Terrorism and attitudes towards minorities: the effect of the Theo van Gogh murder on house prices in Amsterdam

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Abstract

Does fundamentalist-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 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 3%, with a widening gap over time. Our results are robust to several adjustments including using synthetic control groups. 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 neighborhood after the murder than before.

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1 Introduction

On the morning of November 2, 2004, the tv-show host and film maker Theo van Gogh was shot in an Amsterdam street. The killer was a 26-year old Dutchman of Moroccan origin, and a recent convert to radical Islam, who considered Van Gogh an 'enemy of Islam'. He also attached a farewell letter and a death threat to another controversial public figure, Hirsi Ali, on the dead body. The murder featured prominently in national and international media and spurred a nation-wide outrage. In the weeks following the murder, mosques and, to a lesser extent, churches, were targets of violence. Many feared an escalation in tensions between the different communities in Dutch society.[1]

Survey evidence right after the murder suggests that people believed the murder affected intergroup relations, see SCP (2006). While only 33% responded that the murder directly affected themselves, 86% believed that the murder had an effect on the relationship between Muslims and non-Muslims. In this paper we investigate whether the change in public opinion had an impact on house prices. The survey evidence suggests that it is important to take into account that a potential buyer is not just valuing the direct benefits that follow from owning a house, but also takes into account the resale value, which depends on the expected preferences of future buyers. We expect that in particular this resale value is affected by the murder.

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. We find that after the murder, the difference in house prices between type I and type II neighborhoods increased statistically significantly. The relative house prices in type I neighborhoods decreased on average by about 2.4 percent in the year after the murder. Over time, the average decrease in the house prices was about 0.07 percent per week in the period after the murder. Besides using type II neighborhoods as controls we also created synthetic-control-neighborhoods, see Abadie, Diamond and Hainmueller (2007). The idea is to create a control group for each type I neighborhood that matches the pre-murder trend of that type I neighborhood as close as possible. We then sample placebo

[1]About 5% of the Dutch population is Muslim and the majority (69%) of them comes from Turkey (38%) and Morocco (31%), 90% of the Turkish and 81% of the Moroccans are registered Muslims. The largest groups of non-western immigrants in the Netherlands are Surinam, Indonesian, Turkish and Moroccan. Even though Surinam and Indonesian immigrants have their ethnic background from countries with a high concentration of Muslims, less than 5% of the Dutch Muslims comes from those countries, see Statistics Netherlands (www.cbs.nl).

neighborhoods from the set of control neighborhoods and show that in more than 95% of the placebo cases, the trend effect of the murder is weaker than for the actual type I neighborhood. Finally, we treat the fraction of Muslims to be a continuous variable and find that the effects are strongest in the neighborhoods with the highest fractions of Muslims.

The difference-in-difference (DID) approach that we use to identify the impact of the murder has become very popular in labor and development economics. There are few papers that apply DID to the housing market, examples include Abadie and Dermisi (2006) and Chay and Greenstone (2005).[2] Many of the problems related to this method are less severe for the housing market than for other markets. 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. DID methods have often been applied to study policy changes but it is often difficult to establish whether the policy changes are really exogenous.

We show that most sellers of type I neighborhoods moved out of Amsterdam and that too few of them moved to type II neighborhoods to affect house prices there. 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.[3]

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. 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

[2]Black (1999) does not take differences in time but in space. She measures the price of good schools by comparing prices of similar houses at both sides of a school district border.

[3]Bisin, Patacchini, Verdier, and Zenou (2008) focus on the differences in cultural integration between Muslim and non-Muslim immigrants and show that this does not depend on the degree of segregation.

the murder.

Aslund and Rooth (2005) find for Sweden that the 9-11 events affected the attitudes toward immigrants from the Middle-East negatively but not the labor market state of this group. Ahmed and Hammarstedt (2008) give evidence that people with Arabic/ Muslim names are discriminated in the Swedish housing market. 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.

The decrease in relative prices over time can be explained by the fact that home owners face a "beauty contest" problem for the resale value of their house and that agents have to learn over time about its value. This is of course not trivial because the resale value depends on the expected valuation of future buyers and sellers.

Our paper contributes to the literature on the effect of immigration on house prices and neighborhood dynamics, see for example Cutler, Glaeser and Vigdor (1999) and Saiz and Wachter (2006). Benabou (1996) and Bayer, Ferreira and McMilan (2007) 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 with house prices after an unexpected shock in attitudes towards immigrants.

Our work is also related to the literature on 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 vacancy rates 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. 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.

The paper is organized as follows. Section 2 discusses briefly the hedonic market approach. Section 3 discusses our identification strategy and our empirical specification. Section 4 describes the data and Section 5 discusses the main results on prices and presents additional evidence on compositional shifts of the neighborhoods. Section 6 contains robustness checks and some extensions. Section 7 concludes.

2 Theory

The conceptual framework that we have in mind is the Hedonic market model of Tinbergen (1956) and Rosen (1974).[4] According to this view, a house is a commodity that consists of many attributes like size, neighborhood and the number of rooms. Following Rosen (1974) we can describe those attributes by a vector, $z = (z_1, ..., z_n)$ where each attribute has a value which we do not observe directly but we do observe the market price, $p(z) = p(z_1, ..., z_n)$. This price is the result of a set of "kissing" offer and expenditure curves of sellers and buyers with different tastes. In this framework, we can interpret the murder of Theo van Gogh and the enormous media attention as follows. Suppose that there is a shock that makes it less attractive to live in type I neighborhoods for some individuals but that others are unaffected by this shock. The individuals who are affected by the shock are willing to pay more to live in a type II neighborhood or outside Amsterdam relative to living in a type I neighborhood than before the shock. Therefore, the price for houses in type II neighborhoods will go up (relative to the price in type I neighborhoods) if enough people are sufficiently affected by the shock. From our data we cannot infer whether this is due to the fact that seller's offer curves and or the buyers value functions change. Both result in a similar outcome on equilibrium prices: the difference between the average price in type II and type I neighborhoods increases after the shock and individuals who are

[4] See also Roback (1982) for a specific example of the housing market.

unaffected or less affected by the shock will buy houses in type I neighborhoods while individuals who are strongly affected by the shock will sell houses in type I neighborhoods. We show that Amsterdam is not a closed marked because most type I sellers leave Amsterdam and the number of type I sellers that buys a house in a type II neighborhood is too small relative to the size of type II neighborhoods to affect the price of houses in type II neighborhoods.[5]

The fact that houses have a speculative component makes things a bit more complicated than in the standard hedonic models. An individual might be perfectly happy to live in a type I neighborhood but if she believes that a large fraction of the market values type I neighborhoods less after the murder, she will also be less willing to live in a type I neighborhood. In other words, the offer and expenditure curves depend on the expected valuations of other market participants. It is therefore likely that there will be learning going on about the effect of the shock over time. In Kyle (1985) where all informed agents have the same information, this learning goes fast but Foster and Viswanathan (1996) show that in environments where traders have heterogeneous pieces of information, prices may adjust slowly because they play a wait (for information) game. In the context of our setting, it is likely that the information about the general attitudes on Muslims after the murder was heterogeneous. Ellison and Mullin (2001) also give evidence that important events like President Clinton's health care reform proposal had a gradual effect on pharmaceutical stock prices. We therefore believe that it is important to look at the movement of house price effects over time.

