# There Goes the Neighborhood?
# Estimates of the Impact of Crime Risk on Property Values From Megan's Laws


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We combine data from the housing market with data from the North Carolina Sex Offender Registry to estimate how individuals value living in close proximity to a convicted criminal. We use the exact location of these offenders to exploit variation in the threat of crime within small homogenous groupings of homes, and we use the timing of sex offenders' arrivals to control for baseline property values in the area. We find statistically and economically significant negative effects of sex offenders' locations that are extremely localized. Houses within a one-tenth mile area around the home of a sex offender fall by four percent on average (about $5,500) while those further away show no decline. These results suggest that individuals have a significant distaste for living in close proximity to a known sex offender. Using data on crimes committed by sexual offenders against neighbors, we estimate costs to victims of sexual offenses under the assumptions that all of the decline in property value is due to increased crime risk and that neighbors' perceptions of risk are in line with objective data. We estimate victimization costs of over $1 million—far in excess of estimates taken from the criminal justice literature. However, we cannot reject the alternative hypotheses that individuals overestimate the risk posed by offenders or view living near an offender as having costs exclusive of crime risk.



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## 1. Introduction

Crime is predominantly a local issue. The majority of both violent and non-violent offenses take place less than one mile from victims' homes, and most government expenditures on police protection are local (Bureau of Justice Statistics, 2004, and Census of Governments, 2003). In response to the fear of crime, residents generally have two options: they can vote for anti-crime policies, or they can vote with their feet. When individuals exercise the latter option, local response to crime will be observed in the housing market. This may be particularly salient for crime, since individuals can reduce their exposure without moving great distances, and empirical evidence on urban flight supports this notion (Cullen and Levitt, 1999).

To decide how to respond to crime, we must understand the costs that crime imposes on individuals. Estimates of the demand for public safety, for example, are necessary to determine the appropriate level of public expenditures, such as the optimal provision of police services. But many jurisdictions are also considering various regulatory options for individuals deemed likely to commit specific crimes. Sex offenders, for example, have been a particular target. Offenders may be restricted from living in close proximity to areas with significant numbers of children. A small number of local governments and real estate developers in the U.S. have begun considering rules designed to restrict the ability of sexual offenders to reside in their communities. And in some states, property sellers are required to notify potential buyers of local offenders.

Historically, information about an individuals' future risk for being victimized by a criminal was limited to crime statistics for specific geographic locations. A number of papers have documented an inverse relationship between property values and crime rates.

In one of the earliest studies, Thaler (1978) finds a negative relation between property crimes per capita and property values. His estimates imply that a one standard deviation increase in the incidence of property crime reduces home values by about 3%. A more recent study by Gibbons (2004) finds a decrease in property values of 10% for a one standard deviation increase in property crime.

These studies, however, face potential omitted variable problems in both cross sectional and time series. In the cross section, crime rates are likely to co-vary with other geographic amenities for which researchers cannot adequately control. Over time, crime rates may change as the composition and characteristics of neighborhoods change. Reductions in crime levels, for example, may correspond to other changes that increase the value of property located in a particular neighborhood.

In this paper, we combine data from the housing market with data from sex offender registrations to estimate individuals' valuation of living in close proximity to a convicted sex offender. By exploiting both the timing of move-in and the exact locations of sex offenders, we can improve on past estimates of individuals' responses. The exact location of these offenders then allows us to exploit variation in the threat of crime within small homogenous groupings of homes. The timing of a sex offender's arrival allows us to confirm the absence substantive pre-existing differences in property values and to control for the remaining minor differences.

Our study is the first to exploit both inter-temporal and cross-sectional variance in the presence of an offender, but not the first to exploit the cross-sectional variation alone. Larsen et al. (2003) examine the cross sectional relationship between property values and proximity to sex offenders using a single year of data from Montgomery County, Ohio.

They find a reduction in housing prices of 17% within a tenth of a mile of an offender's home, and find significant changes in price up to a third of a mile. Although their study is similar to ours in the empirical question it addresses, their empirical strategy suffers from the same potential biases mentioned above.

Sex offender registries are not simply an important source of data for research. The advent of sex offender registration laws and public access to offender registries has changed the kind of information available to individuals about their propensity for being victimized by a crime. Based on the belief that an individual convicted of a sex offense is likely to commit a similar crime in the future, these registries publish the names, addresses, and sometimes even the employers of convicted sex offenders. Thus, individuals can now find out not only historical crime rates, but also the number of specific types of criminals living in an area and, usually, their exact addresses.

Anecdotal evidence suggests that individuals are extremely averse to living in close proximity to convicted criminals and that they have put the information obtained from the offender registries to use. Neighbors have encouraged sex offenders to leave neighborhoods. Real estate broker associations provide information on sex offenders and the sex offender registry to their members. Law suits have been filed both against sex offenders for reducing property values and against appraisal agencies for not considering the proximity of local sex offenders. And a small, but growing number of localities have passed laws that would prevent sex offenders from living within their borders.

The results of our analysis suggest that these laws reflect a strong distaste for living in close proximity to an offender. Prices of homes near a sex offenders decline considerably following an offender's arrival in the neighborhood. We find that, on average, the housing market reacts strongly to a sex offender living in a neighborhood. We estimate that the sale price of homes closest to the offender decline by about 10% in value or about $10,000 for the median value home in our data. Roughly four percentage points of this decline is due to real decline in the value of homes located near offenders. The remaining decline is due to changes in the composition of sales due to the offender's arrival and neighborhood level changes in property values. However, these effects are extremely localized and dissipate quickly with distance. We find no evidence of any impact on homes located more than a tenth of a mile away from offenders' locations.

This paper is organized as follows. In the next section, we describe the nature of both the national and North Carolina sex offender registration laws. In Section 3, we describe the data used in our study, and then in Section 4, we describe our empirical methodology, present graphical evidence on the impact of sex offenders' arrivals, and describe the model we use for formal statistical analysis. We present our empirical results in Section 5. We conclude in Section 6.

## 2. Sex Offender Registration Data Bases

In 1994, a seven year old girl named Megan Kanka was brutally raped and murdered by her next door neighbor. The man had been convicted in 1981 for an attack on a 5-year-old child and an attempted sexual assault on a 7-year-old, but none of his neighbors knew these facts. This tragic event was the motivation for the body of legislation known as Megan's Laws, requiring the notification of the public regarding the location and description of convicted sex offenders. By imposing requirements on a class of individuals previously convicted of a crime after they have completed their sentences, these laws represent a significant change in the legal practice of dealing with convicted criminals after they have been released from prison.

At the Federal level, sex offender registration laws comprise two sets of state requirements. In 1994, the Jacob Wetterling Crimes Against Children and Sexually Violent Offender Registration Program created a mandatory state requirement for the registration of sex offenders.[2] Congress enforced the act by threatening states with a reduction of Federal grants provided for state law enforcement efforts. The registry must include a range of identifying information including the offenders' names, addresses, photographs, etc. The law applies to individuals convicted of committing a specific set of sexual offenses and non-sexual crimes against minors. Offenders are required to register this information with state authorities, update authorities regarding changes, and to verify periodically the accuracy of the currently provided information. Congress expanded this legislation in 1996 to require the dissemination of information in the registry.

Megan's Laws have been extremely controversial and subjected to numerous court challenges. Two such challenges reached the Supreme Court in 2003. The first, Connecticut Department of Public Safety et al. v. Doe, claimed that registration laws violated the due process clause of the 14th amendment by depriving registered sex offenders of a "liberty interest" and depriving them of a hearing to determine whether they posed to a significant danger. The second challenge, Smith et al. v. Doe, was brought on grounds that the registration laws violated the ex post facto clause in Article I of the Constitution by creating a retroactive punishment. In both cases, the Court has upheld the laws as a legitimate civil regulation (rather than a criminal punishment) in

[2] 42 U.S.C. § 14071 (2000). Jacob Wetterling was abducted in Minnesota in 1989; neither he nor the perpetrators were ever found.

response to the recidivism threat imposed by sex offenders on the communities in which they live.

While federal law requires registration of offenders and community notification, states are given significant latitude in their implementation of these provisions. All 50 states currently maintain a registry which makes some information available to the public, but the method of compliance varies significantly. Forty-six states provide public internet access to the offender registry. Hawaii, South Dakota, and Oregon provide more limited access either only through local law enforcement agencies or only to small subsets of the data base. Rhode Island provides no public access to the database, but requires the notification of individuals likely to be at risk from a given offender. Individuals in many states can also request information by mail or through designated telephone numbers.

Louisiana has perhaps the most aggressive notification law. It requires offenders to, "give notice of the crime for which he was convicted, his name, and his address to at least one person in every residence or business within a one mile radius of his residence in a rural area and a *three tenths of a mile radius* in an urban or suburban area [italics added]." Louisiana courts can also require additional methods of notification including specially labeled clothing.

Despite the legal controversies surrounding their creation, searchable sex offender registries are extremely popular. In December of 2004, California unveiled a site that allowed residents to search the state's registration database and obtain offenders names, addresses, and proximity to parks and schools. On the first day that the state made the site publicly accessible, it was so popular that the host failed to keep up with demand. Within 4 days, the site had registered 14 million visits.

## 2.1 North Carolina Sex Offender Legislation

The North Carolina sex offender registration law is similar to many of the registration laws that exist in other states. Originally, adopted in 1996 as the "Amy Jackson Law", the law was amended in 1998 and 2001 to comply with the requirements of the federal registration laws.[3] All individuals convicted on or after January 1, 1996 of kidnapping, prostitution, sexual exploitation of a minor, or sexually violent offenses against anyone, are required to register. In addition, all sexual offenders released from prison on or after January 1, 1996 must register, even if their convictions took place prior to this date.[4] The law applies equally to individuals convicted in other states who move to North Carolina.

An individual with a reportable offense must register with the state within 10 days of being released from prison. If an individual moves, he or she must notify the state of their new address within 10 days. Failure to register an address is a felonious offense and cause for revocation of parole. Individuals are required to register for 10 years after being released from prison. In addition to these reporting requirements, the state is required to verify offenders' addresses periodically. A non-forwardable post card is mailed to the individual, if this card is not returned with the current address, the

[3] Article 27A of Chapter 14 of the North Carolina General Statutes (NCGS 14-208.5).
[4] The degree of retroactivity for States' Megan's laws varies considerably. In other (ongoing) work, one of us is examining how the discontinuity created by laws' retroactivity can be used to measure the impact of sex offender registration on criminal activity.

individual is subject to criminal penalties and the local sheriff is required to verify whether or not the individual still resides at the registered address.

