With Open Eyes - Neighborhood Aesthetics, Apartment Prices and Residential Sorting

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EEA Conference Presentation Bordeaux
25 August 2025

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2. We implement it by combining **street view imagery data** of houses with precise **preservation records**, and estimate the effect of aesthetics on rental prices.

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3. We leverage **exogenous variation** in the housing stock of **East Berlin and Leipzig** following the urban transformation after German reunification.
4. In addition to the price effect, we plan to look at **residential sorting and neighboring change**, with empirics and a stylized model (in progress).

A Three-Pronged Approach to Measuring Aesthetics

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Lower Level Visual Features: Complexity and Order

Mid Level Visual Features: Basic Cityscape Components

Higher Level Visual Features: Contextualization of Complex Structures

Theoretical Basis:

- Information Theory
- Cultural Studies
- Urban Economics and Computer Science
- Psychology and Neuroscience

Low Level Aesthetics

Low-level features of visual perception, measured following **Information Theory** (Birkhoff 1933, Eyseneck 1942, Gartus and Leder 2017, Mather 2018)

- Aesthetics arises from the interplay of order and complexity.
- Order captured by symmetry, complexity by entropy
- We follow Rigau et al. (2008) and define the **low-level aesthetics LL_j of the visual neighborhood j as the ratio of uncertainty reduction to the initial information content**. Formula
- High value LL_j if, for example:
  - High information content $N \cdot H_{rgb}$ (Buildings with intricate features)
  - Low K (regularities and symmetries so that the information involved can easily be compressed)

Mid Level Aesthetics

Mid-level visual features require a higher degree of visual processing. The visual surroundings are segmented into components: Buildings, greenery, traffic, sky...

- We categorize each image into its components using insights from **computer vision** (Fu et al. 2019, Wang et al. 2019).
- We use the HRNet-48+OCR semantic segmentation model (Borse et al. 2021), pretrained on the Cityscape Dataset (Cordts et al. 2016)
- 19 classes are aggregated into four groups: **buildings, greenery** (trees, bushes, grass, etc.), **sky, and traffic** (roads, signs, cars, etc.).
- We define the **Green View Index (GVI)** and **Construction View Index (CVI)** as the share of proportion the image that is covered by the respective segment:

$$VI_{obj} = \frac{\sum_{i=1}^{n} \sum_{pixel_{obj}}^{m}}{pixel_{total}}, \quad obj \in \{\text{building}, \text{greenery}, \text{sky}, \text{traffic}\} \tag{1}$$

Mid Level Aesthetics

Mid Level Aesthetics

Figure 3 – Example of the segmentation process: traffic elements (purple, pink, yellow, and dark blue), sky (light blue), buildings (grey), and greenery (green)

(a) Original Image

(b) Segmented Image

High Level Aesthetics

High-level visual features include ornate facades, traditional construction techniques, and iconic designs

- **Cultural value:** Educated and higher income groups demand historic aesthetic housing as a way to distinguish themselves as cultured and knowledgeable (Rapaport 1980, Chang 2016). Also reflecting cultural identity and local history (Moro et al., 2013).
- **Architectural style:** Wilhelminian (Gründerzeit, 1870-1914), Art Nouveau (Jugendstil, 1890-1910), Reform Style (after 1900)

(a) Wilhelminian Style

(b) Art Nouveau (Jugendstil)

(c) Reform Style

High Level Aesthetics

- The **'Monument register'** of Leipzig and Berlin contains the addresses of buildings with a status of preservation
- 'Aesthetics are at the heart of historic preservation' (Been et al., 2016)
- **Semantic analysis** of features from descriptions made by experts of the monument protection authority.
  - Mentions of the main **architectural style** (Wilhelminian, Art Nouveau and Reform)
  - Categorize **building features** that make the building worthy of protection:
    - Facade elements (e.g., stucco, ornaments, paintings or obelisks), front yards, gates or doors and oriels
- For each apartment, we determine the design features *d* of the house and of the neighboring houses

