Does Local Politics Matter?
Quasi-experimental Evidence from Italian Municipal Elections

ROBERTO BASILE
Department of Economics
Second University of Naples

SERGIO BERALDO
Department of Economics
University of Naples

VALERIO FILOSO
Department of Law
University of Naples

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Abstract

Do differently oriented political parties implement radically divergent policies which impact the citizenss welfare? The overheated political debate notwithstanding, it is far from clear if this is really the case. Whereas current literature on this issue narrows the focus on specific policy outcomes and instruments, we use the real estate market to evaluate the impact of the whole spectrum of municipal policies. Using a novel dataset on Italian municipal elections for the years 2003-2011 and the corresponding changes in real estate market prices, we employ a regression discontinuity approach to detect the causal effect of a change in municipal majorities. *We find robust evidence of no difference between the effects of the policies enacted by left-wing and right-wing parties after three, four, and five years since the election.* Finally, we are able to detect an average increase of 4.2% in the price of peripheral housing in areas ruled by left-wing municipalities.

Keywords: Real estate prices, Municipal politics, Regression discontinuity.
JEL codes: R3, H11, H7.

Contents

1 Introduction

1.1 Motivation

Do differently oriented political parties implement radically divergent policies which impact the citizens' welfare? The overheated political debate notwithstanding, it is far from clear if this is really the case. According to the standard theory of median voter (Downs, 1957), when citizens' preferences are unimodal, rational politicians find profitable to move their political platforms towards the center of the political spectrum: over time, this results in increasing similarities between political platforms and negligible differences between implemented policies.

One implication of the median voter theory is that, in two-parties or bipolar political systems, left-wing and right-wing parties would tend to be increasingly similar: to test such implication is the aim of the present work. As testing the theory at the national level can be confounded by a formidable number of variables, we approach the problem at the municipal level and test whether left-wing and right-wing parties differ substantially in their contribution to the welfare of their cities.

1.2 Why current literature is faulty

The current literature on the effects of local partisanship deploys a set of variables which represent the outcome of a given majority upon either some final economic variable or on some intermediate variables that are supposed to influence the final outcome of interest (Gerber and Hopkins, 2011; Ferreira and Gyourko, 2009; Pettersson-Lidbom, 2008). While this methodology, if correctly applied in a quasi-experimental design, can deliver credible estimates of the size of the causal effect of a given majority on the outcome of interest, nonetheless it does not capture the net effect of the whole bundle of benefits and costs as originated by a local municipality.

Municipalities provide a mix of local public and private goods and bads which impact on the welfare of their citizens. Some municipalities can succeed on some margins, while others can fall short on different margins. To fully assess the value of the net benefits provided by a municipality would require a complete set of observations on every aspect of life affected by the municipality. This would not be only impractical, but also impossible to obtain since many relevant variables are nondimensional by nature – the value of an embellished square or the deteriorated air quality being natural examples.

1.3 Our solution – Using the housing market

An indirect pathway can be taken to estimate the effect of the bundle of costs and benefits originated by a given municipality and it is based on the peculiar features of the housing market. Since, at least in the medium run, the supply of housing can be safely considered rigid, this is a factor of production which tends to accrue the net value of geographically concentrated benefits, including those generated by municipalities.

Suppose that, in a given geographical area exist two separate cities, namely Shelbyville and Springfield. At $t = 0$ all citizens have the same level of utility, irrespective of which city they live in.[1] At $t = 1$ the municipality of Shelbyville passes a budget plan which develops the green spaces and enhances air quality, resulting in an improved quality of life. The Simpsons, a family currently living in Springfield, start pondering whether to relocate to Shelbyville. If they moved there, they would surely increase their utility. Nonetheless, as the information on the benefits of living in Shelbyville start spreading to the citizens living in Springfield, the housing prices in Shelbyville will increase (and those in Springfield will decrease) up to the point to offsetting the gain to relocating to Shelbyville. The Simpsons, in the end, would find that there is no point in leaving their hometown after all equilibrium adjustments have taken place. When rational agents correctly foresee the final outcome of migrations between the two cities, housing prices will adjust in anticipation of future costs and benefits even before actual relocation takes place, with the prices in Shelbyville moving upward and the prices in Springfield moving downward.

In general, while municipalities are relatively free to choose their preferred mix of costs and benefits to reflect the preferences of their citizens, the housing market adjusts accordingly to reflect the value of the available amenities. As municipalities modify the net value of their services, ceteris paribus, housing prices change as well. As general microeconomic theory predicts, in the long run, all economic gains are reaped by the owners of the factors in fixed supply. This mechanism is driven by the spatial mobility of economic agents (Tiebout, 1956). In a frictionless world in which all markets adjust to the new equilibrium, relocating to a new place is just a matter of indifference for the marginal citizen.

1.4 Implications of the theory

The application of general equilibrium theory to the case of the production of local goods by a municipality leads to two main predictions:

1. In the short run, housing prices tend to adjust in the same direction of the change in the net value of the goods provided by the municipality: some losers and some winners, but effects are not required to cancel out in the aggregate.

2. In the long run, the owners of nonreproducible factors are the only ones to gain from an increased value of locally-provided benefits: the effects of the municipal policies are purely distributive in nature.

These two statements are observationally equivalent: they both imply that housing prices move upward (downward) in those cities whose municipalities provide a bundle of net benefits (costs). Establishing this causal link from municipal policies to housing prices is our crucial theoretical step. We apply this framework to identify the difference between the effects of public policies enacted by left-wing and right-wing majorities on housing prices, using Italian municipal data.

1.5 Why using the RD design

Given that, in general, left-wing parties promise more income redistribution and redistribution is easier to attain the higher the level of the local income, it turns out that housing prices

[1] We due the inspiration for this example to Landsburg (2012).

(positively related to local income) and the presence of a left-wing municipality display a positive association. The sign of this correlation, nonetheless, could be misleading since it does not reflect any genuine causation going from municipality's political color to housing prices, but just a spurious association that would disappear as a complete set of controls were included in a regression model.

The Italian local electoral system provides an opportunity to test the theory of the median voter. In 1993, the Italian National Parliament passed a law which regulates municipal elections according to a majority principle. Cities with more than 15,000 inhabitants have a top-two runoff voting system: if there is no absolute majority at the first round, then a ballot election is held between the two highest voting mayor candidates. Cities with less than 15,000 inhabitants have a single-winner voting system, with the highest voting mayor candidate being elected. In both systems, either the party or the coalition backing up the winning mayor candidate obtains a sufficient number of seats in the Municipal Council to become majority. The mayor and the corresponding Municipal Council remain in charge for five years. In sum, this is winning-party-takes-all system.

