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Abstract

We use a recent policy experiment in Rio de Janeiro, the installation of permanent police stations in low-income communities (or *favelas*), to quantify the relationship between a reduction in crime and the change in the prices of nearby residential real estate. Using a novel data set of detailed property prices from an online classifieds website, we find that the new police stations (called UPPs) had a substantial effect on the trajectory of property values and certain crime statistics since the beginning of the program in late 2008. We also find that the extent of *inequality* among residential prices decreased as a result of the policy. Both of these empirical observations are consistent with a dynamic model of property value in which historical crime rates have persistent effects on the price of real estate.

Key words: wealth distribution, amenity value, real estate

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Introduction

Residential property prices are an important gauge of economic conditions writ large. They reflect many macroeconomic factors as well as the particular local microeconomy of the property's location. Home values also compose an important part of household wealth, especially in lower income areas where residential property is typically a family's primary (or only) asset. In the United States, about a third of total assets for a given family are accounted for by owner-occupied housing, with that figure closer to two thirds for families below the median level of net wealth.[1] This statistic might be further skewed in developing countries, where the capacity of poor families to accumulate financial assets is more limited. Taken together, these observations suggest a powerful mechanism by which any policy affecting the determinants of house prices can alter the level and dispersion of household wealth.

In this paper, we investigate one example of this mechanism as it pertains to the connection between crime and house prices. Our first objective is to empirically identify and document the relationship between crime and house prices. As a public 'bad,' we fully expect crimes to exert a downward force on prices; indeed, this is a common finding in the related literature on house amenity valuation and the economics of conflicts. We quantify the extent to which prices are responsive to crime-related outcomes, as demonstrated by a recent policy experiment and with the use of highly detailed property price data from the online classified website ZAP (*www.ZAP.com.br*), and find that these effects can be quite large and economically meaningful. Our main innovation will then be to document and explain the distributional consequences of removing the public bad of crime; that is, the removal of crime may have heterogeneous effects on the prices of different residences in a manner which alters the degree of overall inequality among property values. This would happen, for example, if lower valued properties appreciate or depreciate disproportionately to a given change in the crime rate. We will discuss the circumstances under which that would occur in the context of a dynamic model of property valuation.

[1] Kennickell (2009) presents a broad array of statistics on U.S. family income and wealth for the years 1989-2007, drawing on the Survey of Consumer Finances (SCF) compiled by the Federal Reserve Board. Family net wealth and its components for various years of the SCF are provided in Table A2 of that paper.

Our empirical work will show that decreasing crime does, in fact, benefit lower valued properties disproportionately, reducing the inequality among properties. This relationship is suggested in Figure 1, which plots indices of homicides, robberies and a Gini coefficient of house prices for the city of Rio de Janeiro since 2008.[2] Both homicides and robberies declined markedly since mid-2009. Though the series for homicides is more volatile, the average decrease for both types of crime is about 15 percent by mid-2011. The Gini coefficient measures the level of inequality of house prices across Rio's neighborhoods. It was rather stable at roughly 0.28 through the beginning of 2010 before falling to 0.265 by mid-2011. The fact that both crime and inequality pivoted and then fell at about the same time is suggestive of a relationship between them.

Since there are many different factors that can affect house prices simultaneously, we study the housing market around the time of a specific policy event tightly linked to the objective of crime reduction. This policy is the introduction of the Unidade Pacificadora da Policia ("Pacifying Police Unit," or UPP) program in Rio de Janeiro beginning in late 2008. As in many metropolitan areas in developing countries, a significant fraction of the population of Rio live in very low-income communities with a high concentration of substandard, informal housing; in Rio, home to some of the largest of these communities in Latin America, they are called *favelas*. Over the past three decades, the city has been plagued by conflicts over territory in its favelas with drug gangs and militias, with many favelas effectively being occupied and governed by the drug gangs. The UPP program, in response, re-occupies specific favelas by force using elite police units, drives out the drug gangs and roots out caches of weapons and drugs, and then installs permanent police stations staffed by highly trained, well-paid and newly-recruited officers; eighteen such stations have been installed since 2008. The basic objective of re-occupation is the renewed assertion of the rule of law and the abatement of drug gang-related crimes.

The program, to the extent it is effective, is responsible for many positive externalities associated with the accomplishment of these objectives. Using detailed monthly data on residential property prices in Rio's formal housing market, as well as on homicide and

[2] Data sources and the details of index construction for the series in Figure 1 are provided below in Sections III and V.

robbery rates in each of Rio's neighborhoods, we formally test the hypotheses that neighborhoods closer to a UPP station experienced larger than average decreases in crime and larger than average increases in house prices after the UPP was put into place. In addition to the variation across neighborhoods and time, we exploit the staggered timing of the policy across the 18 UPPs by jointly estimating the individual effect of each one on house prices and crime. We find that, conditional on a UPP being installed nearby, house and apartment sales prices increased by an average of 5-10 percent, homicides decreased by an average of 10-25 percent, and robberies decreased by an average of roughly 10-20 percent. To gain perspective on the economic significance of the decrease in crime due to the UPPs, we use our regression results to construct counterfactual price and crime rates and, with those, city-wide statistics. In the absence of the UPPs, the overall house price index in Rio would have grown about 15 percent slower since 2008, and homicide and robbery rates would have fallen by about 14 and 20 percent less than they did, respectively. We note that since we do not observe house prices inside the favelas themselves, our estimated price effects are quite likely to be underestimates of the true city-wide effects.

The empirical results, notwithstanding some heterogeneity in the effectiveness of individual UPP stations, confirm widely reported anecdotes of abated violence and of skyrocketing residential property prices in the formal housing markets surrounding the favelas. Our findings complement and extend previous work on the effectiveness of the UPPs. Based on household survey data, Neri (2011a) found that rental prices *within* all favelas in Rio rose by about 7 percent between 2007 and 2009. However, those results are not specific to each community protected by a UPP and do not control for secular trends in the Rio housing market. The positive externalities of UPPs are also explored in Cunha and Mello (2011), which focuses on the formalization of services provision in a favela following the installation of a UPP. In addition to the direct valuation of disamenities due to crime that we emphasize below, formalization and urban regularization are other important channels through which crime reductions affect property prices, and which are captured in our estimates of the effect of the UPPs.

Having established that the UPPs influenced crime and house prices in opposite directions (that is, that the UPPs seem to be a reasonable instrument for the effect of crime on house prices), we use our estimates to analyze the association between crime and the *dispersion* of house prices. We present a model of property valuation in which there are diminishing returns to crime reduction; this implies that properties with either high initial crime rates or low amenity values have disproportionately large increases in price for a given decline in crime which, in turn, lowers inequality among properties. The mechanism in the model that gives rise to diminishing returns is the inclusion of historical crime rates as a determinant of current property values.

This treatment of the dynamic transmission of crime rates into house prices is quite similar in spirit to the way Besley and Mueller (2011) model the number of killings due to conflict as a function of the latent state of the peace process in Northern Ireland. In that model, the persistence of crime in a particular area has a bearing on what signal agents take from a change in the number of killings about the probability of entering a state of peace, and hence on the transmission of the rate of killings into house prices. In our model, we have a simpler treatment of agents' expectations but the transmission of a change in the crime rate into prices depends similarly on the history of crime, which is an additional state variable. Thus, current and future consumption flows from housing depend on both the level and duration of crime rates in the past; lower initial crime rates with low historical duration gives rise to the biggest increases in price when the crime rate declines.

We document that the disparity in house prices in Rio did in fact decline following the implementation of the UPP policy. A Gini coefficient constructed with the actual and counterfactual house prices described above shows that the disparity in house prices across neighborhoods has been falling faster after installation of the UPPs than for the counterfactual Gini. Moreover, in several neighborhoods with a UPP nearby, we find evidence that the dispersion in property prices within those neighborhoods narrowed, suggesting that even within more homogeneous sets of properties the lowest valued ones are most sensitive to a change in the crime rate.

This paper contributes to several areas of active research, ranging from studies of the economics of conflict to the analysis of the wealth distribution. Most closely related are the works identifying the impact of crime and violence on property prices, with the paper by Besley and Mueller (2011) as a closest antecedent; as below, Besley and Mueller (2011) exploit both spatial and temporal variation in crime data to identify the effect on house prices, and they provide a model in which the response of property prices depends on the level and persistence of historical crime rates. The present study uses more disaggregate price data, at the level of neighborhoods in Rio, and has a different modeling approach that focuses more on the implications of crime for the dispersion of house prices. To our knowledge, ours is the first study to draw a connection between crime reduction and wealth inequality.

Our empirical measurement of the crime elasticity of house prices is connected to a sequence of papers estimating this (largely negative) elasticity. Early examples include Thaler (1978), in which a one standard deviation increase in per capita property crime decreased single-family home prices by 3 percent, and Hellman and Naroff (1979), in which the elasticity was -0.63. A known drawback of these estimates is that they each treated the crime rate as exogenous, which may have biased the elasticity estimates if, for example, crime occurs disproportionately in poorer neighborhoods with low property values or, conversely, if criminals target areas with higher-priced homes. In a recent survey, Ihlanfeldt and Mayock (2009) found 12 instances in of a set of 18 empirical studies relating house prices and crime that treat crime as exogenous – as such, those studies do not account for this reverse causality or other sources of endogeneity. Of the recent studies that do instrument for crime, Gibbons (2004) and Tita, Petras and Greenbaum (2006) again find a negative significant relationship, an effect that is particularly pronounced for violent crimes.

We attempt to get around issues of cross-sectional endogeneity by exploiting the time variation around an exogenous policy experiment, the UPPs in Rio. A widely acknowledged objective of the UPP policy is to increase the safety around key venues for the 2014 soccer World Cup and 2016 Summer Olympics, the locations of which are not systematically related to historical crime rates or the levels of property prices. As such, we will argue that the UPPs are a reasonable instrument for the effect of crime on house prices. We proceed by estimating a difference in differences estimator of property values in neighborhoods with a nearby UPP, straddling the public announcement that a UPP would be installed in those neighborhoods. This method for estimating the (dis)amenities of housing is used analogously in Linden and

Rockoff (2008) in their study of the effect of the proximity of registered sex-offenders on house prices.[3]

Finally, this paper is related to a large literature on the determinants of wealth inequality. Wolff (1992) illustrates that wealth concentration and inequality in the United States varied a lot over much of the 20th century (both increasing and decreasing) and moved fairly closely with changes in the income distribution. Brazil, in particular, has made great strides recently to reduce its level of inequality.[4] Our work demonstrates a novel and potentially important channel by which policy can contribute to changes in the distribution of wealth.[5]

The paper proceeds as follows. The next section provides some background on the favelas in Rio and the official mandate of the UPP program. Section II describes the empirical model, followed by the details of the property price data and crime data in Section III, and the empirical results in Section IV. The valuation model and its predictions for the dispersion of house prices, as well as some empirical measures of house price inequality in Rio, can be found in Section V. Section VI concludes.

I. Background on the UPP program

Most of Rio de Janeiro's favelas are situated on the hillsides of the city and many are located in close proximity to affluent neighborhoods. Both of these factors have made them a favored haven for drug gangs. By commanding the high ground and through a mix of cooptation and explicit threats, heavily-armed gangs have gained effective control over the resident populations of certain favelas and have used these locations as bases to process, stockpile and distribute drugs. The profitability of such trafficking operations has led to

[3] There are many other studies that estimate property (dis)amenities more broadly defined to include factors such as environment. Boyle and Kiel (2001) provide a thorough, if dated, survey of that literature.

[4] Since 2001 the Gini coefficient for Brazil's income distribution has decreased monotonically from 0.596 in 2001 to an estimated 0.53 in 2010 – still relatively high compared to 0.36 for India or 0.42 for the U.S. For a recent discussion, see Neri (2011b).

[5] Though our results suggest that crime reductions have benefited the owners of low-priced housing disproportionately, low-wealth households are less likely to own a home than wealthier households. In a recent study of U.S. households during the financial crisis, Bricker et al. (2011) show that household wealth declined most severely in the upper percentiles. This reflects both the dramatic fall in house (and other asset) prices and the fact that wealthier families are more likely to own those assets. In the bottom quartile of wealth, only 15 percent of families had any home equity in 2007, compared to 96.8 percent in the top quartile.

intensifying territorial dispute, growing levels of violence and, through bribes to "protect" the operation from other drug gangs and other illicit activities, the increasing complicity of the police. Over the past three decades, a complex system has crystallized in which drug-related and other criminal activities have fed on police corruption, and spilled over into the political arena, with drug money used to finance politicians in the municipal and state legislatures, and reportedly reaching the highest levels of the state government.

A new, reformist state government assumed power in 2007, setting improving security and reducing the levels of violence as priorities. The selection of Brazil as the host of the 2014 World Cup and Rio as the seat of the 2016 Olympics added impetus to these objectives. The new government recognized that achieving these goals entailed dealing simultaneously with the territorial power of drug lords in the favelas as well as police corruption. There was also a realization that a new security policy for the favelas would have to be more permanent in nature. Previous attempts to combat drug traffic involved occasional incursions into the favelas for specific operations, often resulting in the deaths of innocent bystanders caught in the crossfire. The core of the new policy, which took nearly two years to design and deploy, was built round the concept of territorial occupation by state forces, and the installation of a large, permanent presence of a newly trained police force of young officers untainted by corruption.[6] This presence would manifest itself in a large police station, a UPP, and would be preceded by a carefully planned and swiftly executed process of expulsion of the drug gangs by crack police units and special forces. The program, initiated in December 2008, is considered to be a new paradigm of police action against the encroachment of drug gangs in the favela communities.[7]

Of the many favelas affected by drug gangs, the selection of which favelas were to receive a UPP was largely a political outcome. This is important for our empirical identification of the effect of UPPs on crime and house prices, since it mitigates the extent of reverse causality

[6] Breaking with traditional repression techniques, newly trained officers are taught to be "community policemen" or "proximity police" by integrating themselves within the occupied community. Acknowledging the skepticism and mistrust that local populations have historically had with police activity, all UPP staff are newly admitted and trained for this specific purpose. This hiring and training practice is consistent with the idea that UPPs are meant to be the gateway for many other services beyond the suppression of criminal activity.
[7] In an op-ed in the newspaper Globo, State Public Safety Secretary José Mariano Beltrame compared the UPP program (which he manages) to the Plano Real in 1994, which drastically reduced inflation and stabilized the economy (http://oglobo.globo.com/opiniao/apenas-primeiro-passo-3516738).

between our policy variable (the UPP) and each outcome. In other words, UPPs were not simply placed in the neighborhoods with the highest crime rates or lowest house prices. Rather, the policy has been implemented by prioritizing important locations for the World Cup and Olympic Games, giving geographic factors a dominant role in determining the location of UPPs. This can be seen in the top panel of Figure 2, in which the exact locations of the 18 existing UPPs are mapped with the gradient of average apartment sales prices for each neighborhood in Rio. It is evident that some UPPs were placed in high-priced neighborhoods while others were placed in low-priced neighborhoods. Similarly for the rate of homicides, shown in the bottom panel of Figure 2, UPPs appear in some low homicide neighborhoods in the south zone, high homicide neighborhoods in the north zone, and neighborhoods with intermediate homicide rates in the west. Media commentary on the UPPs has suggested that while some neighborhoods received a UPP due to their high incidence of crime, UPPs were installed to garner political support for the UPP program and protect key World Cup locations in the high- and middle-income South Zone (or *Zona Sul*).[8]

Implementation of a UPP in a given favela occurs in a four-stage process. A similar protocol has been observed for most favelas, though it is not an official standard. First, the community or set of communities to be occupied is announced by the police up to 6 months in advance, though no specific date is given. Second, a series of announcements indicating the imminence of the occupation occur, including an announcement that it will happen in the next 1-2 weeks. Between 4-7 days prior to the occupation, the specific date is made public and police begin encircling the favela(s). Third, heavily-armed Civil and Military Police, led by elite forces, invade a favela in the early twilight hours and expel the drug traffickers in the neighborhood. Over the next few days of week, they systematically sweep the area to clear any remaining criminals or contraband and set up a temporary station. Finally, the permanent physical station is installed and control is handed over to a new UPP battalion. In the majority of cases, and as an intended consequence of the pre-announcements, this process has led to very little violent confrontation as criminals have already left the area.

