European Commission

JRC TECHNICAL REPORT

House price dynamics and affordability in the city of Amsterdam

European Commission, Joint Research Centre (JRC)

Unit for Territorial Development

Joint Research Centre

EUR 30883 EN

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EU Science Hub
https://ec.europa.eu/jrc

JRC125425

EUR 30883 EN

PDF ISBN 978-92-76-43360-6 ISSN 1831-9424 doi:10.2760/700246

Luxembourg: Publications Office of the European Union, 2021

How to cite this report: Barranco, R., Van Heerden, S.C., and C. Jacobs-Crisioni, House price dynamics and affordability in the city of Amsterdam, EUR 30883 EN, Publications Office of the European Union, Luxembourg, 2021, ISBN 978-92-76-43360-6 , doi:10.2760/700246 , JRC125425.

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Acknowledgements

The authors would like to thank the City of Amsterdam - City Strategy team, as well as the City of Amsterdam - Unit of Research, Information and Statistics, for their input, support, and collaboration on the City lab, in particular:

Janne Taks; Marije van Mens; Guus Smal; Marike ter Linden (City Strategy team).

Hester Booi; Peter van Hinte (Unit of Research, Information and Statistics).

The editors would further like to thank the EU representative of the City of Amsterdam for supporting the collaboration between the City of Amsterdam and JRC:

Mark Boekwijt

Lastly, the editors would like to thank their colleagues from JRC B.3 Territorial Development, as well as the anonymous reviewers for their valuable input and feedback to the report.

Executive summary

This report shows the results of fine-grained data analyses of residential property transactions and private rental supply in the municipality of Amsterdam. The analyses follow from a collaboration in the form of a City Lab between the Joint Research Centre's (JRCs) LUISA team, and the City of Amsterdam's City Strategy team, and its department of Research and Statistics.

Between 2015 and 2018, average house prices in Amsterdam significantly increased. In that same period, the share of social rental housing decreased, while the private rental market expanded, and rents increased. Also, investments in housing increased, particularly showing growth in ownership by large professional investors, such as private equity and pension funds. In some areas of the city only one out of five buyers is a private investor. These developments sparked concern over housing affordability, especially for the middle class incomes that are not eligible for social housing, nor have the financial backing most investors have.

The main objective of this report is to gain insight in the spatial dynamics of Amsterdam's housing market, and to uncover the driving factors behind the city's spiraling-up house and rental prices, in order to provide empirical support to the further development of an inclusive and accessible housing market.

The analyses are based on a number of data sources. First, transaction data from 2015, containing information on the transactions of 10,958 houses located within the municipality. Second, rental offerings collected from the Dutch private rental platform Pararius.com. Third, income data from the National Bureau of Statistics (CBS). And finally, several thematic data layers that have been created in the context of the JRC's LUISA territorial modelling platform.

Two main findings are distinguished. First, analyses indicate that Amsterdam house prices are mainly driven by location, aesthetic, and buyer type. Closer proximity to the city centre, older buildings, and private investors and companies, are the main determinants behind higher prices. Moreover, about 45% of the sold floor space seems to have been purchased for capital gains.

The second main finding is that looking at asking prices, it is suggested that Amsterdam's middle income households would potentially need to spend a higher share of their incomes on long-term rents, in comparison to middle income households at country level. For Amsterdam's middle income households, asking prices reflect rents that would be considered highly 'overburdened', indicating low housing affordability.

This suggests that middle-income households looking for alternative rental housing (e.g. for family expansion) are less likely to find housing in the city, and more likely to move out, although more detailed analysis should further determine this.

While further research is needed, this study provides more insight into the main determinants (and possible interactions) influencing Amsterdam house prices, while also shedding light on housing affordability. Depending on data availability, the methodological workflow presented in this report can be adapted and replicated for other cities, enabling comparison and providing additional case studies.

1 Introduction

This report shows the results of fine-grained data analyses of residential property transactions, and private rental supply in the municipality of Amsterdam. The analyses follow from a collaboration in the form of a City Lab between the Joint Research Centre's (JRCs) LUISA team, and the City of Amsterdam's City Strategy team, and its department of Research and Statistics. The overarching goals are to gain insight in the spatial dynamics of Amsterdam's housing market, and to uncover the driving factors behind the city's spiraling-up house prices.

Similar to various other EU cities, Amsterdam has experienced a large increase in house prices over the past decade, raising concerns over housing affordability. In response, cities have implemented policies to support housing affordability, such as more strict regulation of short-term rental accommodations. At the same time, many cities are still trying to design, develop and implement policies in support of an inclusive and affordable housing market. This report aims to support such efforts, providing several empirical analyses that shed more light on the housing market dynamics.

A number of data sources are used for the presented analyses. Property transactions are explored using 2015 transaction data, which contains information on the transactions of 10,958 houses located within the municipality. In addition, rental offerings were collected from the Dutch private rental platform *Pararius.com*. These data are explored in conjunction with income data from the national bureau of statistics (CBS) and several thematic data layers that have been created in the context of the JRC's LUISA territorial modelling platform[1].

