

How do housing prices adjust after an environmental shock? Evidence from a state-mandated change in aircraft noise exposure

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February 15, 2013

Abstract

We analyze the adjustment of housing prices after an exogenous shock. Using continuous records of the housing market around a major European airport (ZRH, Switzerland) and an unexpected change in flight regulations induced by the neighboring country Germany, we find that apartment rents take about two years to stabilize to a new equilibrium value. After this period we find a constant markup for apartments in regions exposed to less aircraft noise, and a constant discount in regions with more noise. Alternative demand-side indicators like search effort and turnover adapt to the new macro situation and reach pre-shock levels after two years, whereas little evidence is found for supply-side effects.

JEL Classification: Q51, D58, C23

Keywords: Hedonic pricing, dynamics, noise pollution, matching, difference-in-differences.

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1 Introduction

The impact of environmental goods on housing prices is a recurring theme on the public policy agenda. Because such goods are rarely traded in explicit markets, revealed-preference methods have been used to learn about their implicit prices. Probably the most common approach is Rosen's (1972) hedonic pricing model. It is based on the idea that the utility derived from the consumption of a composite product like housing is determined by the utility associated with its constituent parts, i.e., characteristics of the house (e.g., square footage, construction quality), the neighborhood (e.g., crime rates, population structure, schools), and the environment (e.g., noise pollution, air quality). Empirically, implicit prices are estimated by a regression of housing prices on the vector of objectively measured characteristics.

While the hedonic approach provides an important device for the valuation of non-traded goods, it has several drawbacks that impede a meaningful interpretation in terms of the individuals' marginal willingness-to-pay. Among the foremost concerns is the misspecification of the regression model including issues of functional form and omitted variable bias (e.g., Parmeter, Henderson and Kumbhakar 2007; Kuminoff, Parmeter and Pope 2010; Parmeter and Pope forthcoming). For that reason, the recent hedonic literature has relied on quasi-experimental approaches as a promising alternative. Examples include the valuation of school quality (Black 1999), clean air (Chay and Greenstone 2005), hazardous waste (Gayer, Hamilton, and Viscusi 2000; Greenstone and Gallagher 2008), power plants (Davis 2011), and aircraft noise (Pope 2008; Boes and Nüesch 2011).

Using policy interventions as a source of experimental variation carries the problem that the market of interest may at least temporarily be out of equilibrium, which would violate an important assumption of the Rosen (1972) model. Empirical methods such as difference-in-differences (DID) are sensitive to the choice of the post-policy period and estimation results may be upward or downward biased compared to the true capitalization effect depending on the

adjustment processes.

We contribute to the literature by explicitly addressing the equilibrium conditions. In 2003 a large-scale change in flight regulations at Zurich airport (Switzerland) altered the exposure to aircraft noise in the local housing market (Boes and Nüesch 2011). We interpret this intervention as an exogenous shock and look at continuous records of rental apartments to investigate how prices adjust during the post-policy period. Because some regions around the airport are exposed to less noise and some regions to more, we analyze whether these two scenarios are equally valued in terms of apartment rents (i.e., similar effects with opposite signs).

Our identification strategy relies on a DID model with two critical extensions compared to the standard two-groups/two-periods specification. First, since we are interested in price adjustments for two different treatment regions we allow for heterogeneous time-varying treatment effects, following the discussions of Bertrand, Duflo, and Mullainathan (2004), Donald and Lang (2007), and Angrist and Pischke (2009). Second, due to the heterogeneity of neighborhoods in treatment and control groups and due to their differential pre-treatment trends, we invoke a coarsened exact matching (CEM) algorithm (Iacus, King and Porro 2011a,b) as a data pre-processing device to select only those municipalities in the treatment regions and in the control region that have similar pre-policy trends. In doing so, we follow the recent developments in the DID literature including synthetic controls (Abadie and Gardeazabal 2003; Abadie, Gardeazabal and Hainmueller 2010) and the multiple groups/time periods extensions to DID (for an overview see for example Imbens and Wooldridge [2009]).

Our results indicate that both aspects, CEM pre-processing and dynamic treatment effects, significantly affect the conclusions drawn from the analyses. First, the policy intervention redistributed flight movements around the airport, leaving some municipalities with more and some with less noise than before the intervention. For these two treatments we do not expect that the same control units (in principle consisting of all municipalities not affected by the change) serve as an equally valid comparison group. Indeed, we find that only a few, non-overlapping

municipalities in the control region show comparable pre-treatment trends in prices to the two treated groups. Second, the time-varying treatment effects show a significant price discount for the positive treatment, i.e., municipalities with more noise, that grows in magnitude for almost two years and is stable afterwards. For the negative treatment we find similar adjustments but with the opposite sign. Our finding of a two-year adjustment period is confirmed by an alternative analysis of a proxy of search effort, the average number of clicks per advertisement and day. This outcome significantly increases immediately after the intervention and returns to the pre-policy level about two years later.

The paper makes two important contributions to the expanding quasi-experimental literature on the valuation of non-market goods. A valid treatment effect requires that in the absence of the treatment the dependent variable would have changed identically in the treatment and control groups. While the inclusion of time-varying controls and fixed effects may help to mitigate the difference between treatment and control (Greenstone and Gayer 2009), differences in their unobserved time trends may still be present and lead to biased treatment effects. CEM helps in this respect as it compares treated units and controls only if they had the same pre-treatment time trends. Second, a flexible dynamic analysis of the treatment effect helps to test the necessary equilibrium condition in hedonic price models. Static DID estimates are therefore only valid if the off-equilibrium adjustment period is excluded from the analysis.

The remainder of the paper is structured as follows. In Section 2, we briefly review the literature underlying the hedonic valuation of aircraft noise and related health impacts. We introduce our data on aircraft noise exposure and the data for the housing market in Section 3, also providing details about the flight regulations at Zurich airport and the 2003 intervention. Section 4 outlines our identification strategy and presents the results. Section 5 critically assesses the implications of our analyses and concludes.

2 Background and related literature

2.1 Aircraft noise exposure and human well-being

Permanent exposure to aircraft noise is known to have serious negative impacts on physical and mental health (Stansfeld and Matheson 2003; Black et al. 2007; Jarup et al. 2008; Boes, Nüesch and Stillman 2012). Apart from the rather obvious effect on sleep quality, other health impacts include increased risks of cardiovascular diseases, hypertension, performance reductions, and psychological symptoms like anxiety, depression and nervousness. Haines et al. (2001a,b) and Stansfeld et al. (2005) find that aircraft noise is negatively associated with children's reading comprehension and long-term memory. Huss et al. (2010) find a significant relationship between aircraft noise and mortality due to myocardial infarction.

As a direct consequence of these detrimental health effects, people living close to major airports regularly express their displeasure about being exposed to aircraft noise, for example by means of organized demonstrations or legal disputes. Given the concurrence of a high population density and the increasing demand for air services in metropolitan areas, targets of such protests include leading airports like Atlanta International (Cohen and Coughlin 2009), Chicago O'Hare (McMillen 2004), Frankfurt (Geis 2010), and Heathrow (Griggs and Howarth 2004).

2.2 Aircraft noise exposure and housing prices

The negative effects of aircraft noise on health and well-being decrease the willingness-to-pay for housing in noisy regions. Quietness is generally considered a valuable good and individuals either consciously or subconsciously take the exposure to noise into account when looking for a new apartment or a new house. The meta-analysis of Nelson (2004) finds noise discounts to be around 0.6 percent per decibel in cross-sectional studies.

Over the past few years the validity of cross-sectional work has been subject to considerable dispute. Unobserved housing characteristics like the quality of the house or the neighborhood

are suspected to confound the relationship between noise and housing prices. For example, noisy residential areas are often close to industrial areas or traffic arteries. As a consequence, noise is highly correlated with air pollution and a lower environmental quality in general. Identifying the effect of noise on housing values in a cross-sectional analysis is therefore very difficult. More recently, quasi-experimental approaches have been used to address the problem of confounding (e.g., Chay and Greenstone 2005; Greenstone and Gayer 2009; Davis 2011). Quasi-experimental hedonic valuations of aircraft noise can be found in McMillen (2004), Pope (2008), Cohen and Coughlin (2009), and Boes and Nüesch (2011). These studies identify the impact of aircraft noise on housing prices by using exogenous changes in the exposure to aircraft noise and by calculating average price changes in affected as opposed to unaffected regions.

In this paper, we build on the quasi-experimental literature. Unlike in previous work we take advantage of continuous records of the housing market around Zurich airport. We investigate how the market for rental apartments adapts to a large, policy-invoked change in the exposure to aircraft noise, and we evaluate the total effects on apartment rents. Our results contribute to a better understanding of the adjustment processes in the housing market after an exogenous shock and therefore provide new and critical evidence regarding the use of before/after and treatment/control comparisons common in the hedonic literature. Our approach heavily relies on the clear separation of treatment and control regions through an exogenous intervention with lasting impact, and on records of housing prices over a sufficiently large and finely measured time frame. These data requirements are detailed in the next section.

3 Data

3.1 Flight regulations around Zurich airport

Zurich airport is the largest airport in Switzerland and the 8th largest in Europe. It operates around 270,000 take-offs and landings per year on three different runways. The directions of the

runways are northwest/southeast (14/32), north/south (16/34), and east/west (10/28). Figure 1 shows the relative frequencies of starting and landing aircraft by flight direction. In 2002 around 90% of the landing aircraft approached from the northwest on runway 14, about 5% from the north on runway 16, and about 5% from the east on runway 28. Almost 70% of the aircraft took off in direction west from runway 28, about 10% took off in the north directions (runways 32/34), and about 20% in the south direction.

