The Effects of Indoor Prostitution on Sex Crime: Evidence from New York City

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Abstract

We use a unique data-set on the opening dates and locations of indoor prostitution establishments and crimes in New York City to study the effect of these establishments on sex crimes. We built a unique daily panel from the 1st of January of 2004 to the 30th of June of 2012 that uses the exact location of sex crimes and the day of opening and location of indoor prostitution establishments. We find that indoor prostitution decreases daily sex crime by 0.4% with no effect on other types of crimes. The reduction is mostly driven by potential sex offenders that are now indoor prostitutes' customers. We also rule out other mechanisms such as an increase in the number of police officers and a possible reduction of potential victims in areas where these businesses opened.

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1 Introduction

Sex crime, as sexual violence against women and rape, is considered one of the major public health concerns and violations of human rights. Apart from its enormous psychological and fisical burden, it can also lead to public health issues such as unintended pregnancies, gynecological problems, induced abortions and sexually transmitted infections.[1] However, little is known about how to prevent sex crime. One argument that has often been advanced is that having access to paid-for sex (i.e. prostitution) may help reduce the incidence of sex crimes. Yet so far there is little evidence of this possible effect.

Does prostitution increase or decrease sex crimes? Answering this question is important for both scientific research and social policy, but it is difficult to gather reliable data that allows a causal interpretation on the effect of prostitution on sex crime. On the one hand, it is difficult to get data about rapes since it is often protected by privacy laws and because it might suffer of systematic underreporting. On the other hand, since prostitution is illegal in many countries it is complicated to get reliable data about prostitutes. Although in the US (except Nevada) prostitution is illegal, there is a lack of agreement about how to legislate prostitution.[2] As a matter of fact, legalization of prostitution is one of the most discussed topics related to gender issues.[3]

A priori the effect of prostitution on rape is not clear and to our knowledge there is no clear evidence in the economic literature on this issue. Indoor prostitution may increase rape if prostitution reinforce the view of women as objects and therefore violence against women[Brownmiller, 1993].[4] At the same time, it may also reduce sex crimes if prostitution is a substitute to sex crime [Posner, 1992]. This might also be consistent with evolutionary biological theories [Thornhill and Thornhill, 1983, Thornhill and Palmer, 2000b,a] that suggest that rape might be an evolutionary adaptive strategy: when individuals are faced with the choice between forced sex (i.e. rape) and genetic extinction, they would choose force in order to avoid the second outcome.[5] Thereby this theory supports that the effect of indoor prostitution should be negative since it represents a cheaper alternative to rape.[6]

As for economic literature, two papers (contemporaneously to ours) tried to study similar issues: Cunningham and Shah [2014] and Bisschop et al. [2015]. The first paper exploits an unperceived decriminalization of

[1] A 2007 national study of the Department of Justice found that 18% of American women experienced rape (or an attempt to be raped) at least once in their life. Furthermore, according to the World Health Organization, sexual violence has important negative consequences on the physical, mental and reproductive conditions of women.

[2] European ountries such as Germany, the Netherlands or Belgium legalized and regulated prostitution via licenses, while countries as Sweden and Norway opted for criminalizing the purchase of prostitutes. On the 26th of February of 2014 the European Union parliament discussed and passed a resolution to follow the Swedish model. According to this resolution countries in the European Union should criminalize the purchase of prostitutes.

[3] As a matter of fact, in the last four years *The Economist* published many articles and discussions about legalization/criminalization of prostitution: see amongst others *Prostitution debate* (S. Baskin and M.Farley, 6th September 2010), *A job like any other* (8th August 2014) and *A personal choice* (9th August 2014).

[4] Prostitution can be classified as indoor and outdoor. Prostitution that takes place in the streets is known as outdoor prostitution. Prostitution that occurs in closed spaces is known as indoor prostitution. In states where prostitution is illegal indoor prostitution usually occurs in strip clubs, gentlemen clubs and escort girl services.

[5] Other disciplines, such as sociology or criminology, analyzed many different explanations that might justify either a positive or a negative estimated coefficient (see Svalastoga [1962], Guttentag and Secord [1983], Cohen and Felson [1979], Schwendinger and Schwendinger [1983], Obrien [1991], Bailey [1999],).

[6] Note that in evolutionary biology this reasoning is assumed to happen unconsciously. Indeed nowadays sex generally does not imply procreation.

indoor prostitution in Rhode Island, their estimates come from a year-state specification with only a treated group; Bisschop et al. [2015] studies the effect of street prostitution in special red-light zones, also their estimates are at year frequency. Both papers find that prostitution decreases rape.

This paper benefits from a unique dataset with daily precinct-level information of NYC. We collected data from indoor prostitution establishments from Reference USA, these data include names and addresses of establishments but don't include the date of registration of these businesses. We added to this dataset, information on registration dates, the closest approximation to the date these establishments opened their doors, from the Department of the State of New York, Yellow Pages or Super Pages.[7] We organized these establishments into New York Police Department (NYPD) precincts to match our crime data. Finally, we merged this dataset with crime data from the "Stop and Frisk" program of the NYPD. These data are at the precinct-level and include hourly information on crimes observed by the police, including rape. The dataset covers the period from the 1st of January of 2004 to the 30th of June of 2012.

This paper exploits the exogenous variation of the date of registration of indoor prostitution establishments to study the effect of these establishments on sex crime in New York City (NYC). To address the effect of indoor prostitution on sex crime, we use daily rape data combined with dates of registration of indoor prostitution establishments. Our main identification assumption is that the date of registration of such establishments is not linked with variables correlated with rape. That is, we assume that the opening date of an indoor prostitution business is exogenous to any other factor affecting sex crime. Since opening a businesses in NYC requires a long bureaucratic procedure we can take the day of registration as a quasi-natural experiment to study the effect of these businesses on rape. Another advantage of this study is that treated and control groups are easily comparable since our data is at precinct level. We are comparing precincts of NYC which likely are more similar between them than comparing cities or states.

We find that the presence of an indoor prostitution establishment in a given precinct leads to a 0.4% daily reduction in sex crime per precinct. This estimated coefficient comes from our preferred specification that includes fixed effects at precinct, year, month, day-of-the-year, day-of-the-week and holidays level, and precinct-year time trends.We run many robustness checks and our results do not change.

Furthermore, indoor prostitution establishments are less likely than outdoor prostitution to be correlated to unobservable characteristics that affects sex crime. These businesses provide a way for the whole transaction to occur behind closed doors as is documented in Farley [2005]. 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.

This paper also identifies a mechanism for how indoor prostitution affects rape: we find robust evidence that suggests that sex crime is reduced since potential sex offenders are indoor prostitutes' customers. We name this mechanism the *potential criminal channel*. We find that at night the effect of the establishments is larger in absolute value than our benchmark and negative. This suggests that it is at night when the indoor prostitution businesses prevent the most of the sex crimes to be committed. Since it is also at night when the majority of the indoor prostitution establishments are opened and the demand for the services they provide is higher, the results suggest that potential sex offenders prefer to use the services offered by these establishments rather than committing rape. Thereby, these results suggest that potential criminals consider sex crime and indoor prostitution as two substitute activities, as Farley et al. [2009] documents by interviewing men who purchase prostitution.

We find that there is neither an anticipated effect on sex crimes before the opening establishments nor a

[7] We also tried to call some establishments, though they were unwilling to offer their dates of opening.

contemporary effect. The results highlight two decreases of sex crime one after two weeks of the opening, the other after roughly one month and a half of the opening. More precisely after the first two weeks sex crime decreases by 9.39% whereas after the 5th and the 6th week the decrease is by 16.5%. Although our estimates are smaller, this result is essentially in line with Cunningham and Shah [2014] who find that decriminalization of indoor prostitution in Rhode Island reduced sex crime by 30 percent from 2004 to 2009.

This paper makes three important contributions. First, to our knowledge it provides the first causal evidence of the effect of indoor prostitution on sex crimes. While previous research have focused on year and state variations, this is the first study to show short-term effects using daily and precinct level-data on sex-related crimes within one of the main metropolitan areas in the US. Second, we provide the first evidence on the possible mechanisms behind the effect. Third, this paper uses the event study approach to show that the effect of these establishments changes over time even in the very short run (two months).

The *potential criminal channel* is similar to the incapacitation effect found byDahl and DellaVigna [2009] where violent movies reduce crime rate by keeping potential offenders into the cinemas. Nonetheless, in their case it is not known whether potential criminals commit crimes after leaving the cinema: violent movies and crimes are not substitute activities, possibly they are complementary activities but due to the time constraint crimes cannot be committed during the movie.