Finally note that the price effect can be accompanied by an increase in the supply of houses in type I neighborhoods but if markets function well this need not be the case. Similarly, the duration that houses are for sale before and after the murder in the various neighborhoods is also informative about the functioning of the market, i.e. how fast house prices absorb new information. In a well functioning market, an unexpected shock mainly affects prices and not the duration that houses are for sale.

3 Research design

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

[5]We find that 95% of the sellers in type I neighborhoods is native Dutch, most of them leave Amsterdam while most of the Turkish and Moroccan sellers remain in type I neighborhoods.

use the following formulation:

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

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.* square feet, the type (apartment, family home, etc.) and additional characteristics, such as whether there is a garage attached to the house. Following a long tradition in real estate economics, we treat the shadow prices on the structural attributes as constant in the main analysis, i.e. $\beta(t) = \beta$.[6] In section 6.3, we allow β to vary over time and this turns out to increase the estimated effects of the murder. 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 ξ_i is a house fixed effect and ε_{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 σ^2. This is a simplifying but also strong assumption, since list prices change very infrequently. We investigate the impact of this assumption in Section 6.1.

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. With 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. Other reasons to take averages over neighborhoods are: (i) individual observations within neighborhoods are not independent which leads to too small standard errors, (ii) it reduces the impact of the independence assumption of ε_{it}. As we will show in Section 6.1, house prices do not change on a weekly basis and

[6] See e.g. Harding, Rosenthal, and Sirmans (2003) and Harding, Knight and Sirmans (2003).

this implies a correlation of ε_{it} with $\lambda(t)$ and $\mu(t)$. Taking averages makes the i.i.d. assumption of ε^*_{jt} defendable. Still, serial correlation is a potential problem in our specification. This is investigated in 6.2.

Let p^*_{jt}, be the average of the logarithm of the list price of the houses that are for sale in neighborhood j in period t. Likewise, let x^*_{jt} be the vector of average properties for houses in neighborhood j that are for sale at time t. Then, in our baseline specification, we estimate

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

The unobserved neighborhood fixed effect in (2), ν^*_j includes both the original neighborhood fixed effect ν_j as well as the average of the individual fixed effects within a period and neighborhood. A potential drawback of this method is that unlike equation (1) x^*_{jt} is a time varying variable and this implies that it will not drop out of the estimation when we take first differences for the fixed effects model. It implies that unlike equation (1) the set of observed characteristics is relevant and as will be clear in the next section we have a small set of observed characteristics. This rises the question whether there may be a potential source of omitted variable bias with the setup presented in this paper. In Appendix B.1, we show that a necessary condition for unbiased results is that the expectation of ν is constant over time.[7] This implies that the unobserved characteristics of the houses for sale in a particular neighborhood are not allowed to change in a systematic way. Next to this, we also need to make the assumption that the distribution of x^* does not change over time. We test this assumption in 6.3. We show in Appendix B that this allows us to make the assumption that x^* and ν are correlated and this eliminates the problem of omitted variable bias.

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,

[7]For related models, this is also discussed in Blundell and MacCurdy, 1999, see page 1612.

$$\mu(t) = \pi(t)(1 - d_{1t}) + \omega(t)d_{1t}, \tag{3}$$
$$\lambda(t) = \zeta(t)(1 - d_{1t}) + \eta(t)d_{1t}, \tag{4}$$

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.

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. Appendix B.2 provides the details for this analysis. As mentioned before, our specification allows for possible learning effects. It is 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) can bias the effect of the murder on market prices. For our DID strategy it is important that: (i) there are not many more sellers from type I neighborhoods who buy houses in type II neighborhoods after the murder than before the murder and (ii) there are no differential trend effects for type I and II neighborhoods. Concerning (i) we find from register data (to be discussed below) that before the murder 38% of the type I sellers with a Turkish or Moroccan name bought a house in a type II neighborhood while after the murder this was only 28% (most of them stayed in a type I neighborhood). For the other type I sellers (95% of total), 23% moved to a type II neighborhood before the murder and 24% after the murder (most of them moved outside Amsterdam). Hence, we can ignore effects of type I sellers on type II neighborhoods. Concerning (ii), we do not want type I and II neighborhoods to be hit by different shocks and we also do not want them to have different responses to similar shocks. This is a general challenge for DID models and we will consider synthetic control groups as in Abadie et al. (2007) in section 5.3 and address compositional changes in the supply of houses (in section 6.3). Finally, there is an issue concerning the definition of a type I neighborhood. In our main analysis we use a cut-off rule of 25% Turkish or Moroccan inhabitants but in section 5.2 we treat this fraction as a continuous variable.

4 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 owner-occupied homes 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, size (square foot) 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 asking price by the seller and there are no legal restrictions in the Netherlands concerning this price and the characteristics that are posted on 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 square feet of a house differs from the actual price and square feet, 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. We merge our Funda 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.[8] 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

[8]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.

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 register data also contains information on name, current location and new location of the sellers and buyers. We only use this matched data set for the questions where we need both register and Funda data.

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 square feet). 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 also 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.[9] 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.[10] Our findings are in line with earlier research by Card (2005).

Home ownership is typically very low among Muslim minorities. In 2002, owner-occupied housing was 57 percent among the ethnic Dutch in the Nether-

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

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

lands while for the Dutch-Moroccan it was 9 percent and for the Dutch-Turkish it was 20 percent[11]. 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.

In order to obtain some ideas about the development of house prices in the two types of neighborhoods, Figure 1 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 2, which illustrates the development of square footage over the observation window. Looking at the development in Figure 1 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.