— Insert Figure 1 about here —

In 2003 the flight movements around the airport significantly changed. One particular feature of Zurich airport (and the exposure to aircraft noise) is the involvement of two countries because it is located close to the Swiss-German border (dark dash dot line in Figure 1). As a protective action against noise pollution, the German government issued a binding decree on April 17, 2003 that prohibited landings from the north in the early morning (6 to 7 am on weekdays and 6 to 9 am on weekends) and in the late evening (9 pm to 12 am on weekdays and 8 pm to 12 am on weekends). As a result, landing aircraft had to be redirected to approach from the east on runway 28 because at that time the flight regulations did not allow for any other direction. On May 21, 2003 the Federal Office of Civil Aviation changed the regulations such that landings were also allowed from the south on runway 34. The new flight regime took effect in the first week of November 2003 with aircraft landing from the south between 6 and 7 am on weekdays (6 to 9 am on weekends) and aircraft landing from the east between 9 pm and 12 am on weekdays (8 pm to 12 am on weekends).¹

These regulations are still in effect today (although there are ongoing negotiations between the Swiss and the German governments about future developments of the airport and flight movements in particular). Figure 1 also shows how the relative flight occupancy by flight

¹Exceptions to this general flight regulations are only allowed in special weather conditions (strong wind, fog and mist), or in the case of emergency flights (Flughafen Zürich 2012).

direction changed from 2002 to 2004. The relative number of flights approaching from the north dropped by almost 14 percentage points as a consequence of the new regime. These incoming flights were redistributed to approach from the east (+6.9 percent from 2002 to 2004) and the south (+6.8 percent from 2002 to 2004).

Figure 2 (upper panel) shows the monthly number of landings in the early morning (6 to 7 am) by flight direction relative to the average number of landings during the pre-treatment period. Before 2003 aircraft approached the airport from the north, between April 2003 and October 2003 mainly from the east, and thereafter from the south. Figure 2 (lower panel) illustrates the number of monthly landings in the late evening (9 pm to 12 am) per flight direction and relative to the pre-treatment average. Before 2003 most aircraft approached from the north, after 2003 from the east. The temporary decrease in late landings from the east in winter can be explained by weather conditions and the corresponding safety regulations.²

— Insert Figure 2 about here —

The re-distribution of incoming flights also affected take-offs. Due to the introduction of landings from the south after October 2003 the fraction of take-offs in the direction south decreased by 9.5 percent from 2002 to 2004. Most of these take-offs are now operated from runway 32 (+10.6 percent) in the direction northwest combined with a left turn such that they do not violate the German flight restrictions.

We use high resolution annual aircraft noise data provided by the *Swiss Federal Laboratories for Material Science and Technology* (EMPA). The EMPA model calculates the aircraft noise exposure around Zurich airport based on effective radar flight track information, statistics of movements per aircraft type and period of day, sound source data of an aircraft type, and environmental characteristics such as terrain with a resolution of 250m-by-250m, and then in-

²The weather around Zurich airport is often very foggy in winter. Safety regulations state that aircraft have to approach from the south when visibility is less than 4300 m but more than 750 m. If visibility is less than 750 m, aircraft have to approach from the north (Flughafen Zürich 2012).

terpolates to a 100m-by-100m grid (see Krebs *et al.* (2010) for details about the EMPA aircraft noise model and Thomann (2007) for information about model precision). Following the acoustic literature (Tomkins *et al.* 1998), we use an equivalence metric L_{eq} as continuous noise measure. L_{eq} indicates the steady sound level between 6 am and 10 pm that would produce the same energy as the actual time-varying noise intensity. The units of measurement are A-weighted decibels, abbreviated by dB(A). While the time frame from 6 am to 10 pm does not allow us to distinguish between the effects caused by the morning and evening re-distribution of flights, we capture both aspects very well with the changes in L_{eq} from 2002 to 2004, and hence our estimates must be interpreted as total policy effects.

Figure 3 illustrates the local noise exposure in 2002, one year prior to the flight regime change. The dark regions correspond to the highest levels of exposure. As one would expect, the regions directly surrounding the airport and in the direction of the three runways are the most heavily exposed to aircraft noise.

— Insert Figure 3 about here —

3.2 Treatment and control structure

We impose the following definitions for treatment and control regions:

- Positive treatment: Increase of L_{eq} from 2002 to 2004 by more than 3 dB(A)
- Negative treatment: Decrease of L_{eq} from 2002 to 2004 by more than -3 dB(A)
- Control: Change of L_{eq} from 2002 to 2004 in the interval $[-2, 2]$.

In all cases we constrain the area of interest to have at least 30 dB(A) of aircraft noise exposure in 2002. This restriction is imposed to spatially constrain the control group and to conduct the analyses in an area where aircraft noise is deemed a potentially disturbing environmental factor (WHO 2009). We used ± 3 dB(A) as the threshold values for the treatment regions because

only changes above that level can be identified by the human ear (Reindel 2001). By the same reasoning, we take the interval $[-2, 2]$ as a plausible choice for the control group because it is within the range of no noticeable changes in aircraft noise exposure. Figure 3 marks the positive treatment with (+) signs, the negative treatment with (-) signs.

While the noise pollution in the north generally decreased - in some areas by more than 6 dB(A) - noise exposure in the south generally increased, with a maximum of 14 dB(A). Only those communities in the south close to the airport are exposed to less aircraft noise, due to the substitution of starting and landing aircraft, the latter generating less noise.

3.3 Housing data

We use data for online advertisements from *homegate.ch*, the major online platform for housing in Switzerland. Our time frame starts in January 2002, about 15 months prior to the policy intervention, and ends in mid 2010. We only keep listings for residential apartments for rent, and delete those for office space, parking places and storage. We do not consider the property market because of low turnover rates (Werczberger 1997), high relocation and transaction costs (Bayer, Keohane and Timmins 2009), and the rather low fraction of homeowners in Switzerland (about one third). After carefully checking for data consistency, we obtain a final sample of 142,223 observations (advertisements) in the canton of Zurich, which we use as the basis for our empirical investigation.³ Data cleaning affected less than 0.3% of the total sample. Average rents by apartment size and the distribution of apartment sizes in the final sample are consistent with the information in the 2000 census data. We therefore consider the data from *homegate.ch* as representative for the housing market in the canton of Zurich.

For every apartment listed we observe the monthly rent (in Swiss Francs, CHF, including utilities), the exact date when the advertisement appeared online, the number of clicks per advertisement, the duration of the offer (in days), the size of the apartment (in squared meters),

³We dropped duplicate advertisements and apartments with very low rents (less than CHF 100 per room and month) or very high rents (more than CHF 30,000 per month).

the number of rooms, the year built, and the zip code. The exact address information is often missing or misspelled. As a consequence, street information could not be used for geocoding. The next higher level of spatial resolution, the zip codes, are accurately recorded. We matched the housing data to the high-resolution aircraft noise data based on the coordinates of the population-weighted center of gravity for each zip code (provided by *MicroGIS*). One zip code usually corresponds to one municipality as the smallest political unit in the Swiss legislative system. Larger municipalities are occasionally divided into several zip codes.

Table 1 summarizes the changes in noise exposure for zip codes in the two treatment and the control groups. The changes are based on the pre-treatment (2002) and the post-treatment (2004) average noise levels.

— Insert Table 1 about here —

Table 1 indicates that the positive treatment consists of 10 zip codes, the negative treatment of 24. In the positive treatment region, the maximum increase in noise is +14.1 dB(A) with a mean increase of +7.5 dB(A). The negative treatment region experienced a maximum drop in noise exposure of -6.9 dB(A) with a mean decrease of about -3.6 dB(A). By defining non-treatment regions as those zip codes that experienced little changes in noise exposure, in the interval ± 2 dB(A), we end up with 102 control zip codes which experienced a mean change of -0.6 dB(A). The final row of Table 1 shows the number of advertisements that we have for each of the regions (about 7,400 for the positive treatment, 11,000 for the negative treatment, and about 124,000 for the control).

Descriptive statistics for our outcome variables, log apartment rent and the number of clicks per day and advertisement, are displayed in Table 2. Panel A refers to the pre-treatment period, defined as before January 2003, because there is no indication of the policy intervention before that. A comprehensive content analysis using the LexisNexis database that includes all articles published in several quality newspapers and weekly magazines in Switzerland reveals no reference

to the flight ban before 2003. Panel B refers to the post-treatment period, which for the moment we define as the entire period not classified as pre-treatment, i.e., from January 2003 until July 2010. Clearly, this separation is not sharp because this captures two months of anticipation effects, the first change in flight regulations in April 2003, the second change at the end of October 2003, and finally the adjustment processes of the housing market afterwards. The timing of these events will be explicitly accounted for later in the paper.

A first observation in Table 2 is that both treatment regions (positive and negative) show higher pre-treatment rents than the control region. Using the rough before/after comparison we find increases in rents for the negative treatment and for the control region, and a slight decrease for the positive treatment region. The number of clicks per day increased over time for both treatment groups and the control group.

— Insert Table 2 about here —

Given the information in Table 2, we can estimate two average treatment effects. First, the difference in pre- and post-treatment average rental prices and between the positively treated and the control units gives a difference-in-differences (DID) estimate of the average treatment effect on the treated (ATT) of CHF -261.1 [= (1818.8 – 1887.4) – (1720.5 – 1528.0)]. That is, the average apartment rent under the positive treatment (i.e., the region exposed to more aircraft noise) is about 261 CHF lower than that for the average control. Second, the average treatment effect on the negatively treated units (the region exposed to less aircraft noise) is estimated with this approach as CHF -81.9. This seems rather implausible given that the absence of noise is usually valued positively, *ceteris paribus*, and the willingness-to-pay for an apartment should increase in this case. While simple and straightforward to calculate, the basic DID approach is likely to be too restrictive. We therefore refine our estimation approach in the following sections to be able to account for the specific features of our data (imbalanced pre-treatment trends, region and time specific effects, heterogeneity, etc.).

3.4 Examining pre-treatment imbalance

The data structure at hand allows us to estimate the average treatment effect on the treated (ATT) on the basis of pre-treatment and post-treatment comparisons for both treated regions and the control region. The resulting DID approach has several advantages over alternative estimators applied to cross-sectional data where pre-treatment information is usually missing (Meyer 1995). However, some assumptions inherent in DID, e.g., the need for a common time trend of the treated group and the control group in the absence of the treatment, are critical for the credibility of the approach and they deserve some additional attention (Meyer 1995; Heckman, Lalonde and Smith 1999; Abadie 2005).

