Housing Bubbles and Support for Incumbents

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Abstract

Abstract here

1 Introduction

In this article we examine whether local changes in property values play a part in shaping the electoral success of incumbents. Our focus is on Danish Parliamentary elections between 2005 and 2015. A period in which the Danish real-estate market experienced a dramatic boom and bust, the extent of which was largely driven by policies which deregulated the housing market (Dam et al., 2011). Following the literature on economic voting (Healy and Malhotra, 2013; Lewis-Beck and Stegmaier, 2013), we want to examine whether voters held governing parties electorally accountable for how the housing bubble played out in their local context .

We do this using two complementary empirical approaches. First, we link detailed registry data on local housing prices to election results at the precinct-level across five national elections, allowing us to study whether within-district differences in property values are related to changes in support for governing parties. Second, to test the hypothesized causal mechanism, that voters are able to make inferences about government based on the state of their local housing market, we zoom in on individual voters' local contexts. Specifically, we link a two-period panel survey to uniquely detailed data from the Danish administrative registries, which allows for precise measures of how individuals' neighborhoods –measured at very low levels of aggregation– were affected by changes in house prices.

Analyzing these data, we find that changes in housing prices do leads to a change in support for governing parties; a relationship which is consistent across precinct-level and individual-level data. In particular we find that support for governing parties is 3-5 pct. higher in contexts where the price of property has increased 50 pct the last year than it is in contexts where the price of property has decreased 50 pct.

We are not the first to investigate, whether voters might draw inferences about policy outcomes from local economic conditions. A number of studies have examined the extent to which voters draw inferences about national economic conditions from local economic conditions (Books and Prysby, 1999; Reeves and Gimpel, 2012; Anderson and Roy, 2011; Ansolabehere et al., 2014; Bisgaard et al., 2015), and a number of studies have examined the extent to which voters draw inferences about whether to support incumbent politicians (Hansford and Gomez, 2015; Eisenberg and Ketcham, 2004; Kim et al., 2003; Healy and Lenz, 2014). The results from these studies are somewhat mixed, but on balance they find that voters do make inferences based on local economic conditions; asserting that the national economy declining or that incumbent politicians are doing a bad job when local economic conditions are declining.

Our study adds to these literature in two ways. It does so by examining a new type of local economic condition: property values. Compared to other features of the economy, the quality and status of one's home has received scant attention in extant literature on economic voting. A small literature exists on patrimonial economic voting (Nadeau et al., 2010; Stubager et al., 2013), that is the extent to which owning assets, like real estate, makes it more likely that you will vote for right-wing parties (see Ansell, 2014, for a similar argument). However, very few studies and have focused on whether housing prices, similarly to other economic indicators like unemployment and GDP per capita, influence electoral support for governing parties (e.g. Hopkins and Pettingill, 2015), and no studies have looked at how local differences in property values affect economic conditions.

We also adds to the existing literature by addressing some methodological shortcomings with previous studies. First, previous studies have generally relied on rather large geographical units (e.g. US counties) when estimating the effects of local economic conditions. This is potentially problematic, as the local context voters react to might not map on to these (typically large) geographical areas. Further, to the extent that these larger geographical units map unto media markets the effect of local economic conditions may be confounded with the effect of mass media communications about these issues (Bisgaard et al., 2015). Second, the studies do not generally take structural differences between local contexts into account when relating economic conditions to attitudes or voting behavior. This is potentially problematic, since it seems likely that voters will at least take some structural factors into account. In the present case, voters are probably not likely to infer much about the government based on the fact that there are differences in property values between cities and rural areas. They are more likely to infer based on the fact that properties are selling for more (or less) than they used too in their own area. More broadly, if one does not take structural differences into account, one risks conflating re-distributive concerns, i.e. voters in comparatively less well off areas having different demands from government than those in well of areas, with inferential concerns, i.e. the question of what my local contexts tell me about the national economy or about the quality of the government. Third, measures of local economic conditions are often based on samples which, while large enough to estimate precise national economic conditions, are not sufficiently precise on geographical levels (Healy and Lenz, 2014).

It is important to note that some previous studies do address some of these methodological challenges, however, our study contributes by addressing all of these shortcomings at once. We do so by (1) employing data on a very small geographical level of aggregation, (2) using panel data which removes influence of time invariant structural factors, and (3) by using detailed register data on all real estate transactions in the period under investigation.

