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HOW DO HOUSEHOLDS ADJUST HOUSE PRICE EXPECTATIONS IN AN ERA OF HIGH INFLATION? EXPERIMENTAL EVIDENCE

by Gioia M. Mariani*, Eleonora Porreca* and Concetta Rondinelli*

Abstract

To understand how households adjust house price expectations in a period of high inflation, we implement a survey-based randomized information treatment. After eliciting respondents' priors about past and future local house price changes, we provide a random subset of them with factual information about past changes, and then re-elicit expectations. We find that treated respondents, on average, revise their expectations in the direction of the gap between revealed past house price growth and their perceptions. The extrapolation is heterogeneous across households' demographic and economic conditions, while no effect of local housing conditions is found. We show that the updating behavior is asymmetric, depending on whether the information received is higher or lower than the perceived past price growth, and non-linear, relying on the difference between the treatment and the perceived past price changes. Households struggling with their finances extrapolate more when they realize past house price growth is lower than they thought.

JEL Classification: D83, D84, R20.

Keywords: housing, expectation formation, information treatment.

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1 Introduction[1]

House price expectations are a key factor in both macroeconomics and finance and are thought to play an important role in housing dynamics, but we have limited understanding of how they are formed and how they affect household behavior in a context of high inflation and interest rates on mortgages. House price expectations can be important drivers of aggregate outcomes, as much of the literature has found for the US, such as household consumption (Mian, Rao, and Sufi, 2013; Duca, Muellbauer, and Murphy, 2021; De Bonis et al., 2023), construction activity (Glaeser and Gyourko, 2005) and financial stability (Bekiros, Nilavongse, and Uddin, 2020). They played a relevant role in driving booms and busts in the housing market (Piazzesi and Schneider, 2009; Case, Shiller, and Thompson, 2012; Leombroni et al., 2020), especially during the 2008 US housing crisis (Shiller, 2015). Additionally, house price expectations can significantly influence individual household decisions (Kuchler, Piazzesi, and Stroebel, 2023): to become homeowners (Bailey et al., 2018), to sell the house (Bottan and Perez-Truglia, 2025) and how much leverage to take on mortgages (De Stefani, 2021).

This paper examines how households form house price expectations during a period of high inflation and rising interest rates using a survey-based randomized information treatment. We focus on whether households extrapolate from recent house price trends and how this behavior varies across socio-demographic and economic characteristics. In particular, we explore the role of heightened exposure to inflation and differences in local housing market conditions in shaping expectation formation. Additionally, we investigate whether expectation revisions exhibit asymmetries and non-linearities, as households may react differently to positive versus negative news or adjust expectations differently when receiving signals extremely distant from their the perceived past price changes.

To empirically test these hypotheses, we use data from the second edition of the Conjunctural Survey of Italian Households (CSIH), conducted by the Bank of Italy between August and September 2023. The survey includes a randomized information treatment: respondents first report their perceived house price changes in their local area over the past year and their expectations for the coming year. They are then randomly assigned to either a treated group, which receives objective information on actual local house price changes over the past year, or a control group, which receives no information. The CSIH provides granular data on households' expectations and economic conditions and allows us to examine possible heterogeneous responses across households.

The Italian case is particularly striking in this study. In 2023, the year of the survey experiment, nominal house prices increased by 1.3 per cent compared to the previous year, while

[1]The views expressed herein do not reflect those of the Bank of Italy. We would like to thank for their useful comments and suggestions S. Fabiani, E. Guglielminetti, S. Emiliozzi, D. Loschiavo, R. Perez-Truglia, A. Rosolia.

in real terms they fell by 4.2 per cent (Figure 1). At the same time, inflation averaged 6% and interest rates on variable mortgages surged to 4.4% (those with fixed rate reached 4%, the highest value since 2014); housing transactions continued to decline after the boom occurred in 2021. This environment may have led Italian households to overestimate house prices. Indeed, the Italian housing cycle, which had been on a downward path until 2016 (cumulating an overall decline of around 20% between 2011 and 2016), began to resume in nominal terms in 2017, while continuing the downward path in real terms, albeit at a lower level. With the Covid-19 pandemic and the sharp rise in inflation in 2021, the divergence between nominal and real house prices widened.

House price and transactions dynamics (2015=100)

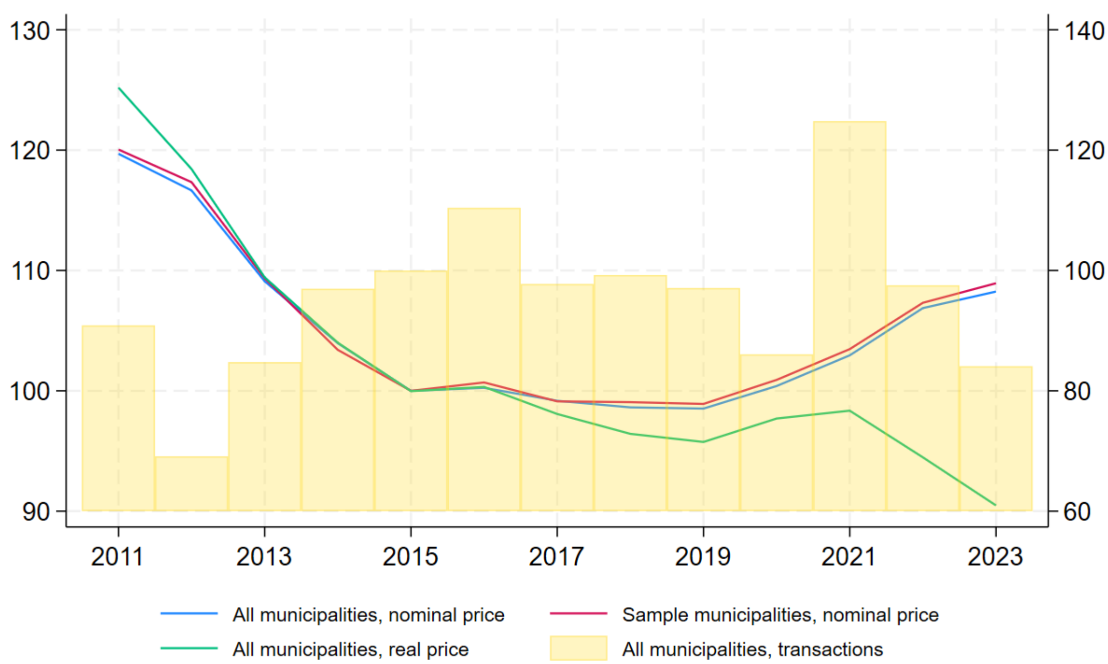


Figure 1

Source: authors' calculation on data from OMI-Revenue Agency, Bank of Italy and Istat.
Notes: the figure shows average house price and transactions from 2011 to 2023, 2015 as base year. Real prices obtained with the price consumer index. Transactions are shown on the right-hand axis.

The study of extrapolation from recent price changes is particularly relevant in the housing market because, unlike stock markets, house prices exhibit strong serial correlation in the short run and mean reversion in the long run (Case and Shiller, 1989; Cutler, Poterba, and Summers, 1991; Glaeser et al., 2014; Guren, 2018; Armona, Fuster, and Zafar, 2019). Some of these studies analyze whether households form their expectations in a data-consistent way, and most of them find that households extrapolate from recent house price changes to form expectations about the near future, but not enough, while overreacting to past house price changes in forming expectations over a longer period. In other words, households underestimate momentum in the short run and overestimate it in the long run when forming expectations about future house price changes. Moreover, the empirical evidence shows that extrapolation is heterogeneous across individuals and areas, with younger individuals, those with a short tenure in their locality, those with higher financial literacy and those living in areas with relatively inelastic housing supply are more likely to extrapolate over the short horizon.

We find that in the context of our study, charcaterized by high inflation and high interest rates, the perception of past price growth is much higher than the actual one, contrary to what Armona, Fuster, and Zafar (2019) found in the survey fielded at the beginning of 2015. On average, treated Italian households are "extrapolators", i.e. they revise their expectations in the direction of the gap between revealed past house price growth and their perception; they believe in the short-term dynamics of house price changes, in line with other work from the US (Armona, Fuster, and Zafar, 2019) and the macro evidence for Italy (Loberto and Zollino, 2016; Emiliozzi, Guglielminetti, and Loberto, 2018). Women extrapolate more than men; younger households are more sensitive to the signal, as they are likely to have less experience of the local housing market and are therefore more prone to updating, as in Malmendier and Nagel (2016). Households in economic difficulties, i.e. those more exposed to high inflation, also extrapolate more than better-off households. We test the relevance of local housing markets by supplementing the CSIH with data on listings and land supply. Following Saiz (2010), we construct a developable land index, where inelastic supply leads to price increases rather than new construction, making past price fluctuations more informative (Glaeser and Gyourko, 2005). To measure market tightness, we use *Immobiliare.it* data to create an indicator based on the average number of clicks per housing unit (Loberto, Luciani, and Pangallo, 2018), as high demand shortens time on the market, driving short-term price persistence (Carrillo, de Wit, and Larson, 2015). We find that in the context of our study local housing conditions appear irrelevant. We also evaluate the asymmetric and non-linear updating behaviour and show that households revise their expectation more when they learn that realised past house price growth is lower than they thought. Given that our sample is mainly composed of homeowners who do not intend to change their main residence, we interpret this type of information as "bad news" for them, as households learn of a lower than expected appreciation of their asset. This is particularly the case for households that are struggling with their finances and in a bad mood.

