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## ABSTRACT

### The Effect of the Theo van Gogh Murder on House Prices in Amsterdam\*

Does Islamic terrorism have an effect on the general attitudes towards Muslim minorities? We use the murder of Theo van Gogh as an event study to address this question. Specifically, we use the hedonic-market model and test for an effect on listed house prices in neighbourhoods where more than 25% of the people belong to an ethnic minority from a Muslim country (type I). Relative to the other neighbourhoods, house prices in type I neighbourhoods decreased in 10 months by about 3%, with a widening gap over time. We use a unique weekly data set from a multi listing service that contains over 70% of all houses for sale and obtain the actual transaction prices from the registers office. Our results are robust to several adjustments including changes in the control group. There is no significant difference in the time it takes for houses to be sold in type I versus other neighbourhoods. Finally, we find evidence that segregation increased. People belonging to the Muslim minority were more likely to buy and less likely to sell a house in a type I neighbourhood after the murder than before.

JEL Classification: C21, C41, C81 and R31

Keywords: economics of terror, housing market, hedonic market method and differences in differences

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# 1 Introduction

The murder of columnist, tv-show host and film maker Theo van Gogh on November 2, 2004 in Amsterdam by a fundamentalist Muslim, had a huge impact on Dutch society. Figure 1 shows the number of Dutch newspaper articles per week that mentioned the murder. In the first two weeks, the murder was mentioned in almost 4,000 unique articles. Later spikes in attention coincide with the trial and conviction of the murderer (around week 30 of 2005), and the week one year after the murder (November 2005, week 45). This peak in news coverage is in the same order of magnitude as the coverage of the 9-11 events in the Netherlands, see Atteveldt et al. (2005).<sup>1</sup> Given the large effects of the murder of this public figure on Dutch society, the key question in this paper is whether this event in combination with the enormous media attention that it caused, had a measurable effect on the attitudes towards Muslims in general. We test this with an hedonic-market approach.

Specifically, we compare posted house prices in Amsterdam neighborhoods with more than 25% Moroccan and Turkish inhabitants (which we label type I neighborhoods) before and after the murder with house prices in the other (type II) neighborhoods.<sup>2</sup> We also use alternative control groups that look more like the type I neighborhoods in terms of other characteristics. We find that after the murder, the difference in house prices between type I and type II neighborhoods increased statistically significantly. We find that the relative house prices in type I neighborhoods decreased on average by about 1.5 percent in the year after the murder. Over time, the average decrease in the house prices is about 0.1 to 0.2 percent per week in the period after the murder. This negative impact stops after about 10 months resulting in a decrease of 3 percent in the type I neighborhoods if we make the conservative assumption that the trend in type I neighborhoods would have been the same as in type II neighborhoods while it was actually steeper before the murder.<sup>3</sup>

We use a difference-in-difference (DID) approach to identify the impact of the murder. This approach has become very popular in labor and development economics. The only other paper that we are aware of that applies DID to the

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<sup>1</sup>The murder also drew a lot of media attention outside of the Netherlands, i.e. see a recent article by Kramer in the New Yorker of April 3, 2006.

<sup>2</sup>The largest groups of non-western immigrants are Surinam, Indonesian, Turkish and Moroccan. Even though the first two groups have their ethnic background from countries with a high concentration of Muslims, the concentration among immigrants in the Netherlands is low. In addition these groups are usually not associated with the other groups.

<sup>3</sup>If we assume the trend in type I neighborhoods to be the same as before the murder, the estimated effect would have been 5%.

housing market is Abadie and Dermisi (2006). Many of the problems related to this method are less severe for the housing market. This is due to the fact that houses are fixed and cannot move between neighborhoods. Therefore, we do not have to worry about mobility between the treatment and control group (see for example Blundell and Costa-Dias, 2000). In addition, the murder can be regarded as an unanticipated and exogenous event. Difference-in-difference methods have often been applied to study policy changes where it is always questionable whether the policy changes are really exogenous. Still, serial correlation is a potential problem for reasons pointed out in Bertrand, Duflo and Mullainathan (2004). We deal with this in our robustness checks. Another fundamental problem in cross sectional neighborhood-effect studies is to distinguish between a neighborhood effect and the aggregation of individual effects: the so called reflection problem, see Manski (1993, 2000). However, in this paper we are not so much interested in identifying neighborhood effects but more in the effects of the Van Gogh murder (which can be treated as an unexpected event) on different neighborhoods.

Home ownership is typically very low among Muslim minorities. In 2002, owner-occupied housing was 57 percent among the ethnic Dutch in the Netherlands while for the Dutch-Moroccan it was 9 percent and for the Dutch-Turkish it was 20 percent (Sociaal en Cultureel Planbureau, 2005). In Amsterdam, those figures are lower. For the whole of Amsterdam, home ownership is only 20% while in the type I neighborhoods it is even smaller. We show that less than 5% of the people who sold their house in a type I neighborhood had a Moroccan or Turkish origin. Therefore, if house prices change in type I neighborhoods relatively to type II neighborhoods, we interpret this as a change in the common attitude towards type I neighborhoods and hence towards immigrants. We do find some evidence that the share of Turkish and Moroccan sellers decreased and the share of buyers increased relatively strongly in type I neighborhoods after the murder. This suggests that segregation increased.

Our findings can be explained by a standard hedonic market model, i.e. Tinbergen (1956) or Rosen (1974). The price of a house is determined by many attributes of which the composition of the neighborhood is just one. After the murder and the media attention, the value of living in a type I neighborhood decreased relatively to living in a type II neighborhood for sufficiently many native Dutch agents. Since the inhabitants of the type I neighborhoods have nothing to do with the murder, one can interpret the drop in house prices as a negative externality. Recent evidence from the Social and Cultural Planning Office of The Netherlands (SCP, 2006) suggests that relatively few individuals actually experience a change after the murder in their personal life but more than 80% believes

that the murder affects the relationship between Muslims and non-Muslims in the Netherlands. Other studies have found that attitudes of the population towards immigrants are strongly based on perceptions. For example, it is widely believed that immigrants decrease wages and increase crime while there is often no or even opposite evidence for those claims, see Butcher and Piehl (1998), Card (2005) and Card et al. (2005). Glaeser (2005) shows that if some political groups have interest in spreading hatred towards other groups and there are small incentives to learn the truth, the hatred can be self-fulfilling. When house prices drop substantially, the incentives about learning the truth increase. However, house prices also have a resale component which makes it less profitable to deviate from a common-belief market equilibrium that values houses in type I neighborhoods less than in type II neighborhoods even if one's private value towards living in type I neighborhoods have not changed. Furthermore, it is likely that agents have to learn about the change in resale value which explains the decrease of relative prices over time. Our results on the compositional changes in type I neighborhoods after the murder suggest that the value of living in a type I neighborhood was larger for Moroccan/ Turkish people than for native Dutch people. Either because their preferences did not change but relative prices dropped in type I neighborhoods or because they actually preferred to live among their peers after the murder.

There are a number of papers that study the cost of terrorism and conflicts. Abadie and Gardeazabal (2003) find substantial effects from the Basque terrorist conflict on the Basque Country. Glaeser and Shapiro (2002) find weak evidence that terrorism leads to less urbanization but they also argue that the causal link is dubious. Enders and Sandler (1991) and Fleischer and Buccola (2002) study the effect of terrorism on tourism and find mixed evidence. Abadie and Dermisi (2006) find that the 9-11 events still have an impact on office prices in high rise buildings in Chicago. Eckstein and Tsiddon (2004) argue that besides the lower life expectancy, Israel suffered a substantial drop in GDP per capita due to the high defense expenses to reduce terrorism. Frey et al. (2006) survey the literature on the economic impact of terror and claim that at the date they wrote their survey, no study has undertaken the hedonic market approach that we do in this paper. There also exists a large literature on the effect of immigration on house prices and neighborhood dynamics, see Cutler, Glaeser and Vigdor (1999) and Saiz and Wachter (2006). Benabou (1996) and Bayer, Ferreira and McMillan (2003) argue that if natives have preferences for living with other natives, immigration may decrease relative house prices in immigrant neighborhoods. Our paper is informative on what happens after an unexpected shock in attitudes

towards immigrants.

Finally, we would like to emphasize that our paper also contributes to understanding the working of the housing market in general. In our duration analysis we estimate a mixed proportional hazard model allowing for unobserved heterogeneity. We do not find evidence that the time it took to sell a house increased after the murder. This indicates that the housing market functions well in the sense that prices change quickly leaving no room for changes in the time it takes to sell a house. In addition, we find that the hazard first increases and then after two quarters gradually decreases. The increasing part can be explained by learning, non-sequential search of the sellers (they wait until a number of buyers arrive) or the fact that sellers become desperate after some time, see Albrecht et al. (2005).

The rest of this paper is organized as follows. Section 2 discusses our identification strategy and our empirical specification. Section 3 describes the data and Section 4 discusses the results. Section 5 examines other causes that might be driving the results, while Section 6 gives an hedonic market explanation for our findings and presents additional evidence on compositional shifts of the neighborhoods. Section 7 concludes.

