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

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Abstract

We use a unique data set to study the effect of indoor prostitution establishments on sex crimes. We built a daily panel from January 1, 2004 to June 30, 2012 with the exact location of police stops for sex crimes and the day of opening and location of indoor prostitution establishments. We find that indoor prostitution decreases sex crime with no effect on other types of crime. We argue that the reduction is mostly driven by potential sex offenders that become customers of indoor prostitution establishments. We also rule out other mechanisms such as an increase in the number of police officers and a reduction of potential victims in areas where these businesses opened. In addition, results are robust to different data sources and measures of sex crimes apart from police stops.

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1 Introduction

Sex crime, including sexual violence against women and rape, imposes a large burden on both psychological and physical health.[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 for a causal interpretation of the effect of prostitution on sex crime. First, it is difficult to obtain data about sex crimes due to privacy issues as well as systematic under-reporting. Second, it is also difficult to obtain reliable data on prostitution given that it is illegal in many countries.

A priori, the effect of prostitution on sex crime is not clear, and may depend on whether the prostitution is indoor and outdoor. Prostitution that is solicited on the streets is known as outdoor prostitution while prostitution that is solicited in closed spaces is known as indoor prostitution. This paper focuses on indoor prostitution. In states where prostitution is illegal, indoor prostitution usually occurs in strip clubs, gentlemen clubs, and as part of escort services. Indoor prostitution may increase sex crimes if prostitution reinforce the view of women as objects and therefore violence against women(Brownmiller, 1993). Alternatively, prostitution may reduce sex crimes if it is a substitute for sex crime (Posner, 1992).[2]In addition, indoor prostitution establishments may keep potential sex crime offenders away from potential victims, leading to futher substitution away from sex crimes.[3]

This paper benefits from a unique data set with daily precinct-level information for New York City (NYC). We collected data for indoor prostitution establishments from Reference USA. These data include names and addresses of establishments but do not include the date of registration of these businesses. Information on business registration date indicating when these establishments opened is separately obtained from the Department of the State of New York, Yellow Pages, or Super Pages. We categorized these establishments into New York Police Department (NYPD) precincts to match our crime data. Finally, we merged this data set with crime data from the NYPD "Stop and Frisk" program. These data are at the precinct-level and include hourly information on crimes observed by the police, including sex crimes. The data set covers the period from the Jan-

[1]Apart from its enormous psychological cost, it can also lead to public health issues such as unintended pregnancies, gynecological problems, induced abortions and sexually transmitted infections. 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]In addition, evolutionary biological theories 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 the former (Thornhill and Thornhill, 1983; Thornhill and Palmer, 2000a,b).

[3] Other disciplines, such as sociology or criminology, have also hypothesized that there may be other mechanisms linking prostitution and sex crimes which go in various directions (see Guttentag and Secord, 1983; Cohen and Felson, 1979; Schwendinger and Schwendinger, 1983; Obrien, 1991; Bailey, 1999).

uary 1, 2004 to June 30, 2012. While these data contain information of street sex crimes, we also check the robustness of the results with data on reported crime.

This paper exploits exogenous variation in the date of registration of indoor prostitution establishments to provide causal evidence of these establishments on sex crime using crime data at the daily level. Our main identification assumption is that the date of registration of such establishments is not linked with variables correlated with sex crime. 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 sex crime. Another advantage of this study is that treated and control groups are easily comparable since our data is at the precinct level.[4] The identification assumptions are more likely to hold comparing precincts within NYC relative to identification strategies that rely on variation across 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 crimes per precinct. This estimated coefficient comes from our preferred specification that includes fixed effects at the precinct, year, month, day-of-the-year, day-of-the-week and holidays level, and precinct-year time trends. Results are robust to other specifications, as well as the use of different data sources to measure sex crimes.

Furthermore, relative to outdoor prostitution, indoor prostitution establishments are less likely to be correlated with unobservable characteristics that affects sex crime. As documented by Farley (2005), indoor prostitution establishments allow the whole transaction to occur behind closed doors. In the US, indoor prostitution is the major source of prostitution and is estimated to constitute roughly the 85% of all sex work activity.[5]

This paper sheds light on the mechanisms behind the effect of indoor prostitution on sex crimes. Results 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 magnitude of the negative effect of the establishments is larger. 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 sex crimes. Furthermore, these results suggest that sex crime and indoor prostitution are substitutes. This is consistent with qualitative evidence from men who purchase prostitution (Farley et al., 2009).

Using our data we are also able to rule out other mechanisms such as an increase in the number of police officers or a reduction of potential victims in areas where these businesses opened. Consistent with the fact that results are not driven by increased policing or endogenous crime reporting in the data, we find that the openings do not affect other types of crimes. In addition, we do not find evidence of negative spillover effects on bordering precincts. We also check if there is a reduction in street prostitution and find no effects of reallocation to bordering districts. Moreover, we do not find that the establishments affect reallocation of street sex workers. This suggests that

[4] Each NYPD precinct is a relatively small geographic area of the city. In total, there are 77 NYPD precincts.

[5] See Urban Justice Center (2005).

results are not driven by a reduction of potential victims avoiding the area.[6]

This paper makes two contributions. First, it provides causal evidence of the effect of indoor prostitution on sex crimes at a very fine time and geographic level. While previous research Cunningham and Shah (2014) and Bisschop et al. (2015) have focused on year and state variations, we complement this studies by showing 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 shed light on the possible mechanisms behind the effect.

The results of this paper have strong policy implications. With the exception of Nevada, prostitution is illegal in the US. European countries 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. In 2014, the European Union parliament discussed and passed a resolution to follow the Swedish model, pushing European Union members criminalize the purchase of prostitutes. In addition to debate about whether prostitution should be legal, there has also been a debate about what type of prostitution should be targeted by law enforcement and how prostitution regulation intersects with gender policy.[7] Although both indoor and outdoor prostitution may generate negative externalities, this paper finds that indoor prostitution establishments can also generate a positive externality in the form of lower sex crimes, which is potentially important from a policy perspective.

The results in this paper show that indoor prostitution establishments have a negative effect on sex crime and also 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 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.

2 Data

This section describes the data. We also provide the main summary statistics and describe the general patterns in the number of sex crimes and the number of indoor prostitution establishments.

