Online Appendix:

When Do Citizens Respond Politically to the Local Economy? Evidence from Registry Data on Local Housing Markets

Martin Vinæs Larsen* Frederik Hjorth† Peter Thisted Dinesen‡

Kim Mannemar Sønderskov §

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*Corresponding author. mvl@ps.au.dk. Department of Political Science, Aarhus University.

†Department of Political Science, University of Copenhagen.

‡Department of Political Science, University of Copenhagen.

§Department of Political Science, Aarhus University.

A Creating a Balanced Precinct Panel and Linking Precincts to Zip Codes

A number of precincts are redistricted between each election, which is problematic, as we want to use the precincts as part of a panel data set. One way to deal with this is to drop precincts if their geographical boundaries were altered. Using this strategy, roughly 15 pct. of the data on the dependent variable would be dropped. We therefore opt for an alternative solution, namely to fix the precincts geographical boundaries at one reference election (2015), and then recalculate vote returns in any changed precincts to match up with precincts in the reference election. We prefer this strategy, allowing us to use the full sample of precincts, as the changes in geographical boundaries from election to election are generally minor with only a few major changes.[1] The results presented in the main article do not change substantially if we drop precincts that change boundaries, see Appendix J.

Zip codes are a substantively interesting level of aggregation when it comes to the price of housing, as it is the level at which housing prices are most often reported in Denmark (evidenced by the fact they are published by The Danish Mortgage Banks' Federation). However, merging zip code-level data on housing prices to the precinct-level data on electoral outcomes is non-trivial. Ideally we would 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 use 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 (the full resulting string is of the format 'Streetname streetnumber, City, Denmark'). Second, we pass this string to the Google Maps API, which geocodes the string and returns latitude-longitude coordinates.[2] Third and last, we pass these coordinates to the Danish Addresses Web API (DAWA), a public service provided by the Danish Geodata Agency.[3] The DAWA returns the zip code for each address, allowing us to link polling places to zip codes.

[1] For details of how returns from the redistricted precincts are calculated, see Søren Risbjerg Thomsen's research note at `bit.ly/205O1Pi`.

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

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

B Estimates of Local Housing Prices

We use all housing sales registered in the national register EJSA except for those that fall into one or more of the following categories:

1. Sales of part of a house or apartment (10 pct. of all sales). We exclude these as these are typically quasi-commercial, as part of a house or apartment is sold to a business. Many of these sales are between farmers who sell and buy land from one another.

2. Sales of commercial real estate (9 pct). These are excluded because we are interested in residential real-estate.

3. Sales of apartments or houses valued at more than DKK 10 million (0.2 pct. of all sales). These are considered outliers, which tell us little about the state of the local housing market experienced by the typical Danish voter.

4. Sales with what Statistics Denmark calls an irregular price (i.e. if the sales price is more than three times the public valuation or less than forty percent of the valuation, 6 pct. of all sales). This will usually mean that sellers and buyers are not part of the regular housing market (e.g., family members or friends selling or buying).

For more details on the EJSA register see `http://www.dst.dk/`.

C Descriptive Statistics

Descriptive statistics for the precinct-level data can be found in Table C1. Descriptive statistics for the individual-level data can be found in Table C2. We do not include maximum and minimum values for the individual-level variables, because this would go against the data protection guidelines provided by Statistics Denmark.

Figure C1 graphs the distribution of housing price changes in the precinct-level data.

Table C1: Descriptive statistics, Precinct-level data

	Mean	SD	Min	Max	n
Support for Governing Parties (pct.)	35.92	9.58	6.01	75.35	5476
Support for Prime Minister party (pct.)	29.12	8.47	4.57	58.72	5476
Support for Social Democratic Party (pct.)	24.51	6.14	4.25	52.25	5476
Support for Social Liberal Party (pct.)	5.86	3.55	0.00	27.77	5476
Support for Conservative Party (pct.)	6.69	4.39	0.28	35.29	5476
Support for Liberal Party (pct.)	28.21	9.20	3.82	58.72	5476
Change in Support for Governing Parties (pct.)	-3.87	2.91	-17.97	9.97	4107
Log(voters)	7.65	0.87	4.08	10.03	5476
Δ housing price	4.36	14.37	-41.94	127.12	4199
Δ housing price (2 years)	11.57	17.88	-55.36	167.12	4183
Δ housing price (positive)	7.89	10.47	0.00	127.12	4199
Δ housing price (negative)	3.53	6.41	0.00	41.94	4199
Trades	46.44	51.22	0.00	459.00	4980
Log(trades)	3.25	1.21	0.00	6.13	4928
Median income (1000 DKK)	149.03	18.68	96.36	267.86	5000
Unemployment rate	11.99	2.85	4.54	30.26	5000
Δ median income	3.29	3.02	-94.40	21.58	5000
Δ unemployment rate	-0.46	0.74	-11.13	5.88	5000
7 Quarter (housing price)	8.44	16.66	-53.68	126.19	4124
6 Quarter (housing price)	6.44	15.22	-50.99	70.61	4149
5 Quarter (housing price)	5.86	16.35	-53.20	144.27	4147
3 Quarter (housing price)	3.62	13.75	-54.90	91.10	4113
2 Quarter (housing price)	3.07	12.67	-51.36	106.17	4100
1 Quarter (housing price)	0.93	11.56	-40.73	69.42	4190
Income growth (pct.)	2.33	1.66	-37.58	16.75	5000
Estimated vote returns	0.15	0.35	0.00	1.00	5476
Change in Log(Trades)	-0.02	0.57	-2.77	2.43	3664

Δ signifies year over year change; the word ‘changes’ signify election over election changes.