Our paper relates to three different strands of the literature.

First, the paper that is most closely related to ours is Armona, Fuster, and Zafar (2019), which presents novel evidence on how house price expectations are formed, but unlike that paper, our experiment is conducted in a period of high inflation and high interest rates. We contribute to this strand of the literature by highlighting that households in financial distress because of higher exposure to the inflation are more responsive to the treatment.

Second, the core of the paper is a randomised control trial (RCT), where after eliciting respondents' priors about past and future local house price changes, we provide a random subset of them with factual information about past changes and then re-elicit expectations, in the same vein as Armona, Fuster, and Zafar (2019); Fuster et al. (2022); Coibion et al. (2023); Bottan and Perez-Truglia (2025). In contrast to this literature, we allow the adjustment of household expectations to be asymmetric and non-linear. We borrow from Hastie and Tibshirani (1993) and Rios-Avila (2020) a smoothly varying coefficient model, where we estimate a flexible semi-parametric model that allows for a linear relationship between the treatment and the revision, but allows its effect to vary smoothly with the perception gap, i.e. the difference between the actual and perceived price change.

Third, our paper is relevant to policymakers because of the impact of house price expectations on housing markets and aggregate outcomes (Case, Quigley, and Shiller, 2005; Cooper and Dynan, 2016; Glaeser and Nathanson, 2017; Duca, Muellbauer, and Murphy, 2021; De Bonis et al., 2023). We add to this literature by examining the distributional effects of high inflation on house price expectations. Indeed, during bad times, Kuhnen (2015) and Kuhnen and Miu (2017) show that agents tend to overreact to negative news, probably due to risk aversion (Malmendier and Nagel, 2011). This suggests that economic adversity leads to asymmetric learning and that households struggling with their economic resources are more likely to extrapolate from what we interpret as "bad news". Understanding shifts in house expectations helps policymakers and analysts to predict future market trends, assess potential risks and design strategies for economic stability.

The remainder of the article is organized as follows. Section 2 presents the survey, details the experimental design and describes the Italian setting, providing a benchmark at the macro level of the experimental setting. In section 3 we discuss the results of the revision of respondents' expectations, focusing also on possible heterogeneities and asymmetric and non-linear updating behaviour. Section 4 concludes.

2 Data

2.1 Survey data

We use data from the new Bank of Italy's Conjunctural Survey on Italian Households (CSIH) 2023-H2 wave. The CSIH is a new survey led by the Bank of Italy to follow households over the business cycle in years when the Survey on Household Income and Wealth (SHIW) is not conducted. The SHIW is a face-to-face survey conducted by the Bank of Italy since the 1960s

to study the socio-demographic and economic conditions of Italian households. The core information collected is household members characteristics, their income sources (from employment, pensions, transfers, etc.) and household wealth (financial and real assets, liabilities). The survey represents the population of official residents in Italy, excluding people living in institutions (convents, hospitals, prisons, etc.). The CSIH was introduced in 2022 to gather timely variation on income and wealth and to collect conjunctural information on households' economic behaviour when the SHIW is not available. Differently from the SHIW, the CSIH is implemented through a CAWI (Computer Assisted Web Interview) mode and the questionnaire is mainly characterized by qualitative questions aimed at capturing the economic condition and consumption and saving preferences during the business cycle. The targeted sample in each wave is drawn from the households who have participated to the most recent SHIW wave.
The 2023-H2 wave of CSIH was conducted in August-September of 2023 on a sample of households interviewed in the SHIW 2022. The final sample consists of 1,863 households.

Survey weights, which adjust for potential composition bias and make the sample representative of the Italian households, are used throughout the analysis. From the CSHI 2023-H2 we use, on top of the experimental design, qualitative information on the economic situation of each household at the time of the interview (such as occupational status, how they make ends meet, etc). To exploit quantitative information on income and wealth and on main residence characteristics (as the property right, how long they lived there, etc.) we link the CSIH data with the SHIW 2022. The advantage of interviewing the same households in the two surveys is that some variables, such as the main dwelling in which the household lives, are the same in the two surveys; the experimental design of the CSIH refers precisely to this dwelling and its location.

Importantly, the SHIW, matched with administrative cadastral data, provides the GPS position of the main residence and we link it to the zone obtained from the Real Estate Market Observatory (OMI), which is part of the Italian Revenue Agency and is the main source of information on the national real estate market. The OMI distributes each property within each municipality into micro-zones – OMI zones – which are homogeneous in terms of socio-economic and environmental conditions. Within each OMI zone and for each cadastral category of residential property (standard, economic, luxury, etc.), an average market value per square metre is estimated twice a year using information on transaction prices registered in the OMI zone and for each type of property. Thus, information on the location and cadastral type of the main residence of households from the SHIW allows us to determine the average annual market value for each OMI zone and each cadastral category.

2.2 Experimental design

The aim of this experiment is to analyse how perceived past house price changes affect households' expectations of future house price changes and how providing them with information on realised past house price changes shapes their revision of expectations. Specifically, the experiment consists of the following steps:

1. **Households' perceptions about price changes over the past year** in their neighbourhood and for a property similar to theirs are elicited. The exact question is: *"According to your opinion, by how much did the price of a house similar to yours in your neighbourhood change from 2021 to 2022?"*. Respondents are asked to specify the percentage change, either positive or negative.

2. **Households' perception about price changes over the next 12 months** in their neighbourhood and for a property similar to theirs are elicited immediately after. The exact question is: *"According to your opinion, by how much will the price of a house similar to yours in your neighbourhood change over the next 12 months?"*. Again, respondents are asked to specify the percentage change, either positive or negative.

3. After questions on expectations on inflation and consumption, and housing characteristics (such as environmental efficiency, investment in environmental renovation, etc.) **the sample is randomly split into two groups – treated and controls –** of equal size. The treated households were informed about the **realized past home price changes** for a property similar to theirs in their zone, as follows *"According to the Real Estate Market Observatory, which provides reliable estimates on real estate market values, the price of a house similar to yours and in your neighbourhood has varied by XXX% from 2021 to 2022"* (XXX% is the household specific OMI-zone price change realized, according to the OMI, from 2021 to 2022). Whereas, the control groups did not received any information. Then, **households' perception about price changes over the next 12 months were elicited again** in order to measure revisions in expected price changes after having received the information. The following question was asked to both groups: *"In a previous question you have stated that the price of a house similar to yours in your neighbourhood will change by YYY% over the next 12 months. We would like to ask you your opinion again. By how much will the price of a house similar to yours in your neighbourhood change over the next 12 months?* (YYY% is the household specific price change stated in the previous question). Respondents are asked to specify the percentage change, either positive or negative. The random allocation of households between the two groups allows us estimating the direct effect of providing information on the revision in expected price change.

Before describing the variables of interest derived from the experiment, it is worth analysing

the meaning of the information provided to respondents and the sample characteristics.
In this experiment we focus on the correlation in home price changes over the short horizon. The literature (see, among others, Loberto and Zollino (2016) and Emiliozzi, Guglielminetti, and Loberto (2018)) has extensively documented the positive short term serial correlation in home price growths, whereas in the longer-run the evidence shows mean reversion. If this pattern holds, households should incorporate this information into their expectation formation process. The experimental design is carried out at the level of the OMI zones, but a sufficiently long time series is not available at this disaggregated level.[2] The following fixed effect regression model is estimated considering both all Italian municipalities and only the sampled ones in the CSIH:

$$\Delta_1 log(OP_{z,t}) = \alpha_z + \beta\Delta_h log(OP_{z,t-1}) + u_{z,t}, \quad h = 1, 3, 5 \tag{1}$$

where $\Delta_1 log(OP_{z,t})$, which is one year OMI-price growth rate in municipality z at year t, is regressed on lagged one/three/five ($h = 1, 3, 5$) price years growth rates.

Correlation in home price changes (municipality level, 2005-2022)

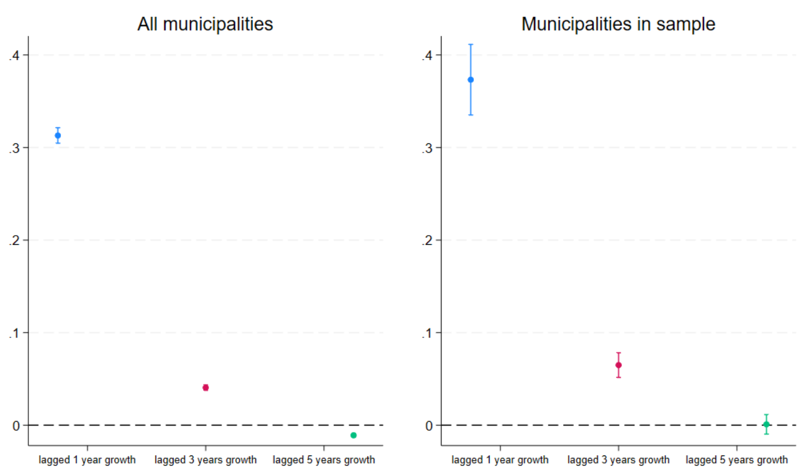


Figure 2
Source: authors' calculation on data from OMI-Revenue Agency, Bank of Italy and Istat.
Notes: the figure shows the coefficient estimates from a fixed effect regression of one year home price variation on lagged one/three/five year variation in all municipalities (on the left) and in sampled municipalities (on the right) from 2005 to 2022.