NYC is divided into 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 starting January 1, 2004 and ending June 30, 2012. We will combine two data sources: police stops

[6]It is commonly argued that street sex workers are victims of sex crimes.

[7]Examples from the popular press include *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) in *The Economist*.

and indoor prostitution establishments.

2.1 Sex Crime

Sex crimes are from the "Stop and Frisk" data. These data were obtained from the New York City Police Department (NYPDn) 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" dataset 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 a non-decreasing 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. Figures 6 to 10, in the appendix, 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 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 include month fixed effects to address this issue.

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]

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 2 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 2 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.

In addition, we check the robustness of the results using crime complaints for the same period of analysis.

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, or 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 Superpages 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

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

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 some 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 Yellowpages and Superpages 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 establishments on sex crime. We analyze the evolution of indoor prostitution establishments over time in Figure 3. 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 4. 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 4 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 to Dahl and DellaVigna (2009), we estimate the following specification:

$$\log\left(Sex\,Crime_{p,y,m,DoW}\right) = \beta Indoor\ Prost_{pt} + \theta_p + \gamma_y + \kappa_m + \eta_{DoW} + \rho_{DoY} + Holiday_{p,y,m,DoW} + PrecinctTrend_{py} + \varepsilon_{pt} \quad (1)$$

pages.com.au/pages/help/advertisers and http://wp.superpages.com/addnewlisting.php

The dependent variable is the logarithm of the number of sex crimes committed in precinct p in a given day t. 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 using the Inverse Hyperbolic Sine and also without log.$Indoor\ Prost_{pt}$ are the total number of indoor prostitution establishments in precinct p for day t. This variable accumulates 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 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.[11]

Our identification relies on the exogeneity of the variation in time of openings and registration of indoor prostitution establishments across precincts in NYC. The 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 as random. 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. However, 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 was 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.[12]

Note that comparability of 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.[13] For example, it could be argued that the number of working policemen could be an important control variable for our specification, however 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

[11] 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.

[12] Since the 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.

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

simply due to temporal changes in trends by precincts.[14]

Another threat could be measurement error. It might be the case that we have measurement error in the dependent variable and/or in the explanatory variable. On the one hand, measurement error in the 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 larger standard errors, suggesting that the level of statistical significance of the 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. Usually, in crime economics literature (especially for sex crimes), 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 this concern is minimized 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. Another concern is that officers are not randomly assigned as it has been shown in previous studies. However, this concern is addressed by analyzing in which extent we see a reduction of sex crimes and not other crimes. In addition, our identification relies on daily variation in the opening of an indoor prostitution establishment. Thus, there is no reason to believe that a larger number of officers would be assigned to that location in that specific date.

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. In Column (1) of Table 7 we just show the correlation between our dependent and independent variable. We find a negative relationship between the number of indoor prostitution businesses and sex crimes. Results are robust to the inclusion of precinct and year fixed effects. 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 significant and negative indicating that having an indoor prostitution establishment in a certain precinct decreases the number of sex crimes by approximately 0.22%.

Table 8 presents the results including, respectively in each column, day-of-the-week, day-of-the-year and holidays indicators. Results do not change. The last column of table 8 presents the results also with the inclusion of precinct-year trends. Adding precint-year trends increases the

[14] 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.

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%. [15]

Results 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, the inclusion of controls are exactly netting out this effect. Moreover, the inclusion of precinct-year trends are capturing all the variation that is due to precinct specific linear trends over time.

4.1 Additional Specifications and Robustness checks

In this section, we also explore the robustness of the results by changing the specifications. First, 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. Second, 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 9 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(Pence, 2006). 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 10 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. In addition, we computed also the model in levels finding a negative statistically significant coefficient at 10% level.

[15] 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 of 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.

5 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 crimes caused by indoor prostitution. We call these three mechanisms: *police channel*, *potential victims channel* and *potential criminals 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.[16] 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)*. Second, 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 criminals channel).*

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.[17] Nonetheless, since this data is not publicly available, 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 11 has as dependent variable the number of stops for drugs use. Column (3) 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 increasing 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).[18] Column (2) and (4) repeat the same analysis but using the IHS transformation of the two crimes, again there is no significant effect. These results do not support the *police channel*.

To explore the *potential victims channel*, we estimate two models. First, to address if indoor

[16]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 (i.e. same day) than a new indoor prostitution establishment opens in a certain precinct.

[17]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.

[18]The data on these two crimes come from The Stop and Frisk data set. Again we take our usual $\log(1 + y)$ due to the presence of some days in which there are no such crimes.

prostitution are changing the location of street prostitutes, we estimate model (1) but replacing the dependent variable by street 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 there has not been a reallocation of street sex workers to other precincts, 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 Table 14. Column (1) and (2) present respectively the results for our usual $\log(1+y)$ and for the IHS transformation.[19]

Second, 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 account bigger geographical units. Column (3) and (4) of Table 12 show 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*.

Moreover, if women are just avoiding the precincts where there is at least an indoor prostitution establishment in favour of precincts without any of these establishments 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 a lower number of women passing through precincts with at least an establishment, it implies we should observe an increase in the bordering precincts that do not have any establishment opened. Therefore we restrict our sample to precincts that had all their bordering precincts without any establishment, and at a later time, one of these bordering precincts experienced at least an opening of an establishment. If it is true that women are avoiding indoor prostitution establishments, we should find that increasing the number of these establishments increases sex crimes in bordering precincts that do not have any indoor prostitution establishment.

Hence, 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 no 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

[19] 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.

precincts with indoor prostitution establishments the interaction should be statistically significant. In other words, sex crimes would be moving from precincts with openings of establishments to precincts without such establishments. We find that the estimated coefficient is not statistically significant. Table 13 reports the coefficient of the this regression. The coefficient of the interaction term is not statistically significant suggesting that a decline in potential victims is not the main channel.[20] In fact, we conclude that the data do not support *potential victims channel*.

Finally to address the *potential criminals 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 effect should be larger 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) and (2) of Table 14 show the results for this specification. 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, but it is not statistically significant at standard levels for both $\log(1+y)$ and the IHS transformation.[21] These results show that the effect of indoor prostitution 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 than in the mornings.

