TI 2023-059/VIII
Tinbergen Institute Discussion Paper

The effect of urban trees on house prices: evidence from cut-down trees in Amsterdam

Lynn Bouwknegt[1]
Jan Rouwendal[2]

1 Vrije Universiteit Amsterdam

2 Vrije Universiteit Amsterdam and Tinbergen Institute

Tinbergen Institute is the graduate school and research institute in economics of Erasmus University Rotterdam, the University of Amsterdam and Vrije Universiteit Amsterdam.

Contact: discussionpapers@tinbergen.nl

More TI discussion papers can be downloaded at https://www.tinbergen.nl

Tinbergen Institute has two locations:

Tinbergen Institute Amsterdam
Gustav Mahlerplein 117
1082 MS Amsterdam
The Netherlands
Tel.: +31(0)20 598 4580

Tinbergen Institute Rotterdam
Burg. Oudlaan 50
3062 PA Rotterdam
The Netherlands
Tel.: +31(0)10 408 8900

The effect of urban trees on house prices: evidence from cut-down trees in Amsterdam

Lynn Bouwknegt *†
Jan Rouwendal *‡

September 18, 2023

Abstract

This paper studies the effect of urban trees on house prices in Amsterdam by utilizing a detailed data set of trees that were cut-down near the house. By using exogenous reasons the tree was cut-down such as disease or storm, unobserved heterogeneity can be dealt with, and a causal effect established. We use a staggered difference-in-difference approach to hedonic pricing analysis. We find an effect of 1.19 percent decrease in house prices when a tree is cut-down within 75 meters of the house. The effect is largest when trees within that area are scarce. This provides further evidence that urban trees are a valued aesthetic amenity for home owners and should be treated accordingly.

1 Introduction

Urban trees greatly improve live-ability within cities. This improvement happens in multiple ways. Mullaney et al. (2015) show that environmental effects associated with growing trees in an urban environment include improving air quality, improving water drainage, and providing shade. Besides their environmental benefits, urban trees also generate positive economic externalities. The economic effect that we discuss in this paper is the positive effect that urban trees have on residential house prices. The premium that houses in attractive green areas have, reflect the aesthetic amenity value of trees. Our paper will position itself on this crossover between ecology and economy.

The elevated level of house prices in many cities provides a strong incentive to densification, e.g., as per Broitman and Koomen (2020), through infill development and the replacement of detached houses with gardens by apartment buildings. This puts increasing pressure on Green Infrastructure. By gaining insights and reliable quantitative information on the economic benefits of urban trees can help in making trade-offs between floor space and green, which is what we aim to do within this paper.

There are several papers that try to capture the effect of green on house prices. Most of those papers study the USA. For example, Hammer et al. (1974) study the effect of a large urban park on house prices in Philadelphia, USA. Anderson and West (2006) use hedonic pricing analysis in Minneapolis to estimate proximity of open space on house prices. Most papers use one type of green space for their analysis. For example, Donovan and Butry (2010) estimate the effect of street trees on the sales price and the time-on-market in Oregon, USA. They find a positive effect of houses with a view on trees of around 2.5%. Tyrväinen (1997) studies the effect of urban forests on house prices in a town in North Carelia, Finland. All papers mentioned find a positive premium for house prices close to urban green.

Luttik (2000) points out that hedonic pricing models are quite context specific. Hedonic pricing analyses that study the Netherlands in this context are for example those by Bervaes and Vreke (2004), Luttik (2000) and Rouwendal and van der Straaten (2008). Bervaes and Vreke (2004) study the effect of view of green and water on house prices. Luttik (2000) finds a +/- 7% premium on house prices if they have a view of a park, and a +/- 5% premium if there is a view of a green strip. Rouwendal and van der Straaten (2008) estimate the value of urban parks and public garden in three major cities in the Netherlands. The authors find especially positive effects for highly valued green space, in particular for Amsterdam's most famous park, the Vondelpark.

Measuring the value of urban trees is not an easy task. As is so often the case in hedonic price analysis, omitted variable bias is a prominent issue. For instance, neighborhoods that are attractive because of the de-

*Vrije Universiteit Amsterdam (VU) - Boelelaan 1105, 1081 HV Amsterdam
†Environmental Assessment Agency (PBL) - Bezuidenhoutseweg 30, 2594 AV Den Haag
‡Tinbergen Institute Amsterdam (TI) - Gustav Mahlerplein 117, 1082 MS Amsterdam

sign of street patterns and buildings - aspects that are difficult to quantify - often have more trees and other green elements than less attractive neighborhoods do. The omitted variable bias issue can sometimes be addressed by using fixed effects as was done, for instance, by Rouwendal et al. (2016) in their study of the value of proximity to water. Difference-in-difference methods deal with the issue even more extensively, as they allow for changes in amenity valuation over time. These methods have been often combined with hedonic pricing models in the recent literature. However, fixed effects can only control for aspects that are constant over time, whereas local trends may still cause bias. We aim to deal with this issue in our paper by including these trends.