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 3 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.

5 Main Results

In this section we present the estimation results using the specification of Section 3. First, we estimate (2). Second, we focus on the fraction of Moroccan and Turkish inhabitants rather than the discrete cut-off point of 25%. Third, we consider control groups that are as similar as possible in terms of average income as the treatment groups. In section 6 we consider a number of robustness checks and extensions.. Finally we look at the identity of the buyers and sellers of type I and type II neighborhoods and give evidence that segregation increased.

5.1 Baseline Specification

Our baseline results for the constant, linear and quadratic specification of $\lambda(t)$ -the neighborhood price effect- are presented in Table 2 and Figure 4 . 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 only using a constant term. Due to the high frequency of our data

[11]See SCP (2005).

(weekly), the time fixed effects fluctuate a lot. Nevertheless, we find a significant negative price effect of 2.4 percent on the house prices in type I neighborhoods.

As the fixed effects estimates in Figure 4 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 0.07 percent per week after the murder of Van Gogh and reaches a high of 3 percent 10 months 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 6.1. 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.[12] We also ran the same regression with the Public Register Agency data which contains the true selling price. This results in almost the same negative trend estimate. The drawbacks of using the Register's data are that we have only one observation per house and only know at what date the new buyer formally becomes the owner and no information on the date that the contract is signed (we only know when the new buyer becomes the owner). Unfortunately, there can be substantial lags between both.

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 but that the quadratic term by itself is not significant.[13] 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.

5.2 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

$$p^*_{jt} = \alpha + \beta x^*_{jt} + \nu^*_j + \mu(t) + \lambda(t)\gamma(s) + \varepsilon^*_{jt}, \tag{5}$$

[12] Imagine that the relative house prices 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.

[13] A χ^2 on joint significance gives a value of 115 (critical value at 95% level is 8).

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

The DID estimation results using a step function with 8 steps of 5% are summarized in Table 3 where we interact the steps with t and t^2, before and after the murder. A higher density of Turkish and Moroccan immigrants increases the estimated impact of the murder in a non linear way. 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 percentages above 30, the relative decrease in house prices is close to 0.1%. Figure 6 shows the polynomial approximation of 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.

5.3 Synthetic control groups

The assumption underlying the neighborhood equation (2) is that the 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 using the method of synthetic control groups by Abadie et al. (2007). For each type I neighborhood we construct a synthetic control group from a weighted average of type II neighborhoods. The weights are chosen such that the house prices of the synthetic control group match the pre-trend of our treatment type I neighborhood as good as possible. Specifically, we minimize the mean squared prediction error (MSPE) before the date of the murder. An additional requirement that we impose on the type II neighborhoods to be included in the synthetic control neighborhood is that they should contain less than 5 percent of Muslims because else they could be affected by the murder as well. This would lead to biased results because the neighborhoods with close to 25% Muslims will get a high weight in the synthetic control group implying that we end up comparing 25% Muslim neighborhoods with 20% Muslim neighborhoods. In our baseline results the weights are only based on the size of the neighborhood and not on its predictive power of the pre-murder trend so the problem is smaller there. In our analysis we use the index numbers of the price per square foot as the left-hand side variable which is consistent with fitting the relative price development over time.

For each of the type I neighborhoods we create a synthetic control neighborhood from the type II neighborhoods and compare the post-murder trend differences. We aggregate them up, taking their relative sizes into account. For some of the type I neighborhoods the synthetic control group has a very poor fit of the pre-murder trend and hence we excluded those type I neighborhoods from the analysis because they will not be helpful to predict the counterfactual prices after the murder.[14]

The results as weighted are depicted in Figure 5. They are very similar to the ones we found for the fixed effects of the baseline model. Again, it is important to keep in mind that because we use weekly data, the series are less smooth than the low frequency data that are typically used in labor economics. Therefore, it is more informative to fit a line through the points after the murder. The slope of this linear specification is -0.0759, slightly steeper than the corresponding slope in the baseline specification presented in Table 2 which was -0.0683.

Finally, we follow the Abadie et al. (2007) bootstrap approach on statistical inference. We construct 11 placebo type I neighborhoods by random sampling from the control neighborhoods with less than 5 percent Muslims. For these placebo neighborhoods we apply the same analysis and aggregation scheme as we did on the original type I neighborhoods. After repeating this 100 times we can again compute the slope of the trend after the murder has taken place for each iteration. We find that the slope of the 5-th lowest percentile placebo neighborhood equals -0.0587. This is lower in absolute figures than the value for the linear specification of the true type I neighborhoods so we conclude that the relative drop in house prices in type I neighborhoods is statistically significant.

5.4 Segregation

If valuations for houses in type I and type II neighborhoods diverge after the murder because of ethnic preferences, we should see this in the ethnicity of buyers and sellers. To obtain the ethnicity of the buyer and seller of a house, we had

[14] Abadie et al. (2007), do something similar in the inference part of their paper. The decision rule that we use here is that we exclude a neighborhood as soon as the MSPE is larger than 0.0001. This implies that 6 out of 11 neighborhoods of our treatment group are selected. This procedure is rather ad-hoc but our results are not very sensitive to the exact choice of the tolerance level since the excluded neighborhoods have MSPE's that are at least ten times as large.

research assistants from both countries determining whether the surnames of buyers and sellers where of Turkish or Moroccan origin. Table 4 lists the fraction of transactions that involved a Turkish or Moroccan buyer or seller, both before and after the murder.

Table 4 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. 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. 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.

Besides the change in buyer and seller ethnicity, we can compute the change in a segregation index for Muslim and non-Muslim ethnicities. The most widely used measure of evenness and the most-widely used measure of residential segregation in general, is dissimilarity, see for example Echenique and Fryer Jr. (2007). Dissimilarity ranges from 0 (complete integration) to 1 (complete segregation) and measures the percentage of a group's population that would have to change residence for each neighborhood to have the same percent of that group in the metropolitan area overall. Formally, the dissimilarity index D is given by

$$D = \frac{1}{2} \sum_i |m_i/M - n_i/N|, \tag{6}$$

where m_i is the fraction of Muslims in neighborhood i, M the total number of Muslims in Amsterdam, n_i be the fraction of native Dutch in neighborhood i, and N the total number of Muslims in Amsterdam. A value of 0 refers to a completely mixed neighborhood and a value of 1 to a completely segregated neighborhood. Using data from Statistics Amsterdam we compute the dissimilarity index for the entire market, including renters. The index increased between 2004 and 2005 from 40.3 to 41.7.