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 and saturate the model with the interactions. Our results in Column (3) and (4) of Table 16 corroborate our initial finding: the two coefficients are jointly statistically significant and negative at 10% level.[22] These results imply that we cannot reject the *potential criminals channel*.

[20] In addition the results of this last specification support the hypothesis that sex crimes are not "moving"to bordering precincts.

[21] Note that in both cases the coefficient is not statistically significant at standard levels but it is extremely close to be. Indeed, in both cases, the coefficient is significant at 11%. 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.

[22] The coefficients of the interaction terms in the evening and at night are negative and respectively statistically significant at 11% and 12%. Note 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 of table 15.

6 Conclusion

This paper provides causal evidence of the effect of indoor prostitution businesses on sex crimes in NYC. To our knowledge, this paper also provides new evidence on the mechanisms behind this effect. Using a unique daily data set on the opening date and location of indoor prostitution businesses and crime in NYC, we find that new indoor prostitution establishments significantly affects the number of sex crimes. 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 unobserved characteristics affecting sex crime. The estimates are based on daily data suggesting that there is an effect in the very short-run. We nd that a single indoor prostitution establishment leads to a 0.4% daily reduction in sexual violence per precinct.

We analyze several potential mechanisms that could explain why indoor prostitution businesses affect sex crimes. We find evidence consistent with the fact that potential perpetrators substitute towards indoor prostitution establishments instead of engaging in sex crimes. We do not find evidence that businesses increase security in the area or more police officers are assigned to the area. In this case, a decline in sex crimes should reflect a general decline in crime. In addition, we do not find evidence that women avoid precincts where indoor prostitution establishments are present, reducing the potential victims. Similarly, we do not find evidence that that indoor prostitution establishments are employing street sex workers, who would otherwise be potential victims working on the street.

This mechanism is in line with a survey of men who had purchased sex from women in London. About 54% of these men 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).

These results suggest that policy makers regulating indoor prostitution establishments should take into account the fact that these businesses can generate a positive externality due to the decrease in sex crimes. Further research is needed to quantify other potential externalities associated with these establishments, as well as examine the effect of outdoor prostitution establishments which may generate substantially different effects.

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Tables and Figures

Table 1: Daily summary statistics of sex crimes and establishments

	Sex Crimes	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	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 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) log(Sex Crime)	(2) log(Sex Crime)	(3) log(Sex Crime)
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) log(Sex Crime)	(2) log(Sex Crime)	(3) log(Sex Crime)	(4) log(Sex Crime)
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: Robustness check

	(1) Log(Sex Crime)	(2) Log(Sex Crime)	(3) Log(Sex Crime)
Indoor Prostitution Est.	-0.00414*	-0.00214**	-0.00442*
	(0.00220)	(0.000943)	(0.00245)
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
Mean of Sex Crime	.0313	.0313	.0313
Std Deviation of Sex Crime	.3405	.3405	.3405
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 10: Robustness check

	(1) IHS of Sex Crime	(2) Probit Sex Crime	(3) LPM Sex Crime	(4) Level Sex Crime
Indoor Prostitution Est.	-0.00801*	-0.0166	-0.00457*	-0.00760*
	(0.00435)	(0.0105)	(0.00231)	(0.00433)
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
Mean of Sex Crime	.0313	.0313	.0313	.0313
Std Deviation of Sex Crime	.3405	.3405	.3405	.3405

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

Table 11: Police channel

	(1) Log Drug Stops	(2) IHS of Drug Stops	(3) Log Burglaries	(4) IHS of Burglaries
Indoor Prostitution Est.	0.00545	0.0109	-0.00768	-0.0154
	(0.00795)	(0.0159)	(0.0137)	(0.0274)
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	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: Potential victims channel

	(1) Log Street Prostitutes	(2) IHS of Street Prostitutes	(3) Log Sex Crimes	(4) IHS of Sex Crime
Indoor Prostitution Est.	-0.000642	-0.00128	-0.00685***	-0.0137***
	(0.00113)	(0.00227)	(0.00223)	(0.00445)
Observations	238,931	238,931	68,266	68,266
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 13: Potential victims channel

	(1) Log(Sex Crime Border Pct)	(2) IHS of Sex Crime Border Pct
Indoor Prostitution Est.	-0.00853	-0.0171
	(0.00720)	(0.0144)
Dummy	0.00278	0.00555
	(0.00748)	(0.0150)
Interaction	0.0156	0.0312
	(0.0107)	(0.0215)
Observations	77,575	77,575
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

Table 14: Potential Criminal Channel

	(1) Log(Sex Crime)	(2) IHS of Sex Crime	(3) Log(Sex Crime)	(4) IHS of Sex Crime
Indoor Prostitution Est.	-0.00168*	-0.00336*	-0.000347	-0.000695
	(0.000927)	(0.00185)	(0.000284)	(0.000569)
Dummy Evening			0.00135	0.00270
			(0.000975)	(0.00195)
Dummy Night	0.00283***	0.00566***	0.000322	0.000644
	(0.000914)	(0.00183)	(0.00102)	(0.00203)
Interaction Evening			-0.00145	-0.00289
			(0.000889)	(0.00178)
Interaction Night	-0.00108	-0.00216	-0.00150	-0.00301
	(0.000673)	(0.00135)	(0.000968)	(0.00194)
Observations	477,862	477,862	955,724	955,724
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

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Figure 1: Evolution of Sex Crimes in NYC from January 2004 to June 2012