This paper will follow, to some extent, the working paper by Han et al. (2021). The authors study the amenity value of urban trees by studying the exogenous shock of the emerald ash border infestation and thus the loss of trees from this infestation on house prices in Toronto. The authors stress the importance of using exogenous and permanent shocks to the tree canopy to best estimate the causal effect of trees on property values. The authors find a 0.5% - 0.8% reduction in property prices per tree lost. Similar to these authors, we have a data set of public trees that were cut-down including tree species and geolocations. Combining this detailed data set with satellite images, we are able to gather the exact date the tree was cut-down. This way we can utilize a staggered difference-in-difference approach. This method takes treatment, in our case cut-down trees, as a staggered roll out instead of using one long treatment period. To our knowledge, this has not been done before within our context.

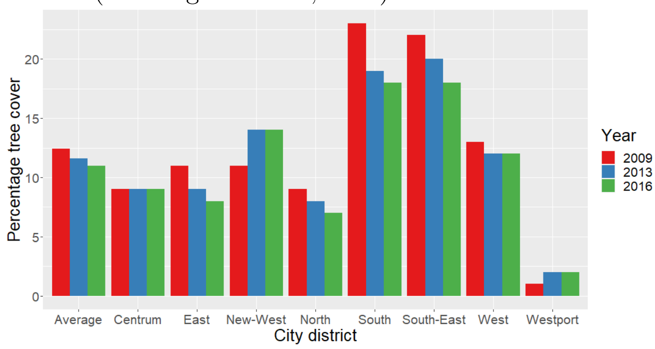
We apply the staggered technique here to study the impact of cutting down trees on house prices in the immediate vicinity. With this approach we follow, to some extent, Lin et al., 2022. The authors of this paper study the initiative in Philadelphia to green vacant lots using a staggered difference-in-difference model. Furthermore, this paper uses several reasons the trees were cut down as well as different species, we are able to gather a well distributed data set that helps limit bias. Lin et al. (2022) find a large effect of around 5.8%. We expect to be in a range similar to Han et al. (2021), because we focus on trees and not lots. This paper will proceed as follows. Firstly, we introduce the study area. Secondly, we describe the methodology and specification. We show results and a sensitivity analysis, and finally a discussion.

2 Data

2.1 Study area

We use detailed data on houses and urban trees in Amsterdam. As the capital of the Netherlands and its most popular city, the marginal price of floor area is exceptionally high for Amsterdam. This reflects the huge pressure on the housing market, further enhanced by the less than average size of houses compared to other major Dutch cities. We can see in figure 1 that on average there is a decline in how much city districts are made up of tree canopy cover over time. Tree cover is defined as the area of the tree crown, i.e., the space the leaves of the tree cover. Over the period 2009-2016 the average percentage tree cover in Amsterdam went down from around 12.5 to 10.5 percent. This makes Amsterdam an interesting case study for this paper. In other words, we can look at how this increasing scarcity affects house prices. Research by de Vries et al. (2023) shows that a scarcity in public green also strongly implies scarcity in private green. Thus, the private green can not compensate for the average decline in tree cover. Furthermore, not just the average declined, almost all city districts see a decline in tree cover. The tree cover increased only in the new residential areas New-West and where the docks are in Westpoort, but no residents live.

Figure 1: Percentage tree canopy cover in each city district (Tree register data, 2023)



Because of the increasing pressure on green space and the steady decline in average tree cover this has resulted in, recently the municipality of Amsterdam has begun to focus more on increasing and restoring public green space in the city. The plan attached to this idea is called the Green Vision by the Gemeenteraad (2020), and lasts from 2020 to 2050. The plan surrounds accessibility to green, and involves small parks, green strips and trees in front of houses. The latter is important for our paper - as the municipality has started to replace trees that were cut-down in recent years, they have also kept record of locations, species, and more. This data set is key for our research, and will be discussed in section 2.3.

2.2 House transaction data

The house transaction data is provided by the Dutch Association of Real Estate Agents (NVM). The data includes house transactions between (2011-2021), their respective locations and structural characteristics. The

NVM data set does not cover all house transactions (70+%), but Bervaes and Vreke (2004) argue that having an NVM real estate agent involved in purchasing a home will not be correlated with the effect of amenities on the price of the house. In turn, representativity of the sample set is not affected. The level of detail in this data set is an important advantage. It does not only contain the property value - it is also made up of the set characteristics that the house consists of. The transaction date is the date the buyer and seller agree on the price, not the date of transfer. This is important because it allows us to estimate a more immediate effect after the cut of the tree.