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.

6 Robustness checks and extensions

In this section we carry out a number of robustness checks and extensions. In 6.1 we check how sensitive our results are to the assumption that ε_{it} is iid and in 6.2 we correct for possible serial correlation. Then in 6.3, we investigate the possibility that the composition of sellers and buyers changed after the murder. Finally, we present two extensions namely whether the list price differentials are accompanied by (i) changes in the average difference between list price and transaction price (in 6.4), and (ii) changes in the time on the market of listed houses (in 6.5). 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 and we corrected for possible differential effects of interest rates in the different neighborhoods. We start in the next section with discussing potential heteroskedasticity and serial correlation issues.

6.1 Sticky List Prices

An important assumption is that ε_{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. It 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), the reluctance of sellers to adjust the list price downwards due to nominal loss aversion, see Genesove and Mayer (2001) or learning about uncertain demand, see e.g. Lazear (1986).

To circumvent the problem of sellers who 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. Since the number of houses that are for sale for the first week is much lower than the total number of houses, we decided to change the aggregation level to a 4 week period instead of one week. Table 5 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 are the same as we had before. The results in the linear specification are harder to compare with the other results, but dividing the coefficient by 4, we find that these results are similar as well.

6.2 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) is 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: (i) the number of periods is long, (ii) the dependent variable is likely to suffer from serial correlation and (iii) 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 using block bootstraps as suggested in Bertrand et al. (2004). Unfortunately, this method only works when the panel is balanced so we drop the 12 (out of the 90) neighborhoods with fewer observations than time periods.

Table 6 lists the results of the block bootstrap exercise where 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 of the estimates for the balanced panel. Below the estimates we report the critical values found by the block bootstrap exercise. In the second column, we find that the critical values are higher in absolute terms than those of a standard normal distribution but our estimates remain statistically significant. So our conclusions are not affected by allowing for serial correlation.

6.3 Changes in the supply of houses and in the hedonic prices of housing attributes

One may worry that potential sellers of expensive houses in type I neighborhoods postpone placing their house on the market after the murder in the hope that the market will eventually calm down while sellers of cheap houses might not do this. One way to check this 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: square feet, we do not find that the average quality of houses for sale decreased in type I neighborhoods, see Figure 2. Note that square feet 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. Of course, we cannot rule out that the unobserved characteristics of houses for sale within a neighborhood changed after the murder. This would lead us to mistakenly take a composition change of the houses before and after the murder as a change in house prices.[15] If observable and unobservable house characteristics are correlated, the findings in this section suggest that this is unlikely.

One other way to look for the potential impact of omitted variable bias is to look at another period for which we have more characteristics available. We look at the period 2006-2007 for which we had the original characteristics plus the age of the house, the number of rooms, whether there was a garden attached, 15 type of house characteristics, 10 type of heating characteristics, 12 type of isolation characteristics and 10 street characteristics. We compared the results of a comparable regression as our baseline result for the period of analysis with the same regression including all these additional characteristics. We find that apart from our apartment coefficient - which is highly correlated with the type of house characteristics - the coefficients are quite robust for the specification. The R^2 within groups increases from 0.69 to 0.73 when we include the additional regressors.[16]

Another concern is that the hedonic prices of the various housing attributes change over time. This turns out to be particularly relevant for the size of the house. In general we find that the relative demand for small apartments increased over time. A possible reason for this is that starters at the housing market are most credit constrained so in a period of rising house prices, they can only afford small houses. Since the houses for sale in the Muslim neighborhoods are relatively small this process tends to downwardly bias our DID effects of the murder. If we allow β to vary over time we can isolate the effect of the murder and find effects that are roughly twice as large as our baseline results.

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

[16] This is lower than our baseline specification because we do not include additional time effects before the murder, since the murder was not in the time window.

6.4 Changes in the Average Discount

An additional check on house price effects around the Van Gogh murder is to use actual transaction prices from the 'Kadaster'. 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 7. 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 7 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 houses in type II neighborhoods. 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 7 displays the level of the average discount per neighborhood over time. As can bee seen in the figure, there is an 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 discount seems large, it is not statistically significant. Glower, Haurin and Hendershott (1995) argue that the list price markup is informative on how motivated sellers are. They argue that motivated sellers (who have a planned date to move) have relatively low asking prices but that motivation does not affect the list price mark up.[17] Our results suggest that one reason why relative house prices did not immediately drop after the murder is that the murder did not directly affect the number of motivated sellers.

6.5 Duration analysis

Sass (1988) gives evidence for the idea of Grossman, Kihlstrom and Mirman (1977) and Lazear (1986) that when sellers face uncertainty about the demand side, they can extract information from the number of buyers who inspect their house. This is particularly relevant after a large shock with uncertain outcomes

[17]See Albrecht, Anderson, Smith and Vroman (2007) for a theoretical model on motivated sellers..

that we analyze here. Rather than immediately decreasing house prices, sellers keep their prices high and then either cut prices as their homes remain on the market or accept a higher discount. 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. 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, τ 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).[18] The variable v represents the unobserved characteristics of the house. We use the following specification for the hazard rate

$$\theta(t_i, \tau_i, x_i, v) = \exp\left(x\beta + \nu_{J(i)}\gamma_1(\tau_i) + \gamma_2(\tau)d)\psi(t_i)\right) u_i \tag{7}$$

where ν_j is a neighborhood fixed effect and, as before, $J(i)$ maps a house i to its neighborhood $j = J(i)$. The function γ_1 represents the overall time-on-the-market effect, while γ_2 represents the additional effect for houses in type I neighborhoods. The function ψ 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 8. As before, we do not list the levels of the neighborhood fixed effects. First of all, Table 8 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 house is already for sale for more than one month, see Albrecht et al. (2005). It also

[18] 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.

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 8 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 8 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 8, 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.

