Housing price indices for small areas

NBP International Workshop
Recent trends in Real Estate Market ant its Analysis

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Zalesie Górne,
December, 5, 2019

Outline

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- Increased information needs for policy making.

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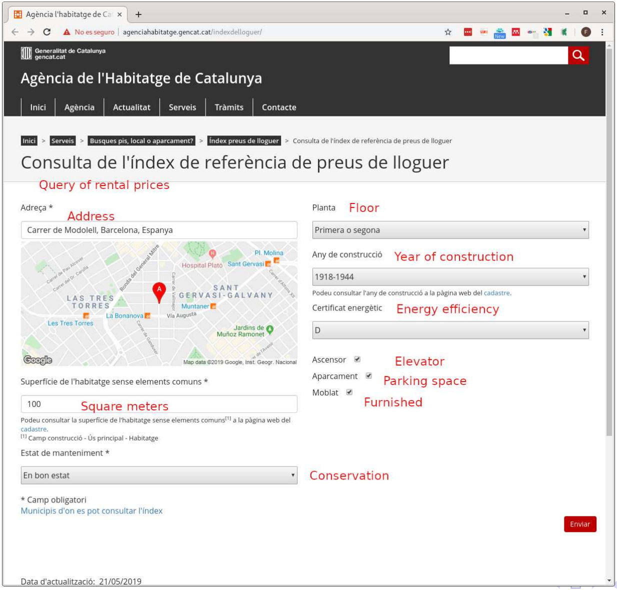
- Spatial detail of price indices down to areas a few hundred meters wide..
- A "rent advisor" needs to be programmed, feeding from the same data.

Interface of a web consulting tool



Laspeyres index

- Index at t base 0 defined as

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- We need to observe the prices of all products at 0 and t.

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- No "basket" of houses is repeatedly traded at all times to allow computation of a Laspeyres-type index.
- Plus: opaque market, prices difficult to observe, expensive and slow to survey.

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$$I_{t_0}(t_k) = \exp\left(\sum_{j=0}^{k} \hat{\gamma}_{t_j}\right) \times 100$$

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- . . .and we need much more information (attributes of each hose)

Geographically Weighted Regression (GWR)

- We can fit the model **locally**, with implicit prices different at each location (u_i, v_i):

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- With a spline replaced for $\gamma(t)$ this was the model in Barcena et al.(2013).

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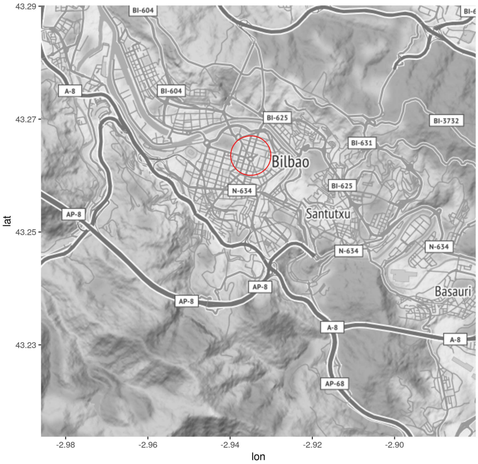

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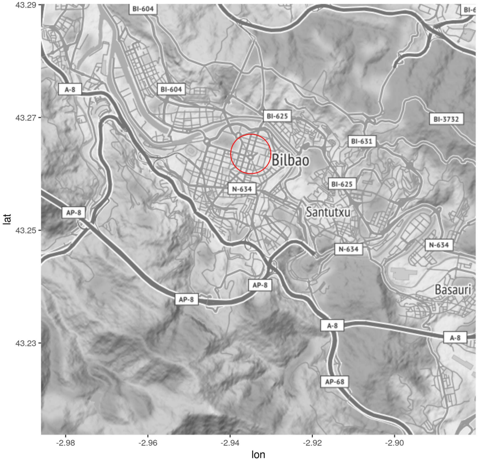

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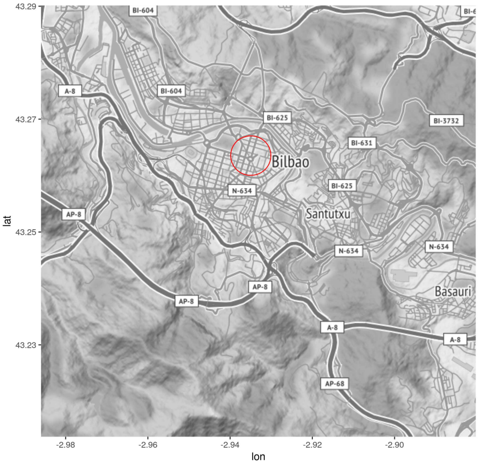

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$$\hat{\gamma}(t) = \arg\min \sum_{i,t} (\hat{\epsilon}_{it} - \gamma(t))^2$$

How do we fit the model? (II)

- Iterate now (1)–(2)–(3) until convergence:

$$\log(P_{it}) - \hat{\gamma}(t) = \sum_k \beta_k(u_i, v_i)x_{ik} + \epsilon \tag{1}$$

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- In all cases we have tried the iteration invariable converges.

