we use low-frequency data about all sex crimes committed in NYC, which is available from the NYPD.[35] This data already calculate the number of occurrences of each crime. Yet, since this data is at the precinct-year level, we cannot use it in our main specification or rely on the identification assumption. Therefore we run the following specification:

$$Sex\,CrimeSF_{pt} = \delta Sex\,CrimeNYPD_{pt} + \Gamma X_{pt} + \varepsilon_{pt} \tag{4}$$

where $Sex\,CrimeSF_{pt}$ and $Sex\,CrimeNYPD_{pt}$ are sex crimes from the ″Stop-and-Frisk″ and NYPD data set, respectively, and X_{pt} include year fixed effects, precinct fixed effects and precinct-year time trends. The correlation δ captures whether sex crimes from the two data sets are correlated, netting out time and geographic differences. Column (3) of Appendix Table A.22 shows the results for this specification. These findings demonstrate that even if the year-to-year changes and geographic distribution differ across the two data sets, and even if the number of sex crimes in the ″Stop-and-Frisk″ data set is lower than in the NYPD data set (7,478 reported sex crimes in the former, compared to 52,910 in the latter), the sex crimes from the ″Stop-and-Frisk″ data set can be representative of all sex crimes recorded in NYC.

Even taking precinct and year fixed effects and year trends into account, we find that sex crimes drawn from the ″Stop-and-Frisk″ data set are closely correlated with the complaint sex crimes. Column (4) of Appendix Table A.22 includes precinct-year trends, and we find that sex crimes drawn from the ″Stop-and-Frisk″ data set represent around 27%

[34] In this case, computations differ since the average value of the dependent variable is 0.1118. Therefore, using the same formula as before

$$\frac{\partial \log{(y)}}{\partial x} = \frac{\partial \log{(1+y)}}{\partial x}\frac{\partial \log{(y)}}{\partial \log{(1+y)}} = \beta\frac{1+y}{y} \simeq \hat{\beta}\frac{1+\bar{y}}{\bar{y}} = -0.7\%\frac{1+0.1118}{0.1118} = -6.96\%$$

[35] `http://www1.nyc.gov/site/nypd/stats/crime-statistics/historical.page`

of complaint sex crimes. In other words, for every four complaint sex crimes, there is one sex crime from the "Stop-and-Frisk" data set. The results at the IHS level are substantially similar. As a further robustness check, Appendix Table A.23 shows the same regression but using the Complaint Disaggregated data set at the daily level as the regressor. These two different measures of sex crimes are positively significantly correlated in this regression as well.

5.5 Sensitivity test: urban development

There might be the concern that our deterministic precinct trends do not capture urban development. To explore this concern, we collect data on the day of opening of Apple Stores and Starbucks across NYC. Hereafter, we refer to these two control variables as urban development controls.

In Appendix Table A.24 we present the results of running our main specification in logs including these two establishments as control variables. Panel A, B and C respectively present the results without trends, with trends and with Double LASSO selected trends. Moreover, Column (1), (2), (3) and (4) respectively present the results without urban development controls, only with Apple Stores, only with Starbucks and with both establishments. Results are reassuring, inclusion of urban development controls do not affect our coefficient. If at all, the effect seems to be larger in absolute value (i.e. the estimated coefficient is negative and larger in absolute values once we include both urban development controls). This would suggest that there is a positive correlation between urban development and adult entertainment establishments and, as a consequence, our estimates are a lower bound of the true effect. Appendix Tables A.25, A.26 and A.27 respectively repeat this analysis using the dependent variable in IHS, levels and LPM finding the same results.

5.6 Placebo test: randomization inference

To address the concern that the data are highly serially correlated across precincts, all our regressions are clustered at the precinct level. Yet, this section presents a further test to explore this concern. In this section we present the results of randomizing the number of adult entertainment establishments across precincts.[36]

Appendix Figures A.11 and A.12 present the results of randomizing the number of opened establishments stratified at the borough level with 1,000 permutations. In the

[36]Similar approaches and results are developed in Pinotti (2017) and Aglasan et al. (2017).

latter, the red vertical line represents the estimated coefficient in our main specification. The intersection between the red vertical line and the estimated distribution could be interpreted as the probability of finding the same effect found in our main specification by chance.

Figure A.12 shows that finding the same estimated coefficient as in our main specification is extremely unlikely: out of 1,000 permutations, none could replicate the estimate. This finding seems to exclude the possibility that our estimates were driven by serial correlation across precincts.[37] Appendix Section M presents the same figures without stratifying at the borough level.

6 Mechanisms driving the effect of adult entertainment establishments on sex crimes

This section explores three mechanisms that can help explain the decrease in sex crimes caused by adult entertainment establishments: police channel, potential victims channel and potential criminals channel. Each of these mechanisms can be tested using our database.

First, it could be the case that adult entertainment establishments reinforce security in the precinct if more police officers are assigned to the area. In this case, a decline in sex crimes could reflect a general decline in crime due to the higher number of officers present in the area after an establishment is opened (police channel).[38] Given our identification strategy, this would imply that the number of police officers increases at the same time (i.e. on the same day) that a new adult entertainment establishment opens in a certain precinct. Second, women may be avoiding precincts where adult entertainment businesses have opened and are moving to bordering precincts where there are no establishments. Thus, the decline in crime could be explained by a reduction in potential victims. It could also be the case that adult entertainment establishments are employing potential street sex workers who, in absence of opportunities for indoor prostitution, would work on the streets. If most sex crimes are committed against street sex workers, adult entertainment establishments might reduce sex crimes by merely providing protection to street workers (potential victims channel). Finally, potential offenders might prefer to use adult entertainment establishments services instead of committing sex crimes. As a matter of fact, these establishments are a major supplier of consensual sexual activities,

[37]These results are robust to using 10,000 permutations. Figures are available upon request.

[38]Draca et al. (2011) and Di Tella and Schargrodsky (2004) provide evidence on how increasing the number of police officers reduces crime.

and comprise a large share of the sex work market (see Urban Justice Center (2005)), so they are a cheaper alternative to committing sex crimes. To put it another way, they provide consensual sexual activities that could substitute forced sexual activities (potential criminals channel).[39]

6.1 Police channel

The ideal way to explore the police channel is to use data about the number of police officers working in each NYC precinct on each day. However, since this data is not publicly available, to explore this mechanism we estimate the effect of adult entertainment businesses on other crimes, such as the number of stops for drugs use and the number of burglaries from the "Stop-and-Frisk" data set. Table 5 presents the results of this specification. Each specification resembles Equation (1) but with a different dependent variable – the number of stops for drug use (Column (1)) and the number of burglaries (Column (3)). In these specifications we cluster the variance at the precinct level and include precinct, year, month, day-of-the-week, day-of-the-year and holiday indicators and precinct-year trends.

If sex crimes decline because there are more police officers in the area when an adult entertainment establishment opens, we should also find a decrease in the number of crimes that are more frequent and easier to control, such as burglaries and drug use. However, we find no effect of adult entertainment establishments on these crimes, suggesting that an increase in security is not the main channel behind the decline in sex crimes.

Furthermore, the results of this specification suggest that adult entertainment establishments have no effect on crimes other than sex crimes (e.g. drugs and burglaries, which might be affected by the number of these establishments). Columns (2) and (4) repeat the same analysis but using the IHS transformation of the two crimes, and again there is no significant effect. These results do not support the police channel. In Appendix Section N we provide further analysis and evidence by analyzing the effect of adult entertainment establishments on 10 different crimes. Table A.28 shows that we find no empirical evidence supporting the police channel. Furthermore, we run our two event study analyses using these 10 different crimes. No other crime presents a decrease pattern similar to that of sex crimes. Tables of such regressions are available upon request. These findings

[39]The hypothesis that consensual sexual activities are substitutes to non-consensual sexual activities (i.e. forced sexual activities) is consistent with evolutionary biological theories (see, inter alia, Thornhill and Thornhill (1983); Thornhill and Palmer (2000a,b)). These theories suggest that rape might be an evolutionary adaptive strategy: when individuals face the choice between forced sex (i.e. rape) and genetic extinction, they would unconsciously choose force in order to avoid the second outcome.

therefore do not support the police channel.[40]

6.2 Potential victims channel

To explore the potential victims channel, we estimate two models. First, to determine whether adult entertainment establishments are changing the location of street sex workers, we estimate specification (1) replacing the dependent variable with street prostitution stops. If this were the case, we would observe that adult entertainment establishments have a negative effect on street prostitution. The results of this specification are reported in Columns (1) and (2) (Panel A) of Table 6. We find no statistically significant effect on this new outcome. This result suggests that there has not been a reallocation of street sex workers to adult entertainment businesses, and it rules out the possibility that the decline in crime is driven by a reduction of street sex workers who could be the main potential victims of sex crimes in the street.[41]

The New York State Division of Criminal Justice Services classifies loitering as including "loitering for prostitution".[42] Thus, Columns (3) and (4) in Table 6 present the same analysis but for loitering. Both coefficients are positive and not statistically significant. Hence, we conclude that there is no evidence that the reduction in sex crimes is due to a reallocation of outdoor sex workers to indoor venues.

Second, we also analyze whether there is a spillover effect caused by women moving to other precincts. If women are simply avoiding precincts with adult entertainment establishments, we should observe an increase in sex crime in neighboring precincts. We consider a specification with 22 precincts in which we group precincts on the basis of their geographic position. For example, we group precincts 1, 5 and 7 together; precincts 6, 9, 10 and 13 together, and so on. A complete list of groupings is available in Appendix Section O. If the effect found is only due to women avoiding precincts with adult establishments, then we would observe sex crimes moving from one precinct to another. Therefore, this would imply that sex crimes are increasing in precincts with no establishments but which have neighboring precincts with at least one establishment. If this were the case, the total effect in larger precincts should compensate and be closer to zero than the main estimated

[40] These findings are in line with Linz et al. (2004).

[41] A further concern is that sex crimes transfer from other women to indoor prostitutes. Three points are worth mentioning in this regard. First, Section 5.4.1 provides evidence against this since indoor sex crimes decrease as well. Second, we acknowledge this concern would be difficult to address since there is evidence in the literature that prostitutes in the U.S. rarely report sex crimes (Anderson 2004). Third, there is evidence in the literature that adult entertainment establishments provide protection to their workers, making this concern particularly unlikely (Church et al. 2001; Shively et al. 2012).

[42] For further information, see Urban Justice Center (2005).

coefficient. If sex crimes are not moving, the coefficient should still be negative and larger in absolute value since we are taking into account larger geographic units.

Panel B in Table 6 presents the results. We still find a negative effect on sex crimes. Since in these regressions there are only 22 precincts, standard errors could be smaller due to the smaller number of clusters. Therefore, Columns (3) and (4) in Panel B present the same regressions but using wild cluster-bootstrap methods. The results do not change. Overall, the findings do not support the notion that women avoid precincts where adult entertainment establishments are located. In Appendix Section P, we also perform other robustness checks which provide further evidence that sex crimes are not moving to neighboring precincts.

6.3 Potential criminals channel

To address the potential criminals channel, we focus on sex crimes committed at night. If potential criminals prefer to use adult entertainment establishments services rather than commit sex crimes, the effect should be larger when the supply of the services offered by these establishments is higher. It seems plausible to assume that the supply of these services is higher at night, given that most of these establishments are only open at night.

We divide the day into four quarters – morning (from 6 A.M. to 12 P.M.), afternoon (from 12 P.M.to 6 P.M.), evening (from 6 P.M.to 12 A.M.) and night (from 12 P.M.to 6 A.M.) – and create four corresponding dummy variables and saturate the model with the interactions. Table 7 presents the results of the fixed effect at evening and night, and their corresponding interactions. As benchmarks, Columns (1) and (3) of this table present the results for our logarithmic transformation and IHS, respectively, without the interactions. Columns (2) and (4) present the results of the fully saturated model. The results in Table 7 corroborate the initial finding: the two interaction coefficients are jointly statistically significant and negative at the 1% level. In addition, their total effect is statistically different from zero at the 10% level. These results imply that we cannot reject the potential criminals channel.

7 Conclusion

This paper presents the first causal estimates of the effect of adult entertainment establishments on sex crimes. Using high-frequency daily data for all NYC, we find that opening adult entertainment establishments reduces sex crimes by 13%, and that these effects are driven by potential customers who substitute sex crimes with services provided by adult entertainment businesses.

These results have several policy implications. First, while previous academic and policy research has focused on the role of deterrence policies, here we focused on an alternative tool – providing legal substitute services. Second, adult entertainment establishments appear to be a viable alternative to decriminalizing prostitution. Indeed, their effect on rape is similar to the one of decriminalizing prostitution, but prostitution law is a contentious issue, regulation of these establishments is not. Third, the fact that these services are legal may explain why we do not find an increase in other types of crimes. Fourth, the results show that providing substitute services may have positive externalities not only for sex workers but also for all women in the areas where these businesses opened.

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Tables and Figures

Table 1: Descriptive statistics sex crimes and adult entertainment establishments

Panel A

	Sex crimes	Adult enter. est.
Observations	238,931	238,931
Mean	0.031	1.957
Standard Deviation	0.341	5.128

Panel B

	Sex crimes by borough	Openings by borough
The Bronx	454	10
Brooklyn	1,464	20
Manhattan	3,844	150
Queens	1,646	24
Staten Island	170	2
Total	7,478	206

Panel C

	Sex crimes by season	Openings by season
Winter	1,554	42
Spring	1,894	39
Summer	2,115	70
Fall	1,915	55
Total	7,478	206

Panel D

	Sex crimes by male offenders (per day)	Percentage over total
Weekend	2,431	95.9%
-Friday	1,013	96.85%
-Saturday	712	95.57%
-Sunday	706	94.89%
Weekdays	4,776	96.62%
Total	7,207	96.38%

Notes: Panel A presents descriptive statistics (mean and standard deviation) during our sample period for sex crimes and adult entertainment establishments. The two statistics are computed using daily data. Panels B and C present the distribution of sex crimes and openings of adult entertainment establishments in our sample period by NYC borough and season, respectively. Panel D presents the distribution of sex crimes committed by male offenders by day of the week. Column (1) presents the absolute frequency, while Column (2) presents the percentual frequency. As expected, male offenders commit almost 90% of all such crimes. Further sex crimes are not concentrated on weekends.

Table 2: The effect of adult entertainment establishments on sex crimes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Adult Entertainment Est.	-0.00209**	-0.00214**	-0.00215**	-0.00215**	-0.00215**	-0.00215**	-0.00401*
	(0.000855)	(0.000947)	(0.000947)	(0.000947)	(0.000948)	(0.000948)	(0.00217)
Observations	238,931	238,931	238,931	238,931	238,931	238,931	238,931
Clustered variance at Precinct level	Y	Y	Y	Y	Y	Y	Y
Precinct FE	Y	Y	Y	Y	Y	Y	Y
Year FE		Y	Y	Y	Y	Y	Y
Month FE			Y	Y	Y	Y	Y
Day of the week FE				Y	Y	Y	Y
Day of the year FE					Y	Y	Y
Holiday FE						Y	Y
Precinct Trends							Y
Mean of Sex Crime	0.0313	0.0313	0.0313	0.0313	0.0313	0.0313	0.0313
Std Deviation of Sex Crime	0.3405	0.3405	0.3405	0.3405	0.3405	0.3405	0.3405

Notes: This table presents the results of running specification (1). The dependent variable is the logarithm of one plus the number of sex crimes committed in precinct p on a given day t. $Adult\ Enter_{pt}$ denotes the total number of adult entertainment establishments in precinct p on day t. This variable cumulates all the opened businesses up to day t. X_{pt} is a set of seasonal and geographic control variables: indicators for precinct, year, month, day-of-the-week, day-of-the-year and holidays, and geographic (at precinct level) year trends. All standard errors are clustered at the precinct level. Note that besides the classical year and month fixed effects, our daily specification allows us to include day-of-the-week, day-of-the-year and holiday fixed effects to capture deeper variation due to timing factors. In each column we add a different control. Clustered standard errors at the precinct level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3: Short run falsification test

	(1)	(2)	(3)	(4)	(5)	(6)
6 days prior	-0.000209					
	(0.000288)					
5 days prior	-2.47e-05	-2.69e-05				
	(0.000944)	(0.000940)				
4 days prior	-0.00146	-0.00146	-0.00147			
	(0.00109)	(0.00109)	(0.00108)			
3 days prior	0.000720	0.000716	0.000719	0.000739		
	(0.000667)	(0.000669)	(0.000670)	(0.000685)		
2 days prior	0.000253	0.000256	0.000237	0.000245	0.000237	
	(0.000865)	(0.000861)	(0.000878)	(0.000877)	(0.000874)	
1 day prior	-6.03e-06	-1.12e-05	1.58e-07	-1.30e-06	-6.32e-06	-1.39e-05
	(0.000307)	(0.000296)	(0.000312)	(0.000314)	(0.000309)	(0.000307)
0	-6.63e-05	-6.54e-05	-6.24e-05	-5.64e-05	-5.51e-05	-6.78e-05
	(0.000594)	(0.000598)	(0.000581)	(0.000574)	(0.000578)	(0.000576)
1 day after	0.000931	0.000933	0.000931	0.000946	0.000944	-0.00391*
	(0.000765)	(0.000760)	(0.000759)	(0.000756)	(0.000761)	(0.00212)
2 days after	-0.000282	-0.000283	-0.000277	-0.000304	-0.00388*	
	(0.000201)	(0.000203)	(0.000210)	(0.000195)	(0.00209)	
3 days after	0.000109	0.000114	0.000124	-0.00381*		
	(0.000608)	(0.000613)	(0.000617)	(0.00206)		
4 days after	-0.00117	-0.00116	-0.00378*			
	(0.00130)	(0.00129)	(0.00206)			
5 days after	-0.000508	-0.00369*				
	(0.000381)	(0.00200)				
6 days after	-0.00370*					
	(0.00203)					
Observations	238,931	238,931	238,931	238,931	238,931	238,931
Clustered variance at Precinct level	Y	Y	Y	Y	Y	Y
Precinct FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
Precinct Trends	Y	Y	Y	Y	Y	Y
# of days	6	5	4	3	2	1

