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## ABSTRACT

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

This paper estimates the impact of the murder of film maker Theo van Gogh on November 2, 2004, on listed house prices in Amsterdam with a unique dataset. We use an hedonic-market approach to show that general attitudes towards Muslim minorities were negatively affected by the murder. Specifically, we test for an effect on listed house prices in neighborhoods where more than 25% of the people belong to an ethnic minority from a Muslim country (type I). Relative to the other neighborhoods, house prices in type I neighborhoods decreased in 10 months by about average 3%, with a widening gap over time. The 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 neighborhoods. Finally, people belonging to the Muslim minority were more likely to buy and less likely to sell a house in a type I neighborhood after the murder than before.

JEL Classification: C31, C41, R21, R23, R31

Keywords: difference-in-differences, migration, terror, housing market

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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). Atteveldt et al. (2005) give evidence of a strong peak in the joint occurrence of the words “Islam”, “terror”, and “immigration” on any page of a Dutch national newspaper. This peak in news coverage is in the same order of magnitude as the coverage of the 9-11 events in the Netherlands.[1] 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 media attention 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.[2] 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 housing 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. [3]

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 eco-

[1]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.

[2]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.

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

nomics. The only other paper that applies DID to the 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, 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.

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 and 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). We do not find evidence that the time it took to sell a house increased after the murder.

The rest of this paper is structured 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 a 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 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:

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

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 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 Abowd, 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. Unlike a worker and his or her employment status, we cannot separate a house from its neighborhood, i.e., it is not possible to separately identify a house and a neighborhood fixed effect. One way to solve this problem is to take averages over the neighborhoods, measuring the treatment effect on the average ask price by neighborhood.[4] That is also 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 $t$

$$p^*_{jt} = \alpha + \beta x^*_{jt} + \nu^*_j + \mu(t) + \lambda(t) d_j + \varepsilon^*_{jt}, \tag{2}$$

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

$$p^*_{jt} = \frac{1}{N_{jt}} \sum_{i \in H_j} x_i \cdot FS_{it}, \tag{3}$$

and

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

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

$$N_{jt} = \sum_{i \in H_j} FS_{it}. \tag{6}$$

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

$$x^*_{jt} = \frac{1}{N_{jt}} \sum_{i \in H_j} x_i FS_{it}, \tag{7}$$

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

[4] 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.

fixed effects within a period and neighborhood. Note that it is assumed 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, after 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,

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

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

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. Hence, when $\zeta(t)$ equals zero, we can interpret $\eta(t)$ as the impact of the murder on the house prices in the type I neighborhoods.

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, 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.[5]

Note that our specification allows for possible learning effects. It is quite likely that the market only gradually learns about how housing prices are af-

[5]Details of this method are provided upon request.

fected. Hence, only comparing two stages (one before and one after the news was announced) might understate 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* which contains more than 70% of the supply of houses listed by real estate agents. 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 (ask price), the surface of the house and other features (like a garage) that may increase the value of the house. In addition we have information on whether the house is conditionally sold.[6] 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. Although for about 50% of the houses we have an indication about the week in which the conditional contract is signed (which is the date of agreement on the price), we are not able to verify this information 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.

We identify the date at which a house enters the market as the date it first

[6]Conditionally sold implies that the buyer and seller arranged a contract but that the buyer still has the possibility to cancel the transaction due to financial incapabilities.

appears on the Funda website. In our main analysis we identify the date a house leaves the market as the first week it does no longer appear at the website, conditionally on the observation that it does not re-appear. This implies that we do not take account of the additional information on whether the house is conditionally sold. The problem with the latter variable is that different real-estate agents use different strategies regarding the information that they provide to potential buyers. Some real estate agents do not provide this information since it might discourage bidders and these can be useful at the moment the transaction is canceled. It can be found that only 50 percent of the houses disappear from the website with an intermediate period in which it is conditionally sold. This is in contrast with common practice that private buyers of residential properties always use conditions in their contract. In addition, it is not uncommon that the buyer uses its right to cancel the transaction. We find that in 7 percent of the cases the house appears to be not sold after Funda reported it to be conditionally sold. Finally, we do not expect that our results are affected by the different definitions of the period at which a house is for sale since the average time the house is conditionally sold is relatively short. We find that the medium period in which the house is reported to be sold conditional on the event that this is reported equals 6 weeks. We expect this number to be an overestimate of the medium for all houses, since agents might be more likely to report the sold status when the contracted period is relatively long. We investigate this in our robustness checks in section 5.

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.[7] 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

[7]The fraction of other Muslim immigrants is negligible.

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.[8] 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 the next section.

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

## 4.1 Linear and Quadratic Trends

We use a constant, linear and quadratic approximation of $\lambda(t)$ for all the empirical exercises in this paper. Our baseline results are 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

[8] Many of the drug-related crimes take place in the more expensive touristic neighborhoods.

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, this is not due to 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.[9]

The results are visualized in Figure 7. In the third column of Table 2, we see that the estimates for a second degree polynomial are less precise. However, the parameters of the polynomial after the murder are still jointly significantly different from zero for both models, as the Wald statistics show. See Figure 8 for a graph of the results for the quadratic model. 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 having a garage has a positive impact.

## 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 5 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.

To examine the potential impact of sticky list prices, consider a model that takes 'menu costs' into account. 'Menu costs' is the term used for costs associated with a change in the public price of a good, see Mankiw (1985). Whatever the nature of these costs, monetary or non-monetary, direct or indirect, the presence

[9] 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.

of costs makes sellers reluctant to change the listed price immediately in response to a change in the market price of the house. To model such an effect, define $\dot{p}_{it}$ as the logarithm of the market price of house $i$ in period $t$ and assume the same specification for this house as in equation (1). In addition, denote the listed price by $p_{it}$, and let $\rho$ be an arbitrary constant. We have

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

where $\widetilde{t}(t)$ is the time period of the last price change which is defined as

$$\widetilde{t}(t+1) = \begin{cases} \widetilde{t}(t) \text{ if } \left(\left|P_{it} - \dot{P}_{it}\right| < \rho\right) \\ (t+1) \text{ if } \left(\left|P_{it} - \dot{P}_{it}\right| \geq \rho\right) \end{cases}$$

Sellers only change their prices if the difference between the actual and the desired price is sufficiently large. If this is the case, then the price is updated towards the present market price. Note that the model is identical to our original model when $\rho = 0$, whereas $\rho = \infty$ results in a model in which sellers never adjust their prices.