What is the result?

- A fitted model **at each location** (u_i, v_i) of the form

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- By-product: shadow prices $\hat{\beta}_k(u_i, v_i)$ at all locations and $t = t_0$

The gory details

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- $\hat{\gamma}(t)$ "smooth"; in our use, a cubic spline (set of cubic polynomials which connect smoothly). Using 1 df per year of data, more than enough.

How to make an index local?

- Ideally, we might fit GWR's for $t = t_0, \ldots, t_k$:

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- Price a "median house" at i in times t_0 and t and compute:

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- …i.e. Laspeyres' index with homogeneous attributes (rather than houses) priced in location i at t_0 and t.
- Heavy computation and data requirements.

Can our model be adapted to do something similar?

$$\log(P_{it}) = \underbrace{\sum_k \hat{\beta}_k(u_i, v_i)x_{ik}}_{\text{Base price}} + \underbrace{\hat{\gamma}(t)}_{\text{Effect of time}} + \hat{\epsilon}$$

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- Could repeat the process for each area, but this would neglect information from neighbouring areas.

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- Define $w_{ij} = \left(1 - \frac{d_{ij}}{b}\right)^2$ (or zero if $d_{ij} > b$ for chosen b).

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- In computing $\hat{\gamma}_j(t)$, residuals close in space weighted more.

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- ...but trying to set the two bandwidths by cross-validation very expensive.

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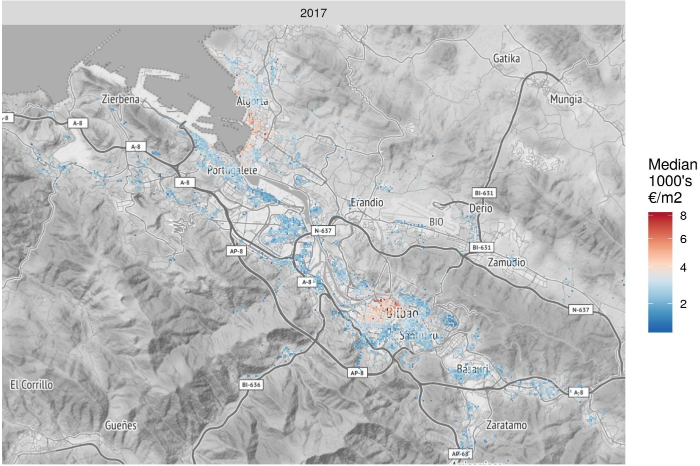
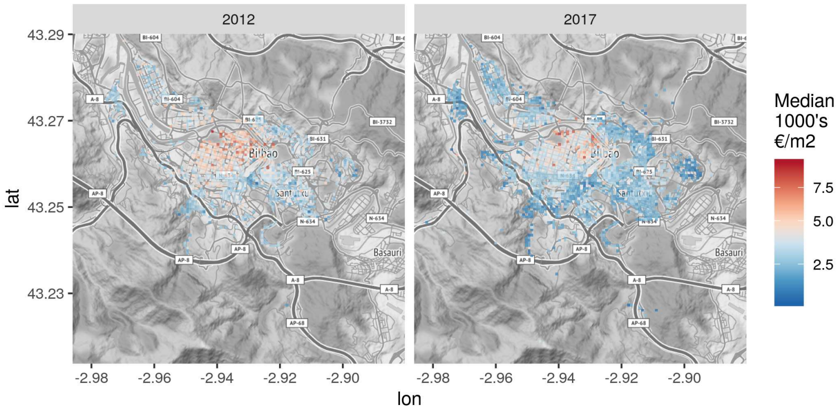
- Median offered price in thousands of euros color coded.