[8] Several sources indicate that geography rather than crime rate is the dominant factor in determining the location of UPPs. In an interview in January 2012, the director of communication for the state police force, Frederico Caldas, linked expanding the number of police at UPPs with the goal of ensuring security ahead of the World Cup and Olympic Games. A prime example of this goal is the invasion of Rocinha, Vidigal and Chacara do Céu in the affluent (relatively low-crime) South Zone of Rio, an operation which is widely cited for protecting tourist infrastructure.

As shown in Table 1, 20 favelas have been occupied and 18 UPP units installed between late-2008 and the end of 2011, as part of a plan to reach 40 UPPs by 2014. The rollout of the program has been fairly steady over time, with a new occupation taking place on average every few months.[9] The territorial footprint of the current 18 UPPs encompasses over 50 communities, containing more than half of a million inhabitants. Over 3 thousand police officers are currently deployed in the program, which is expected to reach 12 thousand by 2014.[10] Table 1 also shows the names of the neighborhood (or *bairro*) in which the favelas are located. In some instances, due to their sprawling layout over hillsides, they are located in more than one neighborhood; for example, the favela Santa Marta is located in Botafogo and Humaitá. Due to the large number and proximity of the neighborhoods (there are 153 official bairros in the municipality of Rio), we also list those which have a border within 2km of the address of each UPP; this significantly widens the number of neighborhood and the size of the population classified as 'close' to a UPP. Finally, cognizant of the fact that one neighborhood might share a border with another where a UPP is located but only have a small fraction of its population living close to the border, we use ArcGIS mapping software to compute the distance between each UPP and the central point (called 'centroid') in each bairro. The set of neighborhoods with a centroid within 2km of a UPP station is a subset of those with a border within 2km, and is used below as another measure of UPP proximity.

II. Estimating the effect of UPPs on property prices and crime rates

Our baseline measure of the effect of the UPPs is a difference in differences estimator for all of the 18 UPPs installed between November 2008 and November 2011.[11] Our elemental

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[9] When available in media reports, Table 1 includes the date that the UPP was announced, though in many instances these dates, if reported, were only a few days prior to occupation. Since the announcement data are not published officially, we rely on media reports to ascertain their timing; newspaper coverage tends to pick up the story of a UPP only once invasion is imminent (i.e., shortly before the third stage described above).

[10] In addition, as of the date of this manuscript, the cluster of favelas known as Complexo do Alemão, containing approximately 125,000 inhabitants, was occupied by 3,000 highly trained army troops, while another immense tract of communities in Rocinha, Vidigal and Chácara do Céu, occupied in November 2011, had an unknown number of crack units still searching for drugs and weapons.

[11] Two large clusters of communities, Complexo do Alemão and Rocinha/Vidigal, are excluded as no UPP was installed yet by the end of 2011 (as of January 2012, two new UPPs were established in Vidigal and Chácara do Céu, to be followed by Rocinha). Given significant differences in the size and scope of those UPPs, it is difficult to apply our findings for the first 18 UPPs to them (or, for that matter, to subsequent UPPs). However, under the

unit of measure is the monthly average listing price of a property with certain characteristics, such as dwelling type (i.e., apartment or house) and number of bedrooms, in a given neighborhood. For instance, one price observation would be the average price of a 3-bedroom apartment in Botafogo in January 2010. The localized nature of the policy in specific favelas as well as its sequential rollout leads to variation in property prices across neighborhoods, time and property characteristics. The elasticity of house prices to the installation of a UPP is estimated using the following specification:

$$(1) \qquad \ln\left(\overline{P}_t^{ib}\right) = \alpha_0 + \sum_n \alpha_{1,n} UPP_n + \sum_n \alpha_{2,n} Dist_n^b + \sum_n \alpha_{3,n} UPP_n * Dist_n^b + \gamma_t Z^i + \kappa^b + \delta_t + \varepsilon_t^{ib}$$

where $\overline{P}_t^{ib}$ is the average sale price of property type *i* in bairro *b* in month *t*, UPP_n is a dummy taking the value 1 for periods after the occupation date (or, if available, the announcement date) of the n^{th} UPP, $Dist_n^b$ is a dummy denoting proximity of bairro *b* to UPP *n*, Z^i is a vector of control variables for property characteristics, including the type of property (i.e., apartment or house) and the number of rooms, and ε_t^{ib} is a mean zero error. A full set of bairro (κ^b) and time (δ_t) fixed effects are included to absorb common neighborhood factors and aggregate month-to-month variation in the housing market, respectively. Since the average prices of properties in the same bairro but with different characteristics might have correlated errors, the standard errors of the estimates are clustered by bairro and period.

Our treatment group consists of properties that are in neighborhoods within close proximity of a UPP. Ideally, one would use the exact distance between a property's address and the UPP as the measure of proximity. However, given that we observe property prices only within the geographic unit of neighborhood, we operate under a range of assumptions about how 'close' adjacent neighborhoods are to a UPP. A set of three specifications of the variable $Dist_n^b$ is used: (i) the neighborhood in which the UPP is located (the penultimate column of Table 1), (ii) neighborhoods with a border within 2km of the UPP address (the final column of Table 1), and (iii) neighborhoods whose centroid is within 2km of the UPP address.

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assumption that subsequent UPPs are on average as effective as previous ones, our estimates of the overall effect of UPPs on house prices and crime understate the effects of the program as a whole.

The influence of each UPP on house prices is given by the coefficients $\alpha_{3,n}$, the interaction between $Dist_n^b$ and UPP_n. $\alpha_{3,n}$ can be interpreted as the percent increase in average property prices in neighborhoods proximate to a UPP after its installation *relative* to the change in price for properties that are not located close to a UPP. We identify the separate contribution of 15 out of 18 UPPs to house prices. In three instances, the overlap of the timing or the neighborhood of multiple UPPs is such that the effect of each UPP cannot be separately identified. For example, the occupation of the favela in São Carlos (in the neighborhoods Estácio and Rio Comprido) was announced in February 2011, the same month as favelas in Coroa, Fallet and Fogueteiro (in the neighborhood Rio Comprido). The resulting colinearity led us to merge these two UPPs into a single estimate of $\alpha_{3,n}$. We did likewise for Borel, Formiga and Salgueiro, three UPPs in the Tijuca neighborhood introduced within months of one another in 2010.

An important concern about the use of average price changes (of a sample of listings) to measure trends in the housing market is that the composition or quality of the sample could be changing over time. Changing property composition, such as the entry of a high-quality, high-priced property into the listings, would affect the average price used in the estimation of (1) even if the true quality-adjusted price of housing had not changed. This is a relevant issue if composition is changing systematically in a way that is correlated with the timing of the UPP policy. It is therefore important to check whether housing composition might be changing in response to the introduction of UPPs and to correct for this selection bias in equation (1). To do so, we use the two-stage correction procedure by Heckman (1976, 1979) and estimate the probability that a property with certain characteristics (i.e., neighborhood, type, # rooms) is listed. The first stage probit regression is of the form:

(2)
$$\begin{aligned} z_t^{ib} &= \alpha_0 + \sum_n \alpha_{1,n} UPP_n + \sum_n \alpha_{2,n} Dist_n^b + \sum_n \alpha_{3,n} UPP_n * Dist_n^b + \gamma_t Z^i \\ &+ \sum_n \alpha_{4,n} UPP_n * Dist_n^b * StateListings_t + \kappa^b + \delta_t + \varepsilon_t^{ib} \end{aligned}$$

where $z_t^{ib} = \begin{cases} 1 & \text{if } \overline{P}_t^{ib} > 0 \\ 0 & \text{otherwise} \end{cases}$.

In (2), the treatment group is additionally interacted with the total number of property listings on ZAP.com.br in the state of Rio de Janeiro. We thus allow listings to be a function of all of the explanatory variables in (1), including the UPP policy, as well as any factors that affect the aggregate listings on ZAP.com.br. Stated differently, the first stage allows for the possibility that crime has an outsized influence on listings when other factors affecting listings are high. We implement (2) as a standard Heckman correction factor by adding the inverse Mills ratio of this regression as an additional explanatory variable in (1).

We note that the sample selection correction, while useful as a gauge for the determinants of listings for groups of properties (e.g., 2- versus 3-bedroom apartments in Botafogo), still does not account for compositional effects within those groups (e.g., high- versus low-quality 2-bedroom apartments in Botafogo). These compositional effects might be tainting our results below, though it is not obvious whether one would expect a decrease in crime induced by the UPPs to cause higher- or lower-quality properties within each group to be listed.

Finally, estimates of the UPP effect on house prices from equations (1) and (2) are used to construct a series of counterfactual average property prices; these are the prices that the regressions suggest would have been observed in the absence of the UPP policy. The growth rate of the counterfactual price, $\tilde{P}_t^{ib}$, in a given period is constructed as follows:

$$(3) \qquad \frac{\tilde{P}_t^{ib}}{\tilde{P}_{t-1}^{ib}} = \begin{cases} \dfrac{\overline{P}_t^{ib}}{\tilde{P}_{t-1}^{ib}} & \text{if } \sum_n UPP_n * Dist_n^b = 0 \\[2ex] \dfrac{\exp\left[\ln\left(\hat{\overline{P}}_t^{ib}\right) - \sum_n \hat{\alpha}_{3,n} UPP_n * Dist_n^b\right]}{\tilde{P}_{t-1}^{ib}} & \text{if } \sum_n UPP_n * Dist_n^b > 0 \end{cases}$$

where $\ln\left(\hat{\overline{P}}_t^{ib}\right)$ is the predicted value of average prices from the regressions (1) or (2), $\hat{\alpha}_{3,n}$ is the estimated elasticity of property prices due to the UPPs and $\tilde{P}_0^{ib} = \overline{P}_0^{ib}$ for every property type and neighborhood. Counterfactual prices are equal to observed prices prior to the arrival of a UPP or in neighborhoods that do not have a UPP nearby (i.e., $\sum_n UPP_n * Dist_n^b = 0$) but subtract out the estimated effect of the UPP otherwise. Therefore, $\hat{\alpha}_{3,n} > 0$ implies that counterfactual prices are lower than observed prices.

Our treatment of crime rates is broadly analogous to that of house prices in equation (1), except we substitute the neighborhood crime rate, r_t^b, for property prices and remove the controls for property characteristics:

$$(4) \qquad \ln\left(r_t^b\right) = \alpha_0 + \sum_n \alpha_{1,n} UPP_n + \sum_n \alpha_{2,n} Dist_n^b + \sum_n \alpha_{3,n} UPP_n * Dist_n^b + \kappa^b + \delta_t + \varepsilon_t^b .$$

Since crime rates are reported in each neighborhood and time period, there is no need to correct for selection issues. Given estimates of (4), the growth of counterfactual crime rates can be computed as:

$$(5) \qquad \frac{\tilde{r}_t^b}{\tilde{r}_{t-1}^b} = \begin{cases} \dfrac{r_t^b}{\tilde{r}_{t-1}^b} & \text{if } \sum_n UPP_n * Dist_n^b = 0 \\ \dfrac{\exp\left[\ln\left(\hat{r}_{t-1}^b\right) - \sum_n \hat{\alpha}_{3,n} UPP_n * Dist_n^b\right]}{\tilde{r}_{t-1}^b} & \text{if } \sum_n UPP_n * Dist_n^b > 0 \end{cases}$$

which differs from (3) only in interpretation. If UPPs cause a decrease in crime rates, then $\hat{\alpha}_{3,n} < 0$ and the counterfactual crime rates lie above the observed ones.

III. <u>House prices and crime data</u>

This section describes the sources of detailed property price and crime data for the city of Rio.

a) <u>ZAP.com.br price data</u>

Real estate prices are drawn from the '*imóveis*' section of the online classifieds website, ZAP. We were provided with a confidential extract from the ZAP database containing average monthly offer prices of real estate in Rio for the period March 2007 through August 2011. Each observation is the simple average of prices across listings with specific characteristics such as neighborhood, type of property and number of rooms. Prices are in units of Brazilian reais per square meter. We were also provided with the number of listings and the standard deviation of the listing prices for each observation.

Altogether, the extract contains 54,064 monthly price observations of apartments and houses for sale spanning all 153 neighborhoods in Rio. Underlying these observations are 3,302,036 individual property listings. The numbers of neighborhoods, property types and transaction types have been growing steadily over the course of the sample (that is, the panel is unbalanced), which likely reflects the growth of ZAP as an advertising service provider, and not necessarily the number of properties bought and sold in the real estate market over time. Table 2 summarizes the average listing prices by property type and number of rooms, with the average prices at the of the bottom panel weighted by the number of listings underlying each observation. A few patterns in the composition of the data are worth noting. First, about three quarters of the listings are apartments. Second, for both apartments and houses, the price observations are fairly evenly distributed across properties with 1 through 4 bedrooms, with roughly 10-20 percent of the observations fitting into each one of those categories. Third, particularly in the weighted statistics, there are large differences in price levels across property types; house prices per square meter of R$2,846 are a full third lower than apartment prices. And fourth, the price per square meter tends to increase with the number of bedrooms for apartments and houses, notwithstanding a relatively high price level for 1-bedroom apartments in the sample.

The richness of the dataset is further demonstrated by the large numbers of listings in most neighborhoods, with even the 100th largest bairro by number of listings containing over 1,000 listings over the sample period. There is also a fair amount of heterogeneity among wealthy and poorer neighborhoods, with the average property price in the most expensive neighborhood of almost 9,000 reais per square meter dwarfing the average price of 1,300 in the least expensive.

Interestingly, looking at the raw price data already suggests some effect of the UPPs on property prices. Figure 3 shows one such example for the average price of houses in the neighborhoods Leme and Copacabana. The vertical lines show the announcement dates of two UPPs, the first directly adjacent to formal communities in Leme and the second abutting Copacabana and Ipanema. Immediately following the announcement of Chapéu-Mangueira in Leme, house prices jumped by about one third in Leme and only edged upwards slightly in Copacabana. Conversely, after the occupation of Pavão-Pavãozinho in Copacabana, house prices jumped by over 25 percent in Copacabana and stayed roughly flat in Leme. It is precisely price responses like these that our difference in differences estimator will attribute to the UPPs; in each case, the bairro containing the UPP (the treatment group) increased relative to the other (the control) after the occupation of the favela. A more subtle, and more common, case is illustrated in Figure 4, showing the average apartment prices in four neighborhoods as well as vertical lines denoting the occupations of the aforementioned favelas. One difference in Figure 4 is that the prices all have secular upward trends and so the difference in differences estimator will attribute to the UPPs increases in the *slope* of the treatment group price index relative to the control group indices after the installation of each UPP. Another difference in Figure 4 is the inclusion of prices for Botafogo and Leblon, neighborhoods that share a border with Copacabana and Ipanema, respectively. The inclusion of these neighborhoods in the treatment group (or not) will clearly have a bearing on the measured price effects of the UPPs in this example. We will consider both cases below.

b) <u>ISP crime data</u>

The crime data are compiled by the Institute of Public Safety of Rio de Janeiro (the *Instituto de Segurança Pública do Rio de Janeiro*, or ISP). ISP is responsible for consolidating and publishing an array of official statistical data pertaining to public safety. The crime data that we use are drawn originally from incident reports written by the state civil police and then aggregated into groups of different types of crime;[12] the assignment of incidents to categories of crime undergoes quality control checks by the civil police's internal affairs department. From these counts of different crime types in each month from January 2007 to June 2011, we construct two aggregates: homicides and robberies. Homicides is an aggregate of incident counts for three crime classifications related to violent acts with the intent to kill: murder, attempted murder and vehicular homicide. Robberies is an aggregate of incident counts for the following crime classifications: robbery of a commercial establishment, robbery of a residency, robbery of a vehicle, robbery of a passer-by, robbery of

[12] The categories of crime use are standardized groups defined by the National Secretary of Public Safety (SENASP).

a bank, robbery of an ATM, robbery where the victim is driven to a financial institution, extortion, kidnapping, extortion through kidnapping, and embezzlement.