This electoral law can be seen as a natural experiment in the electoral districts in which the majority at the second – and also at the first – turn is formed *without* a large margin. These districts can be seen as experiencing a sort of random assignment to a policy which is almost orthogonal to the prevailing political preferences. Since minor differences in political preferences may result in large differences in the type of policies implemented, this becomes an opportunity to employ a sharp Regression Discontinuity Design (RDD) (Imbens and Lemieux, 2008) to evaluate the *causal* effect of political parties on real estate prices at 3, 4, and 5 years after the election.

1.6 Data

Our dataset contains a collection of municipal election results linked to real estate prices for the years 2003–2011, for a total of 1,246 observations in which left-wing and right-wing party confront in a given municipal election. We are able to observe average annual growth rates of real estate prices after three, four, and five years from the election. Furthermore, our data is detailed enough to distinguish between residential or commercial usage and central or peripheral location.

1.7 Results

In the empirical section, we implement two different estimators: (1) a local linear estimator with three alternative bandwidths, and (2) a penalized regression spline estimator. The key finding is striking: *we find no evidence of a difference in housing price dynamics in cities ruled by left-wing and right-wing majorities.* The results are extremely robust when checked across different types of land use and support the thesis that political partisanship, at the local level, is not able to impact the overall level of citizen's welfare, as measured by real estate price dynamics. Finally, we perform a meta-analysis on our results to provide evidence of no bias in results reporting and to check for study-level effects: we aggregate the estimated impact coefficients and find a moderate effect of left-wing majorities on the growth rate of real estate prices in peripheral locations. According to our estimates, in a five-year legislature, peripheral locations can expect to register a rise of real estate prices of 4.2%.

The paper is organized as follows. Section 2 reviews the current literature on the effect of mayor partisanship, with a special focus on RDD methods. Section 3 presents a theoretical model for assessing our priors about the effect of different political majorities on real estate prices. Section 5 provides the necessary econometric background for our estimates. Section 4 describes the dataset used in the estimation. Section 6 discusses the estimation results and elaborates on alternative explanations. Section 7 concludes and provides lines of future research.

2 Survey of the current literature

Since the seminal work of Lee (2001), economists have been increasingly attracted by the potential of regression discontinuity estimators for the study of political partisanship. A number of articles, in recent years, has dealt with the issue of estimating the difference in intermediate and outcome variables linked to alternative local political majorities.

Ferreira and Gyourko (2009) estimate the impact of a democratic mayor on policy outcomes at the municipal level using a sample of nearly 2,000 direct mayoral elections in over 400 U.S. cities in the period 1950–2000. They focus on budgetary variables (total revenues per capita, total taxes per capita, total expenditures per capita, total employment per capita), allocation of resources (percent spent on salaries and wages, police and fire department, parks and recreation), and crime indexes (murders, robberies, burglaries, larcenies). Using a RD estimator, they are able to show no evidence of systematic differences between Conservative and Democratic mayorships. These results seem consistent with Alesina (1988)'s claims that cities should be more homogeneous in their political preferences than higher levels of government and that municipal competition may lead to decreased partisanship as the costs of switching to another municipality is relatively low. Ferreira and Gyourko (2009) also claim that the small numbers of media available at the municipal level lowers the incentive to target specific populations and fostering partisanships, though this could be less than true in large cities.

Ferreira and Gyourko (2009)'s results are problematic since they *control* for median house value. This amounts to considering the log of house value as a predetermined feature of a given municipal district, quite hard an assumption to maintain as household values tend to reflect the value of local amenities and the capitalized value of local goods provided by the public sector.[2] Actually, the value of housing can well be an outcome variable determined by the political *treatment*: according to econometric theory (Angrist and Pischke, 2008), these variables cannot validly qualify as genuine exogenous controls.

Gerber and Hopkins (2011) hypothesize that mayoral partisanship will more strongly affect policy outcomes in policy areas where there is less shared authority between local, state, and federal government. Political science literature assumes that the two major parties have distinct electoral coalitions and governing philosophies that should lead to quite different policy outcomes, especially on issues of taxing and spending. On one hand, left-wing parties might pursue increased taxes and expanded services, and right-wing might pursue tax cuts and

[2]For a systematic survey on the issue of the provision of local public goods and housing prices, see Wildasin (1987).

service reductions. On the other hand, if the various constraints on local policymakers are binding, the impact of mayoral partisanship might prove negligible. Mayor's partisanship is an important determinant of fiscal outcomes in some policy areas where local decision makers are less constrained by other levels of the U.S. federal system. Using an RD quasi-experimental design with a sample of U.S. mayoral election in large cities from 1990 to 2006, Gerber and Hopkins (2011) find evidence that the difference between Conservative and Liberal municipalities is negligible in areas where federal and state actors exert more authority. In somewhat the same fashion, Leigh (2008) uses a panel data of U.S. states over the period 1941–2002 and finds that the differences between Democratic and Conservative governors are almost negligible.

Pettersson-Lidbom (2008) estimates the causal effect of party control on fiscal and economic policies employing a dataset of Swedish municipalities. Using panel data plus RD design, the author uses 5,913 observations for the period 1974–1994 and finds differences between parties: Left-wing local governments spend and tax 2-3% more than right-wing counterparts. Left-wing governments also have 7% lower unemployment rates due a higher level of employment in public sector.

Some applied work suggests that ideological differences may drive systematic differences in enacted policies. For example, Picazo-Tadeo, González-Gómez, Wanden-Berghe, and Ruiz-Villaverde (2011) find that ideological differences between parties at the municipal level lead to different water management regimes in Andalusia, Spain, with right-wing majorities leading to more outsourcing. Also, Blom-Hansen, Monkerud, and Sørensen (2006) detect a financially significant difference between left-wing and right-wing municipalities in Denmark and Norway with regard to tax policy: according to their data, left-wing municipalities, especially in Denmark, appear to levy higher income and property taxes. Nonetheless, these works do not control for endogenous sorting and preexisting political preferences, so their results must be taken with a grain of salt.

In a related stream of literature, Cellini, Ferreira, and Rothstein (2010) have recently employed a RD design for estimating the value of school facility investments via real estate markets, on the assumption that school districts create value which translates into higher housing prices according to a Samuelson-like rule of optimal allocation of public goods. They provide a theoretical analysis based on previous literature (Barrow and Rouse, 2004; Brueckner, 1979; Tiebout, 1956) in which the intensity of preference for spending in school infrastructure is revealed by changes in housing prices; empirically, with the help of a dynamic RD design, they convincingly manage the issue of endogenous Tiebout sorting across school districts.

In sum, the best available evidence to date suggests that differences in the political composition of municipalities have a small or negligible effect on some given margins of citizens' welfare. However, a definitive complete test of the whole bunch of benefits and costs originated by municipalities is still lacking. This is precisely the point we intend to investigate in the next sections with our RD design.