Notes: This table presents the results of running specification (2). The dependent variable is in logs. J ranges from 1 to 6 to analyse different time windows. Note that each lag (lead) takes the value of the main regressor exactly $-j$ (j) days away from the opening. The last lag takes the value of the main regressor $-J$ days away and forward. Column (1) presents the results for $J = 6$. Columns (2) to (6) respectively display the results for $J = 5$ to $J = 1$. X_{pt} represents a set of seasonal and geographic control variables: indicators for precinct, year, month, day of the week, day of the year and holidays, and geographic (precinct level) year trends. Clustered standard errors at the precinct level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Long run falsification test

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
3 years prior	-0.00799							0.0267
	(0.0128)							(0.0401)
2 years prior		-0.00403						0.0211
		(0.0155)						(0.0403)
1 year prior			-0.0106					0.0273
			(0.0127)					(0.0332)
0				-0.0314*				-0.0678
				(0.0185)				(0.0807)
1 year after					-0.0406**			-0.0367
					(0.0199)			(0.0624)
2 years after						-0.0696**		-0.0390
						(0.0298)		(0.0465)
3 years after							-0.0742	-0.121*
							(0.0457)	(0.0650)
Observations	5,082	6,006	6,930	7,854	6,930	6,006	5,082	2,310
Clustered variance at Precint level	Y	Y	Y	Y	Y	Y	Y	Y
Precinct FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	Y	Y
Precinct Trends	Y	Y	Y	Y	Y	Y	Y	Y

Notes: This table presents the results of running specification (3) where X_{pt} includes month fixed effects, year fixed effects, precinct fixed effects and precinct-year time trends. Columns (1), (2) and (3) respectively present the results of running regression model (3) using either only $t+3$, $t+2$or $t+1$. Columns (4) to (7) of Table 4 repeat the same analysis but only including either the contemporaneousvalue or its corresponding lags. Column (8) shows the results of running the full regression model given by specification (3). These results confirm that the effect takes place after the registration of the establishment, column (8) suggests that the effect is permanent and does not disappear after three years or more. Clustered standard errors at the precinct level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Police channel

	(1) Log drug stops	(2) IHS drug stops	(3) Log burglaries	(4) IHS burglaries
Adult Entertainment Est.	0.00539	0.0108	-0.00769	-0.0154
	(0.00797)	(0.0159)	(0.0137)	(0.0274)
Observations	238,931	238,931	238,931	238,931
Clustered variance at Precinct level	Y	Y	Y	Y
Precinct FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
Day of the week FE	Y	Y	Y	Y
Day of the year FE	Y	Y	Y	Y
Holiday FE	Y	Y	Y	Y
Precinct Trends	Y	Y	Y	Y

Notes: This table presents the results of exploring the police channel. Columns (1) and (3) present the results of the baseline regression, while Columns (2) and (4) present the results for the IHS of drug stops and burglaries drawn from the Stop-and-Frisk data set, respectively. If sex crimes are decreasing because the number of officers increases in precincts where an adult entertainment establishment opens, other crimes should also decrease–particularly crimes that happen more frequently and that are easier to catch, such as drug stops and burglaries. Clustered standard errors at the precinct level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 6: Potential victims channel

	(1)	(2)	(3)	(4)
Panel A				
	Log street prostitutes	IHS street prostitutes	Log loitering	IHS loitering
Adult Entertainment Est.	-0.000636	-0.00127	0.00149	0.00299
	(0.00114)	(0.00227)	(0.000997)	(0.00199)
Observations	238,931	238,931	238,931	238,931
Clustered variance at Precinct level	Y	Y	Y	Y
	(1)	(2)	(3)	(4)
Panel B				
	Log sex crimes	IHS sex crimes	Log sex crimes	IHS sex crimes
Adult Entertainment Est.	-0.00686***	-0.0137***	-0.00686**	-0.0137**
	(0.00223)	(0.00446)	(0.00334)	(0.00668)
Observations	68,266	68,266	68,266	68,266
Clustered variance at Precinct level	Y	Y	Wild	Wild
Precinct FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
Day of the week FE	Y	Y	Y	Y
Day of the year FE	Y	Y	Y	Y
Holiday FE	Y	Y	Y	Y
Precinct Trends	Y	Y	Y	Y

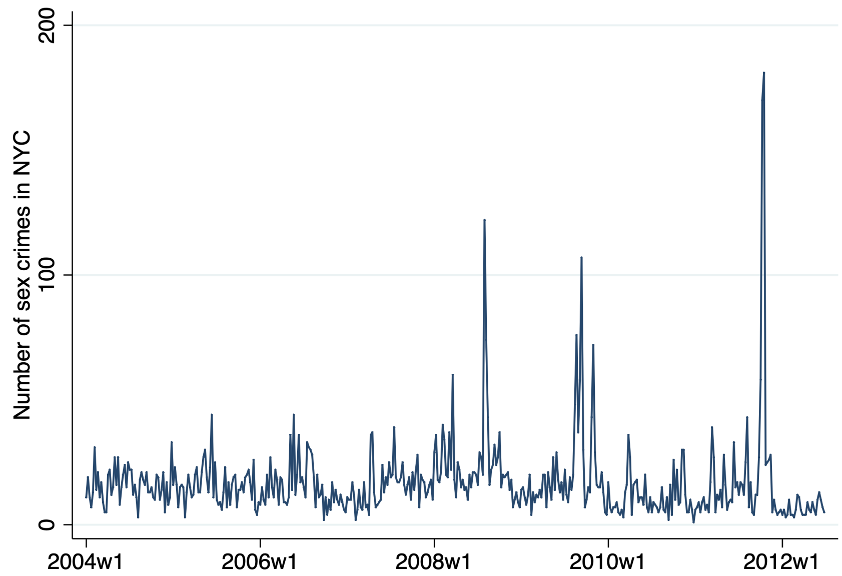
Notes: Panel A presents the results of exploring the potential victims channel. Columns (1) and (2) present the results for the baseline regression using log and IHS of street prostitutes. If sex crimes are decreasing because street prostitutes, who were victims of sex crimes before, are now working in adult entertainment establishments we would observe a statistical negative estimated coefficient. The results suggest that this is not the case. Columns (3) and (4) repeat the analysis using as dependent variable the stops for loitering. Panel B presents results for the baseline regression using log and IHS of sex crimes but using bigger precincts. These precincts were chosen according to their geographic distance. A complete list of the new precincts can be found in the appendix. If women are avoiding precincts where adult entertainment establishments open, we should find either a statistically negative but smaller estimated coefficient in absolute value, a statistically positive coefficient or a coefficient that is statistically equal to zero. In both cases the estimated coefficients are negative and larger in absolute value than the ones in our baseline regression. This evidence rejects the potential victims channel. Clustered standard errors at the precinct level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 7: Potential criminal channel

	(1) Log sex crimes	(2) Log sex crimes	(3) IHS sex crimes	(4) IHS sex crimes
Adult Entertainment Est.	-0.00114*	-0.000373	-0.00229*	-0.000746
	(0.000619)	(0.000292)	(0.00124)	(0.000584)
Dummy Evening		0.00160**		0.00320**
		(0.000715)		(0.00143)
Dummy Night		0.00105		0.00211
		(0.00101)		(0.00202)
Interaction Evening		-0.000954*		-0.00191*
		(0.000567)		(0.00113)
Interaction Night		-0.00146		-0.00292
		(0.000939)		(0.00188)
Observations	955,724	955,724	955,724	955,724
Clustered variance at Precinct level	Y	Y	Y	Y
Precinct FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
Day of the week FE	Y	Y	Y	Y
Day of the year FE	Y	Y	Y	Y
Holiday FE	Y	Y	Y	Y
Precinct Trends	Y	Y	Y	Y
p-value joint effect		0.0841		0.0841
p-value		0.00792		0.00792

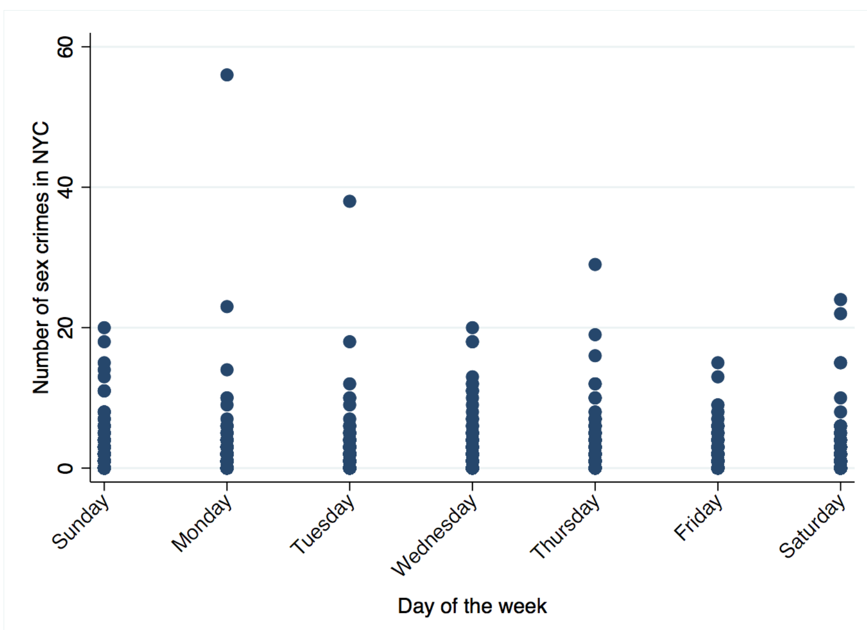
Notes: This table presents specification (1) separating the day in four quarters: morning, afternoon, evening and night and saturating the specification including the dummy variables for three quarters out of four (morning is the base group) – morning (from 6 A.M. to 12 P.M.), afternoon (from 12 P.M.to 6 P.M.), evening (from 6 P.M.to 12 A.M.) and night (from 12 P.M.to 6 A.M.) – and the interactions with the main regressor. As benchmarks, Columns (1) and (3) of this table present the results for our logarithmic transformation and IHS, respectively, without the interactions. Columns (2) and (4) present the results of the fully saturated model. Results of this table corroborate the initial finding: the two interaction coefficients are jointly statistically significant and negative at the 1% level. In addition, their total effect is statistically different from zero at the 10% level. These results imply that we cannot reject the potential criminals channel. Clustered standard errors at the precinct level in parentheses. ***p<0.01, **p<0.05, *p<0.1

Figure 1: Evolution of sex crimes in NYC from January 2004 to June 2012



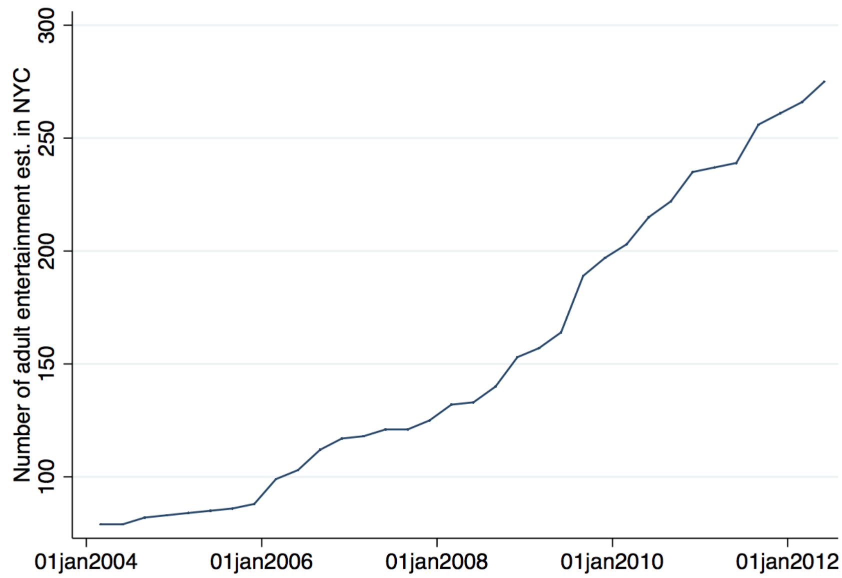
Notes: This figure shows the evolution of sex crimes in NYC between January 1, 2004 and June 30, 2012. For this picture, data has been collapsed weekly. Note in 2012 we only have data till June.

Figure 2: Distribution of sex crimes over days of the week



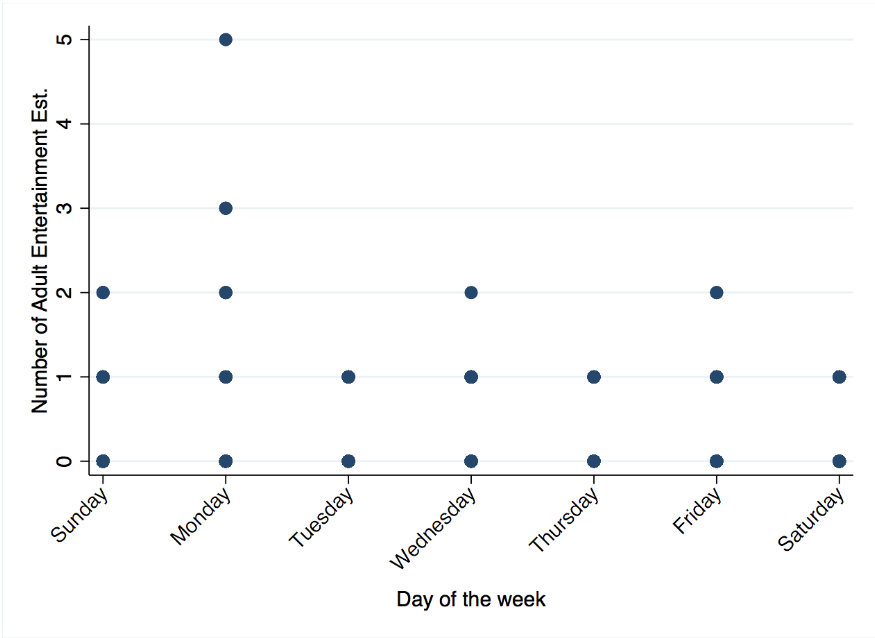
Notes: This figure shows the distribution of sex crimes across days of the week in NYC during the study period.

Figure 3: Evolution of adult entertainment establishments from January 2004 to June 2012



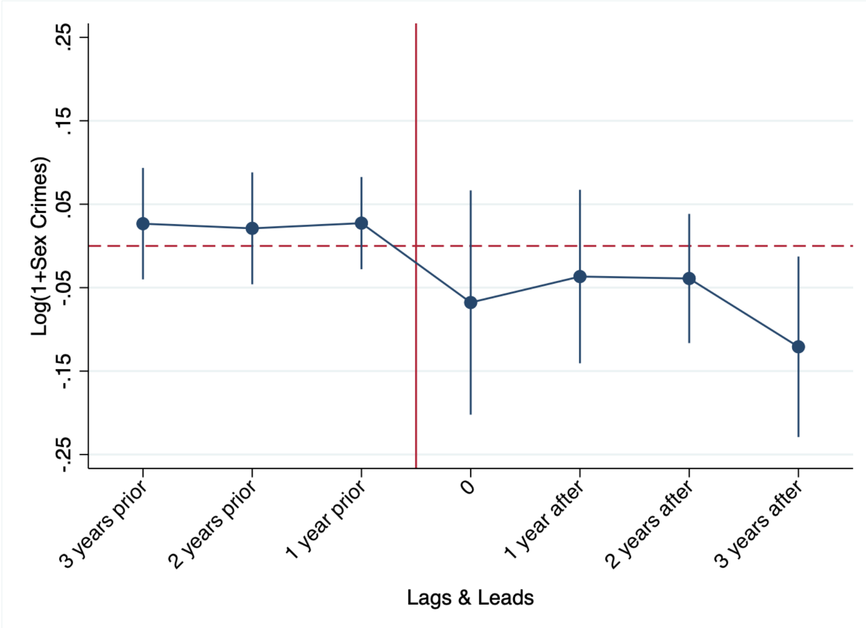
Notes: This figure shows the evolution of adult entertainment establishments in NYC during the study period.