The geographic unit of measure for the crime statistics is the coverage area of specific police stations, called *delegacias de polícia*, or DP. There are forty DPs in the metropolitan area of Rio, with most of them covering more than one neighborhood (the level of aggregation for the ZAP property prices), and a small number that only cover a portion of one neighborhood. Each DP, in turn, is classified within a broader geographic unit called an Integrated Area of Public Safety, or AISP.[13] To compute crime rates, we divide the crime counts for each DP by the corresponding monthly AISP population data.[14]

Figure 5 shows the relationship between our two measures of the crime rate and average sale prices for apartments. Each point is the average crime rate and property price for a particular neighborhood, averaging across time periods. As seen in the top panel, homicide rates range from 4 to 188 homicides per 100,000 people per year, while average robbery rates vary from 48 to 4,333 per 100,000 people per year. For both crimes, the distribution is positively skewed, with most neighborhoods having low rates and only a few having very high rates. Turning to the correlation between crime and apartment prices, the figures demonstrate that having a low crime rate is necessary though not sufficient for a neighborhood to have a high average property price; while there are no neighborhoods with a high crime rate and a high property price, there are several neighborhoods with low crime and low price. One might surmise from this observation that crime is but one amenity affecting property prices, which only becomes a dominant price-determining factor at very high rates.

The triangles in Figure 5 show the neighborhoods where one or more of the UPPs are located. It is worth noting that the UPP stations are located in neighborhoods that vary along

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[13] The official concordance between neighborhoods, DP's and AISP's can be found at the following website: http://urutau.proderj.rj.gov.br/isp_imagens/Uploads/RelacaoAISP.pdf.

[14] We note that the computation of neighborhood-level crime statistics using DP- and AISP-level statistics introduces some imprecision into our measure of the incidence of crime. Specifically, each neighborhood is assumed to have the crime data reported by its DP. This biases the crime statistics upwards as each neighborhood within a DP is erroneously assigned some crimes from other neighborhoods that share their DP. On the other hand, the population data are only available at the AISP level, which typically consist of multiple DP's. By assuming that each neighborhood has the population level of its entire AISP, the crime rate statistic is biased downward. On balance, the average crime rates that we compile are somewhat below their more aggregate published counterparts, though only slightly.

both dimensions. The stations have been built in low and high crime neighborhoods, as well as in neighborhoods with low and high average property prices. The square in each panel shows the average price and crime rate for the entire municipality of Rio, weighting each neighborhood by its average AISP population over the course of the sample. The average price for an apartments is R$2,152 per square meter, lower than the weighted average price by listings computed in Table 2, while the average crime rates are 27 and 538 incidents per 100,000 people per year for homicides and robberies, respectively. Despite the more aggregate data that we use to construct neighborhood crime rates, the average homicide rate falls within the range (albeit on the low end) of the 42 and 27 homicides per 100,000 rate reported by Waiselfisz (2011) for the city as a whole in 2007 and 2010, respectively.[15]

IV. **Results**

Estimates of $\alpha_{3,n}$ are shown in Table 3 for five different specifications of the property price regressions. Each column contains 15 coefficients for the interaction term of the UPP time dummy and proximity measure, one for each UPP station with certain UPPs pooled as described above. The baseline specification, (I), is an OLS regression of equation (1) where the proximity measure is the neighborhood(s) in which the favela receiving the UPP is located. We find that 11 of 15 coefficients on the difference in differences term are positive and statistically significant compared to two coefficients which were negative and significant. An F-test of the hypothesis that the sum of $\alpha_{3,n}$ is zero is strongly rejected and the sum of price effects divided by the 18 UPP stations is 5.8 percent. In other words, conditional on being in the neighborhood of a UPP, property prices increased by 5.8 percent more than in the rest of the city after the UPP was announced. There is also a fair amount of heterogeneity in the price responses across UPPs, from 6 percent following the Batam UPP to the 21 percent jump following the Chapéu-Mangueira UPP.

The estimates of price effects and their distribution across UPPs in (I) are quite stable across estimation methodologies. Column (II) shows estimates of equation (1) using

[15] A closer analogue to public homicide statistics is the aggregate of DP's (instead of neighborhoods) using a narrower definition of homicide (excluding attempted murder and vehicular manslaughter). Doing so with the ISP data yields an estimate of 31 homicides per 100,000 per year over the sample period.

weighted least squares and the number of listings per observation as weights. The intuition for this choice of weights is that observations with very few underlying listings may be more prone to measurement error than those where many properties are listed. To further control for the fact that the number of listings per observation could be endogenous to the UPP policy, we use the total number of listings in 2008 (on the eve of the UPP policy) for each bairro-type-# rooms observation, holding this constant throughout. The average effect of a UPP increases to almost 10 percent, with 12 positive and significant estimates and only 1 negative and significant one.

An even more careful treatment of possible selection effects into the ZAP listing sample models the probability of a given type of observation having non-zero listings, as in equation (2). Column (III) shows the results of the two stage procedure using the Heckman correction factor. In the first-stage selection regression, an F-test with null-hypothesis $\sum_n \alpha_{4,n} = 0$ is rejected and $\sum_n \hat{\alpha}_{4,n} < 0$. In other words, the types of properties with positive numbers of listings in the treatment group vary systematically with the aggregate ZAP listings in the dataset. Moreover, the estimate of rho, which is the correlation between the errors of the selection and outcome (second-stage) equations is statistically greater than zero, which suggests that a sample selection model befits the price data. Applying the correction factor, the resulting marginal effects of the UPP are shown in column (III), and are not substantially different from their OLS analogues in column (I).

The estimates of price effects are also robust to alternative specifications of the treatment group, though these changes in specification have a bearing on the interpretation of the magnitudes of the resulting estimates. Columns (IV) reports the UPP price effects for neighborhoods with a border within 2 kilometers of each UPP station, respectively, estimated using weighted least squares.[16] Strikingly, the inclusion of many more neighborhoods in the treatment group (relative to (II)) yields estimates that, although lower than before, are still positive and very significant. In column (IV), 13 of 15 UPPs have a positive and significant coefficient. Additionally, the variation in the size of price effects across UPPs has gone

[16] In the cases of pooled UPPs, the treatment group includes all bairros with borders within 2km of any of the pooled stations.

down, with the majority of estimates in the range of 5 to 10 percent. It is intuitive that the level of the effect would decrease when spread across a larger geographic area. This phenomenon is illustrated rather dramatically by Chapéu-Mangueira; the border estimate, which includes Copacabana, Urca and Botafogo in the treatment group (in addition to Leme), is less than half the size of the bairro-based estimate. On the other hand, precisely because the effect is applied to a much larger geographic base of listings, it may well have a larger overall influence on Rio house prices. Our counterfactual price series below will be informative of which specification implies a larger effect on the overall price index.

Finally, column (V) shows the results for bairros with a centroid within 2km of a UPP station. While the average effect of 5.7 percent is in line with the other specifications, on a UPP-by-UPP basis results tended to vary without much discernable pattern. In some instances, the effects were in between those of columns (II) and (IV) as one might expect from the addition of an intermediate number of bairros into the treatment group. In others, the results were notably stronger or weaker. In sum, while the average effect held fairly steady at upwards of 5 percent, the disparities across UPPs varied from specification to specification.

To put the overall effect of the UPP policy into perspective, we translate the results of each specification into counterfactual measures of house price growth rates as described in equation (3), then aggregate across property types for the entire city of Rio as follows:

(6) $$\tilde{P}_t = \sum_b \sum_i w_{2008}^{ib} \tilde{P}_t^{ib}$$

where the weight w_{2008}^{ib} is the total number of listings for property type *i* in bairro *b* during the year 2008. The average observed price level for house and apartment sales in the city of Rio is illustrated by the solid red line in Figure 6. The price level rose approximately 100 percent between January 2008 and August 2011 and, notwithstanding methodological and data input differences, our computed index is in the ballpark (though below) published figures of a 130 percent increase in sales price for the city of Rio over the same period.[17]

[17] FIPEZAP, an organization that publishes aggregate price indexes based on the same underlying data that we use here (Rio is one of several regions for which FIPEZAP publishes an index), has a different way of aggregating across types of property and bairros. While the index formula we use is the same (i.e., a weighted average of the levels of price observations) FIPEZAP uses household income data from the 2000 census to weight across geographic areas and number of rooms. In the absence of those weights, we use the number of

We will focus on the change in overall average counterfactual prices (computed in the same manner) relative to the observed aggregate. Each of the counterfactual series in Figure 6 relates to a specification in Table 3. What is striking about the counterfactuals is that, with the exception of the border measure of proximity, the series are quite close together. This implies that the heterogeneity in: (i) econometric technique, (ii) observation weights, and (iii) the geographic scope of the centroid-based treatment group across specifications does not amount to much when applied to the population of prices. The fact that the border-based counterfactual lies below the rest indicates that the estimated overall influence of the UPPs is indeed sensitive to geographic scope when applied as broadly as in that specification. In other words, lower average price effects in the border specification are more than fully offset by the larger base of neighborhoods that they are being applied to. All in all, the range of counterfactuals implies that without the UPP program the cumulative growth rate of property prices in Rio would have been between 12 and 22 percent lower. Taking an average across specifications, the UPPs accounted for 15 percent of the growth in prices since January 2008.

The analogous results for the effect of the UPPs on crime rates, estimated with equation (3), are shown in Table 4. As mentioned above, since the crime data are inclusive of all bairros and dates, neither the selection model nor weighted least squares specifications are employed. This leaves us with three specifications of the scope of the treatment group for both robberies and homicides. The overall effects imply that the UPPs had large negative effects on the levels of each crime, on the order of 10-25 percent for homicides and 10-20 percent for robberies, with the bairro-based estimates at the larger end of the range and the border-based estimates at the smaller end. The effect of the UPPs on crime is very heterogeneous across UPPs. In some instances the effects are very strong, on the order of sixty or even seventy percent declines in the homicide rate. In other instances the effect is not distinguishable from zero. Perhaps due to the lumpiness of the crime data over time, as homicides and robberies in each bairro and month bounce around near the zero level, it is difficult to obtain precise estimates for each UPP. At the very least, there are no statistically significant estimates of crime rates going up due to a UPP.

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listings within bairro/rooms combinations in 2008. Further, FIPEZAP reduces the amount of noise in the data by only including observations with greater than 5 listings and then taking the median value of observations over the past 3 months, steps which we do not take here. (For more information on construction of the FIPEZAP index, see Notas Metodologicas in "Fundacao Instituto de Pesquisas Economicas" (2011)).

The economic and social significance of these estimates are illustrated by the counterfactual crime rate estimates in Figure 7. Crime counterfactuals are computed similarly to the price counterfactuals above, except that they are aggregated across neighborhoods using 2008 bairro population measures as weights. Since the estimates of the UPP elasticity are negative, the actual series (denoted by the red solid line) lies below the counterfactual series; the difference indicates the effect of the policy on the city-wide crime rate. The top panel shows that the UPPs were not the dominant factor in determining the rate of homicides at the city level, as the counterfactuals track the actual series quite closely. That said, by the end of the sample the various counterfactual simulations unanimously show a contribution by the UPPs of 14 percent of the decline in homicides since their peak in May 2009. This translates into about 1 homicide per 100,000 people annually, or roughly 60 people in the municipality of Rio in 2011. By any measure, this is a substantial number lives that potentially owe to improved security. Similar observations can be made about the robbery rate in the bottom panel of Figure 7, in which about 20 percent of the fall in robberies since mid-2009 was attributable to the UPPs.

Finally, we can use the property price effects and crime effects estimated separately in equations (1) and (3) to compute the crime elasticity of house prices. A simple way to do so is to compare the estimates of $\alpha_{3,n}$ from each equation to see whether large crime effects corresponded to large house price effects for a given UPP. Loosely speaking, this is a two-stage instrumental variable regression where the first stage regresses crime on the UPP policy variables. Figure 8 illustrates the homicide elasticity of property prices, where each dot matches the coefficients from (1) and (3) in Tables 3 and 4, respectively. Due to the imprecision of the some of the homicide estimates, only the matches where both policy coefficients are statistically significant at the 5 percent level are shown. There is a clear negative relationship between crime and property prices, with a ten percent decline in the homicide rate corresponding to a 1.8 percent increase in nearby house prices.

V. Crime and house price inequality

Having established an empirical relationship between crime and residential property prices, we now derive formal expressions for the changes in the distribution of house prices due to a discrete change in the crime rate. We then evaluate the predictions of the model by constructing measures of inequality within- and across-bairros in the ZAP data.

a) A model of house price dispersion

The only source of variation in the model is a change in the probability of a crime occurring $(r(UPP))$ in a given bairro (b) conditional on the absence or presence of a UPP denoted by $UPP \in \{0,1\}$. Let us assume that the installation of a UPP will cause the crime rate to drop to $r_b(1) < r_b(0)$. Assuming some disutility from crime, this will have a positive effect on the flow of consumption services embodied in the property, and hence on the net present value of the future stream of those services. The objective of this exercise is to show that the prices of properties with either low initial prices or those in neighborhoods with higher initial crime rates react more strongly to a given change in the crime rate, compressing the distribution of property prices.

First, we assume that the consumption value of housing, denoted U , for a specific property (i) depends on a time-invariant amenity value, h_{ib} , reflecting the property's characteristics, as well as a term summarizing the complete history of crime in the bairro in which the property is located:

$$U_{ibt} = h_{ib} - \sum_{l=0}^{\infty} r_{bt}(UPP)^{l} \tag{7}$$

where $r_{bt}(UPP)^{l}$ denotes the l -th lag of the crime rate relative to time t . This latter term enters negatively into the expression for consumption services as the value of the public 'bad' due to crime. In that summation, we also make an important assumption about the dynamics of consumption services due to the probability of a crime; the contribution of lagged values of crime to consumption services decays geometrically over time, which introduces some non-linearity in the response of utility and, as we will show below, in the response of house prices to a change in r. The price of a property is the stream of future consumption flows, discounted by a factor β, which for a constant crime rate is:

$$\begin{aligned} P_{ibt} &= \sum_{n=0}^{\infty} \beta^n (U_{ib}) \\ &= \frac{h_{ib}}{1-\beta} - \frac{1}{(1-\beta)(1-r_b)} \end{aligned}$$

which brings us to our first proposition relating the levels of prices and crime.

Proposition 1: *Conditional on* h_{ib} *, a decrease in the crime rate increases the price of any given property. This follows immediately from* $\frac{\partial P_{ibt}}{\partial r} < 0$.

Proposition 1 is a close analogue to equation (1) in the empirical exercise above, which relates house prices to the installation of a UPP conditional on the average price level in each bairro and the average growth rate of prices for properties in the control group.

Now let us consider a change in the value of UPP from zero to one. We can rewrite equation (7) in terms of both $r(0)$ and $r(1)$. Thus, n periods after the installation of a UPP, the consumption services of a property in that period are:[18]

(8)
$$\begin{aligned} U_{it}^n(h,r) &= h_i - \sum_{l=0}^{n} r_t(1)^l - \sum_{l=n+1}^{\infty} r_t(0)^l \\ &= h_i - \frac{1}{1-r(1)} + \left(\frac{r(1)}{1-r(1)}\right) r(1)^n - \left(\frac{r(0)}{1-r(0)}\right) r(0)^n. \end{aligned}$$

Notice that the first two terms in this expression represent the consumption services of a property where the entire history of crime in its neighborhood at the level $r(1)$. The combined third and fourth terms are a function of the relative weight given to more recent history at the lower crime rate and more distant history at the higher crime rate. The size of the contribution of this combined term to total consumption services depends crucially on the size of the difference between the old and new crime rate; when there is no difference between $r(0)$ and $r(1)$ the third and fourth terms cancel out, and when $r(0) > r(1)$, the third

[18] The bairro subscript is dropped in (8) for ease of notation.

and fourth terms are a net negative contribution to total consumption services.