2 Empirical Setting: A Policy Driven Boom and Bust

This is an excellent setting because:

1. Housing bubble was induced by policy. As such, not strange that voters infer something about government based on local changes in house prices.
2. We have kick-ass administrative data - all house sale registered, we can link these houses to individuals local contexts (e.g zipcodes or survey respondents).
3. We witnessed a really volatile bubble - there is gonna be a lot of changes in IV.

2.1 Identification strategy

We use a difference-in-difference approach controlling for other economic factors.

Use two different empirical approaches: Precinct level and Individual level data.

3 Precinct-level Evidence

We begin our exploration of the relationship between local housing prices and incumbent support by looking at precinct-level election returns in the Danish Parliamentary elections between 2005 and 2015. In particular, we match support for governing parties in precincts with changes in the prices of houses sold in the proximity of the precinct.

3.1 Data sources and indicators

The key dependent variable in our study is *percent of votes cast for government parties* in each voting precinct.[1] Each voting precinct corresponds to a single polling place and is this the smallest unit at which voting returns can be observed. We measure this for all precincts in five elections: 2001, 2005, 2007, 2011 and 2015. A number of precincts are redistricted between each election. This is problematic, as we want to use the precincts as part of a panel data set. There are two ways to deal with this. We can drop precincts, as their geographical boundaries get altered. This would mean dropping roughly 15 pct. of the data on the dependent variable. The other option is to fix the precincts geographical boundaries at one reference election (i.e. 2015), and then recalculate vote returns in any changed precincts, so they match up with the precincts in the reference election. Since there are a lot of minor changes in geographical boundaries from election to election, but only a few major changes, we opt for the latter, which allows us to keep these slightly altered districts.[2].

The key independent variable is *change in local housing prices*. We obtain housing price data from The Danish Mortgage Banks' Federation (*Realkreditforeningen*), which publishes quarterly data on the average price per square meters of all sales at the zip code level.[3] For each election, we calculate change in housing prices as the percentage

[1]Results are similar for only using the prime minister's party.

[2]For details of how returns from the redistricted precincts are calculated, see Søren Risbjerg Thomsen's research note at `bit.ly/205OlPi`. We use 2015 as a reference elections

[3]Available at `statistik.realkreditforeningen.dk`.

change in the quarter of the election compared to the same quarter one year before.

Zip codes are a substantively interesting level of aggregation when it comes to the price of housing, as it is the level at which house prices are most often reported in Denmark (cf. the fact they are published by The Danish Mortgage Banks' Federation). However, since the dependent variable is observed at the voting precinct level, merging these observations is not trivial. The easiest solution would be to extract the zip code of the address of each polling place and link the polling place to housing prices in that zip code. Unfortunately, full addresses are not available for all polling places. Instead, we take a three-stage approach to linking polling places to zip codes. First, we extract the street address and higher-level voting district of each polling place and add 'Denmark' at the end of the string (the full resulting string is of the format 'Streetname X, City, Denmark'). Second, we pass this string to the Google Maps API, which geocodes the string and returns latitude-longitude coordinates.[4] Third and last, we pass these coordinates to the Danish Addresses Web API (DAWA), a public service provided by the Danish Geodata Agency.[5] The DAWA returns the zip code for each address, allowing us to link the two sources of data. Since voting returns are thus statistically speaking nested inside zip codes, we estimate models using standard errors clustered at the zip code level.

We use changes in housing prices rather than the level of housing prices. This is in part because previous literature on economic voting has focused on prices they have focused on changes (i.e. inflation) rather than levels, and in part because changes in housing prices should be more salient than the level. As such, changes in the house price will mean either very short or very long turnaround time for house sales, as sellers and buyers try to adjust to the new prices, leaving visible traces in the immediate context – such as the amount of for sale signs, and stories from neighbors about the speed at which their house was sold.

In addition to the main independent variable, we measure both the unemployment rate and median income at the zip-code level. We also measure the population density

[4] Available at `developers.google.com/maps/documentation/geocoding/intro`.

[5] Available at `dawa.aws.dk`.

($log(inhabitants/km^2)$) of the municipality in which the precinct is located. These are all population based measures calculated from registers provided by Statistics Denmark.

3.2 Estimating the average effect of housing prices

In table 1 we report estimates from a set of linear regression of electoral support for governing parties using changes in local housing prices as the primary independent variable. For all models we use robust standard errors clustered at the precinct-level.

In the first column we present a simple linear regression between electoral support and changes in housing prices. In the second column we include the unemployment rate and median income as controls for the state of the economy in the precinct. In model 3 we add precinct fixed effects. In model 4 we add year fixed effects, which gives us a difference-in-difference model with controls for trends in the economic situation.