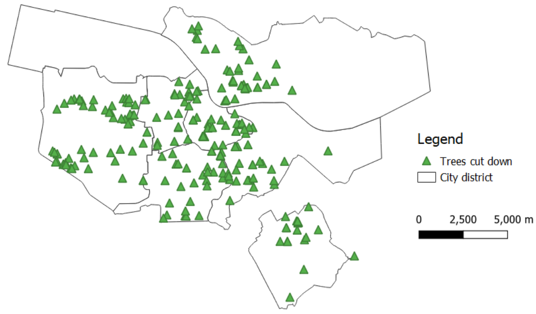
2.3 Urban trees

The data we have on green space can be divided into three data sets, (1) Replacement of public trees from the Municipality of Amsterdam, (2) the Basisregistratie Grootschalige Topografie (BGT) and (3) Tree register. As mentioned before, the data from the municipality of Amsterdam is key in this analysis. This data set is used to locate trees that were cut-down and the reasons behind this. Reasons the trees were removed include diseases such as the elm disease, heavy storm, root infestations and others. Residential development was excluded - only exogenous reasons are important for our data set. For a full list of reasons, we refer to table 8 in the appendix. This way, we estimate a difference-in-difference model by using the exogenous variation in trees, similar to Han et al. (2021). Our data set allows us to explore more diseases and natural causes of cutting trees down. By exploring multiple reasons and in turn multiple tree species, we find quite a random sample scattered over Amsterdam. This will limit biases related to certain species being clustered in specific neighborhoods.

Only trees were included that were not replanted, for best estimation of the full effect. The date of when the tree was cut-down is not provided by the municipality data set (1). To overcome this, the data was cross-referenced with yearly high-quality aerial photography provided by PDOK (Public Services On the Map) from 2016-2022. By looking at the specific location of the tree provided by data set (1) and cross-referencing this with the same location in the aerial photography, the data set was enriched with the date the tree was cut-down. This allows us to employ a staggered roll out estimation.

The (2) Basisregistratie Grootschalige Topografie (BGT) is used to generate other variables such as view on water or percentage of total green space. Because one of the main aesthetic features of Amsterdam is canals, a variable is derived to depict view on water. The BGT data are provided by governments, ministries and others to provide highly detailed information about surroundings. The (3) tree register data is used to examine total tree volume for the city as is depicted in 1.

Figure 2: Distribution cut-down trees (Own data, 2023)



For Amsterdam, we exploit twelve relevant exogenous reasons the trees were cut-down for a total of thirty-six species. More details can be found in table 8 of the appendix, where we show which different diseases, root rotting, storms, etc. we included. Han et al. (2021) point out that growing trees in cities is hard, for example due to compact soil and pollution. The tricky part here is that this means that the city has planted a lot of the same species of trees because these are the ones that do grow in cities. The ash trees were unequally planted across neighborhoods in Toronto, which in turn means that neighborhoods are affected unequally.

In figure 2 we show the distribution of trees across Amsterdam. As can be seen, the trees are quite scattered across Amsterdam. Using multiple species of trees, types of diseases and other random causes helps limit the biases that could still arise by using the exogenous shocks of one infestation due to the unequal distribution. Furthermore, not every species is affected by the same phenomenon. The most common reason a tree was cut-down is the Dutch elm disease, but even this only accounts to about 30%. Another common reason is the results of a storm, which would limit anticipation effects of trees turning brown before the cut.

The district on the north-west side that has no cut down trees is the before-mentioned Westpoort. Besides the fact that Westpoort has very little green space, this is where the ports are in Amsterdam. Consequently, very few residents live there which means that it will not generate bias. For the far north-east side of Amsterdam, that also has no trees that were cut-down, is home to a lot of agriculture and water. In turn, little trees and houses can be found in this area. Therefore, these empty areas are not a problem for our estimation.

3 Methodology

3.1 Hedonic pricing analysis and staggered difference-in-difference

A house in hedonic pricing analysis is comprised of structural and locality characteristics. Structural characteristics could be lot size or number of bathrooms, and locality could be environmental variables such as proximity to water or green space. We base our choice of structural characteristics and locality on existing literature (e.g. Sirmans et al. (2005), Han et al. (2021) and Lin et al. (2022)). Sirmans et al. (2005) studied 125 hedonic pricing analyses to gather the most commonly used variables and specifications. Sirmans et al. (2005) argues that including a semi-log specification can help with interpretation, minimize heteroscedasticity and allow for variation within the characteristics.

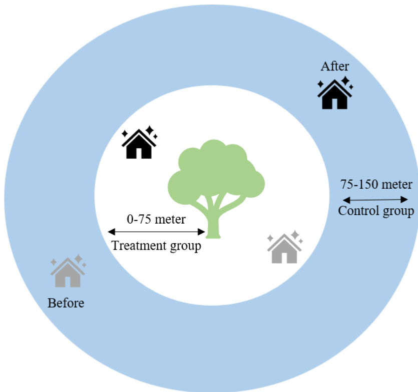
A commonly argued prominent issue with hedonic pricing models is having to deal with omitted variables. Because we want to use data of green space that varies over time, a simple empirical application would be to link the green space to the selling date of the houses. However, because this variation in green may be due to local developments, Han et al. (2021) argue that this would affect property prices nonetheless and therefore omitted variable bias is still present. For example, if the building of new houses is correlated with cutting down trees. By considering only cut-down trees unrelated to these developments there is less concern for this problem. Utilizing the variation in urban trees by only considering exogenous shocks would counter these identification issues.