Using our data we are also able to rule out other mechanisms such as an increase in the number of police officers and a possible reduction of potential victims in areas where these businesses opened. On the one hand, we find that the openings do not affect other types of crimes. This suggests that results on sex crimes are not driven by police presence in the streets. In addition our results suggest that sex crimes are not moving to other precincts, showing that there are no negative spillover effects on bordering districts. On the other hand, we also check if there is a reduction in street prostitution and we find no effects of reallocation to bordering districts. Moreover the openings do not to affect the number of street sex workers.

The results of this paper have strong policy implications. Firstly, they show that indoor prostitution establishments have a causal negative effect on sex crime. Secondly, they suggest that this effect is due to the fact that potential sex offenders attend indoor prostitution establishments instead of committing sex crimes. Some policy makers might argue that the opening of these establishments is positive since they decrease the total number of sex crimes while they do not affect other crimes such as use of drugs or burglaries. Other policy makers might argue that the sector of indoor prostitution should be supervised since there is strong evidence that some of their customers are potential sex offenders. Indeed this paper sets the grounds for policy makers to take into account the effect of indoor prostitution on sex crime when discussing about how to legislate prostitution.

The paper is organized in 8 sections. Section 2 presents and summarizes the main characteristics of the data. Section 3 discusses the identification strategy and the possible threats. Section 4 shows the results of our specification and quantify the size of the estimated coefficient. Section 5 presents the result of additional specifications and robustness checks. Section 6 shows the results of the event study analysis. Section 7 discusses the possible mechanisms that could drive the effect and show evidence in favor of the potential criminal argument. Section 8 concludes.

2 Data

The aim of this section is to describe the data sets we used in this paper: we provide the main summary statistics and describe the general patterns of the number of sex crimes and the number of indoor prostitution establishments.

NYC is divided in 5 boroughs: the Bronx, Brooklyn, Queens, Manhattan and Staten Island. The data are organized in a panel of observations of 77 police precincts in NYC over the period 2004-2012, precisely from the 1st of January of 2004 to the 30th of June of 2012. We will combine two sets of data: police stops and indoor prostitution establishments data.

2.1 Sex Crime

Sex crimes are from the "Stop and Frisk" data. These data were obtained from the New York City Police Department (NYPD now on) and provide information on each stop and frisk encounter documented between 2004-2012. Note that this data set minimizes the problem of self-reporting found in sex crimes since the data come directly from what the NYPD saw in the street. Previous literature has relied on self-reported measures which most likely suffer a high degree of non-random under-reporting. The reasons of under-reporting are multiple: fear of the aggressor, social stigma attached to victims of these crimes, etc.

We use these data for two reasons. Firstly, auto-reported data on sex crimes is not publicly available. Secondly, the "Stop and Frisk" data have information on the exact position and the exact hour and day of crime; this information is crucial for our analysis. Further, this data set includes prostitutes' and sex abusers' demographic characteristics such as age, gender and race, whether an arrest was made or a summon was issued, whether the suspect was frisked and whether the suspect was searched.

The "Stop and Frisk" data set contains 7,875 stops for sex crimes in NYC. Sex crime category includes sexual abuse and rape stops. Table 1 presents the summary statistics of sex crimes per day. We observe that on average only 0.0313 sex crimes were committed per day. Sex crime data have substantial variation over years and precincts. This variation is extremely important for our analysis and does not show any clear trend (see Figure 1 to Figure 6). Figure 1 presents the evolution of sex crimes in NYC. It shows an increasing trend since 2004, and then the trend is reverting in 2008 to 2010. In addition, the data does not present any similar pattern over boroughs. Figure 2 to Figure 6 show the evolution of sex crimes in each borough of NYC. These figures show that there is variation also on the geographical level besides the time level. A possible concern could be the reallocation of sex crimes amongst the boroughs. Despite the fact that in 2010 there was an increase in the number of sex crimes in Brooklyn, it is not evident that the reduction in Manhattan and Queens in 2008 and 2009 has reallocated to this borough.

The total number of sex crimes present huge differences across boroughs and are concentrated in Manhattan. These results are summarized in Column (1) of Table 2 that shows the total number of sex crimes in the whole period of observation across the five boroughs. Manhattan presents 3,930 sex crimes during the eight years and a half of our period of observation. Brooklyn and Queens have roughly half of the sex crimes than Manhattan, they respectively have 1,625 and 1,684 sex crimes. These findings motivate the inclusion of geographical fixed effects, time trends and clustered variance (at geographical level: precinct) in our main specification.

The total number of sex crimes present important differences across seasons. Column 1 of Table 3 presents these results. Winter is the season when the least number of total sex crimes are committed.

We have substantial variation in the number of sex crimes committed even across precincts inside a given borough. For example consider Manhattan, the borough where the majority of sex crimes are committed. We found that out of 22 precincts in Manhattan, the highest proportion of sex crimes is concentrated in precinct 14 (28%), followed by precinct 13 (16%).[8]

[8]Precinct 14 and 13 are both located in mid-town Manhattan. The former is primarily a commercial and entertainment

Sex crimes are primarily committed by male offenders. Table 4 presents the total number and the percentage of sex crimes committed by male offenders for weekends and weekdays. As can be observed the percentage of sex crimes committed by male offenders is approximately constant over the days of the week and fluctuates around 90% of the total crimes.

Sex crimes are neither concentrated over the weekends nor over any given hour of the day. Table 5 shows the total number of sex crimes committed over the weekends and weekdays. This table considers each one of the three different days of the weekend and divides the day in 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.). As stated above, Table 5 shows that sex crimes are not concentrated during the weekend nor at night. In addition to this table, Figure 7 provides the distribution of sex crimes across the days of the week. On the vertical axis there is the number of sex crimes, while on the horizontal axis there are the days of the week where 0 is Sunday, 1 is Monday, 2 is Tuesday, 3 is Wednesday, 4 is Thursday, 5 is Friday and 6 is Saturday. Figure 7 shows clearly that the data do not exhibit any clear pattern over the days of the week: sex crimes do not concentrate in a specific day.

2.2 Indoor Prostitution Businesses

The second data set was obtained from Reference USA and provides information on all registered indoor prostitution establishments from 2004-2012 in NYC. It contains data about the year when the business was registered, the number of employees in each businesses and location of the business through geographical coordinates. We define indoor prostitution establishments as the following categories: escort services, adult entertainers, strip clubs and gentlemen clubs. Using businesses' records such as Yellowpages, Superpages,etc. or whenever possible the Department of the State of NY records we could match almost every business with an opening date, and sometimes also with a closing date.[9]

Using these two data-sets we constructed a panel counting the total number of establishments opened in each precinct for each day of our period of observation. We mainly used three sources to keep track of the opening date of the establishments. The first two are Yellow-pages and Super-pages which are telephone directories of businesses organized by categories. Advertising a business on these telephone directories is free and with the on-line application it takes at most 5 business days to get your establishment advertised.[10] Since businessmen have to write their names and phone number it seems implausible that ads are not true. The third one is the Department of the State of NY which records every business opened in the State of NY, for each business they provide detailed information: jurisdiction, address, current entity status, etc. In few cases the names of the businesses are different than those they used to register to the Department of the State of NY's data-base so they cannot be matched. Although this problem does not apply for Yellow-pages and Super-pages since the name of the business with which they are registered is the same than that used to register to Reference USA.

The number of indoor prostitution establishments experienced a large increase during our period of observation. Indeed in 2004 there were 76 businesses while in June of 2012 they increased by roughly 200 units. Thus our data present roughly 200 openings of indoor prostitution establishments during the eight years and a half of our period of observation. We use this variation to identify the effect of indoor prostitution

oriented precinct. The latter is home to several residential complex, insurance companies and major health care facilities. Deeper descriptions can be found in the NYPD database.

[9]Exactly we could match 90% of the indoor prostitution businesses found in Reference USA. Note that we can see this date as an opening date and/or a registration date. However this interpretation will not affect the validity of our identification strategy.

[10]According to their "Help for advertisers and business owners". https://www.yellowpages.com.au/pages/help/advertisers and http://wp.superpages.com/addnewlisting.php

establishments on sex crime. We analyze the evolution of indoor prostitution establishments over time in Figure 8. On the vertical axis of Figure 8 we measure the total number of indoor prostitution establishments opened in NYC. On the horizontal axis there are the eight years and a half of our period of observation.