Some control units may show a systematically different price pattern than the treated units prior to the treatment, and are therefore unlikely to serve as a good comparison group generating the counterfactual scenario for the treated (Meyer 1995; Iacus, King and Porro 2011a,b). A possible solution to this problem is to estimate a propensity score in the first stage (given a set of covariates) and then run DID on the propensity score weighted data (Abadie 2005). Alternatively, one may calculate the counterfactual trends on the basis of a weighted average of controls (Abadie and Gardeazabal 2003; Abadie, Gardeazabal and Hainmueller 2010). This synthetic control is estimated by minimizing the pre-treatment distance between the treated and the weighted average of potential controls for the outcome of interest (and covariates). Both approaches have in common that they give less (or even zero) weight to inappropriate controls in terms pre-treatment imbalance.

There are several reasons why data pre-processing is important in our context, too. First, our dataset is asymmetric in the sense that we observe advertisements for only about one year prior to the treatment and for about seven years after the treatment. Second, the regions affected by the policy (positively or negatively) and the control regions are very heterogenous. While the region in the south is characterized by very expensive, upper class neighborhoods, in particular

close to Lake Zurich (see Figure 3), the residential region directly surrounding the airport and to its east is characterized by a more working class population and housing in the middle to lower price categories. The control group consists of a rather diverse mix of neighborhoods at the very top end of the price range but also in the middle to lower price ranges. Third, investments in residential housing varied substantially over municipalities in the canton of Zurich. While some municipalities have received little to no investment in residential housing over the last 10-15 years, others are boom areas where whole new neighborhoods have been built.

To identify the causal effect of the flight regime change and the associated change in aircraft noise exposure on apartment rents, we need to argue that the development of prices in the two treatment regions and in the control region would have been the same in the absence of the intervention. Given that the raw data consist of repeated cross-sections (and not a panel), the unit of observation for balance checking is the average apartment rent and the average number of clicks per day aggregated on the zip code level to generate the trend information.

The upper part of Table 3 (panel A) displays the summary statistics of the pre-treatment trends for our two outcomes (apartment rents, clicks per ad) aggregated on the zip code level for both treatment groups and the control group. We calculate the pre-treatment trend as the average over the second half-year 2002 minus the average over the first half-year 2002.⁴ As robustness checks, we altered the time aggregation and compared the first quarter 2002 with Q2-Q4 2002, and Q1-Q3 2002 with Q4 2002 which all did not change our results. We decided for the half-year separation for efficiency reasons as this balances the number of observations in each period for the trend calculation.

— Insert Table 3 about here —

The average price trends per zip code (row 1) show that the two treatment and the control

⁴We were not able to analyze shorter time intervals due to small sample issues (most importantly the sensitivity to outliers, e.g., very expensive apartments in a given month and zip code).

groups developed rather differently during the pre-treatment period. In particular, prices in zip codes receiving the positive treatment went down by CHF -14.5 on average, prices in zip codes receiving the negative treatment by even more (about CHF -72.7). Prices in the control group, on the contrary, increased by CHF 88.4 on average.

To eliminate the observed pre-treatment differences we pre-process the data using an approach recently proposed by Iacus, King and Porro (2011a,b). They suggest a coarsened exact matching (CEM) where observations (in our case trends per zip code) are assigned to strata. That is, CEM ensures that for every pair of treated and non-treated in a given strata there exists at least one exact match. Unmatched observations are excluded from the analysis. This procedure allows us to constrain the imbalance in the pre-treatment trends, and the ATT is then estimated by a (weighted) DID model using matched observations only.

We adopt this empirical strategy for several reasons. First, Iacus, King and Porro (2011a,b) demonstrate that CEM outperforms alternatives like propensity score matching in balancing the data. They argue that the major property of CEM is to reduce imbalance as a prerequisite and not as a result (as most other matching algorithms would do). CEM is therefore similar to exact matching approaches without inheriting their main disadvantages, especially in multivariate and continuous data settings (i.e., the curse of dimensionality). Second, since our sample consists of repeated cross-sections, disaggregate data, and numerous treated units, the synthetic control approach of Abadie, Gardeazabal and Hainmueller (2010), another appealing extension of DID, is not directly applicable. Third, we cannot use propensity scores as proposed by Abadie (2005), because these require the use of covariates that explain the treatment status of different groups, and there is no meaningful covariate in our context that would explain whether a region has been affected by the policy. The decisions of how to allocate aircraft noise among the different regions has mainly been made on the basis of technical constraints (directions of existing runways).

The lower part of Table 3 (panel B) shows the pre-treatment trends of our main outcomes after applying CEM. The first result to note is that the number of zip codes in the control

group decreased sharply, so that the sample sizes of the three groups after CEM are almost balanced. Second, the balance in pre-treatment trends between the groups is now extremely high. This is true for both outcomes (rents and clicks) and treatments (positive, negative). For example, the price increase for the positive treatment (row 4) is now CHF 79.9 in the treatment group compared to CHF 80.4 in the control group. That is, CEM decreased the difference in trends between the two groups by more than 99 percent. Similar improvements in pre-treatment balance through CEM are achieved for the number of clicks per day and the negative treatment region. For the coarsening, we used a fixed amount of equally sized bins to stratify the original variables. The number of bins is reported in the last column of Table 3. In each case, we chose the number of bins such that the $L1$ imbalance statistic proposed by Iacus, King and Porro (2011a,b) is zero, indicating perfect balance (up to the coarsening).⁵

Given the relatively large pre-treatment differences between the treated and control, we estimate two different specifications for each model in the later empirical analysis: (i) an unrestricted model based on the original full sample, (ii) a restricted model using the sample obtained from CEM with the weights suggested by Iacus, King and Porro (2011a,b).⁶

4 Estimation results

4.1 Static difference-in-differences framework

As a starting point we show the results of a static difference-in-differences (DID) model that does not allow for specific after-policy time trends but simply compares the before/after changes in the treatment and control group controlling for a set of potentially confounding variables. We

⁵Iacus, King and Porro (2011a,b) suggest checking imbalance using two multidimensional histograms from the cross-tabulation of characteristics (in our case this is only one variable at a time, i.e., the pre-treatment trend of any of the outcomes) in the treatment and control groups. The bins for the histogram are chosen in advance, in our case with a fixed and relatively large number of equally sized bins to get precise matches. Imbalance is then defined by comparing the relative frequencies f_{l_1, \dots, l_k} for cells l_1, \dots, l_k in the treatment group with the relative frequencies g_{l_1, \dots, l_k} in the control group according to $L1 = 0.5 \cdot \sum_{l_1, \dots, l_k} |f_{l_1, \dots, l_k} - g_{l_1, \dots, l_k}|$.

⁶The weights are zero for all unmatched zip codes, one for all matched treated zip codes, and equal to the relative proportion of treated to control for the control zip codes in each matched stratum.

specify the following static DID model:

$$Y_{ist} = \alpha_s + \beta_t + \delta D_{st} + \gamma X'_{ist} + \varepsilon_{ist} \quad (1)$$

where Y_{ist} denotes the outcome of interest (rental price of the apartment or number of clicks per day) for advertisement/apartment i in zip code s and time t . The model includes fixed effects (FE) for each zip code (α_s) and for each half-year (β_t). The variable D_{st} takes value 1 for the treatment region in the post-treatment period and 0 otherwise, and the corresponding parameter δ measures the average treatment effect on the treated (ATT). The vector X_{ist} summarizes apartment specific covariates and other variables used in all our specifications: dummy variables for the month of the year to control for seasonality patterns, dummy variables for the number of rooms, interactions of district FE and time FE to allow for differential time trends in the various districts of the canton⁷, and interactions of the number of rooms and time FE to allow for differential time trends of large versus small apartments.

Each model is estimated for the full sample, without imposing any restrictions on the regions included in the analysis, and for the CEM weighted sample using linear regression. Estimations are performed separately for the positive and for the negative treatment to allow for heterogenous effects. In all cases, we adjust the standard errors for clustering at the zip code level.

— Insert Table 4 about here —

Table 4 shows the results of the δ coefficient in equation (1) for the total sample and the CEM sample, the positive and the negative treatment group and for log apartment rents and the number of clicks per day as dependent variables. For the full sample, the average treatment effect on the treated is -6.3 percent. Thus, the rents of apartments in regions exposed to more aircraft noise are about 6.3 percent smaller than the rents of apartments in unaffected regions

⁷Our data capture a total of 11 districts in the canton of Zurich and 221 zip codes, excluding Zurich city. The number of zip codes in one district ranges from 12 to 32, about 20 on average. Because districts consist of treated and control zip codes our data allows us to estimate the treatment effects even after controlling for interactions of district fixed effects and time FE.

after the change in flight regulations. In the CEM weighted sample, i.e., after matching the treated and control pre-treatment trends, we obtain an estimate of the ATT of -11.9 percent. Thus, when selecting the control group such that pre-treatment trends are comparable to the treatment group, the ATT effect almost doubles.

The second panel in Table 4 shows the ATT effects for the negative treatment, i.e., less aircraft noise. Whereas the effect on apartment rents is small and not statistically significant for the full sample, we find a significantly positive effect for the CEM sample. Here again, the treatment effect is underestimated if differential pre-treatment trends are not taken into account. The ATTs on the number of clicks per day are not significantly different from zero in all static DID models (irrespective of the sample and the treatment region).

The findings reported in Table 4 are based on the implicit assumption that the positive and the negative treatments have immediate effects and that these effects remain constant over time. Given the nature of the housing market (structural vacancies, turnover rates, slow reaction to changes, etc.) this assumption is rather unrealistic (e.g., Smith 1974; Wheaton 1990). In the next section we explicitly allow for time-varying treatment effects.