The report is structured as follows: The first section presents an exploratory analysis of the data at hand. The subsequent section discusses bi- and multivariate analyses conducted to explain cross-sectional variance in house prices. The last section draws some

1 The LUISA Territorial Modelling Platform is primarily used for an ex-ante evaluation of European Commission policies, to assess its direct or indirect territorial impact(s). This platform uses a substantial amount of fine resolution input data, which are constantly being gathered, harmonised and refined by the LUISA team.

general conclusions from the presented work.

2 Data Exploration

2.1 Mapping house prices

The available data on residential property transactions includes information on the geographical location of the bought property, the transaction price, buyer characteristics and the total floor surface of the property. For the sake of comparability, house prices have been analysed as transaction sum per square meter (euro/m^2). Figure 1a gives an overview of the spatial distribution of house prices in Amsterdam. Prices are clearly higher in the central part of the city area, which is constrained by the A10 ring way, and the main water body in the north (called het Binnen-IJ) that separates the inner city from the northern part of the city. The house price map thus seems to reflect differences between the city's inner and outer ring areas that are well known in Amsterdam, and often referred to in popular culture (UNSense 2018a and 2018b). Figure 1b reflects the construction year for each house under analysis, showing that older houses are mainly located in the inner ring area. The similarity between both spatial patterns is an indication that both location and construction year are correlated with price per square meter, reflecting the city's historical growth.

2.2 Discovering patterns in property ownership turnover

One potentially relevant indicator to understand housing markets is the turnover of

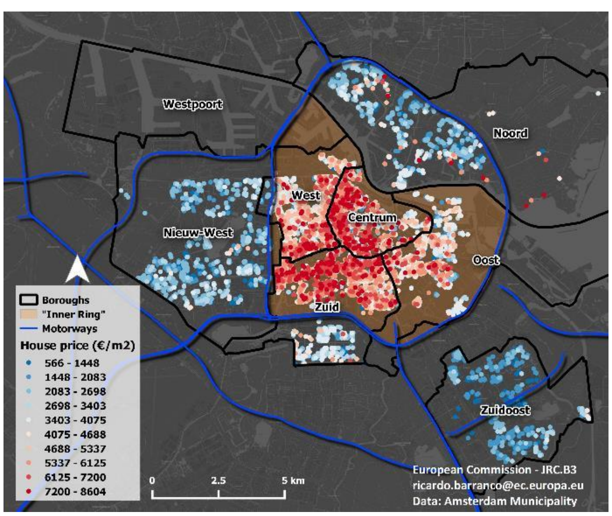

Figure 1a: Amsterdam's house prices spatial distribution for 2015.

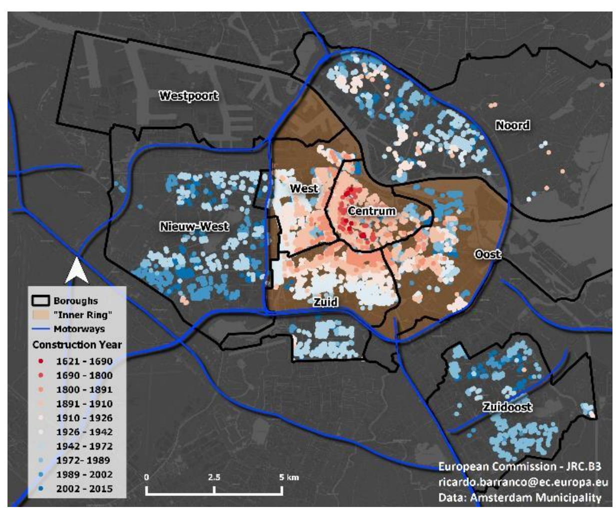

Figure 1b: Amsterdam's house construction year distribution for 2015.