This particular specification of housing consumption services is a departure from related literature, such as Besley and Mueller (2011) in which house prices are a linear function of contemporaneous amenity value and the crime rate, but its treatment of dynamics is quite similar in spirit. In our model, we have a much simpler treatment of agents' expectations (i.e., agents assume a constant crime rate going forward) but the transmission of a one-time change in the crime rate into prices depends similarly on the history of crime. Specifically, immediately after the change ($n = 1$), the value of consumption services does not move all the way up to $-\frac{1}{1-r(1)}$, but rather asymptotically approaches that level as the history of $r(0)$ fades. Thus, current and future consumption flows depend on both the level and duration of crime rates in the past.

Proposition 2: *Conditional on a property's amenity value (h_{ib}), progressively larger decreases in crime lead to smaller marginal improvements in housing consumption services. In other words, there are diminishing marginal returns to crime reduction. This follows directly from the concavity of consumption services in the crime rate:* $U_{ibt}^{''}(r) < 0, \forall n$.

We can illustrate this second proposition graphically using equation (8). Figure 9(a) illustrates the crime-related portion of consumption services (i.e., the combined second, third and fourth terms) for a hypothetical reduction in r from an initial level of $r(0) = 0.25$. It is clear from the concavity of the curves for any n that larger decreases in crime lead to smaller increases in housing consumption services. Further, the degree of curvature in the consumption services schedule increases with n, the number of periods ago that the UPP was installed. This is an intuitive result. The longer ago the UPP was installed (i.e., for larger n) agents care less about incremental units of the decrease in crime.

Diminishing returns to crime reduction could play a key role in the changing distribution of property prices after the establishment of the UPPs. For example, two properties with identical amenity values in bairros with different crime rates could potentially have very different responses to the installation of a UPP and a common decrease in crime. The property in the bairro with a high crime rate will both have lower initial prices and a larger change in its consumption services, which will have the effect of compressing the distribution of property prices across bairros. In principle, this same effect would apply for two properties within the same bairro were they to face either different initial levels of crime or different changes in their crime rate. However, in light of the fact that we only observe bairro-level data, we have assumed in equations (7) and (8) that the crime rate affects the values of all properties within a bairro uniformly.

This assumption need not imply that the distribution of house prices within bairros is unaffected by a uniform reduction in crime. As the next proposition shows, variation in the amenity value of properties within a bairro is sufficient to create concavity in house prices relative to the crime rate. This is because when amenity values are higher, the percent change in crime-related consumption services after a decrease in crime is applied to a higher (time-invariant) base, implying a lower percent change in the sum of the amenity value and crime-related consumption services.

Proposition 3: *Conditional on the initial level and change in the crime rate (i.e., $r(0)$ and $r(1)$), properties with lower amenity value, h_{ib}, will have a higher percent change in price.*

Proof: We will first need to derive an expression for the price of a property immediately after the establishment of a UPP. The net present value of future consumption flows is:

$$\begin{aligned} P_{it} &= \sum_{n=0}^{\infty} \beta^n \left(U_{it}(n) \right) \\ &= \frac{1}{1-\beta}\left(h_i - \frac{1}{1-r(1)} \right) + \left(\frac{r(1)}{(1-r(1))(1-\beta r(1))} \right) - \left(\frac{r(0)}{(1-r(0))(1-\beta r(0))} \right) \end{aligned}$$

Therefore, the percent change in a property when a UPP is established is:

$$\begin{aligned} \frac{dP_{it}}{P_{it}} &= \frac{P_{it}(UPP=1) - P_{it}(UPP=0)}{P_{it}(UPP=0)} \\ &= \frac{\frac{1}{1-\beta}\left(\frac{1}{1-r(1)} - \frac{1}{1-r(0)} \right) + \left(\frac{r(1)}{(1-r(1))(1-\beta r(1))} \right) - \left(\frac{r(0)}{(1-r(0))(1-\beta r(0))} \right)}{\frac{1}{1-\beta}\left(h_{ib} - \frac{1}{1-r(0)} \right)} \end{aligned}$$

which is clearly dependent on the level of h_i , with $\frac{dP_{it}}{dh_i}\frac{h_i}{P_{it}} < 0$. QED.

Figure 9(b) illustrates these "within-bairro" effects of heterogeneous amenity values, again for a hypothetical drop in crime from $r(0) = 0.25$ and for a range of h_i between 6 and 26. As the amenity value of a property goes up, the percentage change goes down at a decreasing rate. The lowest quality properties, those with the lowest amenity value, therefore stand to gain the most from decreases in crime.

b) Empirical results

Propositions 2 and 3 suggest that properties of lower value (whether due to high crime rates or low amenity values), will appreciate disproportionately following a decrease in the crime rate. This would manifest itself both as a decrease in dispersion of property prices city-wide as well as the dispersion of prices within-neighborhoods. To evaluate this claim, we begin by computing a measure of house price inequality across all of the neighborhoods in Rio. We choose a common measure of wealth dispersion, the Gini coefficient, computed using a formula similar to the one in Deaton (1997):

$$(9) \qquad Gini_t = \frac{N+1}{N-1} - \frac{2}{N(N-1)} \left[\frac{\sum_{b=1}^{N} w_{2008}^{b} X_t^{b} \tilde{P}_t^{b}}{\sum_{b=1}^{N} w_{2008}^{b} \tilde{P}_t^{b}} \right]$$

where N is the number of neighborhoods, $\tilde{P}_t^{b} = \sum_i w_{2008}^{ib} \tilde{P}_t^{ib}$ is the average price for either apartments or houses in each neighborhood, and X_t^{b} is the price ranking of each neighborhood relative to all others in that period. Prices for a property with a certain number of rooms are aggregated using the total number of listings of that property type and neighborhood in 2008 (denoted w_{2008}^{ib}). Then, to aggregate across neighborhoods, prices are weighted by their 2008 population (denoted w_{2008}^{b}).[19] Higher values indicate greater inequality of prices across neighborhoods.

[19] Since the panel of price observations is highly unbalanced (i.e., there are many neighborhoods that were not initially in the sample but entered over the course of the past three years) N includes only those that appeared in the ZAP data in January 2008. It is important to have a balanced panel to control for the changing composition

Figure 10 illustrates the Gini coefficient for actual and counterfactual city-wide property prices. The solid red line shows that dispersion has fallen by about two and a half points since the beginning of 2008, from 0.29 to 0.265. To put these numbers into context, recall that the national measure of income inequality in Brazil fell from about 0.60 in 2001 to 0.53 in 2010. The level of income inequality is higher since we only observe listings for formal property markets; were we to observe the lower average real estate prices in the favelas our measure would likely be much more skewed. Instead, one should focus on the magnitude of the change in inequality over time. Over the course of the 2000's, which was a very prosperous decade for Brazil in which millions of people where lifted out of poverty, the Gini coefficient fell by only 5 points. We therefore might expect that even small changes in the Gini coefficient for wealth are economically meaningful.

In terms of the contribution of the UPPs to falling inequality, each counterfactual Gini coefficient in Figure 10 lies above the actual Gini by the end of the sample. This indicates that the UPPs accounted for some portion of the decreasing inequality. That said, there is a lot of heterogeneity across counterfactual specifications; this is a function of the number of neighborhoods that the estimates are applied to, with the bairro-based estimates having the smallest geographic scope and the border-based estimates the largest. For the bairro-based estimates the contribution equals about one quarter of the decline in inequality since 2008 and for the centroid-based estimates, the contribution is about 45 percent. In the most extreme case, applying the UPP price effects to all neighborhoods with a border within 2km of a UPP implies that counterfactual inequality would be back at its initial level by the end of the sample period, a 100 percent contribution by the UPPs.[20]

Proposition 3, which predicts changes in within-bairro dispersion arising from heterogeneous amenity values, is not straightforward to measure with bairro-level house prices data. However, using the standard deviation of prices for each observation provided by

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of listings on ZAP over time; for instance, the systematic entry of low-priced neighborhoods into the ZAP listings could increase measured inequality even if the underlying level of inequality among incumbent neighborhoods had not changed.

[20] A decrease in the house price Gini coefficient of half a point to 2.5 points due to the UPPs seems to compare favorably with other policies aimed at reducing inequality. For example, Soares et al. (2006) decompose the national income Gini coefficient into components owing to the well-regarded Bolsa Família program of conditional cash transfers. They find that Bolsa Família was responsible for a reduction of .571 Gini points, or 21% of the total fall in the national Gini coefficient from 1995 to 2004.

ZAP combined with the estimates of the price effects of the UPPs in Table 3, one can infer whether low-priced properties responded disproportionately to the UPPs. Replicating our analysis of the price effects on UPP levels, we estimate the following difference in differences regression:

$$(10) \qquad \ln\left(stdev_t^b\left(P_t^{ib}\right)\right) = \alpha_0 + \sum_n \alpha_{1,n} UPP_n + \sum_n \alpha_{2,n} Dist_n^b + \sum_n \alpha_{3,n} UPP_n * Dist_n^b + \gamma_t Z^i + \kappa^b + \delta_t + \varepsilon_t^{ib}$$

where the only distinction between equations (10) and (1) is that the dependent variable is the log of the bairro-level standard deviation of property prices as opposed to the log of the average price. A negative estimate of $\alpha_{3,n}$ means that the standard deviation of prices declined due to the UPP at the same time as the average price increased (Table 3). These two observations together necessarily imply that the lower-priced properties grew faster than the higher-priced properties in neighborhoods with a UPP nearby.

Table 5 shows the estimates of $\alpha_{3,n}$ in equation (10). For several UPPs the bairro-level estimates do suggest that prices condensed after the UPP. For instance, after the first UPP in Santa Marta the standard deviation of prices declined by 2-4 percent in Botafogo and Humaita while average prices increased by 10 percent in those neighborhoods. Though the same can be said for about 5 other UPPs, several bairros experienced increases in price dispersion and the border- and centroid-based estimates are even less supportive of declining price dispersion. The weighted least squares specification, along with the border and centroid specifications have positive average effects across UPPs.

In sum, while city-wide price inequality appears to have declined due to the UPPs, the sign of the effect on within-bairro price dispersion is ambiguous across specifications. One likely difficulty with testing Proposition 3 is that the initial crime rates and changes in crime are unlikely to be uniform within a neighborhood, much less for different distances from a UPP. It is also possible that amenity values are correlated with UPP distance within a neighborhood in a way that makes the effect of crime on dispersion difficult to identify. Both of these measurement issues suggest that inequality could be better identified using more disaggregate data on individual listings, which is a worthwhile approach for future work on this subject.

VI. Concluding remarks

The basis of the UPP program is reestablishing the rule of law where order was dictated by groups engaged in criminal activity. Destabilizing such groups by removing their physical domain over the favelas was meant to: (i) reduce criminality and violence; (ii) ease availability and access to public services, including health, education, sanitation; (iii) create a better environment for business and commerce (not limited to popular "social" tourism); and (iv) generally improve quality of life. The UPP policy has been widely regarded as being a successful strategy to achieve these goals, and we have demonstrated that the associated positive externalities manifested themselves in property prices. Between 2008 and mid-2011, we estimate that the UPPs accounted for about 15 percent of price growth in Rio's formal property markets, an observation which we link to the contribution of the UPPs to falling crime rates.

We then describe and document the relationship between crime and property price *inequality*. A key theoretical insight is that incorporating historical crime rates into a property's valuation causes the rate of price adjustment following a decrease in crime to depend on the property's initial value. Thus price inequality can potentially decrease as low-priced properties react more to crime reductions. Indeed, the UPPs account for a non-trivial portion of the trend decline in inequality across neighborhoods in Rio. The mean of our various empirical specifications suggests that almost half of the decline in price inequality over the sample period is attributable to the UPPs.

These findings illustrate a potentially significant new dimension of policies aimed at reducing either crime or inequality. Existing attempts to ameliorate economic disparities tend to focus on transfers of income and policies capable of reshaping the wealth distribution in any meaningful way are uncommon. The UPPs in Rio demonstrate that crime reduction can play a role in reducing economic inequity, operating through the distribution of wealth. In principle, this should be an important consideration for crime- and conflict-laden regions elsewhere.

<u>References</u>

1. Besley, Timothy J. and Hannes Mueller (2011): "Estimating the Peace Dividend: The Impact of Violence on House Prices in Northern Ireland." *American Economic Review* (forthcoming).
2. Boyle, Melissa A. and Katherine A. Kiel (2001): "A Survey of House Price Hedonic Studies of the Impact of Environmental Externalities." *Journal of Real Estate Literature*. 9:2, 117-144.
3. Bricker, Jesse, Brian Bucks, Arthur Kennickell, Traci Mach, and Kevin Moore (2011): "Surveying the Aftermath of the Storm: Changes in Family Finances from 2007 to 2009." Finance and Economics Discussion Series no. 2011-17, Federal Reserve Board, Washington, D.C.
4. Cunha, Neiva Vieira da and Marco Antonio da Silva Mello (2011): "Novos conflitos na cidade: A UPP e o processo de urbanização na favela." *DILEMAS: Revista de Estudos de Conflito e Controle Social*. 4:3, 371-401
5. Deaton, Angus (1997): <u>Analysis of Household Surveys</u>. Johns Hopkins University Press.
6. Fundação Instituto de Pesquisas Economicas (2011): "Índice FIPEZAP de Preços de Imóveis Anunciados: Notas Metodologicas.
7. Gibbons, Steve (2004): "The Cost of Urban Property Crime." *Economic Journal*, 114: 441-463.
8. Heckman, James (1976): "The common structure of statistical models of truncation, sample selection, and limited dependent variables and a simple estimator for such models. *Annals of Economic and Social Measurement*, 5: 475-492.
9. Heckman, James (1979): "Sample selection bias as a specification error." *Econometrica*, 47:1, 153–61.
10. Hellman, D. A. and Naroff, J. L. (1979): "The impact of crime on urban residential property values." *Urban Studies*, 16: 105–12.
11. Ihlanfeldt, Keith and Tom Mayock (2009): "Property Values and Crime," in <u>Handbook on the Economics of Crime</u>, edited by B. Benson and P. Zimmerman, Edward Elgar, forthcoming.

12. Kennickell, Arthur B. (2009): "Ponds and Streams: Wealth and Income in the U.S., 1989 to 2007." Finance and Economics Discussion Series no. 2009-13, Federal Reserve Board, Washington, D.C.
13. Linden, Leigh L. and Jonah E. Rockoff (2008): "Estimates of the Impact of Crime Risk on Property Values from Megan's Laws." *American Economic Review*, 2008, 98(3), 1103-1127.
14. Lynch, A. K. and Rasmussen, D. W. (2001): "Measuring the impact of crime on house prices." *Applied Economics*, 33: 1981–9.
15. Neri, Marcelo Cortes (2011a): "UPP^2 e a Economia da Rocinha e do Alemão: Do Choque de Ordem ao de Progresso." Marcelo Cortes Neri (Coord.), FGV CPS, Rio de Janeiro.
16. Neri, Marcelo Cortes (2011b): "Desigualdade de Renda na Década." Marcelo Cortes Neri (Coord.), FGV CPS, Rio de Janeiro.
17. Rizzo, Mario J. (1979): "The Effect of Crime on Residential Rents and Property Values." *American Economist*, 23: 16-21.
18. Soares, Fabio Veras, Sergei Soares, Marcelo Medeiros and Rafael Guerreiro Osório (2006): "Cash Transfer Programmes in Brazil: Impacts on Inequality and Poverty." UNDP International Poverty Center Working Paper no. 21.
19. Thaler, R. (1978): "A note on the value of crime control: evidence from the property market." *Journal of Urban Economics*, 5: 137–45.
20. Tita, George E., Tricia L. Petras and Robert T. Greenbaum (2006): "Crime and Residential Choice: A Neighborhood Level Analysis of the Impact of Crime on Housing Prices." *Journal of Quantitative Criminology*, 22:4, 299-317.
21. Waiselfisz, Julio Jacobo (2011): "Mapa da Violencia 2012: Os Novos Padrões da Violência Homicida no Brasil." Instituto Sangari. http://www.sangari.com/mapadaviolencia/pdf2012/mapa2012_rj.pdf.
22. Wolff, Edward N. (1992): "Changing Inequality of Wealth." *American Economic Review Papers and Proceedings*, 82(2), 552-558.