Table 1: Estimated effects of house prices on electoral support for governing parties.

	(1)	(2)	(3)	(4)
Δ housing price	0.104**	0.055**	0.040**	0.030**
	(0.008)	(0.008)	(0.007)	(0.007)
Unemployment rate		-1.569**	-0.484**	-1.893**
		(0.057)	(0.086)	(0.221)
Log(Median income)		-0.259**	-0.333**	-0.890**
		(0.010)	(0.010)	(0.064)
Precinct FE			✓	✓
Year FE				✓
Observations	4197	4177	4177	4177
RMSE	8.407	6.737	5.501	5.324

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$

As can be seen from table 1, there is a statistically significant and positive effect of changes in housing prices, indicating that a larger fraction of the electorate casts their vote for governing parties in precincts where housing prices are on the rise. In the most demanding specification the effect is 0.03. This implies that if the price of housing sold in the municipality in the last quarter before the election is twice that of the housing sold in the same quarter the year before, governing parties will get 3.2 percentage points support.

Unsurprisingly, the effect is larger in the models which use fewer controls – the effect size drops from 0.1 to 0.06 when introducing the economic controls, and drops the additional 0.2 when introducing the time and precinct fixed effects. This seems to suggest that having a difference in difference approach and detailed information about other aspects of the local economy is, in fact, important when identifying the effect of local housing markets.

Table 2: Assesing the Robustness of the Precinct-level Evidence

	(1)	(2)	(3)	(4)
Δ housing price (2 years)	0.129**	0.037**	0.022**	0.020**
	(0.007)	(0.007)	(0.007)	(0.007)
Δ housing price (lag DV)	0.043**	-0.039**	-0.034**	0.005
	(0.004)	(0.003)	(0.003)	(0.003)
Δ housing price (FD controls)	0.104**	0.073**	0.086**	0.058**
	(0.008)	(0.008)	(0.009)	(0.008)
Δ housing price (FD DV)	0.037**	0.034**	0.052**	0.019**
	(0.004)	(0.004)	(0.005)	(0.004)
Δ housing price (negative)	-0.081***	-0.072***	-0.057**	-0.030
	(0.022)	(0.017)	(0.019)	(0.019)
Δ housing price (positive)	0.116***	0.045***	0.031**	0.029*
	(0.012)	(0.011)	(0.011)	(0.011)
Economic controls		✓	✓	✓
Precinct FE			✓	✓
Year FE				✓

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$

How robust are these results? In table 2 we try to reanalyze the models above in different ways, to get a more complete picture of the statistical evidence for (or against) the importance of local housing markets for incumbent support.

We begin by looking at whether the time period, i.e. year-over-year changes, matter for the result. To do so we reestimate the models from table 1 using the change over two years instead of one. The results are fairly similar using this measure of more long run changes in housing prices, however, the estimated effects tend to be smaller than what we found above. This fits nicely with previous work showing that voters are, by and large, myopic when it comes to relating economic indicators to incumbent support

(Healy and Malhotra, 2009).

Next, we look at whether the governing parties were already getting more popular in places where house prices would eventually go up and getting less popular in places where house prices would eventually go down. This is important, because a key assumption underlying the difference-in-difference design, is that no such prior trends are present (i.e. the parallel trends assumption). To do this we estimate the same models as before, using support for the governing party at the last election as the dependent variable – the lag of the dependent variable. As can be seen from the second row of table 2 there is an significant effect of housing prices in the less restrictive models. However, in the final model the estimated effect of housing prices is 0.005, less than a sixth of the estimate in the previous model, indicating that their was no identifiable difference in how incumbent support trended in areas where house prices would increase in the future and in areas where house prices would decrease.

As mentioned above, we use changes in house prices rather than levels. However, in our models we control for the level of income and the level of unemployment. One could imagine, that this means that we fail to capture something important about how the economic status of the precinct is changing, which could, in turn, be driving our results. To test this we re-estimate the different models using first-differenced (FD) controls. If anything this strengthens the results, with the estimated effects of housing prices roughly doubling in size, as can be seen in the fourth row of table 2. We also estimated a complete change model, using a first-difference dependent variable as well. The results from these can be seen in the fifth row of table 2. The estimated effect size of housing prices in the completely differenced model is somewhat smaller than what was identified in table 1, but it remains statistically significant.