Now the question is whether this may cause potential problems when we want to use our model instead of the extended model presented here. Of course, estimation of equation (1) results in inconsistent estimates due to the correlation between the error term and the trend effects. However, we do not estimate this equation but instead estimate (2), using the averages over a neighborhood in a single period. Then, as long as there is no change in the composition of the durations of a single neighborhood over time, there is no correlation between the error term and the trend effects.

Still, 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, or the reluctance of sellers to adjust the list price downwards due to nominal loss aversion, see Genesove and Mayer (2001). The possible duration effect is examined in Subsection 5.4, but first we consider a correction based on taking only list prices of houses in the first week that they appear online. Although the same problems as above may apply here, because sellers might be slow to adjust their expectations of the sales price to market developments, the effect will at least be less severe. Again, we exclude all houses listed before week 17 in 2004 (since these houses do not have records on the attachment of a garage), which leaves us with 11,951 observations. The results of the estimation with only first-week prices are given in Table 6.

The results in Table 6 show that using first-week list prices does not have a big impact on our results. The overall effects in the constant specification increase to 1.3 percent, compared to 1.1% in the baseline estimation. For the linear specification we find an increase in the weekly loss in house prices.

## 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, the price difference after the murder, measured by $\lambda(t)$, 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 7. The results in the Table 7 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 per neighborhood directly, by including them in the estimation. I.e., we can rewrite equation 2 as

$$p^*_{jt} = \alpha + \beta x^*_{jt} + \nu^*_j + \mu(t) + \lambda(t)\gamma(s) + \varepsilon^*_{jt}, \tag{10}$$

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.

Using a polynomial representation for $\gamma$, Table 8 shows that a higher density of Turkish and Moroccan immigrants increases the impact of the murder. With a positive second order term, the impact is less than linear. Table 9 presents the results when we use a piecewise constant specification rather than a polynomial. 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. In order to illustrate the impact of the results listed in 8 and 9, we present the total impact after 13, 26 and 52 weeks in Figures 12, 13 and 14. We find that the patterns do not change that much from each other, but the total impact increases over time. Remarkable is the fact that the total impact after 52 weeks is much larger than we found before.

## 4.5 Withdrawals

Not all houses that are removed from the listing service get the status "conditional sale" before disappearing. Private observations tell us that some real estate agents just don't do this when selling a house. However, some house are delisted without being sold, which might distort the dependent variable in our model. To see if it is of influence, Table 10 presents the estimation results using only houses that have gotten the label "conditional sale" before disappearing from the website. We find that the constant effect, -0.8 percent, is slightly smaller than the 1.1 percent of the baseline estimation while the linear coefficient is now twice as large. At this point we can conclude that our general result that there was a relative drop in house prices in type I neighborhoods is robust but that with different definitions of the control group or selling date, the constant might be slightly smaller and the linear effects slightly larger (and vice versa).

## 4.6 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.

Betrand 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 15 lists the results of the block bootstrap exercise. We basically 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 for the original results 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. Nevertheless, our conclusions are not affected since the estimated t-value is still higher than the critical t-values as listed in the table.

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 Robustness and 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.

## 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 prefer the interest rate explanation above the murder explanation in the analysis of the possible change in house prices between neighborhoods. It implies that the interest rate can pick up some effects of the murder but it is impossible that the murder can pick up some effects of the changes in the interest rate. 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 3. 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 residuals of this regression are reported in Figure 10.

The results of the final step are listed in Table 4. 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 is 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.[10] 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 after the murder.

## 5.3 Changes in the Average Markup

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 official register for residential property ownership and transactions in The Netherlands. 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

[10]This situation would also indicate that something happened in the type I neighborhoods after the murder. However, these effects differ from our interpretation.

list price and transaction price.[11] 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, (iv) real-estate agents may have misspelled the street address when it comes to the addendum to the house number. In all, the houses listed on Funda account for 60% of all houses sold in Amsterdam in the period 2004-2005.

Some of the reasons listed above also hold for this data set but in addition to this, many of the unmatched houses were listed at the end of our observation window. This implies that these houses were not yet sold in 2005, which is the end of the observation window for the registered database.

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 12. 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 12 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 representation of the ultimate transaction price.

Figure 16 displays the level of the average discount per neighborhood over time. As can bee 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 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 markup seems large, it is not significant.

[11] 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.

## 5.4 Duration analysis

We have established a persistent negative price effect between type I and type II neighborhoods after the week of the Van Gogh murder. However, as noted in Section 4.2, 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).[12] The variable $v$ represents the unobserved characteristics of the house. We use the following specification for the hazard rate

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

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 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

[12]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.

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 15 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 the present literature on the duration of house sales usually assumes a Weibull distribution for the baseline hazard of the mixed proportional hazards model, see Rutherford et al. (2005) and Zuehlke (1987). For example, Zuehlke concludes that there is no duration dependence for occupied houses while there is positive duration dependence for vacant houses. A drawback of the use of a Weibull baseline hazards specification is that we cannot allow for duration dependence other than duration dependence that is monotonic, see Lancaster (1990). We find in our analysis that the duration dependence is not monotonic, so the use of a Weibull distribution would be inappropriate.

## 5.5 Effect on the Variance of List Prices

In the preceding sections we investigated the impact of the Van Gogh murder on the average list prices. However, it is quite possible that also the variance of list prices changed during this period owing to increased uncertainty. We replicated our main analysis using the variance of the house price instead of the mean. The results of this exercise are summarized in Figure 17. Surprisingly we find that the variance in the type I neighborhoods decreased compared to the type II neighborhoods. In addition we find that this decrease already started before the murder. We therefore conclude that market uncertainty did not increase after the murder.

# 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 thinks 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 assistants from both cultures that checked if a name was typical for their country of origin. Tables 13 and 14 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 13 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. In type II neighborhoods, the changes are a lot smaller, (an increase in net flow from 1% to 1.6%). 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 some evidence that segregation increased. The fraction of Moroccan/Turkish buyers increased and the fraction sellers decreased after the murder.

There are many idiosyncratic shocks which cause people to either buy or sell a house like family or labor market changes. On average they will not affect the market price but they do influence the number of transactions. The murder of Theo van Gogh was more of an aggregate shock which did not cancel out across households and therefore did affect prices. The number of people that changed houses because of this shock just appeared to be small relative to those who move because of idiosyncratic reasons.