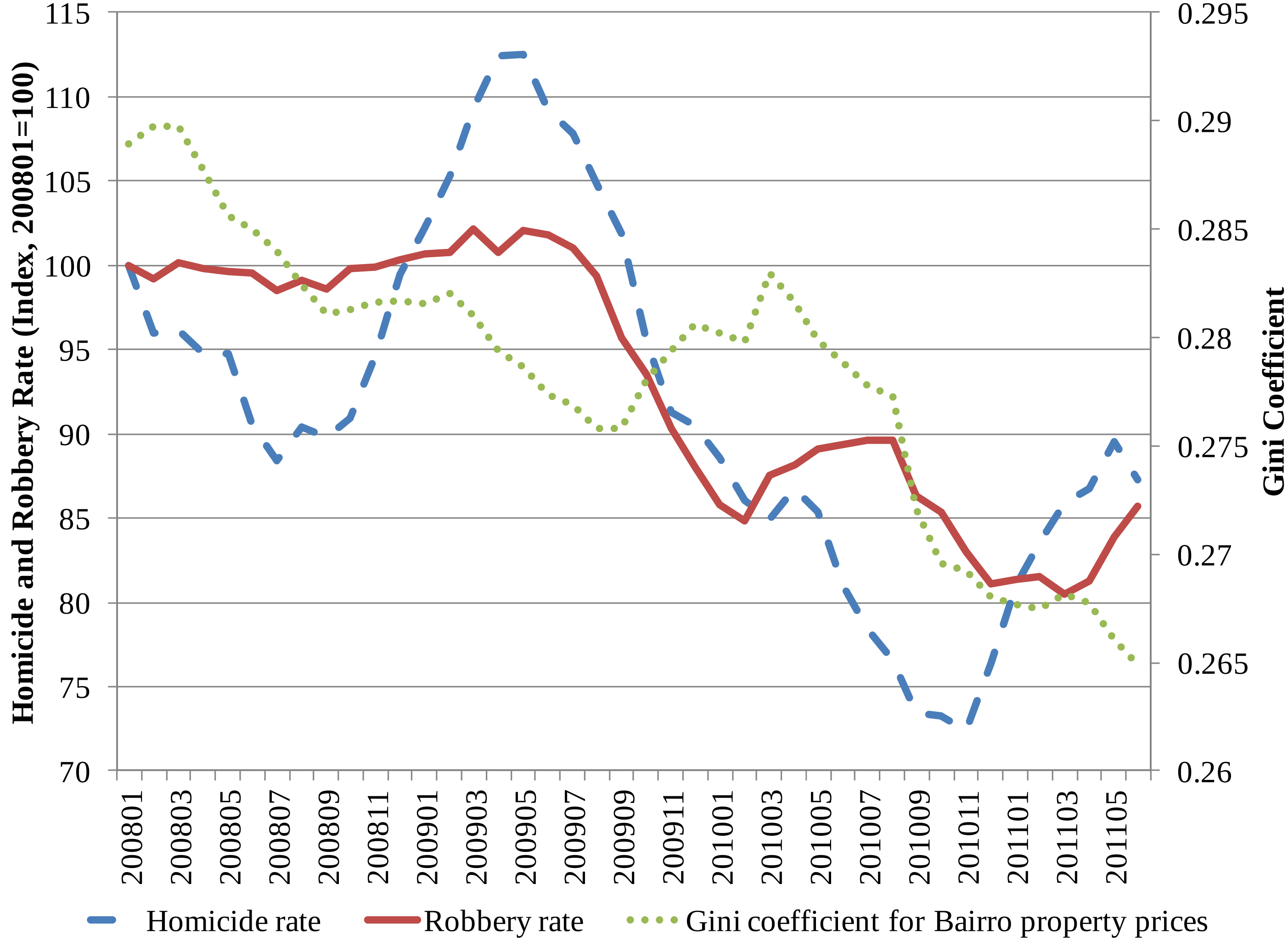
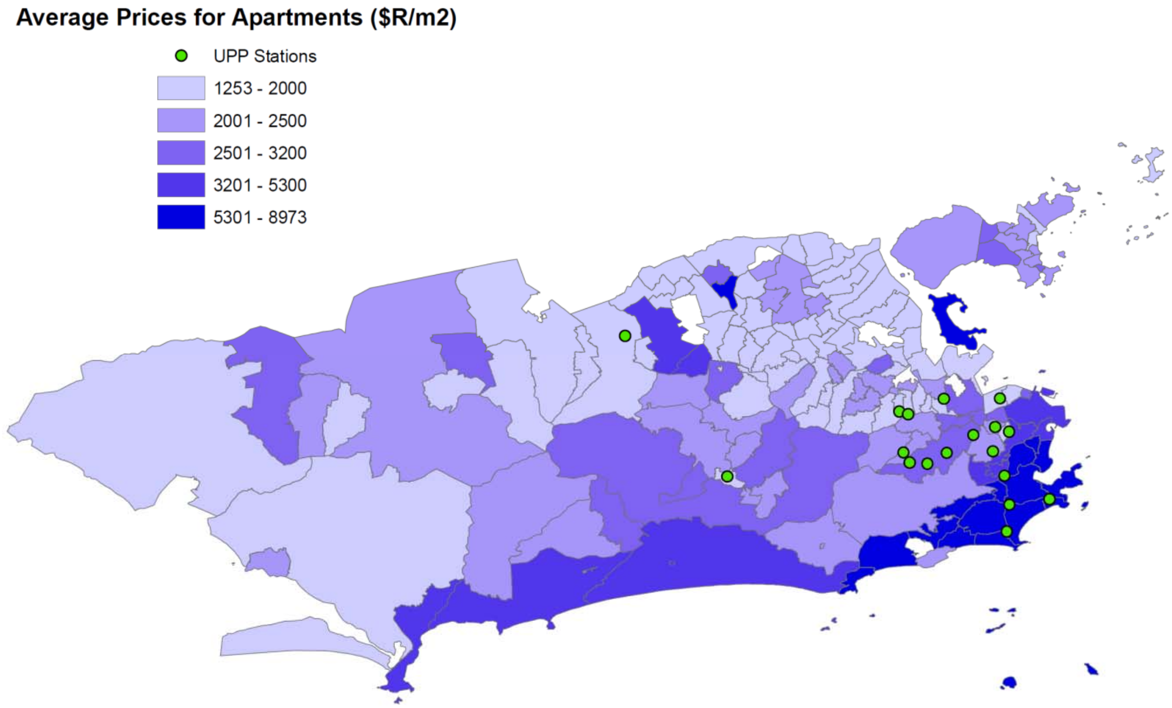


Figure 1: Homicides, robberies and house price inequality in Rio

Notes: The construction of homicide and robbery rates is described in Section III. The construction of the Gini coefficient of property prices is described in Section V.



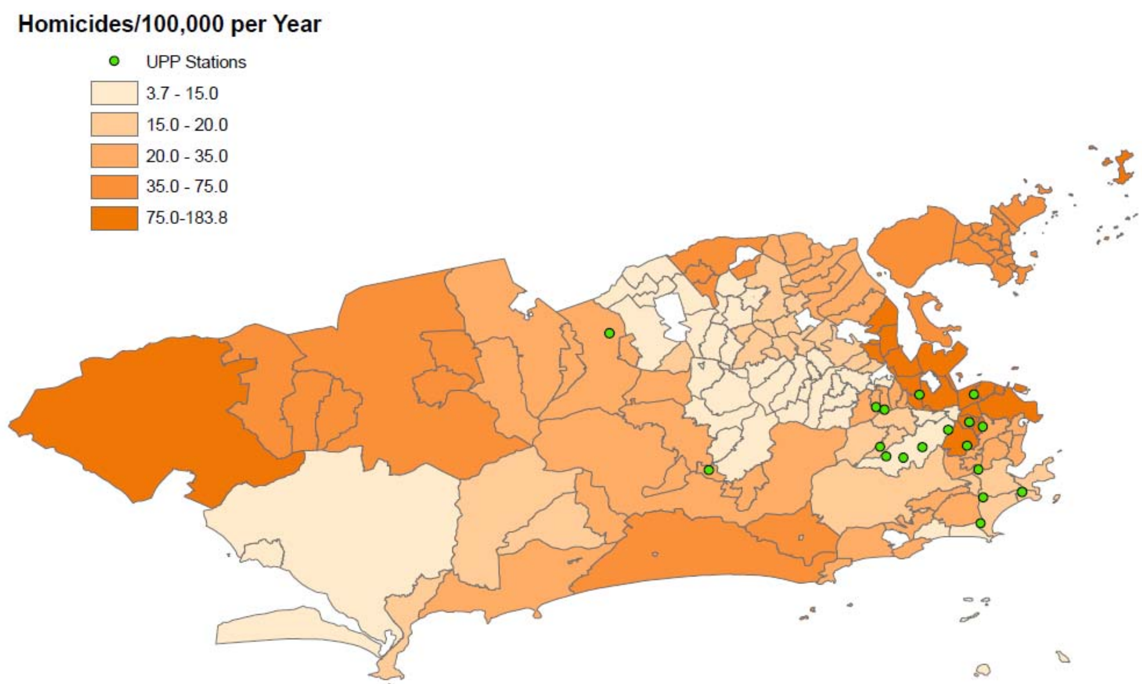


Figure 2: Homicides and property prices by neighborhood

Notes: The location of the UPP stations are shown as green dots. Average apartment prices in each neighborhood are the average of observations across number of rooms and time periods, weighted by the number of listings for each observation. The homicide rate is the average across time periods weighted by population.

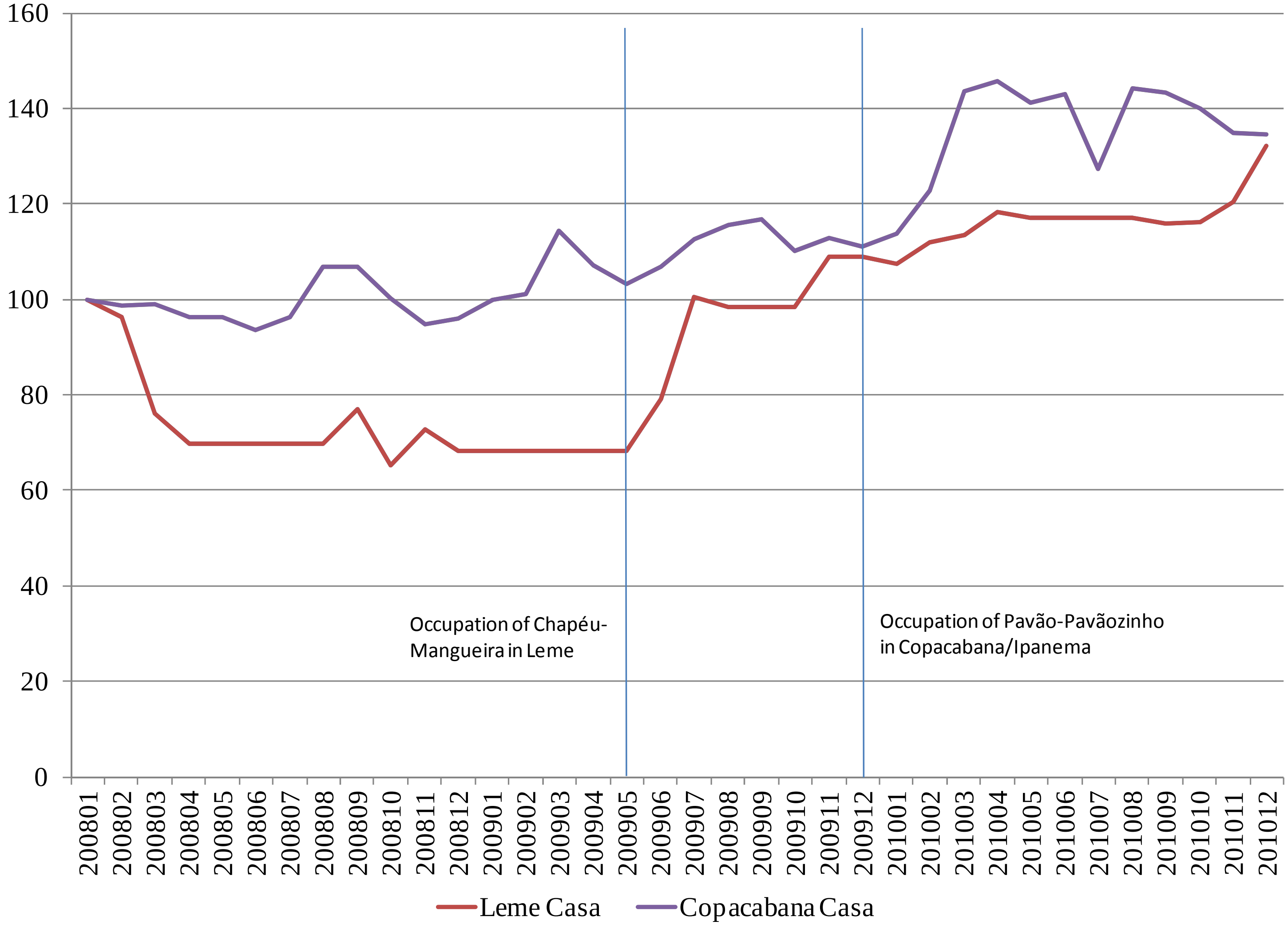


Figure 3: Price indexes of houses in Leme and Copacabana

Notes: Each series represents the average price of house sale listings within each neighborhood.