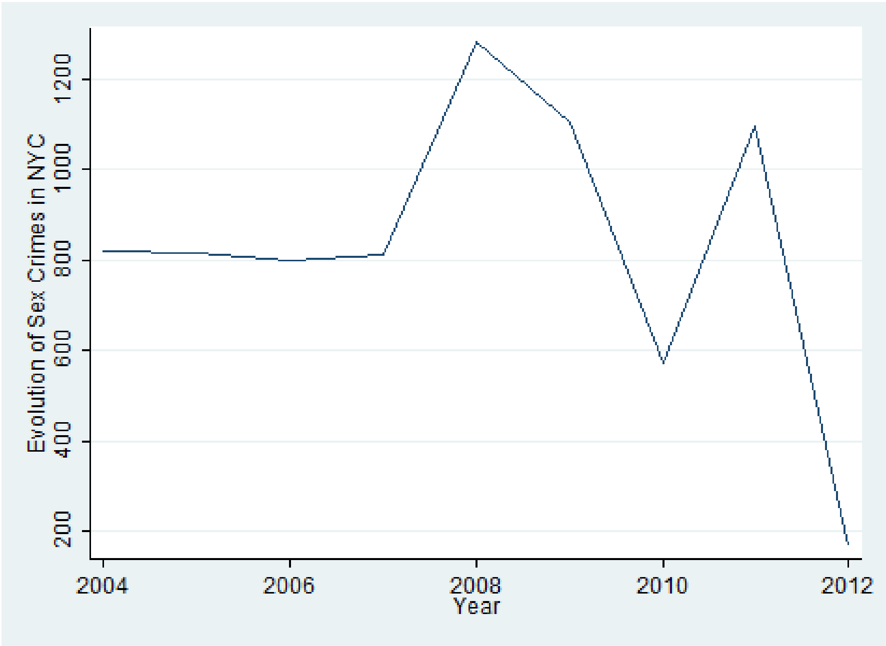
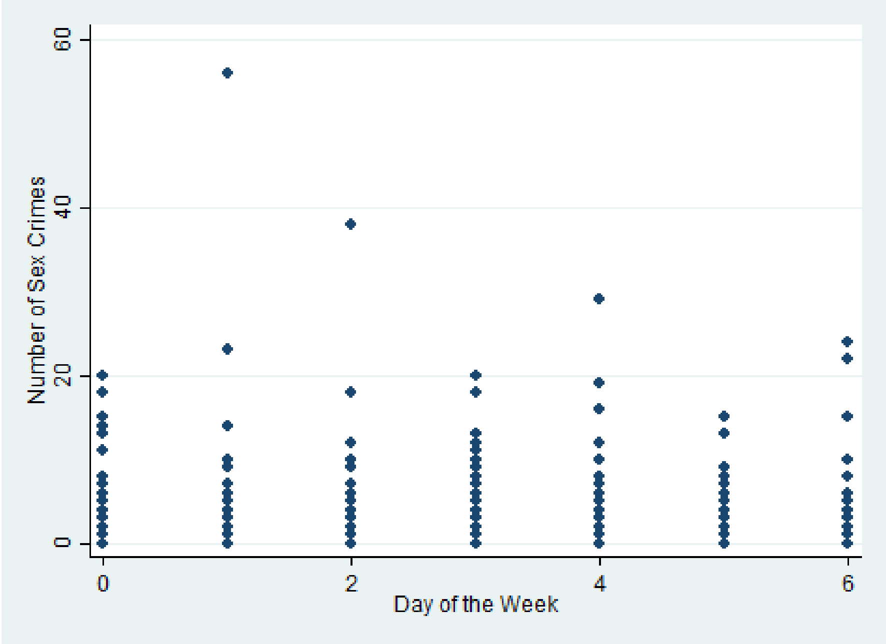


Figure 2: Distribution of Sex Crimes over days of the week



Notes: This figure shows the distribution of sex crimes across days of the week in NYC between the 1st of January of 2004 and the 30th of June of 2012. 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 3: Evolution of establishments from January 2004 to June 2012

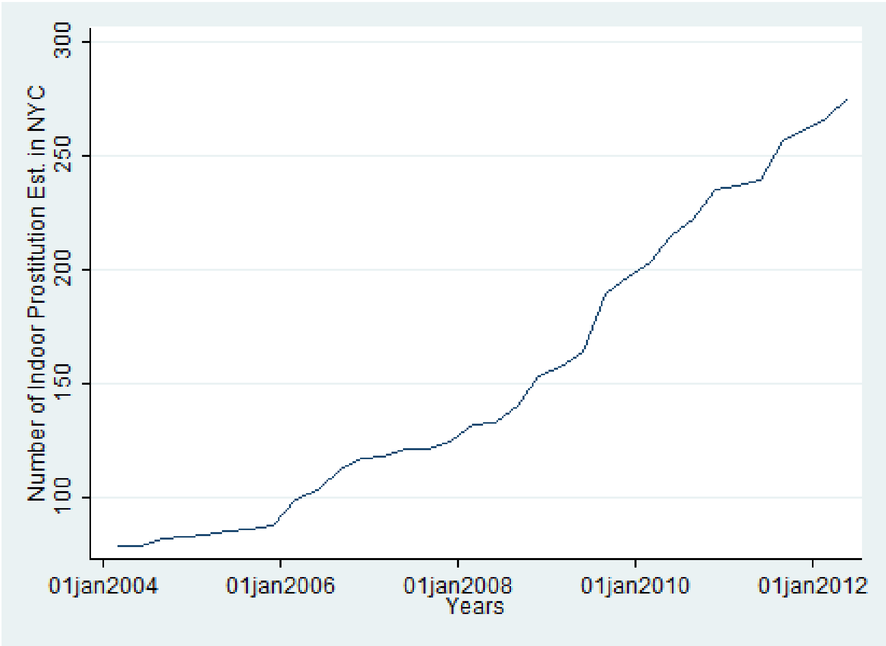
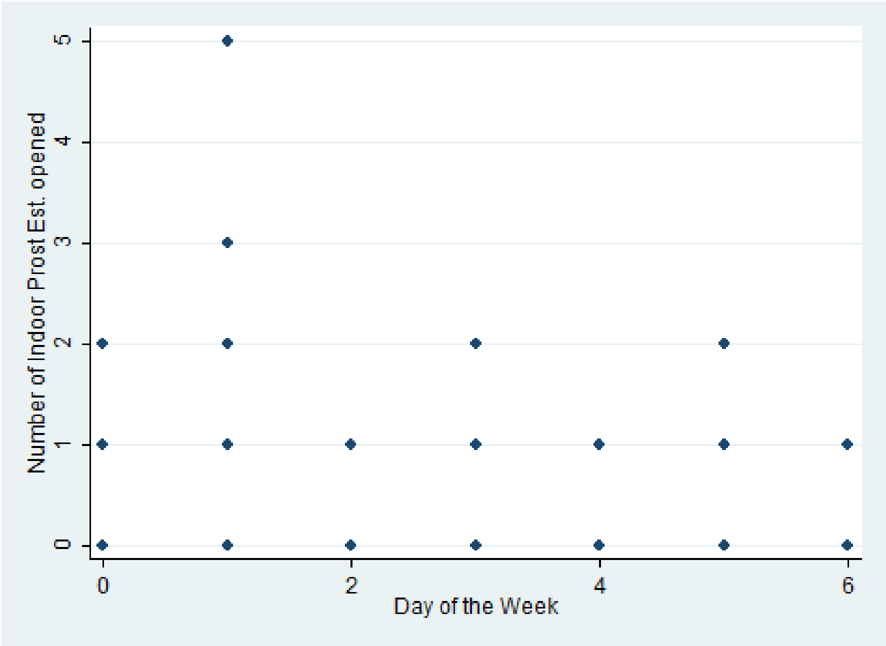