As a final robustness test we split the housing price variable in two, creating one variable which measures the size of positive changes, and which is zero if there is a negative change, and one variable which measures the size of negative changes, and which is zero if there is a positive change. This makes it possible to study the effect of increases and decreases in housing prices separately. We report the result of these analyses in the the two last rows of table 2. As can be seen the effect of negative changes an postive changes do not differ - they are roughly 0.03. This is important because it suggests that incumbent politicians are not only rewarded for the boom or punished for the bust. Instead, voters seem to first reward governing politicians when house prices are on the rise, and then punish them when they fall.

Taken together, these analyses suggest that there was a positive effect of housing prices on support for governing parties, and that we have been successful in identifying the effect.

4 Individual-level evidence

We continue our study of how local housing prices shape incumbent support by tracking individuals intent to vote for governing parties in a two wave panel survey collected between 2002 and 2011. We link these individuals to the prices of houses sold in their residential context using the national Danish registers. The registers contain very detailed information about all individuals legally residing in Denmark, including the exact geographical location of their residence, the price of any real estate they sell, and a range of other characteristics (Thygesen et al., 2011). This makes it possible to calculate the distance between the individuals in the survey and all other individuals in Denmark and, in turn, the distance to any individuals who are selling their home.

Before describing these data in more detail, It is important to highlight what we hope to gain from using an additional data set. While it is always desirable to try and replicate findings using a different methodology and a different set of data, linking individual level data to these detailed registers has some advantages over the the precinct-level data used above. The flexibility and detail of the Danish registers makes it possible to look at multiple levels of aggregation – not just official levels of aggregation, such as zip codes. This makes it possible to eliminate concerns related to the modifiable area unit problem (MAUP), in that we can rule out that the findings are tied to a specific way of geographically aggregating house prices. This approach also makes it is possible to link house prices to individual level characteristics such as attitudes, home ownership etc. This is important, because we can use these variables to rule out alternative explanations and to explore moderators of the housing price effects, which might, in turn, make it possible to get at the causal mechanism underlying the effect.

4.1 Data Sources and Indicators

Our independent variable is once again year-over-year changes in housing prices in the residential context of the respondent. We measure the change by comparing the price of housing sold in the quarter prior to the data collection and the price of housing sold in the same quarter the year before. Unlike for the data used above we do not have data on prices per square meter. This makes our change measure more sensitive to random variation in the types of houses put up for sales in the two time periods we compare. That is, some of the change from year to year might be due to the fact that larger houses were put up for sale. To take this, as well as other structural differences in the type of houses put up for sale, into account we divide the sales price of each house by its publicly valued price , before.[6] As such, we calculate a price change adjusted for the public valuation of the housing sold in the particular quarter. [7]

We estimate these changes in house prices within each survey respondents residential context, measuring residential context in three different ways. First, and similar to what we did for the precinct-data, we use the respondents zip-code, comparing houses sold within the same zip code a year apart. Second, we look at the prices of the 20 or 40 units of housing sold closest to the respondents own home, comparing the prices of houses sold in the immediate proximity of the respondent to that of houses sold one year earlier. Third, we look at the price of houses sold within a fixed radius of 500 or 1500 meters of the respondent. These latter ways of defining the respondents residential contexts have

[6]The Danish government makes a conservative estimate of the price of all houses in Denmark every two years which is used to calculate property taxes. The public evaluation was constant across the time periods we use to estimate house price changes.

[7]We make the following exceptions: (1) Sales of part of a house or apartment (10 pct. of all sales). (2) Sales of commercial real estate (9 pct). (3) Sales of apartments or houses valued at more than DKK 10 million (0.2 pct. of all sales) (4) Sales with what 'Statistics Denmark' calls an irregular price (i.e. if the sales price is more than three times the valuation or less than forty percent of the valuation, 6 pct. of all sales).

the benefit of being centered on the respondent, alleviating the problem that the context of a respondent living on the rim of one zip-code might be better represented by an adjoining zip-code. Note also that these two types of residential context is different in other important ways too – whereas the first method takes number of sales as fixed, but varies the geographical dispersion of these sales, the second method holds geographical dispersion fixed, but varies the number of sales. Since it is not obvious which of the three ways of measuring the state local housing market is superior, we use all three in the analysis below.

To get at support for governing parties at the individual level we utilize a two-wave panel survey, constructed by re-interviewing respondents who had participated in the Danish Version of the European Social Survey (ESS); a nationally representative survey. All in all 1,745 people were re-interviewed in the winter of 2011-12, with some of these having been interviewed for the first time in 2007-8, some in 2003-4 and some in 2001-2 – corresponding to rounds five, three and one of the ESS.