## 2 Identification and Empirical Specification

The most general empirical setup is to specify the list price of a house as a function of individual and neighborhood characteristics. Given that we are interested in the neighborhood effects from a given point in time, such a specification allows for including a cross term consisting of a type I dummy times a time effect. We use the following formulation:

$$p_{it} = \alpha + \beta x_i + \nu_{J(i)} + \mu(t) + \lambda(t)d_{J(i)} + \xi_i + \varepsilon_{it}, \quad (1)$$

where  $p_{it}$  is the logarithm of the list price of house  $i$  in week  $t$ . The function  $J(i)$  maps the house into a particular neighborhood. The vector  $x_i$  contains the characteristics of the house, *i.e.* surface, the type (apartment, family home, etc.) and additional characteristics, such as whether there is a garage attached to the house. The variable  $\nu_{J(i)}$  is a neighborhood fixed effect. The function  $\mu(t)$  contains the time effects for all neighborhoods, while  $\lambda(t)$  is a function of the additional time effects of the type I neighborhoods. The variable  $d_{J(i)}$  is a dummy variable that equals one for a type I neighborhood and zero otherwise. The variable  $\xi_i$  is a house fixed effect and  $\varepsilon_{it}$  is the residual term of house  $i$  in period  $t$ . For now, we assume that the residual term is independent and identically distributed



with zero mean and variance equal to  $\sigma^2$ . This is a simplifying but also strong assumption, since list prices change very infrequently. We investigate the impact of this assumption when presenting the results in Section 4.

For the remainder of our analysis we assume that there are  $K$  houses,  $T$  periods and  $N$  different neighborhoods. The number of individual houses in a neighborhood in a particular time period equals  $k_{jt}$ .

This specification has been used in the literature before (see for example Abood, Kramarz and Margolis (1999) for a labor market example). By estimating equation (1), the estimated  $\lambda(t)$  would give the price effect over time of a house being for sale in a type I neighborhood versus a type II neighborhood.

Although the specification of (1) fits well with existing approaches to panel data in labor economics, in the case of house prices direct estimation is impossible since there is no mobility of houses between neighborhoods. In labor market data one can observe a worker at different jobs but here we cannot separate a house from its neighborhood, i.e., house and a neighborhood fixed effects cannot both be identified. One way to solve this problem is to take averages over the neighborhoods, measuring the treatment effect on the average list price by neighborhood.<sup>4</sup> This is the approach we take in the rest of the paper which results in the following equation for  $p_{jt}^*$ , the average of the logarithm of the list price in neighborhood  $j$  in period  $t$

$$p_{jt}^* = \alpha + \beta x_{jt}^* + \nu_j^* + \mu(t) + \lambda(t)d_j + \varepsilon_{jt}^*, \quad (2)$$

where  $p_{jt}^*$  is the average price per neighborhood, i.e.,

$$p_{jt}^* = \frac{1}{N_{jt}} \sum_{i \in H_j} p_i \cdot FS_{it}, \quad (3)$$

and

$$FS_{it} = \begin{cases} 1 & \text{if house } i \text{ is for sale in period } t \\ 0 & \text{otherwise,} \end{cases} \quad (4)$$

$$H_j = \{ i \mid \text{house } i \text{ belongs to neighborhood } j \}, \quad (5)$$

$$N_{jt} = \sum_{i \in H_j} FS_{it}. \quad (6)$$

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<sup>4</sup>Another reason to take averages over neighborhoods is to reduce the impact of the independence assumption of  $\varepsilon_{it}$ . As discussed in Section 5, house prices do not change on a weekly basis and this implies a correlation between  $\varepsilon_{it}$  with  $\lambda(t)$  and  $\mu(t)$ . Taking averages reduces this problem since the i.i.d. assumption of  $\varepsilon_{jt}^*$  is easier to defend. Still, serial correlation is a potential problem in our specification. We investigate this in Section 5 as well.

Likewise,  $x_{jt}^*$  is the vector of average properties for houses in neighborhood  $j$  that are for sale at time  $t$ :

$$x_{jt}^* = \frac{1}{N_{jt}} \sum_{i \in H_j} x_i F S_{it}, \quad (7)$$

The unobserved neighborhood fixed effect in this specification,  $\nu_j^*$  includes both the original neighborhood fixed effect  $\nu_j$  as well as the average of the individual fixed effects within a period and neighborhood. Note that it is assumed to be constant over time and this implies that systematic compositional changes in the unobserved fixed effects are not allowed in this specification. This is a necessary assumption for identification of the model. We discuss the impact of this independence assumption in Subsection 5.2.

An important choice to be made now is the specification of  $\mu(t)$  and  $\lambda(t)$ , which measure the overall time effect, and type I neighborhood time effect, respectively. A straightforward approach is to use a fixed effects model that allows  $\mu(t)$  and  $\lambda(t)$  to vary each period. This results in estimates for  $\mu(t)$  and  $\lambda(t)$  for every week in the sample, where the estimates of  $\lambda(t)$  after week 45 in 2004 measure the weekly impact of the murder. However, such an approach complicates the interpretation and typically leads to large standard errors. Hence, besides doing the fixed effects estimation for  $\mu(t)$  and  $\lambda(t)$ , we will assume a polynomial in terms of  $t$  for both  $\mu(t)$  and  $\lambda(t)$ . The polynomials parameterize the neighborhood effects in the affected and non-affected periods. Formally,

$$\mu(t) = \pi(t) + \omega(t)d_{1t}, \quad (8)$$

$$\lambda(t) = \zeta(t) + \eta(t)d_{1t}, \quad (9)$$

where  $\pi(t), \omega(t), \zeta(t)$  and  $\eta(t)$  are polynomials in  $t$ , and  $d_{1t}$  is a dummy variable that is equal to one for weeks after the murder and zero otherwise.  $\pi(t)$  measures the overall time effect in all neighborhoods, and  $\omega(t)$  the difference in time-effect from the week of the murder onwards.  $\zeta(t)$  measures the overall time effect in type I-neighborhoods, while  $\eta(t)$  models the time varying effects in type I-neighborhoods in the weeks after the murder. In the estimation, we will use a constant as well as a linear and quadratic specification for  $\pi(t), \omega(t), \zeta(t)$  and  $\eta(t)$ .

Even though we assume that the residual terms in equation (1) are independent and identically distributed, estimation of (2) using standard fixed effects is inefficient due to heteroskedasticity. There are two sources of heteroskedasticity: first there are different absolute price levels per neighborhood, second the number of listed houses per neighborhood varies. Using logs reduces the first source

while we use generalized least squares to correct for the latter effect. Basically, we weight neighborhoods by the inverse of the standard deviation of the dependent variable so neighborhoods with many observations typically receive a larger weight than neighborhoods with few observations.<sup>5</sup>

Note that our specification allows for possible learning effects. It is quite likely that the market only gradually learns about how house prices are affected. Hence, only comparing two stages (one before and one after the news was announced) might bias the effect of the murder on market prices.

### 3 Data

The data are collected on a weekly basis from the largest online multi-listing service in the Netherlands called *Funda*. According to Funda this multi-listing service contains at least 70% of the supply of residential houses for sale at any moment in time. This is the market share of the largest Dutch association of real estate agents (NVM), which sponsors the Funda website. For the Amsterdam region, it has a typical stock of 3700 houses for sale in any given week.

The start of our period of analysis is week 17 of 2004 and the end of our period is week 6 of 2006 (the murder was in week 45 of 2004). For every house we collect the address, zip code, the posted price, the surface of the house and other features (like a garage) that may increase the value of the house. The posted price of the house represents the ask price by the seller and there are no legal restrictions in the Netherlands concerning this price and the characteristics that are posted at the website. Even though this may be interpreted as an important drawback of our analysis, there are no advantages for real-estate agents of giving inaccurate information on easily observable characteristics of the house because buyers always view the house before buying.

In order to investigate whether the price and/or the surface of a house differs from the actual price and surface, we use additional data from the Netherlands' Cadastre and Public Register Agency (Kadaster). This is a public agency that registers and sells the actual selling prices of all houses. Our data set contains all houses sold in the years 2004 and 2005 in Amsterdam. The number of observations equals 16,384. We are not able to verify our selling dates as the Kadaster only registers the date at which the ownership of the house changes. Usually the house changes hands a couple of months after the actual date of agreement, but it is not uncommon that this takes more time. Hence, many of the houses at the end of our observation window may not have been registered as being sold in 2005.

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<sup>5</sup>Details of this method are provided upon request.

We have 328,711 price observations in the raw data set of which 328,449 are usable (48 prices were either below 10,000 or above 10,000,000 euro and 214 observations did not report surface). These price observations are recorded from 20,743 different houses (of which 6 turned out not to be usable). Table 1 lists the averages of the main variables that we use.

We linked the information about individual houses from the Funda website with neighborhood information from the statistics council in Amsterdam. In total there are 90 neighborhoods in Amsterdam which have residential property for sale. A typical neighborhood has 8,000 inhabitants. The most important neighborhood information that we use is the ethnic origin of the residents. As mentioned in the Introduction, we label neighborhoods as type I when the fraction of Turkish and Moroccan inhabitants exceeds 25%, the other neighborhoods are labeled type II.<sup>6</sup> We have in total 12 type I and 88 type II neighborhoods. Table 1 shows that the average price of a house in type I neighborhoods is around 180,000 euro. This is much lower than the average house price of 325,000 euro in the type II neighborhoods. We find that this can be partly explained by the observed characteristics of the houses, which are more favorable for the type II neighborhoods: the houses in type I neighborhoods are smaller, more likely to be an apartment and less likely to have a garage. Houses are listed on average 20 weeks on the website in both types of neighborhoods. Not surprisingly, the income per head is much lower in the type I neighborhoods than in the type II neighborhoods. Finally we find that the crime rates, defined as the number of registered crimes divided by the number of individuals within the neighborhood, are lowest in the type I neighborhoods. This goes against the common perceptions since neighborhoods with many immigrants are usually believed to be more criminal.<sup>7</sup> Our findings are in line with earlier research by Card (2005).