# 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. 'Sold' is the variable that signals whether a house is conditionally sold. 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 |
|---|---|---|---|
| *All neighborhoods* | | | |
| 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 | |
| Sold | 23656 | 0.177 | |
| 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 |
| *Type I neighborhoods* | | | |
| 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 |
| *Type II neighborhoods* | | | |
| 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 |
|---|---|---|---|
| **A: Difference-in-difference estimators** | | | |
| Constant | -0.0113 | -0.0030 | -0.0101 |
| | (0.00201) | (0.00382) | (0.00560) |
| $t$ | · | -0.0013 | -0.0023 |
| | | (0.00020) | (0.00078) |
| $t^2$ (x 100) | · | · | -0.0047 |
| | | | (0.00256) |
| **Other results** | | | |
| *B: Results before the murder* | | | |
| Constant | 11.6299 | 11.6289 | 11.6300 |
| | (0.02281) | (0.02286) | (0.02281) |
| $t$ (x 100) | · | -0.0000 | -0.0002 |
| | | (0.00007) | (0.00024) |
| $t^2$ | · | · | 0.0006 |
| | | | (0.00087) |
| *C: Results before the murder, type I neighborhoods* | | | |
| $t$ | · | 0.0006 | -0.0005 |
| | | (0.00019) | (0.00068) |
| $t^2$ (x 100) | · | · | 0.0044 |
| | | | (0.00250) |
| *D: results after the murder* | | | |
| Constant | 0.0259 | 0.0007 | -0.0012 |
| | (0.00070) | (0.00134) | (0.00196) |
| $t$ | · | 0.0010 | 0.0009 |
| | | (0.00007) | (0.00027) |
| $t^2$ (x 100) | · | · | -0.0009 |
| | | | (0.00089) |
| *Control variables* | | | |
| Surface | 0.0924 | 0.0933 | 0.0933 |
| | (0.0011) | (0.00108) | (0.00108) |
| Surface$^2$ (x 1000) | -0.011 | -0.012 | -0.012 |
| | (0.0003) | (0.0003) | (0.0003) |
| Apartment | -0.1067 | -0.1144 | -0.1141 |
| | (0.0070) | (0.0068) | (0.0069) |
| Garage | 0.1087 | 0.0840 | 0.0832 |
| | (0.0136) | (0.0132) | (0.0132) |
| *Goodness of fit measures* | | | |
| $R^2$ within | 0.6521 | 0.6707 | 0.6708 |
| $R^2$ between | 0.8154 | · | · |
| $R^2$ overall | 0.8324 | 0.8362 | 0.8367 |

**Table 3: Regression of fixed effects on the mortgage interest rates**

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

**Table 4: Results taking account of different impacts of the development in mortgage interest rates.**

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

**Table 5: 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 6: 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 |
|---|---|---|---|
| **A: Difference-in-difference estimators** | | | |
| Constant | -0.013 | -0.001 | -0.001 |
| | ( 0.004) | ( 0.008) | ( 0.011) |
| $t$ | · | -0.005 | -0.012 |
| | | ( 0.002) | ( 0.007) |
| $t^2$ | · | · | -0.001 |
| | | | ( 0.001) |
| **Other results** | | | |
| *B: Results before the murder* | | | |
| Constant | 11.678 | 11.687 | 11.687 |
| | ( 0.023) | ( 0.024) | ( 0.023) |
| $t$ | · | 0.000 | -0.001 |
| | | ( 0.001) | ( 0.002) |
| $t^2$ | · | · | 0.000 |
| | | | ( 0.000) |
| *C: Results before the murder, type I neighborhoods* | | | |
| $t$ | · | 0.003 | -0.002 |
| | | ( 0.002) | ( 0.006) |
| $t^2$ | · | · | 0.001 |
| | | | ( 0.001) |
| *D: Results after the murder* | | | |
| Constant | 0.031 | -0.000 | -0.005 |
| | ( 0.001) | ( 0.003) | ( 0.004) |
| $t$ | · | 0.004 | 0.004 |
| | | ( 0.001) | ( 0.002) |
| $t^2$ | · | · | -0.000 |
| | | | ( 0.000) |
| *Control variables* | | | |
| Surface | 0.001 | 0.001 | 0.001 |
| | ( 0.000) | ( 0.000) | ( 0.000) |
| Surface$^2$ | -0.000 | -0.000 | -0.000 |
| | ( 0.000) | ( 0.000) | ( 0.000) |
| Apartment | -0.159 | -0.188 | -0.186 |
| | ( 0.014) | ( 0.013) | ( 0.013) |
| Garage | 0.113 | 0.090 | 0.088 |
| | ( 0.026) | ( 0.025) | ( 0.025) |

## Table 7: 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 |
|---|---|---|---|
| **A: Difference-in-difference estimates** | | | |
| Constant | -0.0134 | -0.0054 | -0.0124 |
| | (0.00241) | (0.00466) | (0.00685) |
| $t$ | · | -0.0009 | -0.0015 |
| | | (0.00025) | (0.00096) |
| $t^2$ (x 100) | · | · | -0.0038 |
| | | | (0.00314) |
| **Other results** | | | |
| *B: Results before the murder* | | | |
| Constant | 11.5249 | 11.5344 | 11.5393 |
| | (0.02316) | (0.02332) | (0.02328) |
| $t$ (x 100) | · | 0.0003 | -0.0003 |
| | | (0.00011) | (0.00040) |
| $t^2$ | · | · | 0.0022 |
| | | | (0.00147) |
| *C: Results before the murder, type I neighborhoods* | | | |
| $t$ | · | 0.0004 | -0.0004 |
| | | (0.00023) | (0.00084) |
| $t^2$ (x 100) | · | · | 0.0032 |
| | | | (0.00307) |
| *D: Results after the murder* | | | |
| Constant | 0.0284 | 0.0034 | 0.0014 |
| | (0.00116) | (0.00221) | (0.00325) |
| $t$ | · | 0.0006 | -0.0001 |
| | | (0.00012) | (0.00046) |
| $t^2$ (x 100) | · | · | -0.0020 |
| | | | (0.00150) |
| *E: Control variables* | | | |
| Surface | 0.0999 | 0.0994 | 0.0992 |
| | (0.0026) | (0.0025) | (0.0025) |
| Surface$^2$ (x 1000) | -0.013 | -0.013 | -0.013 |
| | (0.001) | (0.001) | (0.001) |
| Apartment | -0.1541 | -0.1705 | -0.1714 |
| | (0.0094) | (0.0094) | (0.0094) |
| Garage | -0.0053 | -0.0155 | -0.0165 |
| | (0.0193) | (0.0190) | (0.01906) |
| *Goodness of fit measures* | | | |
| $R^2$ within | 0.6764 | 0.6825 | 0.6827 |
| $R^2$ between | 0.7162 | · | · |
| $R^2$ overall | 0.7747 | 0.7808 | 0.7819 |