Unique Historical Setting: East German Cities

(East) Berlin and Leipzig as the two largest Eastern German cities

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- **Endogeneity of aesthetics in building supply broken by historical circumstances**
  - Sizeable stock of historic housing with wealthy or upper middle class homeowners until World War II
  - German Democratic Republic (GDR, 1949-1990) with Socialist ideology strived for a uniform housing stock and standardized housing
  - Historical buildings, some of them damaged, fell into disrepair




Unique Historical Setting: East German Cities

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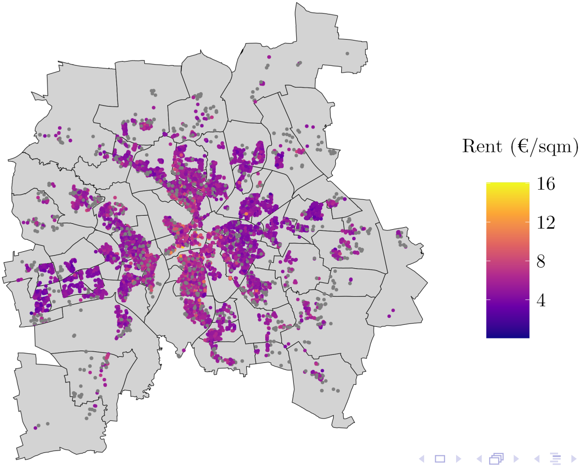
- After re-unification: Large investment schemes for upgrading the cityscape, including refurbishing and retrofitting historical buildings
- Large-scale restoration largely organized and financed publicly, mostly in the 1990s and 2000s. Only afterwards, Leipzig and Berlin grew again and attracted many new residents.
- **Stock of historic houses and their aesthetic features can be considered exogenous to the increasing demand**

Rental Data

Rental Data

Rental Data from Leipzig: 277,155 new rental agreements of apartments, years 2007-2023 (Immobilienscout24 via RWI)



Rental Prices and Building Age

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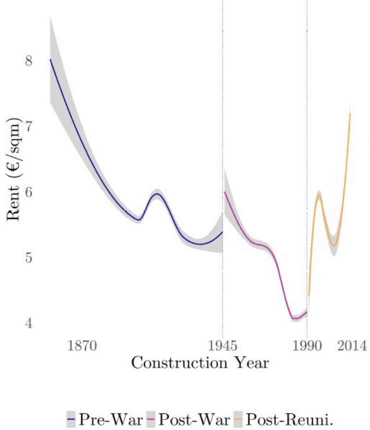
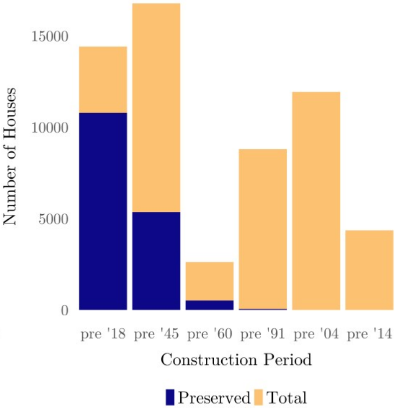
Rents in historic houses come at a premium





Control Variables in the Hedonic Pricing Regression

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- **Structural** characteristics of the apartment
  - Building age, area (linear and squared), number of rooms, balcony dummy, elevator dummy, furnished dummy, central heating dummy, renovation in last five years dummy, high quality interior dummy

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  - Air quality
- **Location** characteristics
  - Distance to the city center (here: Augustus Square)
  - Distance to nearest public transport station (train, tram, bus), distance to highway (linear and squared)
  - Distance to nearest watercourse, water body and green space, distance to nearest recreational area (playgrounds and sports), university, schools and medical center

Visual Surroundings of the Apartment: Image Data

- Three 120-degree images from the Google Street View API for each apartment
- The first image shows the building where the apartment is located, while the other two images complete a 360-degree panorama