Figure 2 shows that the estimated correlation coefficients are similar in magnitude for all municipalities and only for the sampled ones. Looking at all municipalities, the analysis shows that an increase of one percentage point in one year price growth rate in period $t - 1$ leads

[2]The classification of the OMI-zones was revised in 2014, causing a break in the time series for at least half of the zones.

to an increase of 0.31 percentage point in one year growth rate in period t, and the effect is statistically significant at 1% level. Expanding the horizon of the growth rate leads to a weaker correlation: e.g. one percentage point increase in five years price growth rate in period $t-1$ leads to an increase of 0.04 percentage point in one year growth rate in period t, though the effect is still statistically significant at 1% level. Therefore, the analysis suggests the existence of a momentum in home price variations in the short-run.

Table 1: Sample characteristics

	Full sample	Treated	Control	P-value
Age up to 44	22.7	24.5	20.8	0.397
Age 45 54	17.9	20.0	15.7	0.245
Age 55 64	22.4	21.2	23.7	0.520
Age more than 64	37.0	34.4	39.9	0.235
Female	37.6	41.1	33.9	0.127
Secondary education	57.1	61.3	52.7	0.830
Employee	42.5	44.9	40.0	0.310
Self employed	10.5	10.5	10.5	0.977
Not in employment	47.0	44.6	49.5	0.311
Number of components (units)	2.3	2.3	2.2	0.198
Make ends meet difficult	63.1	63.0	63.2	0.959
Homeowner	80.0	80.80	79.1	0.662
Years of residence (in years)	25.7	26.0	25.4	0.744
Main residence value (in €)	194,584	200,931	187,855	0.403
Income (in €)	40,020	40,284	39,739	0.803
Net wealth (in €)	325,798	330,899	320,390	0.857
North	50.0	51.3	48.60	0.569
Center	22.4	23.3	21.50	0.619
South	27.6	25.3	30.00	0.307
Small municipalities	57.0	59.6	54.30	0.239
Housing supply elasticity	49.7	49.4	49.90	0.915
Housing demand tightness	52.1	50.1	54.20	0.410
Observations	1863	937	926	

Source: authors' calculation on data from CSIH 2023-H2 and SHIW2022.
Notes: percentages if not specified. The table shows average characteristics in the full sample (column 1), in the treatment group (column 2) and in the control group (column 3). Column 4 reports p-value of test for equality in means between treatment and control groups. Age, sex, education and occupation refer to the respondent to the CSIH 2023-H2; all the other variables refer to the household.

Table 1 shows that treatment and control groups are on average similar in terms of socio-demographic and economic characteristics. About 37% of respondents is more than 64 years old, 38% is female, 57% holds a high-school qualification, 43% is employee, 10% is self-employed, 47% is not employed and 63% make ends meet with difficulty. Half of the households live in the North and about one-fourth in the Center and in the South. About 80% of households are homeowners, quite in line with the ownership rate estimated in the European Union Statistics on Income and Living Conditions for Italy (80.6% in 2023). The self-assessed value of the main residence is on average 195,000 euro and households report that they have been living there for about 26 years.

We now define the variables of interest derived from the experiment as follows:

- **Perception**, $\tilde{\pi}_i$, of household i on price change from 2021 to 2022 (percent variation) of a house similar to hers in her zone.
- **Perception gap**, $g_i = \pi_i - \tilde{\pi}_i$, defined as the difference between the realized price change of a house similar to the one of household i in her zone from 2021 to 2022 and the price change as perceived by household i. A positive (negative) gap means a household's underestimation (overestimation) of home price variation with respect to OMI official estimates. This quantity is known for each household, regardless of whether they are in the treatment or control group.[3]
- **Expectation**, $E(\pi_i)$, of household i on price change over the next 12 months (percent variation) of a house similar to hers in her zone.
- **Revision**, $\Delta E(\pi_i)$, of household i in expected home price change, defined as the difference in the expectation after and before the informative treatment. A positive (negative) sign means an upward (downward) revision of the household.

The data cleaning process involved removing observations with extreme values of the perception gap and eliminating observations where past perceptions of house prices were clear outliers.

2.3 Hypothesis on home price revisions

The variables described in Section 2.2 are used to analyse the households' expectation formation behaviour and, if any, their updating behaviour.

More precisely, a household can behave according to these hypotheses:

- **extrapolation**: if the household underestimates (overestimates) past home price change, i.e. the perception gap is positive (negative), and thinks that home price changes are positively correlated in the short-term, providing her the true past home price change will induce an upward (downward) revision in expected home price variation, assuming that the household gives some weight to the signal received when updating. Perception gap

[3]Even if the control group did not receive the information treatment, we managed to calculate this based on the OMI zone in which they lived.

and revision should be positively correlated and we can state that the household believes in the short term momentum in house prices;

- **mean reversion**: if the household underestimates (overestimates) past home price change, i.e. the perception gap is positive (negative) providing her the true past home price change will induce a downward (upward) revision in expected home price variation. Perception gap and revision will be negatively correlated;
- **random walk**: there is no systematic revision in response to the information received. The household doesn't realize there is serial dependence in home price changes.

2.4 Listings and land supply data

To complement our analysis and test the relevance of local housing markets, we enrich our dataset with two additional data sources for the housing market and land supply. The *immoit* dataset contains information on all listings posted on one of Italy's largest real estate platforms (*Immobiliare.it*). We construct indicators of house demand by considering the quarterly average of the daily number of clicks on each listing in a specific OMI-zone (see Pangallo and Loberto, 2018, for a more detailed description of the demand index).
A second set of indicators is used to assess the extent of developable land in a specific OMI-zone as a proxy of the elasticity of housing supply, by using the Corine Land Cover (CLC) database, which relies on 100m resolution satellite data and provides information on land cover and land use. Following Saiz (2010) and Gohl et al. (2024) we intersect the CLC data with the OMI-zone to define an index of the proportion of developable land, where all land is considered developable except for artificial surfaces and water bodies. Figure A.1 shows the index for the municipality of Rome as an example.

2.5 Descriptive statistics

Table 2 reports the main descriptive statistics on home price perceptions and expectations and shows that on average the perceived home price variation between 2021 and 2022 is about 2.6%, against a realized average of 1.1%, meaning that households overestimate past home price change. Indeed, the average perception gap is negative and amounts to -1.5 percentage points. The sign of the perception gap is opposite to that found in Armona, Fuster, and Zafar (2019): this is quite a remarkable feature of the period in which Italian households were surveyed, so the increase in nominal house prices, the high levels of inflation and interest rates could have led to this overestimation. Before the treatment, households on average expect an increase in house prices in the next 12 months of about 2.8%, whereas after the treatment it amounts to about 1.6%. The downward revision in the expected house price change is due to the treatment group, which revised its expectation downwards by 2 percentage points on average, in contrast to the control group, whose revision is close to zero. The different updating behaviour between treatment and control groups is plotted also in Figure 3, where we show the average of the revisions across deciles of the perception gap for the two groups: the correlation coefficient between perception gap and revision is about 0.5 and statistically different from zero among the treated households, whereas in the control group is close to zero per cent, and not statistically distinguishable from zero. Preliminary evidence supports the behavioural updating hypothesized.

Table 2: Home price perceptions and expectations

	Past perceptions				
	Min	Max	Mean	SD	P-value
Full sample	-70.0	50.0	2.6	14.3	.
Treated	-70.0	50.0	2.5	15.1	.
Control	-50.0	50.0	2.7	13.4	0.896
	Perception gap				
	Min	Max	Mean	SD	P-value
Full sample	-47.9	66.7	-1.5	14.5	.
Treated	-47.9	66.7	-1.5	15.0	.
Control	-47.7	54.3	-1.5	13.8	0.999
	Expectations pre treatment				
	Min	Max	Mean	SD	P-value
Full sample	-80.0	100.0	2.8	12.5	.
Treated	-80.0	100.0	3.0	14.6	.
Control	-40.0	50.8	2.6	9.8	0.786
	Expectations post treatment				
	Min	Max	Mean	SD	P-value
Full sample	-80.0	60.9	1.6	9.8	.
Treated	-80.0	50.0	0.9	8.6	.
Control	-50.0	60.9	2.3	10.8	0.132
	Revisions				
	Min	Max	Mean	SD	P-value
Full sample	-99.5	50.0	-1.2	10.0	.
Treated	-99.5	50.0	-2.1	12.5	.
Control	-50.2	45.0	-0.3	6.2	0.120

Source: authors' calculation on data from CSIH 2023-H2.
Notes: the table shows descriptive statistics in percentages for past perception, perception gap, expectation (pre and post treatment) and revision for the full sample and for the treatment and control groups; p-value of test for equality of means between treatment and control groups.