Table C2: Descriptive Statistics, Individual-level data

Variable	Mean	Std. Dev.	N
Left/Right Scale	0.532	0.217	3350
Unemployed (household)	0.062	0.241	3483
Years of schooling	12.835	2.829	3437
Unemployment rate 1000 meters	0.067	0.035	3481
Unemployment rate 1500 meters	0.068	0.031	3481
Home Owner	0.736	0.441	3451
Average income zip code	17.928	3.532	3485
Unemployment rate zip code	0.069	0.028	3485
Δ housing price 1000 meters	-0.05	0.236	2792
Average income 1000 meters	17.915	3.905	3481
Δ housing price 1500 meters	-0.051	0.227	2994
Average income 1500 meters	17.892	3.624	3481
Personal income	20.859	22.277	3486
Δ housing price zip code	-0.066	0.138	3396
Δ housing price 20 closest	-0.046	0.218	3482
Δ housing price 40 closest	-0.05	0.182	3482
Seller	0.019	0.138	3405
Buyer	0.014	0.117	3405
Government Voter	0.299	0.458	3486
Prime Minister Voter	0.236	0.425	3486
Mover	0.077	0.267	3486
Outside Market	0.042	0.2	3486
Within Market	0.036	0.185	3486

Figure C1: Distribution of the year-over-year changes in housing prices (precinct-level data).

D Party Specific Analysis in Precinct-level Data

Table D1 presents the estimates for the model underlying Figure 4.

To conduct this analysis we created a dataset that included all precinct-years twice: once with the left-wing coalition support and once with right-wing coalition support. The housing price effect is then conditioned on a two-way interaction between a dummy indicating government coalition (i.e., whether we are predicting support for left-wing or right-wing government coalition) and a dummy indicating whether this coalition is in office. We include precinct and year fixed effects, as well as the local economic controls. Standard errors are clustered at the party-by-precinct level to take within-precinct serial correlation in party-specific electoral support into account.

Table D1: Party Specific Analysis.

	(1)
Δ housing price	0.083*
	(0.007)
Δ housing price × Left-wing Incumbent	-0.123*
	(0.016)
Δ housing price × Left-wing Support	-0.146*
	(0.010)
Left-wing Incumbent × Left-wing Support	10.651*
	(0.233)
Δ housing price × Left-wing Incumbent × Left-wing Support	0.284*
	(0.025)
Unemployment rate	0.104
	(0.080)
Income growth (pct.)	0.005
	(0.040)
Median income (1000 DKK)	-0.003
	(0.022)
Observations	8358

Standard errors in parentheses
Model includes year and precinct fixed effects.
* $p < 0.05$

E Full Models from Robustness Checks of Precinct-level Evidence

Table E1 presents the models shown in Table 3 with covariates. The different models are described in detail in the main text. The most important takeaway is that across specifications and across different definitions of the housing price variable, we find that that the estimated additive effect of changes in housing prices and the estimated interaction effect between housing prices and logged number of trades are consistently positive and statistically significant.

Table E1: Robustness checks of the Precinct-level data.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Δ housing price			0.055*	-0.101*	0.007*	0.005	0.061*	-0.213*			0.016*	-0.043
			(0.009)	(0.031)	(0.004)	(0.004)	(0.008)	(0.029)			(0.008)	(0.022)
Δ housing price (2 years)	0.018*	-0.040*										
	(0.007)	(0.016)										
Δ housing price (positive)									0.028*	-0.232*		
									(0.011)	(0.041)		
Δ housing price (negative)									-0.028	-0.169*		
									(0.019)	(0.061)		
Log(trades)		1.977*		3.406*		0.891*		0.182*		1.274*		2.438*
		(0.479)		(0.460)		(0.111)		(0.082)		(0.546)		(0.468)
Δ housing price × Log(trades)				0.047*		0.013*		0.092*				0.017*
				(0.010)		(0.006)		(0.010)				(0.007)
Δ housing price (2 years) × Log(trades)		0.017*										
		(0.005)										
Δ housing price (positive) × Log(trades)										0.081*		
										(0.013)		
Δ housing price (negative) × Log(trades)										0.049*		
										(0.019)		
Median income (1000 DKK)	-0.962*	-0.920*					-0.033*	-0.023*	-0.907*	-0.864*	-0.702*	-0.651*
	(0.065)	(0.066)					(0.008)	(0.008)	(0.070)	(0.070)	(0.060)	(0.059)
Income growth (pct.)	0.198*	0.077	3.004*	2.013*	-0.940*	-0.912*	-0.200*	-0.286*	0.156	-0.044	0.122	-0.011
	(0.097)	(0.100)	(0.888)	(0.880)	(0.239)	(0.241)	(0.098)	(0.100)	(0.103)	(0.107)	(0.099)	(0.102)
Unemployment rate	-1.942*	-1.664*					-0.224*	-0.203*	-1.902*	-1.725*	-2.104*	-1.830*
	(0.226)	(0.223)					(0.040)	(0.041)	(0.222)	(0.222)	(0.218)	(0.211)
Δ median income			-2.477*	-1.926*	0.645*	0.625*						
			(0.612)	(0.605)	(0.164)	(0.167)						
Δ unemployment rate			0.158	0.105	-0.281*	-0.279*						
			(0.287)	(0.283)	(0.140)	(0.138)						
L.Support for Governing Parties (pct.)							0.516*	0.518*				
							(0.009)	(0.008)				
Precinct FE	✓	✓	✓	✓	✓	✓			✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	4163	4163	4179	4179	3091	3090	3091	3091	4179	4179	4179	4179
RMSE	5.244	5.218	6.679	6.572	2.549	2.523	6.250	6.148	5.325	5.279	5.215	5.181