The model considers the different cut-down dates by applying a staggered difference-in-difference approach, similar to what Lin et al. (2022) do for greening vacant lots in Philadelphia. The strategy leans on the assumption that the allocation of affected trees to be uncorrelated with house prices in comparison to all trees. This identification strategy is threatened when the spatial distribution of affected trees is clustered. In other words, nothing unobserved is happening in the near tree areas that also affects their cutting down. Therefore, it is important to assess parallel trends before the treatment period. This assumption can be found in section 5 along with other robustness checks based on distance and multiple treatments.

3.2 Specification

After cleaning and enriching the data based on conditions mentioned before, we have useful and detailed information on approximately 250 trees that have been cut-down in the Amsterdam area. To estimate the effect of these urban trees that were cut, we restrict the sample to transactions of houses that are located at most 75 meters from a cut-down tree. Earlier literature suggests that the impact of green elements such as parks is restricted to less than 100m (e.g. Dekkers and Koomen (2013)), so we define the treatment area to be as small a distance as possible. Using a smaller distance results in too little observations. We provide more intuition behind the chosen distance in section 5. In essence, there is a circle surrounding the cut-down tree with a radius of 75 meters. The control area is defined as the concentric ring in which the distance to the cut-down tree is between 75 and 150m. A visualisation can be found in figure 3.

Figure 3: Visualisation treatment and control groups (Own data, 2023)



To estimate the effect of cutting down a tree on the value of a house we embed a staggered difference-in-difference specification in a hedonic price function. Let P_i denote the price of house i in the restricted sample and b_i refer to the tree that is closest to this house. The distance between house i and tree b_i is $d(i, b_i)$. Only houses are included closer than 75m, so we define $d_t = I(d(i, b_i) < 75m)$. The time at which the house is sold is $t(i)$ and the time at which tree b_i was cut-down is $t(b_i)$. Houses are included before and after the tree is cut-down, so we define $d_b = I(t(i) > t(b_i))$ for after the treatment. The usual setup of difference-in-difference is than that we estimate a coefficient, α, for being located in the treatment area, another coefficient, β for being transacted after the tree has been cut-down and a third coefficient, γ for the cross effect of these two. The coefficient γ is the treatment effect, which reflects the value of the tree. A last fixed effect that may affect results is seasonal fixed effects, because selling a house in spring may reveal the loss in tree cover more so than it will in winter. We tested this variable, but it did not seem to make a difference in estimated coefficients.

Apart from the three difference-in-difference coefficients the estimating equation contains the usual elements of a hedonic price equation: the characteristics of the house X_i and the associated vector δ of coefficients and fixed effects for location (control area, φ) and time (θ). This location fixed effects implies that for every area surrounding a tree there is a separate fixed effect to account for differences. This is more detailed than simply controlling for postal code. The resulting equation is:

$$ln(P_i) = \alpha d_b + \beta d_t + \gamma d_t d_b + \delta X_i + \varphi_{b(i)} + \theta_{t(i)} + \varepsilon_i \quad (1)$$

Our setup differs from the standard two-way fixed effect approach in that we do not use all observations, but only those located in circles surrounding the cut-down trees. This is common in spatial difference-in-difference studies (e.g. Butts (2023)). Because not all trees are cut-down at the same time, we have a staggered treatment period. This is problematic if treated objects are also used as controls. See Goodman-Bacon (2021) and Roth et al. (2023) for a review of subsequent literature. Our limitation of the control areas to a distance of 150 m surrounding the cut-down trees offer some protection against this phenomenon. If all the circles defined in this way are disjoint, the problem is even completely avoided. For the theory behind staggered difference-in-difference, we follow Goodman-Bacon (2021), as they helped conceptualize the differential timing of treatment.

Even though our data set contains trees cut-down that are pretty scattered across the city, there are still a few with a mutual distance of less than 300m. We have dealt with this problem by assigning each transacted house to the tree to which it is closest. It will therefore never happen that the house is part of the control or treatment area of two cut-down trees. That is, we have adjusted the control and treatment areas so that they never overlap. However, it does not completely exclude the possibility that a house in the control area of one tree is in fact treated by the cutting down of another tree. This happens if a house has a distance of less than 75 meters to one tree and less than 150 meters to the other (this includes the possibility that a house is part of the treatment area of both trees). Note that there is no problem if a house belongs to the control area of two different trees. We discuss this further in section 5.

