Urban Densification and Housing Values in Transforming Neighborhoods

A comparative analysis of Amsterdam and Eindhoven

Master Thesis

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Abstract

Dutch cities increasingly rely on intra-urban densification, including brownfield redevelopment, to accommodate housing growth within existing boundaries. While densification is theoretically expected to raise housing values, brownfield transformation also involves broader changes in land use and amenities, making it difficult to isolate the contribution of densification itself. This study examines to what extent urban densification is associated with changes in housing values per square meter in Amsterdam and Eindhoven between 2018 and 2023, and whether this relationship differs between cities and between brownfield and residential areas. Using a first-difference approach at the level of 500×500 meter grid cells, three parallel models are estimated, differing in the measurement of assessed value and the level of aggregation: a CBS grid-cell measure, an individual-level measure aggregated to the grid cell, and an individual-dwelling-level measure with clustered standard errors. Across all three models, densification is positively associated with value growth, more strongly so in Amsterdam than in Eindhoven. The finding that this effect is smaller in residential cells than in brownfield cells is directionally consistent across specifications but statistically significant only in the CBS-based model, reflecting a trade-off between compositional precision and statistical power. These results suggest that brownfield transformation generates a value premium beyond densification alone, though its precise magnitude remains sensitive to measurement choices.

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1. Introduction

Dutch cities face the fundamental challenge of accommodating substantial housing growth within existing urban boundaries while preserving the quality of urban life. Urban densification has become the dominant planning response to this challenge. The share of new residential development occurring within existing urban structures has increased steadily since the 1980s, while greenfield development at the urban fringe has been constrained by successive national planning frameworks (Nabielek et al., 2012, Claassens et al., 2020). Within this broader trend, the redevelopment of former industrial areas, so-called brownfield sites, has emerged as a fast-growing component of intra-urban housing development in the Netherlands. Claassens et al. (2020) show that the combined share of brownfield and greyfield redevelopment in total national housing output more than doubled between 2000 and 2017.

Brownfield transformation involves the fundamental conversion of non-residential land into new residential neighborhoods, combining physical densification with changes in land use and neighborhood identity (Thomas, 2002). Despite the central role that brownfield transformation plays in Dutch housing policy, the relationship between urban densification and housing values in these areas remains empirically contested. The theoretical expectation is that higher density concentrates economic activity and amenities, which should translate into higher land and property values (De Groot et al., 2010). Empirical studies on brownfield remediation and urban renewal broadly confirm that redevelopment raises property values in surrounding areas (De Sousa et al., 2009; Peng & Tian, 2022; Wu & Deng, 2024). However, these studies typically focus on spillover effects of specific projects on nearby transactions, which does not allow the contribution of densification to be separated from the broader transformation process at a citywide scale, nor does it readily enable comparison across cities with structurally different markets.

What remains empirically unclear is how much of the value growth observed in transformation areas can be attributed to densification itself, and whether this distinction varies between cities operating in different housing market conditions. Studies on this question in the Dutch context, characterized by a large social rental sector, an annual assessed property value system, and a strong planning tradition, are largely absent. A comparative, city-wide empirical analysis of the densification-value relationship in Dutch brownfield transformation areas has not previously been conducted.

This study addresses that gap by applying a first-difference approach with two stacked periods at the level of 500×500 meter grid cells across two full cities, examining whether brownfield transformation areas experience assessed value growth beyond what densification alone predicts, and whether this pattern differs between cities with structurally different housing market conditions. The study period runs from 2018 to 2023, a period of sustained housing market growth in both cities. The central research question therefore is: *To what extent is urban densification associated with changes in housing values per square meter in Amsterdam and Eindhoven over the period 2018 to 2023, and does* *this relationship differ between cities and between transformation areas and existing residential areas?*

To test this question, three models are estimated to ensure that the estimated relationship between densification and housing values is robust to alternative measurement approaches. The first model uses average assessed value per square meter at the 500×500 meter grid-cell level based on CBS data. The second model retains the same spatial unit of analysis but constructs average housing values from individual dwelling-level observations, while restricting the sample to pre-existing housing stock and incorporating additional neighborhood controls. The third model shifts the analysis to the individual dwelling level, allowing housing value changes to be estimated for each dwelling while maintaining densification as an area-level characteristic. Comparing these approaches makes it possible to assess whether the estimated effects are sensitive to the level of aggregation, the measurement of housing values, and the treatment of housing composition effects.

The remainder of this study is structured as follows: Section 2 develops the theoretical framework, discussing the relationship between urban densification, brownfield transformation, and housing values, and introduces Amsterdam and Eindhoven as comparative cases. Section 3 describes the data sources, variable construction, and analytical approach. Section 4 presents the regression results. Section 5 discusses the findings considering the theoretical expectations, reflects on the limitations of the study, and concludes.

2. Theoretical Framework

2.1 Urban densification and the compact city

Urban densification, broadly defined as the net increase of dwellings within existing urban areas through infill development, conversion of non-residential uses, or redevelopment at higher densities (Broitman & Koomen, 2020), has been a central objective in Dutch spatial planning since the Fourth National Policy Document of 1988 (Nabielek et al., 2012). In the context of Dutch spatial planning, densification was explicitly promoted to limit urban sprawl and preserve open space, with national planning frameworks steering residential construction towards existing urban boundaries. Claassens et al. (2020) show that despite the gradual withdrawal of national spatial planning in favor of decentralization, densification within existing urban areas continued to increase, driven by persistent housing demand and local restrictions on greenfield development.

Two types of densification are relevant for this study. The first is the addition of dwellings to existing residential areas, sometimes referred to as infill development. The second is the transformation of former non-residential land into residential use, particularly the redevelopment of former industrial sites, railway yards, and other abandoned or underused urban land. These sites are often referred to as brownfields: a term originating in US environmental policy, defined by the Environmental Protection Agency (EPA) as “abandoned, idle, or under-used industrial and commercial properties where expansion or redevelopment is complicated by real or perceived environmental contamination” (U.S. Environmental Protection Agency, 2017), and applied more broadly in European planning contexts to refer to any previously developed land that has fallen out of productive use and is available for redevelopment (Thomas, 2002). A related concept is greyfield, which refers to similar underused sites that lack the perceived environmental contamination associated with brownfields, such as former offices, shops, and paved-over areas. While greyfields are an important component of urban transformation more broadly, this study focuses specifically on brownfield redevelopment as defined by the presence of former industrial, railway, aviation, landfill, or construction land use, in line with the land-use classification used in the empirical analysis (Section 3.5).

Claassens et al. (2020) show that the share of greyfield and brownfield redevelopment more than doubled between 2000 and 2017, from 14% to 34% of all new housing within existing urban areas, making it the fastest-growing component of intra-urban housing development in the Netherlands. Broitman and Koomen (2020) demonstrate that in all 15 major Dutch historical cities urban density gradients became steeper between 2000 and 2017, contradicting the standard prediction from urban economic models that density gradients flatten over time as cities grow. Rather than uniform infill, densification is concentrated near city centers, which attract disproportionately more growth in both dwellings and population than peripheral areas.

2.2 Densification and housing values

A central proposition in urban economics is that higher density is associated with higher land and property values, because density reflects the concentration of economic activity, amenities, and accessibility that make urban locations attractive. De Groot et al. (2010) show that approximately half of the urban land premium in the Netherlands can be attributed to proximity to employment and half to the availability of consumer amenities such as cultural facilities, shops, and restaurants. A broad review of over 300 studies confirms that economic density is generally associated with positive economic outcomes, including improved productivity and access to jobs and services (Ahlfeldt et al., 2018). As densification increases the concentration of residents and activities in an area, it can strengthen these agglomeration effects and thereby put upward pressure on housing values (De Groot et al., 2010).

However, the relationship between densification and housing values is not straightforwardly positive. A first complication is the compositional effect: when densification occurs primarily through the addition of smaller dwellings, average value per dwelling declines even if locational quality improves, simply because the new dwellings are smaller and therefore worth less in absolute terms (Rosen, 1974). Measuring housing value per square meter rather than per dwelling is essential to correct for this effect, as it holds the unit of measurement constant regardless of dwelling size. Without this correction, studies risk confounding a change in dwelling stock composition with a genuine change in locational quality. The operationalization of this correction and its remaining limitations are discussed in Section 3.3.

A second complication is the time lag between densification and value change. The mechanisms through which densification raises housing values, such as the attraction of new amenities, improved public space, and changing neighborhood reputation, operate gradually over time (Rosenthal, 2008). Anticipatory effects mean that value changes can even precede project completion, as buyers price in expected future improvements (Autor et al., 2014). In areas that are still in early stages of transformation, initial effects may therefore be modest or not yet fully visible

A third complication concerns the tenure composition of new dwellings. Areas where densification occurs primarily through the construction of social rental housing may show a weaker association between densification and assessed value per square meter, as social rental dwellings in the Netherlands tend to be older, smaller on average, and concentrated in less sought-after locations than market-rate housing (Elsinga & Wassenberg, 2014).

A fourth and more fundamental distinction is between densification in existing residential areas and densification through brownfield transformation. In existing residential areas, increased supply may put downward pressure on nearby prices in the short run (Ooi & Le, 2013). In brownfield transformation areas, however, the addition of new dwellings is accompanied by fundamental shifts in land use, amenity provision, and neighborhood identity. Peng & Tian (2022) find that more than 85% of the total price premium near urban redevelopment derives from reconstruction amenity effects rather than from the addition of dwellings per se, and Wu & Deng (2024) show that industrial renewal generates the strongest and most sustained positive price effects among different types of urban transformation. This suggests that in brownfield transformation areas, densification and the broader upgrading process are closely intertwined, making it difficult to isolate the effect of dwelling addition from the effects of land-use change and amenity improvement.