Indoor prostitution establishments' openings are concentrated in Manhattan and during summer. Column (2) of Table 2 shows the total number of openings per borough during our period of observation. We observe that approximately 75% (150 out of 206) of the openings happen in Manhattan. In the same fashion than sex crime data, after Manhattan there are Queens, Brooklyn, The Bronx and Staten Island. While Column (2) of Table 3 shows the total number of opening over season. It shows that roughly 34% (70 out of 206) of the openings took place in summer.

As for sex crimes one might be concerned that openings of establishments take place with higher frequency on certain days of the week (as for instance during the weekend), but this is not the case. We address this concern in Table 6 and Figure 9. Table 6 shows the total openings of establishments over weekends and weekdays. We observe that out of 206 openings 90 took place during the weekend, whereas 116 happened during weekdays. Figure 9 shows the total number of openings for each day of the week. On the vertical axis there is the number of openings of establishments. On the horizontal axis there are the days of the week where 0 is Sunday, 1 is Monday, 2 is Tuesday, 3 is Wednesday, 4 is Thursday, 5 is Friday and 6 is Saturday. In the light of these findings we conclude that openings do not take place more likely on any particular day of the week.

3 Identification strategy

Similar toDahl and DellaVigna [2009], we are going to consider the following specification:

$$ln\, Sex\, Crime_{pt} = \beta Indoor\, Prost_{pt} + \Gamma X_{pt} + \varepsilon_{pt} \tag{1}$$

The dependent variable is the logarithm of the number of sex crimes committed in precinct p in a given day t.[11] $Indoor\, Prost_{pt}$ are the total number of indoor prostitution establishments in precinct p for day t. This variable cumulates all the opened businesses up to day t. The variables X_{pt} are a set of seasonal and geographical control variables: indicators for precinct, year, month, day-of-the-week, day-of-the-year and holidays, and geographical (at precinct level) year trends. All standard errors are clustered at 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 holidays fixed effects to capture deeper variation due to timing factors.[12]

Our identification relies on the exogeneity of the variation in time of openings and registration of indoor prostitution establishments across precincts in NYC. Our main assumption is that both openings and registration dates are exogenous in a model for daily crime. Given that opening a business in NYC requires a long bureaucratic procedure we can take the day of registration as random.[13] Of course there could be

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

[12] Internal validity does not seem to be an issue in our analysis since we examine all NYC for almost 9 years. As for external validity it could be argued that cities too different from NYC might have different crime mechanisms and so results should be interpreted carefully if our goal is to design policy interventions in other cities.

[13] Note that the date we have is the registration date to the Department of NY State database or the registration date in Yellowpages or Superpages.

precincts more prone to have these businesses but for us it is important that the timing of their opening do not correlate with any unignorable characteristic. Note that since our specification is daily this amounts to the opening date of an indoor prostitution business to be exogenous to any other factor affecting sex crime.

There are two caveats: reverse causality and confounding factors. Reverse causality looks implausible in this model. Indeed we did not find any evidence supporting the fact that indoor prostitution establishments may open in a certain precinct due to the number of sex crimes committed there. If the explanatory variable were street prostitution we might expect that street prostitutes choose where to work depending on the number of sex crimes, and we could also assume that this evidence would be hard to find. Yet, this is not the case for indoor prostitution establishments. First these business are legal (not as street prostitution). Secondly, even assuming reverse causality we would expect that indoor prostitution establishments would open in places where there are more sex crimes. This effect would cause upward biased estimates.[14]

Note that comparability of our treatment and control groups boils down to comparability of police precincts inside NYC. Thus this specification allows to think that any confounding factor varying over time or geography would be captured by our indicators.[15] For example, it could be argued that the number of working policemen could be an important control variable for our specification, unfortunately we do not have access to this variable, but given that they would vary across precincts and over days (days of the week, days of the year and even holidays!) our indicators variable will capture their effect. The inclusion of precinct time trends ensures that $\hat{\beta}$ is not capturing any effect simply due to temporal changes in trends by precincts.[16]

One last problem could be measurement error. It might be the case that we have measurement error in our dependent variable and/or in our explanatory variable. One one hand, measurement error in our dependent variable could arise easily if we do not observe all the sex crimes committed in NYC. A possible explanation could be that there are sex crimes that are not seen by the officers. However, assuming that the measurement error is random, this problem would amount to have bigger standard errors, suggesting that the level of statistical significance of our coefficient is smaller (i.e. less significant) than what we found. Measurement error is an issue in every crime data-set and even more in sex crimes ones. In this data-set the major issues related to measurement error are due to victims that for some reason decide not to report the crime. Nonetheless we believe that we have minimized this problem by using the "Stop and Frisk" data-set. Since in this data-set victims do not decide to report or not the crime, it seems reasonable to think that there is less measurement error than in data-set based on sues and complaints.

On the other hand, measurement error in the explanatory variable might arise if some indoor prostitution businesses are not registered on the Reference USA database. In this case, again 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.

4 Results

Table 7 and Table 8 present the results of our regression. In Column (1) of Table 7 we just show the correlation between our dependent and independent variable, in each other column we include a control variable contained in X_{pt}. The last column of Table 8 corresponds to the whole specification considered in equation (1). Standard errors are clustered at precinct level in each column of the table.

[14]Since our coefficient of interest is negative and statistical significant assuming reverse causality would imply that the coefficient of the Population Regression Function is negative but larger in absolute value.

[15]Since any confounding factor would vary at precinct and day level.

[16]A critique to our specification could be that SUTVA is not satisfied. Since possibly the number of indoor prostitution establishments of a precinct could affect the number of sex crimes in bordering precincts.

More precisely in column (1) of Table 7 we just include precinct indicators, in the following two columns we include year and month indicators. It is likely that the economic conditions or other factors that might affect crime change from year to year and over months, then including year and month indicators is important because they are going to net out all the variation that is due to changes from one year to another and to months. In the three columns of Table 7 the coefficient is statistically significative and negative indicating that having an indoor prostitution establishment in a certain precinct decreases the number of sex crimes by approximately 0.22%.

In each column of Table 8 we find that including day-of-the-week, day-of-the-year and holidays indicators do not change our results, but this is not the case when we include precinct-year trends. The last column presents the results also with the inclusion of precinct-year trends. Adding precint-year trends increases the size in absolute value of our coefficient. This pattern suggests that omitted variables were attenuating the estimated coefficient. This is our preferred specification, it shows that having an indoor prostitution establishment in a certain precinct decreases the number of sex crimes by approximately 0.4% daily. [17]

The high-frequency of our data allows us to include controls for almost anything that affects rape and might be changing in our period of observation. Indeed our results are really conservative since the controls added in Table 8 are capturing every change that is happening due to different days of the week, days of the year and holidays. It is plausible to think that patterns of crime might be different over the week, during the year and in holidays: if this is the case our controls are exactly netting out this effect.

Further, even if we are dealing with daily data we decided to include precinct-year trends. These trends capture all the variation that is due to a simple linear trend over time.

The estimated coefficient suggests that increasing the number of indoor prostitution establishment in a certain precinct decreases the number of sex crimes by approximately 0.4% daily. There are two issues we should analyze. Firstly, it is not clear how this effect cumulates over time: the effect estimated is in the very short-run, Section 6 deals with conciliating our findings with the long-run. Secondly, it might be the case that the effect of each indoor prostitution establishment is not linear so before interpreting the coefficient we should address this issue. This is done in Section 5.

5 Additional Specifications and Robustness checks

In this section we explore two different specifications: threshold effects and sex crime by male offenders. The first specification explores whether there are non-linear effects. In fact, it could be that the effect of indoor prostitution establishments differs non-linearly depending on the number of these businesses in a certain precinct. It could be that the impact that the first indoor prostitution establishment has is different from the impact of the second, third or n-th indoor prostitution business. In order to examine this issue we use a dummy variable taking value 1 when the number of indoor prostitution establishments is in a certain range and taking value 0 otherwise.