Goodman-Bacon (2021) shows that with staggered models, one geographic unit receives treatment at different points in time. In our case, trees are cut in different years. The result is that the effect will be differentially timed across houses. Or, the variance weighted Average Treatment on the Treated (ATT) is a weighted average of all possible ATTs. This also means that the more houses have trees cut-down at the same time, the more they influence the final aggregate estimate.

When it comes to clustering, we want to adjust standard errors at the group level. In other words, at the level of treatment. Clustering at the group level would allow for arbitrary serial correlation in errors within a group over time. This is the most common solution to the problem of clustering standard errors in a staggered difference-in-difference case. In our case, we thus cluster at the treatment group level where houses are closest to the tree cut-down.

As mentioned before, Rouwendal et al. (2016) point out that another common issue with hedonic pricing models is bias that may arise through local trends. There might be trends over time within the treatment and control groups that may cause results to be different, because fixed effects can only control for aspects constant over time. Here, we introduce an alternative specification that takes these local trends into account. We again add fixed effects for time and control area, but now we also interact the two. This way we allow the fixed effect of the areas to vary over time. The resulting equation is:

$$ln(P_i) = \alpha d_b + \beta d_t + \gamma d_t d_b + \delta X_i + \varphi_{b(i)} + \theta_{t(i)} + \varphi_{b(i)} \theta_{t(i)} + \varepsilon_i \quad (2)$$

A detailed list of which variables were included in the model and their respective description can be found in table 2. Again, the selection was based on previous literature such as that by Sirmans et al. (2005). For a descriptive overview of all variables including summary statistics, we refer to table 3.

Table 2: Summary statistics all variables

Variable	Description
House characteristics	
Price	House price in natural logarithms.
M^2	Square footage of the house in natural logarithms.
Build year	Categories the house was built in such as 1906-1930.
Isolation	Whether the house has proper isolation.
Parking	Whether there is owned parking available.
Monument	Whether the house has monumental status.
Balcony	Whether the house has a balcony.
Elevator	Whether the house has an elevator.
Bathrooms	How many bathrooms the house has.
Attic	Whether the house has an attic.
Environment characteristics	
Water	Whether there is water within view.
Garden	Whether the house has a garden.
Percentage green	How much other green there is in the 75m range.
Fixed effects & Difference-in-difference	
Treatment	Whether the house is in the treatment or control group.
After	Whether the house was sold after the cut.
Year	What year the house was sold in.

4 Results

4.1 Descriptive statistics

Descriptive statistics can be found in table 3. Around 26,000 house transactions remain with an average value of about 440,000 euros and a median of around 365,000 euros. In the table, we include all variables that we used in our specifications as previously stated in table 2. We also note mean, minimum and maximum values of the variables within the table. Note that we mention the distribution of the log of price, because this is the variable we use in our regressions.

Table 3: Summary statistics all variables

Variable	Unit	Mean	Min	Max
Price	log of euro's	13	11.5	14.9
M^2	log of M^2	4.5	3.2	5.8
Build year	dummy 1-9	1	4.532	9
Isolation	dummy 0-1	0.75	0	1
Parking	dummy 0-1	0.15	0	1
Monument	dummy 0-1	0.05	0	1
Balcony	dummy 0-1	0.47	0	1
Elevator	dummy 0-1	0.19	0	1
Bathrooms	dummy	1.11	1	5
Attic	dummy 0-1	0.04	0	1
Water	dummy 0-1	0.08	0	1
Garden	dummy 0-1	0.54	0	1
Percentage green	%	26.25	0	91
Treatment	dummy 0-1	0.2	0	1
After	dummy 0-1	0.45	0	1
Year	dummy	2017	2013	2021

For a more detailed description of distribution between control and treatment groups as well as before and after periods, we refer to table 4. The control group is slightly larger than the treatment group, as well as the before group. The latter is because the time after the cut is shorter than the before period, to establish a more immediate effect. In other words, we expect the effect to be notable almost instantly, because the loss of the amenity is felt directly after the cut. The mean in the table refers to the average house price in that category. The number of observations is reported as well. Notably, the prices go up a lot for both treatment and control groups, because of the before mentioned pressure on the Amsterdam house market. However, because we control for year this should not be a problem.

Table 4: Summary statistics between groups

Group	Period	Observations	Mean
Control	Before	8,992	332,246
Control	After	5,963	585,550
Treatment	Before	2,297	348,437
Treatment	After	1,577	564,540

4.2 Main results

In Column 1 of Table 4.2 we present the main results of estimating the staggered difference-in-difference hedonic pricing analysis for Amsterdam. As discussed in table 2, house characteristics are included in the model, as are fixed effects. Furthermore, we control for local trends by interacting control area with year. All models are clustered at the treatment level. Full model results and details can be found in table 9 of the appendix.