In order to obtain some ideas about the development of house prices in the two types of neighborhoods, Figure 2 shows the relative house prices per square footage. After the murder, houses in type 1 neighborhoods were slightly larger than before. This is also reflected in Figure 3, which illustrates the development of square footage over the observation window. Looking at the development in Figure 2 we find that the house prices were stable in the first half of 2004 while they increased strongly in the type II neighborhoods after that period. One potential reason for this strong increase is that the interest rates decreased a lot during this period. We investigate this in our empirical analysis in section 5.

Since we look at the differences in house prices between the type I and type

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<sup>6</sup>The fraction of other Muslim immigrants is negligible.

<sup>7</sup>Many of the drug-related crimes take place in the more expensive touristic neighborhoods.

II neighborhoods it is important that the ask price correctly reflects the situation at the housing market. If however, prices only adjust slowly, big changes in the inflow and outflow over time may occur just after the murder took place. This is not the case. Figure 4 shows the development of the number of houses that are posted for the first time in a given week. These figures do not indicate a large impact of the murder on the number of houses for sale over the period of analysis.

## 4 The Effect of the Murder on House Prices in Amsterdam

In this section we present the estimation results using the specification of Section 2. The estimation of the model in (2) is followed by a number of robustness checks in which we correct for the influence of sticky list prices, biases in selecting type I and type II neighborhoods and the presence of serial correlation.

### 4.1 Baseline Results

Our baseline results for the constant, linear and quadratic specification of  $\lambda(t)$ , the neighborhood price-effect, are presented in Table 2 and Figures 6 to 8. We include the fixed effects estimation of equation (2) in these figures in order to show the quality of our approximation methods. The first column of Table 2 shows the results when using a constant term. We find a significant negative price effect of 1.1 percent on the house prices in type I neighborhoods, see Figure 6.

As the fixed effects estimates in Figure 6 suggest, the price effect is not a once and for all decrease. Column 2 of Table 2 shows the estimation results for the linear model, i.e., the parameters of the linear approximation to  $\lambda(t)$ . It shows that the development of house prices can be described quite well with a linear relationship. The impact is between 0.1 to 0.2 percent per week after the murder of Van Gogh and reaches a high of 3 percent a year after the murder. This suggests that there are either menu costs or there is a learning process in the market. We investigate this further in Subsection 4.2. Since house prices in type I neighborhoods were increasing before the murder and decreasing afterwards we believe that the trend effect is more informative than the constant effect.<sup>8</sup>

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<sup>8</sup>Imagine that the treatment effects increase in each of the  $n$  weeks before the treatment and decrease in each of the  $n$  weeks after the treatment till the original level. Only looking at a constant would make one conclude that there is no effect.

The results are visualized in Figure 7. In the third column of Table 2, we see that the estimates of a second degree polynomial are similar to those of the linear specification. We find that the constant becomes larger in absolute terms and now becomes significant. The estimation results for the control variables are as expected. The price of a house is increasing with size, apartments and flats have a lower selling price than complete houses, while a garage has a positive impact on the price.

## 4.2 Sticky List Prices

An important assumption is that  $\varepsilon_{it}$ , the error term in equation (2), is independent across individual houses as well as over time for a single house. Together with the trend effects  $\mu(t)$  and  $\lambda(t)$ , the time-independence effect implies that prices of a single house can change every period. This is counterfactual since 70 percent of the listed houses never had a single price change. Table 3 gives more details and indicates that there is a strong relationship between the duration that a house is listed and the likelihood that the price is changed. This suggests that list prices are sticky, and that the disturbance term in (1), on which model (2) is based, is not independent over time. As such, it may be possible that a downward price shock in a neighborhood (like the murder) leads to no, or only small changes in the list price, and a longer duration of the time to sale. This may be caused by adaptive learning, menu costs, see Mankiw (1985) or the reluctance of sellers to adjust the list price downwards due to nominal loss aversion, see Genesove and Mayer (2001).

To circumvent the problem of sellers that are reluctant to change the list price, we re-estimate the model taking only the list prices of houses in the *first week* that they appear online. Table 4 lists the estimation results and we see that the estimated impact of the murder on list prices remains. Both the linear and the constant specification show an increased effect of the murder. The overall effects in the constant specification increase to 1.3%, compared to 1.1% in the baseline estimation.

## 4.3 Leaving out Expensive Neighborhoods

The assumption underlying the neighborhood equation (2) is that the trend in list prices of houses in type I and type II neighborhoods share a common trend,  $\mu(t)$ . Under this assumption,  $\lambda(t)$  correctly measures the structural price difference in the period after the Van Gogh murder. However, one might argue that type I and type II neighborhoods are so different in type of housing that it is hard to justify

the existence of a common trend. Perhaps the two types of neighborhoods are separate housing markets that are each influenced by completely different factors.

We study the impact of this problem by restricting the neighborhoods used for the analysis to those with an average net yearly income per head below 20,000 euros. Using a threshold value of 20,000 euros leaves out the more expensive neighborhoods near the centre and southern area of Amsterdam and gives a better justification to view all neighborhoods as belonging to a single Amsterdam housing market. The total number of neighborhoods is now equal to 59 with the number of type I neighborhoods still equal to 12. The yearly income per household is equal to 16,302 euros in type II neighborhoods, practically equal to the 16,408 euros for type I neighborhoods. Estimation results are reported in Table 5. The results in the Table 5 show that the estimate using the constant term is -1.3 percent, an even larger decrease than the -1.1 percent found for the estimation with all neighborhoods in Table 2. The linear specification has a larger absolute value of the constant term but a slightly lower value of the linear coefficient.

Taking a control group that is more similar to the treatment group thus gives very similar results.

#### 4.4 The effect in terms of the fraction of Muslims in a neighborhood

The type I and type II neighborhoods were defined as having a percentage of Turkish and Moroccan inhabitants either above (type I) or below (type II) a threshold level. However, we can also use the information on the percentage Turkish or Moroccan inhabitants per neighborhood directly, by including them in the estimation. I.e., we can rewrite equation (2) as

$$p_{jt}^* = \alpha + \beta x_{jt}^* + \nu_j^* + \mu(t) + \lambda(t)\gamma(s) + \varepsilon_{jt}^*, \quad (10)$$

where  $s$  is the percentage of Turkish and Moroccan originated immigrants and  $\gamma$  is a function of  $s$ . The original specification is a special case of this representation with  $\gamma$  being a step function that jumps from zero to one when  $s$  exceeds 25 percent.

The estimation results using a step function are presented in Table 6. A higher density of Turkish and Moroccan immigrants increases the estimated impact of the murder. We find that the negative impact on the trend term is especially relevant when the percentage of Turkish and Moroccan immigrants increases from below 10 to above 10 percent. For higher percentages it stays stable up to 30 percent. It increases again above 30 percent. Figure 11 shows the polynomial

approximation to the total impact of the murder after 13, 26, and 52 weeks. The patterns have a similar shape, while the impact is clearly the largest 52 weeks after the murder.

## 4.5 Serial Correlation

As indicated in the Introduction, our method does not suffer from many of the problems related to the use of difference-in-difference estimations. However, given that the list price of a house does not change frequently, it is likely that the error term in the specification of  $p_{jt}^*$  in (2) will be serially correlated. I.e., a large neighborhood mis-pricing (in terms of the specification in (2)) in one period is likely to carry over to the next period.

Bertrand et al. (2004) point out that the standard errors from simple difference-in-difference estimators can be biased when the number of periods is long, the dependent variable is likely to suffer from serial correlation and the treatment variable changes very little over time. Unfortunately, our analysis is potentially sensitive to all these factors. Therefore, it is important to investigate the possible impact of serial correlation on the standard errors of the estimates of  $\lambda(t)$ .

One possible way to correct for this is by using block bootstraps as suggested in Bertrand et al. (2004). Unfortunately, this method only works when the panel is balanced. In order to correct for this we use a balanced panel in our analysis, dropping those neighborhoods with fewer observations than time periods. This results in dropping 12 of the 90 neighborhoods.

Table 7 lists the results of the block bootstrap exercise. We sample neighborhood rows rather than time/neighborhood cells to obtain the empirical distribution of estimates and the "correct" t-values at the 5% level. The first three rows list the t-values when we drop the 12 neighborhoods. There are some small changes in comparison with the original results. In particular, the trend term in the second column has a lower t-value than the original one in Table 2. The rows below list the critical values found by the block bootstrap exercise. In the first column, we find that the critical values are much higher in absolute terms than those of a standard normal distribution. This suggests a big impact of serial correlation in the original results.

The second column suggests that the changes in critical values for the  $t$ -values are smaller. In addition, we find that our conclusions are again not affected.



## 5 Extensions

Although the estimation results clearly indicate a price effect taking place after the murder, it is still possible that other effects than the Van Gogh murder are driving the results. Demand and supply factors unrelated to the Van Gogh murder might impact the relative prices of houses in type II neighborhoods vis-à-vis the houses in type I neighborhoods. Probably the most important demand factor is the mortgage interest rate while on the supply side the characteristics of the houses for sale in both neighborhoods are important.

In this section we also present two extensions to analyze whether the list price differentials are accompanied by (i) changes in the average difference between list price and transaction price, and (ii) changes in the time on the market of listed houses. In the working paper version, Gautier et al. (2007) we have also looked at what happened with market uncertainty, measured as the variance of house prices before and after the murder, but we did not find statistically significant effects.

### 5.1 Mortgage Interest Rates

It is possible that the reported effect is caused by house prices reacting to interest rate changes. Figure 9 illustrates the development of these interest rates during our observation window. We find that the interest rates are rather stable before the date of the murder, but decrease quite sharply the months following the murder.