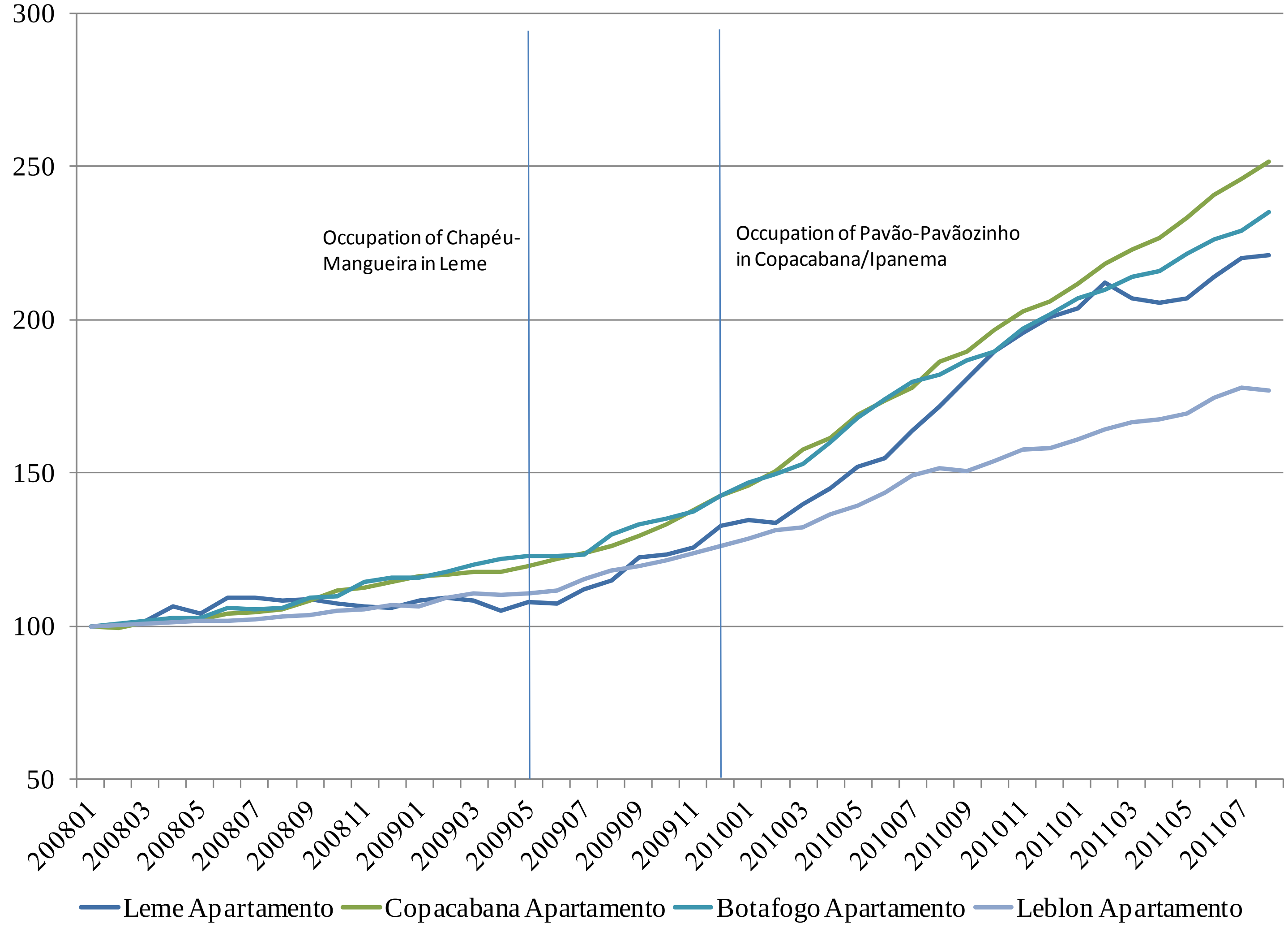
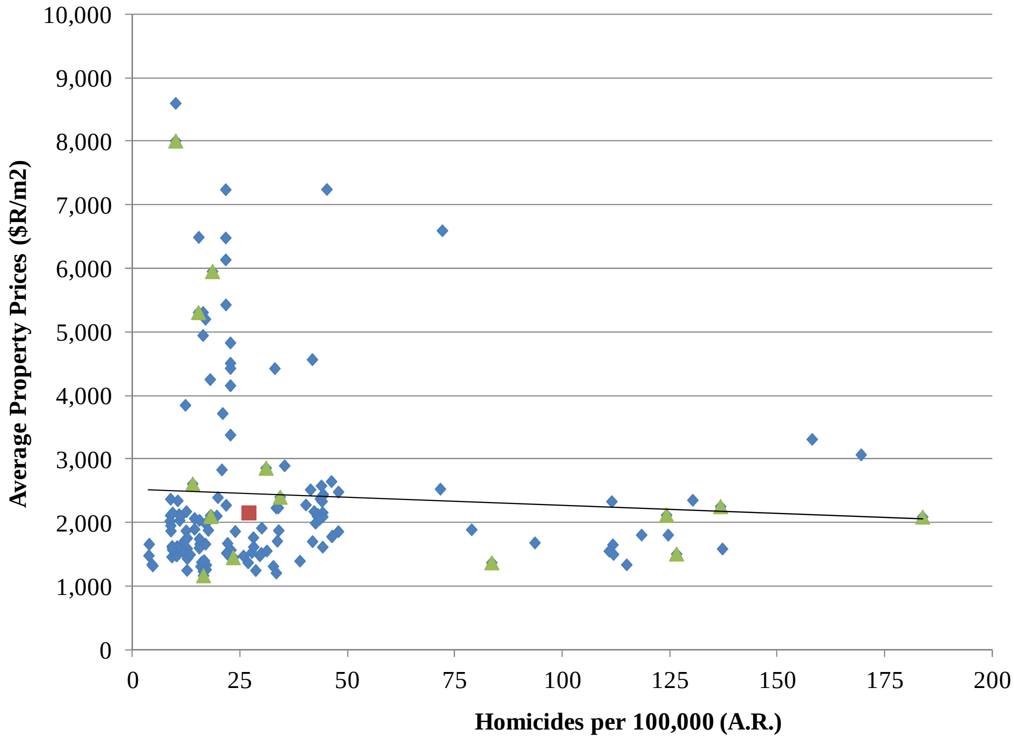
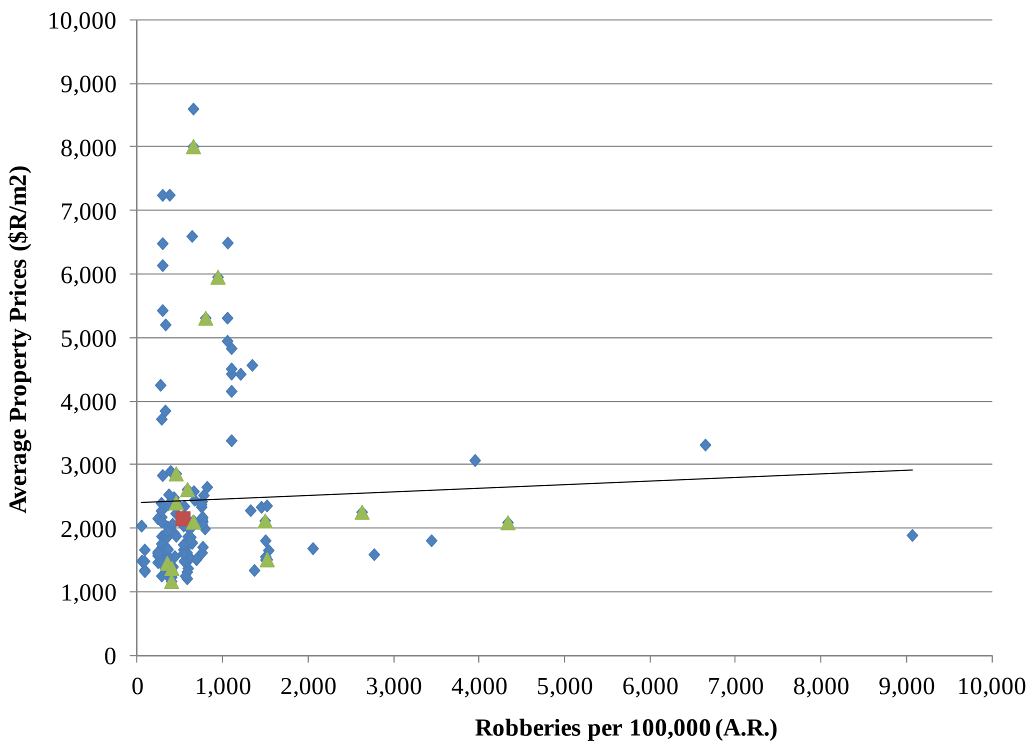


Figure 4: Price indexes of apartments in Leme, Copacabana, Botafogo and Leblon

Notes: Each series represents the average price of apartment sale listings within each neighborhood.



(a) Property prices and homicide rates



(b) Property prices and robbery rates

Figure 5: The correlation of property prices and crime across neighborhoods

Notes: Each point represents the average crime rate and property price for a neighborhood, averaging across the time periods January 2007-June 2011. The neighborhoods with UPPs are indicated by triangles. The red square represents the average across all neighborhoods, weighted by average neighborhood population.

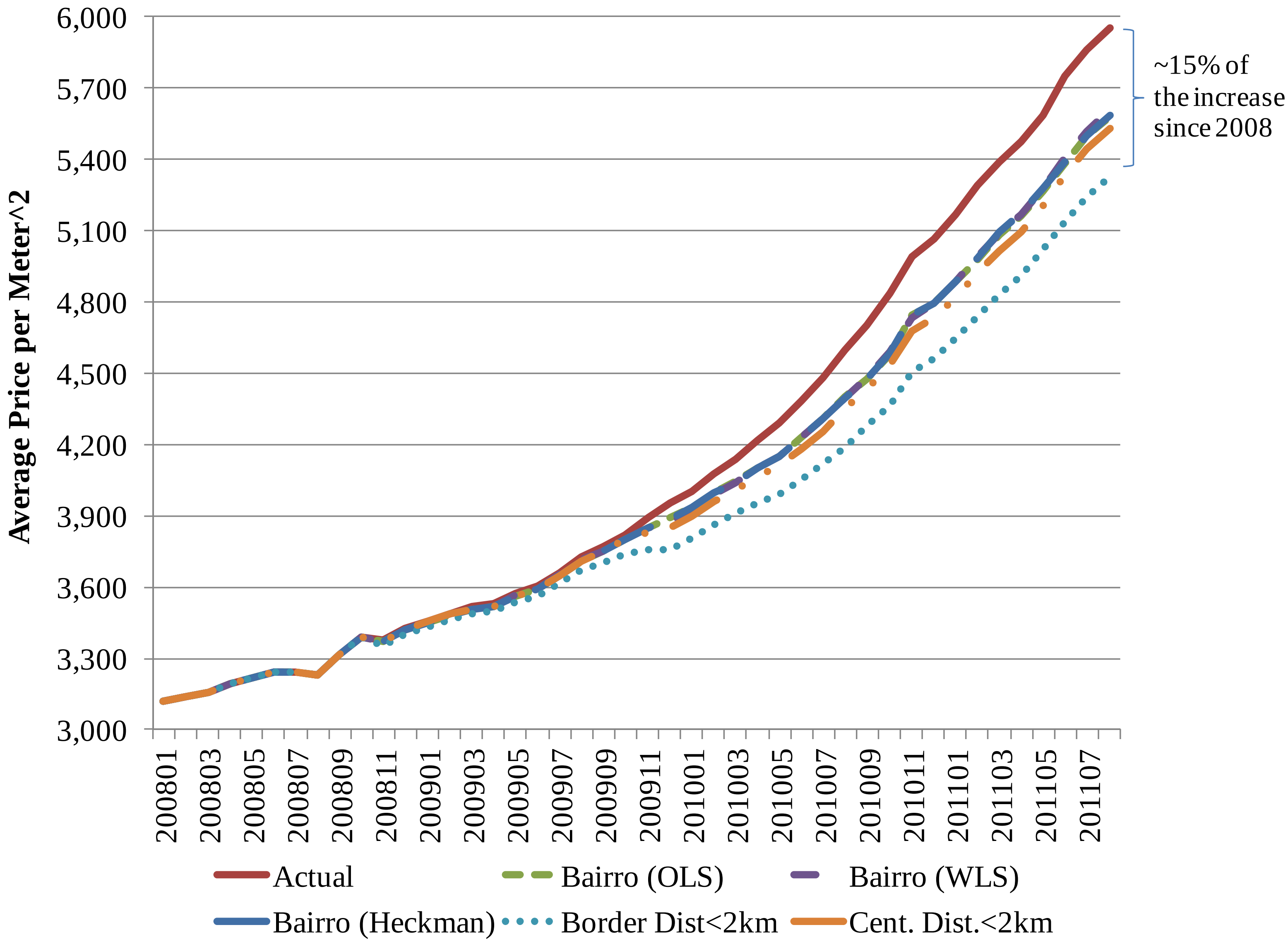
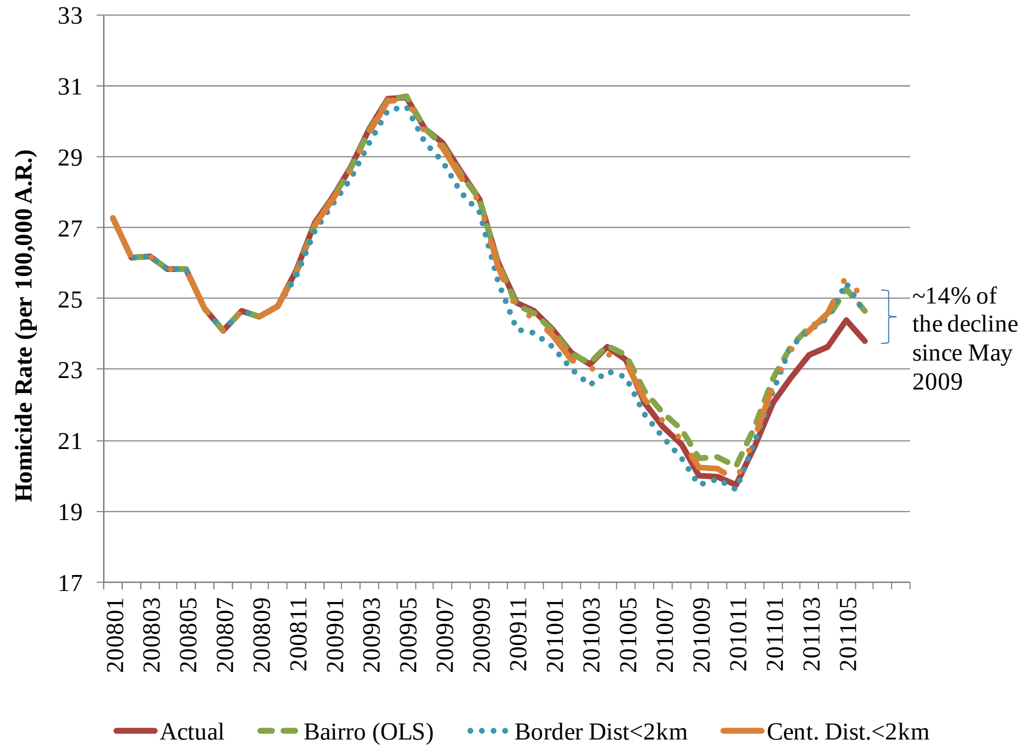
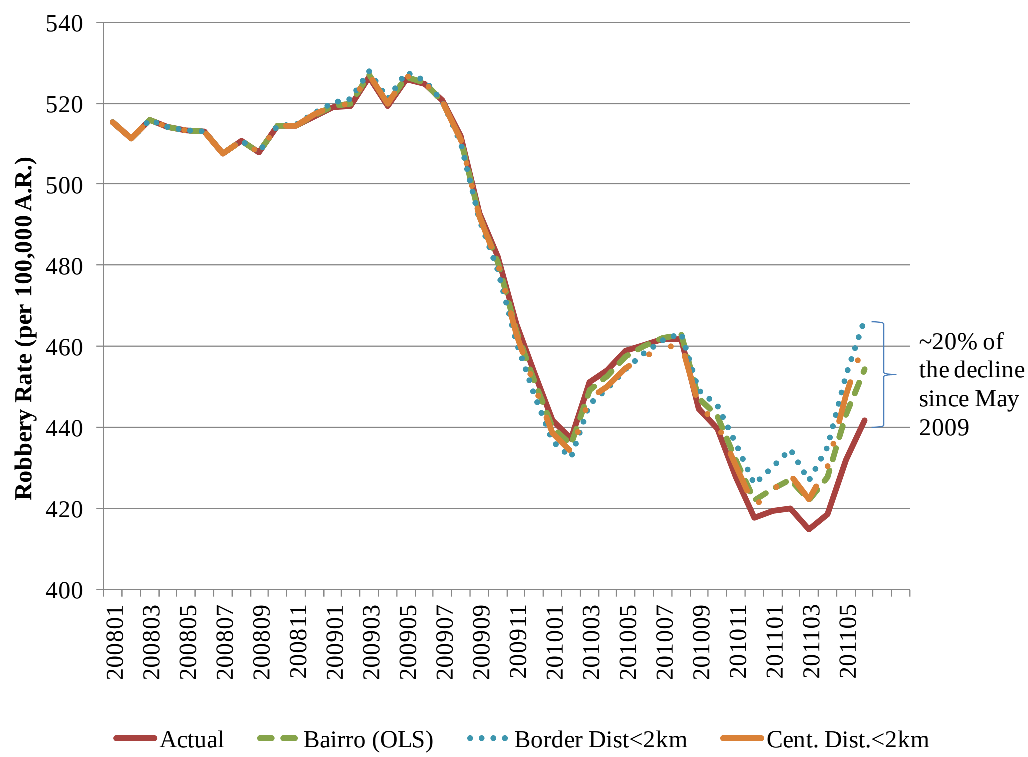


Figure 6: The contribution of the UPPs to average residential property prices

Notes: The construction of the city-wide price aggregates is described in Section IV. Counterfactual prices are based on equation (3).



(a) Overall homicide rate



(b) Overall robbery rate

Figure 7: The contribution of the UPPs to average crime rates

Notes: The construction of the city-wide crime aggregates is described in Section IV. Counterfactual crime rates are based on equation (5).