The estimated coefficient in model (1) for the effect of a tree being cut-down within 75 meters of a house is -0.0119. This translates to a 1.19% decrease in house prices when a tree is cut-down. The effect is statistically significant at the 5% level. Note as well that the standard errors are quite low (0.0006). As cutting down the tree will result in a lower house price, results suggest that people highly value trees nearby their houses. The post treatment period and treatment area are not statistically significant because they are almost fully absorbed by using year and group fixed effects. The R^2 is quite high, 0.787, but not unusual for hedonic pricing models. For an analysis of distance and local trends, we refer to section 5.2.

Table 5: Main results

	log(Transaction price)
	(1)
Effect of tree cut-down near house	−0.0119**
(**Difference-in-difference**)	(0.0006)
Post treatment period	−0.0296
	(0.0175)
Treatment area	0.0018*
	(0.0002)
Observations	26,244
R^2	0.787
Control area dummies	Yes
Year dummies	Yes
House characteristics	Yes
Local trends	Yes

*Note: *p<0.1; **p<0.05; ***p<0.01*

To further study the found effect, we are interested in spatial variation of our result. One aspect of this spatial variation is the difference in 'green-ness' of different areas in Amsterdam. Konijnendijk (2021) proposes a rule of thumb for green space which is increasingly used by municipalities in the Netherlands. The rule states that to allow trees to contribute to health and well-being neighborhoods should have at least 30% tree canopy cover. As we saw in figure 1, Amsterdam does not meet this standard yet and is even moving further away from it. However, some of the treatment and control group areas do meet the standard. Here, we divide the sample up by tree cover and estimate our model again. In the figure, having a tree cover of less than 30% makes green space scarce. As can be seen in table 4, the more scarce the tree cover is, the more extreme the negative effect on house prices is. The respective percentages are shown at the top of the table. The decline in effect can be expected, as losing one tree where few trees are available is likely to have a bigger effect on house prices than for neighborhoods where many trees are available. We do note that the number of observations is quite small, especially in the 0 to 10% range. Because of this scarcity result, we believe the 1% average effect we found in our main results is comprised of a few extremely high effects on house prices where trees are scarce, i.e. when the only tree in near proximity is cut-down. Once there is enough tree cover around (>30%) the found effect becomes statistically insignificant. In other words, the surrounding trees make up for the tree lost.

Table 6: Scarcity analysis

	log(Transaction price)		
Percentage tree cover included	(0-10%)	(10-30%)	(30%+)
Effect of tree cut-down near house	−0.0514***	−0.0262**	−0.0027
(**Difference-in-difference**)	(0.0006)	(0.0018)	(0.0064)
Post treatment period	-0.0817*	-0.0867	-0.0259
	(0.0045)	(0.0155)	(0.0128)
Treatment area	0.0440	0.0139.	-0.0131
	(0.0071)	(0.0015)	(0.0028)
Observations	873	10,562	6,418
R^2	0.95	0.93	0.96
Control area dummies	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
House characteristics	Yes	Yes	Yes
Local trends	Yes	Yes	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01		

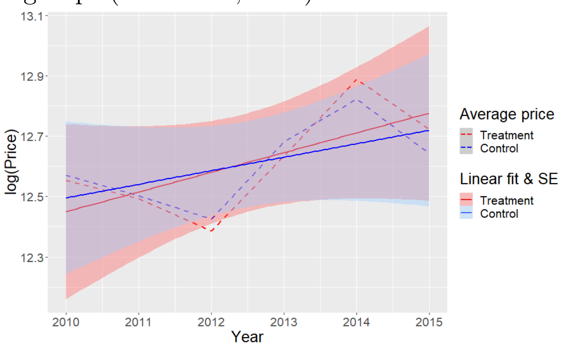
5 Sensitivity analysis

5.1 Parallel trends assumption

In this section, we do a sensitivity analysis where we look at three elements of the model. We start of by showing proof for the parallel trends assumption. Besides this, we study various distances for our treatment and control groups and deal with double treatments. Where the former will help proof robustness by obtaining similar results and add intuition to distance choice, the latter will help limit bias by only including observations with one tree cut-down nearby. All models in our sensitivity analysis include local trends fixed effects, control area and year fixed effects similar as in section 3.

Goodman-Bacon (2021) argues that it is important when it comes to any difference-in-difference analysis is the study of parallel trends. The key assumption is that there are no time-variant group specific unobservables. Thus, in absence of treatment, the difference between treatment and control groups are constant over time. There is no statistical test for this assumption, so we plot the average house price of both the control and treatment group before the trees were cut-down to show the trends. The dashed lines in the graph represent these averages for each group, the straight lines represent the linear trend or fitted line for both groups. The larger areas represent the respective standard errors. Keeping the time period small before and after the cut will help hold the assumption.

Figure 4: Pre-treatment trends for treatment and control groups (Own data, 2023)



5.2 Distances

In model (2) we show results for both 75 meter and 100 meter treatment groups, with respectively 150 and 200 meter control groups. We do this to support our choice of 75 meters. We also show both models in- and excluding local trends. The results including local trends are statistically more significant. This could imply that without including these area specific trends, we underestimate the effect of cutting down urban trees on house prices.