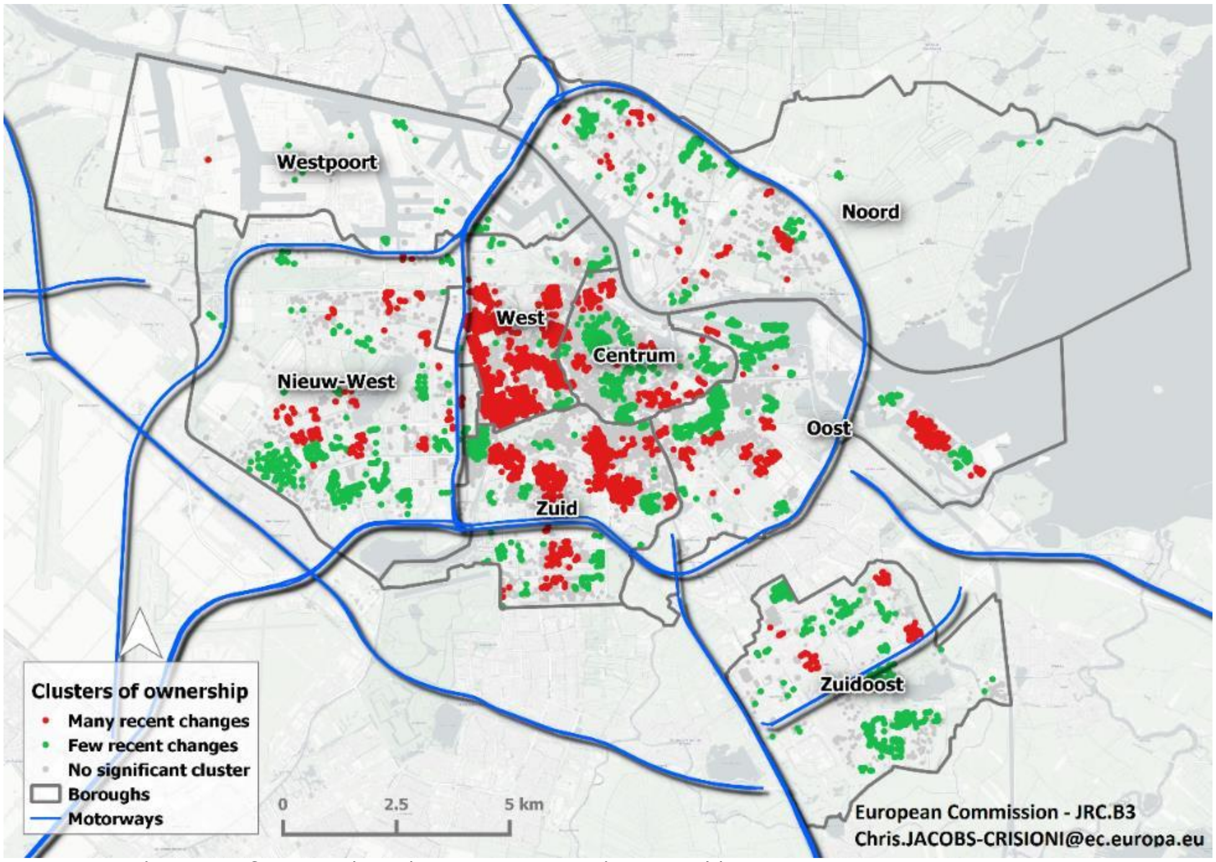

Figure 2. Clusters of ownership change in privately owned houses: 2007-2017.

property. If one assumes that individuals buying a property to live in do so for the long run, high property turnover can be an indication of speculative investment with short-term aims; the sort of investment often considered most detrimental to housing markets (Gilderbloom and Appelbaum, 1987). To better understand the spatial dynamics of the Amsterdam housing market, turnover has been mapped and relevant turnover hotspots have been identified. For this end, all real estate that is privately owned by natural persons or companies and underwent at least one ownership change between 2007 and 2017 has been mapped. Subsequently, the Getis Ord-Gi*[2] statistic was computed to identify clusters of property change within a 250 meter radius, indicating where turnover

2 First, the Getis-Ord Gi* z-scores and p-values are calculated for each point in the dataset. Then, the tool looks at each point within the context of neighbouring points. To be a statistically significant hot spot, a feature will have a high value and be surrounded by other features with high values as well. The local sum for a feature and its neighbours is compared proportionally to the sum of all features; when the local sum is very different from the expected local sum, and when that difference is too large to be the result of random chance, a statistically significant z-score indicates a high/low cluster.

Cluster	Type of buyer	Type of residence	Lots owned	Classification	Count	Average Cost (€)	Average Cost (€/m²)	Average Area (m²)
1	Natural person	Amsterdam resident	Unknown	Resident	5116	308.000	3679	92
2	Natural person	Amsterdam resident	1-9 parcel	Resident	3355	290.750	4096	75
3	Natural person	Amsterdam no-resident	10-24 parcel	Private owner < 25 addresses	2241	553.000	3056	221
4	Company	Amsterdam no-resident	Unknown*	Unknown*	246	899.000	3504	343

Table 1. Buyer types and corresponding characteristics

is significantly higher or lower than a random distribution of turnover would yield.

Figure 2 shows properties that, in a 5% confidence interval, are part of structurally high or low turnover clusters. Such clusters exist in Amsterdam, above all in the 'West' and 'Zuid' boroughs of the city[3]. This is an indication that structural speculative investments occurred in the city. Such investments targeted specific areas in the city and possibly were to the detriment of the local housing market.

2.3 Breaking down transactions by buyer type

To gain new insight in buyer types (and their motives) on the market, customer segmentation was applied to the dataset. Hereby the customer base is divided into groups of individuals that are similar in specific ways. Four variables were used to construct clusters of buyer types. Those variables indicate:

1) Type of residence of the buyer;

2) Whether the buyer and/or seller are a natural person, or company;

3) The number of lots (parcels of real property/immovable property) owned by the buyer and seller;

4) Classification of buyer and seller type, pre-compiled by the municipality of Amsterdam. Table 1 depicts the four main buyer clusters that were identified.