In order to investigate the possible source of bias in our results due to different impacts of the interest rate on house prices in the two types of neighborhoods, we proceed by using a multiple step estimation procedure. First, we estimate the fixed effects model as represented in for example Figure 6. Next, we regress the fixed effects on a flexible specification of the mortgage interest rates. The residuals of this regression can be interpreted as the impact of the murder after the difference in impacts of the interest rates between the neighborhoods have been taken out. As a final step we regress the residuals on a polynomial over time and in order to investigate the impact of the murder we allow for interaction effects with the date of the murder. Note that this procedure is very conservative in the sense that we attribute all the possible covariance between the murder and the interest rate to the latter. An alternative would be to use the interest rates in equation (2) and report the difference-and-difference estimates directly. We found that this procedure did not produce different results from the baseline analysis.

The results of our regression of the fixed effects on the mortgage interest rates are reported in Table 8. The coefficients of this Table are somewhat difficult to interpret. In general, a minus sign implies that the house prices in type I neighborhoods are more sensitive to mortgage interest rate changes and a positive sign implies the opposite. However, the inclusion of multiple interest rates and the high level of multicollinearity between these regressors makes the interpretation difficult.

The results of the final step are listed in Table 9. We find that the single coefficient in the constant specification does not differ significantly from zero which implies that on average house prices in the type I neighborhoods did not decrease after the murder but again, this might be due to the fact that the interest rate picks up some of the murder-effect. Moreover, as we argued before the trend effect is more informative and we still find a negative and significant impact over time for both the linear and quadratic specification.

## 5.2 Compositional changes in the supply of houses

Our main identifying assumption is that the house fixed effects are independently distributed within a neighborhood through time. This implies that the unobserved characteristics of houses for sale within a neighborhood do not change in any systematic way. This assumption may be violated when proportionally more ill-maintained houses enter the market in a particular neighborhood. For our analysis this is a potential problem when it occurs simultaneously with the date of the murder, which would lead us to mistakenly take a composition change of the houses before and after the murder as a change in house prices.<sup>9</sup> One way to check the validity of our identifying assumption is by looking at the observed characteristics of the type I and type II neighborhoods and compare the development before and after the murder. With respect to the most important component: surface, we do not find that the average quality of houses for sale decreased in type I neighborhoods, see Figure 3. Note that surface and neighborhood together explain 80% of the variance in house prices. We therefore conclude that the composition of houses for sale in type I and type II neighborhoods did not change in terms of observables after the murder.

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<sup>9</sup>This situation would also indicate that something happened in the type I neighborhoods after the murder. However, these effects differ from our interpretation.

### 5.3 Changes in the Average Discount

An additional check on house price effects around the Van Gogh murder is to use actual transaction prices. To this end, we purchased data from the ‘Kadaster’. The data provided gives the transaction price of all house transactions in Amsterdam for the year 2004-2005. We merge our data set with the data set of the register by street address and zip code, taking only those houses from the register that have appeared on Funda. Also, we deleted some of the matches that had either a remarkably low transaction price or a large deviation between list price and transaction price.<sup>10</sup> We were able to match 10,479 out of 16,384 of the houses recorded to be sold in the period 2004-2005. Apart from our own removal of some awkward houses, there are a number of reasons why we were not able to match all houses: (i) the house was sold by an agent outside the NVM organization that is behind Funda or sold without being listed on Funda, (ii) the house was sold before February 2004, the start of the Funda data set, (iii) real-estate agents may have misspelled address, in particular the addendum of the house number, and (iv) the houses from the Funda data that were not yet sold in 2005 could obviously not be matched with the registered database. The houses listed on Funda account for 60% of all houses sold in Amsterdam in the period 2004-2005.

The average differences between house prices in the final week that the house is listed on Funda and the actual transaction price are reported in Table 10. The list prices presented are lower than those in Table 1 because here we only take the price in the final week of listing, whereas Table 1 considers the list prices for all houses in the weeks that they are listed. Also, the houses that are matched have a slightly lower house price than those we were not able to match. The mean transaction price for all recorded transactions is 285,213 euros. The entry ‘discount’ in Table 10 represents the percentage difference between the finally posted and the transaction price, and is 4.17% for all houses, 3.82% for houses in type I neighborhoods, and 4.23% for type II houses. In addition, the correlation between posted and transaction price is over 99%, implying that the list price is a good indicator of the ultimate transaction price.

Figure 13 displays the level of the average discount per neighborhood over time. As can be seen in the figure, there is a sharp increase in the average discount for houses in type I neighborhoods right after the week of the Van Gogh murder. This effect is in line with the ‘menu costs’ hypothesis, i.e., list prices do not drop immediately although market (transaction) prices do. Using the

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<sup>10</sup>The houses we deleted had a selling price under 10,000 euros and we deleted the matches with deviations over 30 percent of the selling price. In total we deleted about 3 percent of the dataset.

difference-in-difference estimate of this increase we find a point estimate of 1.4 percent with a standard deviation of 1.2 percent. Hence, even though the increase in the discount seems large, it is not statistically significant.

## 5.4 Duration analysis

In addition to a price effect, the number of weeks it takes for a house to be sold gives additional information on the effect of the murder on the housing market. To test for duration effects, we use a mixed proportional hazard model with both duration and time dependence, see Van den Berg (2001). Let  $\theta(t, \tau, x, v)$  be the (hazard) rate at which houses are sold. In this notation,  $t$  is the duration in weeks that the house is on the multi-listing service,  $\tau$  is calendar time as measured in weeks starting from the first week of 2004. The vector  $x$  represents the observed characteristics of the house, just as in the earlier price equation (1).<sup>11</sup> The variable  $v$  represents the unobserved characteristics of the house. We use the following specification for the hazard rate

$$\theta(t_i, \tau_i, x_i, v) = \exp(x_i\beta + \nu_{J(i)}\gamma_1(\tau_i) + \gamma_2(\tau)d)\psi(t_i) u_i$$

where  $\nu_j$  is a neighborhood fixed effect and, as before,  $J(i)$  maps a house  $i$  to its neighborhood  $j = J(i)$ . The function  $\gamma_1$  represents the overall time effect, while  $\gamma_2$  represents the additional effect for houses in type I neighborhoods. The function  $\psi$  represents the duration dependence. For all functions we use a piecewise constant specification, see Lancaster (1990). We use a fixed mass point distribution for the stochastic variable  $u_i$  and assume it to be independent and identically distributed among the observations. Since all houses that are for sale in the first week of the sample period are left-censored with respect to duration, we only include newly arrived houses after the first week of the sample period.

Estimation results for the mixed proportional hazard specification are listed in Table 11. As before, we do not list the levels of the neighborhood fixed effects. First of all, Table 11 shows that larger houses, apartments and houses with a garage attached sell faster. Houses have a relatively small probability to be sold in the first four weeks, while the highest probability to sell a house is in between weeks 9 and 13. In the second quarter the probability decreases somewhat but it

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<sup>11</sup>We choose not to include price itself in our analysis since we expect this variable to be correlated with the unobserved characteristics. There have been a number of attempts to correct for this (for example Rutherford et al. (2005)), but these methods are not suitable for the present analysis. In our opinion only a full information maximum likelihood approach with the inclusion of a price and duration equation would solve this problem. However, such a method is more restrictive in terms of parameters.

is never as low as it is in the first four weeks. This indicates that sellers need some time to advertise their property or that sellers become more impatient when the house is already for sale for more than one month, see Albrecht et al. (2005). It also indicates that learning effects are important since even if a seller gets many offers from potential buyers in the first quarter (s)he may not sell the house because it may signal that the house is of good quality. Only after sellers learn about the quality of the house they start to accept bids of potential buyers.

An important result in Table 11 is that  $u_1 = 0$ , which means that unobserved heterogeneity is negligible.

The possible impact of the murder can be found by comparing the cross effects of time and type I neighborhoods in the quarters before and after the murder. This shows that after the Van Gogh murder, there is no significant increase in the expected time to sell a house in type I versus type II neighborhoods. To show how the probabilities of selling a house are related, Figure 12 shows the development of the hazard rate, scaled as the probability to sell the house in the first week of listing. The probabilities for type I neighborhoods are always below those of type II neighborhoods. In addition, the probabilities are increasing over time for all neighborhoods, with a larger increase for type I neighborhoods. However, we should take into account that the standard errors of the difference, i.e., the time effects times the type I neighborhood effects in Table 11, are large.

Note that we find the duration dependence to be non-monotonic, which contrasts with the specification used by, for example, Zuehlke (1987) and Rutherford et al. (2005). The present literature on the duration of house sales usually assumes a Weibull distribution for the baseline hazard of the mixed proportional hazards model, which implies a monotonic duration dependence. For our dataset with list prices a monotonic duration dependence is rejected, suggesting the use of a Weibull distribution is inappropriate.

## 6 How Did the Murder Impact House Prices?

The following story is consistent with our results. The murder of Theo van Gogh and all the related media attention decreased the willingness of native Dutch buyers and sellers to live in type 1 neighborhoods. This resulted in a lower equilibrium price. Since house prices have a large resale component, the price drop also reflects the expected preference shift of future buyers and sellers. The decrease of relative prices over time suggests that there was learning going on about this resale component. Below we discuss some direct evidence that the public believed that the murder had an impact on attitudes towards Muslims.