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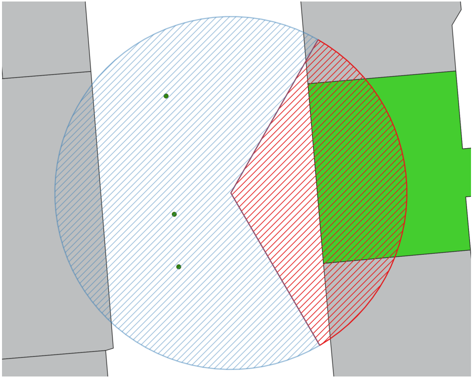

Hedonic Pricing Regression

$$\ln(p_{khjt}) = \alpha + \sum_{m=1}^{M} \Big(\beta_m \, a_{hj}^{(m)} + \delta_m \underbrace{\left(\frac{\sum_{l=1}^{n_j} a_{lj}^{(m)} - a_{hj}^{(m)}}{n_j - 1} \right)}_{a_{-hj}^{(m)}} \Big) + X_{kjt}' \gamma + \zeta_{z(j)} + \eta_t + \varepsilon_{hj}$$

- Regress rental price P_{khjt} of apartment k in house h in vicinity j in year t on...
  - $a_{hj} = (a_{hj}^{(1)}, a_{hj}^{(2)}, ..., a_{hj}^{(M)})$ as a vector of M aesthetic attributes of h and a_{-hj} as the mean of all other houses in its visual vicinity j with n_j houses
  - $X_k j$ as the standard hedonic characteristics of the apartment
  - $\zeta_{z(j)}$ as district fixed effects
  - η_t as year fixed effects

Estimation Results of the Hedonic Pricing Regressions

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Dependent Variable:	log(Rent €/sqm)				
Model:	(1)	(2)	(3)	(4)	(5)
Low-Level Aesthetics		0.057			
		(0.054)			
Mean Low-Level Aesthetics Nerby Houses		0.057			
		(0.122)			
Construction View Index			-0.054**		
			(0.025)		
Green View Index			0.081*		
			(0.044)		
Preservation Status				0.012***	0.013**
				(0.004)	(0.005)
Share Nearby Houses Preserved				-0.006	-0.007
				(0.005)	(0.006)
Preserved Window					-0.010
					(0.006)
Preserved Entrance					0.001
					(0.005)
Preserved Yard					0.027***
					(0.007)
Preserved Artistic Elements					0.014***
					(0.006)
Share Nearby Houses with Preserved Windows					0.005
					(0.007)
Share Nearby Houses with Preserved Entrances					-0.002
					(0.006)
Share Nearby Houses with Preserved Yards					-0.004
					(0.009)
Share Nearby Houses with Preserved Artistic Elements					0.004
					(0.007)
Fixed Effects					
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Adjusted R^2	0.75780	0.76725	0.76733	0.75793	0.75847
Observations	276,155	220,786	220,786	276,155	276,155

Estimation Results of the Hedonic Pricing Regressions

- **Spec 1: Baseline regression**, significant coefficients have the expected signs: positive relationships with structural amenities (e.g., area, balcony) and negative relationships with distances to locational amenities (e.g., CBD, watercourse).
- **Spec 2: Low-level aesthetic measurements** of the house of the apartment (LL_{hj}), as well as the immediate urban surroundings (LL_{-hj}), are positive but not significant
- **Spec 3: Mid-level aesthetic measurements**: 1 percentage point increase in the street segment's greenness is associated with an average 8.1% increase in rental price, construction share is associated with a -5.4% change
- **Spec 4: High-level aesthetic measurements**: Preservation status carries a small premium (1.2%), but not for surrounding houses
- **Spec 5: High-level aesthetic measurements disaggregated**: Coefficients for facade art and front yards are positive and significant, showing a 1.4% and 2.7% price premium. Again, **only for own houses and not for surrounding houses**.