3 The red cluster identified in the recently built neighborhood of IJburg (far right side, in the middle) is most likely based on transactions that served to buy newly constructed housing, and does not necessarily point to turnover.

Clusters 1 and 2 concern natural persons, registered as a resident in Amsterdam, and with unknown or a limited amount of housing units (between 1 and 9) owned prior to the registered purchase[4]. These are considered mainly 'regular' home-owners, including some small portfolio private investors. Cluster 3 represents natural persons, not residing in Amsterdam and owning a medium sized portfolio (between 10 and 25 units). Cluster 4 consists of companies that are not registered in Amsterdam. In fact, only 9 of the over 15,000 analysed transactions concerned purchases by companies registered in Amsterdam. Clusters 1 and 2 are considered largely representative for individuals buying a house to live in, including some smaller portfolio private investors; while clusters 3 and 4 are considered representative for purchases done exclusively for capital gains. It is acknowledged that this is a rough estimate of buyer type, as motives for purchase are not registered. Furthermore, it should be noted that, as with other cities, often there is missing information concerning buyers, so that in two out of the four cluster types at least one attribute is marked as unknown.

The data clearly shows that Amsterdam residents purchased housing units with a relatively small surface. Housing units with small surfaces are relatively more expensive in terms of price per square meter. Companies and private owners bought larger surfaces at lower relative costs (price per square meter). These larger properties can also potentially be split into subunits and then used, resold or rented out. Some further computations learn that, between the buyer types identified in Table 1, only about 55% of the floor space sold in the city was purchased by people buying a property to live in; while about 45% of the sold floor space seems to have been purchased for capital gains.

2.4 Long term rental and income analysis

From the previous results, it can be derived that a substantial part of the properties in Amsterdam are bought to let. This is not necessarily socially problematic if rental prices are affordable. However, it has repeatedly been noted that Amsterdam's private rental prices have rapidly become less affordable to most of its residents. To further explore this assumption, this section ex-

4 The housing input data with the buyer characteristics was provided by Amsterdam municipality, including predefined classifications, such as the 1-9 parcel range.

amines the ratio between long-term rent asking prices, and incomes in the postal code where the offered rental house is located.

To do so, information has been collected for 5,974 rental house advertisements from the Pararius.com[5] website, and combined data indicating the average income per postal code and population shares per income, obtained from the National Bureau of Statistics (cbs.nl).

Figure 3 shows that, compared to the overall situation in the Netherlands, Amsterdam has a wider gap between the different income classes.

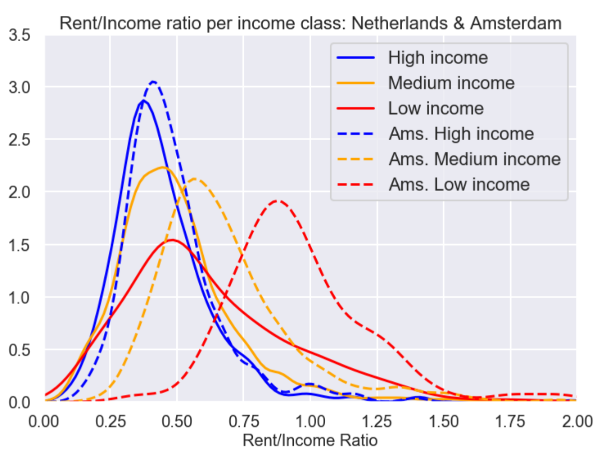

Figure 3 Correlation Matrix for Amsterdam price/m^2 and spatial indicators.

The differences are larger for low-incomes, followed by medium and higher incomes. While the city's highest incomes can afford the asked rents, and the city's lowest incomes are often protected by social housing schemes and regulatory mechanisms, medium incomes are largely overburdened by rental costs, with rents representing 63% of the city's median income, while in general the (EU) overburden rate is defined as the percentage of people whereby the total housing costs is more than 40% of the disposable income. This suggests that private rents have become unaffordable for Amsterdam's middle class, even though the highest overburden increase is on low incomes.

5 Asking prices on pararius.com are not necessarily the actual final rental prices agreed upon.

3 Explaining the drivers of house prices

3.1 Looking at surrounding characteristics

For each of the 10,958 observed house transactions, a further 13 variables describing locational features have been mapped. Those variables represent five general themes: Health, Education, Basic Services, Consumption & Recreation, and Transportation. These variables are based on a wide range of harmonised datasets created in the context of the LUISA platform, covering all EU Member States. In addition to the main themes, the variables can be further divided into either distance-based measures (e.g. distance to the closest facility) and density based measures (e.g. the number of facilities in a 500 meter range). These variables help characterise the neighborhood features surrounding each property transacted. Table 2 summarizes these features with distances expressed in meters, and house price in euros per m^2.