2.3 Amsterdam and Eindhoven as comparative cases

The theoretical mechanisms described in Sections 2.1 and 2.2 are expected to operate differently across cities. The relationship between brownfield densification and housing values is likely to be shaped by city-specific factors, including the degree of housing market pressure and the scale of maturity of ongoing transformation processes (van Duijn et al., 2016). Comparing two cities that differ on these dimensions allows for a more nuanced understanding of when and where densification in transformation areas translates into housing value effects.

Amsterdam is one of the most supply-constrained housing markets in the Netherlands. Persistent excess demand, driven by population growth, household formation, and international migration, has resulted in sustained upward pressure on housing values throughout the study period, with average assessed values substantially higher than the national average (CBS Vierkantstatistieken, 2018). Broitman & Koomen (2020) show that density gradients in all major Dutch cities steepened, driven in part by the attraction of historical city centers and urban amenities. This dynamic is particularly relevant in Amsterdam, where the historical city center and waterfront locations have long been among the most sought-after residential areas in the Netherlands. In this context, the addition of new dwellings (whether in existing residential areas or on former industrial land) takes place against a background of structural scarcity, which may amplify the value effects of densification. Amsterdam's brownfield transformation is, among other places, concentrated in areas along the IJ waterfront, including the western harbor area and parts of Amsterdam-Noord, where large-scale redevelopment of former port and industrial sites has been ongoing since the early 2000s (Gemeente Amsterdam, 2023).

Eindhoven presents a structurally different urban context. As a mid-sized city with an industrial legacy rooted in the former Philips manufacturing complex, Eindhoven has experienced significant brownfield transformation (RVO, 2016). Housing market pressure in Eindhoven is substantially lower than in Amsterdam, as reflected in average assessed values that are roughly half those observed in Amsterdam over the study period (CBS Vierkantstatistieken, 2018). While assessed values are an outcome rather than a direct measure of market pressure, they capture the cumulative effect of supply constraints, demand dynamics, and locational attractiveness, and can therefore be used as a proxy for housing market conditions (De Groot et al., 2010). Eindhoven's housing market is structurally different from Amsterdam's. Not only in terms of scale, but also in the nature of its urban economy. Musterd et al. (2020) show that Amsterdam has developed a multi-layered economy, combining creative industries, knowledge sectors, tourism, and financial services. This drives gentrification and urban transformation more intensively than cities with a more mono-layered economic base. Eindhoven, whose urban economy remains more strongly anchored in a single sector through its technology and design cluster rooted in the Philips legacy, is therefore expected to see weaker demand-driven transformation dynamics than Amsterdam.

The comparison between the two cities is therefore intended to examine whether the densification-value relationship is contingent on urban market context. Amsterdam and Eindhoven differ in housing market pressure, economic structure, and the spatial concentration of brownfield redevelopment, making them useful comparative cases for assessing whether densification is associated with different housing value dynamics under different urban conditions.

3. Method

3.1 Research design and spatial unit

This study employs a quantitative, longitudinal research design at the level of spatial grid cells. A temporal analysis is used to describe the relationship between densification and housing values as change over time. The method is based on a first-difference approach with two stacked periods, in which the change in the number of dwellings per grid cell is related to the change in assessed value per square meter between 2018 and 2021, and again between 2021 and 2023. By focusing on changes rather than levels, time-constant cell characteristics such as location, proximity to amenities, and historical development patterns are implicitly held constant, which produces a cleaner estimate of the effect of densification on housing values than a cross-sectional analysis would allow. Claassens and Koomen (2017) apply a comparable first-difference approach at the grid-cell level (100×100m) in the Dutch context, showing that this method eliminates time-constant locational characteristics and thereby yields a more precise estimate of the densification effect than cross-sectional analysis. The use of two stacked first-difference periods, rather than a single difference spanning the full 2018-2023 window, increases the number of observations per cell and allows period fixed effects to control for differences in market conditions between the two periods.

This first-difference design is applied identically across three parallel analyses, which differ in how the dependent variable (assessed value per square meter) is measured, and consequently in their spatial unit of observation. Model 1 uses assessed value data reported directly by the CBS Vierkantstatistieken at the grid-cell level. This model offers a directly available measure based on many observations and a wide range of control variables, but the compositional effect still holds. When the newly added dwellings differ in size, quality, or other characteristics from the existing stock, this might influence the estimated densification effect. Model 2 uses individual-level assessed value data, aggregated to the grid-cell level. This model resolves the inconsistency in Model 1, but at the cost of some statistical power (Section 4.2) Model 3 uses the same individual-level data without aggregation, such that each individual dwelling forms a separate observation. This provides the most granular measure of assessed value, but this model has by far the lowest statistical power (Section 4.3). As a result, Models 1 and 2 share the grid cell as their unit of observation, while Model 3 is estimated at the level of the individual dwelling, with grid-cell characteristics on densification merged onto each dwelling based on its location. The full construction of these three measures is described in Section 3.3.

The spatial unit underlying all three analyses, whether used as the unit of observation directly (Models 1 and 2) or as the source of merged cell-level characteristics (Model 3), is a 500×500 meter grid cell, derived from the CBS Vierkantstatistieken (Centraal Bureau voor de Statistiek, 2018, 2021, 2023). The choice for grid cells rather than administrative neighborhood boundaries is a deliberate methodological decision. Neighborhood delineations are regularly revised by CBS, meaning that a longitudinal analysis at neighborhood level would be confronted with the boundary change problem. Grid cells are geographically stable and refer in each year to exactly the same 0.25 km² of land, regardless of administrative revisions. The 500×500 meter resolution was preferred over the finer 100×100 meter alternative because CBS applies privacy masking to cells with insufficient observations, which disproportionately affects smaller cells. The 500m resolution provides a sufficient number of stable, non-masked cells with valid assessed value observations across both cities while still capturing meaningful spatial variation in densification and housing values.

The analysis covers all grid cells within the municipal boundaries of Amsterdam and Eindhoven for the measurement years 2018, 2021 and 2023. Including both cities in their entirety generates sufficient statistical variation and allows the effect of densification in transformation areas to be compared against the broader urban average. Within this framework, grid cells are classified according to their dominant land use prior to the study period, distinguishing between brownfield transformation cells and residential cells (see Section 3.5). This classification is applied identically across all three analyses.

3.2 Data sources and time period

The primary data source used in all three models is the CBS Vierkantstatistieken 500m, available via PDOK (Centraal Bureau voor de Statistiek, 2018, 2021, 2023). For each measurement year, the following variables were extracted per grid cell: the number of dwellings, the average assessed value per dwelling, the number of multi-family dwellings, the number of dwellings owned by housing corporations, and the address density (omgevingsadressendichtheid, OAD). Only grid cells for which a valid assessed value is available in all three measurement years are included in the analysis.

The assessed value is a government-determined valuation of immovable property, established annually by Dutch municipalities under the Wet Waardering Onroerende Zaken (Valuation of Immovable Property Act). It applies to all residential properties in the Netherlands, regardless of tenure: both owner-occupied and rental dwellings receive an assessed value, as the assessed value also forms the basis for property tax and is used in calculation of the rental points system for regulated rental housing. The valuation is based on comparable market transactions within the same area, but unlike a transaction price, it does not represent a sale. It is rather a model-based estimate that municipalities update annually using sales data from the preceding period (Waarderingskamer, 2024). How this assessed value is subsequently used to construct the dependent variable of this study, including the compositional sensitivity this entails, is discussed in Section 3.3.

The CBS Bestand Bodemgebruik was used to classify grid cells according to their dominant land use prior to the study area (Centraal Bureau voor de Statistiek, 2017). Grid cells in which at least 25% of the surface areas consisted of former industrial land, railway terrain, sanitary landfill, or construction site were classified as brownfield transformation cells. Grid cells in which at least 50% of the surface area consisted of residential land use were classified as residential cells. All other cells, including urban greenfield locations, were excluded from the analysis to ensure a clean comparison between the treatment and control group. This classification is applied identically across all three models and is further explained in Section 3.5.

The selection of 2018, 2021 and 2023 as measurement years is driven by data availability. The assessed value per dwelling is consistently available in the CBS Vierkantstatistieken from 2018 onwards for a sufficient number of grid cells. The 2024 data was masked by CBS for virtually all cells due to privacy protection thresholds. The individual-level assessed value data used in Models 2 and 3 covers the same three measurement years, allowing for a consistent comparison across the three analyses.

As an additional data source, the Basisregistratie Adressen en Gebouwen (BAG) (Kadaster, 2024a) was used to calculate the average dwelling floor area per grid cell. The BAG records the usable floor area in square meters for each residential unit. Each apartment is registered as a separate residential unit with its own floor area measurement, regardless of the floor level within a building. The average floor area per grid cell was calculated by spatially linking all dwellings within a cell using their BAG coordinates. As a check on data consistency, the number of dwellings according to the CBS Vierkantstatistieken was compared to an independent count based on the BAG, in which dwellings were spatially linked to grid cells using their coordinates. The two sources show close agreement: in 2018, the BAG count was 0.8% lower than the CBS count in Amsterdam and 1.4% higher in Eindhoven. In 2023, The BAG count was 0.04% higher in Amsterdam and 2.0% higher in Eindhoven. These small and stable changes, confirm that the CBS dwelling counts used in this study are a reliable representation of the housing stock in both cities across the study period (see Appendix Table A1).

As a further data source, the full Basisregistratie Adressen en Gebouwen (Kadaster, 2024b) was used to construct amenity controls. All objects with a non-residential function were spatially linked to the 500×500 meter grid cells using their BAG coordinates and counted separately for six functional categories: hospitality and accommodation, retail, healthcare, office, education, and sport. These amenity controls are included identically in all three models. Their construction and selection are described further in Section 3.4.