Figure 4: Opening of adult entertainment establishments by day of the week



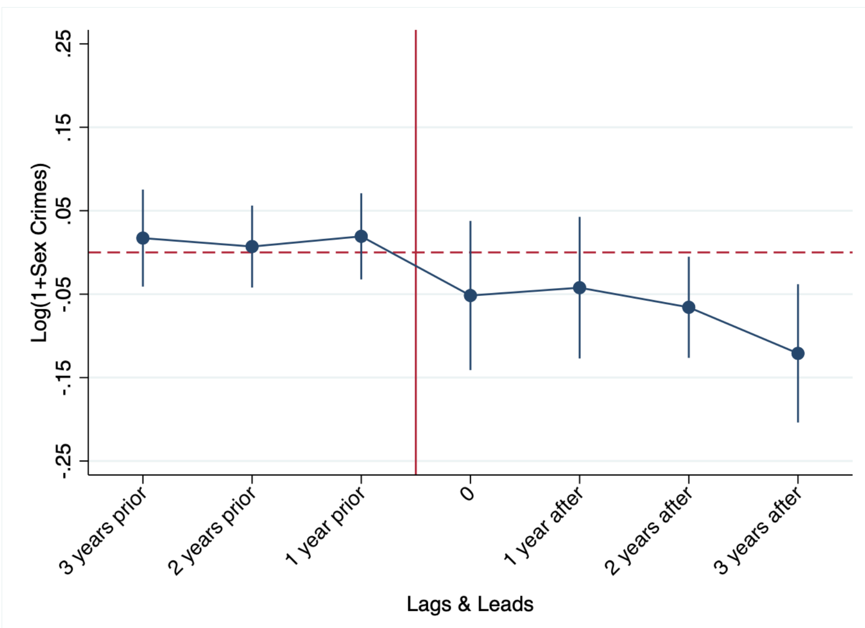
Notes: This figure shows the distribution of the day of opening of adult entertainment establishments across days of the week in NYC during the study period.

Figure 5: Long run falsification test



Notes: This figure shows the estimated coefficients of $\sum_{j=-3}^{3} \beta_j Adult\ Enter_{p,t+j}$ in specification (3).

Figure 6: Long run falsification test using Double LASSO techniques



Notes: This figure shows the estimated coefficients of $\sum_{j=-3}^{3} \beta_j Adult\ Enter_{p,t+j}$ in specification (3) with Double LASSO selected precinct-year trends.

Appendix

A Classification of crimes in the ”Stop-and-Frisk” data set

The ”Stop-and-Frisk” data set classifies crime using the following 113 categories. We classified sex crimes using categories 7, 18, 77, 87 and 88. A possible concern could be whether sex crimes contain public lewdness crimes. Such crimes are connected to sex crimes but are considerably different from them. Yet, as this table shows such crimes are classified in category 76.

1	ABANDONMENT OF A CHILD
2	ABORTION
3	ABSCONDING
4	ADULTERY
5	AGGRAVATED ASSAULT
6	AGGRAVATED HARASSMENT
7	AGGRAVATED SEXUAL ABUSE
8	ARSON
9	ASSAULT
10	AUTO STRIPPING
11	BIGAMY
12	BRIBE RECEIVING
13	BRIBERY
14	BURGLARY
15	COERCION
16	COMPUTER TAMPERING
17	COMPUTER TRESPASS
18	COURSE OF SEXUAL CONDUCT
19	CPSP
20	CPW
21	CREATING A HAZARD
22	CRIMINAL CONTEMPT
23	CRIMINAL MISCHIEF
24	CRIMINAL POSSESSION OF CONTROLLED SUBSTANCE
25	CRIMINAL POSSESSION OF COMPUTER MATERIAL
26	CRIMINAL POSSESSION OF FORGED INSTRUMENT
27	CRIMINAL POSSESSION OF MARIJUANA
28	CRIMINAL SALE OF CONTROLLED SUBSTANCE
29	CRIMINAL SALE OF MARIJUANA
30	CRIMINAL TAMPERING
31	CRIMINAL TRESPASS
32	CUSTODIAL INTERFERENCE
33	EAVES DROPPING
34	ENDANGER THE WELFARE OF A CHILD
35	ESCAPE
36	FALSIFY BUSINESS RECORDS
37	FORGERY
38	FORGERY OF A VIN
39	FORTUNE TELLING
40	FRAUD
41	FRAUDULENT ACCOSTING
42	FRAUDULENT MAKE ELECTRONIC ACCESS DEVICE
43	FRAUDULENT OBTAINING A SIGNATURE
44	GAMBLING
45	GRAND LARCENY
46	GRAND LARCENY AUTO
47	HARASSMENT
48	HAZING
49	HINDERING PROSECUTION
50	INCEST
51	INSURANCE FRAUD
52	ISSUE A FALSE CERTIFICATE
53	ISSUE A FALSE FINANCIAL STATEMENT
54	ISSUING ABORTION ARTICLES
55	JOSTLING
56	KIDNAPPING

57	KILLING OR INJURING A POLICE ANIMAL
58	LOITERING
59	MAKING GRAFFITI
60	MENACING
61	MISAPPLICATION OF PROPERTY
62	MURDER
63	OBSCENITY
64	OBSTRUCTING FIREFIGHTING OPERATIONS
65	OBSTRUCTING GOVERNMENTAL ADMINISTRATION
66	OFFERING A FALSE INSTRUMENT
67	OFFICIAL MISCONDUCT
68	PETIT LARCENY
69	POSSESSION OF BURGLAR TOOLS
70	POSSESSION OF EAVES DROPPING DEVICES
71	POSSESSION OF GRAFFITI INSTRUMENTS
72	PROHIBITED USE OF WEAPON
73	PROMOTING SUICIDE
74	PROSTITUTION
75	PUBLIC DISPLAY OF OFFENSIVE SEXUAL MATERIAL
76	PUBLIC LEWDNESS
77	RAPE
78	RECKLESS ENDANGERMENT
79	RECKLESS ENDANGERMENT PROPERTY
80	REFUSING TO AID A PEACE OR POLICE OFFICER
81	RENT GOUGING
82	RESISTING ARREST
83	REWARD OFFICIAL MISCONDUCT
84	RIOT
85	ROBBERY
86	SELF ABORTION
87	SEXUAL ABUSE
88	SEXUAL MISCONDUCT
89	SEXUAL PERFORMANCE BY A CHILD
90	SODOMY
91	SUBSTITUTION OF CHILDREN
92	TAMPERING WITH A PUBLIC RECORD
93	TAMPERING WITH CONSUMER PRODUCT
94	TAMPERING WITH PRIVATE COMMUNICATIONS
95	TERRORISM
96	THEFT OF SERVICES
97	TRADEMARK COUNTERFEITING
98	UNLAWFULLY DEALING WITH FIREWORKS
99	UNAUTHORIZED RECORDING
100	UNAUTHORIZED USE OF A VEHICLE
101	UNAUTHORIZED USE OF COMPUTER
102	UNLAWFUL ASSEMBLY
103	UNLAWFUL DUPLICATION OF COMPUTER MATERIAL
104	UNLAWFUL POSSESSION OF RADIO DEVICES
105	UNLAWFUL USE OF CREDIT CARD, DEBIT CARD
106	UNLAWFUL USE OF SECRET SCIENTIFIC MATERIAL
107	UNLAWFUL WEARING A BODY VEST
108	UNLAWFUL IMPRISONMENT
109	UNLAWFULLY DEALING WITH A CHILD
110	UNLAWFULLY USE SLUGS
111	VEHICULAR ASSAULT
112	OTHER
113	FORCIBLE TOUCHING

Notes: This table shows all the 113 categories of crimes in the ”Stop-and-Frisk” data set.

B Sex crimes by hour and day

Table A.1: Total number of sex crimes by day of the week and time of the day

	Sex Crimes (per day)				
		Morning	Afternoon	Evening	Night
	Entire day	6 A.M. to 12 P.M.	12 P.M. to 6 P.M.	6 P.M. to 12 A.M.	12 A.M. to 6 A.M.
	(1)	(2)	(3)	(4)	(5)
Sex crime data					
Weekend	2,535	444	539	781	771
-Friday	1,046	253	243	322	228
-Saturday	745	78	157	253	257
-Sunday	744	113	139	206	286
Weekdays	4,943	1,567	1,154	1,359	863
Total	7,478	2,011	1,693	2,140	1,634

Notes: This table presents the distribution of sex crimes over weekdays and time of the day. Time of the day is divided in 4 shifts of 6 hours each: morning (6 am to 12pm), afternoon (12pm to 6pm), evening (6pm to 12 am) and night (12am to 6pm).

Table A.2: Total number of openings by day of the week

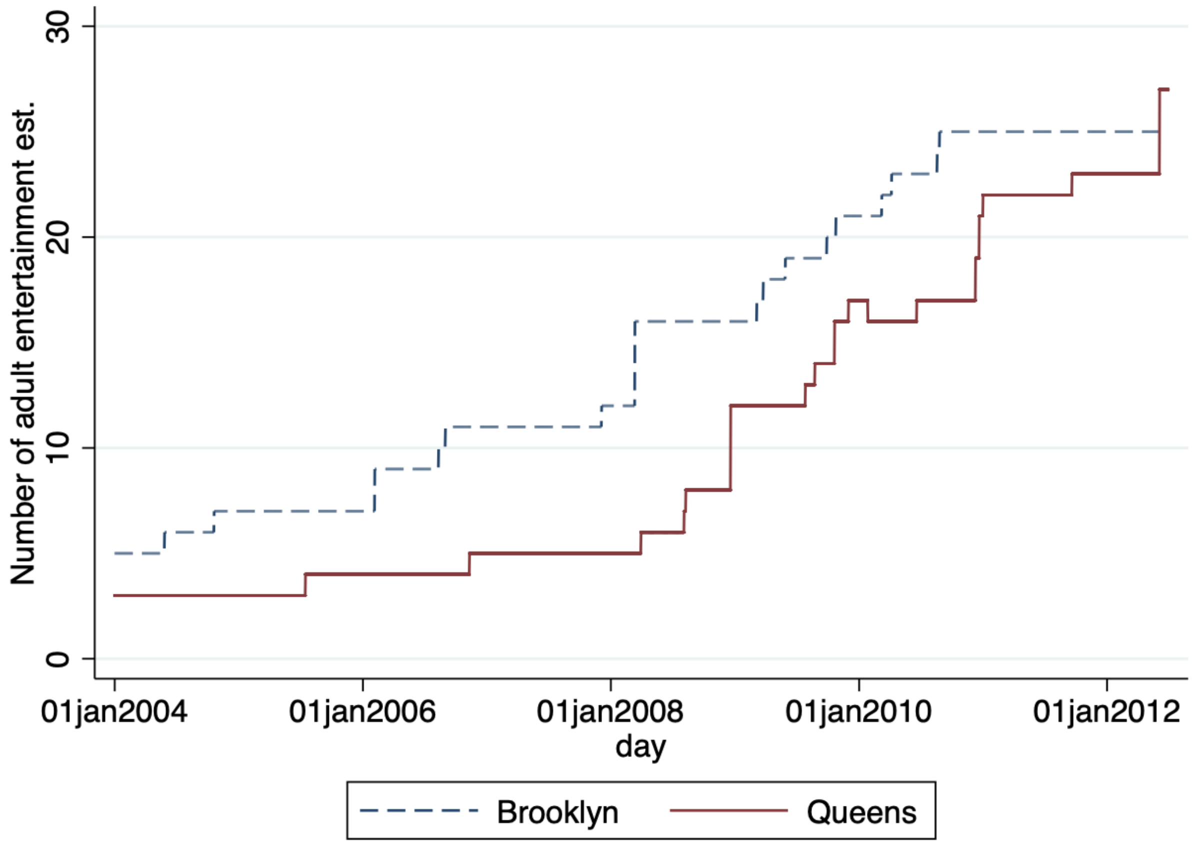
	Openings (per day)
Weekend (Friday-Sunday)	90
-Friday	30
-Saturday	20
-Sunday	40
Weekdays (Monday-Thursday)	116

Notes: This table presents the number of openings of adult entertainment establishments by day of the week.

C Geographic evolution of adult entertainment establishments by precinct

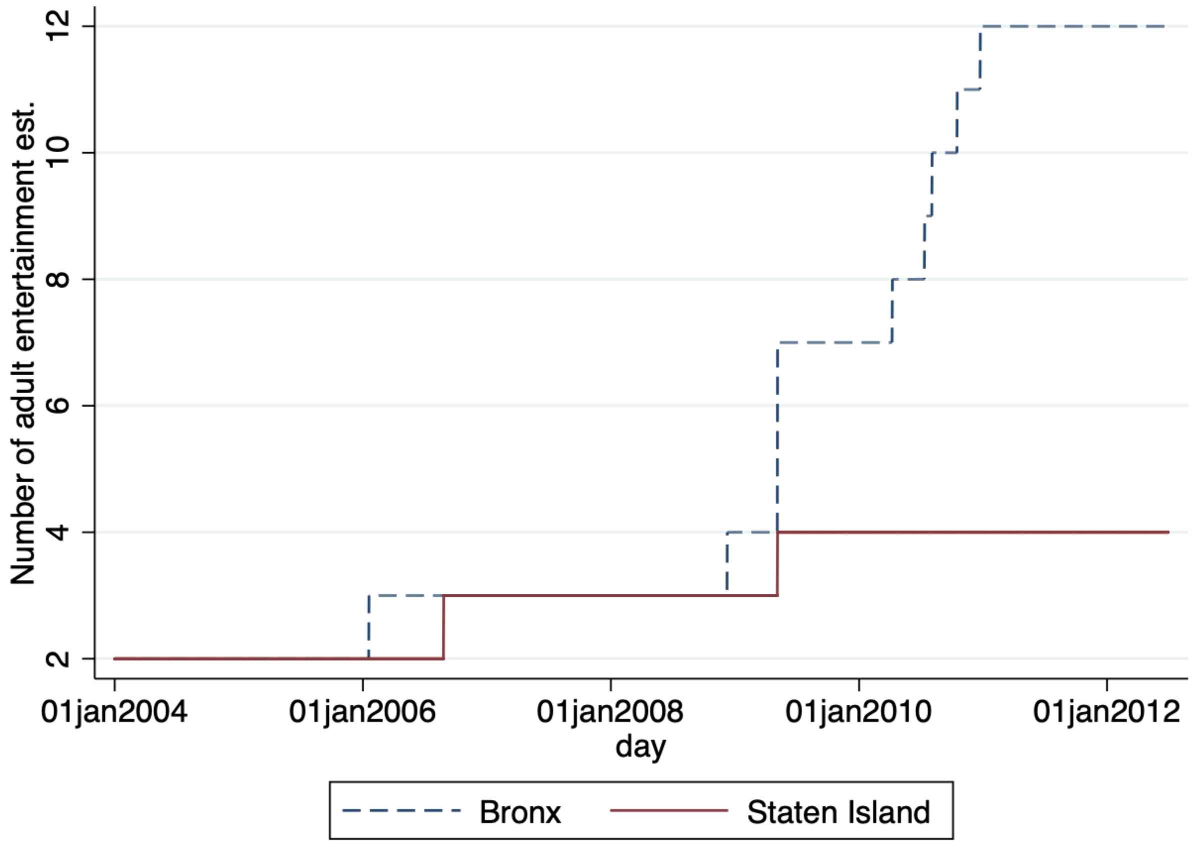
The figures below show the evolution at daily level of adult entertainment establishments disaggregated at borough level.

Figure A.1: Evolution of adult entertainment establishments from January 2004 to June 2012: Brooklyn and Queens



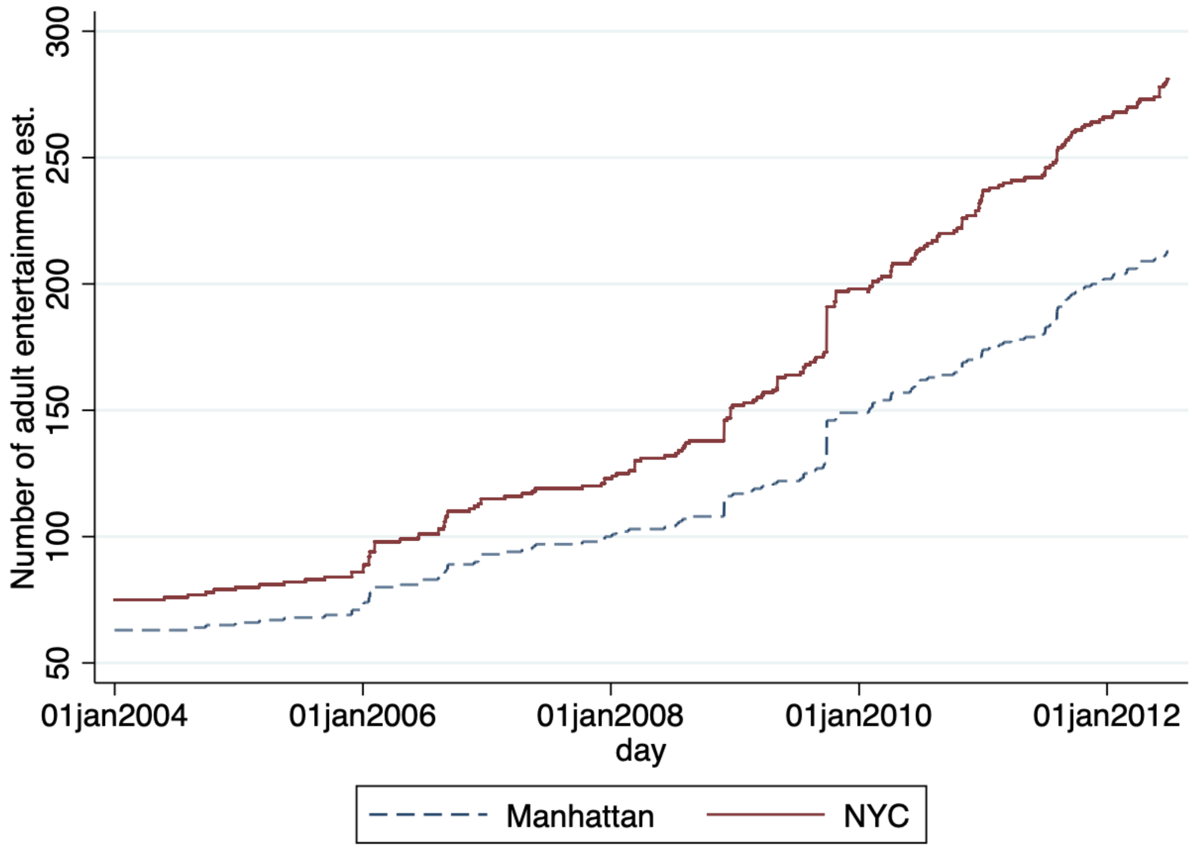
Notes: This figure shows the evolution of adult entertainment establishments in Brooklyn and Queens during the study period.