On average the studied houses are located around 3.38 km from the city centre. 'Con- closest (45.31 meters) and 'Basic Services', like police stations and fire departments, the farthest (275.60 meters). Within the surrounding 500 meters, 'Consumption and Recreation' reaches the highest density with an average of 65 services, while 'Basic Services' indicate the lowest with 1 surrounding service in certain areas. The price per square meter ranges between 574 and 8,400 euros, averaging at 3,676 euros per square meter.

The correlation matrix, shown in figure 4, gives an overview on the Pearson correlation coefficients between all variables. The value of the Pearson correlation coefficient can range between -1 and 1, whereby 1 reflects complete positive linear correlation, 0 no linear correlation, and −1 complete negative linear correlation. From the group of distance-based variables, distance to the centre of Amsterdam ('DistCentre') yields the

	Health Distance	Education Distance	Basic Services Distance	Consumption Recreation Distance	Distance Centre	Metro Distance	Health Density (500 m^2)	Education Density (500 m^2)	Basic Services Density (500 m^2)	Consumption Recreation Density (500 m^2)	Public Transport Density (500 m^2)	Population Density (100 m^2)	Accessibility (100 m^2)	Year	Price m^2
count	10958	10958	10958	10958	10958	10958	10958	10958	10958	10958	10958	10958	10958	10,958	10,958
mean	98.5	126.7	275.6	45.3	3.4	1.5	7.5	5.0	1.1	65.3	5.0	185.9	1.1	1,940	3,676
std	83.8	88.9	189.8	61.4	2.1	0.9	5.0	3.4	1.4	79.4	3.8	67.9	0.0	41	1,600
min	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	9.0	1.0	1,621	574
25%	0.0	100.0	141.4	0.0	2.0	0.8	3.0	2.0	0.0	13.0	2.0	125.0	1.1	1,905	2,320
50%	100.0	100.0	223.6	0.0	2.9	1.3	7.0	4.0	1.0	44.0	4.0	185.0	1.1	1,932	3,680
75%	141.4	141.4	360.6	100.0	4.1	1.9	11.0	8.0	2.0	80.0	8.0	253.0	1.1	1,977	4,788
max	2267.2	2195.4	3046.3	600.0	11.6	9.3	24.0	18.0	10.0	483.0	18.0	397.0	1.1	2,014	8,400

Table 2. Summary statistics of surrounding features and house characteristics.