## Table 8: Minority percentages, polynomial

This table shows the same results as before, but with a direct estimate of the impact of $s$, the fraction Musim population, on the price difference between type I and type II neighborhoods. The variables $s$, $s^2$, etc. refer to the order of the polynomial used to model the relation the minority percentage and the average list price per neighborhood.

| | I | II | III |
|---|---|---|---|
| **Difference-in-difference estimates** | | | |
| $s$ | 0.0037 | 0.0074 | 0.0109 |
| | (0.00070) | (0.00097) | (0.00135) |
| $s^2$ | -0.0004 | -0.0006 | -0.0008 |
| | (0.00006) | (0.00009) | (0.00013) |
| $s^3$ | 0.0000 | 0.0000 | 0.0000 |
| | (0.00000) | (0.00000) | (0.00000) |
| $s^4$ | -0.0000 | -0.0000 | -0.0000 |
| | (0.00000) | (0.00000) | (0.00000) |
| $t \times s$ (x 100) | · | -0.0173 | -0.0614 |
| | | (0.00268) | (0.01061) |
| $t \times s^2$ (x 100) | · | 0.0009 | 0.0035 |
| | | (0.00024) | (0.00098) |
| $t \times s^3$ (x 100) | · | -0.0000 | -0.0001 |
| | | (0.00001) | (0.00003) |
| $t \times s^4$ (x 100) | · | 0.0000 | 0.0000 |
| | | (0.00000) | (0.00000) |
| $t^2 \times s$ (x 1000) | · | · | 0.0080 |
| | | | (0.00192) |
| $t^2 \times s^2$ (x1000) | · | · | -0.0004 |
| | | | (0.00018) |
| $t^2 \times s^3$ (x 1000) | · | · | 0.0000 |
| | | | (0.00001) |
| $t^2 \times s^4$ (x1000) | · | · | -0.0000 |
| | | | (0.00000) |
| **Other results** | | | |
| *Results before the murder* | | | |
| Constant | 11.6211 | 11.6213 | 11.6238 |
| | (0.02264) | (0.02286) | (0.02291) |
| $t$ (x 100) | · | -0.0002 | -0.0007 |
| | | (0.00008) | (0.00026) |
| $t^2$ | · | · | 0.0163 |
| | | | (0.00860) |
| *Results before the murder, type I neighborhoods* | | | |
| $t$ | · | 0.0000 | 0.0000 |
| | | (0.00001) | (0.00001) |
| $t^2$ (x 1000) | · | · | -0.0000 |
| | | | (0.00001) |
| *Results after the murder* | | | |
| Constant | 0.0210 | -0.0158 | -0.0297 |
| | (0.00179) | (0.00275) | (0.00379) |
| $t$ | · | 0.0017 | 0.0028 |
| | | (0.00011) | (0.00037) |
| $t^2$ (x 1000) | · | · | -0.0436 |
| | | | (0.00995) |

## Table 8, continued

| | I | II | III |
|---|---|---|---|
| *Control variables* | | | |
| Surface | 0.0927 | 0.0935 | 0.0934 |
| | (0.00111) | (0.00107) | (0.00107) |
| Surface$^2$ (x 1000) | -0.0011 | -0.0012 | -0.0012 |
| | (0.00003) | (0.00003) | (0.00003) |
| Apartment | -0.0994 | -0.1074 | -0.1077 |
| | (0.00706) | (0.00680) | (0.00683) |
| Garage | 0.1073 | 0.0870 | 0.0887 |
| | (0.01355) | (0.01335) | (0.01337) |
| *Goodness of fit measures* | | | |
| $R^2$ within | 0.6529 | 0.6743 | 0.6743 |
| $R^2$ between | 0.8378 | . | . |
| $R^2$ overall | 0.8450 | 0.8549 | 0.8553 |

## Table 9: 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 precentage 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 |
|---|---|---|---|
| **Difference-in-difference estimators** | | | |
| 5-10 percent | 0.0177 | 0.0209 | 0.0259 |
| | (0.00180) | (0.00250) | (0.00345) |
| 10-15 percent | -0.0157 | 0.0106 | 0.0225 |
| | (0.00226) | (0.00322) | (0.00441) |
| 15-20 percent | -0.0248 | 0.0020 | 0.0082 |
| | (0.00307) | (0.00436) | (0.00592) |
| 20-25 percent | -0.0029 | -0.0014 | -0.0063 |
| | (0.00262) | (0.00391) | (0.00524) |
| 25-30 percent | 0.0049 | 0.0029 | 0.0136 |
| | (0.00434) | (0.00636) | (0.00862) |
| 30-35 percent | -0.0204 | -0.0052 | -0.0075 |
| | (0.00390) | (0.00590) | (0.00799) |
| 35-40 percent | -0.0198 | 0.0030 | 0.0074 |
| | (0.00327) | (0.00501) | (0.00655) |
| over 40 percent | -0.0004 | 0.0115 | 0.0003 |
| | (0.00424) | (0.00630) | (0.00833) |
| $t\times$ 5-10 percent (x 100) | · | -0.0297 | -0.0931 |
| | | (0.00727) | (0.02733) |
| $t\times$ 10-15 percent (x 100) | · | -0.1363 | -0.2814 |
| | | (0.01002) | (0.03497) |
| $t\times$ 15-20 percent (x 100) | · | -0.1576 | -0.2391 |
| | | (0.01374) | (0.04677) |
| $t\times$ 20-25 percent (x 100) | · | -0.0837 | -0.0392 |
| | | (0.01426) | (0.04056) |
| $t\times$ 25-30 percent (x 100) | · | -0.0876 | -0.2086 |
| | | (0.02052) | (0.06683) |
| $t\times$ 30-35 percent (x 100) | · | -0.1700 | -0.1372 |
| | | (0.02104) | (0.06261) |
| $t\times$ 35-40 percent (x 100) | · | -0.2075 | -0.2408 |
| | | (0.02061) | (0.05270) |
| $t\times$ over 40 percent (x 100) | · | -0.1859 | -0.0292 |
| | | (0.02475) | (0.06528) |
| $t^2\times$ 5-10 percent (x 1000) | · | · | 0.0118 |
| | | | (0.00498) |
| $t^2\times$ 10-15 percent (x1000) | · | · | 0.0278 |
| | | | (0.00636) |
| $t^2\times$ 15-20 percent (x 1000) | · | · | 0.0168 |
| | | | (0.00846) |
| $t^2\times$ 20-25 percent (x1000) | · | · | -0.0045 |
| | | | (0.00727) |
| $t^2\times$ 25-30 percent (x 1000) | · | · | 0.0286 |
| | | | (0.01206) |
| $t^2\times$ 30-35 percent (x1000) | · | · | 0.0032 |
| | | | (0.01137) |
| $t^2\times$ 35-40 percent (x 1000) | · | · | 0.0178 |
| | | | (0.00981) |
| $t^2\times$ over 40 percent (x1000) | · | · | -0.0114 |
| | | | (0.01187) |