Difference Regression

- How to control even better for locational confounders?
- **Comparing rent prices of adjacent houses that differ in aesthetic measurements**
  - Two preserved adjacent houses on the same side of the street - with with facade decoration and one without

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  - Two preserved adjacent houses on the same side of the street - with with facade decoration and one without
  - The price difference of ornamentation Δ^{or} can be estimated as

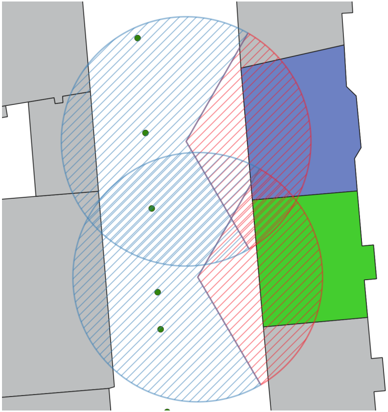
$$\Delta^{or} = E\left[p_{h^{or}} - p_{h^{no}} \,\middle|\, G_h = 1, S_{h^{or}} = S_{h^{no}}, |R_{h^{or}} - R_{h^{no}}| = 2,\ X \right],$$

    where p_h^{or} and p_h^{no} are prices for houses with preservation status G_h, with and without ornamentation, located on street S_h, with address number R_h, covariates X

- Geographical matching results in 238 pairs of adjacent preserved buildings differing in their ornamentation

Difference Regression

Example of a preserved house with ornate facade (green) and adjacent preserved house without (dark blue). Red lined-cone represents the 120 degree view of the house, the blue captures the visual surrounding. Green dots are trees.



Difference Regression

Dependent Variable:	log(Rent €/sqm)
Model:	(1)
Variables	
Ornate House	0.087**
	(0.038)
Controls	Yes
Fit statistics	
Adjusted R^2	0.73726
Observations	476

Clustered (Visual Surrounding) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

- Price premium of 8.7% for ornate facades
- Best isolation of the impact of aesthetic features. The hedonic regression might suffer from downward bias due to uncontrolled negative factors associated with preserved buildings (e.g., poor insulation)

Conclusion and Outlook

- Impact of **neighborhood aesthetic features** on apartment prices
  - Three-pronged approach to **measurement of aesthetics** based on multi-disciplinary insights
  - **Unique historical setting**, where housing stock and aesthetics are plausibly exogenous to increasing demand
  - Results: **Significant rent price premium of neighborhood greenery, preserved status - and particular design elements but only for own houses**
- Outlook
  - Extend the analysis to (East) Berlin
  - Study the relation between **aesthetics and residential sorting / neighborhood change**: Stylized model and micro-level socioeconomic analysis
- Given the premium of aesthetic historic buildings, cities may struggle to combat social segregation solely by constructing new apartments on the outskirts

Supplement: Low-Level Aesthetics

We follow Rigau et al. (2008) and define aesthetic perception of the visual neighborhood j as the ratio of uncertainty reduction to the initial information content.

- H_{rgb} as the Shannon Entropy of a color image, capturing the sum of the average information (or uncertainty) per pixel based on the intensity distributions in the Red, Green, and Blue channels:

$$H_{rgb} = - \sum_{C \in \{R,G,B\}} \sum_{x} p(x)^C \log_2(p(x)^C) \tag{2}$$

  Higher entropy values indicate greater complexity and variability in pixel values, requiring more information to describe the image in bits.

- With N pixels, $N \cdot H_{rgb}$ represents the total entropy for an image.

Supplement: Low-Level Aesthetics

- K is Kolmogorov Complexity is the amount of information contained in a file as the length of the shortest possible description, here approximated by the file size of the image.
- We obtain the **low-level aesthetics as the ratio of uncertainty reduction to the initial information content**:

$$LL_j = \frac{N \cdot H_{rgb} - K}{N \cdot H_{rgb}} \tag{3}$$

Back to Low-Level.