The result for 100 meters is slightly lower than for 75 meters. This makes sense, as the homeowner benefits the aesthetic value of the tree most once said tree is closer to their house. It is safe to say that 100 meters from the house is mostly not within eyesight, making the coefficient lower than for 75 meters. The main model, 75 meters, translates to an average house price decrease of around 5300 euros or median 4300 house price decrease per tree cut-down. Thus, the results are quite economically significant. As mentioned before, parks are documented to have an effect up to 100 meters. The effect for trees is found to be higher for a shorter distance of 75 meter, which is intuitive as trees are much smaller than parks. We found too little observations to study a 50 meter distance so we decided to use 75 meters for our main results.

Table 7: Distance and local trends sensitivity analysis

	log(Transaction price) (1)	(2)
75 vs 150 meter	-0.0119^{**}	-0.0120^{**}
	(0.0006)	(0.0002)
100 vs 200 meter	-0.0106^{**}	-0.04
	(0.0008)	(0.0017)
Control area dummies	Yes	Yes
Year dummies	Yes	Yes
House characteristics	Yes	Yes
Local trends	Yes	No
Note:	*p<0.1; **p<0.05; ***p<0.01	

5.3 Overlap in treatment

As we showed before, scarcity of green can influence the results. The same might be expected from excluding double treatments, as losing more than one tree may be different from losing only one. Dealing with double treatments is important in the case the previously described treatment and control circles overlap, which could bias results. Double treatments in our case are houses that have two or more trees cut-down within the 75 meter treatment group distance. The coefficient without these cases is -1.2%. The results thus suggest that cutting down any tree in near proximity to a house counts for roughly the same effect. In other words, cutting down an additional tree will matter as much as the first one did.

6 Discussion & Conclusion

This paper studied the effect of cutting down trees on house prices in Amsterdam. Utilizing only exogenous reasons the trees were cut-down, we employed is a staggered difference-in-difference application of the hedonic pricing analysis to better establish causality. Results show that cutting down trees within 75 meters of a house leads to a 1.19% decrease in house prices. This result is statistically significant at the 5% level and quite economically significant as well, as this results in a 4000-5000 euro decrease in house prices on average. Homeowners thus lose a highly valued aesthetic amenity near their houses - which is reflected in the drop in house prices. The result is slightly lower for 100 meters, which is intuitive - the closer to the house the tree is, the more extreme the effect.

The scarcity analysis shows that the less green there is in the area surrounding the house, the bigger the effect of cutting down the tree. This is likely because there is less to compensate with - the tree comprises most of the green in the area. This result implies that adding green to the city of Amsterdam should especially focus on areas where little urban green is at the moment. Also, that replacing the trees in these areas where green is scarce is most pressing. Lastly, 80% of our sample are trees planted before 2000, and therefore, this also suggests that the trees are mature and voluminous. Losing a beautiful, mature tree will decrease the aesthetic view of the house, which reflects in the house prices.

The even distribution of trees across Amsterdam that results from our detailed data is one of the strengths of our paper, as this helps reduce heterogeneity bias. The details that are particularly important here are various species of trees, reasons the trees were cut-down and different points in time. Because of the yearly data, we were able to employ the staggered version of the difference-in-difference model, which is new in the context of this paper.

One of the limitations in our paper is the exclusion of private green. The paper by Rouwendal and van der Straaten (2008) suggests that residents in Amsterdam would rather have more private space than open space, which we were not able to confirm in this paper. There is a clear trade-off between accuracy and precision, and for this paper we mainly focused on making the specification econometrically convincing. However, excluding what residents may have done to their own gardens and only focusing on public trees that were cut-down for exogenous reasons resulted in precise coefficients during the sensitivity analysis, but may not the most accurate results. For this reason, in future research we want to investigate the private and public urban green space further. Still, research by Beumer (2018) suggests that Dutch gardens are mostly tiled, which implies there is not much green to compensate the loss in trees with.

These results are in line with earlier results found by e.g. Han et al. (2021) or Donovan and Butry (2010). Our results for 75 meters are slightly lower than that of Donovan and Butry (2010) but higher than that of Han et al. (2021). Both previous and our results amplify the need to keep current green and resist further densification of Amsterdam by cutting down green space. The magnitude of the results indicate that it is important to consider the economic valuation of trees when considering policies related to urban green space.