Standard errors in parentheses
Models 5 and 6 have a first-differenced version of the dependent variable, models 11 and 12 have support for the prime minister party as the dependent variable.
* $p < 0.05$

F Examining Different Lags for the Housing Price Variable

In the main analysis we look at year-over-year changes in housing prices. However, we have housing price data on a quarterly basis, making it possible to look at a number of different time frames. We chose year-over-year changes to strike a reasonable balance between the stylized fact that voters are myopic (Healy and Lenz 2014) while they may at the same time not notice very short run changes (i.e., quarter-over-quarter changes) in housing markets. Even so, there are no clear guidelines for the most appropriate time horizon for changes in housing prices, and we therefore also examined alternatives to the year-over-year lag structure. To that end, Table F1 presents estimates of our difference in difference model with controls using changes in housing prices measured over one, two, three, four, five, six, seven and eight quarters.

This analysis suggests that voters do not respond to short-run changes. At the same time, however, it is not only the year-over-year change that is statistically and substantively significant. Both the two-year change and the 6-quarter change variable have a significant impact of roughly the same size as the year-over-year measure used in the analyses in the article. All in all, this suggest that voters do not respond to very short-run shocks to housing markets (i.e. occurring less than within a year of voting), but they do, relatively consistently, respond to shocks that last between one and two years.

Table F1: Models with different definitions of the change in housing price variable

	(1) 1 QTR	(2) 2 QTR	(3) 3 QTR	(4) 1 YRS	(5) 5 QTR	(6) 6 QTR	(7) 7 QTR	(8) 2 YRS
Δ housing price	-0.002	-0.018	-0.008	0.028*	0.009	0.029*	0.011	0.018*
	(0.009)	(0.011)	(0.009)	(0.008)	(0.007)	(0.009)	(0.007)	(0.007)
Income growth (pct.)	0.175	0.169	0.197	0.156	0.151	0.111	0.159	0.198*
	(0.099)	(0.102)	(0.110)	(0.103)	(0.101)	(0.102)	(0.102)	(0.097)
Median income (1000 DKK)	-0.947*	-0.953*	-0.949*	-0.907*	-0.950*	-0.928*	-0.937*	-0.962*
	(0.068)	(0.069)	(0.069)	(0.070)	(0.068)	(0.068)	(0.069)	(0.065)
Unemployment rate	-1.909*	-1.912*	-1.928*	-1.902*	-1.926*	-1.871*	-1.937*	-1.942*
	(0.223)	(0.227)	(0.225)	(0.222)	(0.226)	(0.224)	(0.228)	(0.226)
Precinct FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	4170	4080	4093	4179	4127	4129	4104	4163
RMSE	5.333	5.379	5.371	5.324	5.297	5.272	5.305	5.244

Standard errors in parentheses

Model (1) measures changes from one quarter before the election, model (2) two quarters before the election and so on.

* $p < 0.05$

G Full Models from Robustness Checks of Individual-level Evidence

Tables G1 and G2 re-estimate the linear regression models presented in Tables 4 and 5 using conditional logit models. While it is hard to compare effect sizes, the substantive findings (i.e., direction and significance of coefficients) from these models line up with those presented in the main analysis.

Table G3 include home-ownership as a control. This does not change the results discernibly. Table G4 presents the results of the home-ownership by housing price interaction. The interaction is positive but statistically insignificant except for in the 20 closest houses specification where it is negative and insignificant. This suggests that homeowners do not respond in substantively different ways than renters.

Table G5 examines the relationship between changes in housing prices and self-placement on an ideological left-right scale. The estimates are for the most part negative and statistically insignificant across all specifications. If anything, voters in our sample thus become more left-wing when local housing prices increase.

Tables G6 and G7 replicate our main analyses of the individual-level data using support for the prime minister's party as the dependent variable rather than support for the government as a whole. The results only change a bit, with the estimated average effect and the estimated interaction effect being roughly 30 percent smaller across models. This was very similar to what we found in the precinct-level data. Unlike in the precinct-level data, the interaction effect does not reach statistical significance in some models (which is partly a mechanic consequence of reduced variation in the dependent variable), but broadly speaking support the same pattern as reported in the manuscript using support for all government parties as dependent variable.

Tables G8 and G9 re-estimates the linear regression models presented in Tables 4 and 5 using two additional control variables: ideological self-placement and years of schooling. Including these controls do not change the results substantively, but their inclusion does in fact increase our estimates of the effect of housing prices slightly.