The respondents in the ESS in Denmark are randomly sampled from the national civil registry, and therefore the civil registration numbers were retained by the data collection agency. This made it possible to identify the respondents for a second interview, and made it possible to link the respondents to the national registers. From the survey, we use the following question: "What party did you vote for at the last parliamentary election?" Respondents were presented with all the parties which ran at the previous election. For the analyses we create a dummy variable indicating whether the respondent voted for the incumbent party.

In addition to these primary variables from the survey and the registers we also include a number of additional variables which we use in the analysis for statistical control, interactive analyses and placebo tests. From the registers we include unemployment and income both for the individual respondent and in this respondents immediate context, we include whether the respondent owns his or her own home, and how long a period expired between the day the respondent was surveyed and the day that this individual relocated. From the survey we include an item on the respondents ideological orientation, measured on a ten point scale going from 'Left' to 'Right', and rescaled to go between zero and one.

4.2 Average Effect

In table 3 we report estimates from a set of linear probability models (LPM), setting the probability of voting for for a party in government as a function of changes in local housing prices. We estimate the models using a linear regression with fixed effects for the respondent, and fixed effect for which of the four different survey rounds the respondent is participating (ESS round 1, 3, 5 or the re-interview). All models include controls for the average income and unemployment rate in the respondents context, as well as indicators of the respondent's own income and whether someone in the household is unemployed. As such, we end up with a difference-in-difference model which controls for trends in the economic situation – however, unlike for the precinct level data we can now control for trends in both the individuals personal economy and for the economy of the larger context. We use robust standard errors, clustered at the individual level.

All models include the same set of variables, but they differ in how the contextual variables are operationalized. In column one we present a model where housing price change is calculated based on the 20 closest sales (cf. above), and the other contextual variables – average income and unemployment rate – is measured within a 500 meter radius of the respondent. In column two we use the 40 closest houses, but leaves the remaining variables operationalized as in column one. In column three and four we operationalize all contextual variables, sales, unemployment rate and average income, as 1000 and 1500 meter radii around the respondent. Finally, in column five, we examine sales at the level of zip-codes, but the other contextual variables are calculated based on people within a 1500 meter radii around the respondent.

The estimated effect sizes across these different models is consistently positive, although the size of the effect varies somewhat, going from 0.04 in column one to 0.11 in column 4. The effect is only statistical in one of the five specification – the one which

Table 3: Linear Regression of Voting for Governing party

	20 Closest	40 Closest	1000 metres	1500 metres	Zip code
Δ housing prices	0.035	0.056	0.064	0.114*	0.063
	(0.036)	(0.044)	(0.052)	(0.051)	(0.056)
Unemployment rate	0.052	0.056	-0.439	0.755	0.796^{+}
	(0.290)	(0.289)	(0.627)	(0.575)	(0.422)
Average income	-0.004	-0.004	-0.005	-0.005	-0.006
	(0.003)	(0.003)	(0.007)	(0.007)	(0.006)
Personal income	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
Unemployed (household)	-0.032	-0.033	-0.066	-0.048	-0.034
	(0.035)	(0.035)	(0.043)	(0.040)	(0.036)
Round FE	Yes	Yes	Yes	Yes	Yes
Voter FE	Yes	Yes	Yes	Yes	Yes
Observations	3479	3479	2790	2992	3384

Standard errors in parentheses
$^{+}$ $p < 0.1$, * $p < 0.05$

focus on the 1500 meter context.

It is hard to say for sure that these results did not happen. However, as can be seen from the large standard errors

Figure 1 examines differences between the two...