Correlation between perception gap and revisions

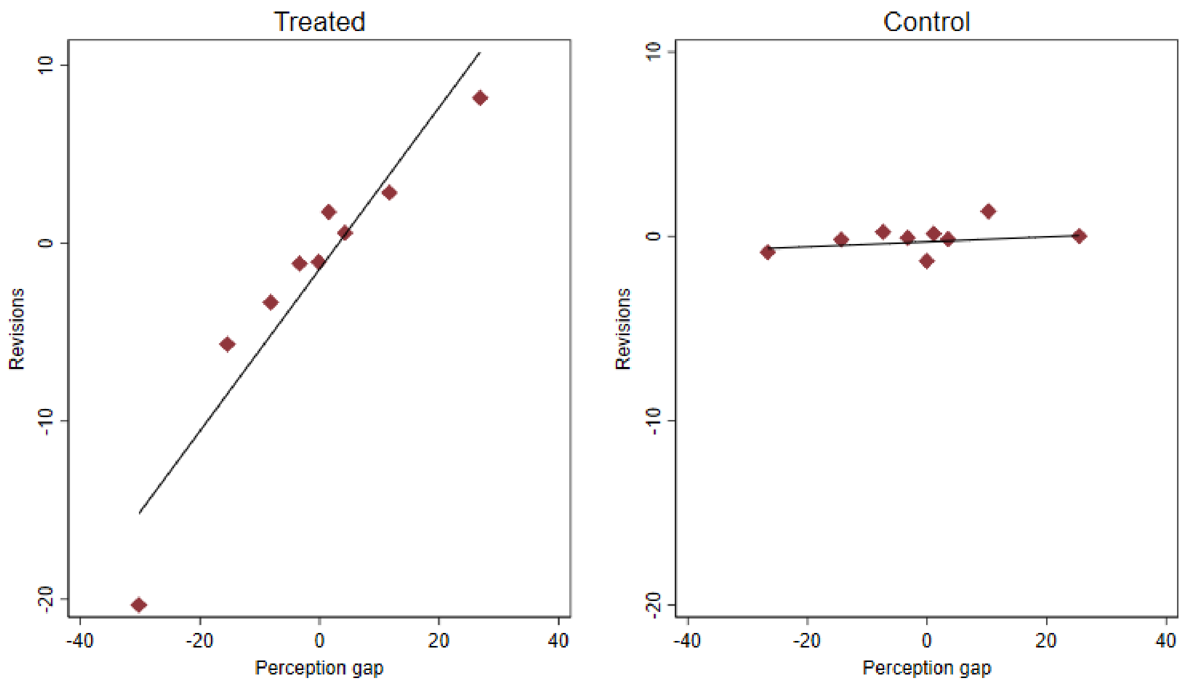


Figure 3

Source: authors' calculation on data from CSIH 2023-H2.
Notes: the figure shows the average revisions of expectation along deciles of perception gap, together with the linear prediction of a regression of revision on perception gap for the treatment (on the left) and the control (on the right) groups.

3 Empirical analysis on home price revisions

3.1 Households' updating behaviour

In order to test the household updating behavior, we estimate Equation 2:

$$\Delta E(\pi_i) = \beta_0 + \beta_1 Thp_i + \beta_2 g_i + \beta_3 (Thp_i * g_i) + u_i \tag{2}$$

where $\Delta E(\pi_i)$ is the revision in expected house price variation, Thp_i is equal to one if the household received the house price treatment and g_i is the perception gap. The parameters of interest are β_3, which is the difference in the effect of the perception gap on revision between the treated and the control groups and, if statistically significant, the revision is driven by perception gap for the treatment group, and $\beta_3 + \beta_2$, which represents the effect of the perception gap on revision of the treatment group.

Table 3 shows the estimates of the coefficients of interest obtained by ordinary least squares with robust standard errors. The estimate of β_3 is positive and significant across all specification, whereas β_2 is always equal to zero: column (4), where we add the most complete set of covariates, implies that for each percentage point of underestimation (overestimation) of past house prices growth, after receiving the treatment the households revises upward (downward) their expectations by 0.43 p.p. Our results suggest that treated respondents are, on average, 'extrapolators', that is they revise their expectations in the direction of the gap between revealed past house price growth and their perception after being provided with the information, i.e. they believe in short term momentum of house price changes.

Table 3: Home price revisions and house price treatment

	(1)	(2)	(3)	(4)
Treatment	-1.148	-1.041	-1.041	-1.061
	(0.855)	(0.761)	(0.761)	(0.756)
Perception gap	0.014	0.001	0.001	0.004
	(0.025)	(0.025)	(0.025)	(0.025)
Treatment*perception gap	0.441***	0.433***	0.433***	0.431***
	(0.103)	(0.090)	(0.090)	(0.089)
Constant	-0.304	0.635	0.635	0.723
	(0.447)	(2.313)	(2.313)	(2.449)
Observations	1,863	1,863	1,863	1,863
R-squared	0.249	0.290	0.290	0.293
Geographic characteristics		Yes	Yes	Yes
Household characteristics			Yes	Yes
Local housing characteristics				Yes

Source: authors' calculation on data from CSIH 2023-H2.
Notes: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Geographic characteristics include geographic area and municipality size indicators; household characteristics include socio-demographic variables of the respondent (sex, age, education, occupation) economic variables of the household (having difficulties in making ends meet, main residence ownership, inflation treatment); local housing characteristics refer to indicators for high demand tightness and high supply elasticity.

3.2 Heterogeneity analysis

In this section we explore heterogeneity in the revision behaviour of the households, according to the following specification:

$$\Delta E(\pi_i) = \beta_0 + \beta_1 Thp_i + \beta_2 g_i + \beta_3 (Thp_i * g_i) + \beta_4 (Thp_i * g_i * x_i) + u_i \tag{3}$$

where the notation is the same as the one of Equation 2, and β_4 captures the dimension of heterogeneity, given by x_i. Specifically, we are interested in whether households behave differently according to: i) demographic characteristics; ii) the household economic situation; iii) local housing market conditions.

In Table 4 (columns 1-3) we start by exploring whether socio-economic characteristics of the respondent have an effect on the expectation revision. In this respect, it is established in the literature that women, the young, the old and the less educated have higher inflation expectations and larger forecast errors (see Menz and Poppitz, 2013, for a comprehensive review) and thus may be more responsive to the information treatment. The table shows that the estimate of interest β_3 is robust to the inclusion of the interaction terms. We find that on average female respondents seem to extrapolate more than men do, which is consistent with the literature on the systematic upward bias for women compared to men Bruine de Bruin et al. (2010); D'Acunto, Malmendier, and Weber (2021). We also find evidence of a differential behaviour of younger respondents, in line with what some literature has theorized: according to Malmendier and Nagel (2016), it is likely that they have less experience of the local housing market and should therefore be more prone to updating. On the other hand, we do not find evidence of different behaviour for more educated respondents.

Given the period of high inflation and interest rates during which house price expectations were elicited, and the positive relationship between house prices and inflation expectations (Figure A.2)[4], we are interested in investigating whether the process of updating house price changes was different for those who were particularly affected by high inflation. Corsello and Riggi (2023); Infante et al. (2023) have found that scars left by the 2021-22 inflation shock, when energy prices rose dramatically, affected some households more and also led to higher inflation expectations, given the high correlation between perceived inflation and expectations (Weber et al., 2022). Therefore, in line with these studies, we identify households more exposed to inflation with the following indicators: having difficulties in making ends meet, having arrears of debt and bills, not being able to put aside savings in the last 6 months, having a high share of food and energy expenditure. Table 5 shows that disadvantaged households have higher inflation expectations along with higher house price expectations before the treatment, in line with the literature that has found that respondents with current or expected financial difficulties, as well as those with pessimistic attitudes, have a stronger upward bias than other households (Ehrmann, Pfajfar, and Santoro, 2017).

In columns 4-7 of Table 4 we investigate the different behaviour of households according to these different economic indicators. Indeed, we find that all the different measures of well-off point in

[4] In the literature Anari and Kolari (2002) investigate the relationship between house prices and non-housing goods and services and find that house prices are a stable hedge against inflation over time.

the direction that households in financial difficulty are, on average, more likely to extrapolate.[5]

Lastly, focusing on the local housing conditions, we look at two indicators. The first is the elasticity of housing supply, as areas with inelastic housing supply are more likely to face higher short term momentum. Glaeser, Gyourko, and Saiz (2008) show that the more inelastic housing supply becomes, the more rising demand translates into persisting rising prices and the less into new houses, assuming that individuals have adaptive expectations and believe that prices will continue to rise at a fixed rate after the initial positive shock. Therefore, households should extrapolate more from past price variation in these areas. We proxy the elasticity of housing supply with an index of developable land in the spirit of Saiz (2010). The second indicator is the housing market tightness. Areas with higher housing market tightness are more likely to be characterized by higher short-term correlation in house price changes. Higher current market tightness, i.e. high demand relative to supply, determines a higher probability of a seller finding a match (lower time in the market) and higher seller bargaining power, which translates into a positive price shock in the current period. Carrillo, de Wit, and Larson (2015) show that when buyers and sellers have imperfect information about changes in market tightness and slowly adjust their optimal strategies as they gather information about it, the initial increase in market tightness leads to house price appreciation also in the following periods, which translates into higher persistent growth rates in the short run. Households should extrapolate more in areas with tighter housing market. Following Loberto, Luciani, and Pangallo (2018); Pangallo and Loberto (2018), we use the average number of clicks per housing units as index of housing market tightness.