Figure A.2: Evolution of adult entertainment establishments from January 2004 to June 2012: The Bronx and Staten Island



Notes: This figure shows the evolution of adult entertainment establishments in The Bronx and Staten Island during the study period.

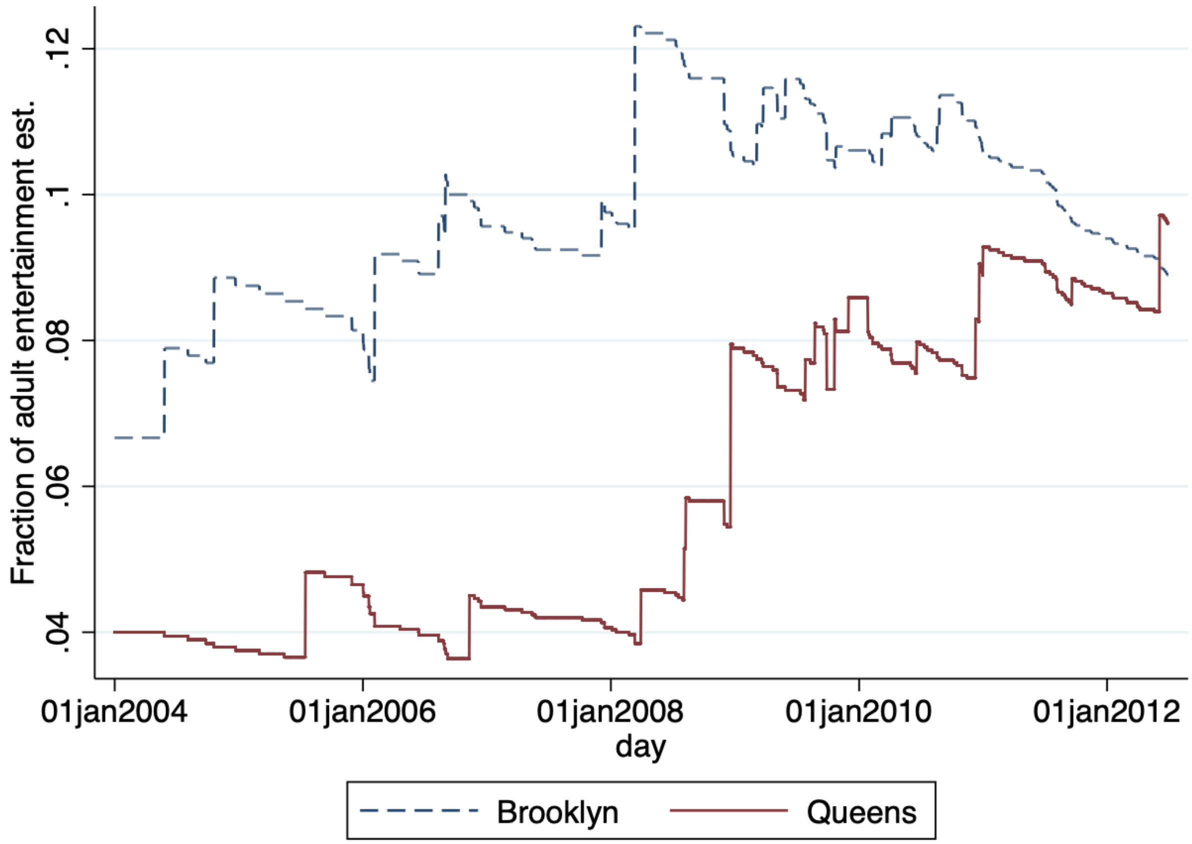
Figure A.3: Evolution of adult entertainment establishments from January 2004 to June 2012: Manhattan and NYC



Notes: This figure shows the evolution of adult entertainment establishments in Manhattan and NYC during the study period.

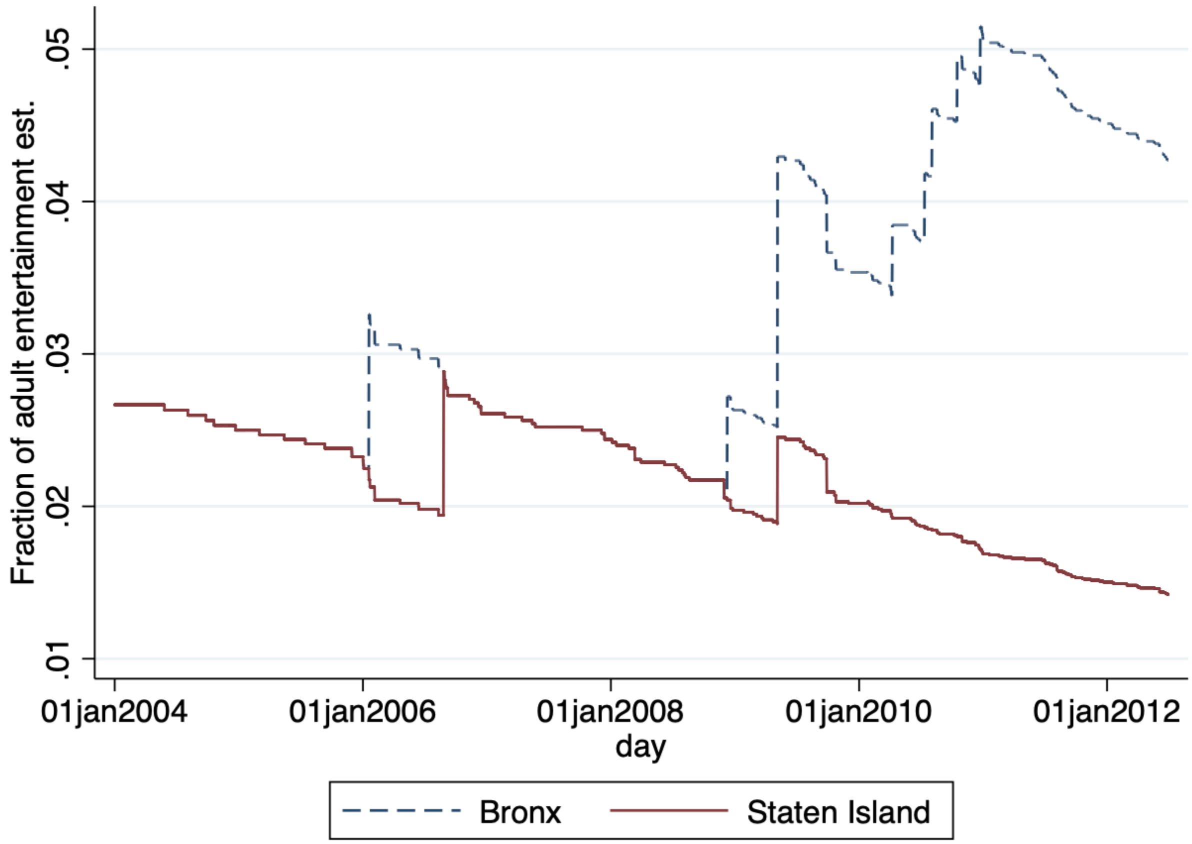
The figures below show the evolution at daily level of the fraction of adult entertainment establishments (with respect to the total) disaggregated at borough level.

Figure A.4: Evolution of the fraction of adult entertainment establishments (with respect to the total) from January 2004 to June 2012: Brooklyn and Queens



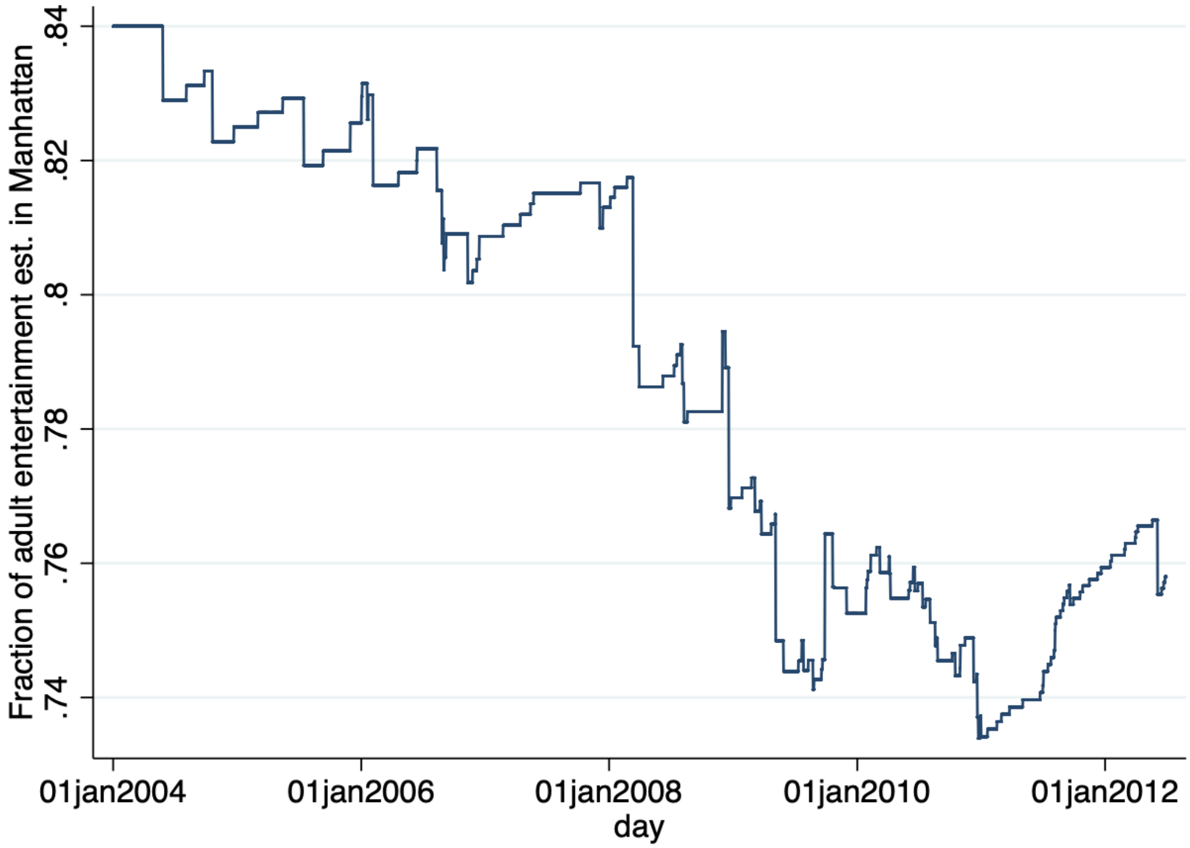
Notes: This figure shows the evolution of the fraction of adult entertainment establishments (with respect to the total) in Brooklyn and Queens during the study period.

Figure A.5: Evolution of the fraction of adult entertainment establishments (with respect to the total) from January 2004 to June 2012: The Bronx and Staten Island



Notes: This figure shows the evolution of the fraction of adult entertainment establishments (with respect to the total) in The Bronx and Staten Island during the study period.

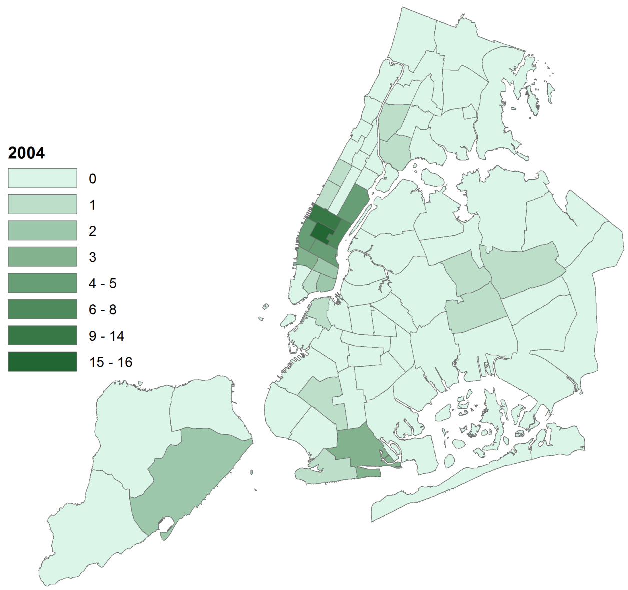
Figure A.6: Evolution of the fraction of adult entertainment establishments (with respect to the total) from January 2004 to June 2012: Manhattan



Notes: This figure shows the evolution of the fraction of adult entertainment establishments (with respect to the total) in Manhattan during the study period.

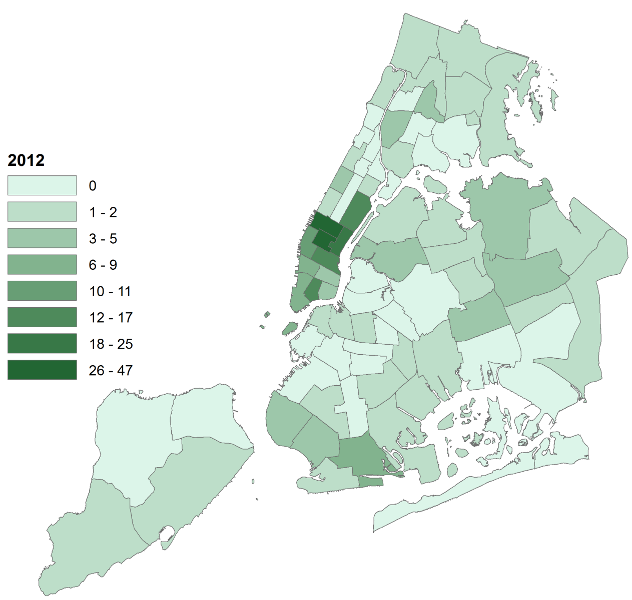
The two maps below show the evolution of adult entertainment establishments during our sample period. The maps show that there has been a substantial increase in the number of these businesses, not only by boroughs, but even between precincts within the same borough.

Figure A.7: Geographic distribution of adult entertainment establishments in NYC in 2004



Notes: This figure shows the geographic distribution of adult entertainment establishments in NYC on January 1, 2004, the first day of our sample period .

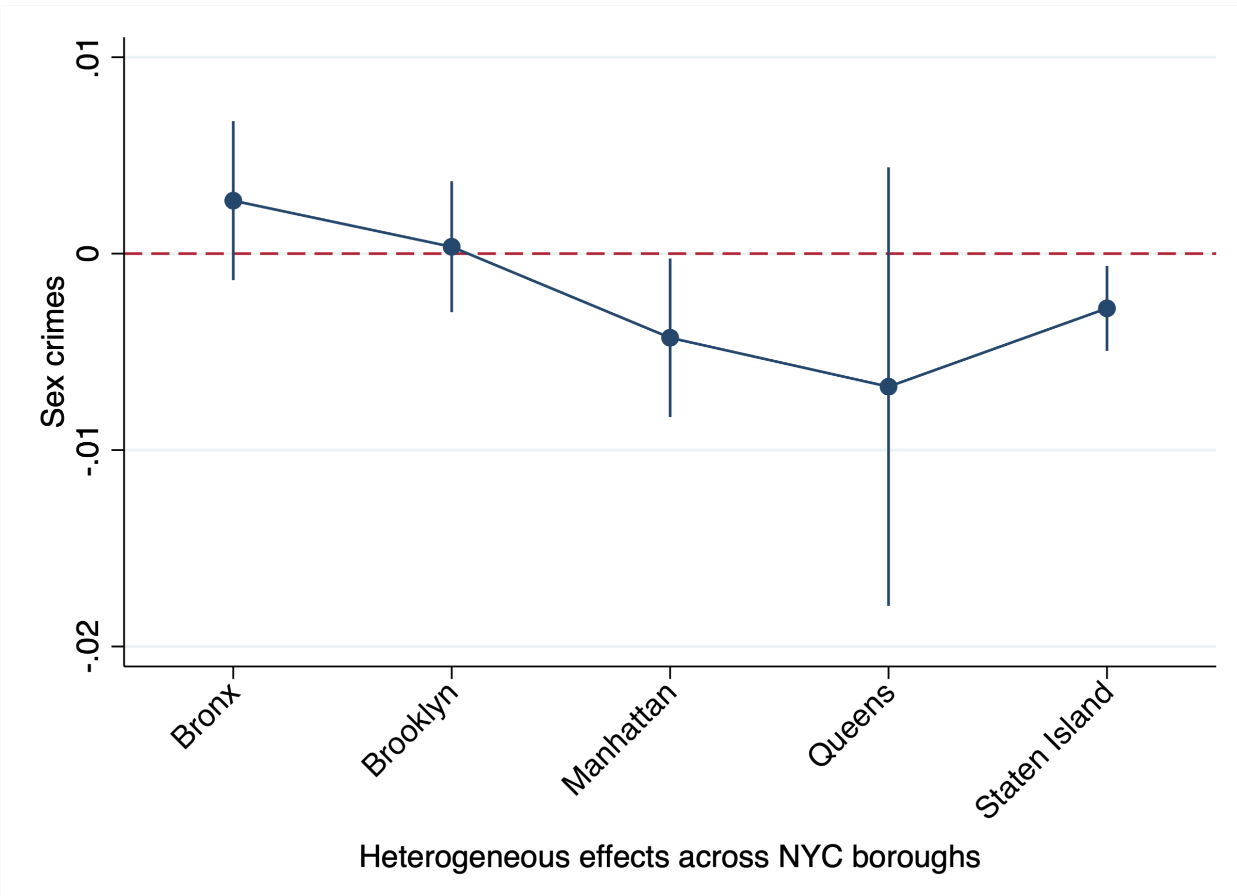
Figure A.8: Geographic distribution of adult entertainment establishments in NYC in 2012



Notes: This figure shows the adult entertainment establishments in NYC on June 30, 2012, the last day of our sample period.