Figure 4: Distribution of the date of opening of indoor prostitution establishments over days of the week



7 Appendix

7.1 List of larger precincts in potential victims channel

The 77 precincts are grouped in 22 precincts according to geographical proximity between them. The table below shows exactly how we grouped them. For instance precincts 1,5 and 7 were gathered in one precincts, precincts 6, 9, 10 and 13 in another one, and so on and so forth as the table explains.

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

Table A.1: List of larger precincts to test the potential victims channel

7.2 Weekly regression

This section presents results of our baseline regression but at weekly frequency. Hence, we exchanged all the fixed effects varying at daily frequency for week fixed effects. Results are negative and statistical significant for both $\log(1+y)$ and the IHS transformation. however, the estimated coefficient is lower in absolute value. This change in estimated coefficients could be due to omitted variable bias stemming from the lower frequency of the data.[23]

Table A.2: Regression at weekly frequency

VARIABLES	(1) Log(1+Sex Crime)	(2) IHS of Sex Crime
Indoor Prostitution Est.	-0.0172*	-0.0345*
	(0.00884)	(0.0177)
Observations	34,034	34,034
Clustered variance at Precint level	YES	YES
Precinct FE	YES	YES
Year FE	YES	YES
Month FE	YES	YES
Week FE	YES	YES
Precinct Trends	YES	YES

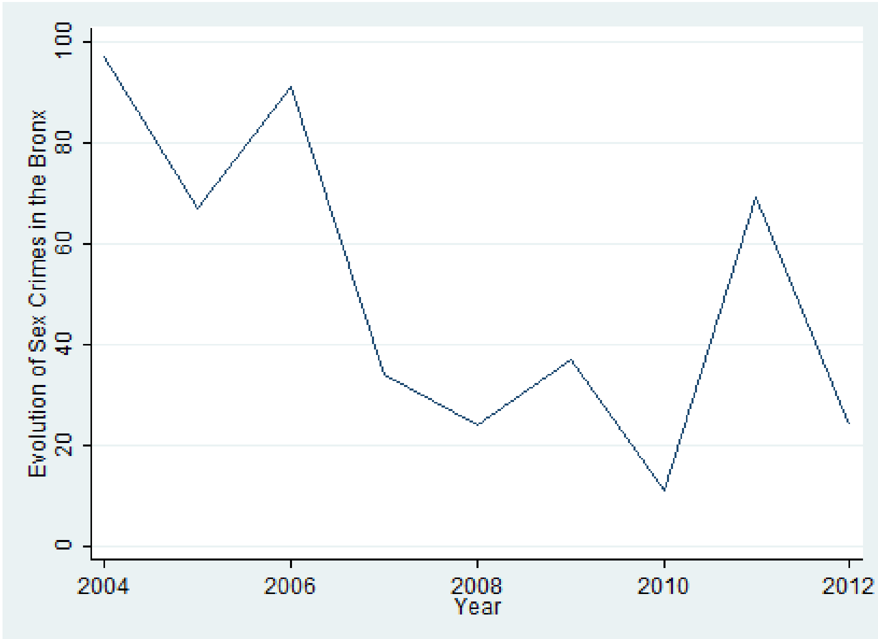
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

7.3 Evolution of Sex crimes by boroughs

This subsection presents time variation of sex crimes across geographical units in NYC. Clearly we decided to organize the figures by borough, since presenting them by precincts would mean to have 77 figures. These figures show that it does not seem that there is a reallocation of sex crimes across boroughs.

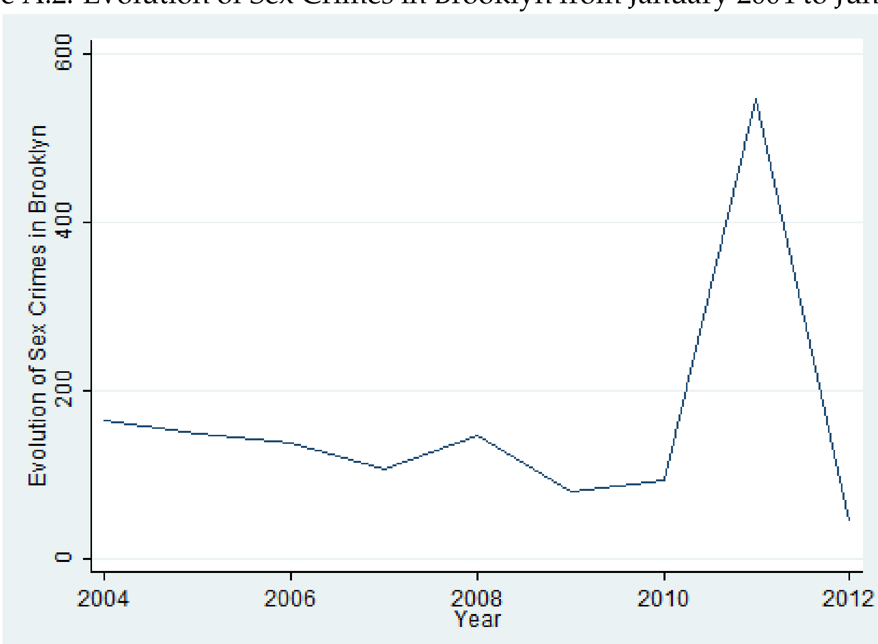
[23]It might be that also our coefficients in the event study analysis suffer a smiliar problem, this would imply that they are bigger in absolute value that the ones we estimated.