The role of housing tenure and local housing markets is explored in Table 6. We do not find a differential effect for homeowners, which is probably due to the high rate of home ownership that characterises Italian households (more than 80 per cent). Moreover, in contrast to what the literature has found, there seems to be no effect for households living in OMI-zones where demand is tighter (i.e. there is a higher number of clicks relative to the number of ads) or supply elasticity is higher. We argue that this may again be due to the peculiar era of high inflation, as it is likely that the perception of higher prices prevails over the state of the local housing market.

[5]It is possible that these variables are a proxy for financial literacy, but in the absence of a specific financial literacy variable, this cannot be formally tested.

Table 4: Home price revisions and house price treatment - heterogeneity (1)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treatment	-0.808	-1.203	-0.460	-1.349	-0.855	-1.163	-1.083
	(0.764)	(0.829)	(0.720)	(0.868)	(0.870)	(0.848)	(0.809)
Perception gap	0.0136	0.0136	0.0136	0.0136	0.0136	0.0136	0.0136
	(0.0254)	(0.0254)	(0.0254)	(0.0254)	(0.0254)	(0.0254)	(0.0254)
Treatment*perception gap	0.177**	0.625***	0.641***	0.510***	0.733***	0.499***	0.601***
	(0.0816)	(0.157)	(0.135)	(0.119)	(0.192)	(0.126)	(0.144)
Treatment*perception gap*female	0.469***						
	(0.155)						
Treatment*perception gap*secondary education		-0.282					
		(0.195)					
Treatment*perception gap*age >= 55 years			-0.488***				
			(0.158)				
Treatment*perception gap*make ends meet easy				-0.384***			
				(0.138)			
Treatment*perception gap*no arrears					-0.381*		
					(0.221)		
Treatment*perception gap*has savings						-0.253*	
						(0.142)	
Treatment*perception gap*low food and energy expend.							-0.372**
							(0.165)
Constant	-0.304	-0.304	-0.304	-0.304	-0.304	-0.304	-0.304
	(0.447)	(0.447)	(0.447)	(0.447)	(0.447)	(0.447)	(0.447)
Observations	1,863	1,863	1,863	1,863	1,863	1,863	1,863
R-squared	0.313	0.271	0.314	0.275	0.280	0.263	0.289

Source: authors' calculation on data from CSIH 2023-H2.

Notes: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. "Make ends meet: easy" is a dummy taking value 1 when the answer to the household's self-assessment of its ability to make ends meet with its disposable income is 'fairly easy', 'easy', 'very easy'. "No arrears" is a dummy taking value 1 the household has no payments (both debt installments and bills) overdue for more than 90 days, 0 otherwise. "Has savings" is a dummy taking value 1 when the household states it had been able to put aside savings in the previous 6 months, 0 when savings were null or negative. "Low food and energy expenditure" is a dummy taking value 1 when the share of the expenditure for food and energy is below the median, 0 otherwise.

Table 5: Descriptive statistics by indicators of economic conditions

	Exp. pre treatment	Past perception	Inflation expectation
Full sample	2.83	2.599	8.233
Make ends meet: easy	1.696	2.651	6.616
Make ends meet: difficult	3.493	2.569	9.178
No arrears	2.291	2.229	7.837
Has arrears	6.653	5.225	11.037
Has savings	2.056	2.404	6.776
No savings	3.259	2.708	9.04
Expenditure ratio below median	2.055	2.318	6.804
Expenditure ratio above median	3.61	2.882	9.669

Source: Authors' calculation on data from CSIH 2023-H2 and SHIW2022.
Notes: The table shows the mean value in percent values for prior house price expectations (before the treatment); perception of past house price growth; inflation expectations by different indicators of economic condition. "Make ends meet" refers to self-assessment of the household; "Arrears" to the household having payments (both debt installments and bills) overdue for more than 90 days. "Has savings" when the household states it has been able to put aside savings in the previous 6 months. "Expenditure ratio" refers to the share of expenditure on food and energy.

Table 6: Home price revisions and house price treatment - heterogeneity (2)

	(1)	(2)	(3)
Treatment	-0.914	-1.248	-1.160
	(0.801)	(0.860)	(0.852)
Perception gap	0.0136	0.0136	0.0136
	(0.0254)	(0.0254)	(0.0254)
Treatment*perception gap	0.624**	0.541***	0.367**
	(0.251)	(0.166)	(0.185)
Treatment*perception gap*homeowner	-0.243		
	(0.275)		
Treatment*perception gap*housing supply elasticity low		-0.227	
		(0.180)	
Treatment*perception gap*housing demand tightness high			0.128
			(0.220)
Constant	-0.304	-0.304	-0.304
	(0.447)	(0.447)	(0.447)
Observations	1,863	1,863	1,863
R-squared	0.262	0.264	0.254

Source: authors' calculation on data from CSIH 2023-H2.
Notes: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Demand tightness is given by the ratio of clicks per ad with respect to the number of builidngs in a given OMI-zone; supply elasticity is defined according to the land supply index mentioned in Section 2.4.

3.3 Asymmetric and non-linear updating behaviour

The baseline specification adopted in the previous section assumes a linear effect of the perception gap for the treated group, i.e. treated households revise their expectations with respect to their perception gap in a constant manner when provided with the information. However, this functional form may misspecify asymmetries and non-linearities in revisions along the perception gap distribution. Treated households may revise their expectations differently depending on whether their perception gap is positive, i.e. realized past house price growth is higher than they thought, or negative, i.e. realized past house price growth is lower than they perceived. Moreover, households might revise their expectations in a non-linear way depending on the size of the information treatment, i.e. they might react differently depending on whether the signal is remarkably distant or not from their prior.

We test the asymmetric and non-linear updating behaviour by performing two exercises. First, we retain the linear model but allow the coefficient β_3 to vary for negative versus positive perception gaps and across quintiles of the gap distribution. Employing quintiles[6] helps to reveal whether updating differs when the signal diverges sharply from the prior –namely, when it lies far from the household's initial view of past growth.

Column (1) of Table 7 indicates that treated households react about three times more strongly to a negative perception gap than to a positive one, and this difference is statistically significant. Column (2) reveals that the influence of the perception gap on treated households diminishes across its distribution: it becomes indistinguishable from zero in the third and fourth quintiles, then rises again in the top quintile – though here it is only marginally significant at the 10 percent level and smaller than the effects observed in the lower quintiles. Taken together, these findings point to a non-constant impact of the perception gap on expectation revisions: treated households are especially responsive when they discover that house-price growth has been much lower than they previously believed.

[6] Average perception gaps by quintile are –22, –5, 0, 3, 19.

Table 7: Home price revisions and house price treatment - by perception gap

	(1)	(2)
Treatment	0.979	1.179
	(0.933)	(1.088)
Perception gap	0.0136	0.0136
	(0.0254)	(0.0255)
Treatment*Perception Gap*$\mathbb{1}(PercGap < 0)$	0.636***	
	(0.172)	
Treatment*Perception Gap*$\mathbb{1}(PercGap \geq 0)$	0.212**	
	(0.106)	
Treatment*Perception Gap*$\mathbb{1}(1PercGapQuintile)$		0.649***
		(0.174)
Treatment*Perception Gap*$\mathbb{1}(2PercGapQuintile)$		0.565***
		(0.217)
Treatment*Perception Gap*$\mathbb{1}(3PercGapQuintile)$		3.348
		(2.391)
Treatment*Perception Gap*$\mathbb{1}(4PercGapQuintile)$		-0.0334
		(0.269)
Treatment*Perception Gap*$\mathbb{1}(5PercGapQuintile)$		0.207*
		(0.109)
Constant	-0.304	-0.304
	(0.447)	(0.448)
Observations	1,863	1,863
R-squared	0.278	0.280

Source: authors' calculation on data from CSIH 2023-H2.
Notes: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

In the second exercise, we consider a flexible semi-parametric model that maintains a linear relationship between the treatment and the revision, but allows its effect to vary smoothly with the perception gap. In particular, we adopt the smooth varying coefficient model (SVCM) (Hastie and Tibshirani, 1993; Rios-Avila, 2020), which can be expressed as:

$$\Delta E(\pi_i) = Thp_i * f(g_i) + e_i \tag{4}$$

where the notation is the same as Equation 2 and $E(e_i|Thp_i, g_i) = 0$. In the SVCM, Thp_i

has a linear effect on the expectation revision, but this effect is a non-linear function of g_i, i.e. the perception gap smoothly changes the effect of the information treatment through the function f. The perception gap is the smoothing variable. This model combines the flexibility of a non-parametric model but keeps the structure of a linear model, overcoming the limitations of the two alternative specifications. In fact, the SVCM reduces the number of parameters to be estimated and the computational burden, which characterize non-parametric models, while allowing for flexibility and for easy interpretation of the results.