In particular, we use 4 dummy variables as described above. The first one takes value 1 if there is only an indoor prostitution establishment in precinct p on day t, the second one takes value 1 if there are between 2 and 4 businesses opened, the third one if there are 5, and the fourth one if there are more than 6 businesses opened. Therefore the first variable is capturing the effect of having one establishment, the second, the third

[17] Note that if we do not transform the variable to logarithmic scale, we find a reduction of 0.0076 which is equivalent to a reduction 0.48% since the average number of sex crimes per day is 1.538 taking into account only precincts and days in which sex crimes were committed, there is no reason to take into account also days in which sex crimes were not committed since these crimes cannot decrease more than 0.

and fourth one respectively of small, medium and large concentration of indoor prostitution establishments. A priori no clear pattern is expected besides all the coefficients being non-positive. Column (1) of Table 9 presents the results of this specification. All the coefficients are negative but just one is statistically different from zero: it is the coefficient of having 5 indoor prostitution establishments opened. We conclude that the data only indicates a clear nonlinear effect of indoor prostitution establishments: the effect of having the fifth establishment opened. Note that our specification is very conservative: we include all the fixed effects and precinct time trends in every specification we run.

The second specification explores equation (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. As can be observed the size, sign and level of statistical significance of our coefficient of interest are practically identical to the one in the more general specification, a result which is easy to interpret knowing that the large majority of sex crimes are committed by male offenders.

We also explore the robustness of the results by changing the specifications. Firstly, we drop the day-of-the-year and holidays indicators and replace them with exact-day indicators. So every day of the year from the 1st of January of 2004 to the 30th of June of 2012 has its own fixed effect capturing whatever differs from day to day. Secondly, include precinct month trends instead of precinct year trends. This specification allows same month in different years to have the same linear trend. Thirdly, 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 from year to year, while these ones are varying from each month of the year to each month of the year. In other words for example, January 2004 will have a different trend than February 2004 and different than January 2005. Table 10 reports the results of these three specifications. Note that even if these robustness checks are very strict our coefficients are negative and statistically significant at most at 10% level in each of the four specifications and their magnitude is substantially similar.

Finally, we apply the Inverse Hyperbolic Sine (IHS) transformation to our dependent variable. Before our dependent variable was $\log(1+y)$ now using the IHS it becomes $\log\left(y+\left(y^2+1\right)^{\frac{1}{2}}\right)$. The IHS is spread used in applied econometrics paper for cases where there are fat tails.[18] The last two columns correspond respectively to a probit and a linear probability model using a dummy variable taking value 0 when no sex crimes are committed and 1 otherwise. Table 11 shows the results for these three specifications. Column (1) deals with IHS, Column (2) with probit and Column (3) with the linear probability model. In the three cases our coefficient of interest is negative. In the IHS case it is significant at 10% level, in the probit model at 12% and in the linear probability model at 5%. The linear probability estimates that an increase in one entertainment business reduces the probability of sex crime by 0.4 percentage points, which is equivalent to a 20% decrease from the baseline. In addition, we computed also the model in levels finding a negative statistically significant coefficient at 10% level.

6 Event Study Analysis: the timing of the effect

In this section we study the timing of the effect. The general approach in the literature to answer this kind of questions is to use an Event Study Analysis. Nevertheless, this approach usually evaluates the introduction of a new policy that is defined as the event. This event usually is introduced just once, so the goal of this approach is to evaluate the effect of this policy by comparing the outcome variable before and after the

[18] Pence [2006]

match. The introduction of the policy is formalized in a binary variable taking value 0 before the policy was introduced and 1 when the policy is introduced and after. It uses lags and leads of this binary variable to study when the effect is taking place.

Based on the analysis of the previous section, we define the event as the opening of the 5th establishment. Consequently, our binary variable takes value 0 before the 5th establishment was opened and 1 when and after it is opened regardless the opening of new establishments. In our sample there is no precinct going back to 4 establishments after the 5th is opened. In other words, there is not any precinct where an establishment closes when only 5 establishments are opened.

Weekly data allows us to observe how estimates change in the week of the introduction of the policy and, using a reasonable number of lags and leads, after 2 months. We use lags and leads of the dummy variable for every two weeks since this allows us to analyze a larger time window. Therefore, variables lagged 1 period take value 1 one and two weeks before the introduction of the policy; variables lagged 2 periods take value 1 three and four weeks before the introduction of the policy and so on. We use 4 lagged/forwarded variables in order to be able to observe what happens before/after 2 months of the introduction of the policy. We estimate the following equation:

$$ln\, Sex\, Crime_{pt} = \sum_{t \neq -4}^{4} \beta_t Event_{pt} + \Gamma X_{pt} + \varepsilon_{pt} \tag{2}$$

where $Event_{pt}$ is a dummy variable defined as specified above, while now X_{pt} contains precinct, year, month and week fixed effects plus precinct-year time trends.

Table 12 shows the results of the Event Study Analysis. Since one of the dummy variables has always to be omitted in order to avoid perfect multicollinearity. In our case, on the presumption that there is no effect before the opening of an establishment we omit the 7th and 8th weeks lags of the dummy variable. We want to keep the first lead variable to check if there is an effect after 1 and 2 weeks and in the long-run.

The results of Table 12 show that are two effects over time. The first effect is after the 1st and the 2nd week of the opening, whilst the second one is after roughly one month and a half (i.e. 5th and 6th week) of the opening of the 5th establishment. More precisely after the first two weeks sex crime decreases by 9.39% whereas after the 5th and the 6th week the decrease is by 16.5%. This magnitude is consistent to the one found using the linear probability model. Moreover results are in line with Cunningham and Shah [2014] who find that decriminalization of indoor prostitution in Rhode Island reduced sex crime by 30 percent from 2004 to 2009.

The high frequency of our data allows to disentangle the exact timing that indoor prostitution needs to decrease rapes. If our data were at lower frequency (quarterly or yearly) we would not be able to identify this effect, in this case the impossibility of controlling for confounding factors happening sistematically simultaneously (at the same year or quarter) than our treatment could even lead to larger estimates in absolute value.

7 Mechanisms Behind the Effect of Indoor Prostitution on Sex Crimes

This section explores three mechanisms that can provide an explanation to the decrease of sex crime caused by indoor prostitution. We call these three mechanisms: *police channel*, *potential victims channel* and *potential criminal channel*. Each one of these mechanisms can be tested using our database.

First, it could be the case that these businesses reinforce security in the precinct and more police officers are assigned to the area.[19] 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 (*police channel)*. Secondly, it might be that women are avoiding precincts were indoor prostitution opened and are moving to bordering precincts where there are no establishments. Thus the decline in crime would be explained by a reduction of potential victims. It could also be the case that indoor prostitution is employing potential street sex workers that in absence of indoor prostitution would be in the streets. If we assume that most sex crimes are committed to street sex workers, indoor prostitution might reduce sex crimes by providing protection to street workers (*potential victims channel)*. Finally, potential offenders might prefer to use indoor prostitution's services instead of committing sex crimes (*potential criminal channel)*.[20]

The ideal way to explore the *police channel* would be to have data about the daily number of police officers that are working in each precinct. Nonetheless we do not have daily data about the amount of officers working in each precinct.[21] In order to explore this mechanism we estimate the effect of indoor prostitution businesses on other type of crimes, such as number of stops for drugs use and number of burglaries. Table 13 presents the results of this specification. Each specification resembles equation (1) but with a different dependent variable. Column (1) of Table 13 has as dependent variable the number of stops for drugs use. Column (2) has as dependent variable the number of burglaries. In these specifications we cluster the variance at precinct level, include precinct, year, month, day-of-the-week, day-of-the-year and holiday indicators and precinct-year trends. If officers were incresing we would find a decrease also in these type of crimes that are easier to control. However, we find no effect of indoor prostitution on other 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 indoor prostitution does not have any effect on other crimes different than sex crimes (e.g. crimes for drugs and burglaries, which potentially might be affected by the number of indoor prostitution establishments).[22]

To explore the *potential victims channel,* we estimate two models. First, if women are just avoiding the precincts where indoor prostitution opened, we should observe an increase in crime in neighboring precincts. We consider a specification with 22 precincts where the number of precincts decrease since we are gathering together precincts on the basis of their geographical position. Thereby e.g. we group precincts 1, 5 and 7 together; precincts 6, 9, 10 and 13 together, and so on. A complete list of how we grouped precincts can be found in the appendix. If the effect found is only due to women avoiding precincts where there are establishments then sex crimes are moving from one precinct to the other. Therefore, this would imply that sex crimes are increasing in precincts, bordered by precincts with at least an establishment, but where there are no establishments; while sex crimes are decreasing in precincts where there is at least an establishment but just for the displacement of the potential victims. If this is the case the total effect in larger precincts should compensate and be closer to zero than our main estimated coefficient (-.4%). Whereas, if sex crimes are not moving the coefficient should still be negative and larger in absolute value since we are taking into

[19]Note that since our data is daily and recalling our identification strategy this would imply that the number of police officers increases at the same time than a new indoor prostitution establishment opens in a certain precinct.