Table G1: Logistic Regression of Voting for Governing party

	20 Closest	40 Closest	1000 metres	1500 metres	Zip code
Δ housing price	0.331	0.657	0.846	1.217*	0.018
	(0.492)	(0.633)	(0.467)	(0.545)	(0.759)
Unemployment rate (context)	3.177	3.053	-4.854	12.371	4.999
	(5.122)	(5.120)	(6.602)	(7.419)	(8.810)
Average income (context)	-0.045	-0.046	-0.073	-0.078	-0.205*
	(0.048)	(0.048)	(0.061)	(0.073)	(0.096)
Personal income	-0.001	-0.001	0.000	-0.000	0.000
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Unnemployed (household)	-0.203	-0.191	-0.524	-0.245	-0.244
	(0.476)	(0.477)	(0.614)	(0.584)	(0.488)
Round FE	Yes	Yes	Yes	Yes	Yes
Voter FE	Yes	Yes	Yes	Yes	Yes
Observations	622	622	458	496	608

Standard errors in parentheses
* $p < 0.05$

Table G2: Logistic Regression of Voting for Governing party

	20 Closest	40 Closest	1000 metres	1500 metres	Zip code
Δ housing price	0.039	0.465	0.479	0.915	-0.235
	(0.512)	(0.643)	(0.491)	(0.540)	(0.773)
Mover	0.079	0.037	-0.026	0.716	0.730
	(0.367)	(0.363)	(0.421)	(0.482)	(0.503)
Δ housing price × Mover	4.052*	5.303*	4.565*	7.713*	9.220*
	(1.884)	(2.421)	(2.063)	(2.910)	(3.780)
Unemployment rate (context)	1.870	3.174	-6.715	13.059	5.438
	(5.237)	(5.236)	(6.781)	(7.672)	(8.883)
Average income (context)	-0.040	-0.042	-0.073	-0.082	-0.191
	(0.048)	(0.048)	(0.063)	(0.076)	(0.098)
Personal income	-0.001	-0.001	0.000	-0.000	0.000
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Unnemployed (household)	-0.226	-0.201	-0.526	-0.191	-0.199
	(0.478)	(0.480)	(0.624)	(0.598)	(0.494)
Round FE	Yes	Yes	Yes	Yes	Yes
Voter FE	Yes	Yes	Yes	Yes	Yes
Observations	622	622	458	496	608

Standard errors in parentheses
* $p < 0.05$

Table G3: Linear Regression of Voting for Governing party

	20 Closest	40 Closest	1000 metres	1500 metres	Zip code
Δ housing price	0.012	0.045	0.044	0.103*	0.020
	(0.035)	(0.041)	(0.043)	(0.044)	(0.070)
Home Owner	-0.013	-0.013	-0.025	-0.018	-0.022
	(0.033)	(0.033)	(0.041)	(0.038)	(0.035)
Unemployment rate (context)	0.146	0.135	-0.786	0.473	0.211
	(0.393)	(0.390)	(0.650)	(0.595)	(0.625)
Average income (context)	-0.003	-0.003	-0.007	-0.006	-0.013
	(0.004)	(0.004)	(0.007)	(0.007)	(0.007)
Personal income	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
Unemployed (household)	-0.024	-0.024	-0.060	-0.043	-0.025
	(0.036)	(0.036)	(0.044)	(0.042)	(0.037)
Round FE	Yes	Yes	Yes	Yes	Yes
Voter FE	Yes	Yes	Yes	Yes	Yes
Observations	3447	3447	2767	2965	3372

Standard errors in parentheses
* $p < 0.05$

Table G4: Linear Regression of Voting for Governing party

	20 Closest	40 Closest	1000 metres	1500 metres	Zip code
Δ housing price	0.043	0.030	0.043	0.029	-0.101
	(0.047)	(0.056)	(0.068)	(0.081)	(0.096)
Home Owner	-0.014	-0.012	-0.025	-0.016	-0.012
	(0.033)	(0.033)	(0.041)	(0.038)	(0.035)
Δ housing price $\times$ Home Owner	-0.047	0.024	0.001	0.096	0.171
	(0.060)	(0.072)	(0.079)	(0.088)	(0.105)
Unemployment rate (context)	0.147	0.134	-0.786	0.500	0.296
	(0.393)	(0.391)	(0.651)	(0.596)	(0.627)
Average income (context)	-0.003	-0.003	-0.007	-0.006	-0.013
	(0.004)	(0.004)	(0.007)	(0.007)	(0.007)
Personal income	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
Unemployed (household)	-0.024	-0.024	-0.060	-0.043	-0.022
	(0.036)	(0.036)	(0.044)	(0.042)	(0.037)
Round FE	Yes	Yes	Yes	Yes	Yes
Voter FE	Yes	Yes	Yes	Yes	Yes
Observations	3447	3447	2767	2965	3372

Standard errors in parentheses
* $p < 0.05$

Table G5: Linear Regression of Left-Right Self Placement (Ideology)

	20 Closest	40 Closest	1000 metres	1500 metres	Zip code
Δ housing price	-0.020	-0.016	0.018	-0.007	-0.002
	(0.022)	(0.021)	(0.024)	(0.019)	(0.031)
Unemployment rate (context)	-0.298	-0.311	-0.392	-0.271	-0.297
	(0.242)	(0.238)	(0.300)	(0.281)	(0.297)
Average income (context)	-0.001	-0.001	0.001	0.003	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Personal income	0.000	0.000	0.000*	0.000*	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Unemployed (household)	-0.021	-0.022	-0.039	-0.035	-0.021
	(0.020)	(0.020)	(0.025)	(0.023)	(0.021)
Round FE	Yes	Yes	Yes	Yes	Yes
Voter FE	Yes	Yes	Yes	Yes	Yes
Observations	3343	3343	2683	2878	3262