The model is estimated using a local linear kernel regression (Li and Racine, 2007, 2010), carried out at some point of interest g_0 as follows:

$$\Delta E(\pi_i) = \alpha_0 + \alpha_1 * Thp_i + \alpha_2 * (g_i - g_0) + \alpha_3 * (Thp_i * (g_i - g_0)) + e_i \tag{5}$$

Denoting with X the matrix of predictors of Equation 5, the estimation of parameters B is obtained as:

$$\hat{B} = (X' K_h(g_0) X)^{-1} (X' K_h(g_0) \Delta E(\pi)) \tag{6}$$

where h is the bandwidth and K is a matrix of Kernel weights, that give more weight to observations with a value of g_i closer to g_0 given h. We estimate the regression for each value of the perception gap and the bandwidth is chosen using the leave-one-out cross-validation procedure.[7] [8]

Figure 4, which plots the combined coefficient for the treated group ($\alpha_2 + \alpha_3$ in Equation 5), confirms that once households receive the information treatment, they extrapolate more when the perception gap is negative. In other words, they adjust their expectations more when they discover that actual past house price growth has been lower than they had assumed. Conversely, when they learn that past growth exceeded their prior belief, treated households do not extrapolate from the recent past in the process of revising their expectations. The Figure shows that the estimated effect of the perception gap on the treated is non-linear: the estimated impact rises to about 0.8 (highly significant at the 1 per cent level) when the perception gap is about -48, falls by about half as the gap approaches zero, and is indistinguishable from zero when the gap exceeds about 38.

Figure 5, which traces the estimated impact of the perception gap for the treated group interacted with various economic indicators, reveals that the same asymmetric, non-linear pat-

[7] This procedure finds the optimal bandwidth h^* such that $h^* = min_h CV(h) = min_h \sum_{i=1}^{n} k(g_i)(\Delta E(\pi_i) - \Delta\hat{E}(\pi_{-i}))^2$, where $k(g_i)$ is the Kernel weight. The procedure is implemented with the Stata package `vc_pack` (see Rios-Avila, 2020).

[8] To corroborate the adoption of the SVCM, we test its specification against other linear specifications that include polynomials of the interaction term $Thp_i * g_i$ (Rios-Avila, 2020). The F-statistic (not shown) suggests that the null hypothesis of correctly specified linear models is rejected at 1% level in favour of the alternative SVCM.

tern appears among financially strained households. In fact, households struggling to make ends meet, those with no savings in the last 6 months and those with debt and bill arrears react far more sharply when the signal is below their original belief. By contrast, extrapolation among treated and financially better off households is more limited and quite constant along the perception gap distribution.

To probe this asymmetry further, we replicate the analysis by respondents' mood — a proxy for overall sentiment at the time of the interview.[9] Figure 6 shows that treated households in a downbeat state extrapolate much more when the perception gap is strongly negative. The results by economic condition and by sentiment are confirmed by Tables A.2, A.3, A.4,A.5 in the Appendix A showing the differentiated linear effect by quintiles of the perception gap.

SVCM - Estimated effect of perception gap on the treated

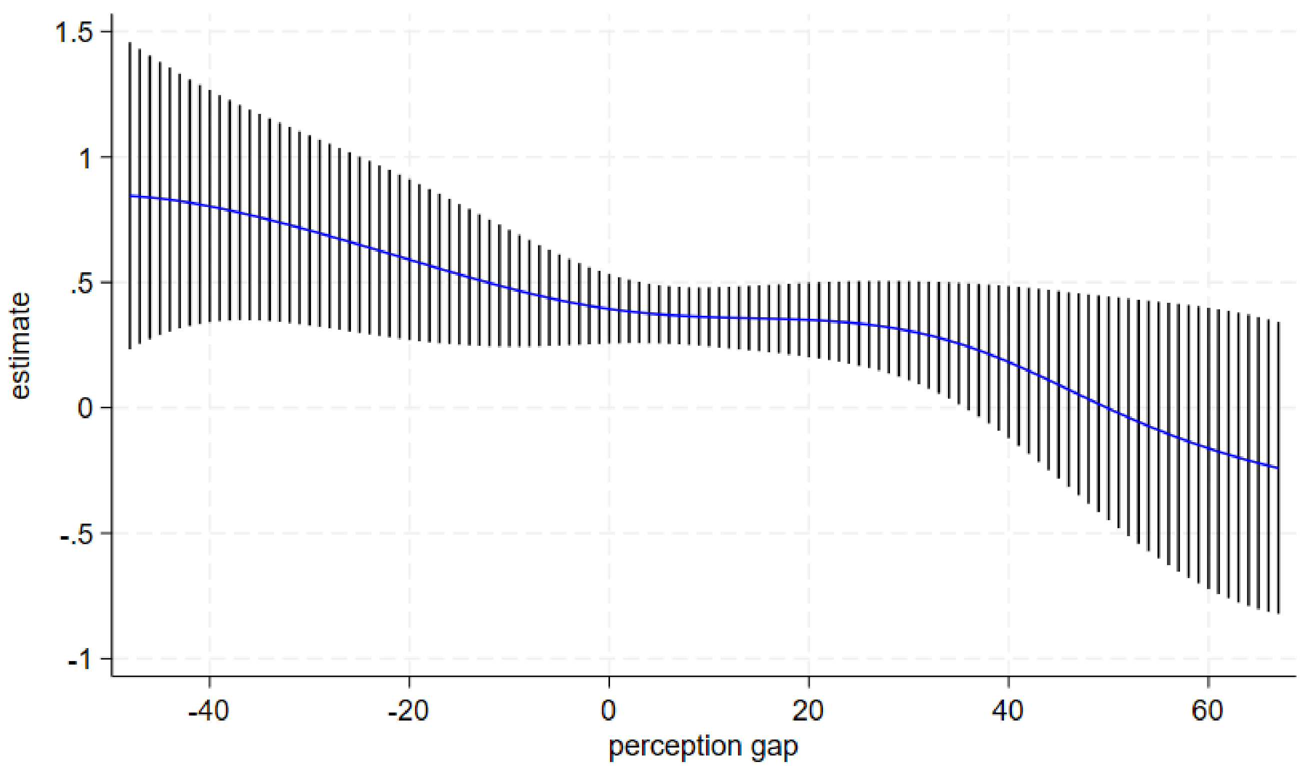


Figure 4

Source: authors' calculation on data from CSIH 2023-H2.
Notes: Robust standard errors. CI at 95 per cent level. Perception gap on the x-axis.

[9]Participants rate their happiness on a scale from 1 to 10; we classify scores below 6 as "sad."

SVCM - Heterogeneous effect of perception gap on the treated by economic indicators

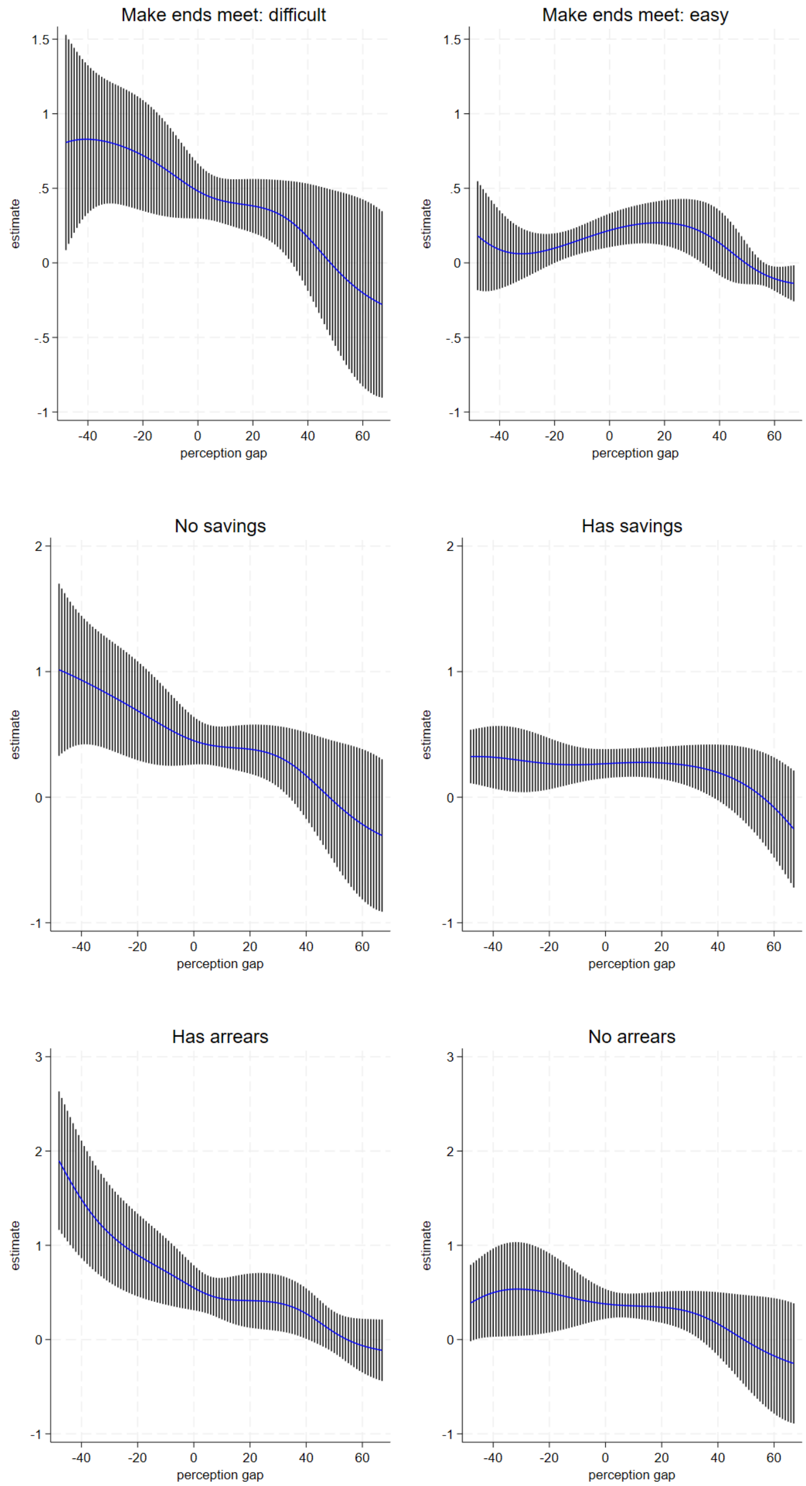
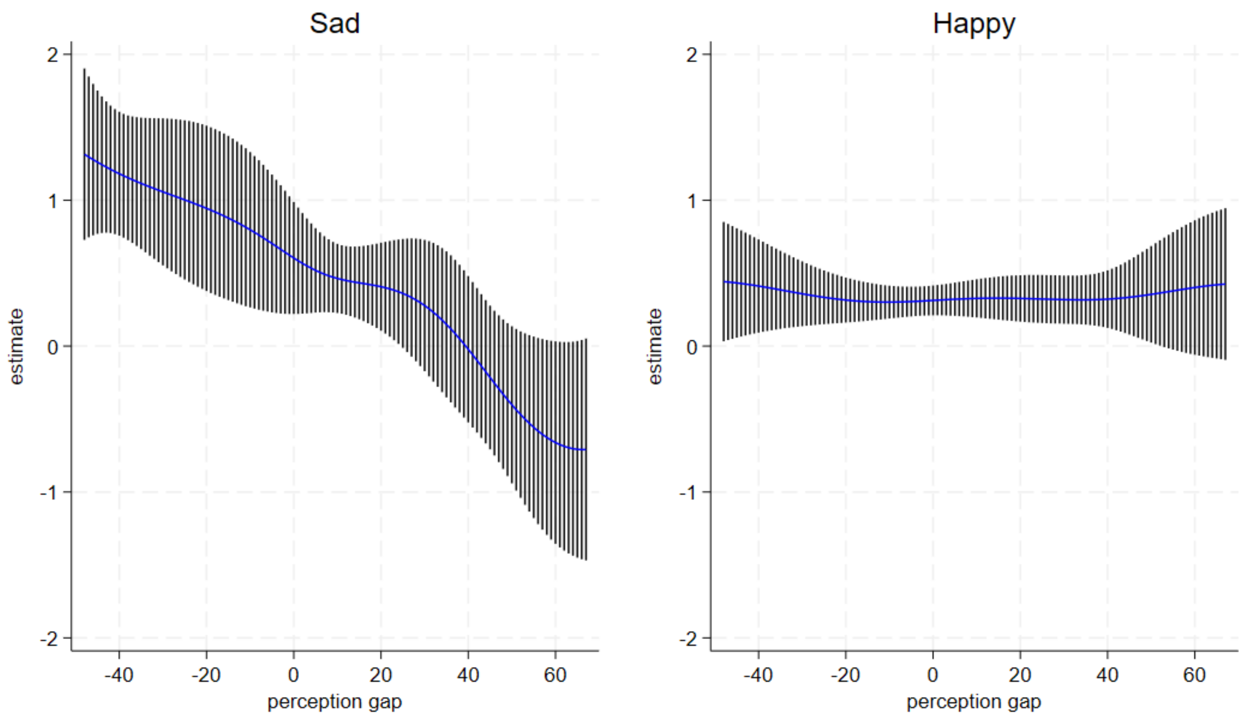