## Table 9, continued

| | I | II | III |
|---|---|---|---|
| **Other results** | | | |
| *Results before the murder* | | | |
| Constant | 11.6154 | 11.6070 | 11.6111 |
| | (0.02252) | (0.02262) | (0.02264) |
| $t$ (x 100) | · | -0.0002 | -0.0006 |
| | | (0.00008) | (0.00023) |
| $t^2$ | · | · | 0.0134 |
| | | | (0.00805) |
| *Results before the murder, type I neighborhoods* | | | |
| $t$ | · | 0.0000 | 0.0000 |
| | | (0.00000) | (0.00001) |
| $t^2$ (x 1000) | · | · | -0.0000 |
| | | | (0.00000) |
| *Results after the murder* | | | |
| Constant | 0.0256 | -0.0052 | -0.0102 |
| | (0.00096) | (0.00167) | (0.00233) |
| $t$ | · | 0.0014 | 0.0014 |
| | | (0.00008) | (0.00028) |
| *Control variables* | | | |
| $t^2$ (x 1000) | · | · | -0.0215 |
| | | | (0.00849) |
| Surface | 0.0930 | 0.0943 | 0.0941 |
| | (0.00111) | (0.00108) | (0.00108) |
| Surface$^2$ (x 1000) | -0.0011 | -0.0012 | -0.0012 |
| | (0.00003) | (0.00003) | (0.00003) |
| Apartment | -0.0972 | -0.0999 | -0.1006 |
| | (0.00710) | (0.00691) | (0.00694) |
| Garage | 0.1089 | 0.0754 | 0.0721 |
| | (0.01352) | (0.01312) | (0.01335) |
| *Goodness of fit measures* | | | |
| $R^2$ within | 0.6526 | 0.6752 | 0.6749 |
| $R^2$ between | 0.8339 | · | · |
| $R^2$ overall | 0.8451 | 0.8565 | 0.8566 |

## Table 10: Conditioning on the explicit conditional sale.

This table shows the neighborhood-effects using only the houses that are ultimately conditionally sold. 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 |
|---|---|---|---|
| **A: Difference-in-difference estimators** | | | |
| Constant | -0.0081 | 0.0061 | -0.0039 |
| | (0.0031) | (0.0063) | (0.0092) |
| $t$ | · | -0.0023 | -0.0044 |
| | | (0.0003) | (0.0013) |
| $t^2$ (x 100) | · | · | -0.0075 |
| | | | (0.0041) |
| **Other results** | | | |
| *B: Results before the murder* | | | |
| $t$ | 11.59 | 11.58 | 11.58 |
| | (0.024) | (0.024) | (0.024) |
| $t^2$ (x 100) | · | -0.0005 | 0.0003 |
| | | (0.0001) | (0.0004) |
| Constant | · | · | -0.0030 |
| | | | (0.0014) |
| *C: Results before the murder, type I neighborhoods* | | | |
| $t$ | · | 0.0011 | -0.0008 |
| | | (0.0003) | (0.0011) |
| $t^2$ (x 100) | · | · | 0.0075 |
| | | | (0.0040) |
| *D: Results after the murder* | | | |
| Constant | 0.0224 | 0.0055 | 0.0014 |
| | (0.0011) | (0.0022) | (0.0032) |
| $t$ | · | 0.0014 | 0.0031 |
| | | (0.0001) | (0.0004) |
| $t^2$ (x 100) | · | · | 0.0013 |
| | | | (0.0014) |
| *E: Control variables* | | | |
| Surface | 0.0907 | 0.0919 | 0.0920 |
| | (0.00109) | (0.00109) | (0.00109) |
| Surface$^2$ (x 1000) | -0.010 | -0.010 | -0.010 |
| | (0.0003) | (0.0003) | (0.0003) |
| Apartment | -0.0463 | -0.0470 | -0.0441 |
| | (0.00750) | (0.00746) | (0.0075) |
| Garage | 0.1026 | 0.1077 | 0.1082 |
| | (0.01290) | (0.01284) | (0.0128) |
| *Goodness of fit measures* | | | |
| $R^2$ within | 0.6510 | 0.6573 | 0.6581 |
| $R^2$ between | 0.8152 | 0.7694 | · |
| $R^2$ overall | 0.8036 | 0.8072 | 0.8079 |

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

**Table 12: 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 registerd by the Kadaster. 'Discount' is the difference between the list price and transaction price.

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

**Table 13: 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 | 8.12 | 9.87 | 1.88 |
| | (0.45) | (0.74) | (0.56) | |
| Sellers | 4.25 | 5.14 | 3.75 | -1.64 |
| | (0.39) | (0.71) | (0.46) | |

**Table 14: 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 | 1.88 | 2.04 | 0.31 |
| | (0.26) | (0.41) | (0.35) | |
| Sellers | 0.59 | 0.81 | 0.42 | -1.16 |
| | (0.16) | (0.29) | (0.19) | |

**Table 15: Results of the block bootstrap exercise**

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

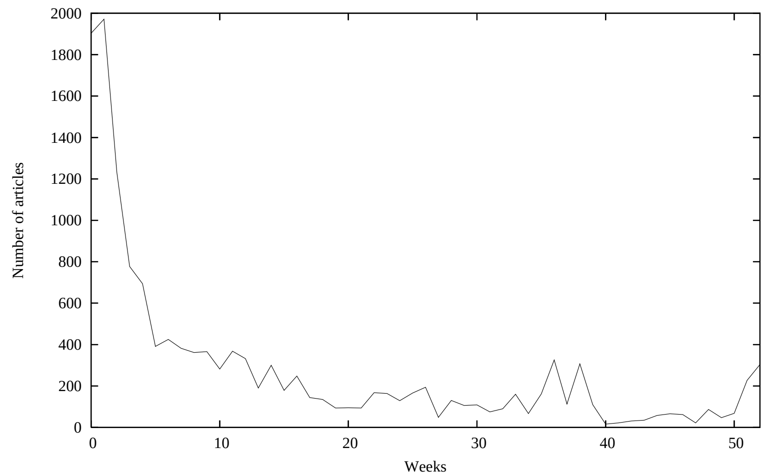



**Figure 1: The murder of Theo van Gogh in the Dutch media.**

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.