The figure below shows the results of running our main specification but interacting our treatment variable with borough fixed effects. This figure depicts the estimated coefficient, and corresponding standard error at 90% level, of each interacted regressor. We see that Manhattan, Queens and Staten Island have negative estimated coefficients. Although, the estimated coefficient in Queens is not statistically significant. The estimated coefficient in Brooklyn is close to zero and not statistically significant. While, the estimated coefficient in The Bronx is positive and not statistically significant. It is encouraging to find that at least two boroughs are driving our results and that Manhattan is one of those.

Figure A.9: Heterogeneous effects across boroughs



Notes: This figure shows the estimated coefficient, and corresponding standard error at 90% level, of running our main regression but interacting our main regressor with borough fixed effects.

D Representability of ”Stop-and-Frisk” data set: summary statistics

Table A.3: Total number of sex crimes. Summary statistics.

	(1) Stop and Frisk	(2) Complaint disaggregated	(3) Combined data set	(4) Complaint aggregated
Observations	238,931	238,931	238,931	693
Mean	0.0312977	.0804751	0.1117729	76.34921
Standard Deviation	0.3405145	0.3022442	0.4647225	40.44663

Notes: This table presents descriptive statistics for the three data sets used to measure sex crimes: ”Stop-and-Frisk”, Complaint Disaggregated and Complaint Aggregated. Furthermore, column (3) displays the descriptive statistics for the *Combined data set* resulting by joining both ”Stop-and-Frisk” and Complaint Disaggregated. This latter data set is used in Section 5.4.1

Table A.4: Total number of sex crimes by borough and season. Absolute and relative frequencies.

Panel A: By Borough

	Stop and frisk	Complaint dissaggregated	Complaint aggregated
The Bronx	454 (6.07%)	3,238 (16.84%)	9,790 (18.5%)
Brooklyn	1,464 (19.58%)	5,746 (29.88%)	17,100(32.32%)
Manhattan	3,844 (51.4%)	4,849 (25.22%)	11,890 (22.47%)
Queens	1,646 (22.01%)	4,806 (24.99%)	12,254 (23.16%)
Staten Island	170 (2.27%)	589 (3.06%)	1,876 (3.55%)
Total	7,478	19,228	52,910

Panel B: By Season

	Stop and frisk	Complaint disaggregated
Winter	1,554 (20.78%)	4,896 (25.46%)
Spring	1,894 (25.33%)	5,551 (28.87%)
Summer	2,115 (28.28%)	4,634 (24.1%)
Fall	1,915 (25.6%)	4,147 (21.57%)
Total	7,478	19,228

Notes: Panel A and B presents the absolute frequencies of sex crimes in our sample period by and season respectively for the three data-sets used: ”Stop-and-Frisk”, Complaint Disaggregated and Complaint Aggregated. Relative frequencies in parentheses.

E Results using Double LASSO techniques

E.1 Main results with different functional forms

Table A.5: Main results using Double LASSO techniques

VARIABLES	(1) Log(1+y)	(2) IHS	(3) Levels	(4) LPM
Adult Entertainment Est.	-0.00243**	-0.00486**	-0.00447*	-0.00281**
	(0.00119)	(0.00238)	(0.00230)	(0.00129)
Observations	238,931	238,931	238,931	238,931
Clustered variance at Precinct level	Y	Y	Y	Y
Precinct FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
Day of the week FE	Y	Y	Y	Y
Day of the year FE	Y	Y	Y	Y
Holiday FE	Y	Y	Y	Y
Precinct Trends	Double LASSO	Double LASSO	Double LASSO	Double LASSO

Notes: This table presents the results of running specification (1) with different functional forms of the dependent variable and using Double LASSO selected precinct-year trends. In this specification, $Adult\ Enter_{pt}$ denotes the total number of adult entertainment establishments in precinct p on day t. This variable cumulates all the opened businesses up to day t. X_{pt} is a set of seasonal and geographic control variables: indicators for precinct, year, month, day-of-the-week, day-of-the-year and holidays, and geographic (at precinct level) year trends. All standard errors are clustered at the precinct level. Note that besides the classical year and month fixed effects, our daily specification allows us to include day-of-the-week, day-of-the-year and holiday fixed effects to capture deeper variation due to timing factors. In each column we consider a different functional form of the dependent variable: logarithm of one plus the number of sex crimes (column (1)), IHS of sex crimes (column (2)), levels (column(3)) and a binary variable taking value 1 if sex crimes are positive and 0 otherwise (column (4)). Results are stable across specifications. Clustered standard errors at the precinct level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

E.2 Falsification tests

Table A.6: Short run falsification test using Double LASSO techniques

	(1)	(2)	(3)	(4)	(5)	(6)
6 days prior	-0.000240					
	(0.000282)					
5 days prior	-1.97e-05	-2.27e-05				
	(0.000939)	(0.000934)				
4 days prior	-0.00144	-0.00144	-0.00145			
	(0.00108)	(0.00107)	(0.00106)			
3 days prior	0.000721	0.000717	0.000720	0.000739		
	(0.000650)	(0.000652)	(0.000652)	(0.000664)		
2 days prior	0.000281	0.000283	0.000265	0.000273	0.000266	
	(0.000865)	(0.000860)	(0.000876)	(0.000876)	(0.000871)	
1 day prior	-9.64e-06	-1.55e-05	-3.65e-06	-4.76e-06	-9.75e-06	-1.70e-05
	(0.000308)	(0.000296)	(0.000312)	(0.000314)	(0.000310)	(0.000308)
0	-1.87e-05	-1.75e-05	-1.37e-05	-8.02e-06	-6.34e-06	-1.82e-05
	(0.000594)	(0.000598)	(0.000581)	(0.000574)	(0.000578)	(0.000576)
1 day after	0.000924	0.000927	0.000925	0.000941	0.000940	-0.00238**
	(0.000764)	(0.000759)	(0.000758)	(0.000755)	(0.000760)	(0.00117)
2 days after	-0.000250	-0.000252	-0.000245	-0.000270	-0.00238**	
	(0.000208)	(0.000210)	(0.000218)	(0.000202)	(0.00115)	
3 days after	0.000100	0.000106	0.000118	-0.00235**		
	(0.000608)	(0.000613)	(0.000617)	(0.00114)		
4 days after	-0.00114	-0.00114	-0.00233**			
	(0.00129)	(0.00129)	(0.00114)			
5 days after	-0.000549	-0.00229**				
	(0.000376)	(0.00111)				
6 days after	-0.00230**					
	(0.00112)					
Observations	238,931	238,931	238,931	238,931	238,931	238,931
Clustered variance at Precinct level	Y	Y	Y	Y	Y	Y
Precinct FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
Precinct Trends	Double LASSO	Double LASSO	Double LASSO	Double LASSO	Double LASSO	Double LASSO
# of days	6	5	4	3	2	1

Notes: This table presents the results of running specification (2) with Double LASSO selected precinct-year trends. The dependent variable is the logarithm of one plus the number of sex crimes committed in precinct p ion a given day t. J ranges from 1 to 6 to analyse different time windows. Note that each lag (lead) takes the value of the main regressor exactly $-j$ (j) days away from the opening. The last lag takes the value of the main regressor $-J$ days away and forward. Column (1) presents the results for $J = 6$. Columns (2) to (6) respectively display the results for $J = 5$ to $J = 1$. X_{pt} represents a set of seasonal and geographic control variables: indicators for precinct, year, month, day of the week, day of the year and holidays, and geographic (precinct level) year trends.Clustered standard errors at the precinct level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.7: Long run falsification test using Double LASSO techniques

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
3 years prior	0.00432							0.0172
	(0.0132)							(0.0349)
2 years prior		0.000452						0.00707
		(0.0124)						(0.0295)
1 year prior			-0.00158					0.0193
			(0.00977)					(0.0310)
0				-0.0187				-0.0516
				(0.0119)				(0.0537)
1 year after					-0.0403***			-0.0422
					(0.0144)			(0.0510)
2 years after						-0.0599**		-0.0658*
						(0.0240)		(0.0364)
3 years after							-0.0639	-0.121**
							(0.0391)	(0.0498)
Observations	5,082	6,006	6,930	7,854	6,930	6,006	5,082	2,310
Clustered variance at Precint level	Y	Y	Y	Y	Y	Y	Y	Y
Precinct FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	Y	Y
Precinct Trends	Double LASSO	Double LASSO	Double LASSO	Double LASSO	Double LASSO	Double LASSO	Double LASSO	Double LASSO

Notes: This table presents the results of running specification (3) with Double LASSO selected precinct-year trends, where X_{pt} includes month fixed effects, year fixed effects, precinct fixed effects and precinct-year time trends. Columns (1), (2) and (3) respectively present the results of running regression model (3) using either only $t+3$, $t+2$or $t+1$. Columns (4) to (7) of Table 4 repeat the same analysis but only including either the contemporaneousvalue or its corresponding lags. Column (8) shows the results of running the full regression model given by specification (3). These results confirm that the effect takes place after the registration of the establishment, column (8) suggests that the effect is permanent and does not disappear after three years or more. Clustered standard errors at the precinct level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

F Sensitivity to model specification changes and to definition of dependent variable

Table A.8: Additional specifications

	(1) Log sex crime	(2) Log sex crime	(3) Log sex crime	(4) Log Sex crime by men	(5) IHS of sex crime by men
Adult Entertainment Est.	-0.00414*	-0.00427*	-0.00442*	-0.00413*	-0.00825*
	(0.00220)	(0.00237)	(0.00245)	(0.00225)	(0.00451)
Observations	238,931	238,931	238,931	238,931	238,931
Clustered variance at Precinct level	Y	Y	Y	Y	Y
Precinct FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y
Day of the week FE	Y	Y	Y	Y	Y
Day of the year FE		Y	Y	Y	Y
Holiday FE	Y	Y	Y	Y	Y
Precinct Trends	Y	Y	Y	Y	Y
Exact Day FE	Y				
Precinct M Trends		Y			
Precinct Y M Trends			Y		

Notes: This table presents the results of running specification (1) with different controls and definition of the dependent variable. Column (1) includes Exact Day FE, column (2) adds precinct-month trends, column (3) precinct-year-month trends. Finally, columns (4) and (5) respectively use sex crimes only committed by men in $log(1+y)$ and IHS. Each column is a different regression and includes a set of seasonal and geographic control variables. Namely: indicators for precinct, year, month, day-of-the-week, day-of-the-year and holidays, and geographic (at precinct level) year trends. All standard errors are clustered at the precinct level. Results are robust across specifications. Clustered standard errors at the precinct level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.9: Robustness check

	(1) IHS	(2) Probit	(3) LPM	(4) Levels
Adult Entertainment Est.	-0.00798*	-0.0165	-0.00455*	-0.00759*
	(0.00435)	(0.0106)	(0.00231)	(0.00434)
Observations	238,931	235,828	238,931	238,931
Clustered variance at Precinct level	Y	Y	Y	Y
Precinct FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
Day of the week FE	Y	Y	Y	Y
Day of the year FE	Y	Y	Y	Y
Holiday FE	Y	Y	Y	Y
Precinct Trends	Y	Y	Y	Y

Notes: This table presents the results of running specification (1) with different functional forms of the dependent variable. Column (1) uses IHS. Columns (2) and (3) use a binary variable taking value 1 if sex crimes are positive and 0 otherwise, column (2) runs specification (1) in a probit framework, while column (3) a linear probability model. Column (4) makes use of the dependent variable in levels. Each column is a different regression and includes a set of seasonal and geographic control variables. Namely: indicators for precinct, year, month, day-of-the-week, day-of-the-year and holidays, and geographic (at precinct level) year trends. All standard errors are clustered at the precinct level. Results are robust across specifications and close to standard levels of significance for column (2). Clustered standard errors at the precinct level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

G Weekly regression

This section presents the results of the baseline regression but at a weekly frequency. Hence, we exchanged all the fixed effects varying daily for week fixed effects. The results are negative and statistically significant for both log, the IHS transformation and in levels.

Table A.10: Regression at weekly frequency

VARIABLES	(1) Log(1+y)	(2) IHS	(3) Levels	(4) LPM	(5) Probit
Adult Entertainment Est.	-0.0172*	-0.0345*	-0.0529*	-0.0113**	-0.0262*
	(0.00884)	(0.0177)	(0.0302)	(0.00551)	(0.0146)
Observations	34,034	34,034	34,034	34,034	33,592
Clustered variance at Precint level	Y	Y	Y	Y	Y
Precinct FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y
Week FE	Y	Y	Y	Y	Y
Precinct Trends	Y	Y	Y	Y	Y

Notes: This table presents the results of running specification (1) at weekly frequency. Column (1) uses the dependent variable in logs, column (2) in IHS and column (3) in levels. Column (4) and (5) respectively consider a LPM and Probit regression of specification (1), where the dependent variable is a binary variable taking value 1 if sex crimes are positive and 0 otherwise. Each column is a different regression and includes a set of seasonal and geographic control variables. Namely: indicators for precinct, year, month, day-of-the-week, day-of-the-year and holidays, and geographic (at precinct level) year trends. All standard errors are clustered at the precinct level. Clustered standard errors at the precinct level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

H Results in levels

H.1 Main results

Table A.11: Main results in levels

	(1) Levels	(2) Levels	(3) Levels	(4) Levels
Adult Entertainment Est.	-0.00421**	-0.00421**	-0.00421**	-0.00759*
	(0.00180)	(0.00180)	(0.00180)	(0.00432)
Observations	238,931	238,931	238,931	238,931
Clustered variance at Precinct level	Y	Y	Y	Y
Precinct FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
Day of the week FE	Y	Y	Y	Y
Day of the year FE		Y	Y	Y
Holiday FE			Y	Y
Precinct Trends				Y

Notes: This table presents the results of running specification (1) with the dependent variable in levels. The dependent variable is the number of sex crimes committed in precinct p on a given day t. $Adult\ Enter_{pt}$ denotes the total number of adult entertainment establishments in precinct p on day t. This variable cumulates all the opened businesses up to day t. X_{pt} is a set of seasonal and geographic control variables: indicators for precinct, year, month, day-of-the-week, day-of-the-year and holidays, and geographic (at precinct level) year trends. All standard errors are clustered at the precinct level. Note that besides the classical year and month fixed effects, our daily specification allows us to include day-of-the-week, day-of-the-year and holiday fixed effects to capture deeper variation due to timing factors. In each column we add a different control. Clustered standard errors at the precinct level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

H.2 Representability of ”Stop-and-Frisk” data set

Table A.12: Representability of ”Stop-and-Frisk” Data

	(1) Levels complaints
Adult Entertainment Est.	-0.0155*
	(0.00921)
Observations	238,931
Clustered variance at Precinct level	Y
Precinct FE	Y
Year FE	Y
Month FE	Y
Day of the week FE	Y
Day of the year FE	Y
Holiday FE	Y
Precinct Trends	Y

Notes: This table presents the results of running specification (1) using also sex crimes from the NYPD’s historical complaints data set in levels.Clustered standard errors at the precinct level in parentheses. ***p<0.01, **p<0.05, *p<0.1

H.3 Mechanisms behind the effect of adult entertainment establishments on sex crime

Table A.13: Potential victims: Street prostitution

	(1) Levels street prostitutes	(2) Levels loitering
Adult Entertainment Est.	-0.00301	0.00184
	(0.00240)	(0.00188)
Observations	238,931	238,931
Clustered variance at Precinct level	Y	Y
Precinct FE	Y	Y
Year FE	Y	Y
Month FE	Y	Y
Day of the week FE	Y	Y
Day of the year FE	Y	Y
Holiday FE	Y	Y
Precinct Trends	Y	Y