7 Appendix

7.1 Details on cut-down trees

Table 8: Reason for cutting down the trees

Bark necrosis
Bark overgrowth
Unsustainable maintenance
Environmental risk
Ash dieback
Elm disease
Emergency cut
Cut because of storm
Root ball anchoring (skewness)
Rotting in trunk base
Poor crown formation
Branches bending towards cycle path

7.2 Full results

Table 9: Hedonic pricing analysis with staggered difference-in-difference

	Dependent variable:
	log(Transaction price)
log(Floor space (m^2))	0.749***
	(0.008)
Monument	0.089**
	(0.004)
Balcony	−0.023*
	(0.002)
Garden	0.039***
	(0.001)
Percentage green within 75m	0.00**
	(0.000)
Elevator	−0.009
	(0.004)
Isolation	0.028**
	(0.001)
Build year: *base category 1500-1905*	
1906-1930	−0.009**
	(0.000)
1931-1944	−0.024
	(0.005)
1945-1959	−0.109*
	(0.012)
1960-1970	−0.025***
	(0.000)
1971-1980	−0.019
	(0.010)
1981-1990	−0.031
	(0.011)
1991-2000	0.013
	(0.008)
> 2001	0.119*
	(0.015)
Parking	0.032
	(0.005)
Number of bathrooms	0.075*
	(0.007)
View of water	0.11
	(0.019)
Attic	−0.042*
	(0.005)
Observations	26,608
R^2	0.864
Control area dummies	Yes
Year dummies	Yes
House characteristics	Yes
Local trends	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01

References

Anderson, S. T., & West, S. E. (2006). Open space, residential property values, and spatial context. *Regional Science and Urban Economics*, *36*(6), 773–789.

Bervaes, J., & Vreke, J. (2004). De invloed van groen en water op de transactieprijzen van woningen.

Beumer, C. (2018). Show me your garden and i will tell you how sustainable you are: Dutch citizens' perspectives on conserving biodiversity and promoting a sustainable urban living environment through domestic gardening [Special feature: Strategic gardens and gardening: Inviting a widened perspective on the values of private green space]. *Urban Forestry Urban Greening*, *30*, 260–279.

Broitman, D., & Koomen, E. (2020). The attraction of urban cores: Densification in dutch city centres. *Urban Studies*, *57*(9), 1920–1939.

Butts, K. (2023). Jue insight: Difference-in-differences with geocoded microdata [Special Issue: JUE Insight Shorter Papers]. *Journal of Urban Economics*, *133*, 103493.

Dekkers, J., & Koomen, E. (2013). The monetary value of open space in urban areas: Evidence from a dutch house price analysis.

de Vries, S., Kramer, H., Smits, M., Spijker, J., Verheij, R., Dückers, M., Baliatsas, C., & Wiegersma, S. (2023). *Een groene tuin, een gezonde tuin?: Onderzoek naar het belang van privégroen bij huis voor de gezondheid van burgers* [Project number: 5200046562]. Wageningen Environmental Research.

Donovan, G. H., & Butry, D. T. (2010). Trees in the city: Valuing street trees in portland, oregon. *Landscape and Urban Planning*, *94*(2), 77–83.

Gemeenteraad. *Green vision 2020-2050: A livable city for human and animal.* 2020.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing [Themed Issue: Treatment Effect 1]. *Journal of Econometrics*, *225*(2), 254–277.

Hammer, T. R., Coughlin, R. E., & Horn, E. T. (1974). The effect of a large urban park on real estate value. *Journal of the American Institute of Planners*, *40*(4), 274–277.

Han, L., Heblich, S., Timmins, C., & Zylberberg, Y. (2021). Cool cities: The value of urban trees. *Working paper.*

Konijnendijk, C. (2021). Promoting health and wellbeing through urban forests - introducing the 3-30-300 rule.

Lin, D., Jensen, S., & Wachter, S. (2022). The price effects of greening vacant lots: How neighborhood attributes matter. *Real Estate Economics.*

Luttik, J. (2000). The value of trees, water and open space as reflected by house prices in the netherlands. *Landscape and Urban Planning*, *48*(3), 161–167.

Mullaney, J., Lucke, T., & Trueman, S. J. (2015). A review of benefits and challenges in growing street trees in paved urban environments. *Landscape and Urban Planning*, *134*, 157–166.

Roth, J., Sant'Anna, P. H. C., Bilinski, A., & Poe, J. (2023). What's trending in difference-in-differences? a synthesis of the recent econometrics literature.

Rouwendal, J., & van der Straaten, J. (2008). *The costs and benefits of providing open space in cities* (WorkingPaper TI 2008-01-07). Tinbergen Instituut (TI).

Rouwendal, J., Levkovich, O., & Marwijk, R. (2016). Estimating the value of proximity to water, when ceteris really is paribus. *Real Estate Economics*, *45*, n/a–n/a.

Sirmans, G. S., Macpherson, D. A., & Zietz, E. N. (2005). The composition of hedonic pricing models. *Journal of Real Estate Literature*, *13*(1), 3–43. Retrieved July 7, 2022, from http://www.jstor.org/stable/44103506

Tyrväinen, L. (1997). The amenity value of the urban forest: An application of the hedonic pricing method. *Landscape and Urban Planning*, *37*(3), 211–222.