Figure A.1: Evolution of Sex Crimes in the Bronx from January 2004 to June 2012



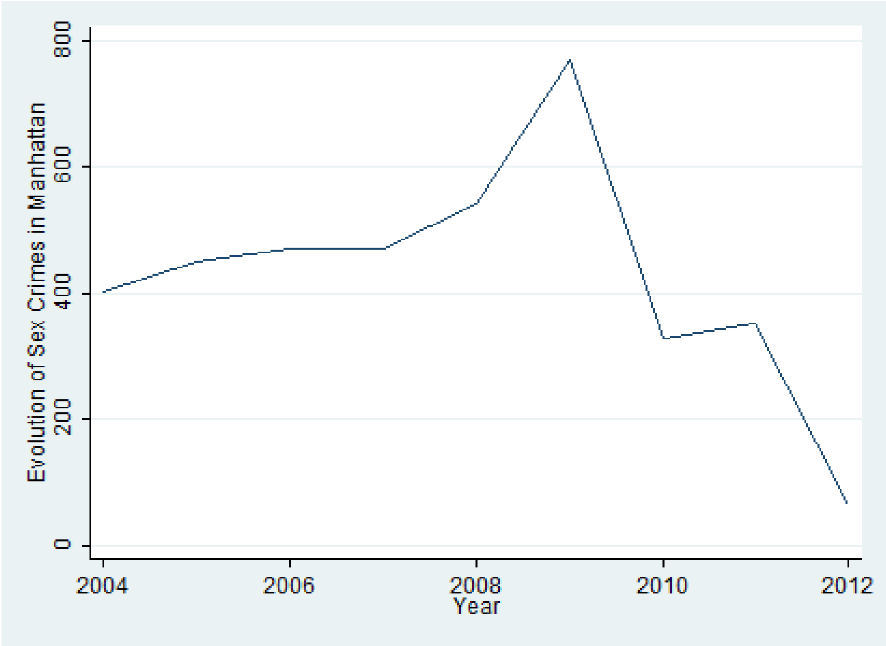
Notes: This figure shows the evolution of sex crimes in the Bronx between the 1st of January of 2004 and the 30th of June of 2012. For this picture data has been collapsed yearly.

Figure A.2: Evolution of Sex Crimes in Brooklyn from January 2004 to June 2012



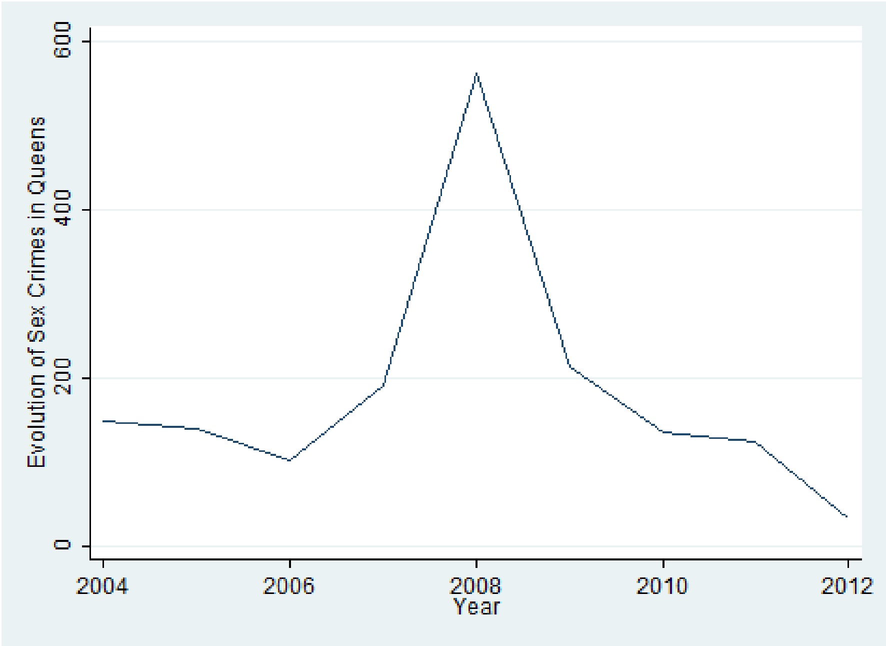
Notes: This figure shows the evolution of sex crimes in Brooklyn between the 1st of January of 2004 and the 30th of June of 2012. For this picture data has been collapsed yearly.

Figure A.3: Evolution of Sex Crimes in Manhattan from January 2004 to June 2012



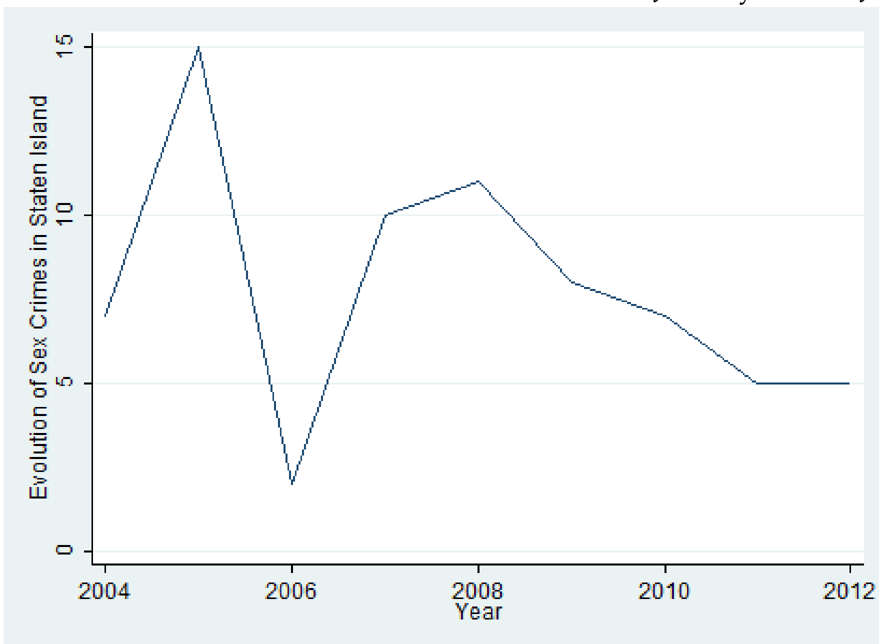
Notes: This figure shows the evolution of sex crimes in Manhattan between the 1st of January of 2004 and the 30th of June of 2012. For this picture data has been collapsed yearly.