4.2 Dynamic difference-in-differences model

We specify the following dynamic difference-in-differences (DID) model:

$$Y_{ist} = \alpha_s + \beta_t + \sum_{\tau=0}^L \delta_{\tau} D_{s,t+\tau} + \gamma X'_{ist} + \varepsilon_{ist}. \quad (2)$$

Unlike (1), equation (2) allows for the treatment effect δ to be time-dependent. Although our data includes the exact date when the advertisement was uploaded, we need to aggregate the information in the time dimension for estimation purposes. A reasonable choice is to look at treatment effects over half-years. On the one hand, this ensures that we have sufficient observations per zip code and half-year t to reduce the sensitivity to outliers, and on the other hand, it still allows us to capture the adjustment dynamics in the housing market after the 2003

intervention in a rather flexible manner.

The variable $D_{s,t+\tau}$ indicates whether zip code s received the treatment in time t . It is zero in the pre-treatment period and switches to one for the treated (positively or negatively) in a specific half-year in the post-treatment period. As the first media citations of the partial flight ban over German territory and the introduction of landings from the south appeared in the first half-year 2003, more specifically in March 2003, the treatment period starts with the first half-year 2003. On May 21, 2003 the Federal Office of Civil Aviation decided to allow landings from the south on runway 34 and the new flight regulation including landings from the south took effect on October 30, 2003. Treatment effects in the first half year 2003 must therefore be considered as anticipatory, whereas treatment effects in the second half year 2003 and thereafter are a direct consequence of the change in aircraft noise exposure. We allow for a relatively long adjustment period by including fifteen half-years post treatment ($L = 15$).

4.3 Adjustment of apartment rents

If we assume the policy intervention caused adjustments in the price of apartment rents, there are many possible ways these price adjustments could have developed with time. Three simple but common forms of this dynamic process are shown for the positive treatment (increased aircraft noise) in Figure 4. First, an increase in aircraft noise may lead to an immediate reaction of the market and a constant discount in prices as sketched by line B. Such a process is typically captured by standard DID, i.e., a simple before/after comparison of treated and control. The intervention may also lead to a permanent decline in prices if the regions are structurally drifting apart due to the treatment (line A), or a temporary shock that eventually results in a recovery of prices towards the old equilibrium (process C). The recovery may be explained by various mechanisms at play during the post-treatment period, e.g., asymmetric residential sorting that results in more people looking for a new apartment in the affected regions where prices decreased, or the affected municipalities increasing their relative attractiveness, e.g., through tax reductions.

In the long run, these mechanisms may at least partially offset the initial shock.

— Insert Figure 4 about here —

Empirically, any of the described processes would lead to a negative estimate of the average treatment effect on the treated (ATT) by standard DID, at least for the early post-intervention observations usually available in the data. Although the long-run consequences of A, B and C differ dramatically, standard DID estimates would not be able to distinguish them. We therefore deem it critical to explore the full model (2) and evaluate the dynamics in apartment rents during the entire post-treatment period.

Figure 5 depicts the dynamic ATTs for the positive treatment and the CEM weighted sample. As the introduction of landings from the south was first announced in March 2003, the first half-year 2003 is likely too early to show any effects on apartment rents, and indeed our results suggest no significant ATT in that half-year. In the second half-year 2003 apartment rents started to react to the treatment. While rather small and statistically insignificant first, we find a significantly negative treatment effect from 2004 on. For the average apartment in the treatment region, the decrease in rents amounts to 13 percent after about two years (after the second half-year 2004).

— Insert Figure 5 about here —

Figure 6 displays the same graph but for the entire sample instead of the CEM weighted sample. Recall that the CEM algorithm was constructed such that the pre-treatment trends in the treatment and control group are matched, and therefore very similar, whereas in the total sample the pre-treatment time trends of apartment rents in the control group may be very different from those in the treated groups. The estimation results for the total sample suggest that there is still a negative treatment effect, but the estimation is much noisier (standard errors

are about twice as large) and the magnitude of the effect is much smaller (only about a half). We explain this discrepancy by the likely inclusion of control units in the total sample that do not meet the critical DID assumption of a common time trend in the absence of the treatment.

— Insert Figure 6 about here —

The dynamic effects of the *negative* treatment (i.e., less aircraft noise) suggest that prices start to increase with a significant and constant mark-up of about 6 to 7 percent from 2005 on (see Figure 7). These results are again obtained for the CEM weighted sample. While the absolute magnitude of the long-term effect seems to be stronger for the positive treatment (more noise), the magnitudes of the effects must be related to the change in average noise exposure in the two regions. The increase by 7.5 dB(A) on average in the positive treatment region compares to only -3.6 dB(A) on average in the negative treatment region (see Table 1). Hence, the marginal effects on apartment rents per decibel aircraft noise are about the same (just with the opposite sign) for the positive and for the negative treatment. The size of the marginal effect is in both treatments around 2 percent.

— Insert Figure 7 about here —

Overall, there is compelling evidence that rental prices converge to a new equilibrium, with significantly different prices. In the positive treatment (more aircraft noise) the new equilibrium is reached after the second half-year 2004, about two years after the policy intervention. The adjustment dynamics therefore resemble a combination of lines C (in the early stages) and B (in the long-term effect) in Figure 4. For the negative treatment region (i.e., less aircraft noise), we also find an adjustment period of about two years. However, whereas the noise *increase* had an almost immediate effect on rents (although insignificant at the beginning), the effect of the noise *decrease* showed a lag of about one year.

4.4 Adjustment of market behavior

The two treatment regions not only differ in their exposure to aircraft noise (more versus less) but also in their structural attractiveness as a residential neighborhood. The positive treatment region in the south, between the two lakes (Lake Zurich and Lake Greifen), is considered as one of the most desirable regions to live in the canton of Zurich. This is reflected by the high number of clicks per advertisement and day registered on the *homegate.ch* website. After the introduction of the new flight regime, the region lost some of its attractiveness due to the additional aircraft noise. On the one hand, we would expect that the demand for housing decreases in response to this negative shock. On the other hand, there could be a stimulating effect because (i) the possibility of price discounts in a desirable region attracts people previously unable to afford to live there, and (ii) media coverage increases public attention.

Figure 8 provides some evidence for this stimulating effect. In particular, we observe an increase in the number of clicks immediately following the policy intervention. The increase is substantial with about 300 to 350 additional clicks per advertisement and day in the positive treatment region compared to the average control. Relative to the baseline of about 470 clicks (Table 2) this corresponds to an increase of more than 60 percent. The effect appears to vanish at about the same time as prices converged to the new equilibrium. More specifically, the number of clicks per advertisement for the positive treatment regions returns to a level consistent with that for the control regions about two years after the policy intervention and remains at that level thereafter.

— Insert Figure 8 about here —

For the negative treatment, we find a similar pattern in the number of clicks as for the positive treatment during the adjustment period (see Figure 9). The increase in clicks is about 150 per advertisement and day (statistically significant at the 5 percent level), which corresponds

to an increase of about 50 percent over the baseline of approximately 300 clicks per day.

— Insert Figure 9 about here —

4.5 Static difference-in-differences model excluding the adjustment period

Our results indicate that about two years after the change in flight regulations a new equilibrium with significantly lower rents in regions exposed to more aircraft noise and significantly higher rents in regions exposed to less aircraft noise is reached. During these two years we observe significantly more clicks per ad and day. As a final exercise and robustness check, we return to the static DID models but restrict the time period analyzed.

— Insert Table 5 about here —

Table 5 shows the static ATT of equation (1) for the entire period 2002 to 2010 covered by the available data and for a restricted time period only (excluding the adjustment period). The first column shows the ATT on log apartment rents for the entire period (replication of column 2 in Table 4) for both the positive and the negative treatment. The second column shows the ATT without the years 2003 and 2004. The ATTs are larger in magnitude for both the positive and the negative treatments in the restricted sample, which is not surprising given the small effects during the (excluded) adjustment period (see also Figures 5 and 7).

Columns 3 and 4 show the ATTs for the number of clicks per day and the unrestricted and restricted treatment periods, respectively. The effects for the entire period are small and statistically insignificant, likely because of the short temporary increase in clicks in the early post-treatment period and zero effects afterwards (see Figures 8 and 9). In the last column of Table 5 we therefore excluded all observations after 2005. During this restricted time period, we find that the number of clicks increased by 331 for ads in the positive treatment group and by

162 for ads in the negative treatment groups. Both effects are statistically different from zero at the 1 percent significance level.

4.6 Effects on Housing Supply

Data constraints often preclude distinguishing between supply- and demand-side effects when using a hedonic pricing approach. Given the substantial effects on equilibrium prices that became apparent in the previous sections, regions affected by more (less) noise are likely to become less (more) attractive for investments in new housing units. As a consequence, one may expect a decrease (increase) in the number of housing units or any factors influencing the supply side such as the price of land (Greenstone and Gallagher 2008).

Whereas our core dataset allows us to investigate demand-side effects (like those on the number of clicks per ad and on turnover rates) it does not contain information about housing supply. Building on Greenstone and Gallagher (2008), we extract data on the number of housing units per community, and we also consider the value of land (CHF/m^2). These data stem from the Statistical Office of the Canton Zurich and cover all communities in the canton and span the years 1995 to 2011. Except for two communities, all zip-codes within a community can be unambiguously allocated to one of the treatment groups (positive, negative treatment or control group).⁸ Due to the long-lasting regulatory process in building new housing units, we expect most of the potential short- to medium-run effects to originate from effects on the value of land.

— Insert Figures 10 and 11 about here —

Using the same DID/CEM methods as before, there is little evidence for effects on housing supply. In particular, we do not find any effects on the value of land for either the positive and the negative treatment regions. Figures 10 and 11 display the results for the number of housing units (in logs). In case of the communities exposed to more aircraft noise, estimates are very

⁸Due to ambiguity, we dropped the city of Zurich and Faellanden from the analysis.

small and statistically insignificant. For the regions exposed to less aircraft noise, we find a positive but rather small (and mostly insignificant) effect which is slightly increasing over time.