[20]In our future research agenda we would like also to analyze whether the decrease of sex crimes is not a specific consequence of opening an indoor prostitution business but rather of the opening of any businesses that is opened at night. Even if extremely unlikely we cannot explore this hypothesis.

[21]We even do not know if a fixed amount of officers work daily in a certain precinct. Possibly officers can work in different precincts in a given day.

[22]The data on these two crimes come from The Stop and Frisk data set. Again we take the log of the dependent variable to have smoother data and interpret the coefficient as a percentage change.

account bigger geographical units. Column (3) of Table 9 shows the results and indeed we find a negative statistical coefficient in absolute value bigger than our benchmark. This result goes against the *potential victims channel*.

Second, we consider a specification like equation (1) but where the dependent variable is the number of sex crimes occurred in the bordering precincts of each precinct and where we add two explanatory variables. The first one is a dummy variable taking value 1 if there is at least an indoor prostitution business in a bordering precinct. The second one is the interaction between this dummy and the number of indoor prostitution businesses in the precinct of interest. If women are avoiding precincts with indoor prostitution establishments the dummy variable, the number of establishments and the interaction should be statistically significant. In other words, rape would be moving from precincts with openings of establishments to precincts without such establishments. We find that the three coefficients are not statistically significant. Column (4) of Table 9 only reports the coefficient of the number of indoor prostitution establishments in the precinct of interest. The coefficient is not either positive or statistically significant suggesting that a decline in potential victims is not the main channel. In addition the results of this last specification support the hypothesis that sex crimes are not "moving"to bordering precincts.

Moreover, to address if indoor prostitution are changing the location of street prostitutes, we estimate model (1) but replacing the dependent variable by prostitution stops. If this were the case we would see that the number of indoor prostitutes establishments has an effect on the number of street prostitutes. We find no statistically significant effect on this new outcome. This result suggests that therehas not been a reallocation of street sex workers to other precincts and as well as 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. Results of this specification are reported in Column (3) of Table 13.[23]

Finally to address the *potential criminal channel,* we focus on sex crimes committed at night. If potential criminals prefer to use indoor prostitution's services rather than committing sex crimes the data should highlight that the effect of these establishments is higher when the supply of the services of these establishments is higher. It seems plausible to assume that the supply of the services provided by indoor prostitutes is higher at night given that most of these establishments open at night. Thus we divide the day in two halves: morning (from 6 am to 6 pm) and night (from 6 pm to 6 am). So now our time unit is not any longer a day but half-day. Further we created a dummy variable taking value 1 at night and zero in the morning. Finally we saturated the specification including the interaction between our explicative variable and the dummy.

Column (1) of Table 14 shows the results of this specification.[24] While the effect of the number of establishments is still negative, 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 and statistically significant at 12%. These results show that the effect of the number of establishments is negative in the morning and at night, however even if more sex crimes are committed at night, the effect of indoor prostitution is higher in absolute value and more negative at night then in the mornings. The level of significance of the coefficient implies that amongst all the channels explored the *potential criminal channel* is the only one that data do not reject clearly.

In order to explore this explanation more deeply and to provide a robustness check we divide the day in 4 quarters. Precisely: morning (from 6 am to 12 pm), afternoon (from 12 pm to 6 pm), evening (from 6 pm to 12 am) and night (from 12 pm to 6 am). Again we create 4 dummy variables respectively in this order

[23]The data about street prostitutes come from the Stop and Frisk data-set. In this case again we take log (1+y) since some days 0 street prostitutes were found in the street.

[24]Which is the reference category.

and saturate the model with the interactions. Our results in Column (2) of Table 14 corroborate our initial finding: note indeed that the coefficients of interaction terms in the evening and at night are negative and respectively statistically significant at 11% and 12%.[25]

8 Conclusion

This paper provides one of the first causal evidences of the effect of indoor prostitution businesses on sex crimes using the quasi-natural experiment of the timing of openings of indoor prostitution businesses in NYC. To our knowledge this paper is also one of the first to explore the possible mechanisms behind this effect and to disentangle the timing of the effect. Using a unique daily data-set on the opening date and location of indoor prostitution businesses and crime in NYC, we find that the number of these businesses on any given day significantly affects the number of sex crimes committed that day. We exploit the quasi-natural experiment generated by timing in openings of these establishments. Our identification assumption is that the opening date of any indoor prostitution businesses is exogenous to any unignorable characteristic affecting sex crime.

Our estimates are based on daily data suggesting that there is an effect in the very short-run. We find that increasing this type of businesses by 1 unit leads to a 0.4% daily reduction in sexual violence per precinct. Our findings are in line with contemporary research carried on by Cunningham and Shah [2014] who find that unexpected decriminalization of indoor prostitution in Rhode Island reduced sex crime by 30 percent from 2004 to 2009.

Our results also show that the most plausible story is that indoor prostitution reduces sex crimes since potential aggressors use the services of these establishments instead of committing sex crimes. We analyze several mechanisms: (i) it could be the case that these businesses reinforce security in the precinct and more police officers are assigned to the area. In this case, a decline in sex crimes could reflect a general decline in crime (*police channel).* (ii) Women could also avoid precincts were indoor prostitution establishments are present and move to bordering precincts where there are no establishments. Thus the decline in crime would be explained by a reduction of potential victims. It could also be the case that indoor prostitution are employing potential street sex workers that in absence of indoor prostitution would be in the streets. If we assume that many sex crimes are committed to street sex workers, indoor prostitution might reduce sex crimes by providing protection to street workers (*potential victims channel).* (iii) Potential offenders might self select into indoor prostitution establishments and instead of being in the street there might be inside this businesses (*potential criminal channel).* Our results do not support the first two mechanisms but cannot discard the *potential criminal channel*.

This mechanism is in line with a survey done to men who had bought sex from women in prostitution in London. About 54% of men who bought sex stated that if prostitution did not exist then they would be more likely to rape women who were not prostitutes. This belief was clearly held by one man who even stated: "Sometimes you might rape someone: you can go to a prostitute instead" [Farley et al., 2009].

Our results are robust to different specifications suggesting that indoor prostitution businesses have no

[25]Note also that this robustness check is quite demanding since we are separating the effect at night in two halves: evening and night. One could argue that the effect is taking place at night when the majority of women are avoiding the precincts with at least an establishment. Hoewever, if this were true we should find evidence in favour of this hypothesis in the daily regressions. In addition, we run the same regression of bordering precincts but dividing the day in quarters. If it is true that the effect is due to more women avoiding this precincts at night then we should find empirical support in this regression: the presence of at least an establishment should cause women to avoid that precinct and so sex crimes should increase in bordering precincts, but the regression rejects this hypothesis.

effects on crime per se and that our coefficient is robust even to stronger specifications. By providing empirical evidence of the impact of indoor prostitution on sex crimes this paper sets the baseline to discuss policy interventions towards legalization or prohibition of these businesses and prostitution.

Table 1: Daily summary statistics of sex crimes and establishments.

	(1) Sex Crimes	(2) Indoor Prost. Est.
Observations	238,931	238,931
Mean	0.0312977	1.957419
Standard Deviation	0.3405145	5.128347

Table 2: Total number of sex crimes and openings over boroughs.

	Sex crimes by borough	Openings by borough
The Bronx	474	10
Brooklyn	1,625	20
Manhattan	3,930	150
Queens	1,684	24
Staten Island	162	2
Total	7,875	206

Table 3: Total number of sex crimes and openings over seasons.

	Sex crimes by season	Openings by season
Winter	1,628	42
Spring	1,938	39
Summer	2,161	70
Fall	2,148	55
Total	7,875	206

Table 4: Total number and frequencies of sex crimes committed by gender.

	Sex crimes by male offenders (per day)	Percentage over total
Weekend (Friday-Sunday)	2,431	90.34%
-Friday	1,013	91.43%
-Saturday	712	89.79%
-Sunday	706	89.37%
Weekdays (Monday-Thursday)	4,776	92.13%

Table 5: Total number of sex crimes over days of the week and time of the day.