3 A theoretical model of left-wing/right-wing choice

4 Data

4.1 Sources

Our dataset is obtained by merging observations from three sources.

Prices This is a dataset on real estate prices released by the *Agenzia del Territorio* (the Italian public agency of territory). The prices are collected on a twice-a-year basis from various market sources and are not linked in any sense to the official prices used to calculate the real estate tax (ICI or IMU), which are known to systematically diverge from actual exchange prices. Different prices are observed by location (generic, central, peripheral), type of use (residential, commercial or industrial), and bounds (highest price, lowest price). Real estate prices for Sicily are not available.

Elections This is a dataset on municipal election results collected by the Italian Home Office. We label "Right-Wing" any coalition containing at least one of the major right-wing parties (*Forza Italia*, *Alleanza Nazionale*, *Polo delle Libertà*, *Il Popolo della Libertà)*. We label "Left-Wing" any coalition containing at least one of the major left-wing parties (*Partito Democratico*, *Democratici di Sinistra*). Dubious cases (unidentified party names) were dropped altogether.

Codes This is a dataset on the city names, codes, and residing population released by ISTAT (the Italian Office of Statistics). These data were used to obtain a safe merging between the two previous datasets.

4.2 Selection

The dataset used for estimation contains a collection of municipal election results linked to real estate prices for the years 2003–2011, for a total of 1,246 observations. Since we focus exclusively on the right-wing/left-wing voting alternative, we discard a number of cases:

1. In cities with less than 15,000 inhabitants, we drop observations for elections in which the either the first or the second highest voting mayor is not backed up by a clearly left-wing or right-wing coalition or party.

2. In cities with more than 15,000 inhabitants, we drop observations for First-round elections in which the either the first or the second highest voting mayor is not backed up by a clearly left-wing or right-wing coalition or party.

3. In cities with more than 15,000 inhabitants, we drop observations for ballots in which the either the first or the second highest voting mayor is not backed up by a clearly left-wing or right-wing coalition or party.

Table 1 displays the regional distribution of municipalities with a right-wing party and a left-wing party majority. There is a higher presence of right-wing party municipalities only in Lombardia and Veneto.

Tables 2 and 3 reports the average levels of real estate prices in the municipalities by type of house and by political party.

Two-sample t tests in table 4 clearly show that municipalities governed by a right-wing party scantly have statistically significant lower growth rates of real estate prices than municipalities governed by a left-wing party, especially after 4 and 5 years from the election.

5 Evaluating the effect of political parties using a regression discontinuity design

The evidence reported in Table 2 cannot represent a proper test of the *causal* effect of political parties on the average annual growth rate of local real estate prices. An accurate evaluation of the left-wing party policy effect must contend with problems of isolating the effect of local public policies from the confounding effect induced by other factors.[3]

To overcome this problem, we rely on a quasi-experimental design, the Regression Discontinuity (RD) design introduced by Thistlethwaite and Campbell (1960). This approach is a way of estimating *treatment* effects in a non-experimental setting where treatment assignment is a discontinuity function of an observed variable at a known threshold value (Lee and Lemieux, 2010; Imbens and Lemieux, 2008). Specifically, the RD design estimates local average impacts around the threshold at the point where treatment and comparison units are most similar. Thus, the RD design well fits the aim to identify a policy impact by separating the effect of other factors influencing the outcome under analysis. As discussed above, a large number of studies have already used a RD design to assess the empirical relevance of median voter models.

In our case, for the municipality i, $\Delta \log(P_{t_0+\delta}/P_{t_0})$ (i.e. the average annual growth rate of real estate prices) is the *outcome* variable, y_i. The *treatment*, w_i, is the left-wing party policy action, while the *assignment* variable, x_i, is the fraction awarded to the left-wing party. When x_i exceeds the cut-off of 50%, the municipality is governed by a left-wing coalition. The presence of a sharp discontinuity in the formation of a majority allows us to implement a sharp RD design: average left-wing party effects are estimated by comparing the average annual growth rate of real estate prices of the group of cities with a value of x_i just above the threshold with the average annual growth rate of real estate prices of the group of cities with a value of x_i just below the threshold. We claim that the municipalities with a vote share for the left-wing party just below the cut-off (50% and just below) will be very similar to municipalities with a vote share for the left party just above the cut-off (for example, those scoring 51%), except that they are governed by a right-wing party. Thus, municipalities just below the threshold can be used as a comparison group for the municipalities just above to estimate the *counter-*

[3]For example, spatial hedonic house price models suggest that local real estate prices depend not only on the characteristics of the houses (size, type, age and other structural characteristics) but also on location characteristics. For example the Harrison and Rubinfeld (1978)'s hedonic pricing spatial dataset (built at the census tract level) includes - among spatial level variables - levels of nitrogen oxides, particulate concentrations, black population proportion, lower status population proportion, crime rate, proportion of area zoned with large lots, proportion of nonretail business areas, property tax rate, weighted distances to the employment centers, index of accessibility, and latitude and longitude of the census tract where the house is located.

factual (what would have happened to the group of cities controlled by the left-wing party if they were controlled by the right party). We can safely assume that individuals have imprecise control over x. This is enough to assure that the treatment is as good as randomly assigned around the cut-off. The local random assignment implies that the discontinuity gap at the cut-off identifies the treatment effect and that we do not need any control and any model to consistently detect the effects of left-wing parties on the outcome.

More formally, let $y_i(1)$ and $y_i(0)$ be the potential outcomes of municipality i with and without exposure to the treatment, that is the outcomes if $w_i = 1$ and $w_i = 0$, respectively. Thus, we can write

$$y_i = y_{1i} w_i + y_{0i}(1 - w_i) \tag{1}$$

Let $\tau_i = y_{1i} - y_{0i}$ be the treatment effect of municipality i. Rewriting the previous expression we have

$$y_i = y_{0i} + \tau_i w_i \tag{2}$$

In a sharp RD design the *treatment assignment*, w_i, is a discontinuous deterministic function of the assignment variable x_i:

$$w_i = 1\{x_i \geq c\} \tag{3}$$

where c is the cut-off point.