Standard errors in parentheses
* $p < 0.05$

Table G6: Linear Regression of Voting for Prime Minister party

	20 Closest	40 Closest	1000 metres	1500 metres	Zip code
Δ housing price	0.007	0.045	0.065	0.091*	0.017
	(0.034)	(0.040)	(0.043)	(0.039)	(0.069)
Unemployment rate (context)	-0.014	-0.035	-0.677	0.737	0.353
	(0.365)	(0.361)	(0.625)	(0.556)	(0.562)
Average income (context)	-0.001	-0.001	-0.001	0.000	-0.004
	(0.004)	(0.004)	(0.007)	(0.007)	(0.007)
Personal income	0.000	0.000	0.001	0.001	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Unemployed (household)	0.006	0.006	-0.025	-0.002	0.006
	(0.034)	(0.034)	(0.040)	(0.038)	(0.035)
Round FE	Yes	Yes	Yes	Yes	Yes
Voter FE	Yes	Yes	Yes	Yes	Yes
Observations	3479	3479	2790	2992	3394

Standard errors in parentheses
* $p < 0.05$

Table G7: Linear Regression of Voting for Prime Minister party

	20 Closest	40 Closest	1000 metres	1500 metres	Zip code
Δ housing price	-0.005	0.033	0.046	0.070	-0.003
	(0.037)	(0.043)	(0.045)	(0.039)	(0.070)
Mover	-0.010	-0.009	-0.013	0.010	0.006
	(0.030)	(0.031)	(0.037)	(0.033)	(0.035)
Δ housing price $\times$ Mover	0.105	0.137	0.199	0.280*	0.258
	(0.079)	(0.115)	(0.120)	(0.117)	(0.186)
Unemployment rate (context)	-0.029	-0.044	-0.696	0.731	0.317
	(0.365)	(0.363)	(0.625)	(0.563)	(0.567)
Average income (context)	-0.001	-0.001	-0.002	0.000	-0.004
	(0.004)	(0.004)	(0.007)	(0.007)	(0.007)
Personal income	0.000	0.000	0.001	0.001	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Unnemployed (household)	0.005	0.005	-0.028	-0.005	0.006
	(0.034)	(0.034)	(0.040)	(0.039)	(0.035)
Round FE	Yes	Yes	Yes	Yes	Yes
Voter FE	Yes	Yes	Yes	Yes	Yes
Observations	3479	3479	2790	2992	3394

Standard errors in parentheses
* $p < 0.05$

Table G8: Linear Regression of Voting for Governing party

	20 Closest	40 Closest	1000 metres	1500 metres	Zip code
Δ housing price	0.021	0.051	0.053	0.108*	0.011
	(0.037)	(0.042)	(0.045)	(0.046)	(0.067)
Years of schooling	0.008	0.008	0.014	0.012	0.010
	(0.008)	(0.008)	(0.009)	(0.008)	(0.009)
Left/Right Scale	0.311*	0.312*	0.299*	0.310*	0.306*
	(0.056)	(0.056)	(0.067)	(0.064)	(0.057)
Unemployment rate (context)	0.356	0.350	-0.472	0.761	0.073
	(0.401)	(0.398)	(0.660)	(0.596)	(0.626)
Average income (context)	-0.000	-0.000	-0.002	-0.003	-0.012
	(0.004)	(0.004)	(0.007)	(0.007)	(0.007)
Personal income	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
Unemployed (household)	-0.028	-0.028	-0.060	-0.044	-0.029
	(0.036)	(0.036)	(0.042)	(0.041)	(0.038)
Round FE	Yes	Yes	Yes	Yes	Yes
Voter FE	Yes	Yes	Yes	Yes	Yes
Observations	3301	3301	2645	2838	3224

Standard errors in parentheses
* $p < 0.05$

Table G9: Linear Regression of Voting for Governing party

	20 Closest	40 Closest	1000 metres	1500 metres	Zip code
Δ housing price	-0.002	0.031	0.029	0.087	-0.017
	(0.039)	(0.044)	(0.046)	(0.048)	(0.070)
Mover	0.010	0.012	0.001	0.025	0.031
	(0.031)	(0.032)	(0.036)	(0.032)	(0.032)
Δ housing price × Mover	0.200*	0.245*	0.263*	0.327*	0.374*
	(0.090)	(0.119)	(0.132)	(0.117)	(0.155)
Years of schooling	0.007	0.007	0.013	0.011	0.009
	(0.008)	(0.008)	(0.010)	(0.008)	(0.009)
Left/Right Scale	0.311*	0.308*	0.291*	0.307*	0.301*
	(0.056)	(0.056)	(0.068)	(0.064)	(0.057)
Unemployment rate (context)	0.310	0.310	-0.527	0.703	-0.020
	(0.400)	(0.402)	(0.661)	(0.608)	(0.633)
Average income (context)	0.000	0.000	-0.002	-0.003	-0.012
	(0.004)	(0.004)	(0.007)	(0.007)	(0.007)
Personal income	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
Unemployed (household)	-0.030	-0.031	-0.064	-0.047	-0.030
	(0.036)	(0.036)	(0.043)	(0.041)	(0.038)
Round FE	Yes	Yes	Yes	Yes	Yes
Voter FE	Yes	Yes	Yes	Yes	Yes
Observations	3301	3301	2645	2838	3224

Standard errors in parentheses
* $p < 0.05$

H The Interaction with Logged Number of Trades

Figure H1 examines how strongly related the logged number of trades in a zip code is with changes in housing prices. As can be seen from this plot, there is a weak correlation between logged number of trades and changes in housing prices, but a stronger correlation between changes in logged number of trades and changes in housing prices. However, even though the correlation is stronger in the latter case, it is evident that there is a lot of independent variation in number of trades for different levels of housing prices, and, as such, it is reasonable to use number of trades as an independent moderator.