	Sex Crimes (per day)				
		Morning	Afternoon	Evening	Night
	Entire day (1)	6 A.M. to 12 P.M. (2)	12 P.M. to 6 P.M. (3)	6 P.M. to 12 A.M. (4)	12 A.M. to 6 A.M. (5)
Sex crime data for all days					
Weekend (Friday-Sunday)	2,691	510	664	805	712
-Friday	1,108	279	309	301	219
-Saturday	793	90	194	276	233
-Sunday	790	141	161	228	260
Weekdays (Monday-Thursday)	5,184	1,720	1,559	1,132	773

Table 6: Total number of openings over days of the week.

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

Table 7: The effect of indoor prostitution establishments on sex crimes.

	(1)	(2)	(3)
VARIABLES	log(Sex Crime+1)	log(Sex Crime+1)	log(Sex Crime+1)
Number of Indoor Prost.	-0.00209**	-0.00214**	-0.00215**
	(0.000855)	(0.000947)	(0.000947)
Constant	0.0240***	0.0218***	0.0184***
	(0.00301)	(0.00271)	(0.00274)
Observations	238,931	238,931	238,931
Clustered variance at Precinct level	YES	YES	YES
Precinct FE	YES	YES	YES
Year FE	NO	YES	YES
Month FE	NO	NO	YES
Day of the week FE	NO	NO	NO
Day of the year FE	NO	NO	NO
Holiday FE	NO	NO	NO
Precinct Trends	NO	NO	NO

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: The effect of indoor prostitution establishments on sex crimes.

	(1)	(2)	(3)	(4)
VARIABLES	log(Sex Crime+1)	log(Sex Crime+1)	log(Sex Crime+1)	log(Sex Crime+1)
Number of Indoor Prost.	-0.00215**	-0.00215**	-0.00215**	-0.00401*
	(0.000947)	(0.000948)	(0.000948)	(0.00218)
Constant	0.0125***	0.00721*	0.00734*	-5.514
	(0.00316)	(0.00391)	(0.00391)	(5.099)
Observations	238,931	238,931	238,931	238,931
Clustered variance at Precinct level	YES	YES	YES	YES
Precinct FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
Day of the week FE	YES	YES	YES	YES
Day of the year FE	NO	YES	YES	YES
Holiday FE	NO	NO	YES	YES
Precinct Trends	NO	NO	NO	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Additional specifications.

	(1)	(2)	(3)	(4)
	Threshold Effects	Committed by M	Large Precincts	Bordering precincts
VARIABLES	Log(Sex Crime+1)	Log(Sex Crime+1)	Log(Sex Crime+1)	Log(Sex Crime+1)
1 est. opened	-0.00385			
	(0.00304)			
2-4 est. opened	-0.00652			
	(0.00467)			
5 est. opened	-0.0155**			
	(0.00727)			
6 or more est. opened	-0.00414			
	(0.00934)			
Number of Indoor Prost.		-0.00412*	-0.00688***	-0.000618
		(0.00226)	(0.00222)	(0.0109)
Constant	3.373	-6.454	-33.94**	-31.69***
	(2.745)	(5.329)	(12.27)	(11.17)
Observations	238,931	238,931	68,266	238,931
Clustered variance at Precinct level	YES	YES	YES	YES
Precinct FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
Day of the week FE	YES	YES	YES	YES
Day of the year FE	YES	YES	YES	YES
Holiday FE	YES	YES	YES	YES
Precinct Trends	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10: Robustness check.

	(1)	(2)	(3)
VARIABLES	Log(Sex Crimes+1)	Log(Sex Crimes+1)	Log(Sex Crimes+1)
Number of Indoor Prost.	-0.00414*	-0.00214**	-0.00442*
	(0.00220)	(0.000943)	(0.00245)
Constant	-13.52*	0.00768**	0.000198
	(6.971)	(0.00361)	(0.00602)
Observations	238,931	238,931	238,931
Clustered variance at Precinct level	YES	YES	YES
Precinct FE	YES	YES	YES
Year FE	YES	YES	YES
Month FE	YES	YES	YES
Day of the week FE	YES	YES	YES
Day of the year FE	NO	YES	YES
Holiday FE	NO	YES	YES
Precinct Trends	YES	NO	NO
Exact Day FE	YES	NO	NO
Precinct M Trends	NO	YES	NO
Precinct Y-M Trends	NO	NO	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 11: Robustness check.

VARIABLES	(1) (IHS) Sex Crime	(2) (Probit) Sex Crime	(3) (Linear Prob) Sex Crime	(4) (Levels) Sex Crime
Number of Indoor Prost.	-0.00800*	-0.0171	-0.00456*	-0.00762*
	(0.00436)	(0.0104)	(0.00231)	(0.00432)
Constant	-11.46	81.77***	-6.165	-10.176
	(27.59)	(0.00231)	(10.025)	
Observations	238,931	235,828	238,931	238,931
Clustered variance at Precinct level	YES	YES	YES	YES
Precinct FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
Day of the week FE	YES	YES	YES	YES
Day of the year FE	YES	YES	YES	YES
Holiday FE	YES	YES	YES	YES
Precinct Trends	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 12: Event Study Analysis.

VARIABLES	(1) Log(Sex Crime+1)
6 and 5 weeks before opening	0.0391
	(0.152)
4 and 3 weeks before opening	-0.0297
	(0.0744)
2 and 1 weeks before opening	-0.0493
	(0.0668)
week of opening	0.0243
	(0.132)
1 and 2 weeks after opening	-0.0939***
	(0.0270)
3 and 4 weeks after opening	0.0487
	(0.0891)
5 and 6 weeks after opening	-0.165***
	(0.0414)
7 and 8 weeks after opening	-0.00299
	(0.0297)
Constant	10.19
	(14.10)
Observations	2,210
Precinct FE	YES
Year FE	YES
Month FE	YES
Week FE	YES
Precinct Trends	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 13: Effects on other crimes.

VARIABLES	(1) Log(Drugs)	(2) Log(Burglarys)	(3) Log(Street Prostitutes+1)
Number of Indoor Prost.	-0.00118	0.00539	-0.0006164
	(0.00456)	(0.00796)	(0.0011319)
Constant	0.161***	8.891	2.6867
	(0.0310)	(20.48)	(2.1494)
Observations	238,931	238,931	238,931
Clustered variance at Precinct level	YES	YES	YES
Precinct FE	YES	YES	YES
Year FE	YES	YES	YES
Month FE	YES	YES	YES
Day of the week FE	YES	YES	YES
Day of the year FE	YES	YES	YES
Holiday FE	YES	YES	YES
Precinct Trends	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 14: Potential Criminal Channel.

VARIABLES	(1) Log(Sex Crime+1)	(2) Log(Sex Crime+1)
Number of Indoor Prost.	-0.00169*	-0.000345
	(0.000927)	(0.000287)
Dummy Afternoon		0.000579
		(0.000383)
Dummy Evening		0.00135
		(0.000975)
Dummy Night	0.00283***	0.000322
	(0.000914)	(0.00102)
Interaction Afternoon		-0.000324
		(0.000252)
Interaction Evening		-0.00145
		(0.000889)
Interaction Night	-0.00108	-0.00150
	(0.000673)	(0.000968)
Constant	-3.317	-1.526
	(2.872)	(1.420)
Observations	477,862	955,724
Clustered variance at Precinct level	YES	YES
Precinct FE	YES	YES
Year FE	YES	YES
Month FE	YES	YES
Day of the week FE	YES	YES
Day of the year FE	YES	YES
Holiday FE	YES	YES
Precinct Trends	YES	YES