We never observe the pair $y_i(1)$ and $y_i(0)$ simultaneously. Thus, we focus on averages of $[y_i(1) - y_i(0)]$ over sub-samples. Note that conditional on $x_i = x$

$$E[y_i|x_i = x] = m(x) + E[\tau_i w_i|x_i = x] \tag{4}$$

where $E[y_{0i}|x_i = x] = m(x)$. In a sharp RD design $E[w_i|x_i = x] = Pr(w_i = 1|x_i = x)$ will be 0 or 1. Assuming that individuals do not sort into x and, as it is common, that $\tau_i = \tau$, it follows that $E[\tau_i w_i|x_i = x] = \tau w_i$. Dropping the index for convenience and using $y = E[y|x] + \epsilon$, where $\epsilon = y - E[y|x]$, the following expression is obtained

$$y = m(x) + \tau w + \epsilon \tag{5}$$

It is important to remark that, in this case, $m(x)$ is the conditional expectation of the outcome variable without treatment, y_{0i}, on the selection variable $x_i = x$. But $m(x)$ is defined in the entire support of x_i, so $m(x)$ includes the counter-factual $E[y_{0i}|x, w = 1]$ since $E[y_{0i}|x] = E[y_{0i}|x, w = 0]Pr(w = 0|x_i = x) + E[y_{0i}|x, w = 1]Pr(w = 1|x_i = x)$. In a sharp design the probabilities will be either 0 or 1.

Equation (5) links the experimental representation of the response variable with an econometric representation, where the assignment variable is smoothly associated with the potential outcomes. In equation (5), τ is a measure of the discontinuity of the conditional expectation of the outcome as a function of assignment variable at the threshold value c. It is interpreted as evidence of a *causal* effect of the treatment, provided that all other factors affecting y_i are evolving smoothly with respect to x. A sufficient condition for identification of τ is to assume continuity of $m(x)$ at c and the existence of the limits $\lim_{x\uparrow c} E[w_i|x]$ and $\lim_{x\downarrow c} E[w_i| = x]$. In the case of a sharp design, $\lim_{x\uparrow c} E[w_i|x] = 0$ and $\lim_{x\downarrow c} E[w_i| = x] = 1$, so as

$$\tau_{SRD} = \lim_{x\downarrow c} E[y_i|x_i] - \lim_{x\uparrow c} E[y_i|x_i] \tag{6}$$

5.1 A local linear estimator

In practice, the treatment effect $\widehat{\tau}_{SRD}$ in an RD design can be consistently computed by estimating two local polynomial regression functions on each side of the cut-off point (Hahn, Todd, and Van der Klaauw, 2008). Thus, for example, after having subtracted the threshold value from the covariate (i.e. after having transformed x to $x - c$), we can fit local linear regression functions - such as $y = m(x-c) + \tau w + \epsilon = \alpha + \beta(x-c) + \tau w + \epsilon$ - to the observations within a distance h (the bandwidth) on either side of the discontinuity point

$$\min_{\alpha_l;\beta_l} \sum_{i:c-h<x_i<c} [y_i - \alpha_l - \beta_l(x_i - c)]^2 K\left(\frac{x_i - x}{h}\right) \tag{7}$$

and

$$\min_{\alpha_t;\beta_t} \sum_{i:c-h<x_i<c} [y_i - \alpha_t - \beta_t(x_i - c)]^2 K\left(\frac{x_i - x}{h}\right) \tag{8}$$

where $K(u)$ is a kernel function which satisfy the two following conditions: $\int K(u)\mathrm{d}u = 1$ and $K(-u) = K(u)\ \forall u$. Several types of kernel functions can satisfy these conditions: uniform, triangle, Epanechnikov, quartic (biweight), tricube, triweight, Gaussian, and cosine.

Given these estimates, the average treatment effect is computed as the difference between the two regressions intercepts on the two sides of the cutoff point:

$$\widehat{\tau}_{SRD} = \widehat{\alpha}_t - \widehat{\alpha}_l \tag{9}$$

Alternatively, one can estimate the average treatment effect (ATE) running a single pooled regression on both side of the cutoff point, and thus solving the following minimization problem:

$$\min_{\alpha;\beta;\tau;\gamma} \sum_{i=1}^{N} [y_i - \alpha - \beta(x_i - c) - \tau w_i - \gamma(x_i - c)w_i]^2 K\left(\frac{x_i - x}{h}\right) \tag{10}$$

which will numerically yield the same estimate of τ_{SRD}. The advantage of estimating the pooled local linear regression model is that the standard error of $\widehat{\tau}_{SRD}$ can be directly obtained from the regression.

As it is well known, for a correct specification of the local linear regression model the choice of the kernel function has little impact in practice, while it is very important to choose an appropriate bandwidth to balance precision and bias: a smaller bandwidth tends to produce lower bias and higher variance, and *vice versa*. Two different approaches have been proposed to estimate the optimal bandwidth, namely (*i*) minimizing the sum of squares of some type of estimated residuals as in cross-validation, generalized cross-validation, and minimum unbiased risk estimation, and (*ii*) estimating the asymptotically optimal bandwidth leading to the so called plug-in estimator. For robustness check, it is customary to estimate the local linear regression using alternative values of bandwidth, both higher and lower than the optimal one.

5.2 A penalized regression spline estimator

Rau (2011) proposes an alternative nonparametric method for estimating treatment effects in a RD design using penalized regression spline and generalized cross-validation to choose the smoothing parameter. He also proposes to exploit the Bayesian interpretation of penalized regression to obtain the standard errors from the posterior variance-covariance matrix. In a Monte Carlo simulation study, Rau shows the Bayesian based confidence intervals perform quite well in terms of realized coverage probabilities and outperforms frequentist based confidence intervals for the local polynomial estimators.

Let us re-write equation (5) as:

$$y = \alpha + f(x-c) + \tau w + \epsilon \tag{11}$$

The univariate smooth term $f(x-c)$ in equation (11) can be approximated by a linear combination of known basis functions b_q

$$f(x-c) = \sum_q \beta_q b_q(x-c) \tag{12}$$

where β_q are unknown parameters to be estimated. To avoid mis-specification bias, $q's$ must be made fairly large. But this may generate a danger of over-fitting. As it will be better clarified below, smoothness of the functions can be controlled by penalizing wiggly functions in the model fitting. Thus, a measure of 'wiggliness' $J \equiv \beta_q^{'} \mathbf{S} \beta_q$, where $\mathbf{S}$ is a positive semi-definite matrix, is associated with the smooth function. Typically, the wiggliness measure evaluates a function like the univariate spline penalty $\int f^{''}(x-c)^2 d(x-c)$ or its thin-plate spline generalization (Wood, 2003, 2006a).

Given the bases for the smooth term and ignoring random effect terms, equation (11) can be re-written in matrix terms as a large linear model

$$\begin{aligned} y &= \alpha + \Sigma_q \beta_q b_q(x-c) + \tau w + \varepsilon \\ &= X^{'} \beta + \varepsilon \end{aligned} \tag{13}$$

where the model matrix X includes the intercept, the dummy variable w and the basis functions evaluated at the covariate value, while β contains α, τ and all the smooth coefficient vectors, β_q.