Figure H2 uses the binning estimator developed by Hainmueller, Mummolo and Xu (2018) to test for linearity of the interaction. As can be seen from this model, the interaction does not seem to be perfectly linear. Rather, the estimated marginal effect is small and invariant at low and middling levels of number of trades and then increases at high levels (i.e., the upper tercile).

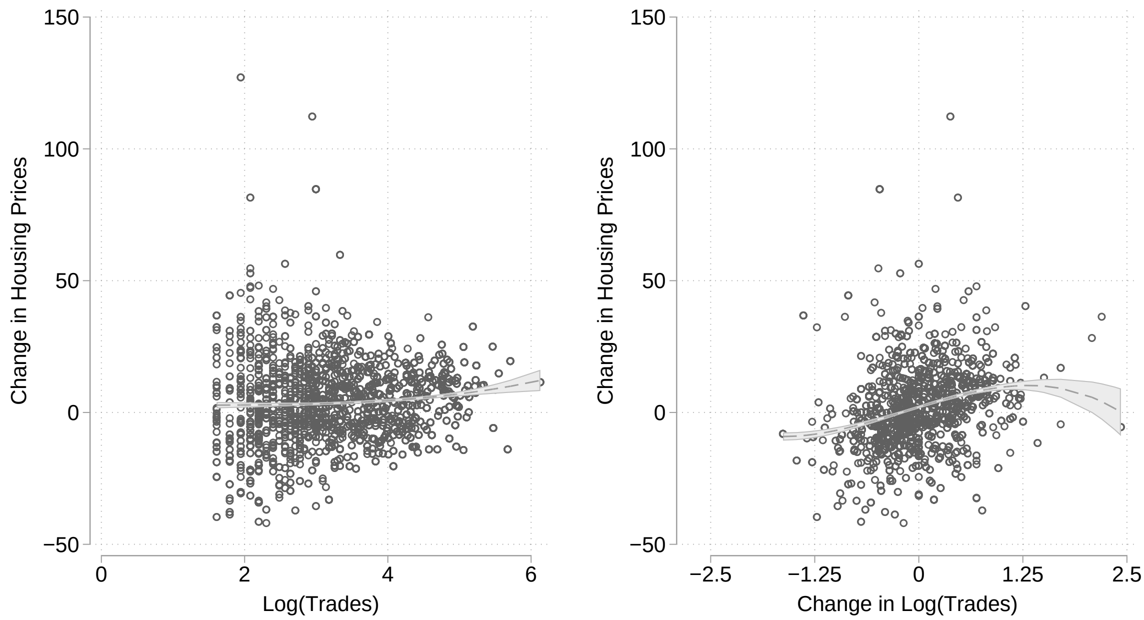

Figure H1: How Closely Related is Number of Trades and Changes in Housing Prices? Dots are observations, line is fractional polynomial fit and area represents 95 pct. confidence interval of this fit. For number of trades the overall Pearson correlation with prices is 0.1 ($n = 4,199$), for the change variable it is 0.3 ($n = 3,100$).

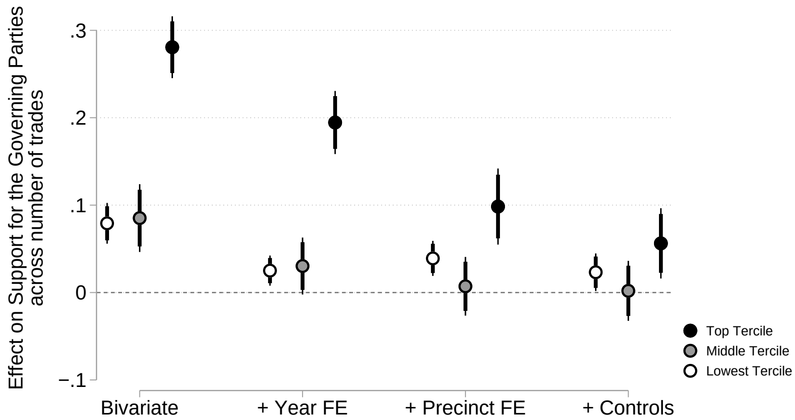

Figure H2: Interaction estimation using the binning estimator developed by Hainmueller, Mummolo and Xu (2018). The binning estimator is applied to all four specification presented in Table 1.

I Some Additional Interactions in the Precinct-Level Data

In model 1 of Table I1 we examine whether there is an interaction effect between the logged number of eligible voters and housing prices. We find no evidence for such an interaction effect. Furthermore, even if we include this interaction the main results hold up in that the housing price by logged number of trades is statistically significant and of the same approximate size. This is reassuring, because it suggests that, as we hypothesized, it is local housing market activity rather than market size that moderates the impact of local housing prices.

In model 2 of Table I1 we examine whether there is an interaction effect between local housing market activity and unemployment. We do identify such an interaction effect. The interaction term is positive, which implies that the negative effect of local unemployment on incumbent support decreases as local housing market activity increases. In particular, we find that moving from the 25th to the 75th percentile of log(trades) decreases the impact of the unemployment rate with 0.4 corresponding to about 20 pct. of the average effect estimated in Table 1.