Robust standard errors 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

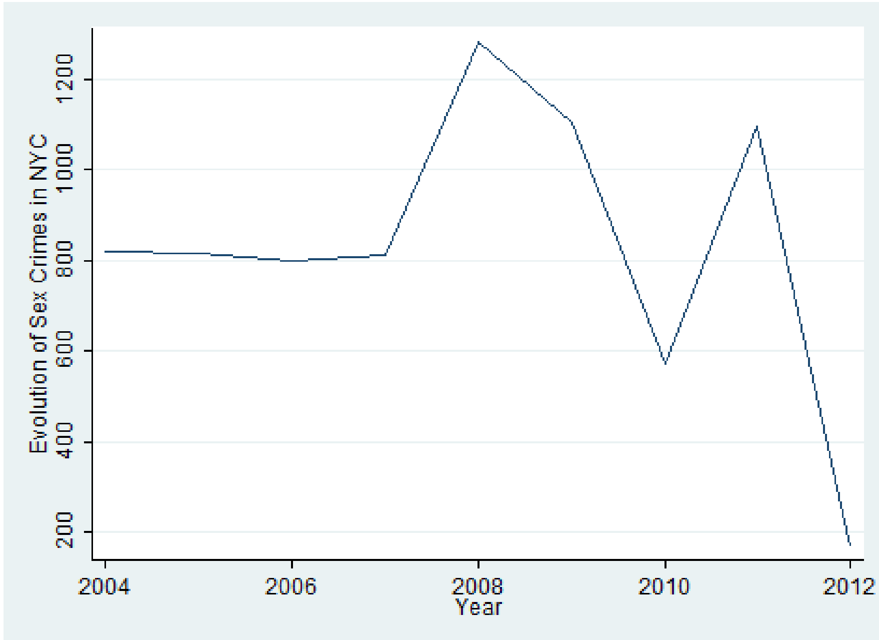


Figure 2: Evolution of Sex Crimes in the Bronx from January 2004 to June 2012

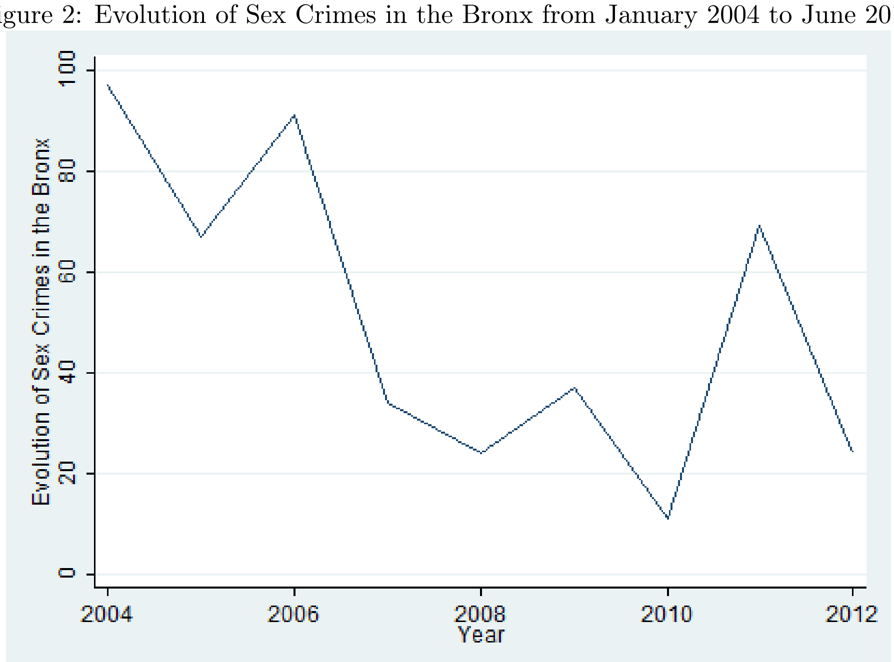


Figure 3: Evolution of Sex Crimes in Brooklyn from January 2004 to June 2012

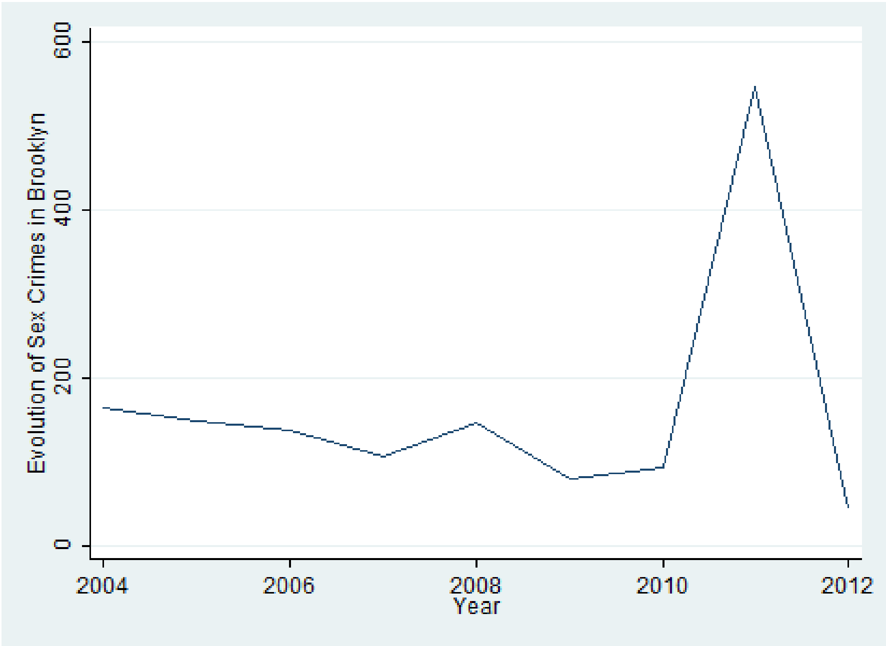


Figure 4: Evolution of Sex Crimes in Manhattan from January 2004 to June 2012

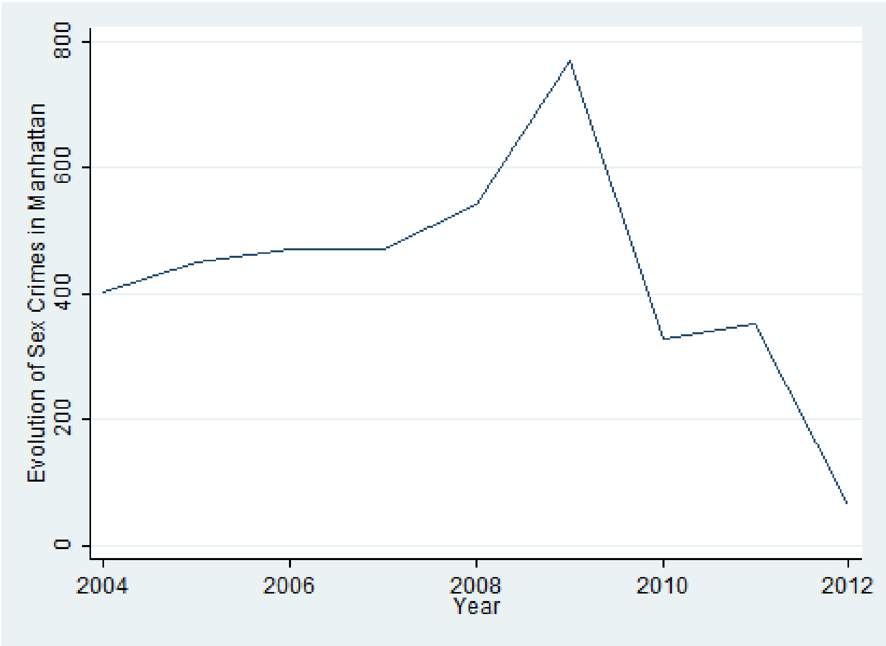


Figure 5: Evolution of Sex Crimes in Queens from January 2004 to June 2012

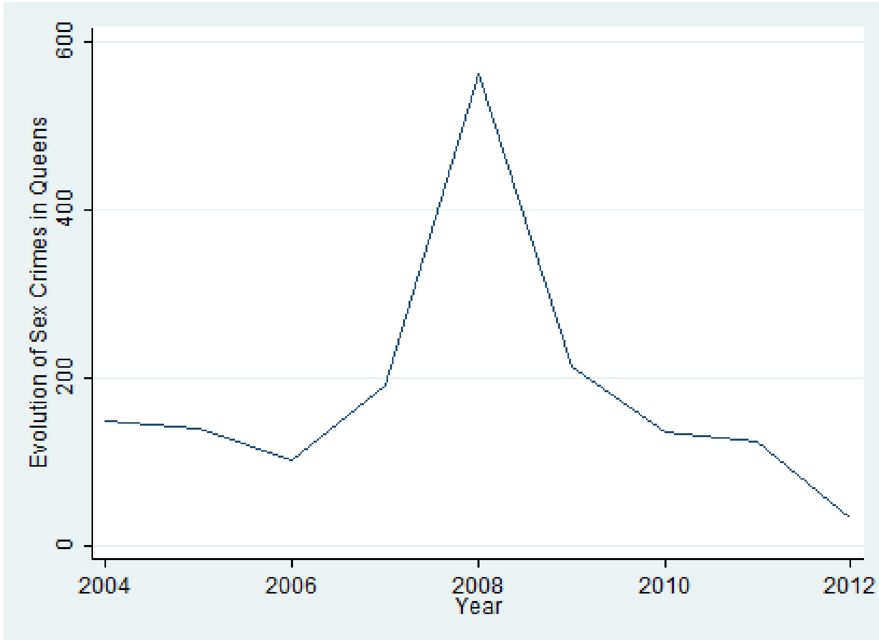


Figure 6: Evolution of Sex Crimes in Staten Island from January 2004 to June 2012