Notes: This table presents the results to explore the potential victims channel. Columns (1) and (2) respectively present results for the baseline regression using street prostitutes and loitering crimes in levels. If sex crimes are decreasing because street prostitutes, who were victims of sex crimes before, are now working in adult entertainment establishments we would observe a statistical negative estimated coefficient. Results suggest that this is not the case. Clustered standard errors at the precinct level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A.14: Potential victims: Big precincts

	(1) Levels	(2) Levels
Adult Entertainment Est.	-0.0137**	-0.0137**
	(0.00499)	(0.00665)
Observations	68,266	68,266
Clustered variance at Precinct level	Y	Wild
Precinct FE	Y	Y
Year FE	Y	Y
Month FE	Y	Y
Day of the week FE	Y	Y
Day of the year FE	Y	Y
Holiday FE	Y	Y
Precinct Trends	Y	Y

Notes: This table presents results for the baseline regression, specification (1), using sex crimes in levels and bigger precincts. These precincts were chosen according to their geographic distance. A complete list of the new precincts can be found in the appendix. If women are avoiding precincts where adult entertainment establishments open, we should find either a statistically negative but smaller estimated coefficient in absolute value, a statistically positive coefficient or a coefficient that is statistically equal to zero. In both cases the estimated coefficients are negative and larger in absolute value than the ones in our baseline regression. This evidence rejects the potential victims channel. Clustered standard errors at the precinct level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A.15: Potential victims: Bordering precincts

	(1) Levels bordering precincts	(2) Levels bordering precincts
Adult Entertainment Est.	-0.0200	-0.0200
	(0.0173)	(0.0185)
Dummy No Adult Enter. Est. in bordering precinct	0.0147	0.0147
	(0.0204)	(0.0190)
Interaction	0.0316	0.0316
	(0.0244)	(0.0409)
Observations	77,575	77,575
Clustered variance at Precinct level	Y	Wild
Precinct FE	Y	Y
Year FE	Y	Y
Month FE	Y	Y
Day of the week FE	Y	Y
Day of the year FE	Y	Y
Holiday FE	Y	Y
Precinct Trends	Y	Y

Notes: This table presents the results for a regression model similar to (1) but where the dependent variable is the number of sex crimes in levels that occurred in the bordering precincts; we also add two explanatory variables. The first is a dummy variable taking value 1 if there is no adult entertainment establishment in a bordering precinct. The second is the interaction between this dummy and the number of adult entertainment establishments in the precinct of interest. If women are avoiding precincts with adult entertainment establishments, the interaction should be statistically significant and positive. In other words, sex crimes would be moving from precincts with adult establishments to those without them. Results are robust to using wild cluster-bootstrap methods. Results do not support this hypothesis. Clustered standard errors at the precinct level in parentheses. ***$p<0.01$, **$p<0.05$, *$p<0.1$

Table A.16: Potential victims: Big precincts, night

	(1) Levels big precincts	(2) Levels big precincts	(3) Levels big precincts	(4) Levels big precincts
Adult Entertainment Est.	-0.00691**	-0.00541**	-0.00691**	-0.00541*
	(0.00249)	(0.00248)	(0.00337)	(0.00309)
Dummy Night		0.0216***		0.0216***
		(0.00748)		(0)
Interaction Night		-0.00300***		-0.00300**
		(0.000152)		(0.00146)
Observations	136,532	136,532	136,532	136,532
Clustered variance at Precinct level	Y	Y	Wild	Wild
Precinct FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
Day of the week FE	Y	Y	Y	Y
Day of the year FE	Y	Y	Y	Y
Holiday FE	Y	Y	Y	Y
Precinct Trends	Y	Y	Y	Y

Notes: This table presents results for the baseline regression, specification (1), using sex crimes in levels, bigger precincts and separating the day in two halves: day and night. Precincts were chosen according to their geographic distance. A complete list of the new precincts can be found in the appendix. If women are avoiding precincts where adult entertainment establishments open only at night, we should find either a statistically negative but smaller estimated coefficient in absolute value, a statistically positive coefficient or a coefficient that is statistically equal to zero for the main regressor and its interaction with the dummy variable taking value 1 at night. In columns (2) and (4) theese estimated coefficients are statistically negative and their sum is larger in absolute value than the ones in our baseline regression or benchmark (columns (1) and (3) respectively). Results are robust to using wild cluster-bootstrap methods. This evidence rejects the potential victims channel. Clustered standard errors at the precinct level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.17: Potential victims: Bordering precincts, night

	(1) Levels	(2) Levels	(3) Levels	(4) Levels
Adult Entertainment Est.	-0.00990	-0.00781	-0.00426	-0.00781
	(0.00859)	(0.0102)	(0.00332)	(0.0149)
Dummy No Adult Enter. Est. in bordering precinct	0.00726	0.00726	0.00204	0.00726
	(0.0101)	(0.0101)	(0.00805)	(0.0155)
Dummy Night		0.0161***		0.0161***
		(0.00521)		(0)
Interaction Night & No Adult Enter. Est. in bordering precinct		-0.00218		-0.00218
		(0.0105)		(1.304e+19)
Interaction Night		-0.00418		-0.00418
		(0.00642)		(0.00798)
Interaction No Adult Enter. Est. in bordering precinct	0.0160	0.0170	0.00792	0.0170
	(0.0123)	(0.0141)	(0.00733)	(0.0292)
Observations	155,150	155,150	155,150	155,150
Clustered variance at Precinct level	Y	Y	Wild	Wild
Precinct FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
Day of the week FE	Y	Y	Y	Y
Day of the year FE	Y	Y	Y	Y
Holiday FE	Y	Y	Y	Y
Precinct Trends	Y	Y	Y	Y
p-value joint effect		0.840		1
p-value		0.838		1

Notes: This table presents the results for a regression model similar to (1) but where the dependent variable is the number of sex crimes in levels that occurred in the bordering precincts separating the day in two halves: day and night; we also add two explanatory variables. The first is a dummy variable taking value 1 if there is no adult entertainment establishment in a bordering precinct. The second is the interaction between this dummy and the number of adult entertainment establishments in the precinct of interest. We also interact these two variable with a dummy variable taking value 1 at night. If women are avoiding precincts with adult entertainment establishments at night, the interaction should be statistically significant and positive. In other words, sex crimes would be moving from precincts with adult establishments to those without them. Results are robust to using wild cluster-bootstrap methods. Results do not support this hypothesis. Clustered standard errors at the precinct level in parentheses. ***p<0.01, **p<0.05, *p<0.1

Table A.18: Potential criminals

	(1) Levels	(2) Levels
Adult Entertainment Est.	-0.00380*	-0.00236
	(0.00218)	(0.00148)
Dummy Night		0.00593**
		(0.00252)
Interaction		-0.00288
		(0.00174)
Observations	477,862	477,862
Clustered variance at Precinct level	Y	Y
Precinct FE	Y	Y
Year FE	Y	Y
Month FE	Y	Y
Day of the week FE	Y	Y
Day of the year FE	Y	Y
Holiday FE	Y	Y
Precinct Trends	Y	Y
p-value joint effect		0.0817
p-value		0.102

Notes: This table presents specification (1) separating the day in two halves: day and night, saturating the specification including the dummy variables for night (day is the base group) – day (from 6 A.M. to 6 P.M.) and night (from 6 P.M.to 6 A.M.) – and the interaction with the main regressor. The dependent variable is in levels. Column (1) presents the results of the specification without the interactions as a benchmark. Column (2) presents the results of the fully saturated model. The total effect at night is statistically negative at the 10% level and the interaction is extremely close to be marginally statistically significant. These results imply that we cannot reject the potential criminals channel. We investigate this channel further dividing the day in four quarters in Table A.19. Clustered standard errors at the precinct level in parentheses. ***$p<0.01$, **$p<0.05$, *$p<0.1$

Table A.19: Potential criminals

	(1) Levels	(2) Levels
Adult Entertainment Est.	-0.00191*	-0.000634
	(0.00108)	(0.000541)
Dummy Evening		0.00376***
		(0.00142)
Dummy Night		0.00303*
		(0.00181)
Interaction Evening		-0.00164*
		(0.000955)
Interaction Night		-0.00236
		(0.00153)
Observations	955,724	955,724
Clustered variance at Precinct level	Y	Y
Precinct FE	Y	Y
Year FE	Y	Y
Month FE	Y	Y
Day of the week FE	Y	Y
Day of the year FE	Y	Y
Holiday FE	Y	Y
Precinct Trends	Y	Y
p-value joint effect		0.0877
p-value		0.000526

Notes: This table presents specification (1) separating the day in four quarters: morning, afternoon, evening and night and saturating the specification including the dummy variables for three quarters out of four (morning is the base group) – morning (from 6 A.M. to 12 P.M.), afternoon (from 12 P.M.to 6 P.M.), evening (from 6 P.M.to 12 A.M.) and night (from 12 P.M.to 6 A.M.) – and the interactions with the main regressor. The dependent variable is in levels. Column (1) presents without the interactions as a benchmark. Columns (2) presents the results of the fully saturated model. Results of this table corroborate the initial finding: the two interaction coefficients are jointly statistically significant and negative at the 1% level. In addition, their total effect is statistically different from zero at the 10% level. These results imply that we cannot reject the potential criminals channel. Clustered standard errors at the precinct level in parentheses. ***p<0.01, **p<0.05, *p<0.1

I Falsification test, IHS

Table A.20: Short run falsification test using IHS

	(1)	(2)	(3)	(4)	(5)	(6)
6 days prior	-0.000446					
	(0.000549)					
5 days prior	-9.64e-05	-0.000101				
	(0.00188)	(0.00187)				
4 days prior	-0.00288	-0.00287	-0.00289			
	(0.00217)	(0.00216)	(0.00214)			
3 days prior	0.00142	0.00141	0.00142	0.00146		
	(0.00132)	(0.00132)	(0.00132)	(0.00135)		
2 days prior	0.000528	0.000534	0.000495	0.000510	0.000495	
	(0.00172)	(0.00171)	(0.00174)	(0.00174)	(0.00173)	
1 days prior	-9.52e-05	-0.000106	-8.23e-05	-8.49e-05	-9.45e-05	-0.000110
	(0.000583)	(0.000560)	(0.000593)	(0.000597)	(0.000588)	(0.000585)
0	-9.40e-05	-9.21e-05	-8.52e-05	-7.36e-05	-7.14e-05	-9.65e-05
	(0.00117)	(0.00118)	(0.00115)	(0.00113)	(0.00114)	(0.00114)
1 days after	0.00185	0.00186	0.00185	0.00188	0.00188	-0.00780*
	(0.00153)	(0.00152)	(0.00151)	(0.00151)	(0.00152)	(0.00425)
2 days after	-0.000519	-0.000522	-0.000508	-0.000560	-0.00775*	
	(0.000406)	(0.000410)	(0.000423)	(0.000399)	(0.00420)	
3 days after	0.000165	0.000177	0.000197	-0.00762*		
	(0.00119)	(0.00120)	(0.00121)	(0.00414)		
4 days after	-0.00243	-0.00243	-0.00755*			
	(0.00266)	(0.00264)	(0.00413)			
5 days after	-0.00108	-0.00735*				
	(0.000807)	(0.00401)				
6 days after	-0.00738*					
	(0.00407)					
Observations	238,931	238,931	238,931	238,931	238,931	238,931
Clustered variance at Precinct level	Y	Y	Y	Y	Y	Y
Precinct FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
Precinct Trends	Y	Y	Y	Y	Y	Y
# of days	6	5	4	3	2	1

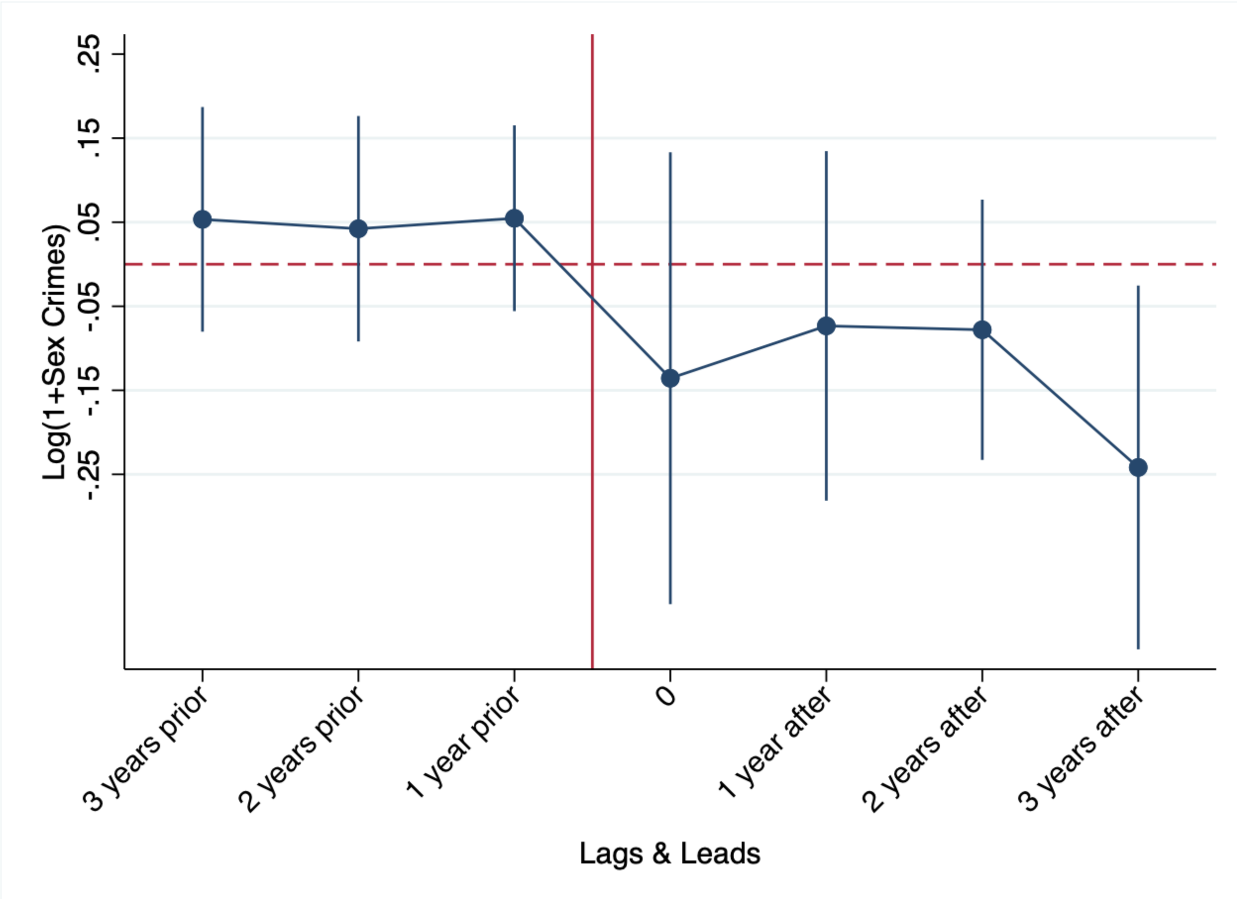
Notes: This table presents the results of running specification (2). The dependent variable is in IHS. J ranges from 1 to 6 to analyse different time windows. Note that each lag (lead) takes the value of the main regressor exactly $-j$ (j) days away from the opening. The last lag takes the value of the main regressor $-J$ days away and forward. Column (1) presents the results for $J = 6$. Columns (2) to (6) respectively display the results for $J = 5$ to $J = 1$. X_{pt} represents a set of seasonal and geographic control variables: indicators for precinct, year, month, day of the week, day of the year and holidays, and geographic (precinct level) year trends. Clustered standard errors at the precinct level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.21: Long run falsification test using IHS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
3 years prior	-0.0160							0.0534
	(0.0256)							(0.0803)
2 years prior		-0.00806						0.0422
		(0.0309)						(0.0805)
1 year prior			-0.0212					0.0547
			(0.0253)					(0.0664)
0				-0.0627*				-0.136
				(0.0371)				(0.161)
1 year after					-0.0812**			-0.0734
					(0.0397)			(0.125)
2 years after						-0.139**		-0.0780
						(0.0596)		(0.0930)
3 years after							-0.148	-0.242*
							(0.0914)	(0.130)
Observations	5,082	6,006	6,930	7,854	6,930	6,006	5,082	2,310
Clustered variance at Precinct level	Y	Y	Y	Y	Y	Y	Y	Y
Precinct FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	Y	Y
Precinct Trends	Y	Y	Y	Y	Y	Y	Y	Y

Notes: This table presents the results of running specification (3) with the dependent variable in IHS where X_{pt} includes month fixed effects, year fixed effects, precinct fixed effects and precinct-year time trends. Columns (1), (2) and (3) respectively present the results of running regression model (3) using either only $t+3$, $t+2$or $t+1$. Columns (4) to (7) of Table 4 repeat the same analysis but only including either the contemporaneousvalue or its corresponding lags. Column (8) shows the results of running the full regression model given by specification (3). These results confirm that the effect takes place after the registration of the establishment, column (8) suggests that the effect is permanent and does not disappear after three years or more. Clustered standard errors at the precinct level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Figure A.10: Long run falsification test using IHS



Notes: This figure shows the estimated coefficients of $\sum_{j=-3}^{3} \beta_j Adult\ Enter_{p,t+j}$ in specification (3) with the depedent variable in IHS.