Information in the offender data base is provided to citizens via a web-based interface that is maintained by the State Bureau of Investigation's Division of Criminal Information. The registry reports each offender's current address, zip codes of past addresses, the offense of which the individual was convicted, a picture of the individual, and identifying information such as height, weight, race, gender, distinguishing characteristics, hair color, and eye color. All address entries include both the data on when the address was reported and if the address was verified, the date on which the address was last verified. To the best of our knowledge, North Carolina, Florida, and Montana are the only states that provide information on the exact timing of offenders' move-in dates.

Unlike other states, compliance with the sex offender registration laws is extremely high in North Carolina. Between January 1, 1996 and March 9, 2003, North Carolina released a total of 8,287 individuals that would be required to register. Of these offenders, 1,007 had moved out of state and of those remaining in the state, only 103 had failed or had yet to register their addresses. This contrasts with the experience of California, for example, whose registry was heavily criticized for missing addresses on a significant number of offenders.

### 3. Data Sources

Our analysis of the impact of offenders' arrivals is based upon three sets of data regarding the location of sex offenders, the location and characteristics of property in

Mecklenburg County, and property level sales data. Information on registered sex offenders in North Carolina were provided by the North Carolina Department of Justice (NCDOJ).[5] This dataset contains information on offenders' basic demographics, type of offense, date of offense, current address, and date of registration at current address.[6] Because of the strict provisions governing timely registration in North Carolina, the date of registration is a close approximation of the actual date an offender moved to their current location.

In January of 2005, there were approximately 9,200 registered sex offenders in North Carolina, though 11% were registered as living in jail or a residence for ex-convicts and 4% had an unknown street address. In Mecklenburg County, where we focus, there were 518 registered offenders, the most of any county in the state.[7] 56 offenders (11%) were registered as living in a jail/halfway-house and 35 offenders (7%) had an unknown street address. We do not include these offenders in our analysis.

A variety of crimes qualify individuals to register their address under North Carolina's sexual offender registration law. Table 1 shows crime frequencies for registered offenders in the state and in Mecklenburg County. Almost 90% of all sexual offenses fall into three categories. The majority of all crimes—70% in the state, 63% in Mecklenburg County—are classified as Indecent Liberty with a Minor.[8] These crimes,

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[5] The registry is updated continually. Our source at the DOJ compiles a monthly data set that is provided to law enforcement agencies, of which October 2004 was the oldest file still available.

[6] We plan to use the historical ZIP code level data to examine the impact of the introduction of the sex offender registry in 1996. If the information provided by the registry was important and spread quickly, one might expect decreases in relative house prices in ZIP codes with more offenders after the registry's introduction. However, there are only 32 ZIP codes in Mecklenburg County, and we are therefore gathering sales data from other counties to pursue this line of investigation.

[7] Mecklenburg County contains the metropolitan area surrounding the city of Charlotte. This is the largest metropolitan area in the state (population 640,000).

[8] Indecent liberty refers to a person who, "1) Willfully takes or attempts to take any immoral, improper, or indecent liberties with any child of either sex under the age of 16 years for the purpose of arousing or

sometimes referred to as 'child molestation,' do not involve physical force or violence. The second most frequent set of crimes is sexual offenses (11% in the state and Mecklenburg County), which refer to sexual acts where force or violence is involved but do not include rape. Rape (9% in the state and 10% in Mecklenburg County) is the third largest category of crimes. The remaining crimes are spread among a variety of categories such as incest, prostitution of a minor, and kidnapping of a minor.

Because we only have access to offenders' current addresses, we are only able to observe how variation in prices relates to offenders' arrivals for offenders that have not yet moved from their current location. In order to have enough post-arrival sales to generate statistically meaningful estimates, we limit our analysis to offenders who have lived in the same location for one year or more. 10% of the offenders in Mecklenburg County were released less than one year before our sales data ends. Of those released prior to this date, roughly 35% had moved into their current address less than one year prior to the end of the sales data. We find similar results to those reported below when we include offenders who had been living in their current locations for at least six months.[9]

It is important to note that differences in sentence lengths affect the distribution of crimes for which registered offenders were convicted. The median sentence lengths for Indecent Liberty with a Minor and Rape are, respectively, 1 ⅓ years and 10 years. Thus, most offenders who committed Indecent Liberty with a Minor since 1996 will be

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gratifying sexual desire; or 2) Willfully commits or attempts to commit any lewd or lascivious act upon or with the body or any part or member of the body of any child of either sex under the age of 16 years." (NC Statute 14 202.1).

[9] If offenders that move frequently would cause different changes in property values than offenders who choose to live in a single place for an extended period of time, our estimates might not be representative of the effects of the average sex offender moving into a neighborhood. Our analysis identifies the effects on property values of the sex offenders we observe in our data base.

registered, in contrast to a relatively small fraction of those who committed Rape or other crimes with long sentence lengths. Many of those in the latter group are likely to be in prison.

Our second source of data comes from the Mecklenburg County division of Property Assessment and Land Record Management. This assessment data contains Geographical Information Systems (GIS) information on all real estate parcels in the county as of March 21, 2005. With GIS information, we can measure the distance in feet between the centers of any two parcels. The assessment data also gives us a comprehensive set of physical characteristics for each parcel: type of structure, building quality, square footage, year of construction, number of bedrooms, number of bathrooms, etc.[10]

All parcels in the county are divided into 1004 "neighborhoods." These neighborhoods are defined by the tax assessor's office within Mecklenburg County and are intended to be sets of similarly valued properties. These neighborhoods are much smaller than census tracts (there were 144 tracts in Mecklenburg County in 1990) or even census block groups (there were 373 block groups in Mecklenburg County in 1990). Neighborhoods encompass just 0.47 square miles on average. The relative homogeneity of property within neighborhoods allows us to control for unobservable fixed and time varying characteristics at the neighborhood level.

In order to measure the proximity of property sales to offender locations, we matched offender addresses from the NCDOJ data to addresses in the assessment data. As

[10] Building quality is measures on a thirty-six point scale. There are six tiers of quality ranging from "Below Average" to "Custom Made". Within each tier there are 6 quality rankings (e.g. Below Average 1, Below Average 2…Below Average 6). Regressions of sale price on quality measures confirm the lexicographic nature of the ranking system.

mentioned above, there were 518 registered offenders in a numbered county as of January 1, 2005. From this population, we exclude 56 offenders who were registered as living in a jail/halfway-house, 35 offenders who had an unknown street address, and 29 offenders whose date of current residence was unknown. We were able to find a match with a parcel in the assessment data for the addresses of 367 (92%) of the remaining 398 offenders,[11] and 192 of these offenders moved before January 1, 2004.

Using the matched offender-assessment data, we flag all parcels within a three-tenths mile radius of each registered sex offender. Distances are calculated as a straight line radiating from the center of the tax parcel to the center of the parcel in which the registered offender resides. We chose 0.3 miles based on the Louisiana law requiring sex offenders to inform all neighbors living within this distance from their home of their presence in the neighborhood. In this way, each offender creates an "offender area" with size of about .28 (.09π) square miles. For each parcel within an offender area, we also calculate the distance to the offender's parcel. Note that the offender areas are smaller than the average size of neighborhoods designated in the assessment data. For those properties that have more than one offender within a 0.3 mile radius, we use the arrival date from the first offender to move into the area.[12]

Finally, the matched offender-assessment data is merged with property sales data from the Mecklenburg County Property Assessment and Land Record Management

[11] 369 of these 373 matches were exact. The remaining four matched offenders claimed to be living at an address whose street number could not be matched with a parcel in the assessment data but whose street name, city, and ZIP code did match. For these offenders, we matched them to the "next closest" parcel on the street based on street numbers, so long as the street numbers seemed reasonably close. For example, an offender who claimed to live on "838 Everett Place" was matched to "836 Everett Place.". Of the remaining 25 offenders, 7 claimed to be living on streets that did not exist in the assessment data, and 18 claimed to live on street addresses that were not within a reasonable distance to a "next closest" parcel.

[12] Of the 367 offenders we successfully link to an address in GIS, 12 offenders were not the first to arrive within 0.3 miles of any parcel. An additional 21 offenders were in locations that did not have a sale of a single family home within 0.3 miles.

Office. This data includes all sales in Mecklenburg County from January 1994 to December 2004. We were able to match 96% of sales with an address in the assessment data. Though we cannot determine the reason why any particular sale did not match, we suspect that many of these are caused by sales of parcels that subsequently are changed or demolished so they do not exist in the assessment data from 2005. All sale prices are normalized to December 2004 dollars using the monthly South Urban CPI. We restrict our sample to sales of single-family homes and drop sales with prices in the range of \$5,000 to \$1 million. These cutoffs are approximately the 1$^{st}$ and 99$^{th}$ percentile of the sales price distribution. We also drop a small number of irregular sales entries, e.g., sales that took place less than 3 days following another sale of the same parcel. Parcels in which the registered offenders reside have also been dropped from the sample. This gives us a sample of 170,239 sales of 121,834 parcels, of which 27,529 lie within a 0.3 mile radius of a registered offender.

Table 2 provides summary statistics of the various parcels that are sold in Mecklenburg County during the period of interest. The first column provides information on all sales in the county and the second column shows the sales that occur within 0.3 miles of where a sex offender either has located or will eventually locate. This demonstrates the importance of the localized data we use in this analysis because the areas in which sex offenders locate have smaller houses that sell for less money. In other words, sex offenders, on average, move to the cheaper neighborhoods. Column three provides a hedonic decomposition of the log of the sale price of homes within 0.3 miles of an offender to gauge the importance of the various characteristics. The regression also includes dummy variables for the composition of the house's exterior and offender area by year fixed effects.

## 4. Empirical Methodology

The purchase of a home is inextricably linked with the selection of a city, a school district, and a neighborhood. Thus, choice of residence represents choice of labor market, school quality, social group, environment, etc., in addition to choice of house characteristics. The demand for homes in areas with particular characteristics is therefore also a measure of individuals' preferences regarding all of the local factors that impact economic outcomes. A large number of studies have examined the relation between property values and location specific (dis)amenities, such as school quality, pollution, crime, and property taxes. Some recent examples are Black (1999), Colwell et al. (2000), Lynch and Rasmussen (2001), Bui and Mayer (2003), Davis (2004), Gibbons (2004), Figlio and Lucas (2004), and Chay and Greenstone (2005).

The difficulties in identifying the hedonic price function for local (dis)amenities are well-known. A major obstacle is that variation in the local amenity may be correlated with unobservable factors (Bartik, 1987, Epple, 1987). In addition, if the long-run supply of housing is perfectly elastic, then changes in demand for local property will, in equilibrium, show up in quantities, not prices (Edel and Sclar, 1974). Thus, an effective empirical strategy for uncovering capitalization might examine short run changes in property values due to arguably exogenous changes in local (dis)amenities.

Geographical heterogeneity in the average demographic characteristics of households makes it abundantly clear that particular kinds of people tend to live in particular kinds of places. Sex offenders, like all individuals, likely choose to live in particular neighborhoods, depending on their income and preferences. Sex offenders do tend to move to areas that, on average, have lower property values. If we simply compared the average sale values of areas with varying numbers of sex offenders, the covariance of sex offender location and other neighborhood characteristics would complicate our ability to identify the effect of a sex offender's presence on changes in the value of home sales.