Figure 5

Source: authors' calculation on data from CSIH 2023-H2.
Notes: Robust standard errors. CI at 95 per cent level. Perception gap on the x-axis.

Figure 6

SVCM - Heterogeneous effect of perception gap on the treated by respondents' mood



Source: authors' calculation on data from CSIH 2023-H2.
Notes: Robust standard errors. CI at 95 per cent level. Perception gap on the x-axis.

Our results support the hypothesis that households value the information they receive differently depending on the sign of the perception gap. Considering that most of the respondents are homeowners (about 80 per cent) and almost all of them do not intend to change their main residence by buying another one, neither at the time of the interview nor in the next year,[10] we argue that when informed, households with positive perception gap receive a kind of "good news" as they learn about their asset value appreciation, whereas households with negative perception gap receive "bad news". In Figure A.3 we estimate the SVCM by economic conditions for the subsample of homeowners and find that non-linearities are indeed more pronounced for this group compared to the full sample. Moreover, financially struggling homeowners seem to be more prone to react strongly to negative news, as for them the value of the main residence

[10]Intention to change the main residence by purchasing it is elicited in the CSIH 2024-H1 wave, where about 70 percent of households from CSIH 2023-H2 were re-interviewed. Lack of intention to change the main residence emerges also from the SHIW 2022, were households were asked their intention to move from 2020 to 2023 (see Column 2 of Table A.1)

accounts for the largest share of their gross wealth (as shown in Table A.1): receiving news about the depreciation of their most valuable asset is indeed a negative piece of information. Indeed, this is consistent with the extensive experimental evidence (Coutts, 2019; Ertac, 2011) showing that agents update their beliefs differently, depending on whether they receive good or bad news. For example, Ertac (2011) finds that updating of beliefs is more responsive to bad news, leading to overly pessimistic expectations in a self-relevant context, whereas in a more neutral context agents update more in line with the Bayesian benchmark. Moreover, a growing economic literature (among others Kuhnen, 2015; Kuhnen and Miu, 2017) shows that agents in bad economic times are the ones who overreact to negative news. One explanation for this is risk aversion, as agents in bad economic times are reluctant to take risks and update their beliefs in a pessimistic way (Malmendier and Nagel, 2011). In other words, this evidence suggests that economic adversity leads to asymmetric learning from economic news. In line with this literature, we find asymmetries in updating behaviour on average, but also by indicators of financial distress: we observe more extrapolation for households more exposed to the inflation shock.

3.4 Robustness checks

- **Interaction with inflation treatment**

  In this section, we show our baseline results, taking into account that the CSIH 2023-H2 survey included a further information treatment on inflation to provide a random sub-sample of households with information on the last realized value of the HICP, which was 6.3 per cent in July 2023. The inflation treatment was administered immediately after respondents answered about perceived past and future house-price growth, and before they received the house-price treatment and reported their revised expectations for house-price changes.[11]

  The sample is therefore split into four different groups:

  - households who are given *only* the inflation treatment
  - households who are given *only* the house price treatment
  - households who are given *both* the inflation and the house price treatment
  - households not receiving any treatment

  As the inflation treatment is given before the house price treatment, we cannot rule out the possibility of an interplay between the two treatments. In this section we first restrict the

[11] Note that there are other questions in the questionnaire between questions on house price experiment and questions on inflation experiment.

analysis to either the units that were not administered the inflation treatment; secondly, we try to disentangle the two effects. Our main results are robust to these two different specifications.

In the first exercise, we restrict the analysis to those units that did not receive the inflation treatment, thus estimating Equation 2 on about half of the original sample: in this way, we isolate the effect of the house price information treatment. Table B.1 shows the estimates of the coefficients of interest: the estimate of β_3 is positive and significant in all specifications and virtually unchanged from that obtained in our main analysis in Table 3.

In the second exercise, we further enrich the analysis by testing the data-consistent updating behaviour across the four treatment groups defined at the beginning of this section, by estimating the following regression:

$$\begin{aligned}\Delta E(\pi_i) = \beta_0 + \beta_1 Thp_i + \beta_2 Tinfl_i + \\ \beta_3 Thpinlf_i + \beta_4(Thp_i * g_i) + \beta_5(Tinfl_i * g_i) + \beta_6(Thpinfl_i * g_i) + \beta_7 g_i + u_i \quad (7)\end{aligned}$$

where $\Delta E(\pi_i)$ is the revision in expected house price variation, Thp_i is equal to one if the household received the house price treatment only, g_i is the perception gap, $Tinfl_i$ is equal to one if the household received the inflation treatment only and $Thpinfl_i$ is equal to one if the household received both treatments.

Table B.2 shows the OLS estimates of Equation 7. As in the previous section, we focus on the coefficients of the interaction between the different treatments and the perception gap: in column 4, where there is the most complete set of controls, the estimate of β_4 implies a revision of 0.4 p.p. for each percentage point of over/under-estimation of past house price growth. Since this coefficient is only slightly lower than the corresponding estimate in Table 3, we can infer that the inflation treatment does not play a role in the updating behaviour of the households. Indeed, it is worth noting that the magnitude of the coefficient of the interaction of the perception gap with the double treatment is also very close to our estimate in the main analysis; consistently, the inflation treatment alone does not significantly affect the revision of house price expectations.

- **Measurement error**

  Measurement error in the independent variable of interest, in our case the perception gap, might introduce attenuation bias on the estimate of the coefficients β_2 and β_3 of Equation 2, invalidating the results. To investigate this issue different exercises are conducted.

  First, we trim and winsorise the sample at the top and bottom 1% of the perception gap distribution to remove potential outliers with unreliable past perceived house price growth, in addition to the outliers already dismissed from the beginning. Second, we exploit paradata collected at the end of the interview on the difficulty and burden of the questions. Respondents are asked to rate the difficulty they encountered during the interview on a scale from 1 to 10. This information is related to the reliability of answers, as more cognitive burden might lead to more measurement error. We test whether the updating behaviour differs according to the perceived difficulty of the interview. The results, reported in Table B.3, corroborate the findings in Table 3, as the estimates are stable across the different checks.