As mentioned above, the number of parameters for a smooth term in a semi-parametric model has to be large enough to avoid mis-specification bias, but not too large to escape over-fitting. To solve this trade-off, we need to penalize lack of smoothness. Thus, parameters β in model (13) can be estimated by minimizing the penalized residual sum of squares

$$\widehat{\beta} \;=\; \arg\min ||y - X\beta||^2 + \lambda\beta'\mathbf{S}\beta \tag{14}$$

where $\lambda \geq 0$ is a smoothing parameter which control the flexibility of the function estimate with large values enforcing smooth estimates and small values allowing for high flexibility. Employing a large number of basis functions yields a flexible representation of the nonparametric effect $f(\cdot)$ where the actual degree of smoothness can be adaptively chosen by varying λ.

Given the smoothing parameter, λ, resulting estimate is

$$\widehat{\beta} = \left(X'X + \lambda\mathbf{S}\right)^{-1} X'\mathbf{y} \tag{15}$$

The covariance matrix of $\widehat{\beta}$ can be derived from that of y

$$V_{\widehat{\beta}} \;=\; \left(X'X + \lambda\mathbf{S}\right)^{-1} X'X \left(X'X + \lambda\mathbf{S}\right)^{-1} \sigma^2 \tag{16}$$

If we also assume normality, that is $y \sim \mathcal{N}\left(0, I\sigma^2\right)$, then

$$\widehat{\beta} \;\sim\; \mathcal{N}\left(E\left(\widehat{\beta}\right), V_{\widehat{\beta}}\right) \tag{17}$$

It must be recognized, however, that frequentist confidence intervals based on the naive use of $\widehat{\beta}$ and the corresponding covariance matrix perform quite poorly in terms of realized coverage probability (Wood, 2006b). Thus, in practice, in additive models based on penalized regression splines frequentist inference yields to reject the null hypothesis too often. To overcome this problem and following Wahba (1983), Silverman (1985), and Wood (2006a,b), a Bayesian approach to coefficient uncertainty estimation can be implemented. This strategy recognizes that, by imposing a particular penalty, we are effectively including some prior beliefs about the likely characteristics of the correct model. This can be translated into a Bayesian framework by specifying a prior distribution for the parameters β. Specifically, Wood (2006b) shows that using a Bayesian approach to uncertainty estimation results in a Bayesian posterior distribution of the parameters

$$\beta|y \;\sim\; \mathcal{N}\left(E\left(\widehat{\beta}\right), \left(X'X + \lambda S\right)^{-1} \sigma^2\right) \tag{18}$$

This latter result can be used directly to calculate credible intervals for any parameter. Moreover, it turns out (Wahba, 1983; Wood, 2006b) that the credibility intervals derived via Bayesian theory are well behaved also from a frequentist point of view, i.e. their average coverage probability is very close to the nominal level $1-\alpha$, where α is the significance level.

So far everything is conditional on λ, the smoothing parameters controlling the trade-off between fidelity to the data and smoothness of the fitted spline. The optimal smoothing parameter can be selected minimizing the generalized cross validation (GCV) score:

$$GCV(\lambda) \;=\; \frac{N\,||\,y - X\widehat{\beta}\,||^2}{[N - tr(\mathbf{A})]^2} \tag{19}$$

where $\mathbf{A} = X(X'X + \sum \lambda \mathbf{S})^{-1}X'$ is the hat matrix for the model being fitted and its trace, $tr(A)$, gives the effective degrees of freedom edf (i.e. the number of identifiable parameters in the model). The edf are a general measure for the complexity of a fucntion estimates that allows to compare the smoothness even for different types of effects (e.g. nonparametric versus parametric effects). If λ=0, then edf is equal to the size of the β vector minus the number of constraints. Positive values of λ lead to an effective reduction of the number of parameters. If λ is high, we have very few edf.

Finally, like for the local linear estimator, also in the case of the semiparametric additive model with penalized regression splines it is convenient to introduce the interaction term $f(x-c)w$ into model (11):

$$y = \alpha + f(x-c) + \tau w + f(x-c)w + \varepsilon \tag{20}$$

and estimate it using the pooled dataset. The nonparametric smooth term $f(x-c)$ in (20) is the conditional expectation of the outcome variable without treatment (i.e. when $w = 0$), while the varying coefficient term $f(x-c)\tau$ is the conditional expectation of the outcome with treatment (i.e. when $w = 1$). In the case of a varying coefficient term like $f(x-c)w$, the basis functions $b_q(x-c)$ are pre-multiplied by a diagonal matrix containing the values of the interaction variable (w). To estimate (20) it is desirable to use the same degree of smoothness (that the the same smoothing parameter λ) for the two smooth terms.

6 Results

As shown in Table 4, municipalities ruled by a right-wing majority (call by convenience the treatment group) scantly show a significantly higher growth rate of real estate prices than municipalities ruled by a right-wing majority (the control group). To properly identify the treatment effect of political parties on the dynamics of municipalities' real estate prices, we have implemented a RD design and in this section we report the estimation results of both local liner and penalized regression models used to implement the RD design.

First, following the classical sharp RD design, we have estimated two local linear regression models on both sides of the cut-off, being interesting examine the behaviour around the threshold. Evidence of a significant jump level at the threshold would mean that the difference between the right limit and the left limit of the two non-parametric local linear regressions with respect to the cut-off point is the policy effect in terms of real estate price dynamics. As it is well known, for a correct specification of the local linear regression model it is very important to choose an appropriate bandwidth to balance accuracy and bias. We took advantage of the contribution of Imbens and Kalyanaraman (2012) that present a data dependent method for choosing an asymptotically optimal bandwidth in the case of a RD design. Local linear regression models have been estimated using a triangular kernel function and bandwidths larger (twice) and smaller (half) than the optimal bandwidth for test the robustness of the results. Standard errors are obtained by a bootstrap procedure.

The results are very clear: *there is no evidence of a significant left-wing party effect on the dynamics of real estate prices*. To give a graphical example of these results, figure X displays the two local linear smooth functions estimated (using the optimal bandwidth) for the cases of maximum and minimum house price dynamics after 4 years from the election in peripheral areas. These two plots show that a discontinuity at the cut-off point between treated and non-treated municipalities, if any, is negligible.

Figure X about here

A more systematic evidence is reported in Tables 5, 6 and 7, which collect the results of 108 local linear regression models. They show that the bootstrap p-value associated to the difference of the intercepts of the two local linear regressions is never lower than 0.1 (except in 3 out 108 cases), whatever the time lag (3, 4 or 5), the type of land use (residential or commercial/industrial), the bound (highest price or lowest price) and the level of the bandwidth (optimal, double and half) considered. Finally, the lack of a significant treatment effect is confirmed the nonparametric estimates based on a penalized regression estimator (Table 8): the Bayesian p-value is again always higher than 0.1.

All in all, our findings corroborate the thesis that left-wing and right-wing majorities tend to implement similar policies, that is they provide similar public and private goods and bads, with similar net effects on citizens' welfare.