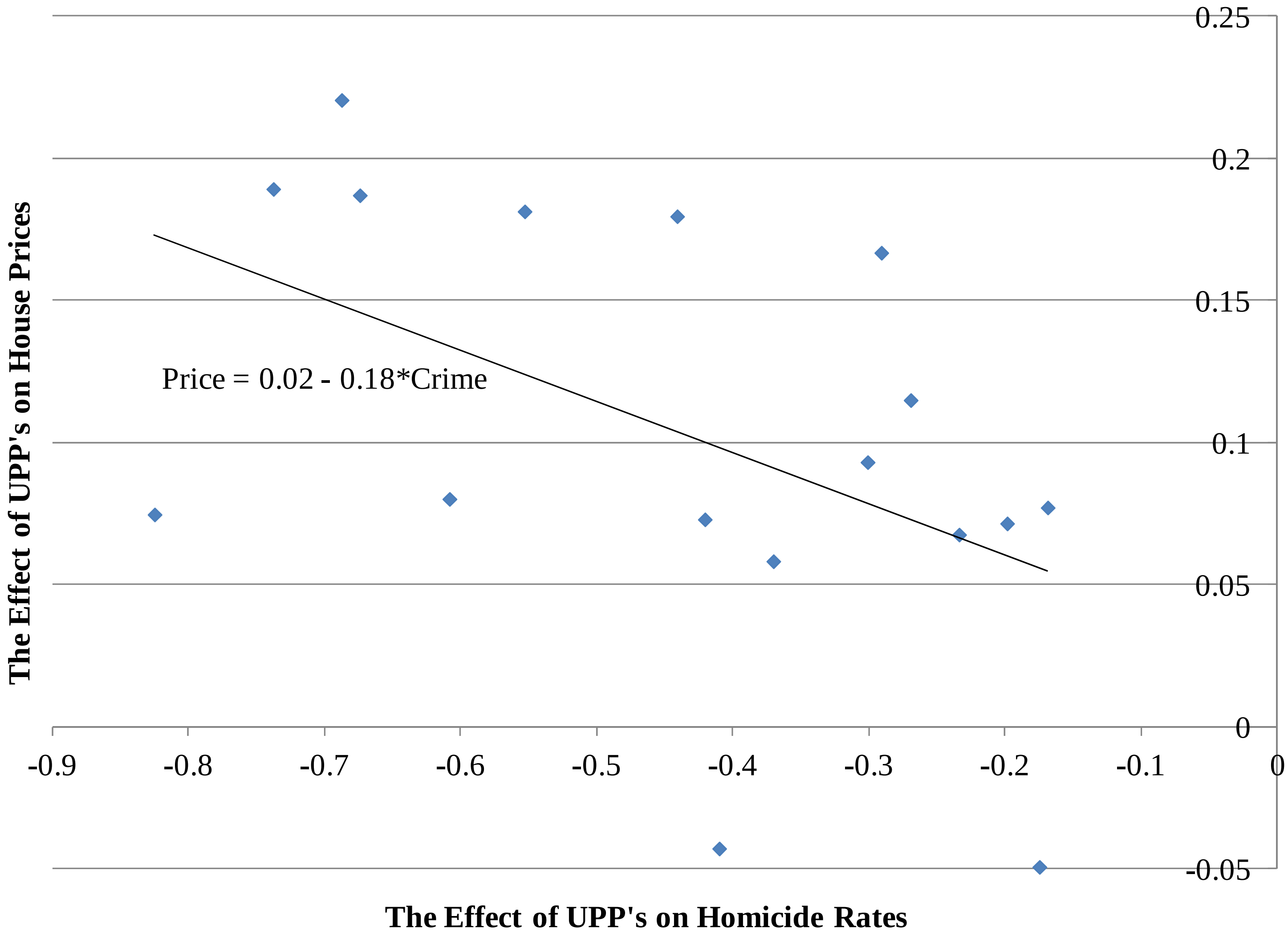
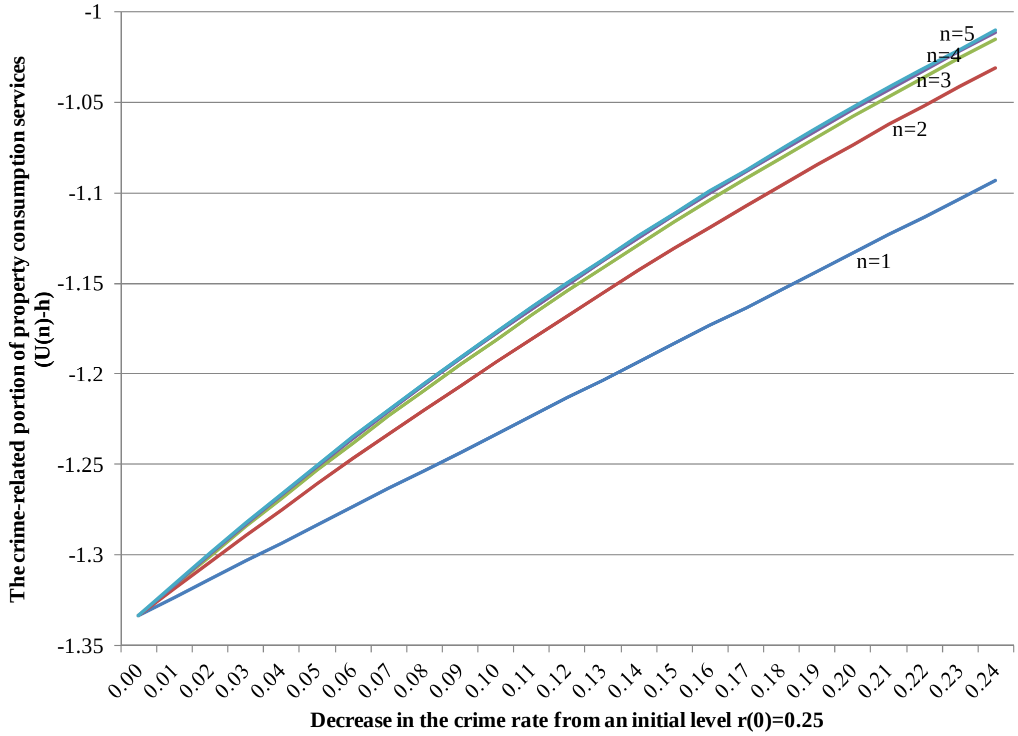
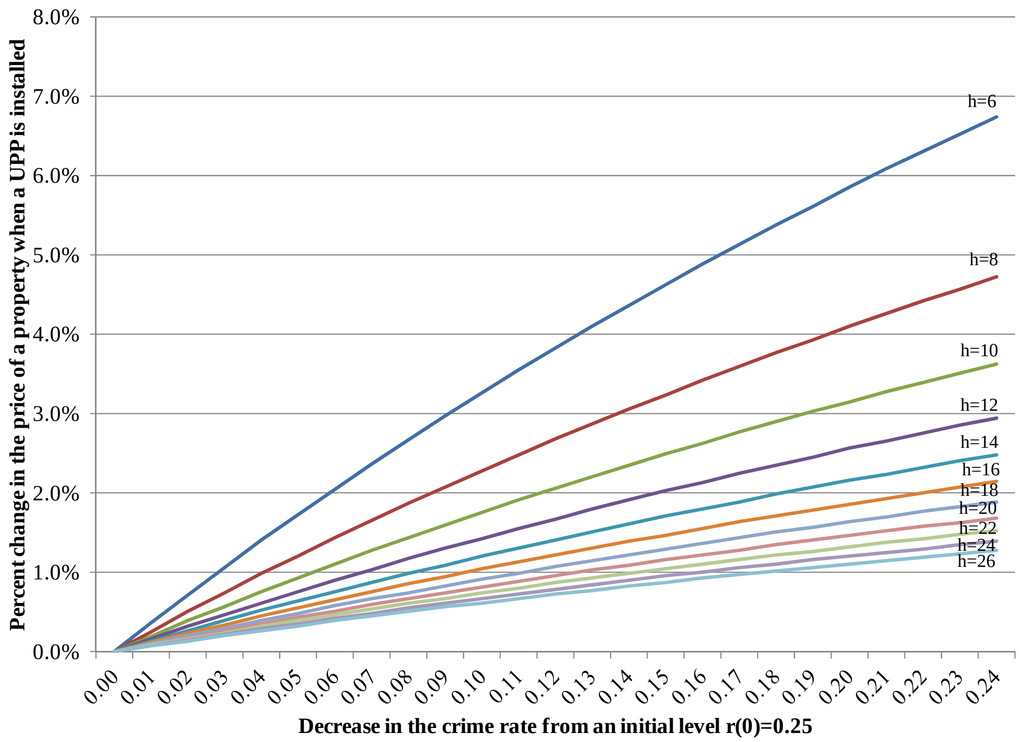


Figure 8: Price and crime elasticities across UPPs

Notes: Each dot represents the price and homicide coefficients from Tables 3 and 4, respectively. For the sake of comparability, only specifications (I), (IV) and (V) are used from Table 3. Coefficients which are not statistically different from zero for either the price or homicide effect of the UPP are excluded.



(a) Higher price changes for lower initial crime rates



(b) Higher price changes for lower amenity values

Figure 9: Diminishing returns to crime reduction

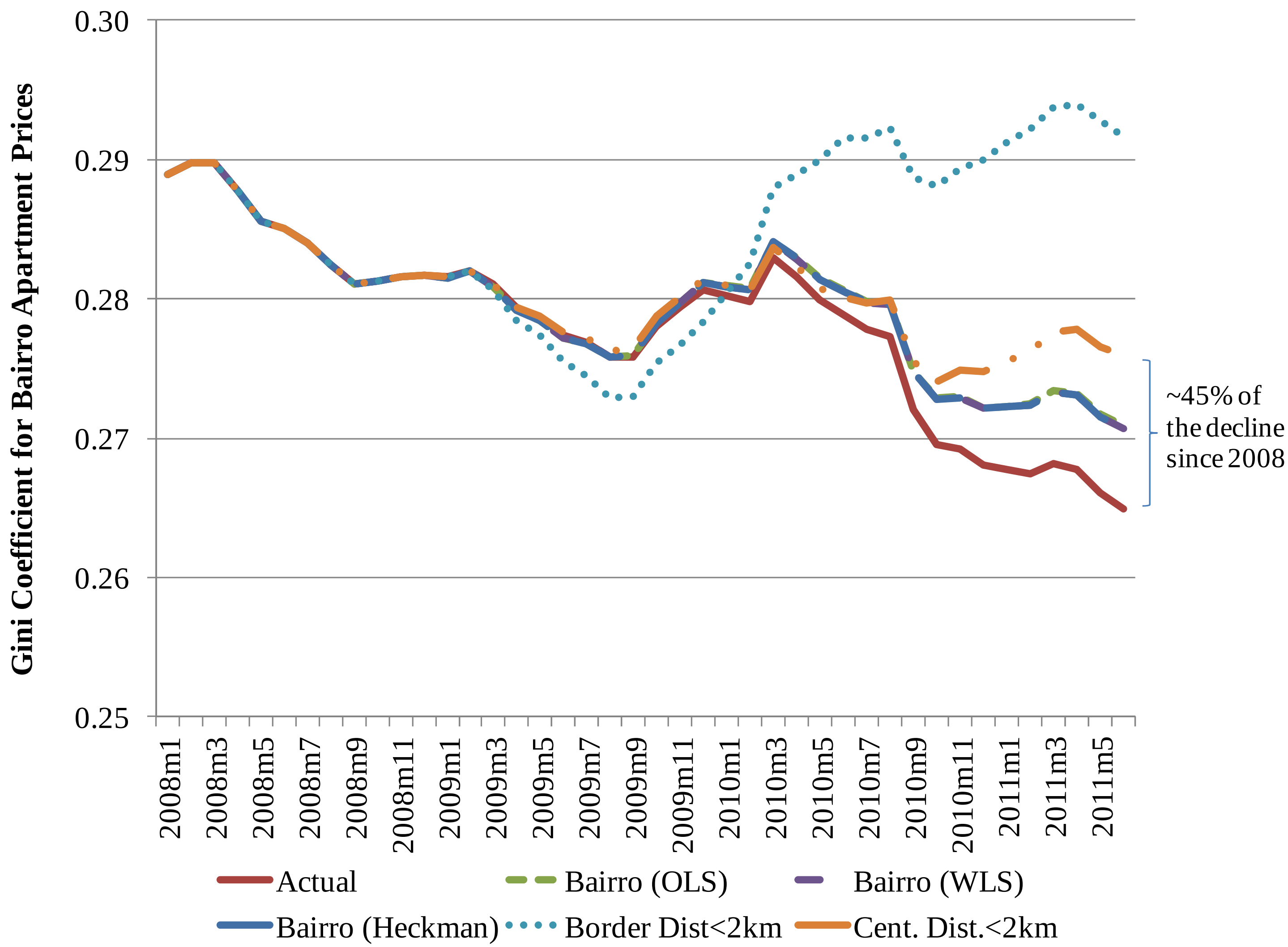


Figure 10: The contribution of the UPPs to the inequality of apartment prices

Notes: Construction of the city-wide price inequality measure is described in Section V. Actual and counterfactual Gini coefficients are based on equation (9).