Rather than compare these aggregated areas, however, we know the specific locations in which sex offenders have chosen to live and the date of their arrival. Compared to previous studies, this provides three advantages. The specific location data allows us to compare the value of home sales within very small areas in which the housing stock is more homogenous than in normal aggregate comparisons. This notion is illustrated by Figure 1, which shows the location of one of the sex offenders in our data, the surrounding parcels grouped by neighborhood, and a circle that outlines all parcels located within 0.3 miles of the offender's location. The offenders' particular choice of residence is extremely close to some houses in the neighborhood and farther from others. Moreover, houses in adjacent neighborhoods vary in their distance from the offender's location.

Relying on cross sectional variation alone, however, would be problematic if property characteristics vary within these small areas in ways that are unobservable to the researcher. If for example, sex offenders move into the cheapest property available in a given area (e.g., next to a local "eye-sore" like the home of a resident who has allowed his or her property deteriorate significantly, the artist who decided to paint his house fluorescent pink, or the local mechanic who has turned his or her front yard into a garage), then variation in the sale value of property around the sex offender's home may reflect distaste for the location to which the offender moved rather than distaste for living near the offender.

This is a constant concern in the literature that attempts to exploit variation in housing prices along geographic administrative boundaries. For example, in an important study of the capitalization of school quality into property values, Black (1999) compares the prices of homes located extremely close to one another but separated by school attendance boundaries. While this strategy may adequately control for fixed factors (e.g., distance from employment center), families may sort based on attendance boundaries so that "neighborhood socio-demographics are likely to vary discontinuously at the boundary" (Bayer et al., 2004).

We therefore examine within-neighborhood variation in property values shortly before and after the arrival of a sex offender. This allows us to control for pre-existing differences in property values between homes closer to the offender and homes farther from the offender within the same neighborhood. This framework would only be compromised if sex offenders consistently moved into properties near which a localized disamenity was likely to emerge. There is no reason to believe that the commission of a sex offense is correlated with such poor judgment in real estate value.

In fact, this possibility seems even more unlikely when one considers that the nature of the search for housing is also a largely random process at the local level. Individuals may choose neighborhoods with specific characteristics, but their choice of exact locations is generally restricted by property availability, i.e., the suitable houses and/or apartments that are currently on the market. Within a fraction of a mile, the exact locations of the properties available at the time individual seek to move into a neighborhood are out of the control the sex offenders, and are arguably exogenous (Bayer, Ross and Topa, 2004).

### 4.1 Graphical Evidence

If living close to a sex offender has a negative impact on property values, we should see prices of homes near the offender's location fall subsequent to the offender's arrival. Moreover, we should observe a larger impact on homes closest to the offender. Figure 2a shows the price gradient of distance to sex offenders' locations during the year after offenders' arrivals. Price gradients are calculated using a linear Fan regression, a nonparametric estimator similar to a kernel. Prices are lowest for homes closest to the offenders, rise with distance until reaching homes about .1 miles away, and then flatten out.

The bottom panel of Figure 2b adds the price gradient of distance to sex offenders' locations during the year before offenders' arrivals. The price gradients are quite similar between 0.1 and 0.3 miles from the offender before and after arrivals. However, there is a clear decline with proximity to a sex offender for homes within 0.1 miles of the offender. Homes located .05 miles from the offender sold for about $145,000 on average before the offenders arrived, but sold for almost $125,000 afterwards. The decline in sale price was greater for homes even closer to the offender.

The notion that the price decline within 0.1 miles of an offender reflects a causal impact of the offender's arrival would be supported if the decline coincides with the offender's arrival and does not reflect a pre-existing downward trend in prices. Figure 3a shows the price gradient of time with respect to sex offenders' arrivals. This gradient is measured separately for the two years before and after offenders' arrivals. Time is measured in days relative to the date sex offenders arrive. If the price decline showed in Figure 2a reflected a pre-existing trend, we would expect to see a gradual downward price movement over this time period. Instead, we find a fairly sharp decrease in prices coincident with offenders' arrivals.

Figure 3b shows the price gradient with respect to offenders' arrivals both for prices within 0.1 miles and houses between 0.1 miles and 0.3 miles of the offender's locations. These latter homes are still quite close to the offenders' locations and (as we saw in Figure 2a and 2b) were selling at similar prices to the affected homes prior to the offenders' arrivals. In contrast to the homes closest to the offenders, prices in these proximate areas did not decline after the offenders' arrivals. It is plausible that the two groups of homes would have had the same trend in prices over time in absence of the offender. This counterfactual is given support by the fact that *prior* to arrivals the prices of homes between 0.1 and 0.3 miles was similar to that of homes within 0.1 miles of the offenders' locations. If so, then these homes slightly farther away from offenders can be used as a control group for measuring the impact of offenders on property values.

### 4.2 Statistical Estimation Framework

Our estimation strategy will proceed by estimating the models inspired by the graphical evidence: a cross sectional difference estimator, and a difference in differences estimator. First, we use only data on parcel sales within offender areas, and estimate the average cross-sectional differences in price and parcel characteristics between the areas that are within 0.1 miles of where the offender will move and those sales that occur between 0.1 and 0.3 miles. We estimate these differences both in the two years prior and two years after the offender arrives. Both comparisons use the same estimation specification:

$$\log\left(P_{ijt}\right) = \alpha_t + \pi_1 D_{ijt}^{1/10} + \varepsilon_{ijt} \tag{1}$$

The log of the deflated sale price of the house is a function of a measure of distance from the offender, a random error term (allowing for year specific correlation in prices by offender area) and $\alpha_t$, a year specific effect. The term, $D_{ijt}^{1/10}$, is the distance measure, an indicator variable set to one if a parcel sale occurs within 0.1 miles of an offender's address. To examine variation in other parcel characteristics, we simply substitute those characteristics for log sale price as the dependent variable.

These difference estimates (shown in section 5) document two facts: little or no preexisting differences in housing characteristics close to offenders' locations and a decline in the value of sales due to the offenders' arrivals. No two groups of property, however, are identical, and those in our data set are no exception. To further isolate changes the in value from changes in composition, we include all of the data on parcel sales from Mecklenburg County and estimate the decline in property values controlling for observable characteristics of the parcels. Other sales in the county help us estimate the value of observable housing characteristics, hold these characteristics constant, and attribute the remaining changes in value to the offenders' arrivals. This model takes the following form:

$$\log\left(P_{ijt}\right) = \alpha_{jt} + \beta X_i + \pi_0 D_i^{1/10} + \pi_1 D_i^{1/10} * Post_{it} + \varepsilon_{ijt} \tag{2}$$

where $X_i$ is a vector of housing characteristics including size, age, and quality measures and $\alpha_{jt}$ is a neighborhood by year fixed effect. The use of these fixed effects allows us to capture any differential movement of prices over time across neighborhoods, and to focus only on variation in distance from offenders' locations within neighborhoods. The coefficient $\pi_1$ is our estimate of the change in property values due to being located close to the offender.

Finally, we estimate a difference-in-differences specification where the counterfactual time trend for homes close to an offender is estimated using the time trend in house prices for homes just slightly farther away. Our difference in differences specification adds a similar indicator variable for homes within 0.3 of a mile of offenders' locations ( $D_{ijt}^{3/10}$ ) and an interaction with $Post_{it}$.

$$\log\left(P_{ijt}\right) = \alpha_{jt} + \beta X_i + \left(\omega_0 D_{ijt}^{3/10} + \pi_0 D_{ijt}^{1/10}\right) + \left(\omega_1 D_{ijt}^{3/10} + \pi_1 D_{ijt}^{1/10}\right) * Post_{it} + \varepsilon_{ijt} \qquad (3)$$

The difference in difference estimate is then given by the term $\pi_1$.

## 5. Estimation Results

### 5.1 Differences in Characteristics of Homes Located Close to an Offender

Figures 2 and 3 illustrate that, prior to sex offenders' arrivals, homes located within 0.1 miles of an offender's location have very similar values as homes between 0.1 and 0.3 miles away from the offender's location. They also illustrate that, after the offender's arrival, homes sold located within 0.1 miles of the offender's location are significantly less expensive than those in the 0.1 mile to 0.3 mile range.

To formally estimate these differences, we take all sales of homes in the offender areas and run regressions of house characteristics (including price) on a dummy variable for whether or not the home is within 0.1 of the offender's location and a set of year fixed effects (equation 1). First, we limit the sample to sales that took place before the offender's arrival (Table 3 Panel A), and find little evidence of any preexisting differences in either sale price or house characteristics. The only difference that is marginally statistically significant is the fraction of homes built in the same year in which they are sold.

Figure 4 shows the distribution of prices in these areas in more detail, highlighting the small differences in homes in these areas. The distributions overlap significantly with three small differences: First, the area between 0.1 and 0.3 miles from where the offender will eventually locate have a small number of homes with values over $400,000. Second, the area within 0.1 miles has slightly more homes in the $150,000 to $300,000 range than the area between 0.1 and 0.3 miles of the offender location. Finally, the area between 0.1 and 0.3 miles of an offender location has more homes that sell for $100,000 to $150,000.

The average differences in the areas can be more precisely estimated by using not just the characteristics of houses that sell, but all of the houses in the offender areas. These differences are provided in Panel B of Table 3. These differences are of the similar magnitude as the characteristics of homes that sold, though of opposite sign. With a much larger sample, the power of the hypothesis tests is sufficiently increased that these small differences are now distinguishable from zero.

Overall, the results in Panels A and B of Table 3 demonstrate the relative homogeneity of the areas compared in our study. The differences between parcels within

0.1 miles of an offender and those between 0.1 and 0.3 miles, for example, are smaller than the differences one would observe walking down a typical street in these areas. The average standard deviation of sale price on the same street within offender areas is 16 percent of the street's average price. The average standard deviation in the size of homes by street is 244 square feet or about 15 percent of the mean. The difference of 60-80 square feet in average size between the areas within 0.1 miles and between 0.1 and 0.3 miles is about the size of a walk-in closet. Given the price elasticity with respect to size (Column 3 of Table 2) this increase in home size is worth about two percent of the average house price.