Table I1: Some additional interactions

	(1)	(2)
Δ housing price	-0.178*	-0.067*
	(0.071)	(0.030)
Log(trades)	1.944*	-0.445
	(0.448)	(1.121)
Log(voters)	2.331	
	(1.690)	
Δ housing price × Log(trades)	0.029*	0.028*
	(0.009)	(0.009)
Δ housing price × Log(voters)	0.014	
	(0.010)	
Income growth (pct.)	-0.003	-0.014
	(0.122)	(0.122)
Median income (1000 DKK)	-0.850*	-0.832*
	(0.047)	(0.047)
Unemployment rate	-1.623*	-2.349*
	(0.190)	(0.351)
Unemployment rate × Log(trades)		0.205*
		(0.086)
Precinct FE	✓	✓
Year FE	✓	✓
Observations	4179	4179
RMSE	6.218	6.215

Standard errors in parentheses
* $p < 0.05$

J Precint-Level Results Without Estimated Precints

As mentioned in Section A, 15 pct. of the electoral precincts merge or split up in different ways across our period of study. For these precincts, we calculate vote returns using an interpolation method developed by Søren Risbjerg Thomsen. This method is described detail in a research note by Risbjerg Thomsen at `bit.ly/205OlPi`. To make sure that this procedure is not driving our results, Table J1 reports results from re-estimating our full model, including year and precinct fixed effects as well as economic controls, with and without the logged number of trades interaction, but without these estimated precincts. The results remain unchanged.

Table J1: Main results excluding amalgamated precincts

	(1)	(2)
Δ housing price	0.036*	-0.092*
	(0.010)	(0.035)
Median income (1000 DKK)	-0.992*	-0.914*
	(0.055)	(0.056)
Income growth (pct.)	0.173	-0.018
	(0.143)	(0.146)
Unemployment rate	-2.104*	-1.723*
	(0.223)	(0.229)
Log(trades)		2.304*
		(0.520)
Δ housing price × Log(trades)		0.040*
		(0.011)
Precinct FE	✓	✓
Year FE	✓	✓
Observations	3523	3523
RMSE	6.558	6.502

Standard errors in parentheses
* $p < 0.05$

K Do the Individual-Level Results Differ Depending on Whether Respondents participated in ESS Round 2?

In Table K1, we examine whether the individual-level results differ based on whether respondents participated in ESS round 2, where the last election was not held right before the survey ran. To do this we include an interaction between whether the respondent initially participated in round 2 and changes in housing prices. The results are not substantially or significantly different for those interviewed in round 2.

Table K1: Linear Regression of Voting for Governing party

	20 Closest	40 Closest	1000 metres	1500 metres	Zip code
Δ housing price	0.001	0.018	0.022	0.069	-0.026
	(0.039)	(0.048)	(0.050)	(0.053)	(0.077)
Δ housing price × ESS round 2	0.092	0.104	0.205	0.163	0.247
	(0.085)	(0.092)	(0.109)	(0.089)	(0.182)
Unemployment rate (context)	0.292	0.298	-0.465	0.767	0.322
	(0.374)	(0.374)	(0.636)	(0.574)	(0.601)
Average income (context)	-0.002	-0.002	-0.005	-0.004	-0.012
	(0.004)	(0.004)	(0.007)	(0.007)	(0.007)
Personal income	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
Unnemployed (household)	-0.032	-0.032	-0.070	-0.054	-0.030
	(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	3475	3475	2787	2989	3390

Standard errors in parentheses
* $p < 0.05$

L Buyers, Sellers and The Effect of Housing Prices

Voters looking to either buy or sell a home might be especially interested in local housing prices; sellers look to gain personally if local housing prices increase, and buyers, who are interested in buying locally, will have to pay more for their house. As such, if voters punish governments for their personal economic grievances, then we might expect sellers to reward the government more and buyers to reward the government less than citizens not looking to buy. We explore whether this is the case in this Appendix.

Importantly, the incentives to punish or reward the government more or less harshly do not apply to voters who are looking to *both* sell their current home and buy a new home, because in this case any potential gains from increases won from selling will be cancelled out when buying. Instead, this logic only applies to owners who want to become renters, or renters who want to become owners. Accordingly, we empirically define buyers as respondents who currently rent their home, but who will live in an owned home a year from now, and sellers as respondents who currently live in an owned home, but who will live in a rented home a year from now. We get this information on respondents from the BOL register in Statistics Denmark. Using this definition, we end up with total of 66 buyers and 74 sellers out of the 3405 observations.

Tables L1 and L2 present the results of models that include interactions between changes in housing prices and an indicator for whether the respondent is a buyer or seller respectively. Interestingly, the interaction effect between price and the buyer indicator is positive, in spite of the fact that buyers potentially stand to lose out personally from the increase in housing prices. The interaction estimates range from 0.026 to 0.214 depending on the specification. None of the interactions are significant, so we should read too much into the result. Yet, the finding runs against a self-interest account as buyers ostensibly have an interest in buying cheaper homes and therefore should punish the incumbent government for increasing housing prices. The interaction between the price and seller indicator is also positive and larger than the interaction for buyers. Estimates range from 0.11 to 0.53. This suggest that sellers might be more likely to reward the government for increasing housing prices, in line with their personal interest, but again none of the interactions are significant.

It is hard to draw any firm conclusions about voters' motives for engaging in local economic voting based on this analysis. Both sellers and buyers seem do in fact seem to reward the government more for housing price increases, although the former more than the latter. Because there are so few voters who are buying or selling, however, our sample of buyers and sellers is not large enough to precisely estimate these differences, leaving our conclusions tentative at best. Perhaps the most important finding is therefore that while the effect of housing prices might be stronger for sellers only a small fraction of people are looking to sell their home (without buying a new one) at any given time, and accordingly this group can only slightly influence the general trends we identified above.