For Models 2 and 3, individual level assessed value data was used instead of the CBS aggregate. This data records the assessed value, floor area, construction year, and dwelling type (apartment, terraced, detached, semi-detached, corner) for each individual residential unit in Amsterdam and Eindhoven, obtained from the WOZ Waardeloket (Kadaster, 2024c).

3.3 Measuring housing value: assessed value per m²

The dependent variable is assessed value per square meter. This variable is constructed in three different ways, corresponding to three parallel analyses that use different combinations of data sources. All three measures are intended to correct for the compositional effect described in Section 2.2: by expressing value per unit of floor area rather than per dwelling, the measure holds the unit of measurement constant regardless of dwelling size.

Model 1 (CBS grid cell) uses the average assessed value per dwelling reported directly by the CBS Vierkantstatistieken for each grid cell, divided by the average dwelling floor area per cell calculated from the BAG: *Assessed value per m² = average assessed value per dwelling (CBS) / average dwelling floor area per cell (BAG)*. The floor area is calculated using all dwellings present in a cell at the time of measurement, without restricting on construction year.

Model 2 (individual assessed value, cell-aggregated) addresses the central limitation of Model 1 by using individual-level assessed value data rather than the CBS cell-level aggregate. This data records the assessed value, floor area, construction year, and dwelling type for each individual residential unit in Amsterdam and Eindhoven, obtained from municipal property valuation records (Kadaster, 2024c). Because the construction year is available at the individual level, this data makes it possible to filter both the assessed value and the floor area on construction year simultaneously, fully resolving the numerator-denominator inconsistency that remains a limitation in Model 1 even after the adjustment described above. For each dwelling, assessed value per square meter is first calculated individually (individual assessed value divided by individual floor area), after which these individual ratios are averaged across all dwellings within a grid cell to obtain a cell-level measure: *Assessed value per m² (cell) = average of (individual assessed value / individual floor area) across all dwellings in the cell*. This differs from Model 1 in two respects. First, the assessed value is drawn from individual-level municipal records rather than the CBS aggregate, allowing for more precise control over which dwellings are included. Second, the cell-level value is computed as the average of individual price per square meter ratios rather than the ratio of cell-level averages. The latter gives relatively more weight to smaller dwellings, which tend to have a higher assessed value per square meter, compared to a calculation based on summed assessed value divided by summed floor area. While Model 2 resolves the compositional inconsistency present in Model 1, it does not include the same set of CBS-derived control variables (such as the share of corporation-owned dwellings), as these are not consistently available at the individual level; the control variables used for Model 2 are therefore based on dwelling-type shares (apartment, terraced, detached) derived directly from the individual-level data, described further in Section 3.4.

Model 3 (individual level) uses the same individual-level assessed value data as Model 2, but without aggregating to the grid-cell level. Each dwelling in the analysis is a separate observation, with its own assessed value per square meter calculated individually based on its own assessed value and floor area. Grid-cell characteristics, including cell type (brownfield or residential) and the change in the number of dwellings per cell, are merged onto each individual dwelling based on its location, but the dependent variable itself is not aggregated to the cell level. This specification represents the most granular level of analysis among the three models and avoids any aggregation-related distortion in the dependent variable. However, it introduces a different methodological consideration: because the unit of observation is the individual dwelling rather than the grid cell, the explanatory variable of interest (the change in the number of dwellings per cell) and the cell-type classification are identical for all dwellings within the same cell. This means that, unlike Models 1 and 2, the effective number of independent spatial units driving the identification of the densification effect in Model 3 is determined by the number of grid cells rather than the number of individual observations, even though the regression is estimated using individual-level data. This has implications for the interpretation of statistical power and standard errors, discussed further in Section 3.7.

Figure 1 illustrates the spatial pattern that all three specifications aim to capture, showing the distribution of the change in assessed value per square meter across grid cells in Amsterdam and Eindhoven over the period 2018–2023, based on the CBS grid-cell measure (Model 1). In Amsterdam, the increase is widespread, with assessed value per square meter rising in almost all cells across the city, forming a contiguous band of growth running from the northeast through the city center to the southwest. In Eindhoven, the increase is more uneven: there is greater variation between cells, and growth rarely reaches the magnitude observed in Amsterdam, with values concentrated in a lower range overall.

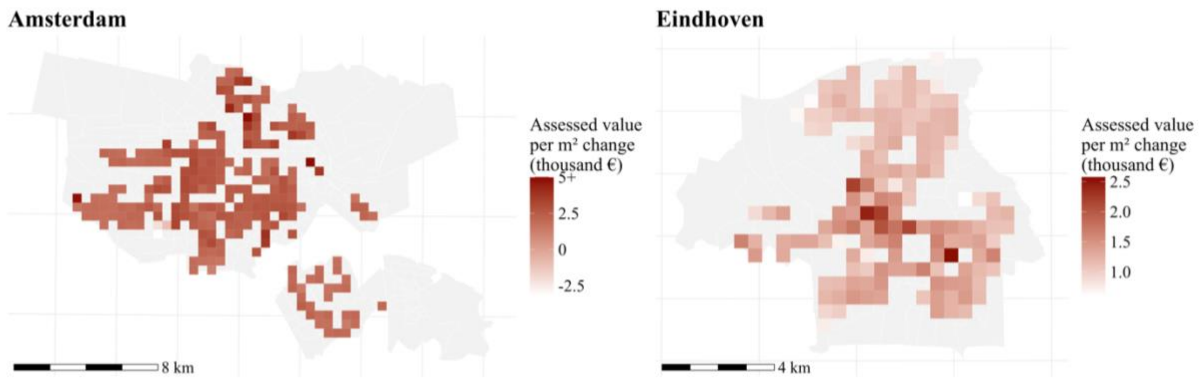

Figure 1. *Change in assessed value per square meter per grid cell, Amsterdam (left) and Eindhoven (right), 2018–2023. Background shading shows neighborhood boundaries for spatial reference. Only stable grid cells with valid assessed value observations in all three measurement years are shown. Values in Amsterdam are capped at €5,000/m² for visualization purposes due to one cell with only five dwellings showing an extreme outlier value; this cell does not materially affect the regression results presented in Section 4. Source: CBS Vierkantstatistieken 500m (2018, 2021, 2023); CBS Wijk- en Buurtkaart (2024)*

3.4 Densification and control variables

The main explanatory variable is the change in the number of dwellings per grid cell between consecutive measurement years. This is a direct measure of physical densification. Although the first-difference approach eliminates all time-invariant cell characteristics by construction (analogous to a fixed-effects estimator) this does not imply that no control variables are needed. First-differencing removes the influence of factors that are constant over time within a cell, such as long-standing locational or structural characteristics. It does not, however, account for time-varying processes that may confound the relationship between densification and assessed value, nor does it capture how the initial composition of a cell may moderate the effect of densification. The specific set of controls differs depending on the data source underlying each model.

Model 1 uses both dynamic and static controls derived from the CBS Vierkantstatistieken (Centraal Bureau voor de Statistiek, 2018). Dynamic controls capture compositional change that occurs within a cell during the study period: the change in the share of multi-family dwellings (delta_share_multifamily) and the change in the share of dwellings owned by housing corporations (delta_share_corporation). Static controls, measured at the start of each period, capture the initial composition of a cell: the share of multi-family dwellings, the share of corporation-owned dwellings, and the address density (OAD). The static and dynamic controls are not strongly correlated: correlations between the lagged share variables and their corresponding first-differenced counterparts range from -0.16 to -0.03, indicating that each variable captures a distinct source of variation rather than overlapping information (see Appendix Table A2 for the full correlation matrix).

Models 2 and 3 use individual-level dwelling-type shares instead, as the corporation-ownership and multi-family-share variables specific to the CBS Vierkantstatistieken are not consistently available in the individual-level data. Model 2 controls for the share of apartments and terraced houses at the cell level, alongside the average construction year of the dwelling stock and the lagged address density, multi-family share, and corporation share. Model 3, using the same individual-level data without cell-level aggregation, retains a more granular set of dwelling-type categories alongside the individual construction year: apartment, terraced, corner, and semi-detached houses, with detached houses as the reference category. This difference reflects the level of aggregation rather than a difference in the underlying data: at the individual level, all five dwelling-type categories are retained, whereas the cell-level aggregation in Model 2 collapses this into a more limited set of share variables.

To further reduce the risk that the estimated densification effect captures differences in the amenity composition between brownfield and residential cells, static amenity controls were constructed using the full Basisregistratie Adressen en Gebouwen (Kadaster, 2024b) and included identically in all three models. All objects with a non-residential function were spatially linked to the 500×500 meter grid cells using their BAG coordinates and counted separately for five functional categories: hospitality and accommodation, healthcare, office, education, and sport. A sixth category, retail, was also constructed but excluded due to a correlation of 0.71 with the hospitality variable, which approaches the conventional threshold of 0.7–0.8 above which multicollinearity becomes a concern. Hospitality was retained over retail because it is more directly linked to the amenity-driven value premiums described in the literature (De Groot et al., 2010; Musterd et al., 2020), and because it was significant in initial model runs ($p=0.009$) while retail was not ($p=0.46$). These amenity variables capture the baseline amenity composition of each cell. Dynamic amenity controls, measuring the change in the number of non-residential functions between 2018 and 2023 per category, were also constructed and tested but proved unreliable: the BAG records the construction year of a building rather than the date on which a particular function became active, meaning that newly opened establishments in existing buildings are not detected as new amenities. As a result, the delta variables showed near-zero variation across cells and were excluded from all three models.