After offenders' arrivals, all of the differences in the average characteristics of homes sold within 0.1 miles of an offender and homes between 0.1 and 0.3 miles are similar to the pre-existing differences except for price. While there were no differences in the price of homes sold before the offenders' arrival, prices are approximately 10% lower among homes sold within 0.1 miles of offenders' location after the offender moves. Otherwise, homes are on average 100 square feet smaller (this difference is statistically significant), have .05 less bedrooms, .04 less bathrooms, and are no longer more likely to be built in the same year they are sold.[13]

### 5.2 Estimates Controlling for Area and House Characteristics

We first present estimates of equation 1 that include sales of homes outside of offender areas. The estimate of $\pi_1$ from this equation when we restrict the sample to pre-arrival homes sales is simply a measure of the average price difference between houses

[13] Based upon results not presented in this version of the paper, this reduction in the average size of homes seems to be the result of more homes selling in areas with large numbers of smaller homes. However, given the sample size, it is difficult to analyze such disaggregated effects.

within 0.1 miles of an offender's future location and other houses sold within the same year. This difference is approximately 34% (Column 1 of Table 4), and confirms that homes close to offenders' locations are cheaper than in other parts of the county. However, when we include neighborhood-year fixed effects and house characteristics in the regression (Column 2 of Table 4), we estimate that homes within 0.1 miles of an offender sell for only .7% less on average.[14] This difference is not statistically different from zero at any reasonable confidence level.[15] These results demonstrate that the household characteristics contained in our data set include sufficient information to capture almost all of the differences between areas in which offenders move and the rest of the county, and that, controlling for these characteristics, sex offenders' locations were not significantly less expensive than other parts of their neighborhoods prior to arrival.

Estimating equation 2, we find that homes located within 0.1 miles of an offender's location sold for 4% less on average than surrounding homes after the offender's arrival (Column 3 of Table 4), but just .7% less on average prior to the offender's arrival. This 3.3% decline in price is statistically significant at the 8% level. Estimating equation 3—our differences-in-differences specification—we find a slightly higher estimate of the impact of a sex offender's arrival. This estimate is -4.1%, and is statistically significant at the 4% level (Column 4). The estimated change in value for homes located between 0.1 and 0.3 miles of an offender's location when the offender arrives is positive (1%) but statistically insignificant. Thus, homeowners living just

[14] Our controls for housing characteristics include dummy variables for the major building quality grades and a linear term for the minor grades, the square footage of the property, fireplaces, number of bedrooms, number of bathrooms, a dummy variable for properties built in the same year they are sold, the age of the house in years, and dummy variables for the number of stories, the external wall type, and air conditioning.
[15] Standard errors are clustered at the neighborhood level for regressions including all sales in the county and at the offender area level for regressions including only offender areas.

slightly farther away from the offender (between 0.1 and 0.3 miles) experienced no decrease in property values on average.

This is a sizable loss. Single family homes within 0.1 miles of offenders' locations sold for about $135,000 in the two years prior to the offenders' arrivals. Thus, our estimates suggest that homeowners who live extremely close to a sex offender and sell their homes lose between $4,500 and $5,500, relative to the amount they would have received if the offender did not move in. Each offender thus causes an average loss to local home owners of $156,912. Countywide, the 373 offenders known to live in private residences depress property values by an estimated $59.5 million.

Implicit in our estimation strategy is the assumption that the relationship between housing characteristics and prices outside of the offender areas are valuable in estimating the relationship between prices and those characteristics in the offender areas. This assumption would be violated, for example, if offender areas were systematically different from non-offender areas. The resulting misspecification could cause us to erroneously attribute residual changes in prices in the offender areas to the arrival of the offender. To check for this, we re-estimate equation 3 using only the data from the offender areas (Column 5 of Table 4). Rather than controlling for neighborhood by year fixed effects, we instead control for offender area by year fixed effects and estimate standard errors clustering at the offender area level. These results (impacts of -3.6%) are consistent with those in columns 3 and 4, suggesting that additional data from the rest of the county did not bias our estimates.

While these differences document the average change in prices resulting from the arrival of a sex offender, Figures 2a and 2b suggest that property closest to the offenders' location declines more steeply in value after the arrival of the offender. To check for this heterogeneity in the treatment effect, we interact distance from the offender with the dummy variable indicating that a parcel is located within 0.1 miles of an offender after the offender has moved in. (Note that distance is measured in hundredths of a mile.) The results are consistent with the figures. Parcels directly adjacent to the offenders' location are estimated to decline by 11.5% and those a tenth of a mile away experience virtually no change in value (a decline of 0.5%).

Given the drop in value for the parcels near an offender, it is possible that offenders' arrivals might have generated a compositional shift in which occupants with a high distaste for living near an offender sell their homes to new occupants who are less averse to the location. For example, families with young children might sell their homes to male-only occupants or couples without children. We do not have information of the actual occupants, but we can check for changes in the probability that a home sells. For this purpose, we construct a monthly panel of all parcels in the offender areas for two years before and after the offender's arrival date. Column 7 of Table 4 presents the estimate of a linear regression of the probability that a parcel sells (measured in percentage points) within the difference in difference framework provided in equation 3. The results suggest that the arrival of an offender does increase the probability that nearby parcels sell by 0.12 percentage points. This is a 20% increase from the baseline probability of sale of 0.57 percentage points.

### 5.3 Falsification Tests

Figures 2 and 3 and the results in Tables 3 and 4 show little evidence of any preexisting differences in homes located close to an offender relative to other homes in their neighborhoods. However, it is theoretically possible that the decrease in values after offenders' arrival is driven by differential trends in values for homes closest to an offender. In other words, the prices of houses in offender areas may be trending over time in a different way than other houses in their neighborhoods. For example, if houses located near the parcel where an offender moves were experiencing slower growth in prices, this could lead to a spurious negative "impact" of the offender's arrival.

We investigate this possibility by estimating equation 3 using arrival dates equal to two years and three years prior to offenders' actual arrival dates. In both of these specifications, we find no evidence of a spurious effect in this specification (Table 5).

## 6. Estimates of the Cost to Victims of Sexual Offenses

The results above present evidence that the arrival of a sex offender has a statistically and economically significant impact on the value of homes in the immediate vicinity. As economists, we seek to measure the welfare cost to victims of crimes committed by sexual offenders so that we can make optimal policy decisions, such as how much to spend on programs that reduce crime. Households' willingness to trade off lower house prices against increased victimization risk can be used to estimate the welfare cost of crimes committed by sexual offenders. If the decline in property value close to offenders is indeed driven by increased risk of victimization, then we can make this calculation.

The Department of Justice currently estimates victimization costs using other methods. In a widely cited DOJ study, Miller et al. (1996) estimate victimization costs for various crimes and include measures of tangible costs (e.g., medical expenses, lost work time, property loss etc.) and intangible costs (e.g., pain, suffering, fear, lower "quality of life"). Estimates of tangible costs use a number of sources, but rely heavily on losses and injuries reported in the NCVS. Intangible cost estimates rely on data from jury awards to compensate victims (i.e., not punitive damages) and, for fatal crimes, the average value of life estimate across studies reviewed by Viscusi (1993). Victimization cost estimates from this study are shown in Table 6.[16] Average victimization costs of Rape and Sexual Assault to be roughly $114,000, 95% of which represents intangible costs. In contrast, the average victimization cost of Burglary is estimated at $2,000, almost all of which is due to direct costs such as property loss.

Relying on survey responses and jury awards to estimate victimization costs is problematic to the extent that this information does not accurately reflect individuals' willingness to pay to reduce crime risk. For example, jury awards are often based upon testimony of experts who estimate intangible victimization costs from contingent valuation surveys. Since these surveys require people to hypothetically make a trade-off between suffering from a crime and paying varying amounts of money, one might think that these surveys are likely to overestimate the true amount an individual would be willing to pay to avoid being the victim of a crime. On the other hand, one advantage of the DOJ estimates is that they are based on actual crimes, not perceived risk. Our empirical strategy enables us to estimate the willingness to pay to live far from convicted

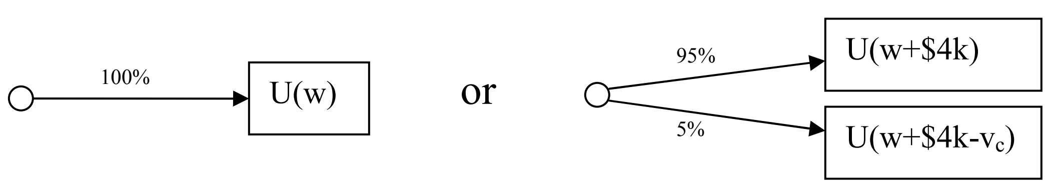
[16] Costs in the DOJ study are given in 1993 dollars. We adjust this to 2004 dollars using the annual CPI for all urban consumers.

criminals. We infer individuals' willingness to pay to reduce crime risk by estimating the actual distribution of crimes committed against neighbors by sex offenders. However, we cannot be certain that the *perceived* risk is the same as the empirical risk distribution. We return to this issue below in the discussion of our findings.

Our calculation is based on a simplistic model of the choice faced by the marginal homebuyer, whose preferences determine the price discount for living close to a convicted sex offender. This household can choose either to live far from a sex offender or to live close to an offender, get a price discount, and expose itself to higher crime risk. The marginal home buyer will have equal utility under either choice, i.e., the discount for living near an offender will compensate them for the increased crime risk. This notion is expressed by equation 4, where utility is a function of lifetime wealth ($w$), the individual knows the discount ($d$) and the increased probability of crime ($f(c)$) for living near an offender, and $v_c$ is a scalar that maps crime victimization into an equivalent wealth loss.

$$U(w) = \int U(w + d - v_c c) f(c) dc \tag{4}$$

For example, if we suppose that living close to a sex offender located nearby decreased property values by $4,000 and increased the risk of being the victim of one crime by 5%. Then equation 4 can be restated as a choice between two simple lotteries:




If the marginal household is risk neutral, the implied victimization cost would be $80,000.

Our estimates suggest that property value declined by about 3.5% in areas within 0.1 miles of an offender. At the median price of homes sold in these areas prior to the offenders' arrivals ($135,000), a 3.5% impact implies a decline in value of $4,725. We specify the utility function to have constant absolute risk aversion equal to 2.[17] This is generally considered a relatively high level of risk aversion, and perhaps even an upper bound given empirical evidence on labor supply decisions (Chetty 2005). We set lifetime wealth at $1.575 million. This is the amount of annual income needed to obtain a mortgage equal to the value of the median home in our sample (about $35,000), multiplied over 45 years.[18]

The amount of additional crime risk faced by neighbors of sex offenders requires a more complex calculation. We estimate the probability distribution with which offenders commit crimes against neighbors using data from the Department of Justice (DOJ), the Federal Bureau of Investigation (FBI), and the National Crime Victimization Survey (NCVS). This calculation requires a number of steps and details are given in the appendix. We make a number of assumptions in this calculation, and we examine the sensitivity of our results to alternate assumptions.[19] For example, the relationship of offender to victim is reported in the NCVS and "neighbor" and "stranger" are both potential responses. Recognizing that some "strangers" may actually be "neighbors," we assume that the true fraction of crimes committed by neighbors is 200% of the fraction of

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[17] Formally, $U(w) = -\frac{1}{2}e^{-2w}$.