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 0.07 percent per week relatively to the other neighborhoods in Amsterdam. This negative impact stops after about 10 months resulting in a decrease of more than 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 house prices in type I were actually catching up in type I neighborhoods with type II neighborhoods before the murder.[19] 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. 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. 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 housing data. List price and Income per individual per neighborhood are in Euros. Apartment and Garage are indicators equal to 1 if the property is an apartment or has a garage, respectively, and zero otherwise. Duration listed is in weeks. The crime rate is the number of registered crimes per neighborhood, with mean 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	
Square footage	20148	1050	655
Garage	18475	0.028	
Duration listed	20148	20.36	18.71
Percentage of muslims	20148	11.70	
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	
Square footage	2497	804.6	265.4
Garage	2278	0.018	
Duration listed	2278	20.83	20.34
Percentage of muslims	20148	37.82	
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	
Square footage	17651	1084	686
Garage	16197	0.029	
Duration listed	17651	20.16	17.92
Percentage of muslims	20148	7.62	
Income per individual in neighborhood	17651	21037	4472
Crime rate in neighborhood	17651	0.157	0.285

Table 2: Baseline results

The effect of the murder on prices is estimated as either a constant, linear or quadratic function of time. We control for the general price effect before and after the murder, as well as the pre-murder price trend in type I neighborhoods. Standard errors are between parentheses.

	Constant	Linear	Quadratic
Difference-in-difference estimators			
Constant	-0.024	-0.0030	-0.0046
	(0.0092)	(0.0091)	(0.0094)
t ($\times 100$)	·	-0.068	-0.00050
		(0.0066)	(0.00027)
$t^2 (\times 100)$	·	·	-0.00020
			(0.00043)
Control variables			
Constant	11.64	11.64	11.64
	(0.023)	(0.023)	(0.023)
Square footage	0.095	0.096	0.096
	(0.0011)	(0.0011)	(0.0011)
Square footage^2 (x 100)	-0.0012	-0.0012	-0.0012
	(0.00003)	(0.00003)	(0.00003)
Apartment	-0.14	-0.16	-0.16
	(0.0068)	(0.0066)	(0.0068)
Garage	0.097	0.072	0.071
	(0.013)	(0.012)	(0.013)
Goodness of fit measures			
R^2 within	0.69	0.71	0.71
R^2 between	0.82	·	·
R^2 overall	0.83	0.83	0.83
Total number of neighborhoods	90		
Total number of time periods	88		
Total number of observations	7661		

Table 3: Interacting with minority percentages

Diff-in-diff estimates are presented with the minority percentage included as a step function with a 5% spacing on the percentage Turkish/Moroccan per neighborhood. We control for the general price effect before and after the murder, as well as the pre-murder price trend in type I neighborhoods. Standard errors are between parentheses.

	Constant	Linear
Constant term		
5-10 percent	0.012	0.017
	(0.0076)	(0.0075)
10-15 percent	−0.031	−0.0012
	(0.0097)	(0.0096)
15-20 percent	−0.016	0.016
	(0.013)	(0.013)
20-25 percent	0.0004	0.0090
	(0.011)	(0.011)
25-30 percent	−0.014	−0.0082
	(0.018)	(0.018)
30-35 percent	−0.030	−0.0044
	(0.018)	(0.018)
35-40 percent	−0.038	−0.0040
	(0.014)	(0.013)
over 40 percent	0.0015	0.025
	(0.018)	(0.018)
Linear term		
$t \times$ 5-10 percent ($\times$ 100)	·	−0.019
		(0.0069)
$t \times$ 10-15 percent ($\times$ 100)	·	−0.11
		(0.0087)
$t \times$ 15-20 percent ($\times$ 100)	·	−0.12
		(0.012)
$t \times$ 20-25 percent ($\times$ 100)	·	−0.035
		(0.0097)
$t \times$ 25-30 percent ($\times$ 100)	·	−0.029
		(0.016)
$t \times$ 30-35 percent ($\times$ 100)	·	−0.099
		(0.015)
$t \times$ 35-40 percent ($\times$ 100)	·	−0.13
		(0.012)
$t \times$ over 40 percent ($\times$ 100)	·	−0.092
		(0.015)
Total number of neighborhoods	90	
Total number of time periods	88	
Total number of observations	7661	

Table 4: Buyers and sellers

The percentage of buyers and sellers per type of neighborhood who are of Turkish or Moroccan origin, both before and after the murder. The type of neighborhood is defined according to whether more (type I) or less (type II) than 25% of inhabitants is of Turkish or Moroccan origin. Standard errors are between parentheses.

	Total	Before	After	T-value of difference
Type I neighborhoods				
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)	
Type II neighborhoods				
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 5: Using only first-week list prices

Baseline estimation results are presented using only the list prices in the first week that a house is listed. We control for the general price effect before and after the murder, as well as the pre-murder price trend in type I neighborhoods. Standard errors are between parentheses.

	Constant	Linear
Difference-in-difference estimates		
Constant	−0.024	−0.0023
	(0.010)	(0.011)
$t(\times 100)$	·	−0.29
		(0.051)
Control variables		
Constant	11.63	11.64
	(0.023)	(0.023)
Square footage	0.096	0.098
	(0.0025)	(0.0024)
Square footage^2 ($\times$ 100)	−0.0013	−0.0013
	(0.00008)	(0.00007)
Apartment	−0.15	−0.17
	(0.014)	(0.013)
Garage	0.11	0.083
	(0.027)	(0.025)
Goodness of fit measures		
R^2 within	0.7081	0.7294
R^2 between	0.8163	·
R^2 overall	0.8347	0.8356
Total number of neighborhoods	90	
Total number of time periods	88	
Total number of observations	7661	

Table 6: Results of the block bootstrap exercise

The bootstrapped critical values represent criticial values for the T-statistics resulting from a block-bootstrap exercise, at 90, 95 and 99%-significance. T-values for both the constant and linear trend specification are reported.

	Constant	Linear
T-statistic from the estimation		
Constant	-2.5	-0.24
$\times t$		-6.9
Bootstrapped critical values		
Constant		
1 percent	-1.9	-4.2
5 percent	-1.4	-3.5
10 percent	-1.2	-3.2
Coefficient for t		
1 percent		-5.6
5 percent		-3.9
10 percent		-3.1
Total number of neighborhoods	78	
Total number of time periods	88	
Total number of observations	6864	

Table 7: Descriptive statistics for the register database

Overview of the transactions as registered in the Kadaster, the Dutch register for (residential) property. Only houses that listed on Funda are included. The discount is the %-difference between transaction price and list price.