After addition of these amenity controls, no correlation exceeds the conventional threshold of 0.7–0.8 after the exclusion of retail. The strongest remaining correlation is between the lagged address density and the hospitality variable ($r = 0.57$), which is expected given that denser cells tend to contain more non-residential functions.

No additional neighborhood-level static controls (such as income or education level) are included in the models with neighborhood fixed effects (Section 3.7), as these are time-invariant within a neighborhood and are therefore already fully absorbed by the neighborhood fixed effects; including them separately resulted in perfect collinearity with the fixed effects. The set of control variables included here is therefore limited to those that vary at the grid-cell level within a neighborhood and are not already captured by the fixed-effects structure.

3.5 Dummy variable for transformation areas

To classify grid cells according to their initial land use, the CBS Bestand Bodemgebruik (BBG) 2017 was used, the most recent land-use dataset available prior to the start of the study period (Centraal Bureau voor de Statistiek, 2017). The BBG distinguishes 38 detailed land-use categories. An initial classification based on a broad set of non-residential categories (including retail, public facilities, and socio-cultural amenities) resulted in 85% of grid cells in Amsterdam and 95% in Eindhoven showing at least some overlap with non-residential land use, indicating that this definition was too inclusive to meaningfully distinguish transformation areas from the rest of the urban fabric.

The classification was therefore restricted to land-use categories that correspond more directly to brownfield-type transformation: former industrial sites, railway terrain, airports, landfills, and construction sites (BBG codes 10, 12, 24, 30, and 34). Grid cells were classified based on the share of their surface area covered by these categories. Three threshold levels were compared (25%, 33%, and 50%) to determine the most defensible cutoff. At a 50% threshold, only 24 stable brownfield cells remained in Amsterdam and 16 in Eindhoven. This is too few for estimating a reliable interaction model. The 25% threshold yielded 69 stable brownfield cells in Amsterdam and 40 in Eindhoven, providing sufficient statistical power while remaining methodologically defensible: a cell in which at least a quarter of the surface area consisted of former industrial or transformation-eligible land use is clearly affected by the transformation process, particularly given the relatively large scale of a 500×500 meter grid cell (25 hectares).

Grid cells were therefore classified as brownfield transformation cells if at least 25% of their surface area consisted of one of the five transformation-eligible land-use categories in 2017. As a clean control group, grid cells were classified as residential cells if at least 50% of their surface area consisted of residential land use in 2017. All remaining cells, including urban greenfield locations and cells with a mixed or ambiguous land-use composition, were excluded from the analysis. Among the stable grid cells with valid dwelling and floor-area data, this yields 63 brownfield cells in Amsterdam and 36 in Eindhoven. Of these, 9 cells in Amsterdam and 1 cell in Eindhoven lack a valid assessed value in one or more of the three measurement years and are therefore excluded from the analytical sample, resulting in a final analytical sample of 54 brownfield and 188 residential grid cells in Amsterdam, and 35 brownfield and 120 residential grid cells in Eindhoven, used as the treatment and the control groups respectively.

This classification is applied identically across all three models, though the way it enters each analysis differs according to the spatial unit of observation described in Section 3.1. In Models 1 and 2, where the grid cell is the unit of observation, the cell-type classification is merged directly onto each grid-cell-period observation. In Model 3, where the individual dwelling is the unit of observation, each dwelling is assigned the cell-type classification of the grid cell in which it is located, based on its spatial coordinates; all dwellings within the same grid cell therefore share an identical cell-type value.

The resulting classification is shown in Figure 2, which maps brownfield and residential cells for both cities. In Amsterdam, brownfield cells are dispersed across the city but are notably absent from the historical city center, consistent with the expectation that the oldest, most established parts of the city were not subject to industrial transformation. In Eindhoven, brownfield cells are similarly dispersed, without a single dominant cluster.

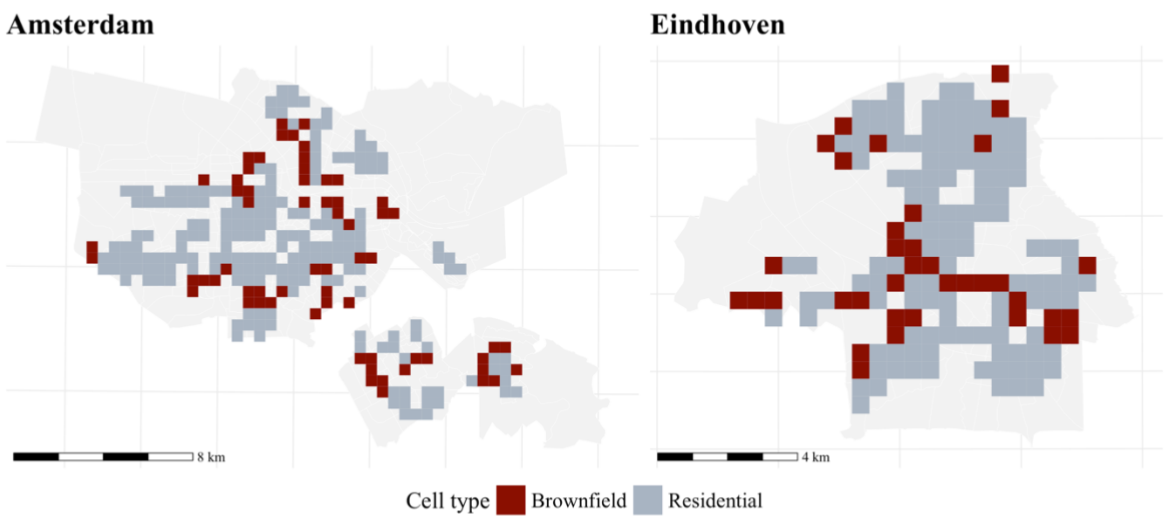

Figure 2. *Classification of stable grid cells as brownfield transformation cells or residential cells, Amsterdam (left) and Eindhoven (right). Brownfield cells are defined as cells in which at least 25% of the surface area consisted of former industrial land, railway terrain, airfield, landfill, or construction site in 2017. Residential cells are defined as cells in which at least 50% of the surface area consisted of residential land use in 2017. Background shading shows neighborhood boundaries for spatial reference. Only stable grid cells with valid assessed value observations in all three measurement years*

are shown. Source: CBS Bestand Bodemgebruik (2017); CBS Vierkantstatistieken 500m (2018, 2021, 2023); CBS Wijk- en Buurtkaart (2024).

3.6 Descriptive statistics

Table 1 presents descriptive statistics for the four groups (brownfield and residential cells in Amsterdam and Eindhoven) in 2018 and 2023, based on the CBS Vierkantstatistieken and BAG data underlying Model 1, to illustrate how these groups changed over the study period. The same cell-type classification applies to Models 2 and 3, which draw on individual-level assessed value data for the same set of grid cells (Section 3.2). Descriptive statistics for this individual-level data are not separately reported, as the underlying cell-level composition is identical to that shown in Table 2.

In 2018, the average grid cell in Amsterdam residential contained 1,573 dwellings, compared to 629 in Amsterdam brownfield, possibly reflecting the lower initial development density of former transformation areas. In Eindhoven the pattern is similar: 683 dwellings in residential cells versus 280 in brownfield cells. Brownfield cells also have substantially larger average dwelling floor areas than residential cells in both cities (75m² versus 83m² in Amsterdam; 126m² versus 118m² in Eindhoven). This difference may reflect several factors, including the larger floor plans common in converted industrial buildings, as well as the fact that residential cells are more likely to include dense, small-unit historical city-center housing stock.

Assessed value per square meter was higher in Amsterdam than in Eindhoven for both cell types in 2018, reflecting the structural housing market pressure in Amsterdam relative to Eindhoven. Within each city, brownfield and residential cells show comparable assessed values in 2018 (€4,123/m² versus €4,033/m² in Amsterdam; €2,130/m² versus €2,062/m² in Eindhoven), suggesting that the two groups did not differ substantially in baseline value prior to the study period.

Between 2018 and 2023, all four groups densified, with brownfield cells adding more dwellings on average: Amsterdam brownfield cells added 193 dwellings on average (629 to 822), compared to 39 in Amsterdam residential cells (1,573 to 1,612). The same pattern holds in Eindhoven: brownfield cells added 74 dwellings on average (280 to 354), compared to 35 in residential cells (683 to 718). Assessed value per square meter rose substantially across all groups, by approximately 58% in Amsterdam brownfield, 56% in Amsterdam residential, 62% in Eindhoven brownfield, and 58% in Eindhoven residential.

The share of multi-family dwellings is substantially higher in Amsterdam (88% in brownfield cells, 79% in residential cells) than in Eindhoven (47% in brownfield cells, 31% in residential cells), reflecting the structural difference in dwelling type composition between the two cities. The address density (OAD) is also notably lower in brownfield cells than in residential cells in both cities (3,397 versus 5,204 in Amsterdam; 1,922 versus 2,355 in Eindhoven), consistent with the lower initial dwelling density observed for brownfield cells. The share of corporation-owned dwellings is somewhat higher in brownfield cells than in residential cells in 2018 (53% versus 46% in Amsterdam; 47% versus 39% in Eindhoven), though this gap narrows by 2023 in both cities.