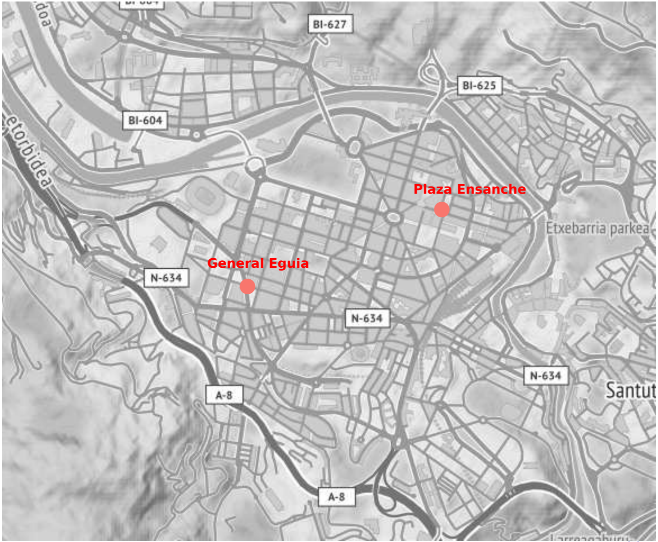
Great Bilbao. Offered prices (1000's €/m2)



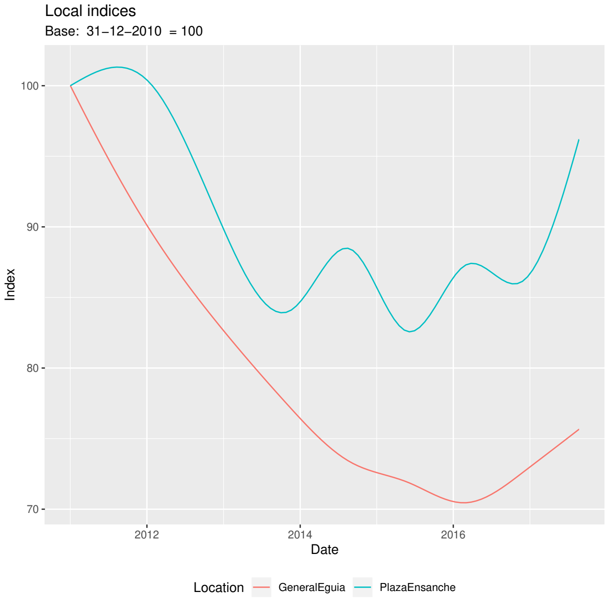
Bilbao: 2012 vs 2017



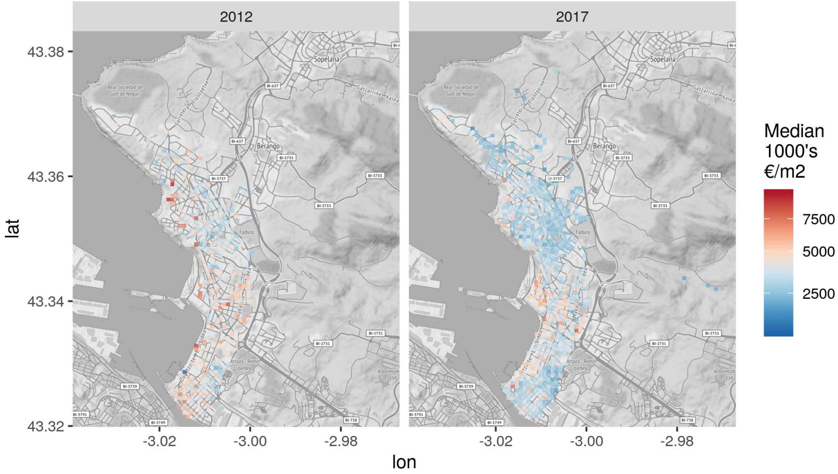
Choice of centroids to investigate different trends



Local trends



Getxo: 2012 vs 2017



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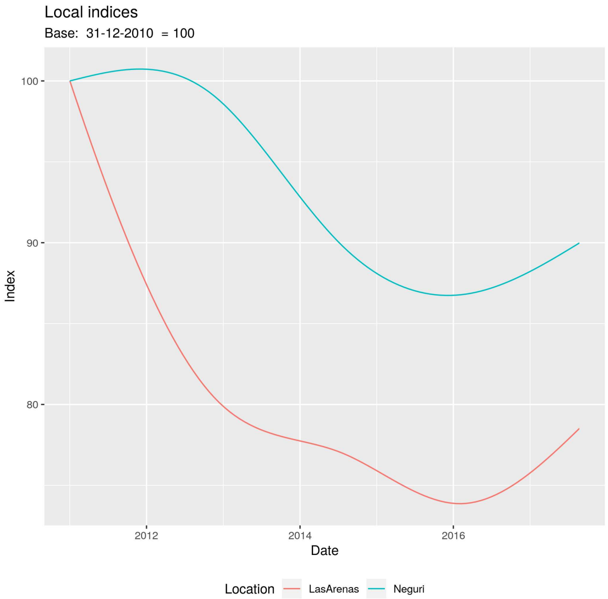

Some resources

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- Associated paper and slides also available, https://github.com/FernandoTusell/NBP2019.git.