[18] Lenders often follow the 28% rule: a family can pay up to 28% of gross monthly income (before other debt payments) as mortgage payments. A 30-year fixed rate mortgage of $135,000 (the median home price) at 6% interest would give rise to payments of $810 per month. Family income must therefore be about $2890 per month or about $35,000 per year.

[19] For example, the relationship of offender to victim is reported in the NCVS and "neighbor" and "stranger" are both potential responses. Recognizing that some "strangers" may actually be "neighbors," we assume that the true fraction of crimes committed by neighbors is 200% of the fraction of victims that claim the offender was a neighbor.

victims that claim the offender was a neighbor. The assumptions we make generally will lead us towards low estimates of victimization costs. However, despite these choices, our estimates remain high relative to the lifetime income of our representative household.

If neighbors are only concerned with the increased risk of sexual offenses (Rape and Sexual Assault) associated with living near a sex offender, then the assumption that $c$ is scalar is fairly trivial and $c$ would represent the number of sex offenses committed by the sex offender. However, sex offenders commit many types of crime, ranging from Murder to Motor Vehicle Theft, and it seems reasonable that neighbors would be concerned with these crimes as well as sexual offenses. In order to incorporate various types of crime into our simple model, $c$ and $v_c$ must be specified as vectors. Unfortunately, we cannot separately calculate victimization costs for various crimes because we do not have variation in the willingness to pay to reduce the risk of various types of crime. We only have the willingness to pay to not live near a sex offender, and therefore must maintain $c$ as a scalar. To do so, we assume that all crimes can be specified as a fraction or multiple of a sex offense. For example, victims of a presumably less severe crime, such as Burglary, can be seen as suffering costs that are equivalent to a fraction of a sex offense.

If we knew the relative severity of various types of crime, all crimes could be specifying all crimes in terms of sex offenses would be a straightforward exercise. Because we do not know these relative severities *ex ante*, we must use estimates of victimization costs from some other source. We choose to use estimates from Miller et al. (1996) as a rough approximation to the *relative* costs of victimization among different types of crime, e.g., the relative cost of Burglary is about 2% the cost of Rape.

We estimate that each sexual offense has a wealth-equivalent welfare cost of almost $1.2 million (Table 7). Thus, the housing market impacts we identify above imply very large costs to victims of sexual offenses—an order of magnitude larger than the DOJ estimates.[20] Moreover, the high amount of risk-aversion assumed and several of the choices made in our estimates of the distribution of crime risk are likely to lead us to overstate crime risk and underestimate victimization costs. We examine the sensitivity of our results to the assumptions embedded in our estimates by estimating victimization costs under wide-ranging alternate assumptions. These alternative estimates vary from about $0.6 to $2.3 million. We therefore feel confident that the large implied welfare losses are not an artifact of the assumptions built into our calculation.

There are, however, other potential explanations for the large implied costs we find. First, it may be that individuals overestimate the amount of crime risk associated with living in close proximity to a sex offender. There is a longstanding literature that shows individuals tend to overweight rare events in making decisions under risk and tend to overestimate the actual probability of rare events. (Kahneman and Tversky (1979), Lichtenstein et al. (1978) and Viscusi (1990, 1999)). If individuals overestimate the risks posed by sex offenders, then cost estimates based on objective probabilities will be too high.[21] To illustrate the power of overestimation of risk, we recalculate our victimization cost estimates assuming that individuals believe that any crime sex offenders commit against a neighbor will happen to them. Under this (albeit extreme) assumption, we estimate that sexual offenses have a victimization cost of $67,000 (bottom of Table 7).

[20] It is important to note that, for our calculation, we only require that the *relative* costs of various crimes are estimated correctly in the Miller et al. study.
[21] See Kask and Maani (1992) for further discussion of the implications of bias in subjective probability estimation for hedonic estimates of the willingness-to-pay to reduce the risk of hazardous events.

Another explanation for our results is that there is additional cost—above any crime risk—to living in close proximity to a released sex offender. This additional cost could come from several sources. First, it is reasonable to believe that individuals derive utility from interaction with their neighbors, and that this utility may vary with their neighbor's characteristics (e.g., shared interests). If individuals derive low utility from interactions with neighbors who are sex offenders, this could lead to a larger impact on house prices. Second, there may be consumption losses that stem from the increased crime risk created by the sex offender's presence (e.g., your friends refuse to visit you). Third, there may be a psychic cost to living near a sex offender, i.e., a cost to living with increased *fear* of crime. The cost of living in close proximity to an offender may include a constant reminder of the possibility of the worst outcomes – such as those faced by the families of Megan Kanka and Jacob Wetterling.

This latter explanation is supported somewhat by the distance gradient of the impact of a sex offender's arrival. Recall that the impact of a sex offender's arrival on housing prices is extremely localized, with no price impact more than .1 miles (about 2 city blocks) from the offender's location and the largest impacts in the homes virtually next door to the offender. We do not know of any evidence on whether the expected change in crime risk should have a similar gradient, but it seems unlikely that the risk posed by the sex offender should decline so quickly in distance and be confined to such a small area. However, it may well be that those neighbors living closest to the offender are far more likely to be aware of his/her presence by passing by the offender's home or come into contact with the offender on the street.

## 6. Conclusion

Local governments spend more than $50 billion per year on police protection, more than five times the amount spent by state governments even including intergovernmental expenditures (Census of Governments, 2003). Comparable expenditure at the federal level is difficult to measure, but the entire budget of the Department of Justice in fiscal year 2003 was less than $20 billion. The magnitude of these expenditures implies that individuals care deeply about crime prevention.

The results of this paper suggest that individuals show a significant distaste for living in close proximity to a convicted criminal. Using very detailed data on the locations of convicted sex offenders (whose identities and residential locations are made public on the North Carolina Sex Offender Registry) and the dates on which they move into a neighborhood, we estimate that on average the values of homes within 0.1 miles of an offender fall by roughly four percent. This effect dissipates quickly with distance of homes from the offender; homes between 0.1 and 0.3 miles away show no effect.

These results are a significant improvement upon the existing literature because we are able to exploit a quasi-random process (the selection of a specific home by a sex offender among those available on the market at the time) that introduces a convicted criminal into a very specific geographic area. We then use both cross-sectional and time series variation in values of homes sales in the specific locations in which an offender chooses to live. This allows us to identify the causal relationship between the risk of crime and changes in property values than previous studies that rely either only on cross sectional variation in risk (Larsen et al., 2003) or those that use panels of crime statistics in aggregate geographic areas.

These estimates suggest that individuals have a strong distaste for living in close proximity to a sex offender. We estimate that a single offender depresses property values in the immediate vicinity by $4,500 to $5,500 per home. If we aggregate these effects across all homes affected and all offenders, we find that the presence of sex offenders depress property values in Mecklenburg County by about $58 million. This suggests that households would be willing to pay a high cost for policies that remove sexual offenders from their neighborhoods.

We combine the estimated decline in property values with data on crimes committed by sexual offenders against neighbors to estimate costs to victims of sexual offenses. Two key assumptions in our calculation are that all of the decline in property value is due to increased crime risk and that neighbors' perceptions of risk are in line with objective data. We estimate victimization costs of over $1 million—far in excess of estimates taken from the criminal justice literature. These estimates imply a high willingness to pay for policies that reduce the incidence of sexual offenses.

Unfortunately, we cannot test the two assumptions underlying this estimate. It is quite plausible that individuals substantially overestimate the risks posed by neighboring sex offenders or experience a cost—unrelated to crime risk—of living in close proximity to an offender. If so, then the willingness to pay for policies that only decrease crime risk would be lower. However, under these alternative hypotheses, households would be willing to support policies that provided accurate information regarding the risks posed by sex offenders or isolate sex offenders without decreasing crime risk.

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## Appendix: Calculation of Crimes Committed Against Neighbors by Sex Offenders

For illustrative purposes, suppose that there is only one kind of crime and that *g(c)* is the probability distribution of crimes committed by sex offenders. Further, let us suppose that there is a constant probability that, conditional on crimes being committed, they are committed against neighbors ($P_N$). Finally, let us suppose that there is a constant number of neighbors ($N$) who are potential victims, that all neighbors are equally likely to be victims, and that crime, conditional on being committed against neighbors, is committed against a single neighbor. *f(c)*, the probability distribution of crimes committed against neighbors, will then be:

$$f(c) = g(c)\frac{P_N}{N}$$

Under these assumptions, we can use data on *g(c)*, $P_N$, and $N$, to estimate *f(c)*.

In order to estimate *g(c),* we first calculate the number and type of crimes for which sex offenders are arrested in the three years subsequent to their release from prison. This information comes from "Recidivism of Prisoners Released in 1994," a data set collected in 1998 by the Bureau of Justice Statistics on prisoners released by 15 states. This data set includes all 10,337 sex offenders who were released from these states in 1994, and gives a complete inventory of all arrests and adjudications of these offenders through 1998. These states are: Arizona, California, Delaware, Florida, Illinois, Maryland, Michigan, Minnesota, New Jersey, New York, North Carolina, Ohio, Oregon, Texas, and Virginia. The data set also includes a stratified sample of all other prisoners released in these states in 1994. Because this data contains offenders' entire criminal histories, we treat as sex offenders all released prisoners who had previously been convicted of a sexual offense, not just those whose most current prison sentence was due to a sexual offense conviction. We use sampling probability weights to construct population averages. We drop offenders for whom a record of arrests and prosecutions (a "RAP sheet") was not successfully located and offenders who died during the three years following their release. We also drop a small number of offenders who had unknown arrest and adjudication dates (making it impossible to distinguish recidivism from prior criminal history) or had adjudication dates that preceded the arrest date for any given offense.

Table A.1 shows the fraction of sexual offenders and other released criminals who are arrested for various crimes during the first three years after their release from prison. Sex offenders are much more likely to be arrested for a sexual offense than other released criminals. The fraction of released sex offenders who are later arrested for Rape and Sexual Assault are 2.1% and 4.0%, respectively. Moreover, the ratio of arrests for sex offenders vs. other criminals is over 4:1 for Rape and over 5:1 for Sexual Assault. Arrests of sexual offenders are similar to other released convicts for violent crime, though somewhat more likely for Kidnapping and Assault, and less likely for Murder, Manslaughter, and Robbery. Arrests of sex offenders are significantly less likely for non-violent crimes such as Burglary, Larceny, and Motor Vehicle Theft.

It is important to note that sample selection into this data set may overstate the frequency of arrests for all criminals at all times. Almost all of the released criminals in our data spent a year in prison for their crimes, whereas 30% of sex offenders registered in North Carolina spent less than one year in prison. Also, we examine offenders just after their release from prison, when they are most likely to recidivate. Indeed, of sexual offenders' arrests for Rape and Sexual Assault, 37% and 49% (respectively) come in the first year after their release. These one-year statistics are also reported in Table A.1.