	Unit	Amsterdam brownfield	Amsterdam residential	Eindhoven brownfield	Eindhoven residential
Dwellings 2018	Count	629	1,573	280	683
Dwellings 2023	Count	822	1,612	354	718
Floor area	m²	75	83	126	118
Assessed value/m² 2018	€	4,123	4,033	2,130	2,062
Assessed value/m² 2023	€	6,525	6,299	3,460	3,263
Multi-family % 2018	%	88.7	78.7	46.7	30.6
Multi-family % 2023	%	87.8	78.7	45.8	31.8
Corporation % 2018	%	52.8	45.7	47.0	39.4
Corporation % 2023	%	45.3	44.5	36.6	38.5
OAD 2018	Addresses/km²	3,397	5,204	1,922	2,355
OAD 2023	Addresses/km²	3,783	5,440	2,148	2,503

Table 1. *Descriptive statistics by group, 2018 and 2023. Note: assessed value per m² expressed in euros. Dwellings refers to the average number of dwellings per 500×500 meter grid cell. Floor area refers to the average dwelling floor area in square meters, based on dwellings built in or before 2018. Multi-family % and Corporation % are shares of total dwellings. OAD refers to address density (omgevingsadressendichtheid, addresses per km²). Values are averages across the analytical sample of stable grid cells with valid assessed value observations in all three measurement years and floor-area data (n = 54 for Amsterdam brownfield, 188 for Amsterdam residential, 35 for Eindhoven brownfield, and 120 for Eindhoven residential). Source: CBS Vierkantstatistieken 500m (2018, 2021, 2023); BAG Lite (Kadaster, 2024).*

3.7 Analytical models

The analysis is conducted across three parallel models, corresponding to the three measures of assessed value per square meter described in Section 3.3. Within each model, the analysis is built up stepwise across four sub-models, allowing the contribution of each additional set of variables to be assessed.

Sub-model 1 estimates the baseline relationship between change in dwellings (delta_dwellings) and change in assessed value per square meter, controlling for city and period. This sub-model tests whether densification is positively associated with value growth across both cities combined, and whether Amsterdam and Eindhoven differ structurally in their overall value development.

Sub-model 2 adds the control variables described in Section 3.4: the compositional and structural controls specific to each model's data source, together with the amenity controls, without yet introducing the cell-type classification or neighborhood fixed effects. This sub-model tests whether the densification effect holds after accounting for changes in dwelling stock composition, initial cell characteristics, and local amenity provision.

Sub-model 3 adds the cell type classification (brownfield or residential, described in Section 3.5), the interaction term delta_dwellings × cell_type, and neighborhood fixed effects. This sub-model formally tests whether the marginal effect of densification on assessed value per square meter differs significantly between brownfield transformation cells and residential cells, while neighborhood fixed effects absorb all time-invariant neighborhood-level characteristics, such as income, education level, and population density, which could not be included as separate static controls alongside the fixed effects due to perfect collinearity.

Sub-model 4 extends sub-model 3 with a three-way interaction, delta_dwellings × city × cell_type, replacing the additive city control. This sub-model tests whether the difference in the densification effect between brownfield and residential cells itself varies between Amsterdam and Eindhoven by conducting an additional linear hypothesis test.

This four-step structure is applied identically across all three models**.** Model 1 (CBS grid cell) and Model 2 (individual assessed value, cell-aggregated) are estimated using ordinary least squares with conventional standard errors, as the grid cell is the unit of observation in both cases and the explanatory variables of interest vary at the same level as the dependent variable.

Model 3 (individual level) requires an additional methodological adjustment. Because each individual dwelling is assigned the cell-level change in dwellings and the cell-type classification of the grid cell in which it is located (Section 3.1), all dwellings within the same cell share identical values for these key explanatory variables, even though the regression is estimated using individual-level observations. This means that, unlike Models 1 and 2, conventional standard errors would understate the true uncertainty around the estimated densification effect, as dwellings within the same cell cannot be treated as independent with respect to cell-level variables. To address this, standard errors for sub-models 3 and 4 of Model 3 are clustered at the grid-cell level, using the cluster-robust covariance estimator implemented in the sandwich package (Cameron & Miller, 2015; Zeileis et al., 2020). This adjustment substantially affects the results: coefficients that appear statistically significant under conventional standard errors are in several cases no longer significant once clustering is applied, reinforcing the conclusion that the individual-level specification provides more limited statistical power to detect the densification effect than its large number of observations might initially suggest.

All analyses were conducted in R (version 4.4.1).

4. Results

This section presents the regression results for the three models. For each model, the tables below report the key coefficients of interest across the four sub-models described in Section 3.7. the full regression results, including all control and amenity variables, are reported in Appendix Tables A3 (Model 1), A4 (Model 2), and A5 (Model 3).

4.1 Model 1: CBS grid cell

Table 2 presents the key coefficients for Model 1, based on the CBS Vierkantstatistieken (Centraal Bureau voor de Statistiek, 2018, 2021, 2023). Sub-model 1 shows a positive and highly significant baseline relationship between densification and assessed value per square meter ($\beta = 0.0012$, $p<0.001$): each additional dwelling per grid cell is associated with an increase of €1.20 per square meter. Amsterdam shows substantially stronger value growth than Eindhoven over the study period (City: $\beta = -0.5149$, $p<0.001$).

Sub-model 2 adds the compositional, structural, and amenity controls. The densification coefficient remains stable and significant $\beta = 0.0013$, $p<0.001$). Among the controls, the lagged share of multi-family dwellings ($\beta = -0.0019$, $p<0.01$) and the lagged address density ($\beta = 0.00003$, $p<0.001$) are significant, as is the lagged corporation share ($\beta = -0.0013$, $p<0.05$). None of the amenity controls are significant in this sub-model (Table A3).

Sub-model 3 introduces the cell-type classification, the interaction with densification, and neighborhood fixed effects. The interaction term is negative and highly significant ($\beta = -0.0011$, $p<0.001$), indicating that the densification effect is smaller in residential cells than in brownfield cells. The hospitality ($\beta = -0.0031$, $p<0.01$) and office ($\beta = 0.0015$, $p<0.001$) amenity controls become significant once neighborhood fixed effects are included, suggesting that within-neighborhood variation in these amenities is associated with assessed value growth in opposing directions (Table A3).

Sub-model 4 extends this with the three-way interaction with city. The cell-type interaction remains negative and significant ($\beta = -0.0014$, $p<0.001$), while the three-way interaction itself is not significant ($\beta = 0.0008$, $p>0.1$), indicating that the brownfield-residential difference in the densification effect does not differ significantly between Amsterdam and Eindhoven. The interaction between city and cell type is significant ($\beta = -0.2664$, $p<0.001$), showing that residential cells in Eindhoven have structurally lower value growth than residential cells in Amsterdam, independent of densification.

Model 1 explains a substantial share of the variance, with R^2 increasing from 0.36 in sub-model 1 to 0.74 in sub-model 4, reflecting the explanatory power added by neighborhood fixed effects in particular.

	(1)	(2)	(3)	(4)
Δ Dwellings (Densification)	0.0012***	0.0013***	0.0009***	0.0009***
	(0.0001)	(0.0002)	(0.0002)	(0.0002)
City (Eindhoven)	-0.5149***	-0.5196***		-0.1979
	(0.0283)	(0.0373)		(0.2378)
Cell type (Residential)			0.1584***	0.3033***
			(0.0425)	(0.0604)
Δ Dwellings × Cell type			-0.0011***	-0.0014***
			(0.0003)	(0.0004)
Δ Dwellings × City				-0.0002
				(0.0004)
City × Cell type				-0.2664***
				(0.0793)
Δ Dwellings × City × Cell type				0.0008
				(0.0007)
Neighborhood FE	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Amenity controls	No	Yes	Yes	Yes
Observations	794	690	690	690
R^2	0.3641	0.4671	0.7313	0.7368
Adjusted R^2	0.3617	0.4568	0.6730	0.6779

Table 2. *Model 1 (CBS grid cell) regression results, key coefficients. The dependent variable is the change in assessed value per square meter (in thousand €), constructed by dividing the average assessed value per dwelling from the CBS Vierkantstatistieken by the average dwelling floor area per grid cell from the BAG (Section 3.3). City is a dummy variable equal to 1 for Eindhoven and 0 for Amsterdam (reference category). Cell type is a dummy variable equal to 1 for residential cells and 0 for brownfield cells (reference category). The city control is omitted from sub-model 3 due to perfect collinearity with the neighborhood fixed effects. "Controls" refers to the compositional, structural, and amenity controls described in Section 3.4. Standard errors are reported in parentheses. *p<0.05, **p<0.01, ***p<0.001. Source: own calculations based on CBS Vierkantstatistieken 500m (2018, 2021, 2023); BAG Lite (Kadaster, 2024a); BAG 2.0 Extract (Kadaster, 2024b).*

4.2 Model 2: Individual assessed value, cell-aggregated

Table 3 presents the key coefficients for Model 2, based on individual-level assessed value data aggregated to the grid-cell level. Sub-model 1 again shows a positive and significant baseline relationship ($\beta = 0.3842$, $p<0.05$): each additional dwelling per grid cell is associated with an increase of approximately €0.38 per square meter (as assessed value in this model is measured in €, as opposed to in thousand € in Model 1). There is also a significant negative city effect (City = -377.76, $p<0.001$), indicating that, holding densification constant, assessed value per square meter increased by approximately €378 less in Eindhoven than in Amsterdam over the study period. This is consistent with Model 1 in direction.

Sub-model 2 adds dwelling-type and amenity controls. The densification coefficient increases somewhat and remains significant ($\beta = 0.5529$, $p<0.001$). The apartment share ($\beta = -17.01$, $p<0.001$) and average construction year ($\beta = -2.05$, $p<0.001$) are strongly significant, as is the lagged multi-family share ($\beta = 14.16$, $p<0.001$) and the lagged corporation share ($\beta = -1.54$, $p<0.05$) (Table A4).

Sub-model 3 introduces the cell-type interaction and neighborhood fixed effects. Unlike Model 1, the densification coefficient remains marginally significant ($\beta = 0.3223$, $p<0.05$), but the interaction with cell type is not significant ($\beta = -0.346$, $p>0.1$).