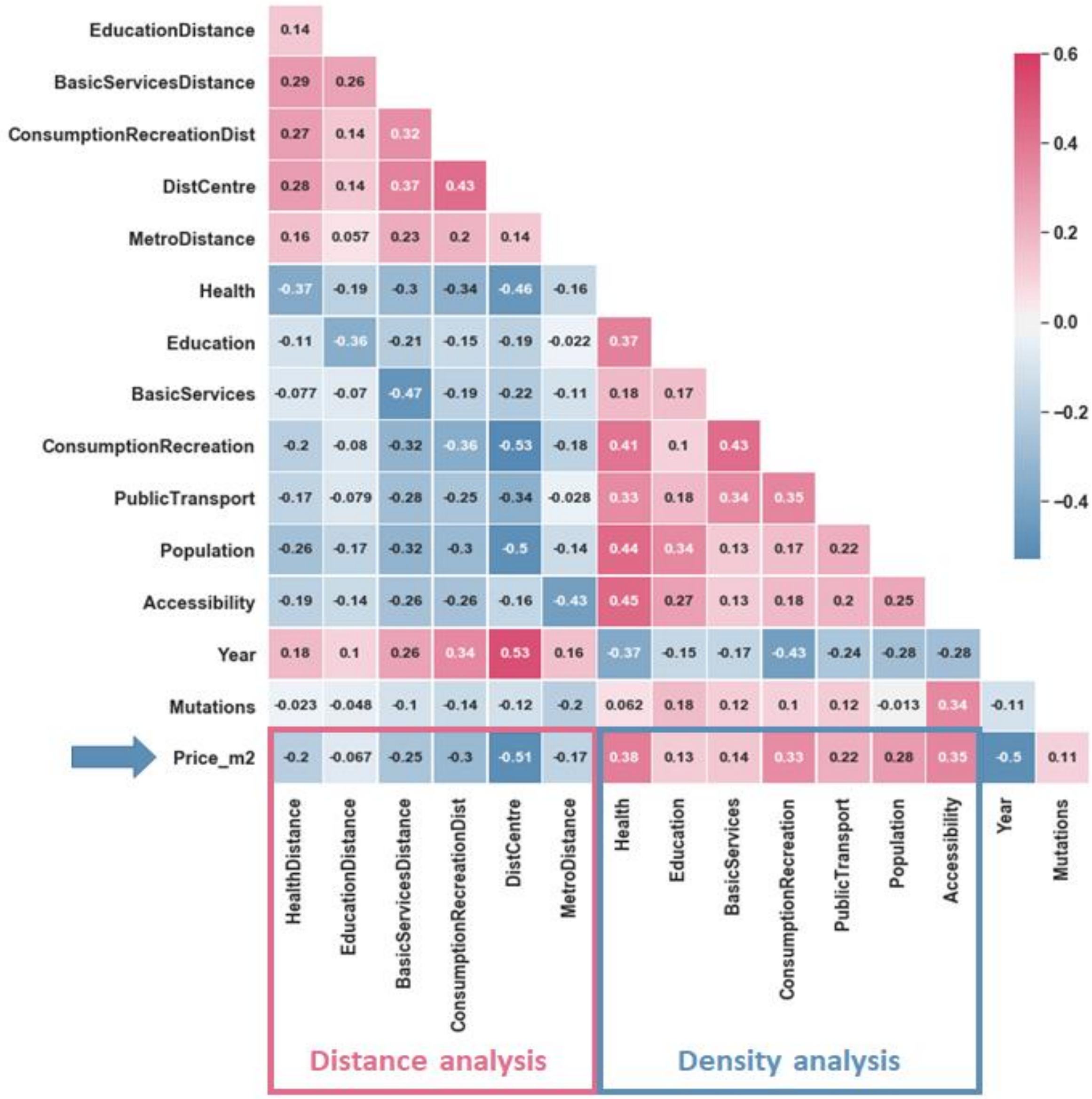

Figure 4 Correlation Matrix for Amsterdam price/m^2 and spatial indicators.

strongest negative value (-0.51), indicating that prices drop farther from the city's centre. With regards to density-based indicators, the number of health facilities in the vicinity of a home has the strongest positive correlation (0.38) with prices. Lastly, construction year has a negative correlation (-0.5) confirming that older houses are associated with higher prices.

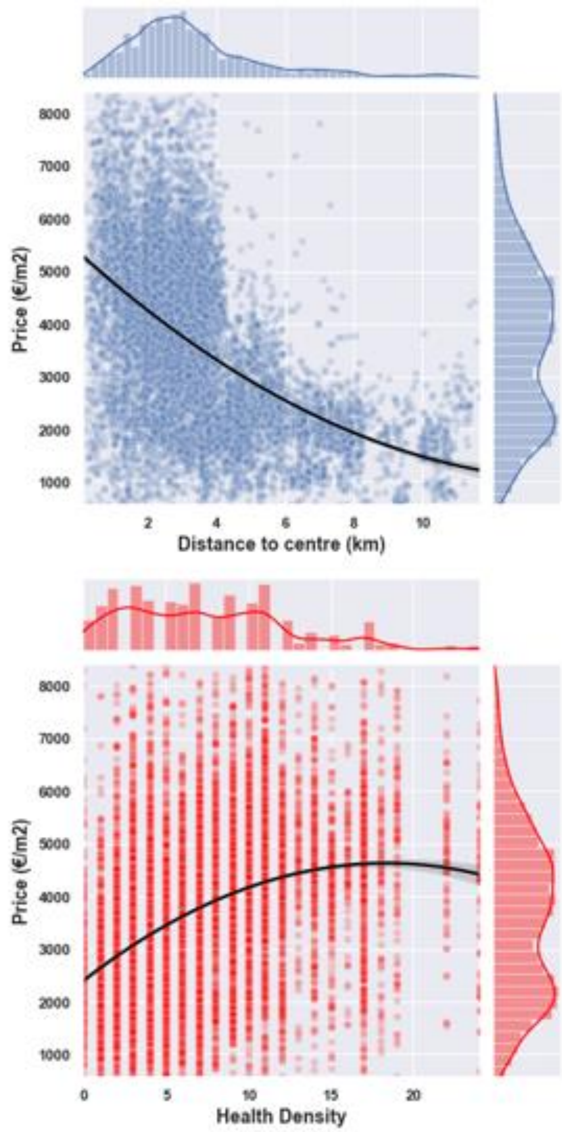

Figure 5a and b Correlation plots for 'Distance to Centre', 'Health Density' and Price (€/m^2).

Furthermore, figure 5a and b plot the correlations between price and both distance to centre, as well as health service density. It should be noted that correlation does not imply causation as for example it is demonstrated for 'Health' average feature im portance in Figures 6a and 6b.

In the case of distance to centre there is heteroscedasticity (variability in lower distances far higher than in larger ones). This phenomenon results from the difference in number of houses and price variance between *Inner* and *Outer* rings. The transition is particularly evident around 4 km from the city centre and was controlled by including a dummy variable depicting the two city areas.

3.2 Modelling housing costs using machine learning

The previous section indicates that multiple housing and location features correlate with house prices. In this section, the driving factors are sought that determine the cross-sectional variance in housing prices.

Following the increasing usage built upon previous work on the suitability of machine learning in the implementation of the hedonic pricing theory (Oladunni and Sharma, 2016), an XGBoost machine learning regression model[6] has been fitted to explain how the previously introduced set of 18 variables

6 XGBoost is an ensemble method that combines the predictions of several non-linear decision tree estimators. Recently this has been dominating applied machine learning and competitions for structured or tabular data. In this exercise, the final trained model accuracy metrics are the following: R^2 = 0.56, Mean Absolute Error: 744€/m^2.