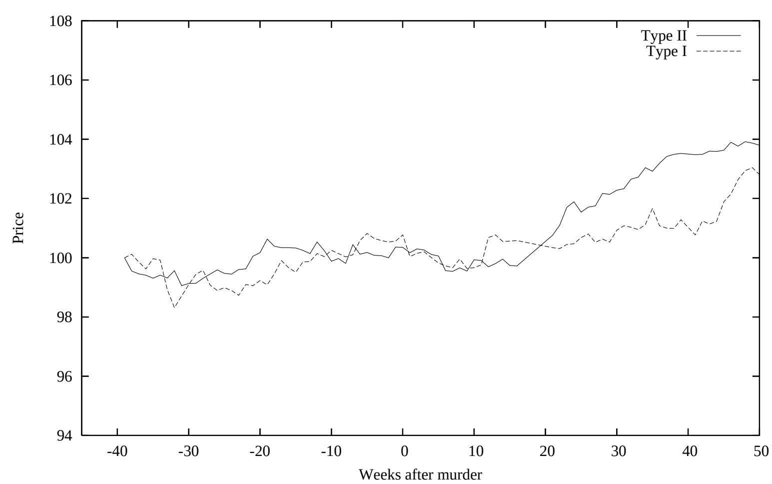



**Figure 2: Development of square footage prices in Amsterdam.**

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

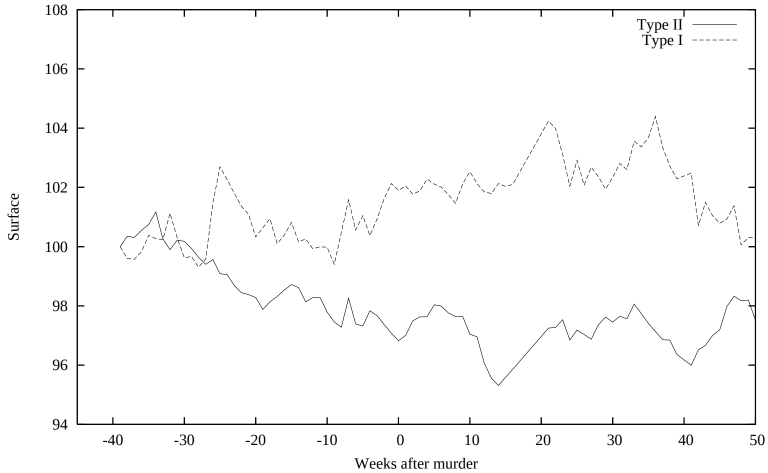



**Figure 3: Development of square footage in Amsterdam.**

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

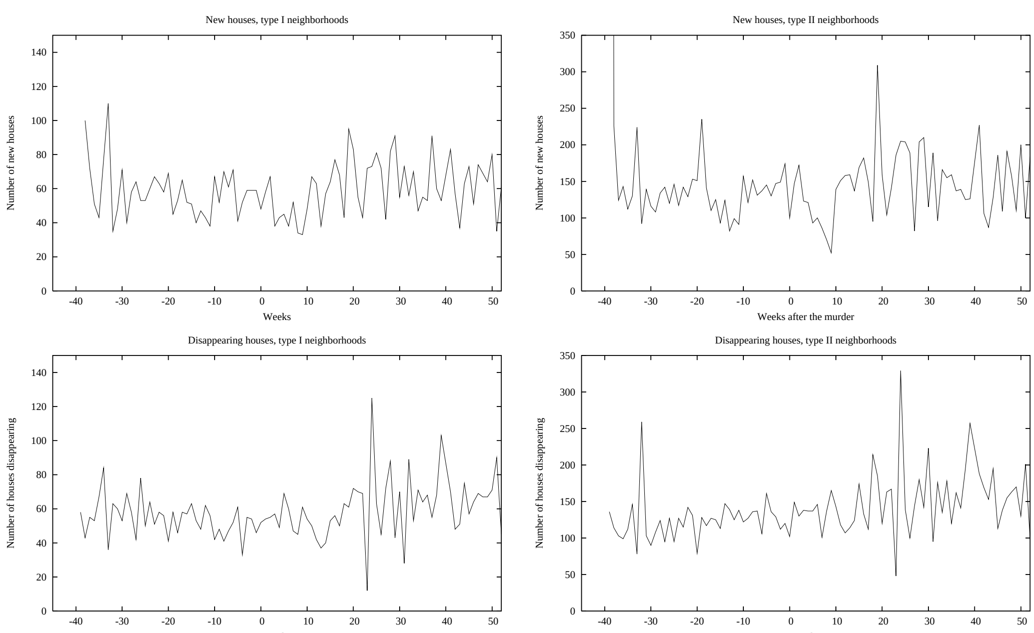



**Figure 4: Development of in and outflow of new houses at the Funda website.**

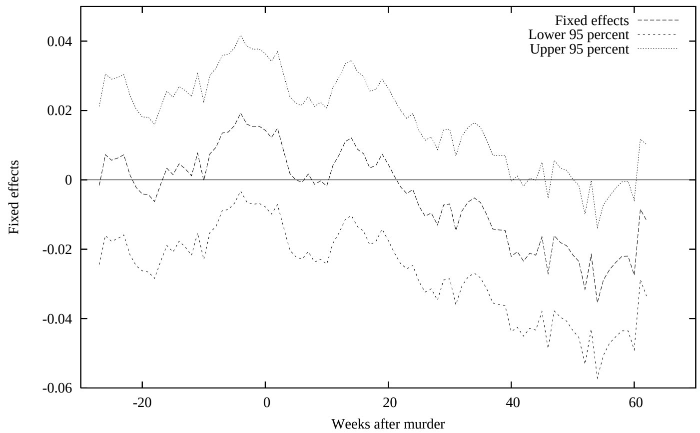



**Figure 5: Results for the fixed effects model**

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.