Sub-model 4 adds the three-way interaction. None of the three-way or two-way interactions involving densification are significant. The interaction between city and cell type is marginally significant (β = -229.69, $p<0.05$), pointing in the same direction as in Model 1.

Model 2 explains less variance than Model 1 in the comparable sub-models (R^2 of 0.12 to 0.58, versus 0.36 to 0.74 for Model 1), though the increase in R^2 across sub-models follows a similar pattern.

	(1)	(2)	(3)	(4)
Δ Dwellings (densification)	0.3842*	0.5529***	0.3223*	0.4002*
	(0.1872)	(0.1424)	(0.1624)	(0.1719)
City (Eindhoven)	-377.7580***	-496.0059***		-282.0902
	(37.1206)	(39.2315)		(273.6927)
Cell type (Residential)			64.8314	186.0214**
			(48.6767)	(69.2942)
Δ Dwellings × Cell type			-0.3460	-0.8112
			(0.3433)	(0.4424)
Δ Dwellings × City				-0.4084
				(0.4948)
City × Cell type				-229.6887*
				(91.1482)
Δ Dwellings × City × Cell type				1.2776
				(0.7641)
Neighborhood FE	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Amenity controls	No	Yes	Yes	Yes
Observations	825	696	696	696
R^2	0.1201	0.2868	0.5765	0.5820
Adjusted R^2	0.1169	0.2721	0.4836	0.4876

Table 3. *Model 2 (individual assessed value, cell-aggregated) regression results, key coefficients. The dependent variable is the change in assessed value per square meter (in €), constructed by first calculating assessed value per square meter for each individual dwelling and then averaging these individual ratios across all dwellings within a grid cell (Section 3.3). City is a dummy variable equal to 1 for Eindhoven and 0 for Amsterdam (reference category). Cell type is a dummy variable equal to 1 for residential cells and 0 for brownfield cells (reference category). The city control is omitted from sub-model 3 due to perfect collinearity with the neighborhood fixed effects. "Controls" refers to the dwelling-type, structural, and amenity controls described in Section 3.4. Standard errors are reported in parentheses. *p<0.05, **p<0.01, ***p<0.001. Source: own calculations based on the WOZ Waardeloket (Kadaster, 2024c); BAG 2.0 Extract (Kadaster, 2024b).*

4.3 Model 3: Individual level

Table 4 presents the key coefficients for Model 3, estimated at the level of the individual dwelling with standard errors clustered at the grid-cell level. Sub-model 1 shows a positive and significant baseline densification effect (β = 0.2845, $p<0.05$) and a significant city effect (City = -381.44, $p<0.001$), consistent in direction with Models 1 and 2.

After adding dwelling-type and amenity controls in Sub-model 2 the densification coefficient remains marginally significant (β = 0.3346, $p<0.05$). All dwelling-type indicators are large and highly significant relative to the detached-house reference category, confirming substantial value differences by dwelling type. The office amenity control is also significant (β = 1.01, $p<0.01$) (Table A5).

Sub-model 3 introduces the cell-type interaction and neighborhood fixed effects. With clustered standard errors, neither the densification coefficient (β = 0.1268, p>0.1) nor its interaction with cell type (β = -0.1684, p>0.1) remain statistically significant. The office amenity control remains significant (β = 1.54, p<0.001).

Adding the three-way interaction in Sub-model 4 results in the following: the densification coefficient and its two-way interactions with city and cell type are not significant. However, the three-way interaction is significant (β = 1.530, p<0.05), as is the interaction between city and cell type (β = -190.75, p<0.010), both consistent in direction with the corresponding estimates in Models 1 and 2. The significant three-way interaction indicates that the cell-type difference in the densification effect is not identical between the two cities. However, a combined hypothesis test of the implied densification effect for residential cells in Eindhoven relative to brownfield cells in Amsterdam is not statistically significant (F(1, 842888) = 1.76, p = 0.184), indicating that this specific combination of effects cannot be confidently distinguished from zero.

Despite the very large number of observations (N = 843,019), Model 3 explains very little variance (R^2 ranging from 0.002 to 0.007), substantially less than Models 1 and 2.

	(1)	(2)	(3)	(4)
Δ Dwellings (densification)	0.2845*	0.3346*	0.1268	0.2386
	(0.1238)	(0.1320)	(0.1665)	(0.1742)
City (Eindhoven)	-381.4390***	-516.2757***		-403.9149***
	(17.1237)	(38.6590)		(100.3721)
Cell type (Residential)			86.6519*	158.6047*
			(43.3548)	(65.7468)
Δ Dwellings × Cell type			-0.1684	-0.5726
			(0.3645)	(0.5018)
Δ Dwellings × City				-0.6760
				(0.3777)
City × Cell type				-190.7523**
				(74.0282)
Δ Dwellings × City × Cell type				1.5299*
				(0.6940)
Neighborhood FE	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Amenity controls	No	Yes	Yes	Yes
Clustered SE (cell)	Yes	Yes	Yes	Yes
Observations	843,019	843,019	843,019	843,019
R^2	0.0023	0.0045	0.0073	0.0074
Adjusted R^2	0.0023	0.0044	0.0072	0.0072

Table 4. *Model 3 (individual level) regression results, key coefficients. The dependent variable is the change in assessed value per square meter (in €), calculated individually for each dwelling based on its own assessed value and floor area (Section 3.3). City is a dummy variable equal to 1 for Eindhoven and 0 for Amsterdam (reference category). Cell type is a dummy variable equal to 1 for residential cells and 0 for brownfield cells (reference category). The city control is omitted*

*from sub-model 3 due to perfect collinearity with the neighborhood fixed effects. "Controls" refers to the dwelling-type and amenity controls described in Section 3.4. Standard errors are clustered at the grid-cell level (Cameron & Miller, 2015) to account for the fact that the key explanatory variables vary only at the grid-cell level, while the unit of observation is the individual dwelling (Section 3.7). Standard errors are reported in parentheses. *p<0.05, **p<0.01, ***p<0.001. Source: own calculations based on the WOZ Waardeloket (Kadaster, 2024c); BAG 2.0 Extract (Kadaster, 2024b).*

4.4 Comparison Across models

The three models point in a broadly consistent direction, despite differing substantially in statistical significance and explanatory power. In all three models, the baseline densification effect (sub-model 1) is positive and statistically significant, and the city effect indicates stronger value growth in Amsterdam than in Eindhoven. The interaction between city and cell type is negative and significant in all three models (Model 1: $\beta = -0.2664$, $p<0.001$; Model 2: $\beta = -229.69$, $p<0.05$; Model 3: $\beta = -190.75$, $p<0.01$), consistently indicating that residential cells in Eindhoven experienced structurally lower value growth than residential cells in Amsterdam, independent of densification.

The central interaction of interest, between densification and cell type, is statistically significant only in Model 1 ($\beta = -0.0011$, $p<0.001$ in sub-model 3; $\beta = -0.0014$, $p<0.001$ in sub-model 4). In Models 2 and 3, this interaction points in the same negative direction but does not reach statistical significance (Model 2: $\beta = -0.346$, $p>0.1$; Model 3: $\beta = -0.168$, $p>0.1$). This suggests that the evidence for a smaller densification effect in residential cells is statistically strongest in the CBS-based specification, though this should not be read as the most reliable estimate of the underlying effect. As discussed in Section 3.3, Model 1 is also the specification most affected by the compositional inconsistency between the assessed value numerator and the floor area denominator, which likely inflates the magnitude of the estimated effect. Models 2 and 3 resolve this inconsistency but provide statistically weaker evidence, possibly due to the additional individual-level noise introduced by the underlying data rather than because the underlying relationship is genuinely absent.

After the linear hypothesis test for Model 3, the three-way interaction between densification, city, and cell type is not significant through all three models. Meaning that this result should be interpreted with caution.

The explanatory power of the three models differs substantially: Model 1 explains the largest share of variance (R^2 up to 0.74), followed by Model 2 (R^2 up to 0.58), while Model 3 explains very little variance despite its much larger sample size (R^2 up to 0.007). This pattern is consistent with the methodological discussion in Section 3.7: Model 1 and Model 2 benefit from a dependent variable that is averaged at the grid-cell level, smoothing out individual-level variation that is unrelated to the relationship under investigation, whereas Model 3's individual-level variation introduces substantial noise relative to the cell-level signal of interest. This difference in explanatory power should not be interpreted as evidence that Model 1 or Model 2 better captures the "true" relationship. It rather reflects a trade-off between the statistical efficiency of cell-level aggregation and the compositional precision of individual-level data.

Taken together, these results suggest that the direction of the core finding (that densification is associated with a smaller increase in assessed value per square meter in residential cells than in brownfield cells) is consistent across all three specifications, but that only Model 1 provides statistically significant evidence for this pattern, likely in part due to a methodological limitation that affects its estimated effect size. Models 2 and 3, while methodologically preferable in their treatment of the numerator-denominator consistency, lack the statistical power to confirm the interaction with confidence. The implications of this trade-off for the interpretation of the main finding are discussed further in Section 5.

5. General discussion

This study examined to what extent urban densification is associated with changes in housing values per square meter in Amsterdam and Eindhoven between 2018 and 2023, and whether this relationship differs between cities and between brownfield transformation areas. Using a first-difference approach with two stacked periods at the level of 500×500 meter grid cells, three parallel models were estimated, differing in the measurement of the dependent variable and the level of aggregation: a CBS grid-cell measure (Model 1), an individual-level measure aggregated to the grid cell (Model 2), and an individual-dwelling-level measure (Model 3).