UPP Name	Zone	Announce. Date	Occup. Date	Inaug. Date	Total community population	Total community area (m^2)	Communities overseen (Favela)	Neighborhood (Bairro)	Neighborhoods with a border within a 2km radius
Santa Marta	South		11/19/2008	12/19/2008	10,000	53,706	Santa Marta	Botafogo and Humaitá	Laranjeiras, Jardim Botânico, Flamengo, Lagoa, Copacabana, Urca, Cosme Velho, Santa Teresa
Cidade de Deus	West		11/11/2008	2/16/2009	45,000	135,392	Cidade de Deus	Jacarepaguá	Cidade de Deus, Gardênia Azul, Anil, Curicia, Pechincha, Freguesia, Taquara
Batam	West	12/17/2008	1/15/2009	2/18/2009	45,000	95,278	Batan	Realengo	Padre Miguel, Magalhães Bastos, Vila Militar, Parque Anchieta
Babilônia / Chapéu-Mangueira	South	5/12/2009	5/15/2009	6/10/2009	10,000	135,392	Babilônia and Chapéu Mangueira	Leme	Copacabana, Urca, Botafogo
Pavão-Pavãozinho / Cantagalo	South		11/30/2009	12/23/2009	13,000	127,954	Pavão-Pavãozinho and Cantagalo	Ipanema and Copacabana	Leblon, Lagoa, Jardim Botânico, Humaitá and Botafogo
Tabajaras / Cabritos	South		12/23/2009	1/14/2010	7,000	103,130	Ladeira dos Tabajaras, Morro dos Cabritos, Pico do papagaio and Mangueira (in Botafogo)	Copacabana and Botafogo	Jardim Botânico, Lagoa, Santa Teresa, Ipanema, Humaita, Cosme Velho, Laranjeiras, Urca and Leme
Providência	Center		3/22/2010	4/26/2010	10,000	102,088	Providência, Morro do Pinto and Pedra Lisa	Gamboa, Santo Cristo and Saúde	Tijuca, Maracanã, Caju, São Cristóvão, Praça da Bandeira, Santa Teresa, Rio Comprido, Estácio, Cidade Nova, Catumbi and Centro
Borel	North	4/26/2010	4/26/2010	6/7/2010	20,000	353,226	Morro do Borel, Chácara do Céu, Casa Branca, Indiana, Catrambi and Bananal	Tijuca	Alto da Boa Vista, Grajaú, Andaraí and Vila Isabel
Formiga	North	5/3/2010	5/5/2010	7/1/2010	5,000	199,991	Morro da Formiga	Tijuca	Alto da Boa Vista, Grajaú, Andaraí, Vila Isabel, Jardim Botânico. Maracanã and Santa Teresa
Andaraí	North		6/11/2010	7/28/2010	13,000	81,347	Nova Divinéia, João Paulo II, Juscelino Kubitschek, Jamelão, Santo Agostinho, Borda do Mato, Rodo and Arrelia	Grajaú and Andaraí	Jacarepaguá, Alto da Boa Vista, Lins de Vasconcelos, Grajaú, Engenho Novo, Tijuca, Sampaio and Vila Isabel
Salgueiro	North		7/30/2010	9/17/2010	5,000	177,121	Morro do Salgueiro	Tijuca	Alto da Boa Vista, Andaraí, Vila Isabel, Mangueira, Jardim Botânico, Maracanã, São Cristóvão, Praça da Bandeira, Santa Teresa, Rio Comprido, Estácio, and Cosme Velho
Turano	North		8/10/2010	9/30/2010	18,000	128,886	Turano, Chacrinha, Matinha, 117, Liberdade, Pedacinho do Céu, Paula Ramos, Rodo and Sumaré	Tijuca and Rio Comprido	Alto da Boa Vista, Andaraí, V Isabel, Mangueira, Jd Botânico, Maracanã, S Cristóvão, Pça da Bandeira, Sta Teresa, Sto Cristo, Estácio, Cidade Nova, Cosme Velho, Catumbi and Laranjeiras
Macacos	North		10/14/2010	11/30/2010	27,000	191,220	Morro dos Macacos, Pau da Bandeira and Parque Vila Isabel	Vila Isabel	Jacarepaguá, Lins de Vasconcelos, Méier, Grajaú, Cachambi, Engenho Novo, Tijuca, Andaraí, Jacaré, Jacarezinho, Sampaio, Riachuelo, Rocha, Benfica, São Francisco Xavier, Mangueira, Maracanã, and São Cristóvão
São João / Matriz / Quieto	North		1/6/2011	1/31/2011	6,000	185,823	Morro do São João, Morro da Matriz and Morro do Quieto	Engenho Novo	Sampaio and Riachuelo
Coroa / Fallet / Fogueteiro	North		2/6/2011	2/25/2011	13,000	123,073	Morro da Coroa, Morro do Fallet and Fogueteiro	Rio Comprido	Rio Comprido
Escondidinho / Prazeres	South		2/6/2011	2/25/2011	7,000	75,102	Morro dos Prazeres and Escondidinho	Santa Teresa	Rio Comprido, Lapa, Cateto, Gloria, Cosme Velho and Laranjeiras
São Carlos	Center		2/6/2011	5/17/2011	17,150	122,071	Morro do São Carlos, Querosene, Mineira and Zinco	Estácio and Rio Cumprido	Catumbi, Cidade Nova, Praça da Bandeira, Santa Teresa, Centro, Tijuca,
Complexo do Alemão / Vila Cruzeiro	North	-	11/25/2010	-	123,842	2,569,098		Complexo do Alemão	Olaria, Ramos, Inhaúma, Engenho da Rainha, Penha, Penha Circular, Bonsucesso, Higienópolis, Del Castilho
Mangueira / Morro do Tuiuti	North	-	6/19/2011	11/3/2011	20,000	209,519		Mangueira, São Cristóvão	Maracanã, São Francisco Xavier, Benfica, Vasco da Gama, Caju, Vila Isabel, Tijuca, Rocha, Riachuelo
Rocinha / Vidigal / Chácara do Céu	South	11/4/2011	11/13/2011	-	108,796	1,181,004			

Table 1: UPP timing and characteristics

Sources: Instituto Pereira Passos, UPPrj; CPP; UPP Social; Censo das Favelas 2010; Censo 2000 IBGE; SABREN; O Globo: O Dia; Valor Econômico.

		# Rooms						
		0	1	2	3	4	N/A	Total
Unweighted								
Apartment	$R/m2	3,587	2,733	2,532	2,774	3,457	2,552	2,755
	Obs	950	4,802	6,623	5,338	3,016	7,064	27,793
House	$R/m2	2,764	1,989	2,169	2,226	2,271	2,186	2,198
	Obs	384	2,541	5,337	5,764	5,342	6,903	26,271
Weighted								
Apartment	$R/m2	5,338	5,454	3,941	4,426	5,525	4,531	4,531
	Listings	8,674	100,614	456,286	480,766	221,228	1,267,568	2,535,136
House	$R/m2	2,842	2,025	2,167	2,473	3,274	2,846	2,846
	Listings	688	5,794	56,439	117,216	203,313	383,450	766,900

Table 2: Average prices of ZAP listings for the city of Rio

Date	UPP	Bairro	(I) Bairro (OLS)	(II) Bairro (WLS)	(III) Heckman Selection (Bairro)	(IV) Border Dist<2 (WLS)	(V) Centroid Dist<2 (WLS)
			Dep. variable: log of average price/m2 by bairro				
Nov-08	Santa Marta	Botafogo, Humaitá	10.9% **	11.5% **	10.6% **	7.1% **	10.4% **
			(1.50)	(1.25)	(1.60)	(0.85)	(1.16)
Nov-08	Cidade de Deus	Jacarepaguá	-5.2% *	-4.2%	-5.9% *	0.3%	-3.0%
			(2.46)	(3.03)	(2.41)	(1.01)	(2.96)
Dec-08	Batam	Realengo	-5.9% **	-4.6% *	-5.7% **	-4.9% *	-19.2%
			(1.80)	(1.99)	(1.81)	(1.94)	(17.25)
May-09	Babilônia / Chapéu-Mangueira	Leme	21.2% **	15.8% **	18.7% **	7.2% **	6.8% **
			(2.60)	(2.51)	(3.16)	(1.04)	(1.29)
Nov-09	Pavão-Pavãozinho / Cantagalo	Ipanema, Copacabana	5.2% **	10.6% **	5.9% **	7.0% **	11.6% **
			(1.40)	(0.88)	(1.35)	(0.76)	(0.88)
Dec-09	Tabajaras / Cabritos	Copacabana, Botafogo	10.7% **	16.3% **	10.2% **	9.5% **	13.0% **
			(1.66)	(1.11)	(1.76)	(0.88)	(1.04)
Mar-10	Providência	Gamboa, Santo Cristo, Saúde	-5.1%	-8.7%	-6.0% *	7.7% **	-4.3% *
			(3.14)	(4.67)	(2.77)	(1.41)	(1.98)
Apr-10 - Jul-10	Borel / Formiga / Salgueiro^	Tijuca	8.0% **	8.0% **	6.7% **	5.8% **	7.5% **
			(2.00)	(1.19)	(1.92)	(1.02)	(1.00)
Jun-10	Andaraí	Grajaú, Andaraí	17.0% **	18.1% **	16.4% **	7.8% **	14.4% **
			(1.82)	(1.77)	(2.11)	(1.02)	(1.52)
Aug-10	Turano	Tijuca, Rio Comprido	5.5% **	15.5% **	4.4% *	7.0% **	23.3% **
			(1.92)	(1.51)	(2.00)	(1.00)	(1.37)
Oct-10	Macacos	Vila Isabel	10.8% **	22.1% **	9.9% **	9.3% **	16.7% **
			(1.51)	(1.32)	(1.63)	(0.75)	(2.41)
Jan-11	São João / Matriz / Quieto	Engenho Novo	8.9% **	18.7% **	9.7% **	5.8% **	3.7%
			(1.83)	(1.41)	(2.05)	(1.26)	(2.42)
Feb-11	Escondidinho / Prazeres	Santa Teresa	10.1% **	18.9% **	7.2% **	6.9% **	-1.5%
			(2.33)	(2.45)	(2.67)	(1.88)	(1.57)
Feb-11	São Carlos / Coroa / Fallet / Fogueteiro^	Estácio, Rio Cumprido	19.5% **	23.2% **	19.5% **	7.3% **	18.0% **
			(2.30)	(2.18)	(2.71)	(1.31)	(1.64)
Jun-11	Mangueira / Morro do Tuiuti	Mangueira, São Cristóvão	-7.0%	11.1% **	-7.2%	3.3% **	5.9% **
			(6.27)	(2.44)	(9.91)	(1.15)	(2.12)
		Overall	5.8% **	9.6% **	5.2% **	4.8% **	5.7% **

Notes: * denotes significant at 5 percent; ** denotes significant at 1 percent. Standard errors are shown in parentheses.

Table 3: The effect of the UPPs on house prices

Date	UPP	Bairro	Dep. variable: log of homicide (I) Bairro	(II) Border Dist<2	(III) Centroid Dist<2	Dep. variable: log of robbery rate (IV) Bairro	(V) Border Dist<2	(VI) Centroid Dist<2
Nov-08	Santa Marta	Botafogo, Humaitá	-26.9% *	-1.4%	-0.5%	4.5%	4.2%	4.3%
			(12.97)	(6.37)	(8.23)	(5.43)	(2.74)	(3.50)
Nov-08	Cidade de Deus	Jacarepaguá	-5.3%	-1.6%	-6.6%	3.0%	-2.3%	2.7%
			(11.33)	(5.83)	(9.26)	(5.09)	(2.60)	(4.16)
Dec-08	Batam	Realengo	-6.9%	-17.5% *	-8.2%	5.9%	-13.4% **	5.6%
			(15.87)	(7.28)	(15.82)	(7.13)	(3.23)	(7.11)
May-09	Babilônia / Chapéu-Mangueira	Leme	9.1%	-19.9% *	-23.4% *	9.1%	-4.0%	3.0%
			(18.06)	(10.00)	(10.56)	(7.06)	(4.14)	(4.26)
Nov-09	Pavão-Pavãozinho / Cantagalo	Ipanema, Copacabana	11.7%	-13.4%	0.4%	-1.3%	-3.0%	3.8%
			(14.64)	(8.28)	(12.60)	(5.98)	(3.43)	(5.20)
Dec-09	Tabajaras / Cabritos	Copacabana, Botafogo	-8.7%	6.2%	-14.3%	-11.0%	1.6%	-7.9%
			(15.49)	(8.03)	(11.76)	(6.34)	(3.34)	(4.80)
Mar-10	Providência	Gamboa, Santo Cristo, Saúde	-66.2% **	-16.9% **	-41.0% **	-39.7% **	-14.7% **	-18.8% **
			(10.00)	(5.84)	(7.86)	(4.49)	(2.60)	(3.52)
Apr-10 - Jul-10	Borel / Formiga / Salgueiro^	Tijuca	-60.8% **	-7.3%	-82.5% **	-19.7% *	-8.6% **	-2.2%
			(22.03)	(6.70)	(24.24)	(9.90)	(2.95)	(10.88)
Jun-10	Andaraí	Grajaú, Andaraí	-55.3% **	-13.8%	21.8%	-52.9% **	-13.9% **	-44.6% **
			(13.47)	(7.87)	(25.47)	(5.85)	(3.46)	(11.40)
Aug-10	Turano	Tijuca, Rio Comprido	3.6%	-2.0%	15.9%	-11.3%	4.1%	-3.9%
			(18.30)	(6.80)	(9.63)	(8.22)	(3.00)	(4.22)
Oct-10	Macacos	Vila Isabel	-68.8% **	-30.1% **	-29.1% *	-52.2% **	-14.2% **	3.7%
			(21.14)	(6.34)	(13.24)	(9.46)	(2.81)	(5.94)
Jan-11	São João / Matriz / Quieto	Engenho Novo	-67.4% **	-37.0% *	-47.6% **	-7.0%	11.9%	-17.6% *
			(24.98)	(15.67)	(15.74)	(11.22)	(7.00)	(7.06)
Feb-11	Escondidinho / Prazeres	Santa Teresa	-73.8% *	-7.7%	-1.5%	-79.7% **	-22.9% **	-13.2%
			(34.47)	(12.39)	(15.86)	(12.17)	(5.41)	(6.90)
Feb-11	São Carlos / Coroa / Fallet / Fogueteiro^	Estácio, Rio Cumprido	-40.9%	-42.1% **	-44.1% **	-58.9% **	-46.0% **	-45.9% **
			(20.81)	(11.33)	(13.71)	(9.35)	(4.89)	(5.96)
Jun-11	Mangueira / Morro do Tuiuti	Mangueira, São Cristóvão	-7.2%	5.5%	21.0%	-32.3%	-21.5% *	-32.5% **
			(41.31)	(20.33)	(26.51)	(18.56)	(8.69)	(10.91)
		Overall	-25.8% **	-11.0% **	-13.3% **	-19.1% **	-7.9% **	-9.1% **

Notes: * denotes significant at 5 percent; ** denotes significant at 1 percent. Standard errors are shown in parentheses.

Table 4: The effect of the UPPs on homicides and robberies

			Dep. variable: log of std. dev. price/m2 by bairro				
			(I) Bairro (OLS)	(II) Bairro (WLS)	(III) Heckman Selection (Bairro)	(IV) Border Dist<2 (WLS)	(V) Centroid Dist<2 (WLS)
Date	UPP	Bairro					
Nov-08	Santa Marta	Botafogo, Humaitá	-4.1% **	-2.1% **	-3.4% **	1.1% *	10.4% **
			(1.05)	(0.72)	(1.17)	(0.51)	(0.01)
Nov-08	Cidade de Deus	Jacarepaguá	0.3%	3.5% *	-0.1%	3.2% **	-3.0%
			(1.03)	(1.41)	(1.03)	(0.89)	(0.03)
Dec-08	Batam	Realengo	6.5% **	12.8% **	6.4% **	10.9% **	-19.2%
			(1.57)	(2.08)	(1.62)	(2.04)	(0.17)
May-09	Babilônia / Chapéu-Mangueira	Leme	-8.3% **	-6.4% **	-7.3% **	0.9%	6.8% **
			(1.44)	(1.03)	(1.87)	(0.72)	(0.01)
Nov-09	Pavão-Pavãozinho / Cantagalo	Ipanema, Copacabana	-10.4% **	-8.7% **	-9.4% **	-6.8% **	11.6% **
			(1.13)	(0.87)	(1.25)	(0.56)	(0.01)
Dec-09	Tabajaras / Cabritos	Copacabana, Botafogo	-4.2% **	2.8% **	-4.1% **	-0.5%	13.0% **
			(1.17)	(0.89)	(1.33)	(0.61)	(0.01)
Mar-10	Providência	Gamboa, Santo Cristo, Saúde	12.7% **	34.9% **	13.0% **	2.7% **	-4.3% *
			(3.29)	(7.75)	(3.36)	(0.60)	(0.02)
Apr-10 - Jul-10	Borel / Formiga / Salgueiro^	Tijuca	-3.3% **	0.8%	-3.2% **	1.2% *	7.5% **
			(1.13)	(0.67)	(1.14)	(0.55)	(0.01)
Jun-10	Andaraí	Grajaú, Andaraí	0.1%	3.3% **	1.0%	0.7%	14.4% **
			(1.06)	(0.53)	(1.19)	(0.57)	(0.02)
Aug-10	Turano	Tijuca, Rio Comprido	0.7%	1.0%	1.3%	0.9% *	23.3% **
			(1.06)	(0.66)	(1.02)	(0.41)	(0.01)
Oct-10	Macacos	Vila Isabel	-6.5% **	2.2% *	-5.2% *	2.2% **	16.7% **
			(1.99)	(1.06)	(2.14)	(0.43)	(0.02)
Jan-11	São João / Matriz / Quieto	Engenho Novo	6.5% **	7.2% **	6.2% **	3.8% **	3.7%
			(0.92)	(1.49)	(0.99)	(1.22)	(0.02)
Feb-11	Escondidinho / Prazeres	Santa Teresa	-5.4% **	3.7% **	-5.2% **	0.1%	-1.5%
			(0.98)	(1.02)	(0.99)	(0.58)	(0.02)
Feb-11	São Carlos / Coroa / Fallet / Fogueteiro^	Estácio, Rio Cumprido	3.2% *	9.9% **	3.1% *	-1.2% *	18.0% **
			(1.39)	(1.33)	(1.33)	(0.55)	(0.02)
Jun-11	Mangueira / Morro do Tuiuti	Mangueira, São Cristóvão	-1.8% *	4.0% **	-1.1%	-0.3%	5.9% **
			(0.89)	(0.92)	(1.01)	(0.68)	(0.02)
		Overall	-0.8% *	3.8% **	-0.4%	1.1% **	5.7% **

Notes: * denotes significant at 5 percent; ** denotes significant at 1 percent. Standard errors are shown in parentheses.

Table 5: The effect of the UPPs on the standard deviation of house prices