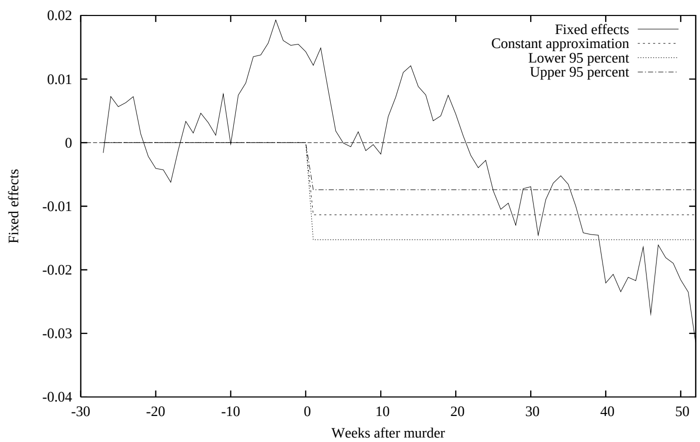



**Figure 6: Quality of the approximation: the constant model.**

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

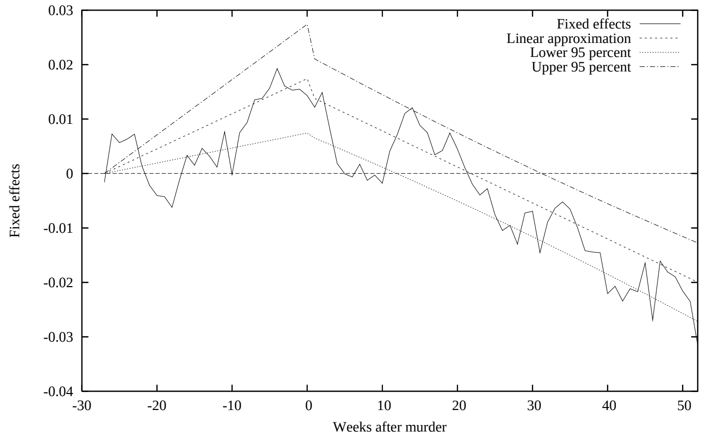



**Figure 7: Quality of the approximation: the linear model.**

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

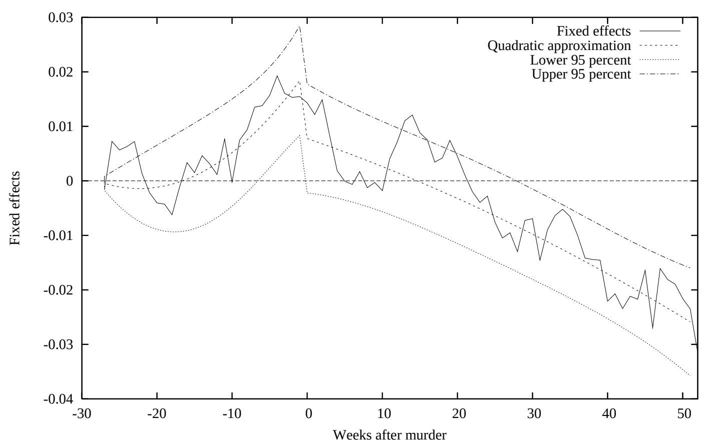



**Figure 8: Quality of the approximation: the quadratic model.**

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

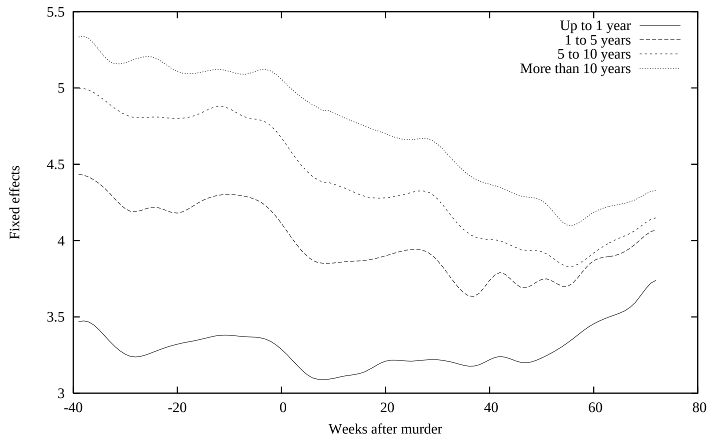



**Figure 9: Mortgage Interest Rates.**

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.

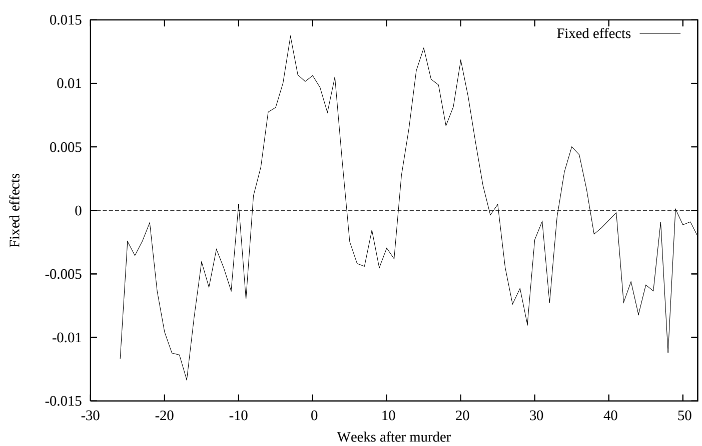



**Figure 10: Residuals of the fixed effects regression over time.**

This figure shows the residuals of estimated fixed effect on the interest rate over time.

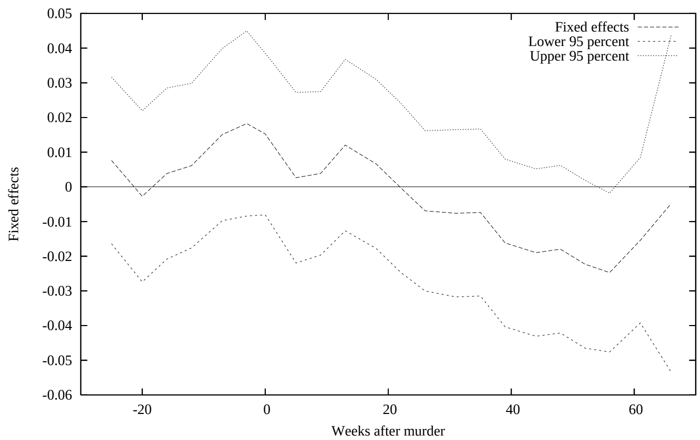



**Figure 11: Using only first week list price observations.**

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.