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

Table 8: Estimation results for the duration model

Estimation results for the mixed proportional hazard specification in equation (7). 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 ($\times$ 1000)	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
	$(\cdot)$
Number of observations	11721

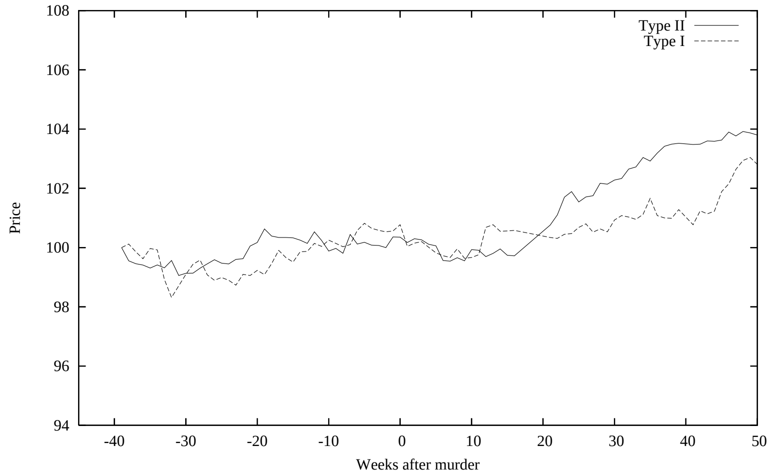

Figure 1: Price per square foot

Index levels of the price per square foot, set to 100 at the week of the murder. The solid line represents the average price index for the neighborhoods of type II (< 25% Turkish/Moroccan), the dashed line for type I neighborhoods.

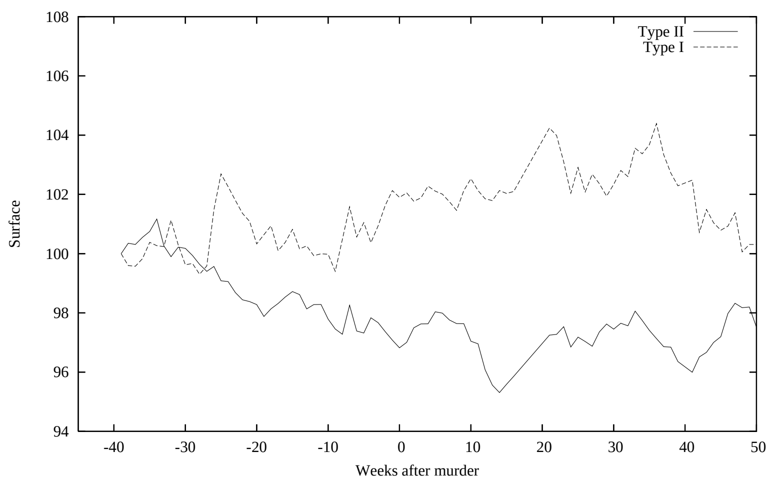

Figure 2: Average square foot for listed houses

Index levels of the average square foot of listed houses, set to 100 at the week of the murder. The solid line represents the square footage for the neighborhoods of type II (< 25% Turkish/Moroccan), the dashed line for type I neighborhoods.

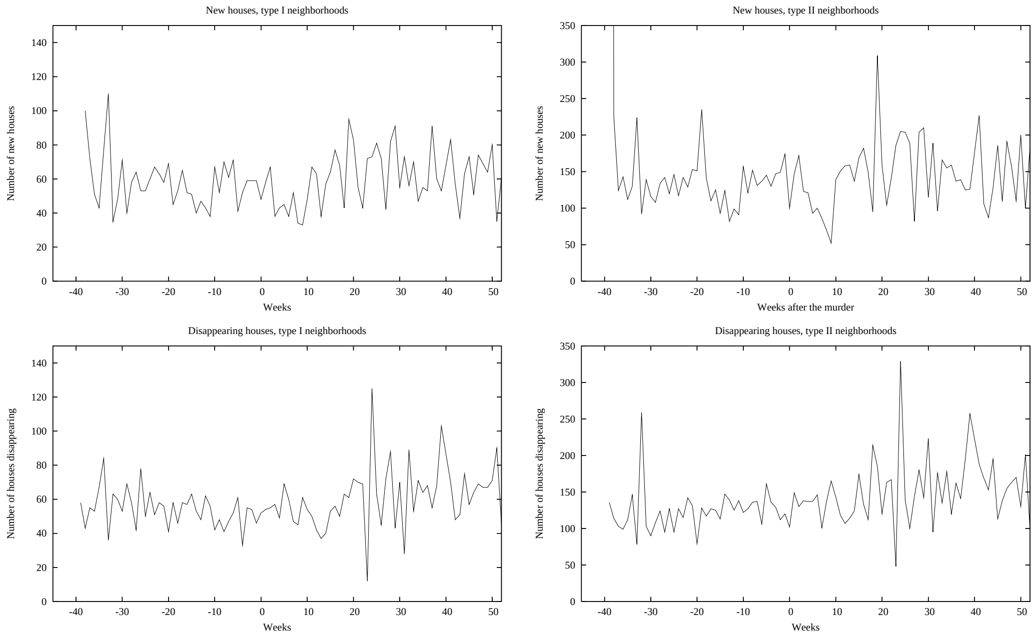

Figure 3: Number of listed houses

The top-left and bottom-left panels show inflow and outflow of houses in neighborhoods of type I (> 25% Turkish/Moroccan). The top-right and bottom-right panels show the in- and outflow of houses in neighborhoods of type II.

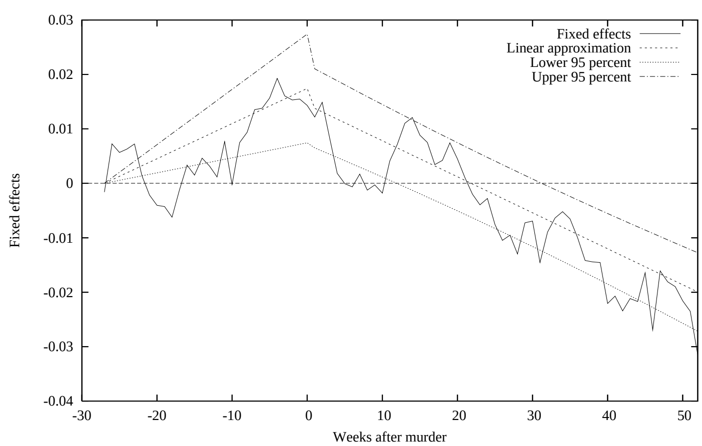

Figure 4: The linear model

The solid line represents the fixed effects estimates per week. The dashed lines show the estimated linear trend effect after the murder and the lower and upper 95% confidence bands.