Figure A.4: Evolution of Sex Crimes in Queens from January 2004 to June 2012



Notes: This figure shows the evolution of sex crimes in Queens between the 1st of January of 2004 and the 30th of June of 2012. For this picture data has been collapsed yearly.

Figure A.5: Evolution of Sex Crimes in Staten Island from January 2004 to June 2012

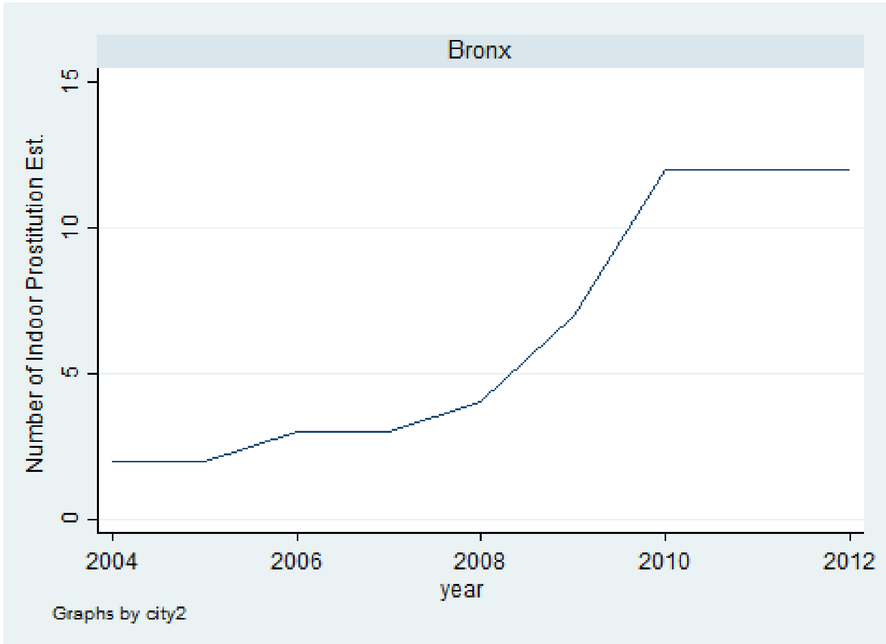


Notes: This figure shows the evolution of sex crimes in Staten Island between the 1st of January of 2004 and the 30th of June of 2012. For this picture data has been collapsed yearly.

7.4 Evolution of Indoor Prostitution Establishments by boroughs

This subsection presents time variation of indoor prostitution establishments across geographical units in NYC. Clearly we decided to organize the figures by borough, since presenting them by precincts would mean to have 77 figures. Note that there is substantial variation and that, as expected, the largest increase is taking place in Manhattan. In addition, we can observe that in every borough there is a raise in these establishments, as in the whole NYC.

Figure A.6: Evolution of Indoor Prostiution Establishments in the Bronx from January 2004 to June 2012



Notes: This figure shows the evolution of indoor prostitution establishments in the Bronx between the 1st of January of 2004 and the 30th of June of 2012. For this picture data has been collapsed yearly.

Figure A.7: Evolution of Indoor Prostiution Establishments in Brooklyn from January 2004 to June 2012

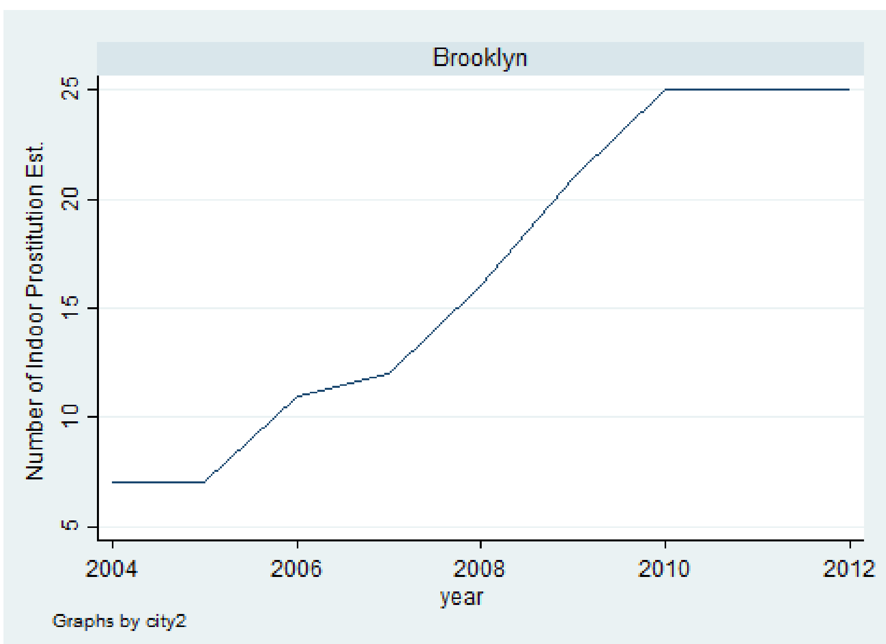


Figure A.8: Evolution ofIndoor Prostiution Establishments in Manhattan from January 2004 to June 2012