Not all crimes lead to arrests. In order to calculate the crimes actually committed by offenders, we use statistics from Lee and McCrary (2005) on the fraction of crimes that are reported to the police and fraction of reported crimes that lead to an arrest (Table A.2). Their calculations are based on comparisons of victimization reports from the National Crime Victimization Survey (NCVS) and crimes reported to the police and reported crimes that lead to arrests from FBI Uniform Crime Reports (UCR). See appendix table II of their study for further explanation. Because the NCVS and UCR data do not break out crimes into great detail, we assume that similar crimes have similar crime/arrest ratios. For example, we assume that the ratios are the same for Rape and Sexual Assault.

According to their estimates, for every individual arrested for a sexual offense, roughly four offenses had actually been committed (i.e., there is a crime/arrest ratio of 4:1). Although we can use the estimates in Table A.2 to gauge crime/arrest ratios, we do not have estimates of the extensive and intensive margins of criminal activity. In other words, even if the crime/arrest ratio is 4:1, it may be that (intensive) all four crimes were committed by the same offender who was arrested, or it may be that (extensive) four different offenders committed one crime each, but only one offender was arrested.

We assume that the crime/arrest ratio is due entirely to the intensive margin, i.e., each arrest is indicative of multiple crimes, but non-arrested offenders do not commit crimes. Given this assumption, the empirical distribution of arrests and the estimated crime/arrest ratios are sufficient to estimate the empirical distribution of crimes committed. It is important to note that the intensive assumption—placing a larger number of crimes on a small number of offenders—will lead us towards estimates of welfare costs that are lower, given risk aversion, than assuming that some of the crime-arrest ratio is due to offenders who commit crimes but are not arrested.[22]

We estimate the fraction of crimes committed against neighbors using the fraction of victims claiming that the offender was a neighbor in the concatenated NCVS files from 1993-2004. Because the NCVS cannot ask murder or manslaughter victims about their offenders, we use the 2003 Supplemental Homicide Reports (a subset of the UCR data) to estimate offenses by neighbors for these crimes. This is, of course, only possible for crimes where the offender is known. Murder and Manslaughter are not separately identified in this data, so we combine them. For Murder/Manslaughter, Rape, and Sexual Assault, the fractions of offenses committed by neighbors are 0.7%, 3.7% and 6.9%, respectively (Table A.3 column 1). These figures suggest that the crime risk from

[22] This can be shown in the following manner: Suppose there is a 1/N chance of being a victim of N crimes. Indifference to this risk implies $U(w) = \frac{1}{N}U(w+d-nv) + \frac{N-1}{N}U(w+d)$, where notation follows equation 4. As N increases, the probability of being a victim falls, but the number of crimes committed per victimization rises. This is essentially the intensive margin assumption. $\frac{dv}{dN}$ is the change in the wealth equivalent value of a *single crime* that sustains the equation when N rises. Solving for $\frac{dv}{dN}$ yields an expression proportional to $\left[U(w+d) - U(w+d-nv)\right] - nvU'(w+d-nv)$. The term in brackets equals the loss in utility from victimization, which must be smaller than the second term if the agent is risk averse, i.e., if U''<0. For a risk neutral agent, $\frac{dv}{dN}$ would be zero.

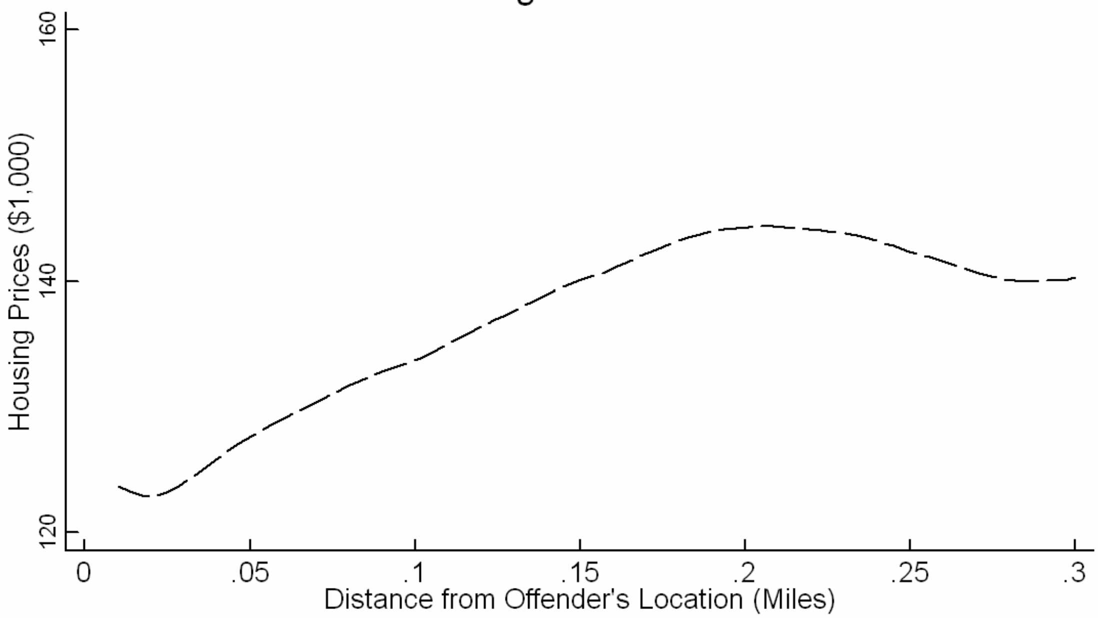
neighbors may be quite small. One potential problem with these measures is that victims may not know their neighbors. The fraction of crimes committed by *both* neighbors and strangers is a possible alternate measure, but it is often an order of magnitude greater than the fraction committed by neighbors alone, and is likely to considerably overestimate crime risk from neighbors (Table A.3 column 2). Recognizing the problems inherent in both measures, we assume that the true fraction of crimes committed by neighbors is 200% of the fraction of victims that claim the offender was a neighbor. In other words, for every crime victim claiming the offender was a neighbor, another victim claimed the offender was a stranger when, in fact, the true offender was a neighbor.

We estimate the number of households in the neighborhood among which crime risk from the sex offender is spread by measuring the number of single family homes located within one tenth of a mile of offenders in Mecklenburg County. The median number of single-family homes within one tenth of a mile of offenders' parcels—at the time they moved in—is 120. This is probably an underestimate of the number of relevant households facing the increased risk of crime, since it does not include other residential structures such as condominiums, multi-family homes and apartment buildings.

## Figure 1: An Offender Area and Surrounding Neighborhoods

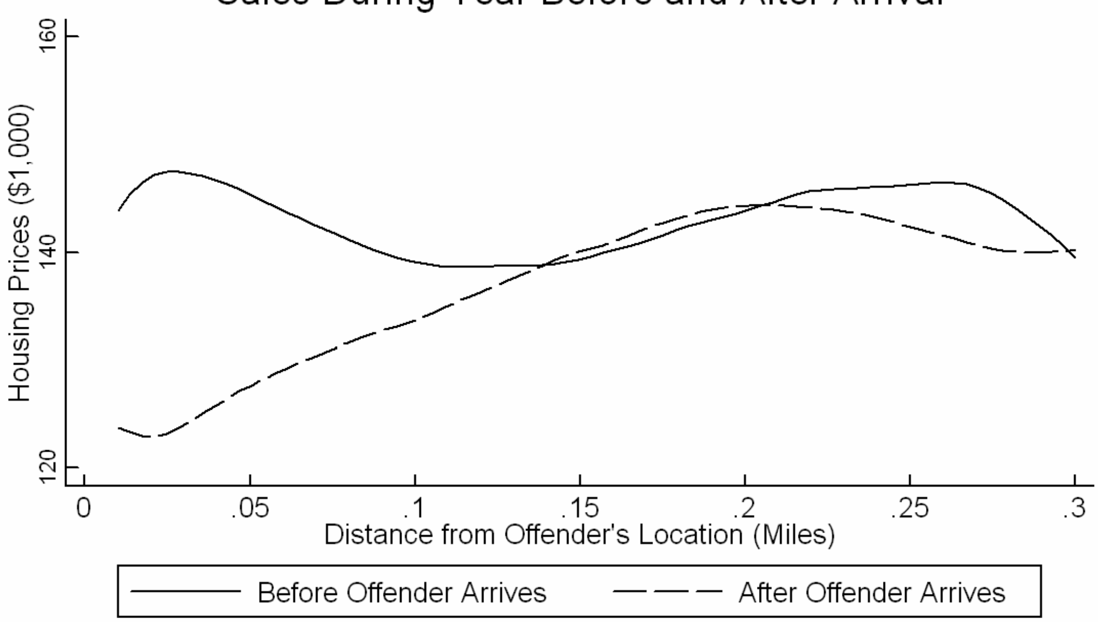
Note: X marks the center of the offender's exact location. The surrounding circle marks all parcels within one-quarter of a mile. Neighborhoods are distinguished by shades of gray. Parcels within a neighborhood are usually, but not necessarily, contiguous.

Figure 2a: Price Gradient of Distance from Offender
Sales During Year After Arrival



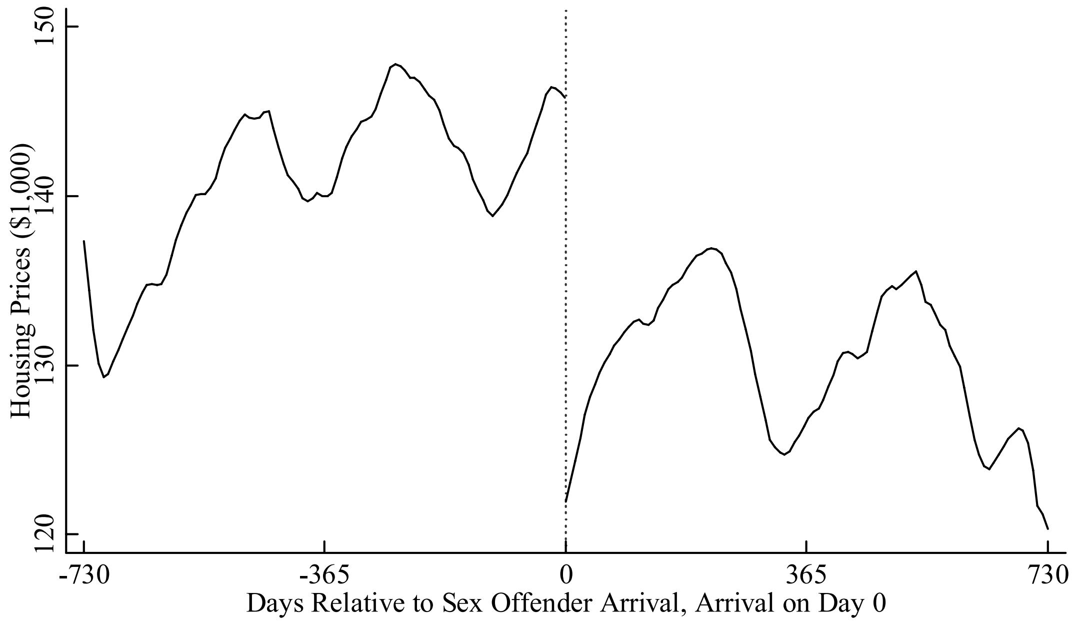

Note: Results from local polynomial regressions (bandwidth=0.075 miles) of sale price on distance from offender's future/current location.