5.1 Summary and conclusion

Across all three models, densification is positively associated with growth in assessed value per square meter, and this relationship is consistently stronger in Amsterdam than in Eindhoven. The central finding of this study that the densification effect is smaller in residential cells than in brownfield transformation cells is directionally consistent across all three models but reaches statistical significance only in Model 1. This pattern is interpreted with the methodological trade-offs of each model in mind: Model 1 benefits from a numerator and denominator that are both grid-cell averages, providing high statistical power, but is also the specification most affected by a compositional inconsistency between the assessed value and floor-area measures that likely inflates the magnitude of the estimated effect. Models 2 and 3 resolve this inconsistency by relying on individual-level data, but at the cost of statistical power, particularly in Model 3, where the very large number of individual-level observations masks a much smaller effective number of independent grid cells.

Taken together, this suggests that brownfield transformation areas in this study experience stronger value growth associated with densification than the broader residential urban context, although the precise magnitude of this difference cannot be pinned down with confidence given the divergence between the three specifications. The central research question can thus be answered with moderate confidence: densification is associated with growth in housing values per square meter in both cities, this relationship is stronger in Amsterdam than in Eindhoven, and there are consistent, though not uniformly significant, indications that this relationship is stronger in brownfield transformation areas than in the residential urban context.

5.2 Theoretical and societal impact

This finding is broadly consistent with the theoretical expectation that brownfield transformation combines physical densification with broader land-use change, amenity provision, and shifts in neighborhood identity (Peng & Tian, 2022; Wu & Deng, 2024), in contrast to densification in established residential areas, where added supply may exert downward pressure on nearby values in the short run (Ooi & Le, 2013). This study's contribution is to show that this distinction also holds when comparing brownfield and residential cells within the same cities and over the same period. At the same time, the finding is only directionally confirmed. It reaches statistical significance only in the most aggregated specification (Model 1), and the comparative design here cannot match the precision reported in these project-level studies. The consistently stronger value growth observed in Amsterdam relative to Eindhoven is in line with the expectation that higher housing market pressure amplifies the value effects of densification (De Groot et al., 2010), and is further consistent with Amsterdam's more diversified, multi-layered urban economy, which is expected to generate more intensive amenity-driven transformation dynamics than the more single-sector-oriented economy of Eindhoven (Musterd et al., 2020).

For urban planning and housing policy, these findings suggest that densification in brownfield transformation areas may generate stronger value growth than equivalent densification in established residential neighborhoods, but that this premium should not be attributed to the addition of dwellings alone. Given the theoretical and empirical evidence that much of the value growth in transformation areas stems from broader amenity and land-use changes rather than densification per se (Peng & Tian, 2022), policymakers aiming to use brownfield redevelopment as a tool for improving housing affordability should be cautious in attributing observed value increases directly to density targets, as a substantial part of this value growth is likely to reflect the broader transformation process rather than the number of dwellings added.

5.3 Strengths, limitations, and future research

This study's main strength lies in its comparative, three-model design, which tests the robustness of the densification-value relationship across different measurements of the dependent variable and levels of aggregation, rather than relying on a single specification. This approach reveals that the direction of the central finding is robust, while also making explicit that its statistical significance is sensitive to methodological choices that are not always made transparent in single-model studies. The use of two full cities, rather than a small set of selected transformation projects, further allows the densification effect in transformation areas to be benchmarked directly against the existing residential context within the same cities.

Several limitations should be considered when interpreting these findings. First, although the floor-area measure in Model 1 was constructed consistently across both measurement years to avoid an internal numerator-denominator mismatch (Section 3.3), it still includes all dwellings present in a cell at the time of measurement, including new construction. This means that compositional change in the dwelling stock, particularly the addition of smaller new dwellings, may still partly confound the estimated densification effect in this specification. Second, the amenity controls included in all three models are static rather than dynamic. Because the BAG records the construction year of a building rather than the date on which a specific function became active, changes in amenity provision over the study period could not be reliably measured. To the extent that amenity development is correlated with densification in brownfield areas, the estimated effect may still partly capture broader upgrading dynamics rather than densification alone. Third, Model 3 illustrates that a large number of individual-level observations does not guarantee strong identification. Because the key explanatory variables vary only at the grid-cell level, the effective statistical power of this specification is closer to that implied by the number of grid cells than by the number of dwellings, even after clustering standard errors at the grid-cell level. This is compounded by individual-level noise in assessed value that Models 1 and 2 average away. Because each dwelling remains its own observation in Model 3, this noise is retained rather than smoothed out, which likely drags the R^2 down further. Fourth, the analytical sample is restricted to grid cells with valid assessed value observations in all three measurement years, which may introduce a degree of selection bias if cells that are masked by CBS due to privacy thresholds differ systematically from those that are not. And lastly, as with any first-difference design, the direction of causality between densification and value growth cannot be fully established: it is possible that areas anticipated to experience future value growth attract more new construction, rather than densification itself driving the observed value changes.

Future research could extend this study in several directions. The construction of dynamic, time-varying amenity controls, for instance using point-of-interest data with verified opening dates rather than building construction years, would allow for a more precise test of whether the value premium associated with brownfield densification operates through amenity development or through the addition of dwellings itself. Applying the same three-model comparison to additional Dutch cities with differing housing market conditions would help establish whether the patterns found here for Amsterdam and Eindhoven generalize to other urban contexts. Given the divergence in statistical significance between the three models used in this study, future work using individual-level assessed value data could explore alternative ways of balancing the compositional precision of disaggregated data with the statistical efficiency of cell-level aggregation, for example through hierarchical or multilevel modeling approaches that explicitly account for the nested structure of dwellings within grid cells. Finally, because the assessed value is a model-based estimate that municipalities update annually using sales data from the preceding period, it responds to market changes with a delay relative to actual transaction prices. Future research could address this limitation either by extending the study period to allow more time for the full effect of densification to be reflected in assessed values, or, where available, by using transaction price data instead, which would capture market responses more directly and without this valuation lag.

Overall, this study provides evidence that urban densification can be associated with growth in housing values per square meter in both Amsterdam and Eindhoven, with consistent indications, though not uniformly statistically significant across specifications, that this relationship is stronger in brownfield transformation areas than in the residential urban context. By comparing three measurement approaches within the same empirical setting, this study has shown that the strength of this evidence depends meaningfully on how housing value is measured and at what level of aggregation, a methodological sensitivity that is rarely made explicit in single-model studies of densification and housing values. As Dutch cities continue to rely on intra-urban transformation to accommodate housing growth, understanding the conditions under which this process translates into housing value gains, and distinguishing this from the contribution of densification itself, remains an important task for both urban economics and spatial planning.

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Appendix

City	Year	CBS total	BAG total	Difference (%)
Amsterdam	2018	439,810	436,304	-0.800
	2023	469,480	469,648	0.040
Eindhoven	2018	109,195	110,735	1.410
	2023	117,600	119,958	2.010

Table A1. *Comparison of dwelling counts according to CBS Vierkantstatistieken and BAG, 2018 and 2023. The CBS total reflects the sum of dwellings across all stable grid cells as reported in the CBS Vierkantstatistieken 500m. The BAG total reflects an independent count of residential units spatially linked to the same grid cells using BAG coordinates, restricted to dwellings built in or before 2018 for the 2018 estimate and all dwellings for the 2023 estimate. The small and stable differences between the two sources confirm the reliability of the CBS dwelling counts used throughout this study. Source: CBS Vierkantstatistieken 500m (2018, 2023); BAG Lite (Kadaster, 2024).*

	Δ Assessed	Δ Dwellings	Cell type (Residential)	Δ Multi-family %	Δ Corporatio	Multi-family %	Corporatio n % (lag)	OAD (lag)	Hospitality	Retail	Healthcare	Office	Education	Sport
Δ Assessed value/m²	1	0.31	-0.12	-0.09	-0.12	0.42	-0.04	0.37	0.34	0.25	0.1	0.21	0.25	0.260
Δ Dwellings		1	-0.29	0.2	-0.43	0.19	0.02	0	0.21	0.06	0	0.21	-0.03	0.090
Cell type (Residential)			1	0.03	0.18	-0.16	-0.12	0.13	-0.05	0.1	0.11	-0.24	0.15	-0.130
Δ Multi-family %				1	-0.01	-0.11	-0.06	-0.04	0.03	-0.03	-0.05	0.02	-0.07	-0.070
Δ Corporation %					1	-0.12	-0.17	0.02	-0.01	-0.01	0.03	-0.07	0.05	-0.050
Multi-family % (lag)						1	0.14	0.6	0.44	0.43	0.18	0.33	0.4	0.390
Corporation % (lag)							1	-0.16	-0.13	-0.13	0.03	-0.07	-0.04	-0.010
OAD (lag)								1	0.57	0.64	0.21	0.32	0.44	0.350
Hospitality									1	0.71	0.11	0.44	0.32	0.310
Retail										1	0.11	0.34	0.33	0.220
Healthcare											1	0.05	0.12	0.070
Office												1	0.17	0.300
Education													1	0.280
Sport														1

Table A2. *Pairwise correlation matrix for the dependent variable and all explanatory and control variables used in the regression models. Source: own calculations based on CBS Vierkantstatistieken 500m (2018, 2021, 2023); BAG Lite (Kadaster, 2024); BAG 2.0 Extract (Kadaster, 2024).*