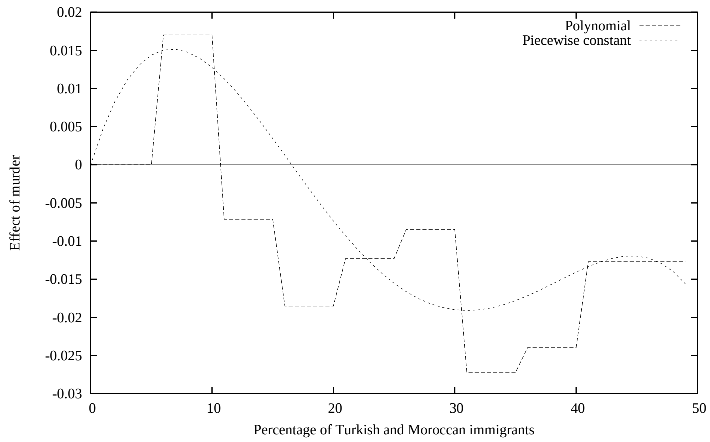



**Figure 12: The impact of the murder after 13 weeks.**

This figure shows the estimated total impact of the murder on list prices at week 13 relative to the selection criterion for type I neighborhoods in terms of the percentage of inhabitants with a Turkish or Moroccan surname.

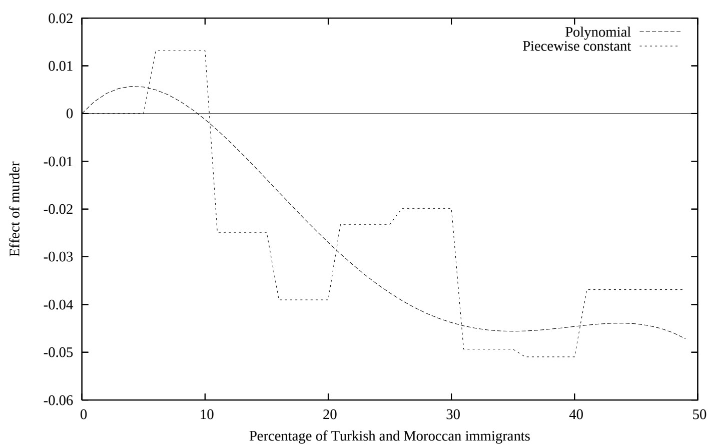
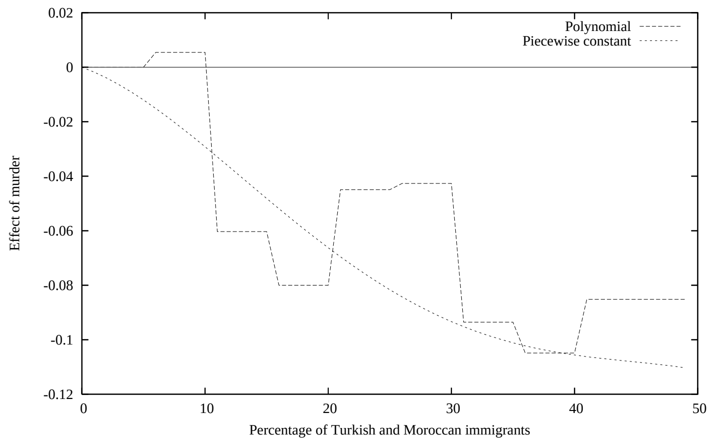


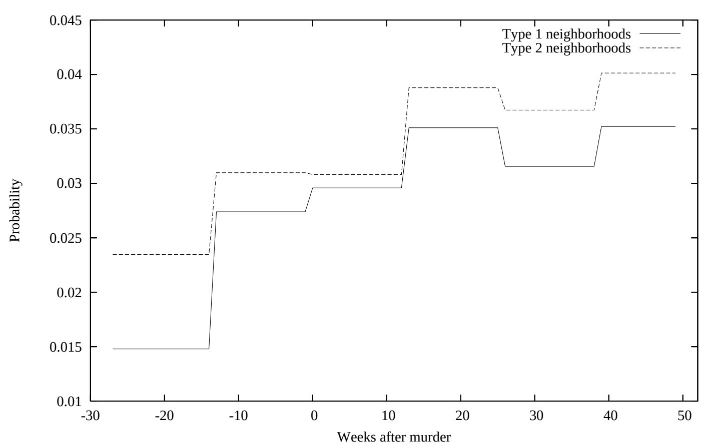

**Figure 13: The impact of the murder after 26 weeks.**

This figure shows the estimated total impact of the murder on list prices at week 26 relative to the selection criterion for type I neighborhoods in terms of the percentage of inhabitants with a Turkish or Moroccan surname.




## Figure 14: The impact of the murder after 52 weeks.

This figure shows the estimated total impact of the murder on list prices at week 52 relative to the selection criterion for type I neighborhoods in terms of the percentage of inhabitants with a Turkish or Moroccan surname.




## Figure 15: 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.

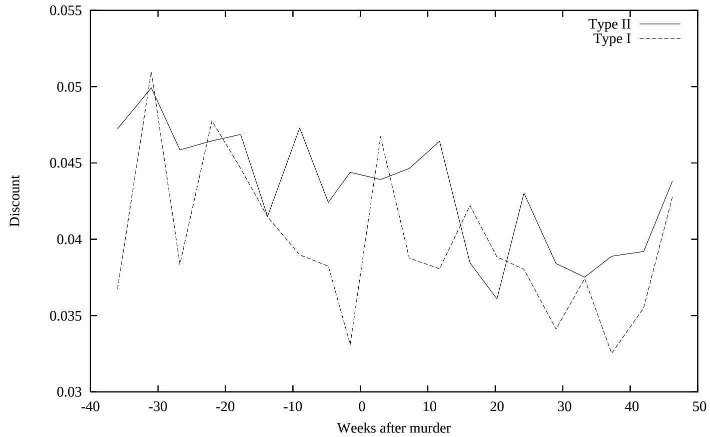



**Figure 16: Average discount over time.**

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

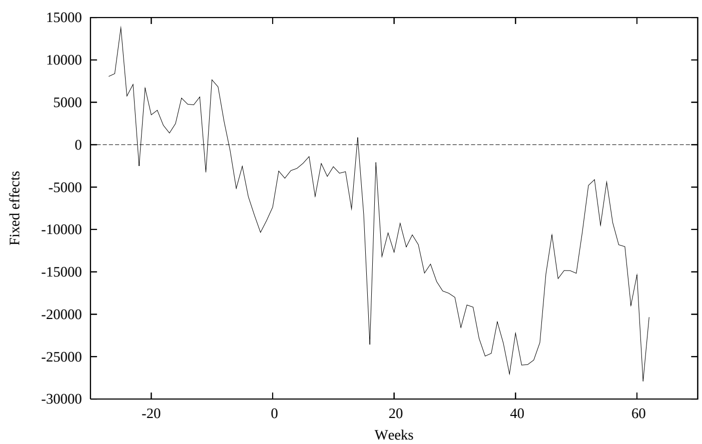



**Figure 17: Impact of the murder on the variance.**

This figure shows the result of the fixed-effects estimation using the cross-sectional variance per neighborhood as the dependent variable.