Direct evidence on the attitudes about Muslims and the relation between Moroccan and Turkish Dutch vis-a-vis native Dutch citizens is given by the LIS (Living situation non-native city inhabitants) questionnaire which was (by coincidence) held in the week after the murder and some questions related to the murder were added, see SCP (2006). Part of the questionnaire concerns the attitude shifts after the murder. Of the native Dutch respondents, 33% personally think differently about the relation between Muslims and non-Muslims after the murder while 86% believes that the murder will have an effect on the relationship between Muslims and non-Muslims. Only 5% believes that the murder will have an effect on themselves or their family. The latter fraction is a lot larger under Moroccans (20%) and Turkish (13%) Dutch inhabitants. Thus the survey suggests that the murder had an impact on the overall expected attitude of non-Muslims towards Muslims. This then, is the effect that is translated directly into the housing market: a potential buyer is not just valuing the direct benefits that follow from owning the house, but also takes into account the resale value, which depends on the preferences of future buyers.

We expect that Muslims value type I neighborhoods after the murder higher than the native Dutch either because their preferences did not change but relative prices did drop or because the desire to cluster together with other Muslims increased. This can be tested. Since the register agency does not provide the explicit ethnicity of the parties involved in a sale, we have to rely on the surnames of buyer and seller to identify whether either one of them is of Turkish or Moroccan origin. For this, we had research assistants from both countries who checked if a name was typical for their country of origin. Tables 12 and 13 provide the results in terms of the fraction of transactions that involves a Turkish or Moroccan buyer or seller, both before and after the murder.

Table 12 shows that in type I neighborhoods, the net inflow of Turkish/Moroccan dwellers changed from about 3% (8.12 - 5.14) of all transactions before the murder to 6% (9.87-3.75) after the murder. The t-value of the difference is 2.50. In type II neighborhoods, the changes are a lot smaller and not statistically significant, (an increase in net flow from 1% to 1.6%). The t-value of the DID estimate of net compositional changes in type I and II neighborhoods before and after the murder is 1.84. Finally, we find that before the murder 65% of the Turkish or Moroccan buyers in type I neighborhoods came from other neighborhoods or from outside Amsterdam while after the murder this fraction was 71% (this information is also in the Kadaster data). For the sellers this fraction does not change. In addition, the small percentages of buyers and sellers from a non-Dutch origin indicate that the changes in house prices are mainly driven

by changes in the preferences of Dutch rather than Turkish or Moroccan homeowners. Summing up, we find evidence that segregation increased. The fraction of Moroccan/Turkish buyers in type I neighborhoods increased and the fraction sellers decreased after the murder.

## 7 Conclusions

The economic impact of terrorism is in general difficult to measure. In this paper we take an hedonic-market approach and show that after the Murder of film maker and journalist Theo van Gogh, house prices in neighborhoods with more than 25% Muslims decreased with about 0.1 to 0.2 percent per week relatively to the other neighborhoods in Amsterdam. After about a year, the difference in trends stops and market sentiments cool down. On average, the price drop is about 1.5 percent while after ten months it is 3 percent. Those results turn out to be robust to many different specifications in the sense that house prices in type I neighborhoods decreased on average and over time although the relative size of the constant and the linear term changes with different definitions of selling dates and control groups. We do not find evidence that the time it takes to sell a house in those neighborhoods increased relatively to our control neighborhoods after the murder. Finally, our results suggest that segregation increased a bit. From the work of Schelling (1969) we know that small changes at the micro level in terms of preferences about neighborhood composition can lead to complete segregation. It is however too early to draw any conclusions about whether this will happen.

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# Appendix A: Tables and Figures

**Table 1: Descriptive statistics**

This table gives the descriptive statistics of the list prices collected. The crime rate per neighborhood is derived from the Amsterdam statistics council and defined as the number of registered crimes. The mean crime rate is computed over the neighborhood population.

Variable	Number of observations	Mean	Standard Deviation
<i>All neighborhoods</i>			
Number of neighborhoods	90		
List price	20148	290487	236261
Apartment	20148	0.85	
Surface in square footage	20148	1050	655
Garage attached	18475	0.028	
Surface (area)	6557	1153	2281
Duration listed	20148	20.36	18.71
Income per individual in neighborhood	20148	20471	4459
Crime rate in neighborhood	20148	0.148	0.268
<i>Type I neighborhoods</i>			
Number of neighborhoods	12		
Price	2497	175732	56533
Apartment	2497	0.93	
Surface in square footage	2497	804.6	265.4
Garage attached	2278	0.018	
Surface (area)	817	958	2347
Duration listed	2278	20.83	20.34
Income per individual in neighborhood	2278	16480	918
Crime rate in neighborhood	2278	0.087	0.014
<i>Type II neighborhoods</i>			
Number of neighborhoods	78		
Price	17651	306721	247260
Apartment	17651	0.839	
Surface in square footage	17651	1084	686
Garage attached	16197	0.029	
Surface (area)	5740	1181	2271
Duration listed	17651	20.16	17.92
Income per individual in neighborhood	17651	21037	4472
Crime rate in neighborhood	17651	0.157	0.285

**Table 2: Baseline results**

This table shows the baseline results for the price effects of the Theo van Gogh murder. The first column lists the estimation results for the specification of  $\lambda(t) = c$ . The second and third column list the estimation results for the linear and quadratic specification, respectively. Panel A gives the difference-in-difference estimates. Panel B to D show the estimation results for the general price effect before the murder, before the murder in type I neighborhoods, and after the murder. The variables  $\eta$ ,  $\pi$ ,  $\zeta$ , and  $\omega$  refer to the variables defined in Equation (8).

	I	II	III
<b>A: Difference-in-difference estimators</b>			
Constant	-0.0113 (0.0020)	-0.0030 (0.0038)	-0.0101 (0.0056)
$t$	.	-0.0013 (0.0002)	-0.0023 (0.0008)
$t^2$ (x 100)	.	.	-0.0047 (0.0026)
<b>Other results</b>			
<i>B: Results before the murder</i>			
Constant	11.63 (0.023)	11.63 (0.023)	11.63 (0.023)
$t$ (x 100)	.	-0.0000 (0.0001)	-0.0002 (0.0002)
$t^2$	.	.	0.0006 (0.0009)
<i>C: Results before the murder, type I neighborhoods</i>			
$t$	.	0.0006 (0.0002)	-0.0005 (0.0007)
$t^2$ (x 100)	.	.	0.0044 (0.0025)
<i>D: results after the murder</i>			
Constant	0.0259 (0.0007)	0.0007 (0.0013)	-0.0012 (0.0020)
$t$	.	0.0010 (0.0001)	0.0009 (0.0003)
$t^2$ (x 100)	.	.	-0.0009 (0.0009)
<i>Control variables</i>			
Surface	0.0924 (0.0011)	0.0933 (0.0011)	0.0933 (0.0011)
Surface <sup>2</sup> (x 1000)	-0.011 (0.0003)	-0.012 (0.0003)	-0.012 (0.0003)
Apartment	-0.1067 (0.0070)	-0.1144 (0.0068)	-0.1141 (0.0069)
Garage	0.1087 (0.0136)	0.0840 (0.0132)	0.0832 (0.0132)
<i>Goodness of fit measures</i>			
$R^2$ within	0.6521	0.6707	0.6708
$R^2$ between	0.8154	.	.
$R^2$ overall	0.8324	0.8362	0.8367

**Table 3: List price changes**

For each interval in weeks of the duration of the house, this table give the number of houses and the percentage of houses that experience a change in list price during the time of listing.

Duration	Number of observations	Percentage price change
1-5 weeks	2970	25.9
5-10 weeks	4097	5.9
10-15 weeks	2961	16.1
15-20 weeks	2182	27.4
20-25 weeks	1558	40.2
25-30 weeks	1270	51.7
30-35 weeks	761	54.5
35-40 weeks	458	61.6
40-45 weeks	342	64.6
45-50 weeks	263	73.4
50-55 weeks	1030	72.3

**Table 4: Using only first-week list prices**

This table shows the baseline results for the neighborhood-effects of the Theo van Gogh murder using only the list prices in the first week that a house is listed. The first column lists the estimation results for the specification of  $\lambda(t) = c$ . The second and third column list the estimation results for the linear and quadratic specification, respectively. Panel A gives the difference-in-difference estimates. Panel B to D show the estimation results for the general price effect before the murder, before the murder in type I neighborhoods, and after the murder. The variables  $\eta$ ,  $\pi$ ,  $\zeta$ , and  $\omega$  refer to the variables defined in Equation (8).

	I	II	III
<b>A: Difference-in-difference estimators</b>			
Constant	-0.013 ( 0.004)	-0.001 ( 0.008)	-0.001 ( 0.011)
$t$	.	-0.005 ( 0.002)	-0.012 ( 0.007)
$t^2$	.	.	-0.001 ( 0.001)
<b>Other results</b>			
<i>B: Results before the murder</i>			
Constant	11.678 ( 0.023)	11.687 ( 0.024)	11.687 ( 0.023)
$t$	.	0.000 ( 0.001)	-0.001 ( 0.002)
$t^2$	.	.	0.000 ( 0.000)
<i>C: Results before the murder, type I neighborhoods</i>			
$t$	.	0.003 ( 0.002)	-0.002 ( 0.006)
$t^2$	.	.	0.001 ( 0.001)
<i>D: Results after the murder</i>			
Constant	0.031 ( 0.001)	-0.000 ( 0.003)	-0.005 ( 0.004)
$t$	.	0.004 ( 0.001)	0.004 ( 0.002)
$t^2$	.	.	-0.000 ( 0.000)
<i>Control variables</i>			
Surface	0.001 ( 0.000)	0.001 ( 0.000)	0.001 ( 0.000)
Surface <sup>2</sup>	-0.000 ( 0.000)	-0.000 ( 0.000)	-0.000 ( 0.000)
Apartment	-0.159 ( 0.014)	-0.188 ( 0.013)	-0.186 ( 0.013)
Garage	0.113 ( 0.026)	0.090 ( 0.025)	0.088 ( 0.025)

**Table 5: Using only lower-income neighborhoods**

This table shows the estimation results using only neighborhoods where the yearly income per head is below 20,000 euro. The first column lists the estimation results for the specification of  $\lambda(t) = c$ . The second and third column list the estimation results for the linear and quadratic specification, respectively. Panel A gives the diff-in-diff estimates. Panel B to D show the estimation results for the general price effect before the murder, before the murder in type I neighborhoods, and after the murder. The variables  $\eta$ ,  $\pi$ ,  $\zeta$ , and  $\omega$  refer to the variables defined in Equation (8).