7 Conclusions

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TABLE 1
Frequencies for the parties in charge

	Observations			Percentages		
	Right	Left	Total	Right	Left	Total
Region						
Abruzzo	13	26	39	33.3	66.7	100.0
Basilicata	6	13	19	31.6	68.4	100.0
Calabria	22	24	46	47.8	52.2	100.0
Campania	67	71	138	48.6	51.4	100.0
Emilia-Romagna	12	136	148	8.1	91.9	100.0
Lazio	38	49	87	43.7	56.3	100.0
Liguria	5	15	20	25.0	75.0	100.0
Lombardia	86	80	166	51.8	48.2	100.0
Marche	13	28	41	31.7	68.3	100.0
Molise	0	2	2	0.0	100.0	100.0
Piemonte	32	57	89	36.0	64.0	100.0
Puglia	71	73	144	49.3	50.7	100.0
Sardegna	9	19	28	32.1	67.9	100.0
Toscana	15	158	173	8.7	91.3	100.0
Umbria	8	25	33	24.2	75.8	100.0
Veneto	38	35	73	52.1	47.9	100.0
Total	435	811	1,246	34.9	65.1	100.0
Geographical partition						
North West	123	152	275	44.7	55.3	100.0
North East	50	171	221	22.6	77.4	100.0
Center	74	260	334	22.2	77.8	100.0
South	179	209	388	46.1	53.9	100.0
Islands	9	19	28	32.1	67.9	100.0
Total	435	811	1,246	34.9	65.1	100.0

TABLE 2
Average real estate prices: Housing

	Year						
	2005	2006	2007	2008	2009	2010	Total
Region							
Abruzzo	958	957	1,060	1,116	1,119	1,161	1,037
Basilicata		829	984	716	724	549	764
Calabria	518	593	796		667	735	601
Campania	1,027	1,183	1,441	1,493	1,273	1,724	1,303
Emilia-Romagna	1,323	1,382	1,725	1,322	1,464	1,115	1,441
Lazio	1,412	1,433	1,620	1,962	1,688	1,711	1,619
Liguria	2,316	1,884	1,955	3,696	2,169	2,250	2,197
Lombardia	1,427	1,475	1,430	1,528	1,364	1,300	1,400
Marche	1,323	1,297	1,412	1,697	1,319	1,548	1,380
Molise		1,076					1,076
Piemonte	1,098	1,114	1,206	1,253	1,253	1,237	1,191
Puglia	658	826	871	964	1,037	958	862
Sardegna	975	957	1,503	1,053		1,180	1,140
Toscana	3,008	1,522	1,835	2,275	1,767	2,166	1,797
Umbria	722	953	1,038		1,068		1,028
Veneto	983	1,129	1,365	1,431	1,126	2,763	1,263
Total	1,054	1,141	1,346	1,496	1,444	1,360	1,313
Geographical partition							
North West	1,492	1,340	1,413	1,690	1,357	1,394	1,405
North East	1,096	1,262	1,425	1,407	1,419	1,527	1,383
Center	1,492	1,395	1,627	2,007	1,623	1,806	1,614
South	790	902	1,113	1,160	1,065	1,178	995
Islands	975	957	1,503	1,053		1,180	1,140
Total	1,054	1,141	1,346	1,496	1,444	1,360	1,313

TABLE 3
Average real estate prices: Store

	Year						
	2005	2006	2007	2008	2009	2010	Total
Region							
Abruzzo	1,145	1,110	1,184	1,318	1,236	1,520	1,198
Basilicata		820	989	703	715	550	759
Calabria	669	721	1,092		730	884	748
Campania	1,199	1,362	1,562	1,586	1,438	1,939	1,455
Emilia-Romagna	1,490	1,597	1,709	1,710	1,495	1,285	1,507
Lazio	1,586	1,509	1,707	2,130	1,942	1,807	1,751
Liguria	1,973	2,204	1,880	2,756	1,805	1,915	2,035
Lombardia	1,406	1,524	1,484	1,554	1,371	1,405	1,434
Marche	1,310	1,292	1,411	1,738	1,307	1,488	1,373
Molise		1,466					1,466
Piemonte	1,156	1,098	1,239	1,117	1,203	1,199	1,177
Puglia	850	876	981	1,111	1,197	1,125	992
Sardegna	1,073	996	1,367	1,042		1,275	1,175
Toscana	1,639	1,363	1,588	2,124	1,566	1,886	1,590
Umbria	801	1,139	1,046		1,137		1,109
Veneto	858	1,227	1,341	1,427	1,064	3,385	1,302
Total	1,130	1,210	1,379	1,579	1,407	1,463	1,347
Geographical partition							
North West	1,430	1,385	1,437	1,587	1,328	1,459	1,401
North East	1,174	1,455	1,408	1,484	1,443	1,810	1,447
Center	1,391	1,396	1,547	2,059	1,503	1,770	1,550
South	978	1,009	1,245	1,302	1,183	1,319	1,130
Islands	1,073	996	1,367	1,042		1,275	1,175
Total	1,130	1,210	1,379	1,579	1,407	1,463	1,347

TABLE 4
Student's t test for the difference between groups
Variable: Average annual growth rate of local real estate prices

After 3 years

Type	Location	Value	$\bar{X}_L$	σ_L	$\bar{X}_R$	σ_R	Δ	p
House	Generic	min	0.020	0.045	0.013	0.043	0.007	0.054
House	Generic	max	0.019	0.044	0.016	0.045	0.003	0.274
House	Central	min	0.018	0.045	0.013	0.044	0.006	0.090
House	Central	max	0.019	0.045	0.015	0.046	0.005	0.147
House	Peripheral	min	0.017	0.046	0.010	0.043	0.007	0.068
House	Peripheral	max	0.016	0.044	0.012	0.044	0.004	0.201
Store	Generic	min	0.011	0.037	0.006	0.042	0.005	0.094
Store	Generic	max	0.013	0.039	0.011	0.040	0.002	0.262
Store	Central	min	0.010	0.037	0.003	0.040	0.007	0.033
Store	Central	max	0.011	0.038	0.008	0.040	0.003	0.241
Store	Peripheral	min	0.010	0.046	0.004	0.040	0.006	0.082
Store	Peripheral	max	0.014	0.045	0.007	0.037	0.006	0.080