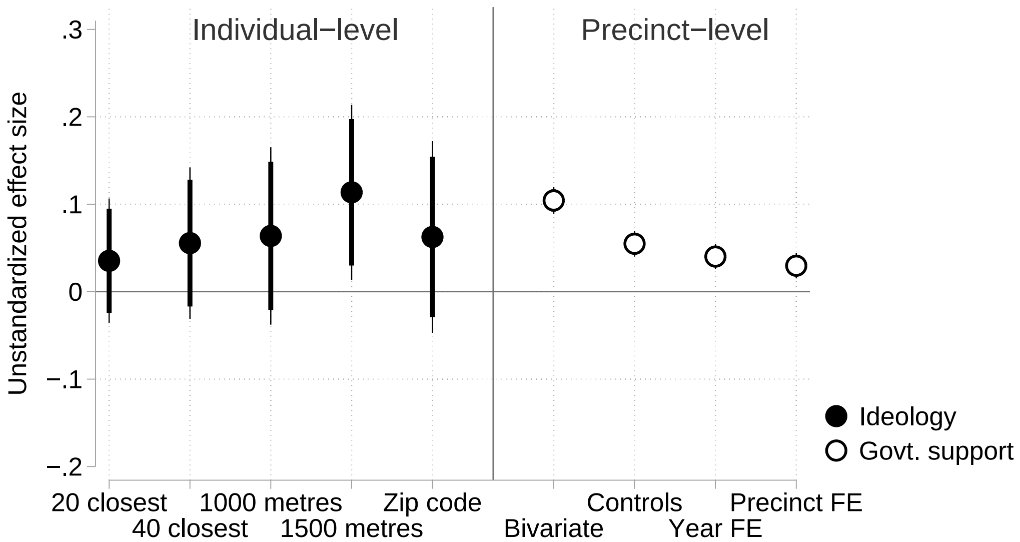

Figure 1: Effects of Housing Prices across levels of analysis with 90 and 95 pct. Confidence Intervals

4.3 Self Interest, Ideology and Inference

Ideology, Self Interest or Inference

(1) Home-ownership

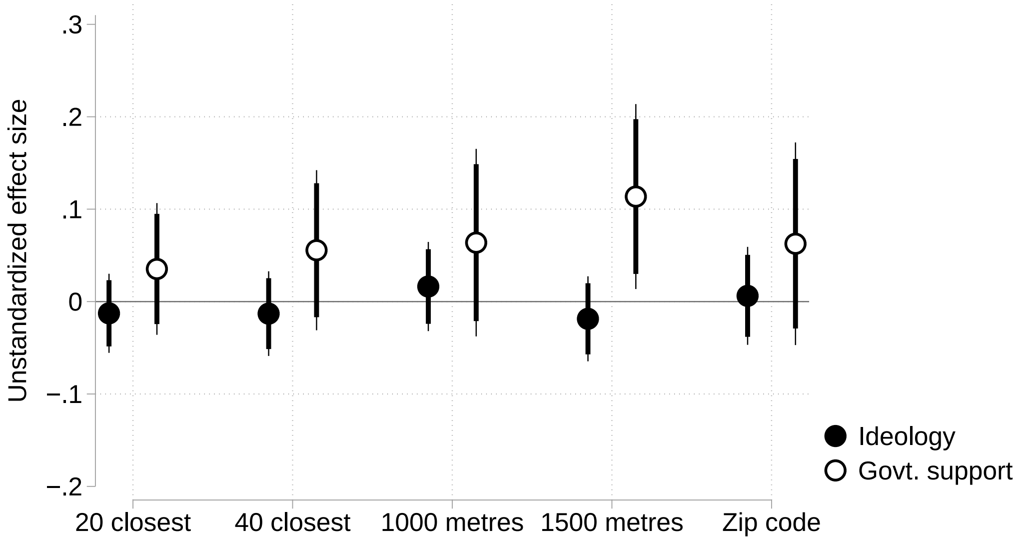

Figure 2: Effects of Housing Prices on Ideological Orientation and Support for Governing Parties with 90 and 95 pct. Confidence Intervals

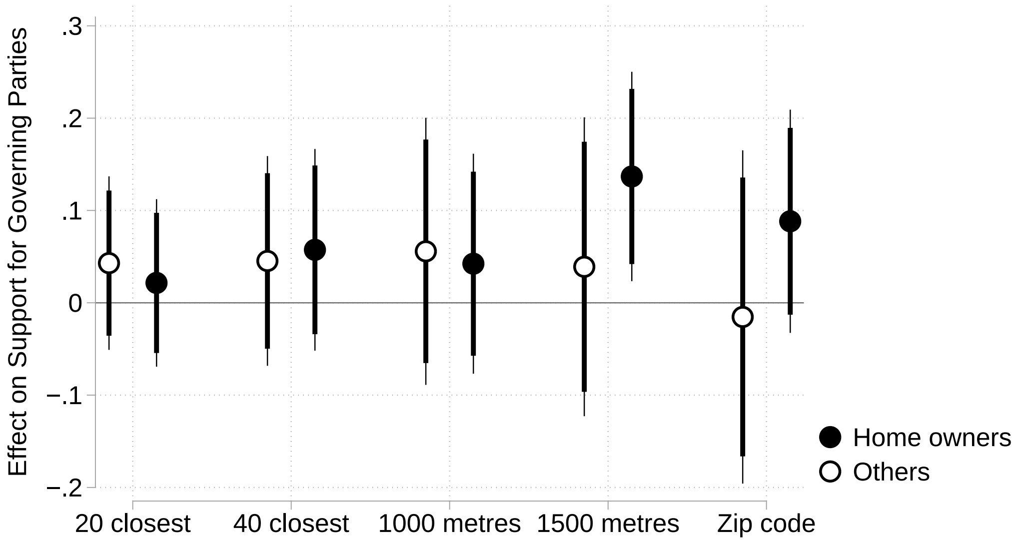

Figure 3: Effects of Housing Prices for those who own their home and those who do not with 90 and 95 pct. Confidence Intervals