Results are also robust to using Double LASSO selected precinct-year trends and considering the dependent variable in levels. Tables and figures of these regression models are available upon request.

J Representability of ”Stop-and-Frisk” data set: regression results

Table A.22: Effect of adult entertainment establishments on sex crimes using complaint data set

	(1) Log Sex crimes	(2) IHS Sex crimes	(3) Sex crimes Stops	(4) Sex crimes Stops
Adult Entertainment Est.	-0.00672*	-0.0134*		
	(0.00396)	(0.00791)		
Sex crimes, NYPD			0.193*	0.265*
			(0.106)	(0.139)
Observations	238,931	238,931	693	693
Clustered variance at Precinct level	Y	Y	Y	Y
Precinct FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Month FE	Y	Y	N/A	N/A
Day of the week FE	Y	Y	N/A	N/A
Day of the year FE	Y	Y	N/A	N/A
Holiday FE	Y	Y	N/A	N/A
Precinct Trends	Y	Y		Y

Notes: Columns (1) and (2) of this table present the results of running specification (1) using also sex crimes from the NYPD’s historical complaints data set. Column (1) uses the logarithm of one plus the number of sex crimes as dependent variable, while column (2) uses the IHS. Columns (3) and (4) of this table respectively present results of running specification (4) without and with precinct-year trends. N/A denotes that such fixed effect cannot be included due to the frequency of the regression model. Clustered standard errors at the precinct level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.23: Representability of ”Stop-and-Frisk” data: complaint sex crimes at the daily level

	(1) Levels Stop & Frisk	(2) Levels Stop & Frisk
Levels, Complaints	0.0383***	0.0391***
	(0.0114)	(0.0120)
Observations	238,931	238,931
Clustered variance at Precinct level	Y	Y
Precinct FE	Y	Y
Year FE	Y	Y
Month FE	Y	Y
Day of the week FE	Y	Y
Day of the year FE	Y	Y
Holiday FE	Y	Y
Precinct Trends		Y

Notes: This table explores the correlation between our main dependent variable and sex crimes from the NYPD’s historical complaints. These two different measures of sex crimes are positively significantly correlated. Clustered standard errors at the precinct level in parentheses. ***p<0.01, **p<0.05, *p<0.1

K Sensitivity test: urban development

Table A.24: Main results using urban development controls, logs

VARIABLES	(1) Log(1+y)	(2) Log(1+y)	(3) Log(1+y)	(4) Log(1+y)
Panel A				
Adult Entertainment Est.	-0.00215**	-0.00198**	-0.00261*	-0.00258*
	(0.000948)	(0.000886)	(0.00154)	(0.00151)
Precinct Trends				
Panel B				
Adult Entertainment Est.	-0.00400*	-0.00402*	-0.00382*	-0.00381**
	(0.00217)	(0.00207)	(0.00201)	(0.00186)
Precinct Trends	Y	Y	Y	Y
Panel C				
Adult Entertainment Est.	-0.00243**	-0.00234**	-0.00327*	-0.00338*
	(0.00119)	(0.00113)	(0.00180)	(0.00175)
Precinct Trends	Double LASSO	Double LASSO	Double LASSO	Double LASSO
Observations	238,931	238,931	238,931	238,931
Clustered variance at Precinct level	Y	Y	Y	Y
Precinct FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
Day of the week FE	Y	Y	Y	Y
Day of the year FE	Y	Y	Y	Y
Holiday FE	Y	Y	Y	Y
Urban development contr.		Apple	Starbucks	Both

Notes: This table presents the results of running specification (1) in logs including Apple Stores and Starbucks establishments as control variables for urban development. Panel A, B and C respectively present the results without trends, with trends and with Double LASSO selected trends. Moreover, Column (1), (2), (3) and (4) respectively present the results without urban development controls, only with Apple Stores, only with Starbucks and with both establishments. Results are robust to the inclusion of such controls. Clustered standard errors at the precinct level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.25: Main results using urban development controls, IHS

VARIABLES	(1) IHS	(2) IHS	(3) IHS	(4) IHS
Panel A				
Adult Entertainment Est.	-0.00429**	-0.00396**	-0.00522*	-0.00515*
	(0.00190)	(0.00177)	(0.00307)	(0.00303)
Precinct Trends				
Panel B				
Adult Entertainment Est.	-0.00801*	-0.00804*	-0.00764*	-0.00762**
	(0.00435)	(0.00413)	(0.00402)	(0.00371)
Precinct Trends	Y	Y	Y	Y
Panel C				
Adult Entertainment Est.	-0.00486**	-0.00468**	-0.00655*	-0.00676*
	(0.00238)	(0.00226)	(0.00360)	(0.00350)
Precinct Trends	Double LASSO	Double LASSO	Double LASSO	Double LASSO
Observations	238,931	238,931	238,931	238,931
Clustered variance at Precinct level	Y	Y	Y	Y
Precinct FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
Day of the week FE	Y	Y	Y	Y
Day of the year FE	Y	Y	Y	Y
Holiday FE	Y	Y	Y	Y
Urban Development contr.		Apple	Starbucks	Both

Notes: This table presents the results of running specification (1) in IHS including Apple Stores and Starbucks establishments as control variables for urban development. Panel A, B and C respectively present the results without trends, with trends and with Double LASSO selected trends. Moreover, Column (1), (2), (3) and (4) respectively present the results without urban development controls, only with Apple Stores, only with Starbucks and with both establishments. Results are robust to the inclusion of such controls. Clustered standard errors at the precinct level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.26: Main results using urban development controls, levels

VARIABLES	(1) Levels	(2) Levels	(3) Levels	(4) Levels
Panel A				
Adult Entertainment Est.	-0.00421**	-0.00394**	-0.00488*	-0.00483*
	(0.00180)	(0.00169)	(0.00283)	(0.00279)
Precinct Trends				
Panel B				
Adult Entertainment Est.	-0.00759*	-0.00763*	-0.00729*	-0.00728*
	(0.00432)	(0.00418)	(0.00406)	(0.00383)
Precinct Trends	Y	Y	Y	Y
Panel C				
Adult Entertainment Est.	-0.00447*	-0.00433*	-0.00599*	-0.00616*
	(0.00230)	(0.00219)	(0.00342)	(0.00334)
Precinct Trends	Double LASSO	Double LASSO	Double LASSO	Double LASSO
Observations	238,931	238,931	238,931	238,931
Clustered variance at Precinct level	Y	Y	Y	Y
Precinct FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
Day of the week FE	Y	Y	Y	Y
Day of the year FE	Y	Y	Y	Y
Holiday FE	Y	Y	Y	Y
Urban Development contr.		Apple	Starbucks	Both

Notes: This table presents the results of running specification (1) in levels including Apple Stores and Starbucks establishments as control variables for urban development. Panel A, B and C respectively present the results without trends, with trends and with Double LASSO selected trends. Moreover, Column (1), (2), (3) and (4) respectively present the results without urban development controls, only with Apple Stores, only with Starbucks and with both establishments. Results are robust to the inclusion of such controls. Clustered standard errors at the precinct level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

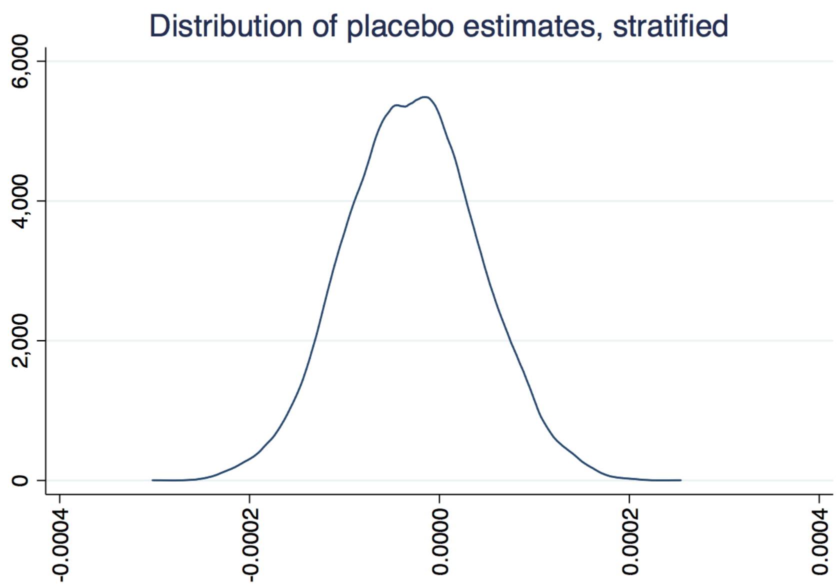
Table A.27: Main results using urban development controls, LPM

VARIABLES	(1) LPM	(2) LPM	(3) LPM	(4) LPM
Panel A				
Adult Entertainment Est.	-0.00234**	-0.00213**	-0.00286*	-0.00282*
	(0.00102)	(0.000956)	(0.00163)	(0.00161)
Precinct Trends				
Panel B				
Adult Entertainment Est.	-0.00457*	-0.00459**	-0.00437**	-0.00436**
	(0.00231)	(0.00218)	(0.00214)	(0.00196)
Precinct Trends	Y	Y	Y	Y
Panel C				
Adult Entertainment Est.	-0.00281**	-0.00270**	-0.00369*	-0.00381**
	(0.00129)	(0.00123)	(0.00192)	(0.00186)
Precinct Trends	Double LASSO	Double LASSO	Double LASSO	Double LASSO
Observations	238,931	238,931	238,931	238,931
Clustered variance at Precinct level	Y	Y	Y	Y
Precinct FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
Day of the week FE	Y	Y	Y	Y
Day of the year FE	Y	Y	Y	Y
Holiday FE	Y	Y	Y	Y
Urban Development contr.		Apple	Starbucks	Both

Notes: This table presents the results of running specification (1) including Apple Stores and Starbucks establishments as control variables for urban development. The dependent variable is a binary variable taking value 1 if sex crimes are positive and 0 otherwise. Panel A, B and C respectively present the results without trends, with trends and with Double LASSO selected trends. Moreover, Column (1), (2), (3) and (4) respectively present the results without urban development controls, only with Apple Stores, only with Starbucks and with both establishments. Results are robust to the inclusion of such controls. In addition, since results hold with the afore-mentioned binary version of the dependent variable, it suggests robustness to urban development controls is not driven by extreme values of the dependent variable. Clustered standard errors at the precinct level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

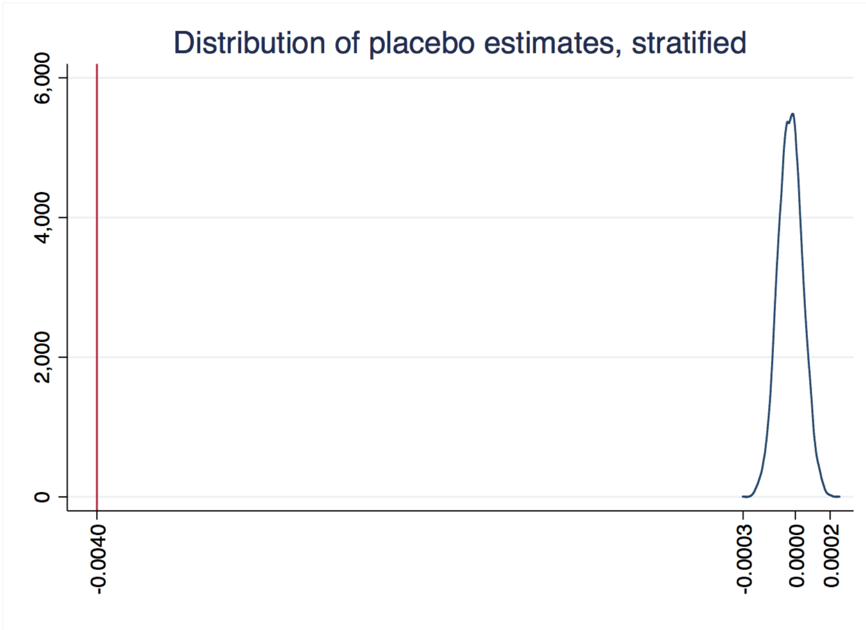
L Randomization inference

Figure A.11: Randomization inference stratified at borough level



Notes: This figure present the results of randomizing the number of opened establishments stratified at the borough level with 1,000 permutations.

Figure A.12: Randomization inference stratified at borough level with estimated coefficient



Notes: This figure present the results of randomizing the number of opened establishments stratified at the borough level with 1,000 permutations. The red vertical line represents the estimated coefficient in our main specification.

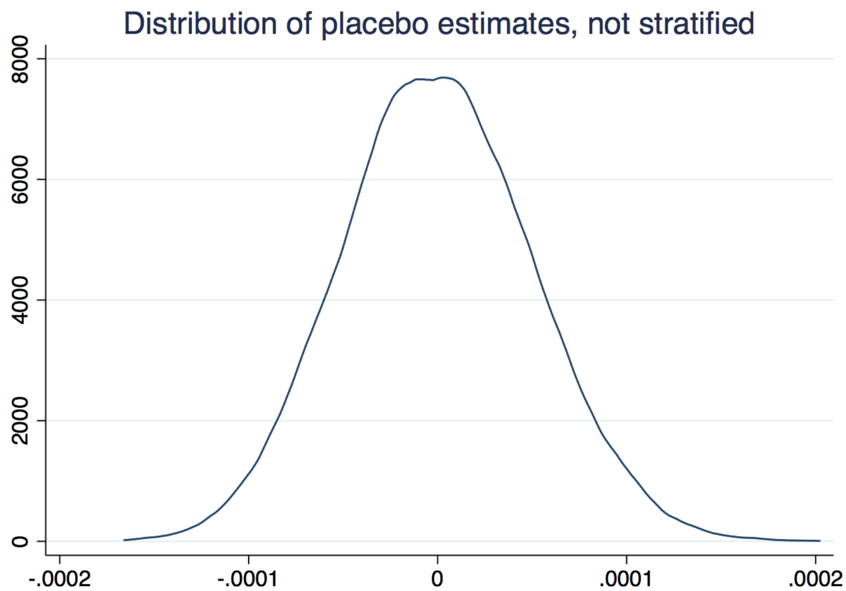
M Further checks: randomization inference without stratifying

This section presents the findings of running the same analysis as Section 5.5 without stratifying at the borough level. Since prostitution and sex crime patterns vary substantially across boroughs, there might be a concern that the results obtained in Section 5.5 are due to the stratification at the borough level.

Figures A.13 and A.14 below show the results of the estimated coefficient found with 1,000 permutations. The vertical red line represents our estimated coefficient (as in Figure A.12).

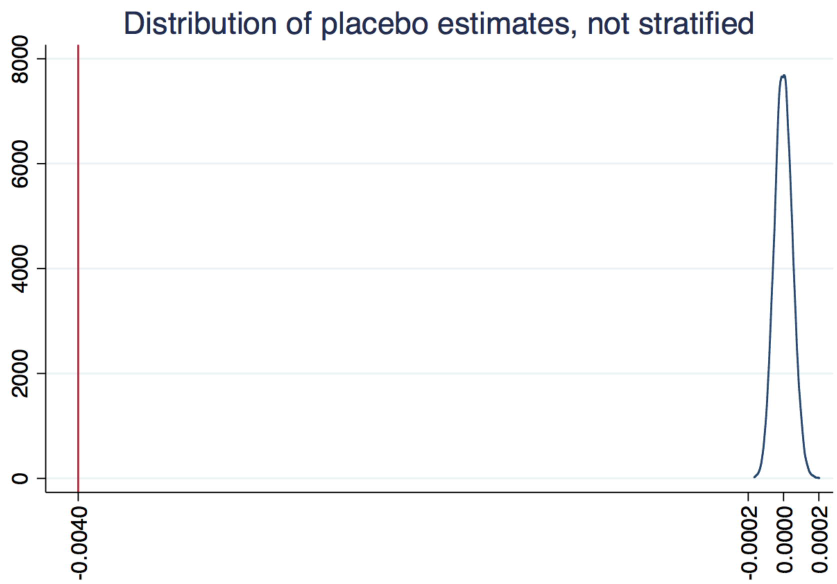
A simple visual inspection of the figures shows that there are no important differences in the findings even without stratification. It is important to note that without stratification, the estimated coefficients obtained by randomly permuting the number of establishments are less dispersed than stratifying (i.e. the support of the distribution depicted in Figure A.13 is smaller than that in Figure A.11). Figure A.14 compares such a distribution to our estimated coefficient: estimating our coefficient with randomization inference seems considerably more unlikely in this case. These results support our main finding that adult entertainment establishments decrease sex crimes.

Figure A.13: Randomization inference



Notes: This figure present the results of randomizing the number of opened establishments with 1,000 permutations.

Figure A.14: Randomization inference with estimated coefficient



Notes: This figure present the results of randomizing the number of opened establishments with 1,000 permutations. The red vertical line represents the estimated coefficient in our main specification.