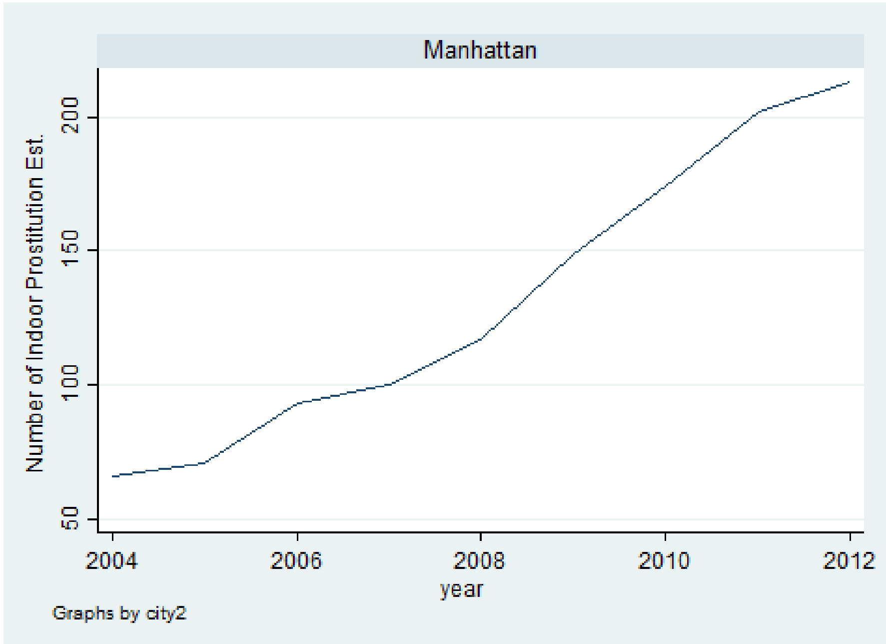


Figure A.9: Evolution of Indoor Prostiution Establishments in Queens from January 2004 to June 2012

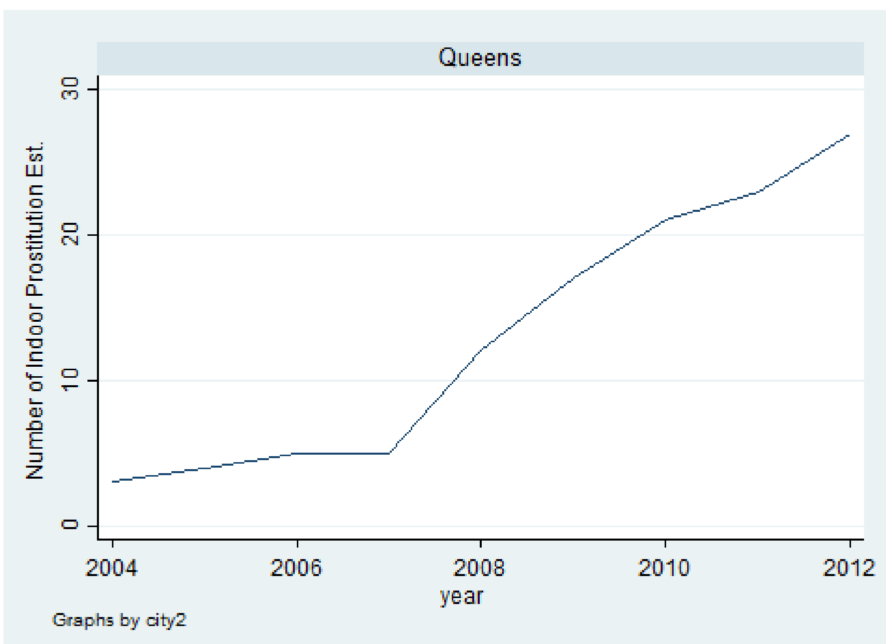
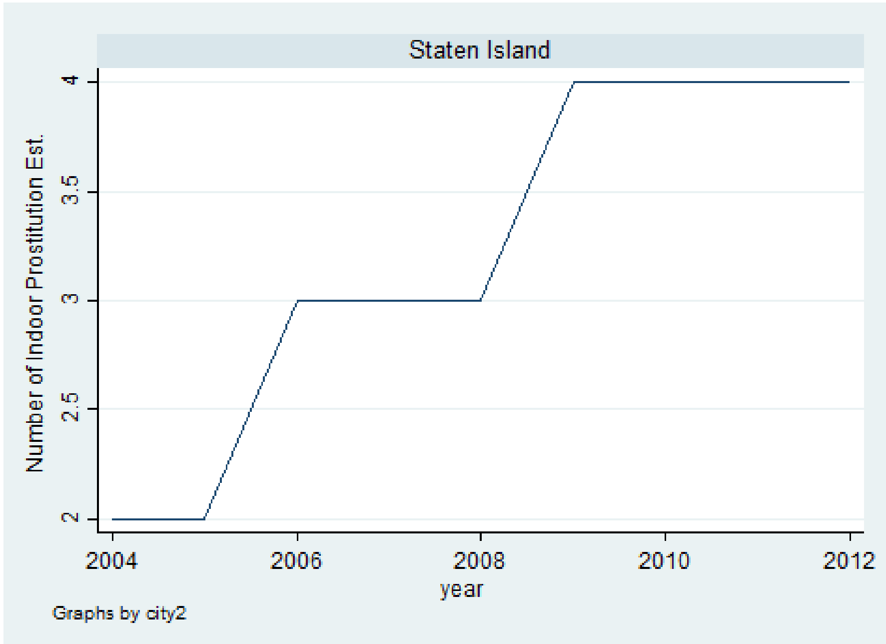


Figure A.10: Evolution of Indoor Prostiution Establishments in Staten Island from January 2004 to June 2012



7.5 Geographical distribution of Indoor Prostitution Establishments by precincts

The two maps below show the evolution of the indoor prostitution 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.11: Geographical distribution of Indoor Prostiution Establishments in NYC in 2004

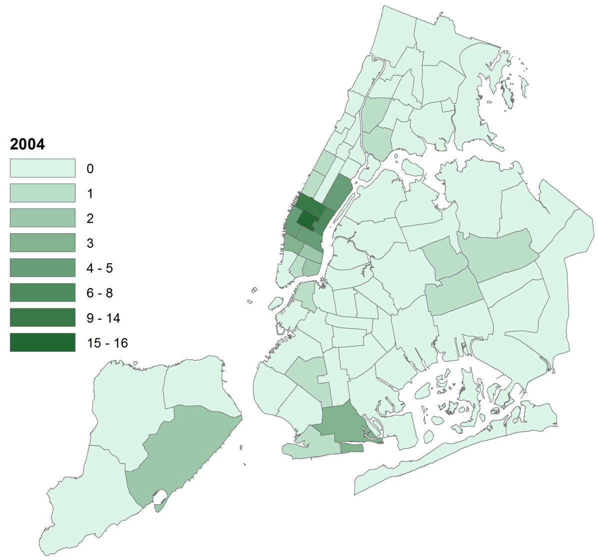


Figure A.12: Geographical distribution of Indoor Prostiution Establishments in NYC in 2012