(2) Moving

(3) Ideology

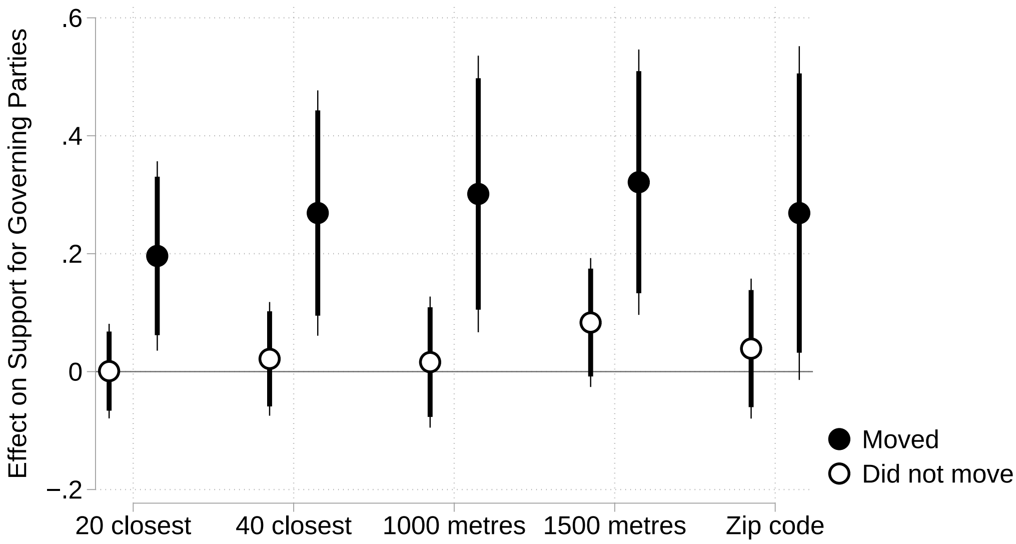

Figure 4: Effects of Housing Prices for those who had just or were going to move soon and those who did not with 90 and 95 pct. Confidence Intervals

5 Conclusion

Conclusion

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Supplementary materials

S1:Descriptive statistics

Table of descriptive statistics

S2: Common trends in precinct-level data

In table 4 we look at whether housing prices can predict changes in support for governing parties in the last period.

Table 4: Estimated effects of house prices on electoral support for governing parties at t-1.

	(1)	(2)	(3)	(4)
Δ housing price (lag DV)	0.043**	-0.039**	-0.034**	0.005
	(0.004)	(0.003)	(0.003)	(0.003)
Precinct FE			✓	✓
Year FE				✓
Observations	3059	3049	3049	3049
RMSE	4.315	2.221	1.654	1.447

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$

S3: Alternative estimation in individual-level data

In table 5 we estimate a conditional logit model on the panel data. We find similar effects as in linear model above.

Table 5: Conditional Logit Model of Voting for Governing party

	10 Closest	20 Closest	40 Closest	500 metres	1000 metres	1500 metres
Δ housing prices	0.687	0.631	1.015	0.557	0.752	0.837
	(0.431)	(0.559)	(0.766)	(0.627)	(0.871)	(0.962)
Unemployment rate	-1.950	-2.044	-2.109	-9.478	2.381	15.116^{+}
	(3.126)	(3.142)	(3.068)	(6.613)	(6.747)	(7.775)
Average income	-0.040	-0.035	-0.036	-0.046	-0.055	-0.081
	(0.040)	(0.039)	(0.039)	(0.071)	(0.059)	(0.075)
Personal income	-0.001	-0.001	-0.001	-0.009	-0.002	-0.003
	(0.004)	(0.004)	(0.004)	(0.017)	(0.004)	(0.005)
Years of Education	0.042	0.030	0.017	0.128	0.023	0.027
	(0.171)	(0.170)	(0.171)	(0.206)	(0.210)	(0.218)
Round FE	Yes	Yes	Yes	Yes	Yes	Yes
Voter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	562	562	562	420	504	528

Standard errors in parentheses
$^{+}$ $p < 0.1$, * $p < 0.05$

S3: Heterogeneous effects in precinct-level data

Tables 6 and 7 examines the heterogeneity of the effects in the precinct level data.