N Police mechanism: further evidence

This section considers the effect of adult entertainment establishments on different types of crimes. Two features are important about such crimes. First, they should not be related to sex crimes, and there should not be a plausible mechanism of why adult entertainment establishments could affect them directly (i.e. other than via a change in the number of police officers). Second, it is preferable to select crimes that are easier to catch/control by officers compared to sex crimes. If it is a change in police presence that is driving the findings, then such crimes are much more likely to experience a decrease as well. [43] Table A.28 explores every sort of crime recorded in the "Stop-and-Frisk" data set that fulfills these two features.

Ten different crimes are presented in Table A.28: burglary, drug use, arson or fire, using a weapon, criminal mischief, murder, forgery, obscenity, graffiti and trespass. The table shows the estimated coefficient of running specification (1) using different transformations of a certain crime. Row (1) shows the effect using the logarithmic transformation,

[43]If it is a change in anything related to officers (e.g. their number or behavior) that is driving the decline in sex crimes, then crimes that are more easy to catch and control by police should be experiencing such a decrease as well.

row (2) uses the IHS and row (3) uses the dependent variable in levels. All regressions (as in our main specification) have clustered standard errors at the precinct level and include precinct, year, month, day-of-the-year, day-of-the-week and holiday fixed effects, as well as precinct-year linear time trends.

It is important to note that the crimes presented in this section, in addition to sharing the two features listed above, are substantially different. Yet, there is no evidence that adult entertainment establishments decrease any of these crimes.

Table A.28: The effect of adult entertainment establishments on other crimes

	(1) Burglary	(2) Drug	(3) Arson	(4) Weapon	(5) Criminal Mischief	(6) Murder	(7) Forgery	(8) Obscenity	(9) Graffiti	(10) Trespass
Log	-0.00766	0.00541	-0.000393	-0.000854	-0.000870	0.000103	-0.0164	-1.14e-06	0.00123	0.0129
	(0.0137)	(0.00796)	(0.000564)	(0.000897)	(0.00274)	(0.000134)	(0.0113)	(1.23e-05)	(0.00199)	(0.00870)
IHS	-0.0155	0.0109	-0.000796	-0.00167	-0.00168	0.000232	-0.0328	-1.95e-06	0.00250	0.0256
	(0.0274)	(0.0159)	(0.00113)	(0.00180)	(0.00547)	(0.000264)	(0.0227)	(2.46e-05)	(0.00398)	(0.0174)
Levels	-0.0242	0.0182	-0.000290	-0.00183	-0.00141	0.000295	-0.0294	-5.36e-07	0.00426	0.0932**
	(0.0520)	(0.0249)	(0.00119)	(0.00248)	(0.00472)	(0.000285)	(0.0207)	(1.79e-05)	(0.00427)	(0.0392)
Observations	238,931	238,931	238,931	238,931	238,931	238,931	238,931	238,931	238,931	238,931

Notes: This table presents the results of running specification (1) for different crimes and functional forms. Crimes are listed in the columns and functional forms in the row. We find no evidence in favour that adult entertainment establishments affect other crimes. Clustered standard errors at the precinct level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

O List of larger precincts in potential victims channel

The 77 precincts are grouped into 22 big precincts according to geographic proximity (see Table A.42). For instance, Precincts 1, 5 and 7 were grouped together, as were Precincts 6, 9, 10 and 13.

Table A.29: List of *Big* precincts to test the potential victims channel

Big precinct	Formed by precincts
1	1, 5 and 7
2	6, 9, 10 and 13
3	14, 17 and 18
4	19, 20, 22 and 24
5	23, 25, 26 and 28
6	30, 32, 33 and 34
7	40, 41, 42, 43 and 44
8	46, 48 and 52
9	45, 47, 49 and 50
10	60, 61, 62 and 68
11	66, 70 and 72
12	71, 76, 77 and 78
13	79, 81, 84 and 88
14	63, 67, 69 and 73
15	83, 90 and 94
16	104, 108 and 114
17	75, 102 and 106
18	110, 112 and 115
19	100 and 101
20	103, 105 and 113
21	107, 109 and 111
22	120, 121, 122 and 123

Notes: This table lists the original precincts that comprise each *Big* precinct to explore the potential victims channel.

P Mechanisms behind the effect of adult entertainment establishments on sex crimes: potential victims channel

In this section we consider the possibility that women are simply avoiding precincts with at least one adult entertainment establishment in favor of those that have none. If this is the case, we should observe an increase in the number of sex crimes in these latter precincts. Indeed, if the estimated negative coefficient is due only to fewer women passing through precincts with at least one establishment, it implies that we should observe an increase in the bordering precincts that do not have any such establishments. Therefore, we restrict the sample to precincts with no adult establishments in bordering precincts, where one of these bordering precincts experienced at least one opening of an establishment at a later point in time. If it is true that the reduction in sex crimes we observe is merely due to women avoiding adult entertainment establishments, we should find that increasing the number of these establishments increases sex crimes in bordering precincts that do not have an adult entertainment establishment.

Hence, we consider a specification like regression model (1) but where the dependent variable is the number of sex crimes that occurred in the bordering precincts; we also add two explanatory variables. The first is a binary variable taking value 1 if there is no adult entertainment establishment in a bordering precinct and 0 otherwise. The second is the interaction between this binary variable and the number of adult entertainment establishments in the precinct of interest. If women are avoiding precincts with adult entertainment establishments, the interaction should be statistically significant and positive. In other words, sex crimes would be moving from precincts with adult establishments to those without them.

Table A.30 presents the results of this specification. Columns (1) and (3) present the results of our logarithmic transformation using, respectively, regular clustered errors at the precinct level and wild cluster-bootstrap (since the number of considered precincts decreases in this case). Columns (2) and (4) repeat the same analysis but for IHS. We find that the estimated coefficient is not statistically significant in any of our four specifications.[44]

A plausible explanation could be that women avoid precincts with adult entertainment establishments only at night. If this is the case, it may be that our previous specifications find no empirical evidence only because they are not separating sex crimes happening at night from those happening during the day. To address this issue, we run the previous specifications separating sex crimes according to the time of day. Table A.31 runs the same regressions as Panel B of Table 6 but separating sex crimes that occurred at night from those occurred during the day. The reasoning behind running these regressions is identical to the previous ones but applied at night.

As a benchmark, Column (1) of Table A.31 presents the results of using only the number of establishments (i.e. with neither a fixed effect for crimes committed at night nor the interaction between such fixed effect and the number of establishments). As expected,

[44]Likewise, the results of this table support the hypothesis that sex crimes are not moving to bordering precincts.

the estimated coefficient is statistically negative and lower in absolute value than the one in Panel B of Table 6. Columns (2) and (3) of Table A.31 report the coefficient of running this regression using our usual logarithmic transformation and the IHS, respectively. Columns (3) and (4) of Table A.31 repeat the same analysis using wild cluster-bootstrap methods due to the low number of clusters in this case.

If women avoid precincts with adult establishments at night, we should find that the estimated coefficient of the interaction term is either statistically significant and positive, or not statistically significant. In fact, if the decrease in sex crimes is due to women avoiding precincts with establishments at night, this would imply that at night sex crimes decrease in precincts with establishments but increase (or do not change) in other precincts. Therefore, the total effect of such establishments in larger precincts at night should be either positive or insignificant. In all four columns, the coefficient of the interaction term is statistically negative, suggesting that a decline in potential victims at night is not the main channel.

Table A.32 repeats the regressions of Table A.30 separating sex crimes happening at night from those happening during the day. In these regressions we are interested in the coefficient of the triple interaction between adult entertainment establishments, the dummy variable taking a value of 1 if there is no adult entertainment establishment in a bordering precinct, and the dummy variable taking a value of 1 for sex crimes committed at night. For ease of comparison, Columns (1) and (4), respectively, present the results of running the model only using the number of establishments and fixed effect and interaction (as in Table 16) for, respectively, regular clustered errors at the precinct level and wild cluster-bootstrap clustered errors at the precinct level. Columns (2) and (3) present the results of running the whole model for, respectively, our logarithmic transformation and IHS with regular clustered errors at the precinct level. Columns (4) and (5) repeat these computations using wild cluster-bootstrap clustered errors at the precinct level. The level of significance of the coefficient of interest (i.e. triple interaction) is shown in the table as the "p-value." Moreover, the row "p-value joint effect" shows the p-values associated with testing whether the total effect (i.e. the sum of the coefficients associated with our main regressor and its interactions) is zero. In our four regressions (i.e. Columns (2), (3), (4) and (5)) the coefficient of interest is statistically insignificant. These findings do not support the hypothesis that women avoid precincts that have adult entertainment establishments.

Table A.30: Potential victims channel

	(1) Log Bordering precincts	(2) IHS Bordering precincts	(3) Log Bordering precincts	(4) IHS Bordering precincts
Adult Entertainment Est.	-0.00853	-0.0171	-0.00853	-0.0171
	(0.00722)	(0.0144)	(0.00726)	(0.0145)
Dummy No Adult Enter. Est. in bordering precinct	0.00280	0.00561	0.00280	0.00561
	(0.00755)	(0.0151)	(0.00481)	(0.00962)
Interaction	0.0158	0.0317	0.0158	0.0317
	(0.0108)	(0.0216)	(0.0135)	(0.0270)
Observations	77,575	77,575	77,575	77,575
Clustered variance at Precinct level	Y	Y	Wild	Wild
Precinct FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
Day of the week FE	Y	Y	Y	Y
Day of the year FE	Y	Y	Y	Y
Holiday FE	Y	Y	Y	Y
Precinct Trends	Y	Y	Y	Y

Notes: This table presents the results for a regression model similar to (1) but where the dependent variable is the number of sex crimes, either in logs or IHS, that occurred in the bordering precincts; we also add two explanatory variables. The first is a dummy variable taking value 1 if there is no adult entertainment establishment in a bordering precinct. The second is the interaction between this dummy and the number of adult entertainment establishments in the precinct of interest. If women are avoiding precincts with adult entertainment establishments, the interaction should be statistically significant and positive. In other words, sex crimes would be moving from precincts with adult establishments to those without them. Results do not support this hypothesis. Clustered standard errors at the precinct level in parentheses. ***p<0.01, **p<0.05, *p<0.1

Table A.31: Potential victims channel

	(1) Log Big precincts	(2) Log Big precincts	(3) IHS Big precincts precincts	(4) Log Big precincts precincts	(5) Log Big precincts precincts	(6) IHS Big precincts
Adult Entertainment Est.	-0.00370***	-0.00289**	-0.00579**	-0.00370**	-0.00289*	-0.00579*
	(0.00122)	(0.00122)	(0.00244)	(0.00180)	(0.00165)	(0.00331)
Dummy Night		0.00616**	0.0123**		0.00616***	0.0123***
		(0.00282)	(0.00564)		(0)	(0)
Interaction Night		-0.00162***	-0.00324***		-0.00162**	-0.00324**
		(5.54e-05)	(0.000111)		(0.000788)	(0.00158)
Observations	136,532	136,532	136,532	136,532	136,532	136,532
Clustered variance at Precinct level	Y	Y	Y	Wild	Wild	Wild
Precinct FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
Day of the week FE	Y	Y	Y	Y	Y	Y
Day of the year FE	Y	Y	Y	Y	Y	Y
Holiday FE	Y	Y	Y	Y	Y	Y
Precinct Trends	Y	Y	Y	Y	Y	Y

Notes: This table presents results for the baseline regression, specification (1), using sex crimes either in logs or IHS, bigger precincts and separating the day in two halves: day and night. Precincts were chosen according to their geographic distance. A complete list of the new precincts can be found in the appendix. If women are avoiding precincts where adult entertainment establishments open only at night, we should find either a statistically negative but smaller estimated coefficient in absolute value, a statistically positive coefficient or a coefficient that is statistically equal to zero for the main regressor and its interaction with the dummy variable taking value 1 at night. In columns (2) and (4) theese estimated coefficients are statistically negative and their sum is larger in absolute value than the ones in our baseline regression or benchmark (columns (1) and (3) respectively). Results are robust to using wild cluster-bootstrap methods. This evidence rejects the potential victims channel. Clustered standard errors at the precinct level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A.32: Potential victims channel

	(1) Log Bordering precincts	(2) Log Bordering precincts	(3) IHS Bordering precincts	(4) Log Bordering precincts	(5) Log Bordering precincts	(6) IHS Bordering precincts
Adult Entertainment Est.	-0.00419	-0.00284	-0.00568	-0.00419	-0.00284	-0.00568
	(0.00378)	(0.00430)	(0.00859)	(0.00327)	(0.00542)	(0.0108)
Dummy Night		0.00546**	0.0109**		0.00546*	0.0109*
		(0.00249)	(0.00497)		(0.00312)	(0.00624)
Interaction Night & No Adult Enter. Est. in bordering precinct		-0.000384	-0.000768		-0.000384	-0.000768
		(0.00416)	(0.00831)		(1.304e+19)	(1.304e+19)
Dummy No Adult Enter. Est. in bordering precinct	0.00203	0.00203	0.00405	0.00203	0.00203	0.00405
	(0.00415)	(0.00415)	(0.00830)	(0.0100)	(0.0100)	(0.0201)
Interaction Night		-0.00270	-0.00540		-0.00270	-0.00540
		(0.00257)	(0.00514)		(0.00211)	(0.00421)
Interaction No Adult Enter. Est. in bordering precinct	0.00787	0.00806	0.0161	0.00787	0.00806	0.0161
	(0.00553)	(0.00640)	(0.0128)	(0.00670)	(0.00958)	(0.0192)
Observations	155,150	155,150	155,150	155,150	155,150	155,150
Clustered variance at Precinct level	Y	Y	Y	Wild	Wild	Wild
Precinct FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
Day of the week FE	Y	Y	Y	Y	Y	Y
Day of the year FE	Y	Y	Y	Y	Y	Y
Holiday FE	Y	Y	Y	Y	Y	Y
Precinct Trends	Y	Y	Y	Y	Y	Y
p-value joint effect		0.722	0.722		1	1
p-value		0.927	0.927		1	1

Notes: This table presents the results for a regression model similar to (1) but where the dependent variable is the number of sex crimes in levels that occurred in the bordering precincts separating the day in two halves: day and night; we also add two explanatory variables. The first is a dummy variable taking value 1 if there is no adult entertainment establishment in a bordering precinct. The second is the interaction between this dummy and the number of adult entertainment establishments in the precinct of interest. We also interact these two variable with a dummy variable taking value 1 at night. If women are avoiding precincts with adult entertainment establishments at night, the interaction should be statistically significant and positive. In other words, sex crimes would be moving from precincts with adult establishments to those without them. Results are robust to using wild cluster-bootstrap methods. Results do not support this hypothesis. Clustered standard errors at the precinct level in parentheses. ***p<0.01, **p<0.05, *p<0.1

Q Mechanisms behind the effect of adult entertainment establishments on sex crimes: potential criminals channel

In this section we run the same analysis as in Section 6.3 but dividing the day into two equal halves: morning (6 A.M. to 6 P.M.) and night (6 P.M. to 6 A.M.). So now the time unit is a half-day. Furthermore, we create a dummy variable that takes a value of 1 at night and 0 in the morning. Finally, we saturate the main specification including the interaction between the number of establishments and this dummy.

Table A.33 presents the results of this specification for the logarithmic transformation and the IHS, respectively. The effect of the number of establishments is still negative, and the coefficient on the night/day dummy variable is positive, showing that at night there are more sex crimes, as expected. The coefficient of the interaction term is negative, but it is not statistically significant at standard levels. Yet, by comparing the size of the coefficients in Columns (1) to (2) to those in Columns (3) to (4), we can observe that most of the effect is driven by the effect of adult entertainment establishments at night. These results suggest that the effect of adult entertainment establishments is mostly driven at times when these establishments are open for business.

Table A.33: Potential Criminal Channel

	(1) Log	(2) Log	(3) IHS	(4) IHS
Adult Entertainment Est.	-0.00215*	-0.00133*	-0.00430*	-0.00266*
	(0.00117)	(0.000761)	(0.00233)	(0.00152)
Dummy Night		0.00183		0.00365
		(0.00115)		(0.00231)
Interaction		-0.00164		-0.00328
		(0.00100)		(0.00201)
Observations	477,862	477,862	477,862	477,862
Clustered variance at Precinct level	Y	Y	Y	Y
Precinct FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
Day of the week FE	Y	Y	Y	Y
Day of the year FE	Y	Y	Y	Y
Holiday FE	Y	Y	Y	Y
Precinct Trends	Y	Y	Y	Y
p-value joint effect		0.0718		0.0718
p-value		0.106		0.106

Notes: This table presents specification (1) separating the day in two halves: day and night, saturating the specification including the dummy variables for night (day is the base group) – day (from 6 A.M. to 6 P.M.) and night (from 6 P.M.to 6 A.M.) – and the interaction with the main regressor. The dependent variable is either in logs (columns (1) and (2)) or IHS (columns (3) and (4)) Columns (1) and (3) respectively present the results of the specification without the interactions as a benchmark for logs and IHS. Columns (2) and (4) respectively present the results of the fully saturated model for logs and IHS. For both functional forms, we find that the total effect at night is statistically negative at the 10% level and the interaction is extremely close to be marginally statistically significant. These results imply that we cannot reject the potential criminals channel. We investigate this channel further dividing the day in four quarters in Table 7. Clustered standard errors at the precinct level in parentheses. ***p<0.01, **p<0.05, *p<0.1