4.7 Welfare Implications

In this section, we make use of our estimates to calculate an overall effect of the flight regime change on people living in the canton of Zurich. Given that we estimated ATTs for the two treatments, necessary assumptions for this exercise are that preferences are homogeneous and effects are linearly dependent on the level of aircraft noise for both treatments (Chay and Greenstone 2005).⁹ Both assumptions are certainly large, but at least for the linearity assumption we find some evidence. The long-run effects per decibel are very similar in the two treatment regions. Based on the long-run noise effects on apartment rents of -13.1 and 7.5 percent for the positive and the negative treatment and the respective average changes in noise exposure (7.5 and -3.6 decibel, respectively) the effects per decibel amount to -2.1 and -1.8 percent on average.

The most recent census data from the Statistical Office of the Canton Zurich provides us with the number of housing units and the average rental rates for each community in 2000. Moreover, the data contains information on the distribution of different apartment sizes (1, 2, 3, 4, 5, 6+ rooms). As a consequence, we are able to conduct the following calculation:

$$\Delta W = \sum_{i=1}^N \sum_{a=1}^T [R_{ia} * A_{ia} * \delta n_i] + \sum_{j=1}^M \sum_{a=1}^T [R_{ja} * A_{ja} * \delta n_j] \quad (3)$$

where ΔW stands for the overall change in rents for both treatment regions, i.e., communities experiencing an increase (i) and a decrease (j) in noise exposure, respectively. Hence, the first term on the right hand side of equation (3) measures the total impact on the regions exposed to more noise (i). R_{ia} is the average rental rate for apartments of size a in region i and A_{ia} and δn_i are the corresponding number of housing units of size a in community i and the normalized average effect on the rental rates in percent (change in noise level in community i times the

⁹For a more general discussion on welfare effects in the context of hedonic pricing, see Parmeter und Pope (2012) and Parmeter and Pope (forthcoming).

estimated percentage effect per decibel), respectively. The overall effect for the regions exposed to less noise (j) is summed up in the second term of equation (3).

— Insert Table 6 about here —

Table 6 displays the results for equation (3) together with some descriptive statistics that are of interest in this context. There are three interesting findings. First, the number of housing units that are exposed to less noise after the flight regime change is almost double the number of housing units exposed to more noise (column 1 of Table 6). Second, regions exposed to more noise have on average higher rental rates (column 2 of Table 6). Third, given the higher rental rates and the relatively large increase in the level of noise the overall effect is negative but moderate (column 3 of Table 6). That is, we observe a decrease in rents of about CHF 3 million per month for the communities exposed to more noise and an increase in rents of about CHF 2.7 million per month for housing units located in communities experiencing less noise. The overall effect, ΔW , therefore amounts to about CHF 0.3 million per month.

It is obvious and inevitable that the present analysis has several limitations. First, we are focusing on the effects for the canton of Zurich leaving out other at least partly affected regions and cantons. Second, information on all costs and benefits that come with the flight regime change including the effects on the airport, industries, etc. is not available. However, we believe that our calculations provide an important ingredient in overall welfare calculations.

5 Concluding remarks

Despite the knowledge that sources of frictions and imperfections cause the rental market to adjust slowly (e.g., Rosen and Smith 1983; Smith 1974; Wheaton 1990), quasi-experimental papers on the valuation of non-market goods through hedonic pricing typically ignore the adjustment processes and implicitly assume immediate and constant effects (see, e.g., Parmeter

and Pope, forthcoming, for an overview and related discussions). This paper explicitly addresses the market adjustments after the exogenous shock. More specifically, we use a large longitudinal data set of apartments around Zurich airport to examine how apartment rents adapted to the unexpected flight regime change that substantially altered noise exposure.

Our results indicate that after the change in flight regulations apartment rents took about two years to readjust to a new equilibrium level with relatively stable price differences between treated and control groups. Specifications that ignore this adjustment process tend to underestimate the treatment effects. Online advertisements for rented apartments in both the negative and positive treatment regions attracted significantly more clicks during the adjustment period, indicating a higher search effort and an increased housing market activity, presumably due to noise-based residential sorting. After the period of two years, noise-sensitive people are likely to have found a new apartment in a quiet region, and noise-insensitive people have decided whether they would like to accept more noise for lower rents. We find that the effects of aircraft noise on apartment rents are symmetric, so that the per decibel discount on rents in regions of increased aircraft noise is consistent with the per decibel rise in regions of lowered aircraft noise.

Last but not least, we introduce the coarsened exact matching (CEM) procedure proposed by Iacus, King and Porro (2011a,b) into the quasi-experimental hedonic literature. CEM helps to eliminate the observed pre-treatment differences in time trends between the treatment and control groups and therefore makes the critical assumption of a common time trend of the treated and control group in the absence of the treatment more credible.

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Tables and Figures

Table 1: Treatment summary

	Positive Treatment $\Delta L_{eq} > 3$	Negative Treatment $\Delta L_{eq} < -3$	Control $-2 \leq \Delta L_{eq} \leq 2$
<i>Change in noise exposure ΔL_{eq}</i>			
Mean	7.45	-3.59	-0.57
Minimum	3.10	-6.90	-2.00
Maximum	14.10	-3.10	2.00
Number of zip codes	10	24	102
Number of observations	7,397	11,051	123,775

Source: EMPA noise data, own calculations. *Notes:* ΔL_{eq} is the change of daytime noise exposure from 2002 to 2004. L_{eq} is an equivalence metric corresponding to a steady sound level, measured in dB(A), for the 16-hour interval from 6:00 am to 10:00 pm that produces the same energy as the actual time-varying sound level. Units of observation are advertisements.

Table 2: Descriptive statistics by treatment region and time

	Positive Treatment		Negative Treatment		Control	
	Mean	SEM	Mean	SEM	Mean	SEM
<i>A. Before flight regime change</i>						
Apartment rent	1887.4	50.7	1532.8	23.2	1528.0	9.9
Clicks per day	470.3	56.6	304.6	36.4	406.4	12.8
Number of observations	356		519		7,270	
Number of zip codes	10		19		86	
<i>B. After flight regime change</i>						
Apartment rent	1818.8	9.3	1643.4	5.6	1720.5	2.9
Clicks per day	543.9	17.5	471.0	12.8	574.3	4.2
Number of observations	7,041		10,532		116,505	
Number of zip codes	10		24		102	

Source: Homegate advertisement data, own calculations. *Notes:* Apartment rents in Swiss Francs (CHF), average number of clicks per day registered on *homegate.ch*. SEM is the standard error of the mean.

Table 3: Pre-treatment trends and CEM

	Positive Treatment			Negative Treatment			Control		
	Mean	#zips	L1	Mean	#zips	L1	Mean	#zips	#bins
<i>A. Total sample</i>									
Apartment rent	-14.53	9	0.29	-72.68	14	0.25	88.38	71	
Clicks per day	-327.88	9	0.31	74.55	14	0.26	-66.09	71	
<i>B. CEM sample</i>									
Apartment rent	79.91	4	0.00				80.42	4	500
Clicks per day	-159.30	5	0.00				-164.42	8	150
Apartment rent				8.63	8	0.00	7.58	11	280
Clicks per day				58.78	8	0.00	58.23	14	400

Source: Homegate data, own calculations. *Notes:* Pre-treatment trend is calculated as average per zip code over 2002 H2 minus average over 2002 H1. Coarsened exact matching (CEM) based on separate comparison of positive/negative treatment and control zip codes. L1 statistic to measure imbalance between treatment groups and control group as proposed by Iacus et al. (2011a,b). L1 = 0 indicates perfect balance (up to the discretization of the original variable into equal sized bins, number of bins in last column).

Table 4: Static DID results with total sample and CEM sample

	Log apartment rents		Clicks per day	
	Total	CEM	Total	CEM
<i>A. Positive treatment</i>				
ATT	-0.063*** (0.024)	-0.119*** (0.009)	-99.88 (99.82)	71.02 (90.59)
Number of observations	131,172	10,273	131,172	16,963
<i>B. Negative treatment</i>				
ATT	0.003 (0.018)	0.063*** (0.014)	1.785 (46.21)	49.10 (24.21)
Number of observations	134,826	28,418	134,826	28,439
Zip code FE	yes	yes	yes	yes
Time FE (half-years)	yes	yes	yes	yes
Month of the year	yes	yes	yes	yes
Number of rooms	yes	yes	yes	yes
District FE \times time FE	yes	yes	yes	yes
Number of rooms \times time FE	yes	yes	yes	yes

Notes: Estimates for the average treatment effect on the treated (ATT) from interaction of treatment region times after the flight regime change. Zip code cluster-adjusted standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Static DID with and without time restrictions

	Log apartment rents		Clicks per day	
	entire period	restr. period	entire period	restr. period
<i>A. Positive treatment</i>				
ATT	-0.119*** (0.009)	-0.131*** (0.009)	71.02 (90.59)	331.2*** (33.10)
Number of observations	10,273	8,503	16,963	3,774
<i>B. Negative treatment</i>				
ATT	0.063*** (0.014)	0.075*** (0.013)	49.10 (24.21)	162.0*** (26.29)
Number of observations	28,418	23,529	28,439	6,561
Zip code FE	yes	yes	yes	yes
Time FE (half-years)	yes	yes	yes	yes
Month of the year	yes	yes	yes	yes
Number of rooms	yes	yes	yes	yes
District FE \times time FE	yes	yes	yes	yes
Number of rooms \times time FE	yes	yes	yes	yes