After 4 years

Type	Location	Value	$\bar{X}_L$	σ_L	$\bar{X}_R$	σ_R	Δ	p
House	Generic	min	0.019	0.044	0.016	0.042	0.003	0.290
House	Generic	max	0.018	0.043	0.019	0.043	-0.001	0.549
House	Central	min	0.019	0.045	0.015	0.043	0.004	0.187
House	Central	max	0.020	0.046	0.017	0.044	0.002	0.303
House	Peripheral	min	0.017	0.043	0.013	0.040	0.003	0.236
House	Peripheral	max	0.017	0.043	0.015	0.041	0.002	0.340
Store	Generic	min	0.011	0.038	0.007	0.038	0.005	0.130
Store	Generic	max	0.012	0.037	0.012	0.037	0.001	0.425
Store	Central	min	0.008	0.035	0.004	0.038	0.004	0.129
Store	Central	max	0.008	0.035	0.010	0.036	-0.001	0.623
Store	Peripheral	min	0.010	0.044	0.003	0.035	0.007	0.062
Store	Peripheral	max	0.013	0.043	0.006	0.033	0.007	0.069

After 5 years

Type	Location	Value	$\bar{X}_L$	σ_L	$\bar{X}_R$	σ_R	Δ	p
House	Generic	min	0.019	0.039	0.019	0.041	-0.000	0.514
House	Generic	max	0.017	0.039	0.023	0.042	-0.005	0.827
House	Central	min	0.019	0.042	0.019	0.042	0.000	0.466
House	Central	max	0.019	0.042	0.021	0.042	-0.001	0.594
House	Peripheral	min	0.018	0.039	0.017	0.038	0.001	0.444
House	Peripheral	max	0.016	0.038	0.019	0.040	-0.003	0.671
Store	Generic	min	0.011	0.035	0.011	0.035	0.000	0.498
Store	Generic	max	0.012	0.033	0.013	0.036	-0.002	0.630
Store	Central	min	0.009	0.032	0.008	0.033	0.000	0.486
Store	Central	max	0.009	0.031	0.012	0.034	-0.003	0.722
Store	Peripheral	min	0.011	0.037	0.005	0.028	0.007	0.092
Store	Peripheral	max	0.013	0.037	0.008	0.032	0.005	0.151

TABLE 5
Regression discontinuity estimates. Bandwidth = Optimal
Dependent variable: Average annual growth rate of local real estate prices

After 3 years

Type	Location	Value	β	se	p-value	n	bw
House	Generic	min	-0.004	0.013	0.782	427	0.234
House	Central	min	0.001	0.014	0.939	426	0.217
House	Peripheral	min	0.004	0.014	0.768	391	0.195
Store	Generic	min	0.002	0.009	0.798	427	0.342
Store	Central	min	0.006	0.010	0.546	425	0.244
Store	Peripheral	min	0.013	0.010	0.222	351	0.334
House	Generic	max	-0.009	0.010	0.353	427	0.374
House	Central	max	-0.006	0.013	0.645	426	0.249
House	Peripheral	max	-0.002	0.013	0.906	391	0.196
Store	Generic	max	-0.007	0.010	0.466	427	0.294
Store	Central	max	0.001	0.012	0.915	426	0.217
Store	Peripheral	max	0.002	0.009	0.870	351	0.313

After 4 years

Type	Location	Value	β	se	p-value	n	bw
House	Generic	min	-0.021	0.015	0.166	348	0.201
House	Central	min	-0.013	0.015	0.387	348	0.228
House	Peripheral	min	-0.012	0.009	0.177	315	0.412
Store	Generic	min	-0.002	0.012	0.840	348	0.230
Store	Central	min	-0.005	0.011	0.644	347	0.251
Store	Peripheral	min	0.010	0.009	0.276	283	0.363
House	Generic	max	-0.023	0.014	0.095	348	0.238
House	Central	max	-0.016	0.016	0.297	348	0.230
House	Peripheral	max	-0.012	0.009	0.180	315	0.446
Store	Generic	max	-0.012	0.014	0.381	348	0.202
Store	Central	max	-0.015	0.012	0.213	347	0.238
Store	Peripheral	max	-0.001	0.009	0.907	283	0.283

After 5 years

Type	Location	Value	β	se	p-value	n	bw
House	Generic	min	-0.019	0.016	0.231	228	0.203
House	Central	min	-0.011	0.016	0.507	228	0.216
House	Peripheral	min	-0.002	0.010	0.830	199	0.378
Store	Generic	min	-0.001	0.014	0.948	228	0.190
Store	Central	min	-0.001	0.012	0.933	227	0.264
Store	Peripheral	min	0.020	0.011	0.054	176	0.170
House	Generic	max	-0.021	0.016	0.188	228	0.207
House	Central	max	-0.017	0.017	0.318	228	0.202
House	Peripheral	max	0.007	0.015	0.651	199	0.158
Store	Generic	max	-0.002	0.013	0.858	228	0.228
Store	Central	max	-0.003	0.010	0.793	227	0.391
Store	Peripheral	max	0.011	0.010	0.310	176	0.183

Table 6
Regression discontinuity estimates. Bandwidth = Half
Dependent variable: Average annual growth rate of local real estate prices

After 3 years

Type	Location	Value	β	se	p-value	n	bw
House	Generic	min	-0.009	0.018	0.626	427	0.234
House	Central	min	0.003	0.019	0.868	426	0.217
House	Peripheral	min	0.009	0.021	0.692	391	0.195
Store	Generic	min	0.004	0.013	0.749	427	0.342
Store	Central	min	0.015	0.014	0.264	425	0.244
Store	Peripheral	min	0.018	0.014	0.209	351	0.334
House	Generic	max	-0.011	0.014	0.423	427	0.374
House	Central	max	-0.003	0.019	0.866	426	0.249
House	Peripheral	max	0.003	0.020	0.879	391	0.196
Store	Generic	max	-0.008	0.013	0.551	427	0.294
Store	Central	max	0.012	0.016	0.445	426	0.217
Store	Peripheral	max	0.003	0.014	0.847	351	0.313

After 4 years

Type	Location	Value	β	se	p-value	n	bw
House	Generic	min	-0.021	0.020	0.293	348	0.201
House	Central	min	-0.010	0.020	0.606	348	0.228
House	Peripheral	min	-0.009	0.013	0.470	315	0.412
Store	Generic	min	0.001	0.016	0.971	348	0.230
Store	Central	min	-0.002	0.015	0.893	347	0.251
Store	Peripheral	min	0.017	0.012	0.140	283	0.363
House	Generic	max	-0.025	0.019	0.201	348	0.238
House	Central	max	-0.011	0.022	0.604	348	0.230
House	Peripheral	max	-0.007	0.013	0.584	315	0.446
Store	Generic	max	-0.008	0.018	0.658	348	0.202
Store	Central	max	-0.008	0.016	0.610	347	0.238
Store	Peripheral	max	-0.000	0.011	0.975	283	0.283