	I	II	III
<b>A: Difference-in-difference estimates</b>			
Constant	-0.0134 (0.0024)	-0.0054 (0.0047)	-0.0124 (0.0069)
$t$	.	-0.0009 (0.0003)	-0.0015 (0.0010)
$t^2$ (x 100)	.	.	-0.0038 (0.0031)
<b>Other results</b>			
<i>B: Results before the murder</i>			
Constant	11.52 (0.023)	11.53 (0.023)	11.54 (0.023)
$t$ (x 100)	.	0.0003 (0.0001)	-0.0003 (0.0004)
$t^2$	.	.	0.0022 (0.0015)
<i>C: Results before the murder, type I neighborhoods</i>			
$t$	.	0.0004 (0.0002)	-0.0004 (0.0008)
$t^2$ (x 100)	.	.	0.0032 (0.0031)
<i>D: Results after the murder</i>			
Constant	0.0284 (0.0012)	0.0034 (0.0022)	0.0014 (0.0033)
$t$	.	0.0006 (0.0001)	-0.0001 (0.0005)
$t^2$ (x 100)	.	.	-0.0020 (0.0015)
<i>E: Control variables</i>			
Surface	0.0999 (0.0026)	0.0994 (0.0025)	0.0992 (0.0025)
Surface <sup>2</sup> (x 1000)	-0.013 (0.001)	-0.013 (0.001)	-0.013 (0.001)
Apartment	-0.1541 (0.0094)	-0.1705 (0.0094)	-0.1714 (0.0094)
Garage	-0.0053 (0.0193)	-0.0155 (0.0190)	-0.0165 (0.01906)
<i>Goodness of fit measures</i>			
$R^2$ within	0.6764	0.6825	0.6827
$R^2$ between	0.7162	.	.
$R^2$ overall	0.7747	0.7808	0.7819

**Table 6: Minority Percentages, step function**

This table shows the impact of  $s$ , the minority percentage, on the price difference between type I and type II neighborhoods. The percentage intervals represent the breakpoints of the step functions used to model the relation the minority percentage and the average list price per neighborhood.

	I	II	III
<b>Difference-in-difference estimators</b>			
5-10 percent	0.0177 (0.0018)	0.0209 (0.0025)	0.0259 (0.0035)
10-15 percent	-0.0157 (0.0023)	0.0106 (0.0032)	0.0225 (0.0044)
15-20 percent	-0.0248 (0.0031)	0.0020 (0.0044)	0.0082 (0.0059)
20-25 percent	-0.0029 (0.0026)	-0.0014 (0.0039)	-0.0063 (0.0052)
25-30 percent	0.0049 (0.0043)	0.0029 (0.0064)	0.0136 (0.0086)
30-35 percent	-0.0204 (0.0039)	-0.0052 (0.0059)	-0.0075 (0.0080)
35-40 percent	-0.0198 (0.0033)	0.0030 (0.0050)	0.0074 (0.0066)
over 40 percent	-0.0004 (0.0042)	0.0115 (0.0063)	0.0003 (0.0083)
$t \times$ 5-10 percent (x 100)	.	-0.0297 (0.0073)	-0.0931 (0.0273)
$t \times$ 10-15 percent (x 100)	.	-0.1363 (0.0100)	-0.2814 (0.0350)
$t \times$ 15-20 percent (x 100)	.	-0.1576 (0.0137)	-0.2391 (0.0468)
$t \times$ 20-25 percent (x 100)	.	-0.0837 (0.0143)	-0.0392 (0.0406)
$t \times$ 25-30 percent (x 100)	.	-0.0876 (0.0205)	-0.2086 (0.0668)
$t \times$ 30-35 percent (x 100)	.	-0.1700 (0.0210)	-0.1372 (0.0626)
$t \times$ 35-40 percent (x 100)	.	-0.2075 (0.0206)	-0.2408 (0.0527)
$t \times$ over 40 percent (x 100)	.	-0.1859 (0.0248)	-0.0292 (0.0653)
$t^2 \times$ 5-10 percent (x 1000)	.	.	0.0118 (0.0050)
$t^2 \times$ 10-15 percent (x1000)	.	.	0.0278 (0.0064)
$t^2 \times$ 15-20 percent (x 1000)	.	.	0.0168 (0.00846)
$t^2 \times$ 20-25 percent (x1000)	.	.	-0.0045 (0.0073)
$t^2 \times$ 25-30 percent (x 1000)	.	.	0.0286 (0.0121)
$t^2 \times$ 30-35 percent (x1000)	.	.	0.0032 (0.0114)
$t^2 \times$ 35-40 percent (x 1000)	.	.	0.0178 (0.0098)
$t^2 \times$ over 40 percent (x1000)	.	.	-0.0114 (0.0119)

Table 6, continued

	I	II	III
<b>Other results</b>			
<i>Results before the murder</i>			
Constant	11.62 (0.023)	11.61 (0.023)	11.61 (0.023)
$t$ (x 100)	.	-0.0002 (0.0001)	-0.0006 (0.0002)
$t^2$	.	.	0.0134 (0.0081)
<i>Results before the murder, type I neighborhoods</i>			
$t$	.	0.0000 (0.00000)	0.0000 (0.00001)
$t^2$ (x 1000)	.	.	-0.0000 (0.00000)
<i>Results after the murder</i>			
Constant	0.0256 (0.0010)	-0.0052 (0.0017)	-0.0102 (0.0023)
$t$	.	0.0014 (0.0001)	0.0014 (0.0003)
<i>Control variables</i>			
$t^2$ (x 1000)	.	.	-0.0215 (0.0085)
Surface	0.0930 (0.0011)	0.0943 (0.0011)	0.0941 (0.0011)
Surface <sup>2</sup> (x 1000)	-0.0011 (0.0000)	-0.0012 (0.0000)	-0.0012 (0.0000)
Apartment	-0.0972 (0.0071)	-0.0999 (0.0069)	-0.1006 (0.0069)
Garage	0.1089 (0.0135)	0.0754 (0.0131)	0.0721 (0.0134)
<i>Goodness of fit measures</i>			
$R^2$ within	0.6526	0.6752	0.6749
$R^2$ between	0.8339	.	.
$R^2$ overall	0.8451	0.8565	0.8566



**Table 7: Results of the block bootstrap exercise**

	I	II	III
<i>Actual levels</i>			
Constant	-5.657	-0.782	-1.808
$t$		-6.428	-2.976
$t^2$			-1.839
<i>Bootstrap critical values at different significant levels</i>			
<b>Constant</b>			
1 percent	-10.296	-9.761	-5.399
5 percent	-7.733	-7.385	-4.194
10 percent	-6.289	-6.698	-3.802
<b>Coefficient for <math>t</math></b>			
1 percent		-5.981	-4.439
5 percent		-4.014	-3.270
10 percent		-3.333	-2.789
<b>Coefficient for <math>t^2</math></b>			
1 percent			-3.459
5 percent			-2.483
10 percent			-1.974

**Table 8: Regression of fixed effects on the mortgage interest rates**

Variable	Estimate
Constant	-0.6460 (0.0696)
<i>Logarithm of the interest rate</i>	
Up to 1 year	0.2731 (0.0479)
Between 5 and 10 years	-0.9538 (0.1782)
Over 10 years	0.8358 (0.098)
<i>Logarithm of the interest rate - One period lagged</i>	
Between 5 and 10 years	0.2905 ( 0.1507)

**Table 9: Results taking account of different impacts of the development in mortgage interest rates.**

	I	II	III
<b>Difference-in-difference estimators</b>			
Constant	0.0019 (0.0016)	-0.0026 (0.0026)	-0.0117 (0.0038)
$t$ (x100)		-0.0891 (0.014)	-0.2541 (0.0543)
$t^2$ (x100)			-0.0070 (0.0018)
<b>Other results</b>			
<i>Results before the murder</i>			
Constant	-0.0013 (0.0013)	-0.0233 (0.0042)	0.0386 (0.0171)
$t$ (x100)		-0.0698 (0.0129)	-0.3507 (0.1134)
$t^2$ (x100)			0.0067 (0.0018)

**Table 10: Descriptive statistics for the register database.**

This table gives the number of houses, mean and standard deviation of the transactions as registered in the ‘Kadaster’, the Dutch register for (residential) property. Only houses that have been listed on Funda are included. ‘Listed price’ is the last price recorded on Funda, the online multi-listing service and our primary source of data. ‘Registered price’ is the transaction price as registered by the Kadaster. ‘Discount’ is the difference between the list price and transaction price.

Variable	Mean	Number of observations	Standard deviation
<i>All neighborhoods</i>			
Listed price	270609	10480	189267
Registered price	259526	10480	177453
Discount	4.17%	10480	4.74%
<i>Type I-neighborhoods</i>			
Listed price	171930	1366	50620
Registered price	165649	1366	52730
Discount	3.82%	1366	4.05%
<i>Type II-neighborhoods</i>			
Listed price	285399	9114	197728
Registered price	273596	9114	185221
Discount	4.23%	9114	4.83%

**Table 11: Estimation results for the duration model**

The variables  $v_0$  and  $v_1$  are mass points of the unobserved heterogeneity distribution and  $p$  is the probability that the unobserved heterogeneity term equals  $v_0$ .