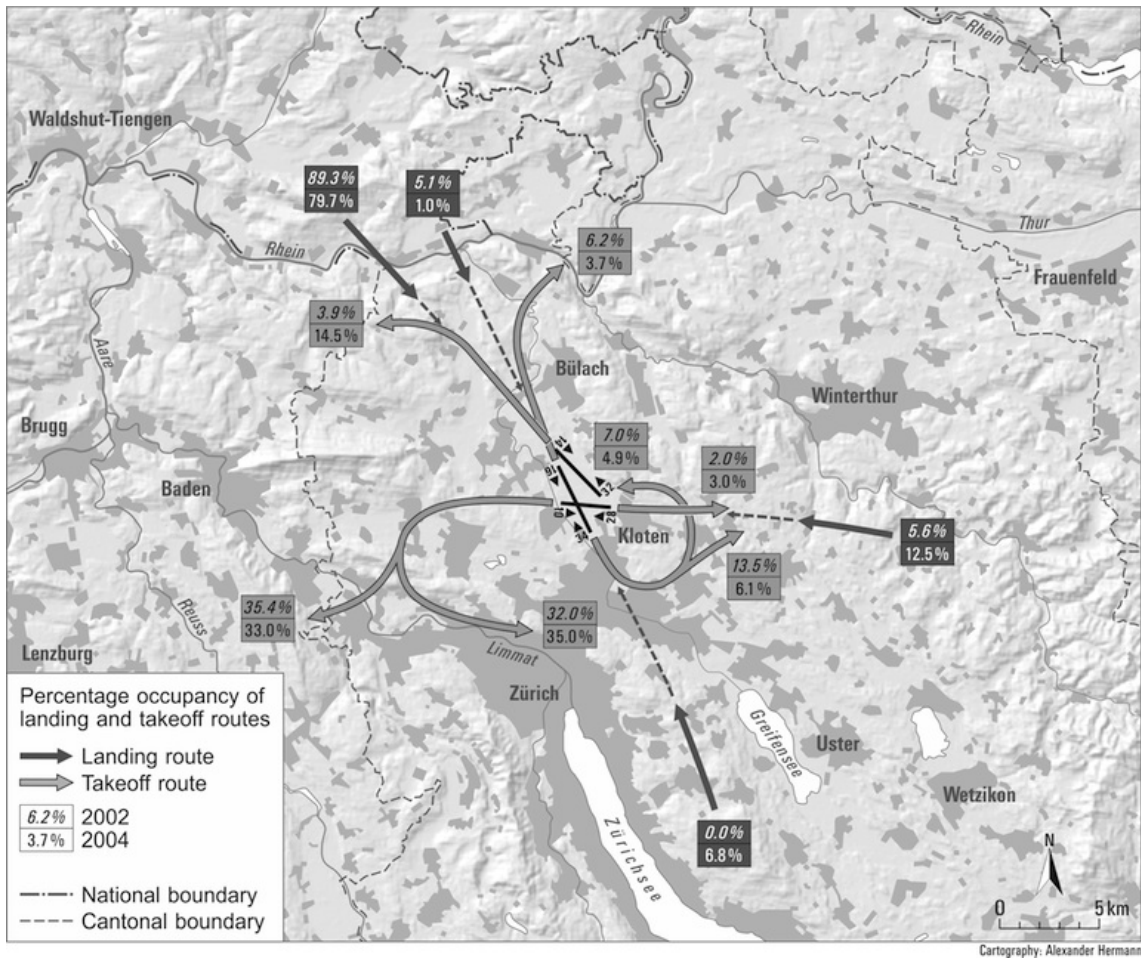
Notes: Estimates for the average treatment effect on the treated (ATT) from interaction of treatment region times after the flight regime change for the CEM sample. Entire period relates to the time between January 2003 and December 2010. Restricted period excludes observations in the years 2003 and 2004 for log apartment rents, and years 2005 to 2010 for clicks per day. Zip code cluster-adjusted standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Welfare Effects of the Flight Regime Change

	No Ap	Av Rent	Agg Effect
Pos	13,592	1,646	-2,974,514
Neg	26,197	1,421	2,721,343
ΔW			-253,171

Note: "Pos" and "Neg" stand for the positive (more noise) and negative (less noise) treatment. "No Ap", "Av Rent" and "Agg Effect" denote for the overall number of housing units, the average monthly rental rates and the overall monthly effect for each treatment, respectively.

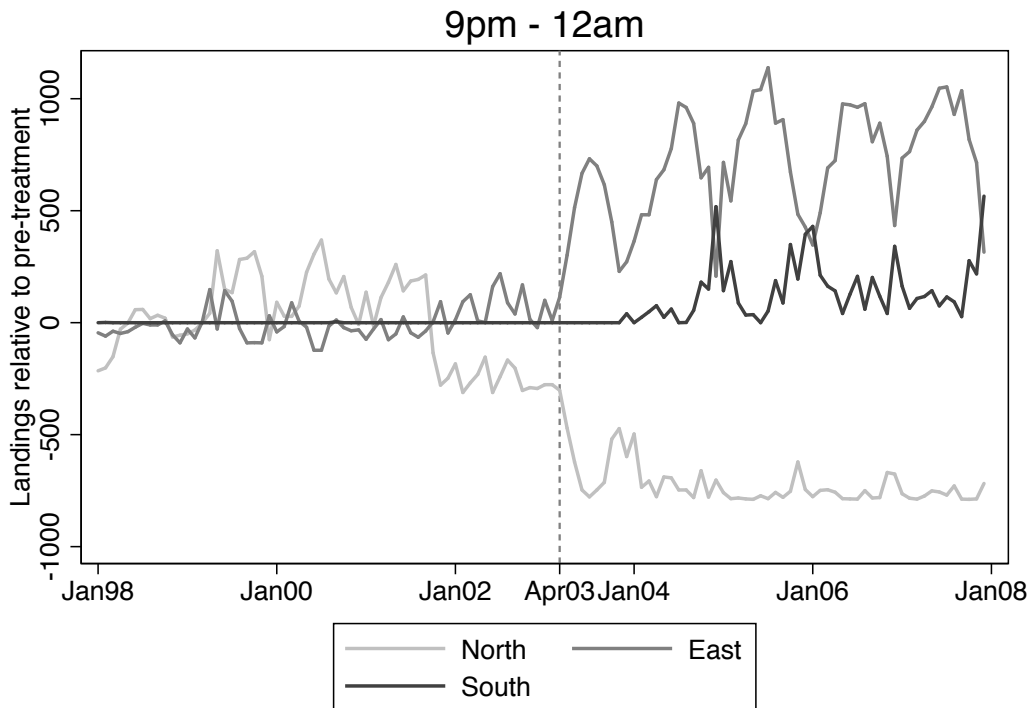
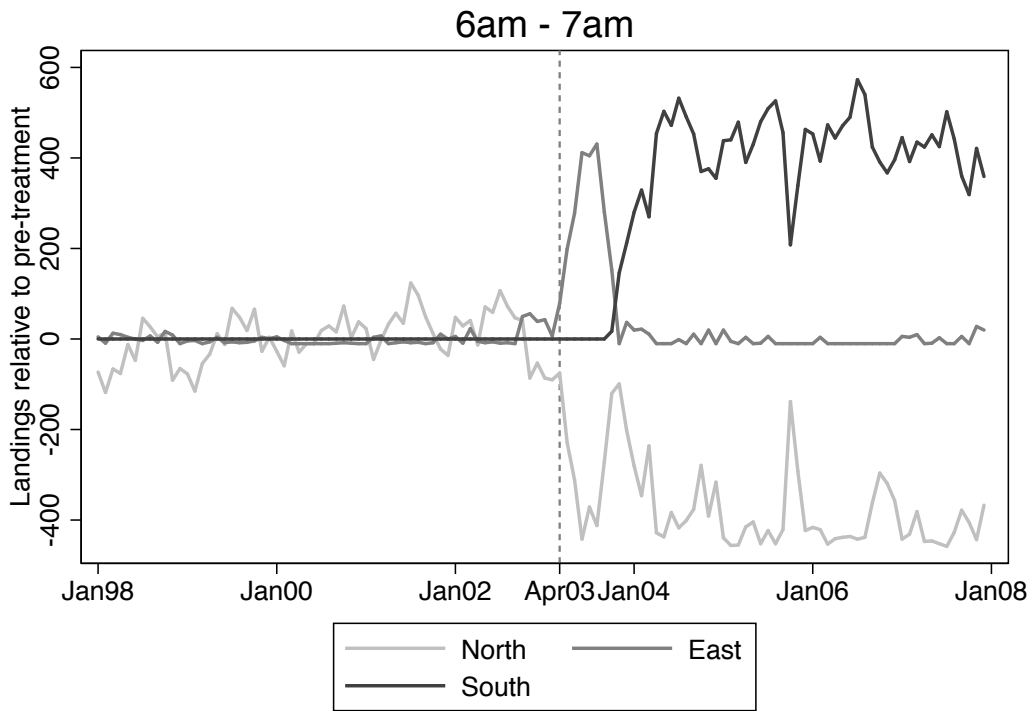
Figure 1: Zurich airport and relative flight occupancy



Notes: Percentage occupancy of landing and takeoff routes in 2002 and 2004. Grey shaded are settlement areas. Swiss-German border marked with dash dot line. Dashed line marks cantonal border. North/south runway 16/34, northwest/southeast runway 14/32, east/west runway 10/28.