Table L1: Linear Regression of Voting for Governing party

	20 Closest	40 Closest	1000 metres	1500 metres	Zip code
Δ housing price	0.023	0.051	0.042	0.090*	0.047
	(0.036)	(0.042)	(0.045)	(0.042)	(0.069)
Buyer	-0.032	-0.030	-0.007	-0.015	-0.010
	(0.060)	(0.058)	(0.065)	(0.059)	(0.073)
Δ housing price $\times$ Buyer	0.088	0.104	0.092	0.026	0.214
	(0.137)	(0.175)	(0.085)	(0.168)	(0.496)
Unemployment rate (context)	0.192	0.188	-0.729	0.520	0.380
	(0.387)	(0.385)	(0.663)	(0.581)	(0.603)
Average income (context)	-0.003	-0.003	-0.007	-0.007	-0.014
	(0.004)	(0.004)	(0.008)	(0.007)	(0.007)
Personal income	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
Unnemployed (household)	-0.023	-0.023	-0.058	-0.040	-0.022
	(0.036)	(0.036)	(0.044)	(0.041)	(0.036)
Round FE	Yes	Yes	Yes	Yes	Yes
Voter FE	Yes	Yes	Yes	Yes	Yes
Observations	3401	3401	2731	2922	3329

Standard errors in parentheses
* $p < 0.05$

Table L2: Linear Regression of Voting for Governing party

	20 Closest	40 Closest	1000 metres	1500 metres	Zip code
Δ housing price	0.020	0.048	0.037	0.079	0.046
	(0.036)	(0.042)	(0.044)	(0.043)	(0.071)
Seller	0.084	0.077	0.144	0.117	0.058
	(0.075)	(0.071)	(0.086)	(0.074)	(0.070)
Δ housing price × Seller	0.196	0.179	0.478	0.535	0.105
	(0.311)	(0.415)	(0.391)	(0.364)	(0.422)
Unemployment rate (context)	0.226	0.225	-0.613	0.567	0.394
	(0.388)	(0.387)	(0.658)	(0.579)	(0.600)
Average income (context)	-0.003	-0.003	-0.008	-0.007	-0.013
	(0.004)	(0.004)	(0.008)	(0.007)	(0.007)
Personal income	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
Unemployed (household)	-0.023	-0.023	-0.057	-0.040	-0.022
	(0.036)	(0.036)	(0.044)	(0.041)	(0.036)
Round FE	Yes	Yes	Yes	Yes	Yes
Voter FE	Yes	Yes	Yes	Yes	Yes
Observations	3401	3401	2731	2922	3329

Standard errors in parentheses
* $p < 0.05$

M Are Effects Driven By Those Who Exit Their Local Market?

As discussed in the section "Why do local economic conditions influence incumbent support?", one way of assessing voters' motives for rewarding the incumbent government for increasing local housing prices is to look at those selling their home and moving within (i) their booming local market or outside of it (ii), respectively. If voters are egotropic we would expect a stronger effect of increasing local housing prices for the latter as they potentially stand to gain more this from local housing prices than the former group, who are acquiring a new home in the same area.

To explore whether the effects are stronger for those who exit their local market we split the mover dummy into two. Those who moved within a zip code and those who moved between zip codes. We then estimate the effect of housing prices across in-market and out-market movers by interacting the two dummies with housing prices in two different regression models using the zip code level context variables.[4] For the model with in-market movers we drop the out-market movers and vice versa. The estimates from these models are presented in Table M1, where we also include the interaction with all movers for comparison.

The results do not indicate a stronger effect of increasing local housing prices for out-market movers. Rather the opposite. The effect is significantly stronger for those who move within the same local housing market. Consistent with our argument, this indicates that the observed local economic voting is more likely driven by sociotropic motives than egotropic ones.

[4] We use the zip code level context variables, because the data structure of the registers makes it impossible to find out whether people relocate out of our custom made local contexts.

Table M1: Linear Regression of Voting for Governing party

	All	Outmarket	Inmarket
Δ housing price zip code	-0.007	-0.022	-0.004
	(0.073)	(0.075)	(0.074)
Mover	0.032		
	(0.031)		
Within Market		0.061	
		(0.051)	
Outside Market			0.003
			(0.036)
Δ housing price zip code × Mover	0.390*		
	(0.148)		
Δ housing price zip code × Within Market		0.667*	
		(0.241)	
Δ housing price zip code × Outside Market			0.117
			(0.176)
Average income zip code	-0.013	-0.015*	-0.013
	(0.007)	(0.008)	(0.007)
Unemployment rate zip code	0.180	-0.230	0.201
	(0.601)	(0.670)	(0.642)
Unemployed (household)	-0.031	-0.020	-0.015
	(0.036)	(0.041)	(0.039)
Personal income	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
Round FE	Yes	Yes	Yes
Voter FE	Yes	Yes	Yes
Observations	3394	3261	3273

Standard errors in parentheses
* $p < 0.05$

References

Hainmueller, Jens, Jonathan Mummolo and Yiqing Xu. 2018. "How Much Should We Trust Estimates from Multiplicative Interaction Models? Simple Tools to Improve Empirical Practice." *Political Analysis* Forthcoming.

Healy, Andrew and Gabriel S Lenz. 2014. "Substituting the End for the Whole: Why Voters Respond Primarily to the Election-Year Economy." *American Journal of Political Science* 58(1):31–47.