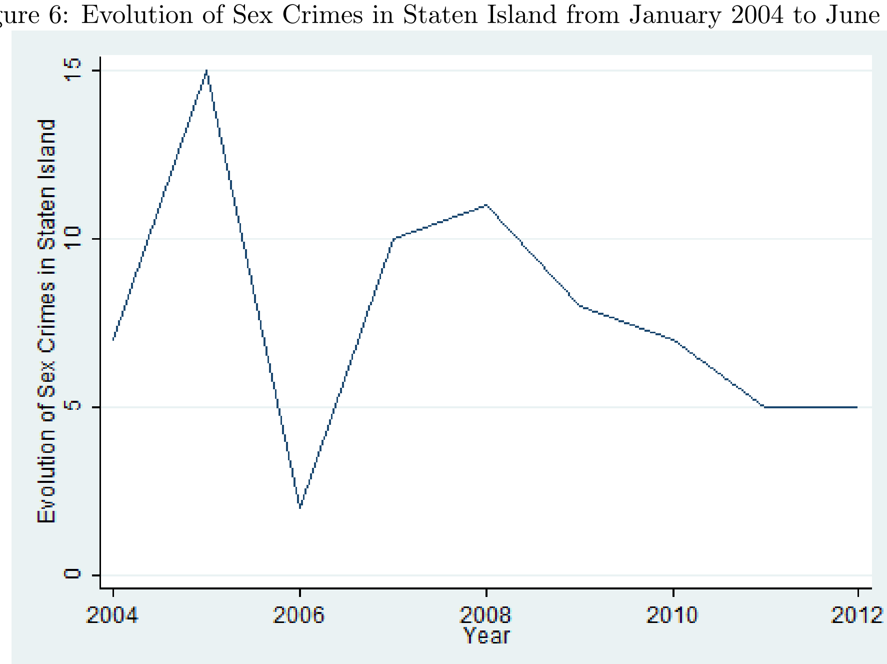
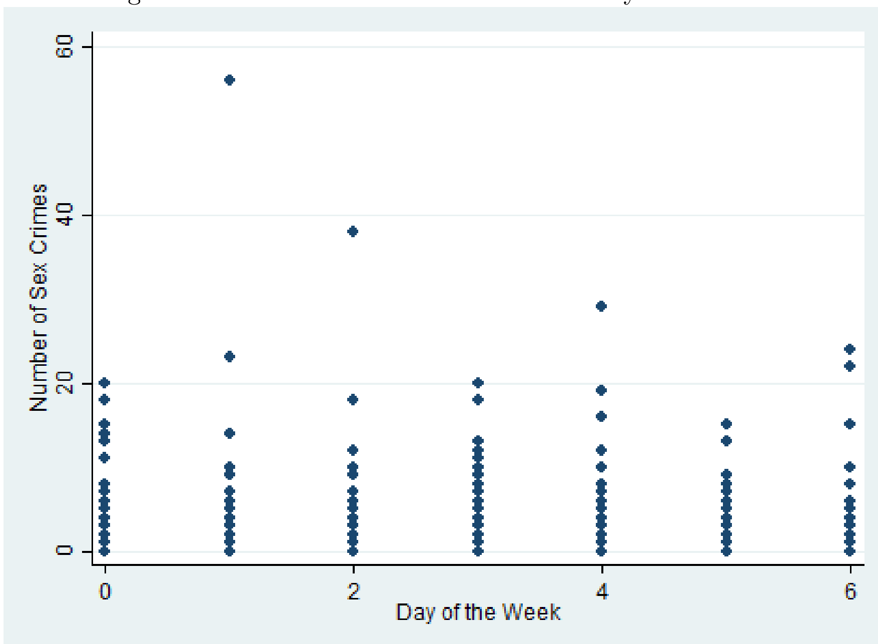


Figure 7: Distribution of Sex Crimes over days of the week



Notes: The "Day of the Week" in the horizontal axis is ordered as in Stata. Hence, 0 corresponds to Sunday, 1 to Monday and so on and so forth.

Figure 8: Evolution of establishments by Boroughs from January 2004 to June 2012

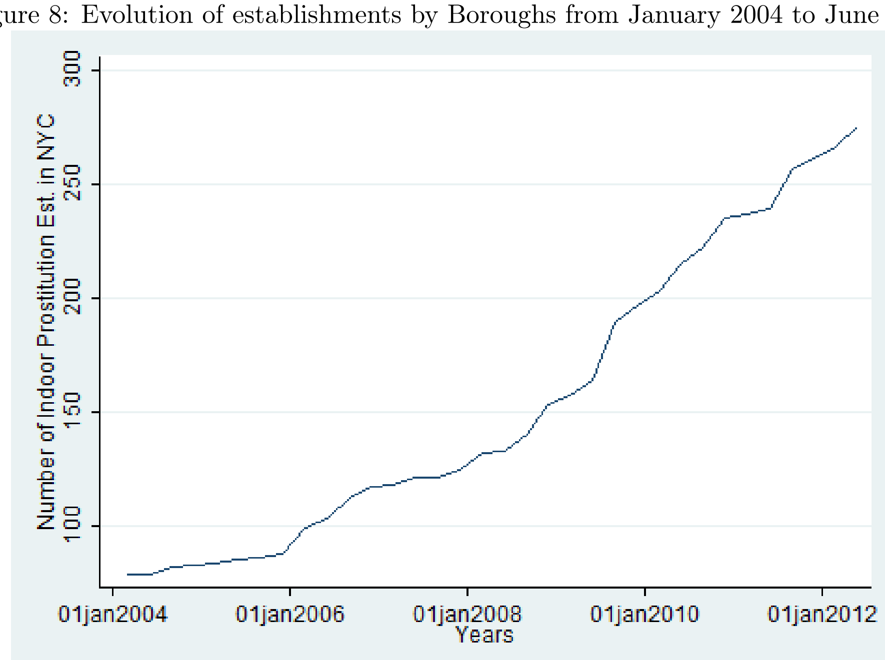
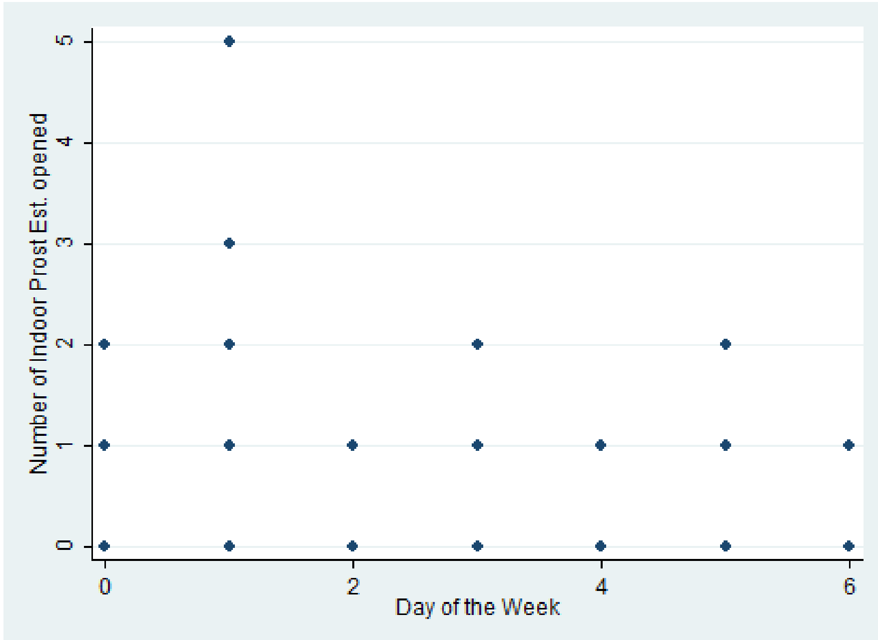


Figure 9: Distribution of the date of opening of indoor prostitution establishments over days of the week



Notes: The "Day of the Week" in the horizontal axis is ordered as in Stata. Hence, 0 corresponds to Sunday, 1 to Monday and so on and so forth.

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9 Appendix

9.1 List of larger precincts in potential victims channel

The 77 precincts are grouped in 22 precincts according to geographical proximity between them.

New Precinct	Formed by old 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

Table 15: List of larger precincts to test the potential victims channel