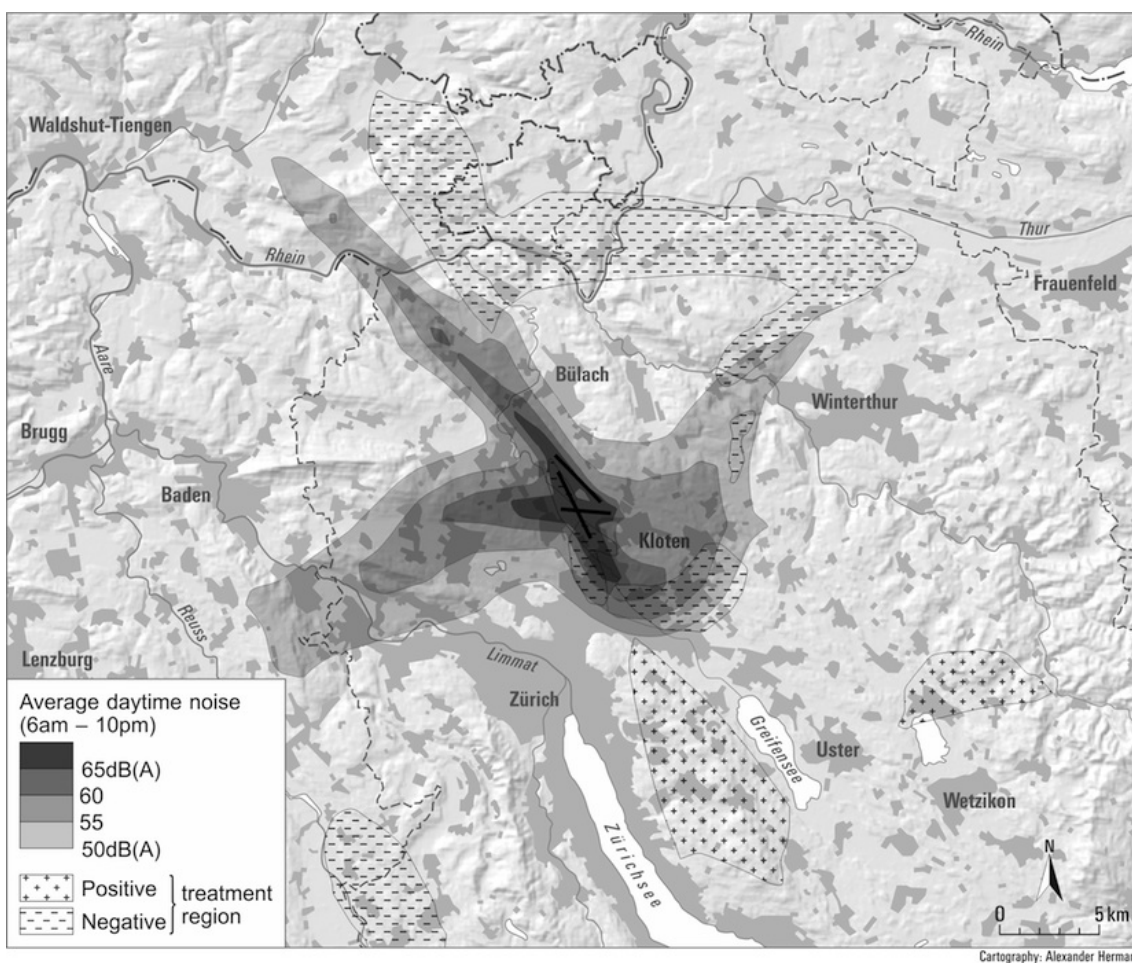
Source: Flughafen Zürich AG.

Figure 2: Monthly landings



Source: Flughafen Zürich AG, own calculations.

Figure 3: Daytime noise exposure in 2022



Notes: Contours show average daytime noise L_{eq} from 6 am to 10 pm in 2022. Plus signs mark the positive treatment (defined as region affected by change in L_{eq} from 2002 to 2004 by more than 3 dB(A) and average noise exposure in 2002 of more than 30 dB(A)). Minus signs mark the negative treatment (change in L_{eq} from 2002 to 2004 by less than -3 dB(A) and average noise exposure in 2002 of more than 30 dB(A)).

Source: EMPA, own calculations.

Figure 4: Sketch of different types of adjustment processes

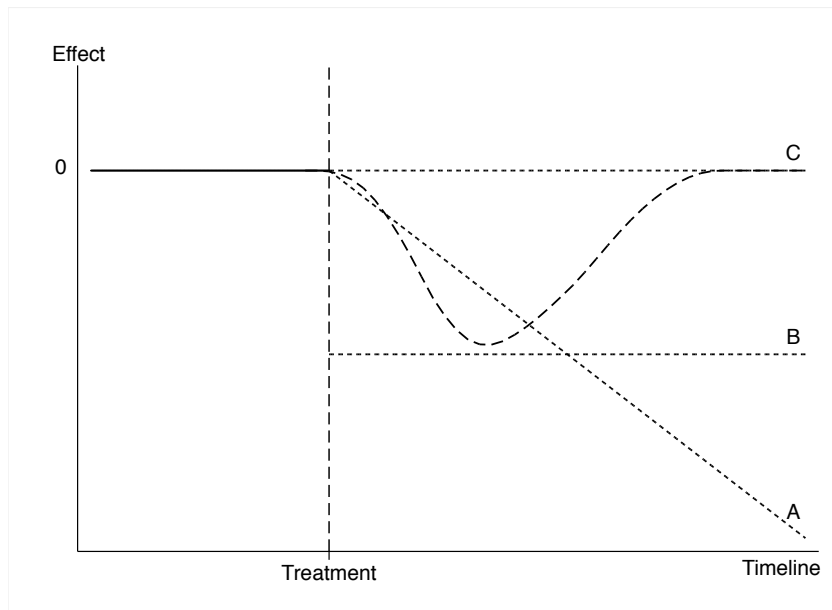
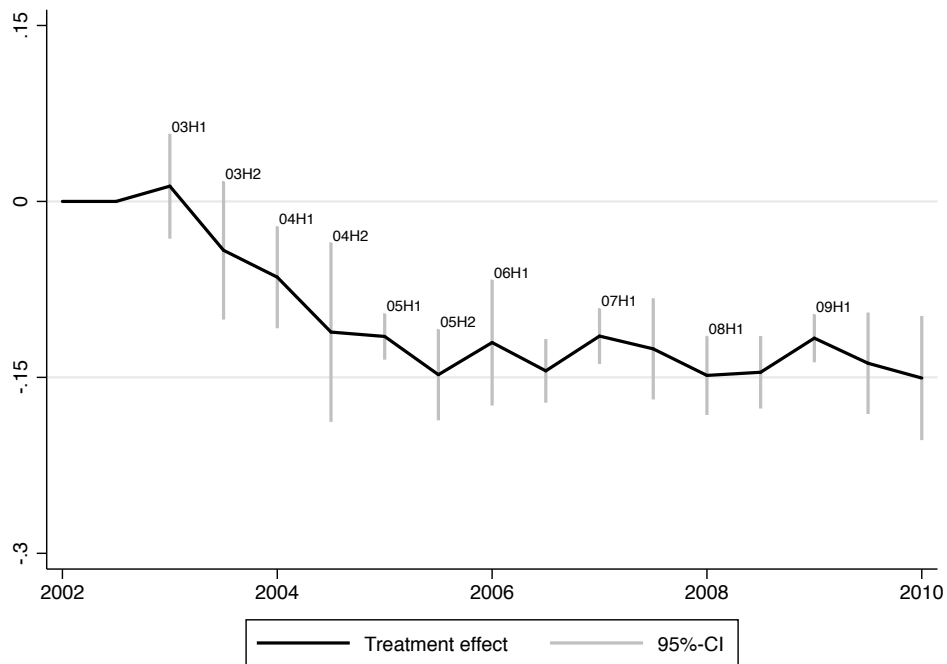
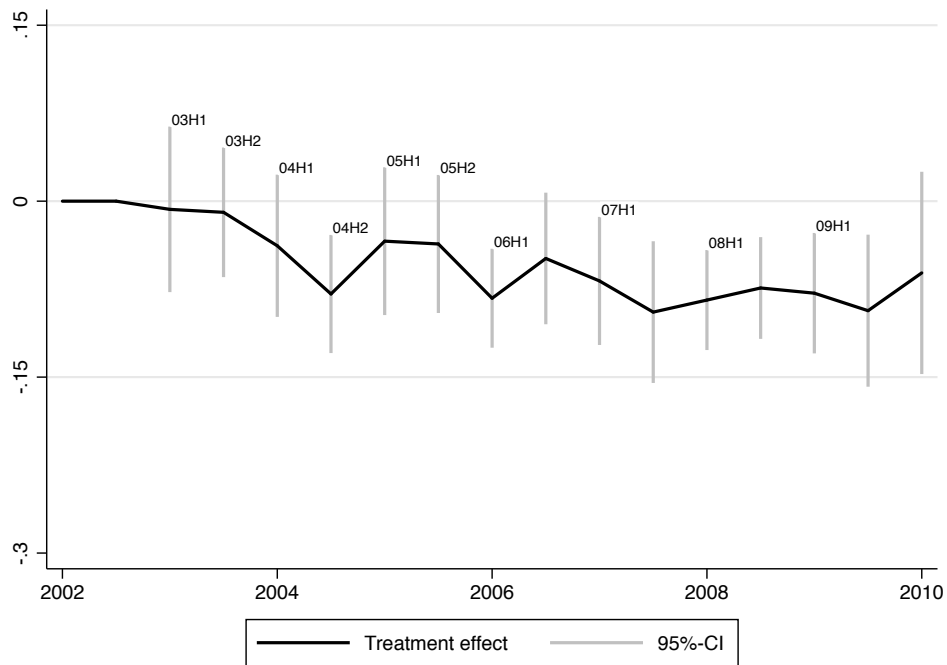


Figure 5: Positive treatment: adjustment of apartment rents



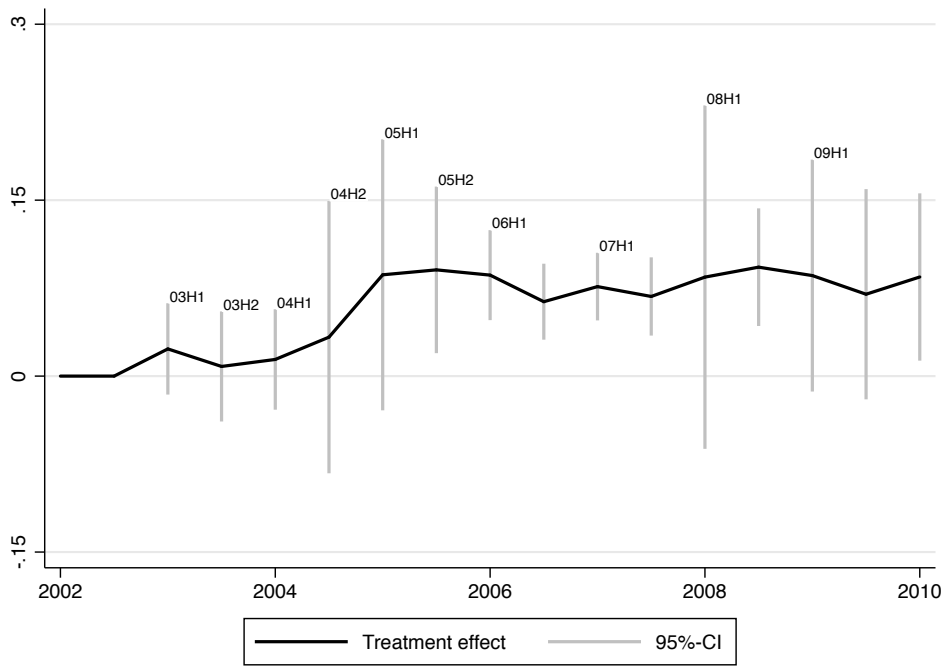
Notes: Estimates shown for DID model with positive treatment interacted with dummies for each half-year since January 2003. Data have been pre-processed with CEM. Model controls for zip code FE, time FE (half-years), month of the year (seasonality), number of rooms, interactions of district FE and time FE, and interactions of the number of rooms (5 categories) and time FE. 95%-CI based on zip code cluster-adjusted standard errors.