Table 6: Estimated effects of house prices on electoral support for governing parties across positive and negative changes.

	(1)	(2)	(3)	(4)
Δ housing price (negative)	-0.081***	-0.072***	-0.056**	-0.029
	(0.022)	(0.017)	(0.019)	(0.019)
Δ housing price (positive)	0.116***	0.046***	0.032**	0.030**
	(0.012)	(0.011)	(0.011)	(0.011)
Precinct FE			✓	✓
Year FE				✓
Test of no difference (p)	0.25	0.27	0.36	0.96
Observations	4197	4177	4177	4177
RMSE	8.41	6.74	5.50	5.32

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Estimated effects of house prices on electoral support for governing parties across volatility.

	(1)	(2)	(3)	(4)
Δ housing price	-0.01	-0.20**	-0.18**	-0.17**
	(0.03)	(0.02)	(0.02)	(0.03)
Log(density)	-5.49**	-2.69**	0.00	0.00
	(0.37)	(0.41)	(.)	(.)
Δ housing price × Log(density)	0.05**	0.12**	0.10**	0.10**
	(0.01)	(0.01)	(0.01)	(0.01)
Precinct FE			✓	✓
Year FE				✓
Observations	4191	4171	4171	4171
RMSE	8.43	6.81	5.50	5.40

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$

S4: Heterogeneous treatment effects in individual-level data

Tables 8 and 9 examines the heterogeneity of the effects in the individual level data.

Table 8: Linear Regression of Voting for Governing party

	10 Closest	20 Closest	40 Closest	500 metres	1000 metres	1500 metres
Δ housing prices (positive)	-0.020	-0.037	0.034	-0.053	-0.005	-0.021
	(0.062)	(0.072)	(0.083)	(0.095)	(0.088)	(0.089)
Δ housing prices (negative)	0.070^{+}	0.071	0.137^{+}	0.063	0.101	0.129^{+}
	(0.041)	(0.065)	(0.075)	(0.074)	(0.063)	(0.075)
Unemployment rate	0.040	0.050	0.044	-0.527	0.035	0.847^{+}
	(0.291)	(0.291)	(0.292)	(0.462)	(0.495)	(0.490)
Average income	-0.004	-0.004	-0.004	-0.004	-0.006	-0.006
	(0.003)	(0.003)	(0.003)	(0.004)	(0.006)	(0.006)
Personal income	-0.000	-0.000	-0.000	-0.001*	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Unemployed (household)	-0.032	-0.031	-0.031	-0.081^{+}	-0.050	-0.041
	(0.035)	(0.035)	(0.035)	(0.041)	(0.038)	(0.037)
Round FE	Yes	Yes	Yes	Yes	Yes	Yes
Voter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3473	3473	3473	2846	3173	3313

Standard errors in parentheses
$^{+}$ $p < 0.1$, * $p < 0.05$

Table 9: Linear Regression of Voting for Governing party

	10 Closest	20 Closest	40 Closest	500 metres	1000 metres	15
Δ housing prices	-0.007	-0.084	-0.166	0.014	-0.127	
	(0.078)	(0.107)	(0.137)	(0.173)	(0.157)	
Log(No. of ppl in context)	-0.010	-0.010	-0.010	0.006	-0.001	
	(0.010)	(0.010)	(0.010)	(0.020)	(0.015)	
Δ housing prices $\times$ Log(No. of ppl in context)	0.008	0.021	0.031^{+}	0.006	0.024	
	(0.010)	(0.014)	(0.019)	(0.023)	(0.019)	
Unemployment rate	0.098	0.102	0.114	-0.580	0.035	
	(0.297)	(0.295)	(0.293)	(0.484)	(0.557)	
Average income	-0.004	-0.004	-0.004	-0.004	-0.007	
	(0.003)	(0.003)	(0.003)	(0.004)	(0.006)	
Personal income	-0.000	-0.000	-0.000	-0.001*	-0.000	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	
Unemployed (household)	-0.034	-0.034	-0.034	-0.081^{+}	-0.050	
	(0.035)	(0.035)	(0.035)	(0.042)	(0.038)	
Round FE	Yes	Yes	Yes	Yes	Yes	
Voter FE	Yes	Yes	Yes	Yes	Yes	
Observations	3473	3473	3473	2846	3173	

Standard errors in parentheses
$^{+}$ $p < 0.1$, * $p < 0.05$