Variable	Estimate
<i>House characteristics</i>	
Square footage	-0.0035 (0.0004)
Square footage <sup>2</sup> (x1000)	0.0027 (0.0006)
Apartment	-0.171 (0.043)
Garage attached	-0.178 (0.088)
<i>Time effects</i>	
1 <sup>st</sup> quarter <i>before</i> the murder	0.057 (0.065)
1 <sup>st</sup> quarter <i>after</i> the murder	0.032 (0.064)
2 <sup>nd</sup> quarter <i>after</i> the murder	0.275 (0.062)
3 <sup>rd</sup> quarter <i>after</i> the murder	0.213 (0.061)
4 <sup>th</sup> quarter <i>after</i> the murder	0.321 (0.062)
<i>Time effects × type I neighborhoods</i>	
1 <sup>st</sup> quarter <i>before</i> the murder	0.315 (0.215)
1 <sup>st</sup> quarter <i>after</i> the murder	0.416 (0.210)
2 <sup>nd</sup> quarter <i>after</i> the murder	0.345 (0.207)
3 <sup>rd</sup> quarter <i>after</i> the murder	0.294 (0.207)
4 <sup>th</sup> quarter <i>after</i> the murder	0.315 (0.207)
<i>Duration dependence, baseline: weeks 1-4</i>	
Weeks 5-8	1.131 (0.052)
Weeks 9-13	1.611 (0.050)
2 <sup>nd</sup> quarter	1.502 (0.049)
3 <sup>rd</sup> quarter	1.415 (0.056)
4 <sup>th</sup> quarter	1.339 (0.067)
After 4 <sup>th</sup> quarter	1.346 (0.087)
<i>Unobserved heterogeneity</i>	
$v_0$	-4.734 (0.178)
$v_1$	-
$p$	1 (·)

**Table 12: Buyers and sellers in type I neighborhoods.**

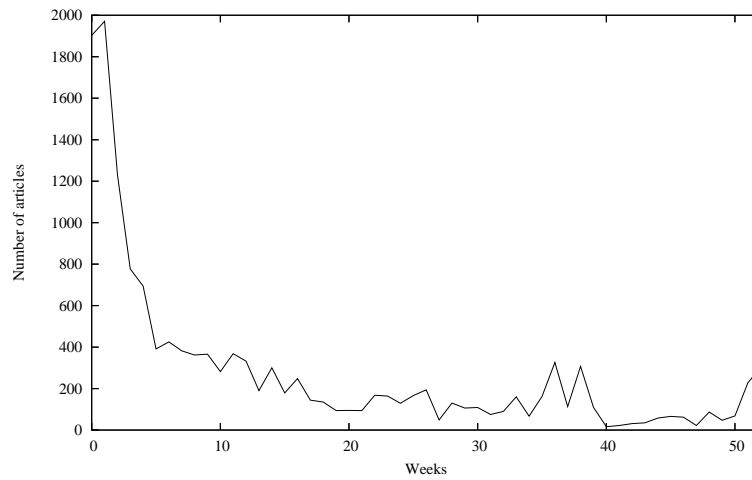
This table shows the percentage of buyers and sellers in type I neighborhoods that are of Turkish or Moroccan origin. Standard errors are between brackets.

	Total	Before murder	After murder	t-value of difference
Buyers	9.29 (0.45)	8.12 (0.74)	9.87 (0.56)	1.88
Sellers	4.25 (0.39)	5.14 (0.71)	3.75 (0.46)	-1.64

**Table 13: Buyers and sellers in type II neighborhoods.**

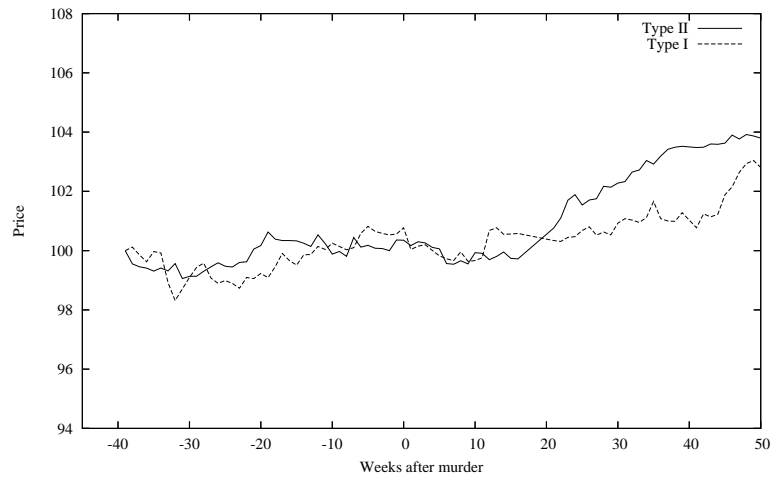
This table shows the percentage of buyers and sellers in type II neighborhoods that are of Turkish or Moroccan origin. Standard errors are between brackets.

	Total	Before murder	After murder	t-value of difference
Buyers	1.97 (0.26)	1.88 (0.41)	2.04 (0.35)	0.31
Sellers	0.59 (0.16)	0.81 (0.29)	0.42 (0.19)	-1.16



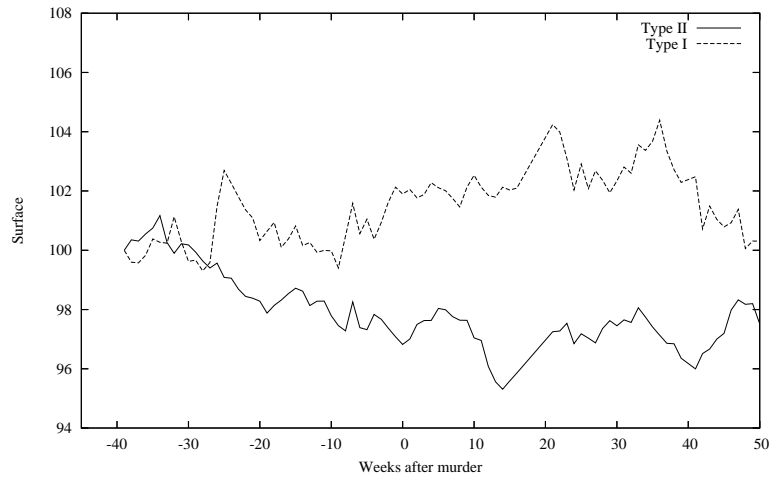
**Figure 1: The murder of Theo van Gogh in the Dutch media.**

This figure displays for any given week the number of newspaper articles found in all Dutch news sources on LexisNexis, that had the (Dutch) words ‘Gogh’ and ‘moord’ in one sentence. The unit at the  $x$ -axis is the number of weeks starting from the first week in 2004.

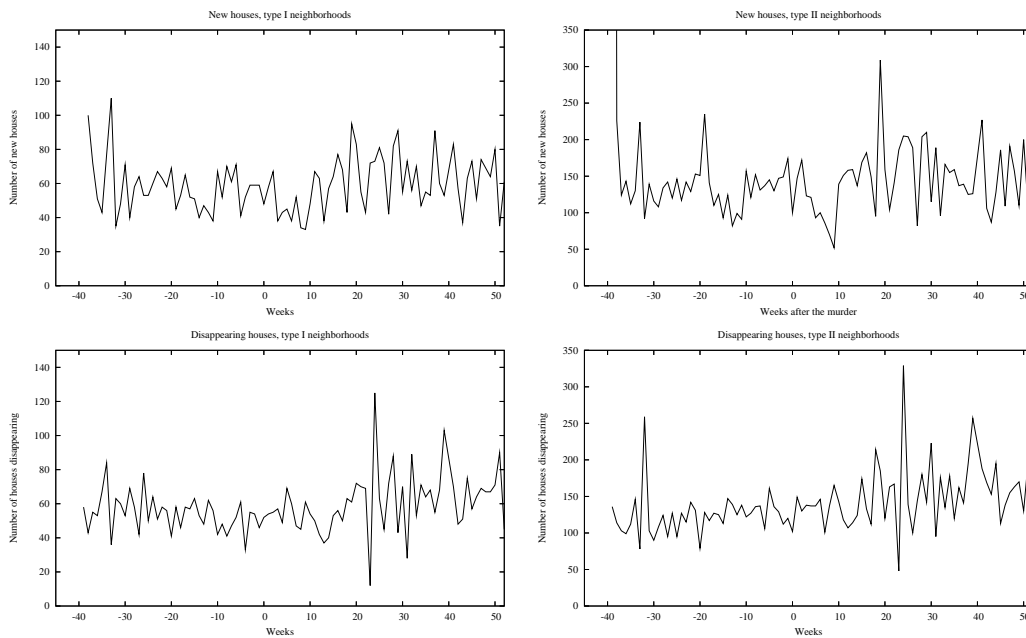


**Figure 2: Development of square footage prices in Amsterdam.**

The  $y$ -axis is measured as an index which equals 100 in week 6 of 2004 for both neighborhood types.