Figure 2b: Price Gradient of Distance from Offender
Sales During Year Before and After Arrival



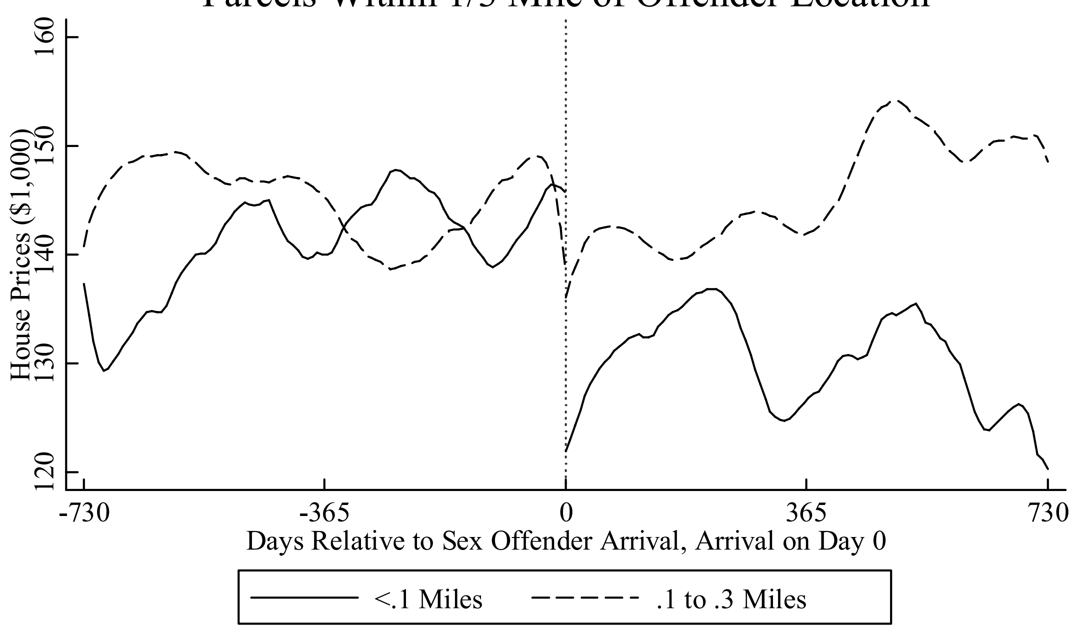

Note: Results from local polynomial regressions (bandwidth=0.075 miles) of sale price on distance from offender's future/current location.

Figure 3a: Price Trends Before and After Offenders' Arrivals
Parcels Within Tenth Mile of Offender Location



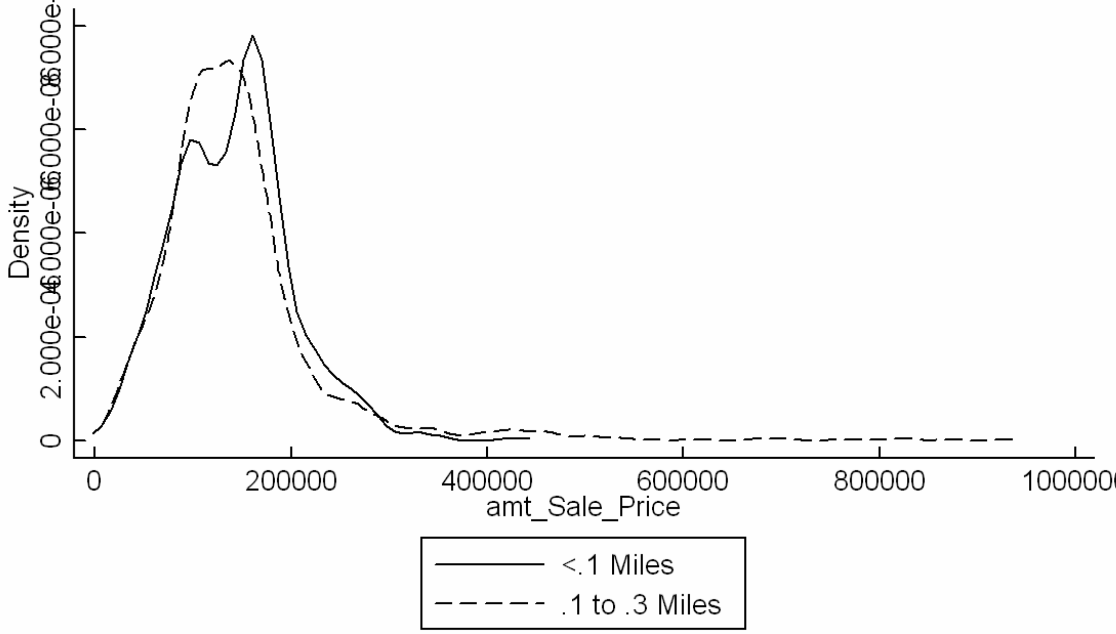

Note: Results from local polynomial regressions (bandwidth=90 days) of sale price on days before/after offender arrival.

Figure 3b: Price Trends Before and After Offenders' Arrivals
Parcels Within 1/3 Mile of Offender Location




Note: Results from local polynomial regressions (bandwidth=90 days) of sale price on days before/after offender arrival.

Figure 4: Distribution of Price
within Three Tenths of a Mile of Offender Location




Note: Results from kernal density estimating using optimal bandwidth

Table 1: Sexual Offenses Committed by Registered Offenders in North Carolina

| Crime Committed | *State* Frequency | *State* Percent | *Mecklenburg County* Frequency | *Mecklenburg County* Percent |
|---|---|---|---|---|
| Indecent Liberty with a Minor | 8874 | 71.6% | 417 | 67.7% |
| Sex Offense | 1338 | 10.8% | 71 | 11.5% |
| Rape | 1085 | 8.8% | 66 | 10.7% |
| Attempted Rape or Attempted Sexual Offense | 467 | 3.8% | 35 | 5.7% |
| Sexual Exploit of Minor | 261 | 2.1% | 5 | 0.8% |
| Incest Between Near Relatives | 152 | 1.2% | 13 | 2.1% |
| Kidnapping Against a Minor - 1st and 2nd Degree | 98 | 0.8% | 6 | 1.0% |
| Felonious Restraint Against a Minor | 55 | 0.4% | 1 | 0.2% |
| Other | 58 | 0.5% | 2 | 0.3% |

Note: Frequencies and percentages represent number of crimes in each category committed by offenders. Offenders may committ multiple crimes.

Table 2: Characteristics of Homes Sold in Mecklenburg County, 1994-2004

| | All Parcels | Within 1/3 Mile of Offender | |
|---|---|---|---|
| | *Mean (Std Dev)* | *Mean (Std Dev)* | *Marginal Effect in Price Regression* [2] |
| Sale Price ($100,000) | 2.048 (1.324) | 1.438 (0.848) | |
| Square Footage (1,000 Sq Ft) | 2.075 (0.880) | 1.620 (0.595) | 0.294 (0.011)* |
| Quality Rating[1] | 3.251 (1.208) | 3.066 (0.979) | 0.015 (0.005)* |
| | *Percentage* | *Percentage* | |
| **Air Conditioned** | 93.3% | 84.6% | 0.111 (0.011)* |
| **Sold in Year Built** | 29.5% | 19.6% | -0.042 (0.012)* |
| **Story Height** | | | |
| 1 Story | 39.4% | 56.5% | |
| 1.5 Stories | 6.4% | 5.4% | 0.058 (0.016)* |
| 2.0 Stories | 49.1% | 32.5% | 0.055 (0.011)* |
| 3 or More Stories | 1.6% | 0.6% | 0.131 (0.048)* |
| Split Level | 1.1% | 1.4% | -0.019 (0.029) |
| Other | 2.4% | 3.5% | -0.014 (0.021) |
| **Bedrooms** | | | |
| 1 Bedroom | 0.1% | 0.1% | |
| 2 Bedrooms | 5.2% | 11.4% | 0.171 (0.094)+ |
| 3 Bedrooms | 60.8% | 71.8% | 0.277 (0.094)* |
| 4 Bedrooms | 30.0% | 15.5% | 0.255 (0.095)* |
| 5 Bedrooms | 3.6% | 1.1% | 0.322 (0.101)* |
| 6 Bedrooms | 0.3% | 0.1% | -0.200 (0.150) |
| **Bathrooms** | | | |
| 1 Bathroom | 14.1% | 30.8% | |
| 2 Bathrooms | 72.4% | 65.1% | 0.087 (0.012)* |
| 3 Bathrooms | 10.9% | 3.7% | 0.112 (0.024)* |
| 4 Bathrooms | 2.5% | 0.4% | 0.182 (0.064)* |
| Sample Size | 170,239 | 9,092 | 9,086 |
| $R^2$ | | | 0.75 |

[1]Quality is rated on a 6 point scale that tends from low quality to high quality; [2]Estimated for parcels sold in offender areas by regressing log(Sale Price) on listed variables and offender area by year fixed effects.