After 5 years

Type	Location	Value	β	se	p-value	n	bw
House	Generic	min	-0.016	0.022	0.470	228	0.203
House	Central	min	-0.007	0.022	0.744	228	0.216
House	Peripheral	min	0.004	0.013	0.737	199	0.378
Store	Generic	min	0.003	0.018	0.883	228	0.190
Store	Central	min	-0.001	0.015	0.941	227	0.264
Store	Peripheral	min	0.021	0.012	0.069	176	0.170
House	Generic	max	-0.017	0.021	0.427	228	0.207
House	Central	max	-0.006	0.023	0.810	228	0.202
House	Peripheral	max	0.013	0.023	0.559	199	0.158
Store	Generic	max	-0.001	0.018	0.948	228	0.228
Store	Central	max	-0.005	0.014	0.705	227	0.391
Store	Peripheral	max	0.011	0.012	0.351	176	0.183

TABLE 7
Regression discontinuity estimates. Bandwidth = Double
Dependent variable: Average annual growth rate of local real estate prices

After 3 years

Type	Location	Value	β	se	p-value	n	bw
House	Generic	min	0.000	0.009	0.973	427	0.234
House	Central	min	0.004	0.010	0.665	426	0.217
House	Peripheral	min	0.001	0.010	0.917	391	0.195
Store	Generic	min	0.002	0.007	0.814	427	0.342
Store	Central	min	0.007	0.007	0.348	425	0.244
Store	Peripheral	min	0.007	0.008	0.387	351	0.334
House	Generic	max	-0.008	0.008	0.368	427	0.374
House	Central	max	-0.000	0.010	0.979	426	0.249
House	Peripheral	max	-0.005	0.009	0.561	391	0.196
Store	Generic	max	-0.004	0.007	0.619	427	0.294
Store	Central	max	-0.000	0.008	0.964	426	0.217
Store	Peripheral	max	0.001	0.008	0.880	351	0.313

After 4 years

Type	Location	Value	β	se	p-value	n	bw
House	Generic	min	-0.015	0.011	0.149	348	0.201
House	Central	min	-0.007	0.010	0.533	348	0.228
House	Peripheral	min	-0.011	0.008	0.177	315	0.412
Store	Generic	min	-0.000	0.009	0.993	348	0.230
Store	Central	min	-0.001	0.008	0.908	347	0.251
Store	Peripheral	min	0.006	0.008	0.480	283	0.363
House	Generic	max	-0.018	0.010	0.080	348	0.238
House	Central	max	-0.010	0.011	0.368	348	0.230
House	Peripheral	max	-0.013	0.008	0.137	315	0.446
Store	Generic	max	-0.006	0.009	0.553	348	0.202
Store	Central	max	-0.010	0.008	0.226	347	0.238
Store	Peripheral	max	-0.001	0.007	0.940	283	0.283

After 5 years

Type	Location	Value	β	se	p-value	n	bw
House	Generic	min	-0.013	0.011	0.245	228	0.203
House	Central	min	-0.004	0.012	0.724	228	0.216
House	Peripheral	min	-0.007	0.009	0.440	199	0.378
Store	Generic	min	0.003	0.010	0.802	228	0.190
Store	Central	min	0.002	0.009	0.820	227	0.264
Store	Peripheral	min	0.014	0.009	0.107	176	0.170
House	Generic	max	-0.016	0.011	0.157	228	0.207
House	Central	max	-0.009	0.012	0.439	228	0.202
House	Peripheral	max	-0.003	0.011	0.815	199	0.158
Store	Generic	max	-0.000	0.010	0.999	228	0.228
Store	Central	max	-0.004	0.009	0.626	227	0.391
Store	Peripheral	max	0.008	0.008	0.310	176	0.183

TABLE 8
Penalized regression spline estimator
Dependent variable: Average annual growth rate of local real estate prices

The effect of a left-wing majority on real estate prices after 3 years

Type	**Location**	**Value**	β	se	p-value	n
House	Generic	min	0.006	0.013	0.650	452
House	Generic	max	-0.002	0.012	0.879	452
House	Central	min	0.008	0.015	0.582	452
House	Central	max	0.003	0.014	0.839	452
House	Peripheral	min	-0.001	0.007	0.920	410
House	Peripheral	max	-0.006	0.007	0.429	410
Store	Generic	min	0.007	0.013	0.612	452
Store	Generic	max	0.001	0.012	0.932	452
Store	Central	min	0.010	0.015	0.500	451
Store	Central	max	0.003	0.014	0.801	451
Store	Peripheral	min	0.004	0.007	0.616	369
Store	Peripheral	max	-0.001	0.007	0.893	369

The effect of a left-wing majority on real estate prices after 4 years

Type	**Location**	**Value**	β	se	p-value	n
House	Generic	min	-0.002	0.008	0.791	371
House	Generic	max	-0.006	0.008	0.444	371
House	Central	min	0.001	0.010	0.940	371
House	Central	max	-0.004	0.008	0.639	371
House	Peripheral	min	-0.006	0.011	0.602	332
House	Peripheral	max	-0.006	0.009	0.537	332
Store	Generic	min	0.005	0.011	0.655	371
Store	Generic	max	0.001	0.010	0.913	371
Store	Central	min	0.005	0.011	0.630	370
Store	Central	max	-0.002	0.011	0.844	370
Store	Peripheral	min	0.009	0.007	0.225	299
Store	Peripheral	max	0.004	0.007	0.554	299

The effect of a left-wing majority on real estate prices after 5 years

Type	**Location**	**Value**	β	se	p-value	n
House	Generic	min	-0.014	0.025	0.568	248
House	Generic	max	-0.010	0.009	0.254	248
House	Central	min	-0.000	0.012	0.982	248
House	Central	max	-0.004	0.009	0.637	248
House	Peripheral	min	-0.007	0.011	0.516	213
House	Peripheral	max	-0.010	0.009	0.259	213
Store	Generic	min	0.004	0.013	0.740	248
Store	Generic	max	0.003	0.012	0.825	248
Store	Central	min	0.003	0.019	0.877	247
Store	Central	max	-0.000	0.014	0.974	247
Store	Peripheral	min	0.008	0.008	0.334	189
Store	Peripheral	max	0.003	0.009	0.693	189

TABLE 9
Self-metaregression
Dependent variable: Average annual growth rate of local real estate prices

	House		Store		Both	
	β	p-value	β	p-value	β	p-value
Estimated treatment	-0.0003	(0.973)	-0.0071	(0.325)	-0.0038	(0.494)
Central location	0.0069	(0.124)	0.0008	(0.811)	0.0038	(0.171)
Peripheral location	0.0075	(0.065)	0.0094	(0.008)	0.0084	(0.002)
Dummy for maximum price	0.0031	(0.365)	0.0076	(0.008)	0.0055	(0.012)
Time horizon	-0.0036	(0.102)	0.0004	(0.817)	-0.0014	(0.312)
Observations	54		54		108	
Prob > F	0.150		0.005		0.002	