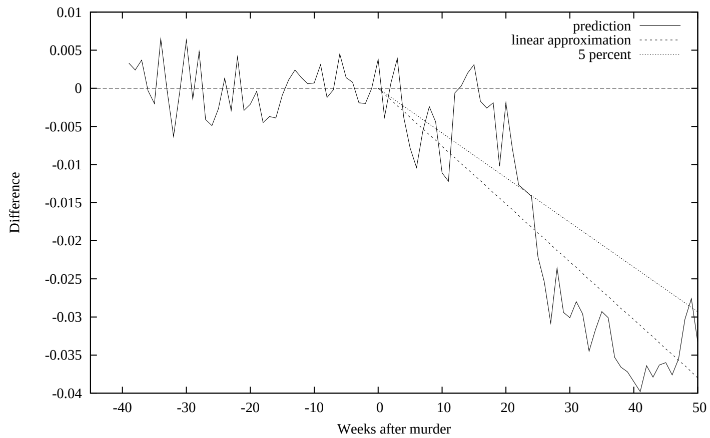

Figure 5: Estimated trend using synthetic control groups

The solid line gives the average difference between the type I neighborhoods and their respective control group. The dashed line represents the linear approximation to the post-murder trend. The dotted line gives the 5% upper bound of the linear trend, as resulting from a block-bootstrap procedure.

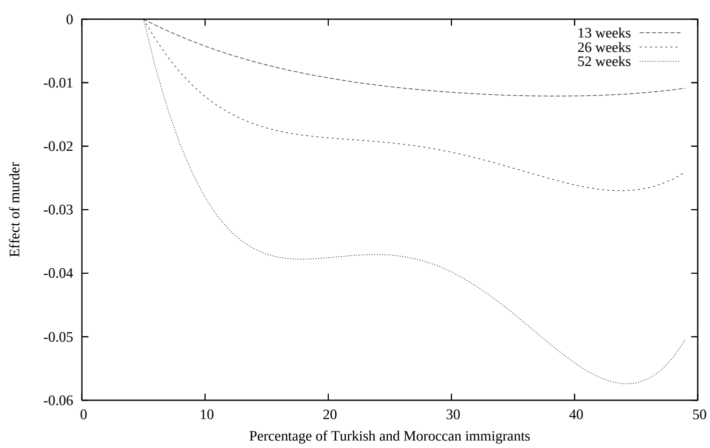

Figure 6: The impact of the murder for different thresholds

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.

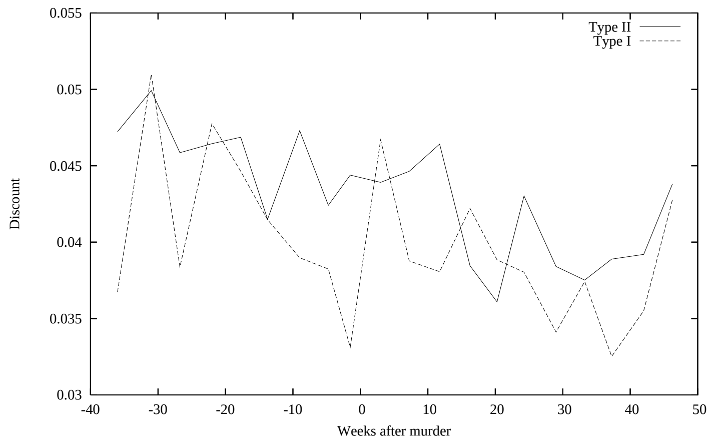

Figure 7: Average discount over time

This figure shows the average discount between transaction price and list price. The discount is computed per month. The solid line represents the discount for neighborhoods of type II (< 25% Turkish/Moroccan), the dashed line for that of type I.

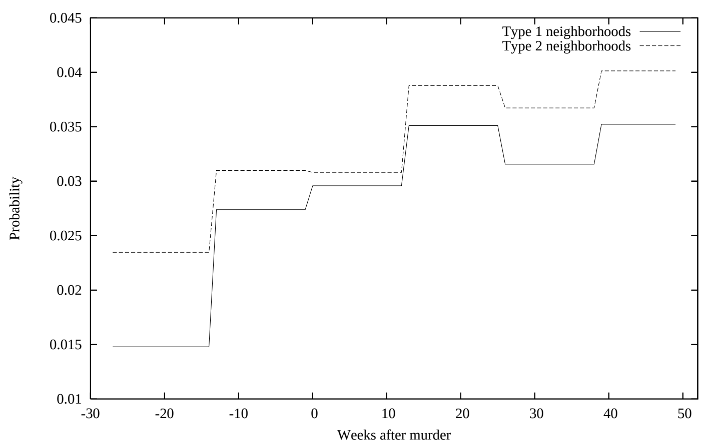

Figure 8: Hazard rates

This figure shows the hazard rates of a house disappearing from the market. The solid line represents the hazard rate for neighborhoods of type II (< 25% Turkish/Moroccan), the dashed line for that of type I.

Appendix B: Econometrics

B.1 Conditions for unbiased results

We assume the following 4 restrictions on the composition within a group: (1) $F_{t,x}(\cdot|d=1) = F_x(\cdot|d=1)$, (2) $F_{t,x}(\cdot|d=0) = F_x(\cdot|d=0)$, (3) $\mathrm{E}_{t,\nu}(\cdot|d=1) = \mathrm{E}_\nu(\cdot|d=1)$, (4)$\mathrm{E}_{t,\nu}(\cdot|d=0) = \mathrm{E}_\nu(\cdot|d=0)$. In addtion we allow for the following extension:

$$\mathrm{E}(\nu x|d=1,t) \neq 0 \quad \mathrm{E}(\nu x|d=0,t) \neq 0$$

These extensions allow for the fact that there is correlation between the observed and unobserved characteristics. Finally, we make the following assumptions on the error term:

$$\begin{aligned}
&\mathrm{E}(\varepsilon x|d=1,x,t) = 0 \quad \mathrm{E}(\varepsilon x|d=0,x,t) = 0, \text{and} \\
&\mathrm{E}(\varepsilon \nu|d=1,x,t) = 0 \quad \mathrm{E}(\varepsilon \nu|d=0,x,t) = 0
\end{aligned}$$

This implies for our main specification:

$$\begin{aligned}
\mathrm{E}_{x,\nu,\varepsilon}(p^*|d=1,t,x) &= \mathrm{E}(x|d=1)\beta + \int_{\mathrm{supp}(F_x)} \mathrm{E}(\nu|d=1,x)dF(x|d=1) + \mu(t) \\
&+ \lambda(t), \text{ and} \\
\mathrm{E}_{x,\nu,\varepsilon}(p^*|d=0,t,x) &= \mathrm{E}(x|d=0)\beta + \int_{\mathrm{supp}(F_x)} \mathrm{E}(\nu|d=0,x)dF(x|d=0) + \mu(t)
\end{aligned}$$

Taking differences with respect to time results in:

$$\begin{aligned}
\Delta_t(d=1) = \Delta_t\mu(t) + \Delta_t\lambda(t), \text{ and} \\
\Delta_t(d=1) = \Delta_t\mu(t)
\end{aligned}$$

Differencing another time over the type I and type II neigborhoods gives:

$$\Delta_d\Delta_t = \Delta_t\lambda(t)$$

This implies that when we only take differences over time and with respect to the different groups, we are able to consistently estimate $\lambda(t)$ over time.