Table 3: Pre- and Post-Arrival Differences in Average Characteristics of Homes Sold Close to Offenders' Locations

| *Panel A, Pre-Arrival Differences in Sales* | Log Price | Built in Year Sold | Age in Years | Sq. Feet (1,000s) | # of Bedrooms | # of Bathrooms |
|---|---|---|---|---|---|---|
| Within .1 Miles of Offender | 0.007 | 0.062 | -1.081 | 0.059 | 0.022 | <.001 |
| | (0.034) | (0.035)+ | (1.117) | (0.047) | (0.034) | (0.036) |
| Constant | 11.605 | 0.186 | 16.616 | 1.589 | 3.050 | 1.716 |
| | (0.036)* | (0.030)* | (1.153)* | (0.039)* | (0.028)* | (0.034)* |
| Sample Size | 4497 | 4497 | 4497 | 4497 | 4497 | 4497 |
| $R^2$ | 0.06 | 0.03 | 0.04 | 0.03 | 0.03 | 0.03 |
| *Panel B, Differences in All Existing Parcels* | | | Age in Years | Sq. Feet (1,000s) | # of Bedrooms | # of Bathrooms |
| Within .1 Miles of Offender | | | 0.205 | -0.079 | -0.048 | -0.081 |
| | | | (1.050) | (0.027)* | (0.025)+ | (0.024)* |
| Constant | | | 37.671 | 1.538 | 2.992 | 1.585 |
| | | | (1.518)* | (0.037)* | (0.029)* | (0.035)* |
| Sample Size | | | 31856 | 31856 | 31856 | 31856 |
| $R^2$ | | | <0.001 | <0.001 | <0.001 | <0.001 |
| *Panel C, Post-Arrival Differences in Sales* | Log Price | Built in Year Sold | Age in Years | Sq. Feet (1,000s) | # of Bedrooms | # of Bathrooms |
| Within .1 Miles of Offender | -0.096 | 0.005 | -0.591 | -0.097 | -0.054 | -0.042 |
| | (0.037)* | (0.050) | (1.504) | (0.043)* | (0.038) | (0.043) |
| Constant | 11.628 | 0.166 | 17.337 | 1.626 | 3.042 | 1.721 |
| | (0.038)* | (0.027)* | (1.080)* | (0.038)* | (0.026)* | (0.033)* |
| Sample Size | 4595 | 4595 | 4595 | 4595 | 4595 | 4595 |
| $R^2$ | 0.04 | 0.03 | 0.05 | 0.02 | 0.02 | 0.02 |

Note: Pre-arrival (post-arrival) refers to the two-year period before (after) the date upon which the offender registered their current address. Standard errors (in parentheses) are clustered at the offender area level. * significant at 5% level; + significant at 10% level

Table 4: The Impact of Sex Offenders' Locations on Property Value and Sale Probability

| | Log(Sale Price) Pre-Arrival | | Log(Sale Price), Pre- and Post-Arrival | | | | Probability of Sale† |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Within .1 Miles of Offender | -0.340 | -0.007 | -0.007 | <.001 | -0.006 | -0.013 | -0.033 |
| | (0.052)* | (0.013) | (0.012) | (0.013) | (0.012) | (0.014) | (0.034) |
| Within .1 Miles * Post-Arrival | | | -0.033 | -0.041 | -0.036 | -0.115 | 0.125 |
| | | | (0.019)+ | (0.020)* | (0.021)+ | (0.060)+ | (0.059)* |
| Dist*≤.1 Miles* Post-Arrival (0.1 Miles = 1) | | | | | | 0.11 | |
| | | | | | | (0.065)+ | |
| Within 1/3 Miles of Offender | | | | -0.010 | | | |
| | | | | (0.007) | | | |
| Within 1/3 Miles * Post-Arrival | | | | 0.010 | 0.010 | 0.010 | -0.055 |
| | | | | (0.010) | (0.016) | (0.017) | (0.040) |
| *$H_0$: Within .1 Miles* Post-Arrival = 0* | | | *P-value = 0.0805* | *P-value = 0.0442* | *P-value = 0.0813* | *P-value = 0.0579* | *P-value = 0.0364* |
| Housing Characteristics | | √ | √ | √ | √ | √ | √ |
| Year FE | √ | | | | | | |
| Neighborhood - Year FE | | √ | √ | √ | | | |
| Offender Area - Year FE | | | | | √ | √ | √ |
| Restricted to Offender Areas 2 Years Pre- and Post-Arrival | | | | | √ | √ | √ |
| Standard Errors Clustered by… | *Neighbor-hood* | *Neighbor-hood* | *Neighbor-hood* | *Neighbor-hood* | *Offender Area* | *Offender Area* | *Offender Area* |
| Sample Size | 164,993 | 164,968 | 169,557 | 169,557 | 9,086 | 9,086 | 1,519,364 |
| $R^2$ | 0.03 | 0.84 | 0.84 | 0.84 | 0.75 | 0.75 | 0.01 |

Note: Pre-arrival (post-arrival) refers to the two-year period before (after) the date upon which the offender registered their current address. Standard errors in parentheses. * significant at 5% level; + significant at 10% level; † Probability sale is measured as percentage points, e.g., Probability of sale = 1 would be 100 percentage points.

## Table 5: Falsification Tests on Impact of Sex Offender Location

| | *Baseline Estimates* | 2 Year Prior Arrival Dates (1) | 3 Year Prior Arrival Dates (2) |
|---|---|---|---|
| Within .1 Miles of Offender | *<.001* | -0.017 | -0.013 |
| | *(0.013)* | (0.016) | (0.016) |
| Within .1 Miles * Post-Arrival | *-0.041* | 0.018 | -0.004 |
| | *(0.020)** | (0.020) | (0.020) |
| Within .25 Miles of Offender | *-0.010* | -0.010 | -0.012 |
| | *(0.007)* | (0.007) | (0.008) |
| Within .25 Miles * Post-Arrival | *0.010* | -0.001 | 0.001 |
| | *(0.010)* | (0.007) | (0.008) |
| $H_0$: Within .1 Miles*Post-Arrival = 0 | *P-value = 0.0442* | *P-value = 0.3669* | *P-value = 0.8577* |
| Sample Size | *169,557* | 169557 | 169557 |
| $R^2$ | *0.84* | 0.84 | 0.84 |

Note: The dependent variable is the log of house price. All regressions contain neighborhood-year fixed effects and housing characteristics (see text for list of characteristics included). Baseline results are taken from column (4) of table 4. Standard errors (in parentheses) are clustered by neighborhood.

Table 6: Estimated Victimization Costs from Department of Justice Study

| Type of Crime | Cost ($2004) |
|---|---|
| *Sexual Offenses* | |
| Rape and Sexual Assault | $113,732 |
| *Violent Crimes* | |
| Murder/Manslaughter | $3,843,363 |
| Assault | $31,374 |
| Robbery | $10,458 |
| Kidnapping | $43,140 |
| *Non-violent Crimes* | |
| Burglary | $2,092 |
| Larceny | $523 |
| Motor Vehicle Theft | $5,229 |

Note: These cost estimates are taken from tables 2 and 4 in Miller et al. (1996). Their cost estimates are given in 1993 dollars. We adjust these for inflation using the 1993 and 2004 annual CPI for all urban consumers. Victimization costs for kidnapping are not listed in their study and we therefore set equal to the cost of assault with injury against a child under the age of 11.

Table 7: Estimated Victimization Cost of a Sexual Offense
Using Housing Market Impact and Objective Data on Crimes Against Neighbors

| Assumptions in Calculation | Estimated Victimization Cost |
|---|---|
| Baseline Assumptions | $1,176,000 |
| Lower Risk Aversion (λ=1) | $2,031,100 |
| Higher Risk Aversion (λ=3) | $839,000 |
| Fewer Neighbors (60) | $1,016,100 |
| More Neighbors (180) | $1,259,000 |
| Fewer Offenses by Neighbors (100% of NCVS) | $2,353,000 |
| More Offenses by Neighbors (300% of NCVS) | $588,100 |
| Systematic Overestimation of Risk: Housholds Neglect to Realize that Risk is Spread Among Neighbors | $66,700 |

Note: Baseline assumptions are as follows: (1) utility function with constant absolute risk aversion equal to 2, (2) lifetime wealth equals $1.575 million, (3) housing market discount equals $4,750, (4) neighborhood risk is spread among 120 neighbors, (5) the fraction of crimes committed against neighbors is 200% of the reported rates in the NCVS.

Table A.1: Probability of Arrest After Release from Prison, by Type of Crime and Type of Criminal

| Type Of Crime | Sexual Offenders | | Other Criminals | |
|---|---|---|---|---|
| | 3 Years | 1 Year | 3 Years | 1 Year |
| *Sexual Offenses* | | | | |
| Rape | 2.1% | 0.8% | 0.5% | 0.2% |
| Sexual Assault | 4.0% | 1.9% | 0.7% | 0.3% |
| *Violent Crimes* | | | | |
| Murder | 0.6% | 0.3% | 0.7% | 0.3% |
| Manslaughter | 0.1% | 0.0% | 0.2% | 0.1% |
| Kidnapping | 1.9% | 1.1% | 0.7% | 0.3% |
| Robbery | 4.3% | 2.3% | 6.2% | 2.8% |
| Assault | 14.1% | 5.1% | 13.5% | 5.8% |
| *Non-violent Crimes* | | | | |
| Burglary | 7.1% | 2.8% | 9.9% | 5.4% |
| Larceny | 11.0% | 4.3% | 16.5% | 9.0% |
| Motor Vehicle Theft | 3.0% | 1.1% | 4.6% | 2.3% |

Note: Shown are the fraction of released prisoners arrested for various crimes of prisoners released in 1994 during the years after their release from prison. See the appendix for a description of this data set.

Table A.2: Crime/Arrest Ratios from Lee and McCrary (2005)

| Type Of Crime | % of Crimes Reported to Police | % Reported Crimes that Lead to Arrest | Ratio of Crimes to Arrests |
|---|---|---|---|
| *Sexual Offenses* | | | |
| Rape | 45.0% | 54.0% | 4.12 |
| Sexual Assault* | " | " | 4.12 |
| *Violent Crimes* | | | |
| Murder | 64.0% | 77.0% | 2.03 |
| Manslaughter* | " | " | 2.03 |
| Robbery | 26.0% | 71.0% | 5.42 |
| Assault | 57.0% | 46.0% | 3.81 |
| Kidnapping* | " | " | 3.81 |
| *Non-violent Crimes* | | | |
| Burglary | 13.0% | 58.0% | 13.26 |
| Larceny | 18.0% | 33.0% | 16.84 |
| Motor Vehicle Theft | 14.0% | 86.0% | 8.31 |

Note: These figures are taken from appendix table II of Lee and McCrary (2005) and are the results of their calculations using data from the National Crime Victimization Survey and Uniform Crime Reports for 2002. "*" denotes that no information is on reporting and arrests was available for this crime and that it is assumed that reporting and arrests follow the same pattern as the preceding (similar) crime.

Table A.3: Percent of Crimes Commited by Neighbors

| Type Of Crime | % of Crimes by Neighbors | % of Crimes by Neighbors or Strangers |
|---|---|---|
| *Sexual Offenses* | | |
| Rape | 3.7% | 18.7% |
| Sexual Assault | 6.9% | 24.8% |
| *Violent Crimes* | | |
| Murder/Manslaughter | 0.7% | 15.5% |
| Robbery | 3.2% | 53.4% |
| Assault | 5.5% | 31.7% |
| Kidnapping* | " | " |
| *Non-violent Crimes* | | |
| Burglary | 11.1% | 46.1% |
| Larceny | 5.1% | 35.6% |
| Motor Vehicle Theft | 3.0% | 50.7% |

Note: With the exception of Murder and Manslaughter, these figures are calculated using victims' reports of offenders' identities in the 1993-2004 Concatenated NCVS. Figures for Murder and Manslaughter are calculated using data from the 2003 Supplemental Homicide Reports. "*" denotes that information was not available for this crime and it is assumed that offenses by neighbors follow the same pattern as the preceding (similar) crime.