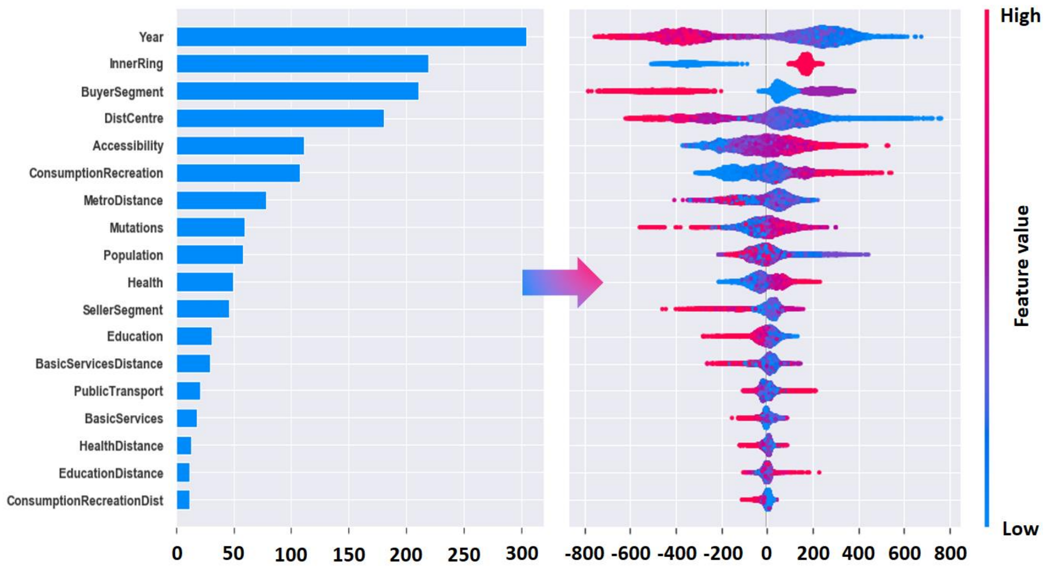

Figure 6a and b. Mean absolute value and values distribution per feature based on SHAP values.

(16 numerical and 2 categorial: *InnerRing* and *BuyerSegment*) determine variation in house prices. This type of advanced analysis provides insights on the main determinants (figure 6a and b) and possible interactions between them influencing house prices (figure 7, 8 and 9). Each feature contribution towards a prediction was based on SHAP (SHapley Additive exPlanations) by Lundberg & Lee (2017). SHAP values close to zero mean little contribution whereas higher indicate the feature contributes more. Figure 6a shows the mean absolute value per feature while 6b the values distribution.

Overall, results show that construction year is the main feature used by the model to determine house prices. Lower values on this variable, which are associated with older houses ('Year' blue dots in figure 6b), have a positive impact on the prices, while newer houses ('Year' red dots in figure 6b) drive prices down. Given that the desired old houses are predominantly located in the most central and most visited parts of the city, this may reflect locational and aesthetic preferences rather than a preference for age of a building per se, even when other locational features such as being within the ring

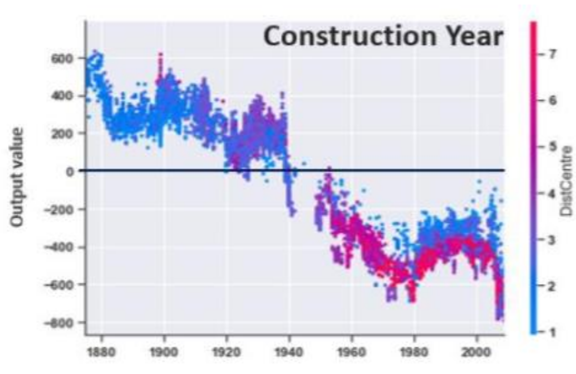

Figure 7. Construction year and distance to centre partial dependence.

road and distance to the city centre are accounted for in the model.

Next to construction year, also location plays an important role, being represented by the 'InnerRing' and 'DistCentre' variables. Consistent with the correlation results presented in the previous section, closer distances to the city centre (blue dots) drive the predicted prices up, while farther distances (red dots) drive prices down. Lastly, according to the results of the model fitting exercise, buyer segment is the third most important variable. Analysing further in detail, houses built between 1950 and early 2000 are linked with lower prices (output values). The market indicates a clear preference for real estate built before 1940 (figure 7).

Figure 8 indicates that the relation between housing costs and distance to centre is not linear. Output values become negative after 4 kilometers, coinciding with the transition from inner ring to outer ring locations. In figure 8, outer ring locations are indicated by blue dots, and inner ring locations are indicated by red dots. There is a clear interaction between these two locational variables (InnerRing and DistCentre), and house price.