	(1)	(2)	(3)	(4)
Δ Dwellings	0.0012***	0.0013***	0.0009***	0.0009***
	(0.0001)	(0.0002)	(0.0002)	(0.0002)
City (Eindhoven)	-0.5149***	-0.5196***		-0.1979
	(0.0283)	(0.0373)		(0.2378)
Δ Multi-family %		-0.0157	-0.0118	-0.0134
		(0.0089)	(0.0080)	(0.0083)
Δ Corporation %		0.0004	0.0002	0.0004
		(0.0026)	(0.0022)	(0.0022)
Multi-family % (lag)		-0.0019**	-0.0028***	-0.0027***
		(0.0006)	(0.0007)	(0.0007)
Corporation % (lag)		-0.0013*	-0.0013	-0.0012
		(0.0006)	(0.0007)	(0.0007)
OAD (lag)		0.00003***	0.00005**	0.00004*
		(0.00001)	(0.00002)	(0.00002)
Hospitality		0.0012	-0.0031**	-0.0034**
		(0.0008)	(0.0012)	(0.0012)
Healthcare		-0.0014	-0.0061	-0.0078
		(0.0041)	(0.0041)	(0.0041)
Office		-0.0001	0.0015***	0.0017***
		(0.0004)	(0.0005)	(0.0005)
Education		-0.0019	-0.0015	-0.0035
		(0.0069)	(0.0071)	(0.0071)
Sport		0.0173	-0.0018	-0.0047
		(0.0120)	(0.0122)	(0.0122)
Cell type (Residential)			0.1584***	0.3033***
			(0.0425)	(0.0604)
Δ Dwellings × Cell type			-0.0011***	-0.0014***
			(0.0003)	(0.0004)
Δ Dwellings × City				-0.0002
				(0.0004)
City × Cell type				-0.2664***
				(0.0793)
Δ Dwellings × City × Cell type				0.0008
				(0.0007)
Neighborhood FE	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Amenity controls	No	Yes	Yes	Yes
Observations	794	690	690	690
R^2	0.3641	0.4671	0.7313	0.7368
Adjusted R^2	0.3617	0.4568	0.6730	0.6779

***Table A3**. Model 1 (CBS grid cell) full regression results. The dependent variable is the change in assessed value per square meter (in thousand €), constructed by dividing the average assessed value per dwelling from the CBS Vierkantstatistieken by the average dwelling floor area per grid cell from the BAG (Section 3.3). City is a dummy variable equal to 1 for Eindhoven and 0 for Amsterdam (reference category). Cell type is a dummy variable equal to 1 for residential cells and 0 for brownfield cells (reference category). The city control is omitted from sub-model 3 due to perfect collinearity with the neighborhood fixed effects. Amenity controls include the number of hospitality, healthcare, office, education, and sport functions per grid cell, constructed from the full BAG (Kadaster, 2024b). Sub-model 1 (N = 794) includes all grid-cell-periods with a valid change in assessed value; sub-models 2 through 4 (N = 690) additionally require non-missing values for the corporation-ownership and multi-family-share controls, which are unavailable for some cells due to separate CBS privacy masking thresholds. Standard errors are reported in parentheses. *p<0.05, **p<0.01, ***p<0.001. Source: own calculations based on CBS Vierkantstatistieken 500m (2018, 2021, 2023); BAG Lite (Kadaster, 2024a); BAG 2.0 Extract (Kadaster, 2024b).*

	(1)	(2)	(3)	(4)
Δ Dwellings	0.3842*	0.5529***	0.3223*	0.4002*
	(0.1872)	(0.1424)	(0.1624)	(0.1719)
City (Eindhoven)	-377.7580***	-496.0059***		-282.0902
	(37.1206)	(39.2315)		(273.6927)
Apartment %		-17.0077***	-7.9726*	-7.3107*
		(3.2223)	(3.2811)	(3.2865)
Terraced %		-1.1880	2.0861	2.2458
		(2.1350)	(2.2351)	(2.2309)
Construction year		-2.0459***	0.4371	0.4794
		(0.6057)	(1.0258)	(1.0229)
OAD (lag)		-0.0026	0.0376*	0.0327
		(0.0085)	(0.0189)	(0.0189)
Multi-family % (lag)		14.1623***	5.4666	5.0907
		(3.2957)	(3.4749)	(3.4658)
Corporation % (lag)		-1.5355*	-2.3269**	-2.2306**
		(0.6062)	(0.7492)	(0.7489)
Hospitality		-0.9474	-0.2564	-0.5027
		(0.8716)	(1.4062)	(1.4062)
Healthcare		6.2010	-0.3706	-1.7034
		(4.3619)	(4.6607)	(4.6739)
Office		0.4466	1.0685*	1.2549*
		(0.4047)	(0.5230)	(0.5496)
Education		-0.5367	1.9732	0.3367
		(7.2789)	(8.1909)	(8.2026)
Sport		-19.4726	-10.8293	-11.8862
		(12.5765)	(13.8977)	(13.9432)
Cell type (Residential)			64.8314	186.0214**
			(48.6767)	(69.2942)
Δ Dwellings × Cell type			-0.3460	-0.8112
			(0.3433)	(0.4424)
Δ Dwellings × City				-0.4084
				(0.4948)
City × Cell type				-229.6887*
				(91.1482)
Δ Dwellings × City × Cell type				1.2776
				(0.7641)
Neighborhood FE	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Amenity controls	No	Yes	Yes	Yes
Observations	825	696	696	696
R^2	0.1201	0.2868	0.5765	0.5820
Adjusted R^2	0.1169	0.2721	0.4836	0.4876

Table A4. *Model 2 (individual assessed value, cell-aggregated) full regression results. The dependent variable is the change in assessed value per square meter (in €), constructed by first calculating assessed value per square meter for each individual dwelling and then averaging these individual ratios across all dwellings within a grid cell (Section 3.3). City is a dummy variable equal to 1 for Eindhoven and 0 for Amsterdam (reference category). Cell type is a dummy variable equal to 1 for residential cells and 0 for brownfield cells (reference category). Control variables include the share of apartments and terraced houses, the average construction year of the dwelling stock, address density (lag), the lagged share of multi-family and corporation-owned dwellings, and the amenity controls used in Model 1. The city control is omitted from sub-model 3 due to perfect collinearity with the neighborhood fixed effects. Amenity controls include the number of hospitality, healthcare, office, education, and sport functions per grid cell, constructed from the full BAG (Kadaster, 2024b). Standard errors are reported in parentheses. *p<0.05, **p<0.01, ***p<0.001. Source: own calculations based on the WOZ Waardeloket (Kadaster, 2024c); BAG 2.0 Extract (Kadaster, 2024b).*

	(1)	(2)	(3)	(4)
Δ Dwellings	0.2845*	0.3346*	0.1268	0.2386
	(0.1238)	(0.1320)	(0.1665)	(0.1742)
City (Eindhoven)	-381.4390***	-516.2757***		-403.9149***
	(17.1237)	(38.6590)		(100.3721)
Apartment		-932.1412***	-949.5223***	-948.6211***
		(184.0617)	(183.1636)	(183.1848)
Terraced		-806.0511***	-775.5992***	-775.3772***
		(174.3358)	(169.7279)	(169.7093)
Corner		-787.8046***	-762.4431***	-761.4313***
		(172.5241)	(167.1683)	(167.1343)
Semi-detached		-725.2939***	-730.6548***	-729.9244***
		(174.2158)	(169.4547)	(169.4424)
Construction year		-0.3926*	-0.0639	-0.0614
		(0.1656)	(0.1537)	(0.1542)
Hospitality		-0.5443	0.8161	0.7331
		(0.5712)	(1.1601)	(1.1782)
Healthcare		3.5008	-1.6839	-2.3394
		(4.7999)	(5.0440)	(5.0386)
Office		1.0120**	1.5382***	1.7252***
		(0.3464)	(0.3694)	(0.4229)
Education		-4.7869	-2.2324	-2.7382
		(6.2571)	(6.8283)	(6.7266)
Sport		-10.5881	-7.3785	-7.2557
		(9.7172)	(7.9558)	(8.0009)
Cell type (Residential)			86.6519*	158.6047*
			(43.3548)	(65.7468)
Δ Dwellings × Cell type			-0.1684	-0.5726
			(0.3645)	(0.5018)
Δ Dwellings × City				-0.6760
				(0.3777)
City × Cell type				-190.7523**
				(74.0282)
Δ Dwellings × City × Cell type				1.5299*
				(0.6940)
Neighborhood FE	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Amenity controls	No	Yes	Yes	Yes
Clustered SE (cell)	Yes	Yes	Yes	Yes
Observations	843,019	843,019	843,019	843,019
R^2	0.0023	0.0045	0.0073	0.0074
Adjusted R^2	0.0023	0.0044	0.0072	0.0072

Table A5. *Model 3 (individual level) full regression results. The dependent variable is the change in assessed value per square meter (in €), calculated individually for each dwelling based on its own assessed value and floor area (Section 3.3). City is a dummy variable equal to 1 for Eindhoven and 0 for Amsterdam (reference category). Cell type is a dummy variable equal to 1 for residential cells and 0 for brownfield cells (reference category). Control variables include dwelling-type indicators (apartment, terraced, corner, semi-detached, with detached as the reference category), individual construction year, and the amenity controls used in Models 1 and 2. The city control is omitted from sub-model 3 due to perfect collinearity with the neighborhood fixed effects. Amenity controls include the number of hospitality, healthcare, office, education, and sport functions per grid cell, constructed from the full BAG (Kadaster, 2024b). Standard errors are clustered at the grid-cell level (Cameron & Miller, 2015) to account for the fact that the key explanatory variables — the change in dwellings and cell type — vary only at the grid-cell level, while the unit of observation is the individual dwelling (Section*

*3.7). Standard errors are reported in parentheses. *p<0.05, **p<0.01, ***p<0.001. Source: own calculations based on the WOZ Waardeloket (Kadaster, 2024c); BAG 2.0 Extract (Kadaster, 2024b).*