B.2 Estimation of the standard error with an unbalanced pseudo panel

Proposition 1 *Define weights w_{it} as follows:*

$$w_{it} = \frac{k_{it}}{\sum_{j=1}^{N} \sum_{t=1}^{T} k_{jt}}$$

then equation 2 can be efficiently estimated using

$$\frac{1}{\sqrt{N}} \sum_{j=1}^{N} \sum_{t=1}^{T} w_{jt} \left(P^*_{jt} - \overline{P}^*_{j\cdot} - \left(X_{jt} - \overline{X}_{j\cdot} \right) \widehat{\Gamma} \right) \left(X_{jt} - \overline{X}_{j\cdot} \right)^T = 0$$

with

$$X = \begin{pmatrix} 1 \\ x^*_{jt} \\ t \\ \widetilde{t} \times d_j \end{pmatrix}$$

and

$$\Gamma = \begin{pmatrix} \alpha \\ \beta \\ \widetilde{\lambda} \\ \widetilde{\mu} \end{pmatrix}$$

where $\widetilde{t}$ is a power sequence of t and $\widetilde{\mu}$ and $\widetilde{\lambda}$ the corresponding parameters. The covariance matrix equals

$$\begin{aligned} \Omega = & \sigma^2 \left(\sum_{j=1}^{N} \sum_{t=1}^{T} w_{jt} \left(X_{jt} - \overline{X}_{j\cdot} \right) \left(X_{jt} - \overline{X}_{j\cdot} \right)^T \right)^{-1} \times \\ & \sum_{j=1}^{N} \sum_{t=1}^{T} \frac{w_{jt}^2}{k_{jt}} \left(X_{jt} - \overline{X}_{j\cdot} \right) \left(X_{jt} - \overline{X}_{j\cdot} \right)^T \times \\ & \left(\sum_{j=1}^{N} \sum_{t=1}^{T} w_{jt} \left(X_{jt} - \overline{X}_{j\cdot} \right) \left(X_{jt} - \overline{X}_{j\cdot} \right)^T \right)^{-1} \end{aligned}$$

Proof. Define X_j as the rows of X. This implies that equation (2) can be rewritten as:

$$p_{jt}^* = X_{jt}^*\beta + \nu_j^* + \varepsilon_{jt}^*$$

Demeaning results in

$$p_{jt}^* - \widetilde{p}_{j\cdot}^* = \left(X_{jt}^* - \overline{X^*}_{j\cdot}\right)\beta + \varepsilon_{jt}^* - \overline{\varepsilon^*}_{j\cdot}$$

The within estimator estimates Γ using the solution of the following equation

$$\frac{1}{\sqrt{N}}\sum_{j=1}^{N}\sum_{t=1}^{T} w_{jt}\left(p_{jt}^* - \overline{p^*}_{j\cdot} - \left(X_{jt}^* - \overline{X^*}_{j\cdot}\right)\widehat{\Gamma}\right)\left(X_{jt} - \overline{X^*}_{j\cdot}\right)^T = 0$$

Using a first order expansion around Γ_0 results in

$$\begin{aligned}0 = \frac{1}{\sqrt{N}}\sum_{j=1}^{N}\sum_{t=1}^{T} w_{jt}\left(p_{jt}^* - \overline{p^*}_{j\cdot} - \left(X_{jt}^* - \overline{X^*}_{j\cdot}\right)\Gamma_0\right)\left(X_{jt}^* - \overline{X^*}_{j\cdot}\right)^T - \\ \sqrt{N}(\widehat{\Gamma} - \Gamma_0)\frac{1}{N}\sum_{j=1}^{N}\sum_{t=1}^{T} w_{jt}\left(X_{jt}^* - \overline{X^*}_{j\cdot}\right)\left(X_{jt}^* - \overline{X^*}_{j\cdot}\right)^T + O_P(1)\end{aligned}$$

Rewriting and using the definition of ε_{jt}^* and $\overline{\varepsilon^*}_{j\cdot}$ we obtain

$$\begin{aligned}\sqrt{N}(\widehat{\Gamma} - \Gamma_0) = \left[\frac{1}{N}\sum_{j=1}^{N}\sum_{t=1}^{T} w_{jt}\left(X_{jt}^* - \overline{X^*}_{j\cdot}\right)\left(X_{jt}^* - \overline{X^*}_{j\cdot}\right)^T\right]^{-1} \times \\ \frac{1}{\sqrt{N}}\sum_{j=1}^{N}\sum_{t=1}^{T} w_{jt}\varepsilon_{jt}^*\left(X_{jt}^* - \overline{X^*}_{j\cdot}\right)^T + O_P(1)\end{aligned} \tag{8}$$

Using the central limit theorem we find:

$$\begin{aligned}\frac{1}{\sqrt{N}}\sum_{j=1}^{N}\sum_{t=1}^{T} w_{jt}\left(\varepsilon_{jt}^* - \overline{\varepsilon^*}_{j\cdot}\right)\left(X_{jt}^* - \overline{X^*}_{j\cdot}\right)^T \rightsquigarrow \\ N\left(0, \sigma^2\sum_{j=1}^{N}\sum_{t=1}^{T}\frac{w_{jt}^2}{k_{jt}}\left(X_{jt}^* - \overline{X^*}_{j\cdot}\right)\left(X_{jt}^* - \overline{X^*}_{j\cdot}\right)^T\right)\end{aligned}$$

Substitution of this into equation (8) and rewriting the result proofs the last part of the proposition. Taking first order derivatives with respect to Ω shows that Ω is minimized when we use the definition of w as defined in the proposition. ■