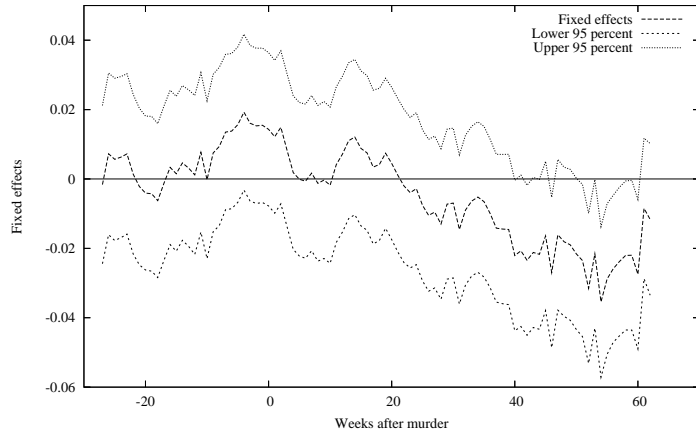


**Figure 3: Development of square footage in Amsterdam.**  
 The  $y$ -axis is measured as an index which equals 100 in week 6 of 2004 for both neighborhood types.



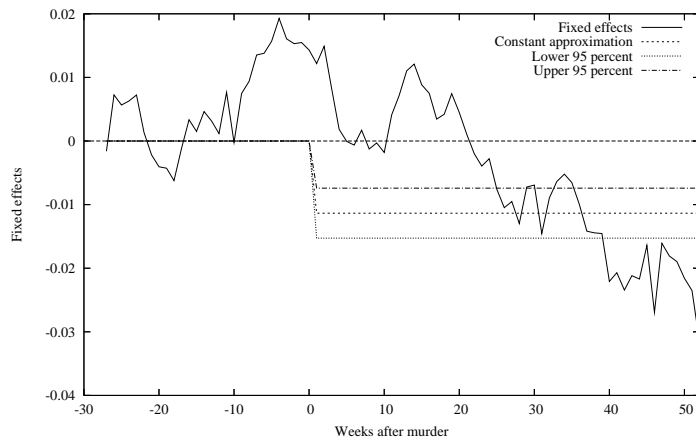
**Figure 4: Development of in and outflow of new houses at the Funda website.**





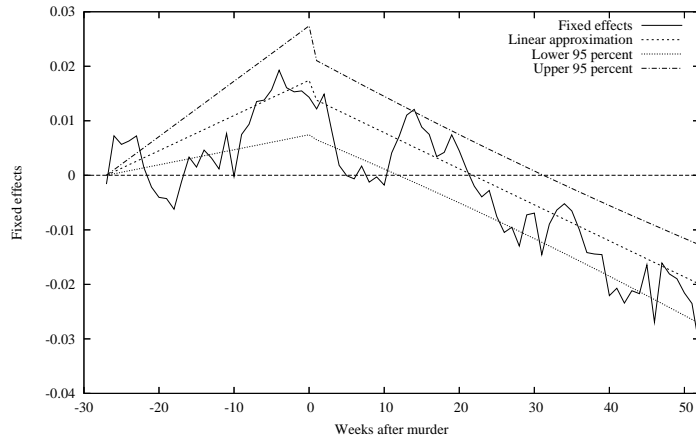
**Figure 5: Results for the fixed effects model**

This figure shows the results of the fixed effects model concerning the Van Gogh murder. The middle line is the point estimation for  $\lambda(t)$  in model (2), the upper and lower lines represent the upper and lower bounds of the 95 percent confidence interval.



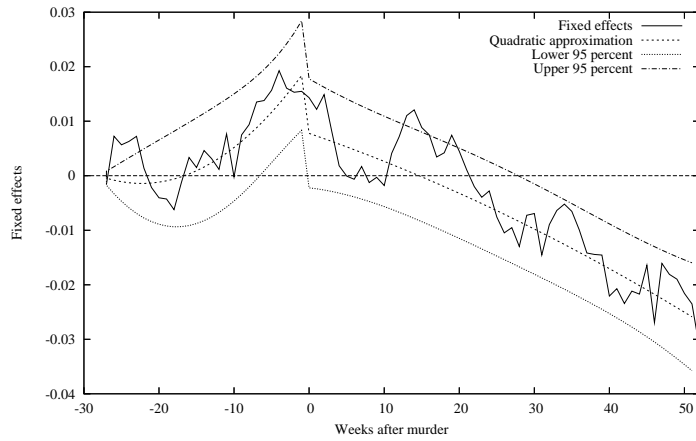
**Figure 6: Quality of the approximation: the constant model.**

This figure shows the results for the fixed effects estimation (solid line) together with the result for the approximating constant model (dashed line).



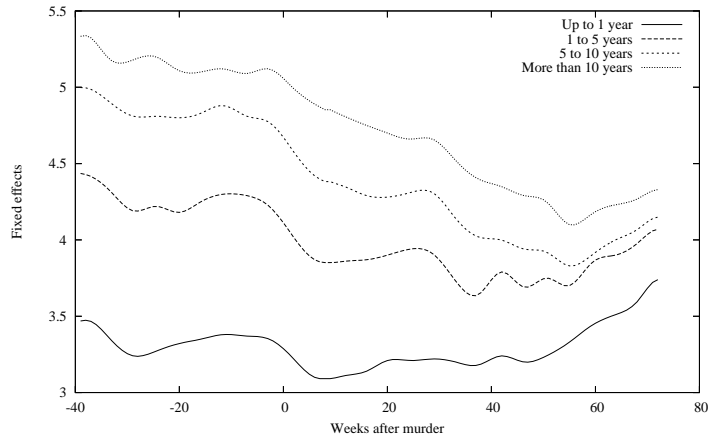
**Figure 7: Quality of the approximation: the linear model.**

This figure shows the estimation result for the linear model, together with the 95% confidence bands.



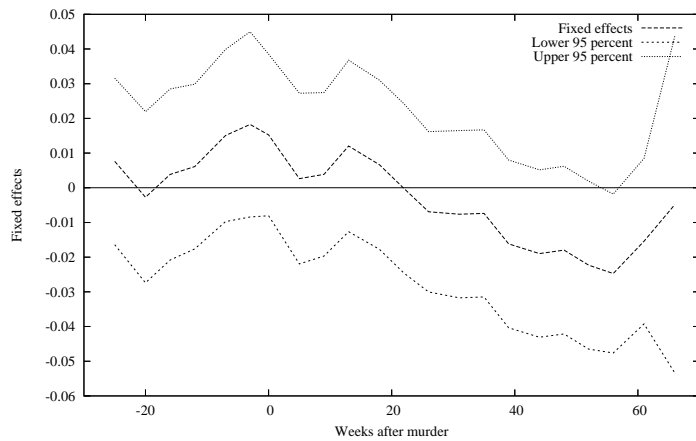
**Figure 8: Quality of the approximation: the quadratic model.**

This figure shows the estimation result for the quadratic model, together with the 95% confidence bands.



**Figure 9: Mortgage Interest Rates.**

This figure shows mortgage interest rates for 4 different maturities. Monthly rates are provided by the Netherlands Central Bank (DNB). The rates in the figure show the weekly interpolations obtained using cubic splines.

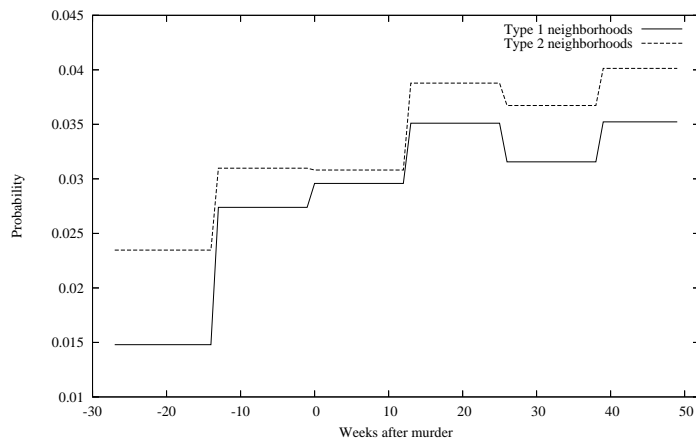


**Figure 10: Using only first week list price observations.**

This figure shows the result of the fixed effects estimation together with the 95% confidence bands when only the first-week list price observations are used.

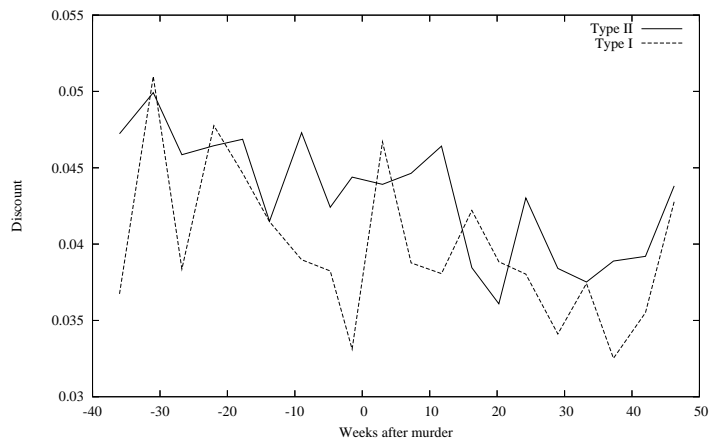
**Figure 11: The impact of the murder for different thresholds.**

This figure shows the estimated total impact of the murder on list prices at week 13, 26 and 52, respectively, relative to the selection criterion for type I neighborhoods in terms of the percentage of inhabitants with a Turkish or Moroccan surname. The lines represent the polynomial approximation to the piecewise linear estimates.



**Figure 12: Hazard rates.**

This figure shows the hazard rates of a house disappearing from the market. The values in the graph can be interpreted as the probability to sell in the first week. The unit at the  $x$ -axis is the number of weeks starting from the first week in 2004.



**Figure 13: Average discount over time.**

This figure shows the average discount between transaction price and list price. The discount is computed per month.