Figure 6: Positive treatment: adjustment of rents without CEM



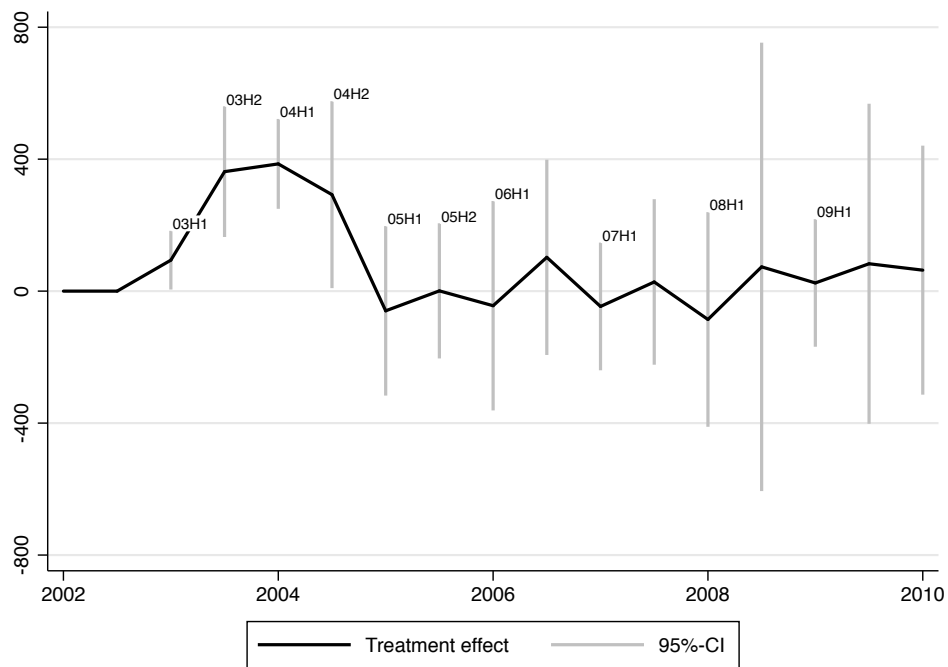
Notes: See Figure 5. Estimation based on total sample instead of CEM weighted sample.

Figure 7: Negative treatment: adjustment of apartment rents



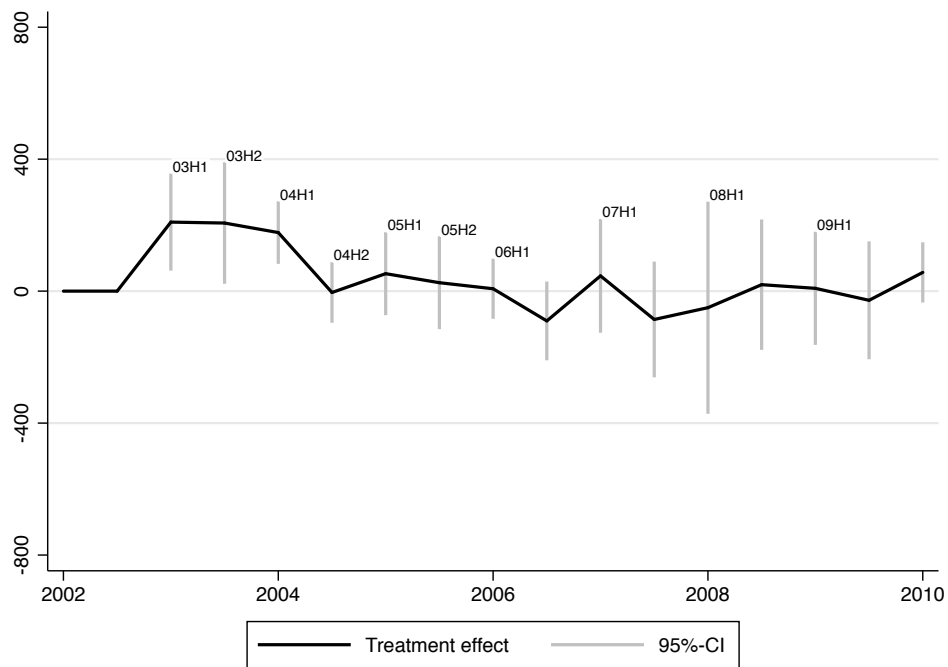
Notes: Estimates shown for DID model with negative treatment interacted with dummies for each half-year since January 2003. See Figure 5 for list of controls. Data have been pre-processed with CEM matching. 95%-CI based on zip code cluster-adjusted standard errors.

Figure 8: Positive treatment: adjustment in number of clicks per day



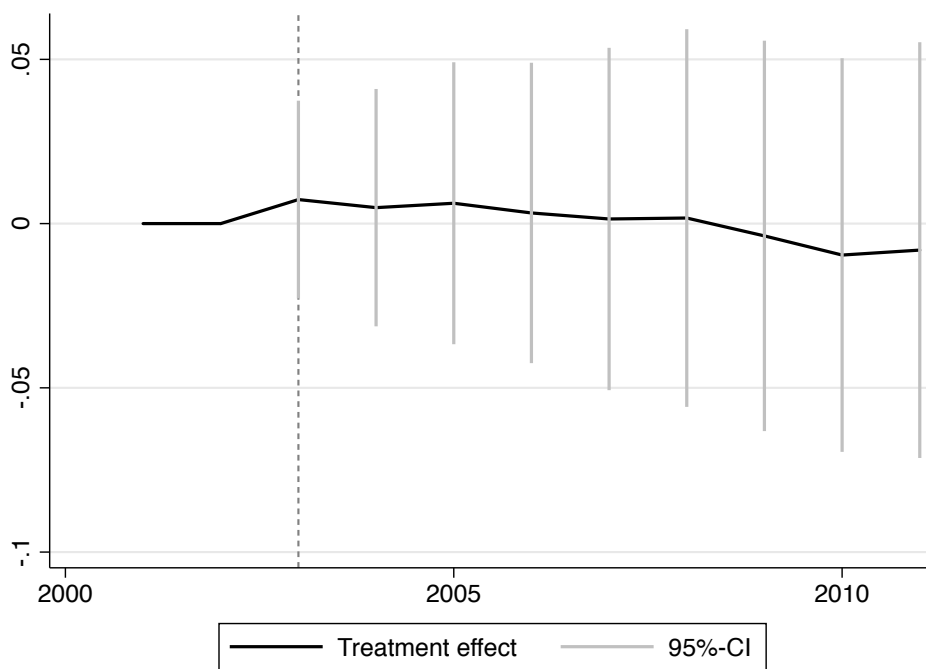
Notes: See Figure 5.

Figure 9: Negative treatment: adjustment in number of clicks per day



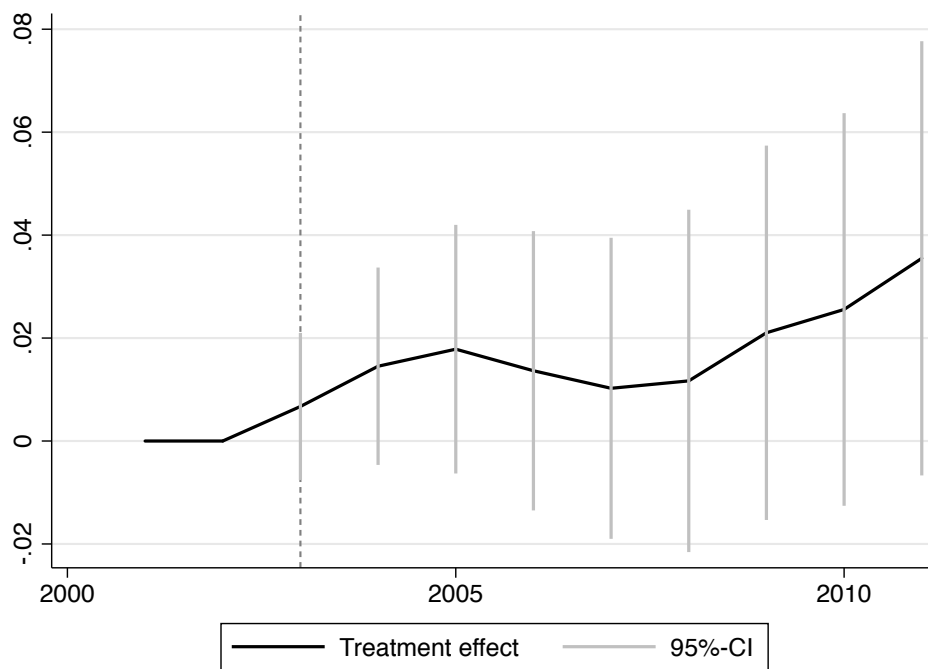
Notes: See Figure 7.

Figure 10: Positive treatment: adjustment in number of housing units



Notes: Estimates shown for DID model with positive treatment interacted with dummies for year since 2003. Data have been pre-processed with CEM. Model controls for community and year FE. 95%-CI based on zip code cluster-adjusted standard errors.

Figure 11: Negative treatment: Number of housing units



Notes: Estimates shown for DID model with negative treatment interacted with dummies for year since 2003. Data have been pre-processed with CEM. Model controls for community and year FE. 95%-CI based on zip code cluster-adjusted standard errors.