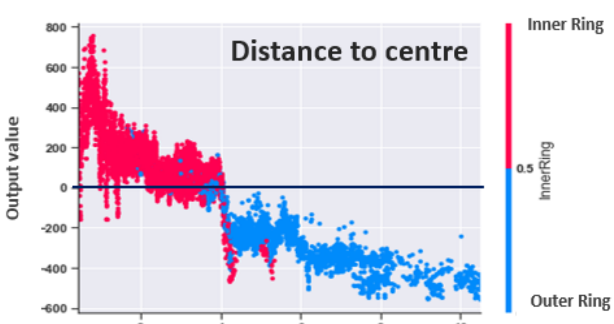

Figure 8. Distance to centre and InnerRing partial dependence.

Lastly, buying residents pay a higher price per square meter, while private investors and companies pay less, especially when buying properties within the ring. This could point to property being split, bought to let, and/or flip, returning it to the market as fully renovated apartments ready for use. The fact that the difference is bigger in the inner city, suggests the potential profits for private owners and companies are also greater in that area (figure 9).

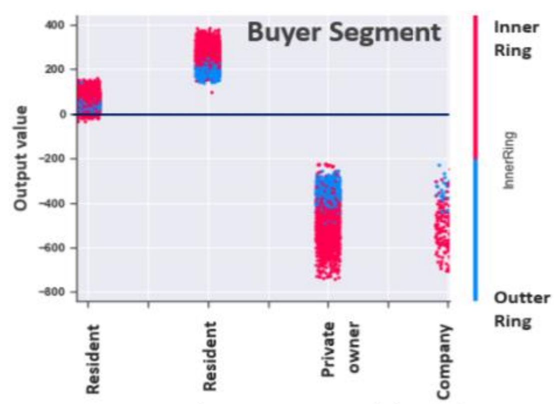

Figure 9. Buyers and InnerRing partial dependence.

4 Conclusions

Based on the modelling exercises conducted within the context of the JRC's City Lab with the City of Amsterdam, two main findings are distinguished.

First, analyses indicate that Amsterdam house prices are mainly driven by location, aesthetic, and buyer type. Closer proximity to the city centre, older buildings, and private investors and companies as buyers, are the main determinants behind higher prices. Moreover, about 45% of the sold floor space seems to have been purchased for capital gains. In this respect, it is important to note that a substantial amount of houses in Amsterdam inner ring (often older houses) have freehold land[7], which makes them generally a bit more expensive than leasehold ground houses, because the property is not tied to a (yearly) fee.

In addition, also other variables are likely to influence prices, such as housing supply and demand in the territory general, as well as supply and demand that is specific to different socio-economic classes, and types of households. Also, a further specification of buyer and seller types and their related motives could support the explanatory framework. For instance, some single entities own hundreds of apartments in the city, and therefore their policies alone can already seriously influence the market. In addition, the analyses could be further refined in order to specifically assess the relationship between house prices and the establishment of short-term rental accommodation for tourists. Ideally, in future analyses, such variables and characteristics should also be accounted for, data availability provided.

The second main finding is that looking at asking prices, it is suggested that Amsterdam middle incomes would potentially need to spend a higher share of their incomes on long-term rents, in comparison to middle incomes at country level. For Amsterdam middle incomes, asking prices reflect rents that would be considered highly overburdened indicating poor housing affordability. This suggests that middle income households looking for alternative rental housing (e.g. for family expansion) are less likely to find housing in

7 Freehold land means property is located on land that is free from hold from any other entity than the owner. Thus, with freehold property you also own the land under your property, rather than the municpality being the owner, as is often the case with leasehold land.

the city, and more likely to move out. At the same time, it must be noticed that since the findings are aggregated to postal code areas, possible variation in income or housing stock (e.g. in quality and price) is not taken into account. For future analysis it would be interesting to explore further the drivers of rent increases, also with regards to policy implications. Did owners increase their profit margin, or do these increases reflect higher costs? That is to say, the analyses largely focus on transaction/rental costs, without looking at owners' (long term) profitability levels, costs associated to property taxes, and/or maintenance/renovation costs.

Moreover, it should be noted that the presented analyses have some more general data limitations. Due to the unavailability of housing characteristics data, more focus was put on surrounding characteristics. While this depicts as close as possible the spatial context in which each house is located, potentially relevant feature such as type of house, floor(s) on which it is located, presence of elevator, outside space, energy certification, and construction quality could not be assessed. In addition, a more complete analysis could also further include and assess housing supply (over time). Taking such features into account would add to the overall picture, possibly also affecting policy implications.

In short, this report studied Amsterdam's house prices by applying a wide range of analytical techniques[8] and by combining different data sources, these types of advanced analyses provide insights into the main determinants (and possible interactions) influencing house prices. The graphical outputs make it also interpretable to non-experts, aiding decision makers on policy and communication to the public.

Depending on data availability, the methodological workflow presented in this report can be adapted and replicated for other cities, enabling comparison and providing more case studies.

8 E.g. spatial distributions, correlation analysis, customer segmentation, hotspot/cold spot detection, and machine learning regression modeling.

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KJ-NA-30883-EN-N

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Publications Office of the European Union

doi:10.2760/700246

ISBN 978-92-76-43360-6