Second, we analyse measurement error in the perception gap by implementing the simulation-extrapolation (SIMEX) method (Hardin, Schmiediche, and Carroll, 2003), according to which the observed perception gap contains noise: $g_i = g_i^* + u_i$, where g_i^* is error-free perception gap and u_i represents classical measurement error with $u_i \sim N(0, \sigma_u^2)$. The idea is to simulate additional measurement error by generating a random variable, $u_i \sim N(0, (1+\theta)\sigma_u^2)$, where the parameter $\theta \in [0, 1]$ adds noise for different values in the interval. For each value of θ the average estimates, obtained from 1,000 simulations, represent the estimated parameter if the measurement error were $(1+\theta)\sigma_u^2$. Then the trend between the estimated average coefficients and θ is uncovered to extrapolate back to the results we would obtain if the perception gap was error-free, i.e. for $\theta \in [-1, 0]$. We fit a quadratic model and use the estimated variance of the perceived past house price growth, $\tilde{\pi}_i$, for σ_u^2. Figure B.1 shows the results of the estimated parameter of interest β_3 for different level of measurement error: if perception gap is measured without error ($\theta = -1$), the coefficient would be 0.49 in place of 0.44. Therefore, the analysis suggests the presence of very limited attenuation bias due to classical measurement error and our conclusions do not change.

Finally, we do replicate the two exercises taking into account also the asymmetric and non-linear updating behaviour, detected in Section 3.3. Specifically, we check whether the results obtained with the SVCM persist if outliers are trimmed or winsorized and if we take into account the cognitive burden of the interview. Results shown in Figure B.2 corroborates the findings from our main specification. Moreover, the SIMEX method is applied also to the interactions between $Treatment * PerceptionGap$ and the indicator variable representing whether the perception gap is negative or positive in order to analyse potential attenuation bias in estimated coefficients of Column (2) in Table 7. Figure B.3 shows that, also in the case of asymmetric updating behaviour, measurement error does not invalidate our results.

4 Conclusions

Using the second edition of the Conjunctural Survey of Italian Households (CSIH), conducted in the summer of 2023, a period of high inflation and high mortgage interest rates, we test whether and how Italian households revise their housing expectations after being provided with information that may differ from their priors about recent house price growth in their local area.

We find that in this context, households tend to overestimate past price growth, differently to what has been found for low-inflation periods for the US; the over-estimation is larger for households more affected by the rise of inflation. On average, Italian households revise their expectations in the direction of the gap between perceived and actual past house price growth, showing extrapolative behaviour. Women, younger and households more exposed to inflation update more, whereas local housing conditions seem to be irrelevant. We also find asymmetric and non-linear updating behaviour of households, which are more sensitive when the signal is much lower than perceived house price growth. This is especially true for those in financial distress or in a negative mood.

As houses represent a significant proportion of household wealth, understanding house price expectations can have important implications for both welfare and policy analysis and can help policymakers to predict trends, assess risks and adjust strategies for economic stability.

References

Anari, Ali and James Kolari. 2002. "House prices and inflation." *Real Estate Economics* 30 (1):67–84.

Armona, Luis, Andreas Fuster, and Basit Zafar. 2019. "Home Price Expectations and Behaviour: Evidence from a Randomized Information Experiment." *Review of Economic Studies* 86 (4):1371–1410. URL `https://ideas.repec.org/a/oup/restud/v86y2019i4p1371-1410..html`.

Bailey, Michael, Ruiqing Cao, Theresa Kuchler, and Johannes Stroebel. 2018. "The economic effects of social networks: Evidence from the housing market." *Journal of Political Economy* 126 (6):2224–2276.

Bekiros, Stelios, Rachatar Nilavongse, and Gazi Salah Uddin. 2020. "Expectation-driven house prices and debt defaults: The effectiveness of monetary and macroprudential policies." *Journal of Financial Stability* 49 (C). URL `https://ideas.repec.org/a/eee/finsta/v49y2020ics1572308920300590.html`.

Bottan, Nicolas and Ricardo Perez-Truglia. 2025. "Betting on the House: Subjective Expectations and Market Choices." *American Economic Journal: Applied Economics* 17 (1):459–500. URL `https://www.aeaweb.org/articles?id=10.1257/app.20230641`.

Bruine de Bruin, Wandi, Wilbert Van Der Klaauw, Downs Julie, Baruch Fischhoff, Giorgio Topa, and Olivier Armantier. 2010. "Expectations of Inflation: The Role of Demographic Variables, Expectation Formation, and Financial Literacy." *Journal of Consumer Affairs* 44 (2):381–402.

Carrillo, Paul E, Eric R de Wit, and William Larson. 2015. "Can tightness in the housing market help predict subsequent home price appreciation? Evidence from the United States and the Netherlands." *Real Estate Economics* 43 (3):609–651.

Case, Karl, John Quigley, and Robert Shiller. 2005. "Comparing Wealth Effects: The Stock Market Versus the Housing Market." *Advances in Macroeconomics* 5:1235–1235.

Case, Karl E and Robert J Shiller. 1989. "The Efficiency of the Market for Single-Family Homes." *The American Economic Review* :125–137.

Case, Karl E, Robert J Shiller, and Anne Thompson. 2012. "What have they been thinking? Home buyer behavior in hot and cold markets." Tech. rep., National Bureau of Economic Research.

Coibion, Olivier, Dimitris Georgarakos, Yuriy Gorodnichenko, and Maarten van Rooij. 2023. "How Does Consumption Respond to News about Inflation? Field Evidence from a Randomized Control Trial." *American Economic Journal: Macroeconomics* 15 (3):109–152. URL `https://ideas.repec.org/a/aea/aejmac/v15y2023i3p109-52.html`.

Cooper, D. and K. Dynan. 2016. "ealth Effects and Macroeconomic Dynamics." *Journal of Economic Surveys* 30 (1):1235–1235.

Corsello, Francesco and Marianna Riggi. 2023. "Inflation is not equal for all: the heterogenous effects of energy shocks." Temi di discussione (Economic working papers) 1429, Bank of Italy, Economic Research and International Relations Area. URL https://ideas.repec.org/p/bdi/wptemi/td_1429_23.html.

Coutts, Alexander. 2019. "Good news and bad news are still news: Experimental evidence on belief updating." *Experimental Economics* 22 (2):369–395.

Cutler, David M., James M. Poterba, and Lawrence H. Summers. 1991. "Speculative Dynamics." *The Review of Economic Studies* 58 (3):529–546. URL https://doi.org/10.2307/2298010.

D'Acunto, Francesco, Ulrike Malmendier, and Michael Weber. 2021. "Gender roles produce divergent economic expectations." *Proceedings of the National Academy of Sciences* 118 (21):2008534118–. URL https://ideas.repec.org/a/nas/journl/v118y2021pe2008534118.html.

De Bonis, Riccardo, Danilo Liberati, John Muellbauer, and Concetta Rondinelli. 2023. "Why net worth is the wrong concept for explaining consumption: evidence from Italy." Economics Series Working Papers 1026, University of Oxford, Department of Economics. URL https://ideas.repec.org/p/oxf/wpaper/1026.html.

De Stefani, Alessia. 2021. "House price history, biased expectations, and credit cycles: The role of housing investors." *Real Estate Economics* 49 (4):1238–1266.

Duca, John V., John Muellbauer, and Anthony Murphy. 2021. "What Drives House Price Cycles? International Experience and Policy Issues." *Journal of Economic Literature* 59 (3):773–864. URL https://www.aeaweb.org/articles?id=10.1257/jel.20201325.

Ehrmann, Michael, Damjan Pfajfar, and Emiliano Santoro. 2017. "Consumers' Attitudes and Their Inflation Expectations." *International Journal of Central Banking* 13 (1):225–259. URL https://ideas.repec.org/a/ijc/ijcjou/y2017q0a6.html.

Emiliozzi, Simone, Elisa Guglielminetti, and Michele Loberto. 2018. "Forecasting house prices in Italy." Questioni di Economia e Finanza (Occasional Papers) 463, Bank of Italy, Economic Research and International Relations Area. URL https://ideas.repec.org/p/bdi/opques/qef_463_18.html.

Ertac, Seda. 2011. "Does self-relevance affect information processing? Experimental evidence on the response to performance and non-performance feedback." *Journal of Economic Behavior & Organization* 80 (3):532–545.

Fuster, Andreas, Ricardo Perez-Truglia, Mirko Wiederholt, and Basit Zafar. 2022. "Expectations with Endogenous Information Acquisition: An Experimental Investigation." *The Review of Economics and Statistics* 104 (5):1059–1078. URL https://ideas.repec.org/a/tpr/restat/v104y2022i5p1059-1078.html.

Glaeser, Edward L. and Joseph Gyourko. 2005. "Urban Decline and Durable Housing." *Journal of Political Economy* 113 (2):345–375. URL https://ideas.repec.org/a/ucp/jpolec/v113y2005i2p345-375.html.

Glaeser, Edward L, Joseph Gyourko, Eduardo Morales, and Charles G Nathanson. 2014. "Housing dynamics: An urban approach." *Journal of Urban Economics* 81:45–56.

Glaeser, Edward L, Joseph Gyourko, and Albert Saiz. 2008. "Housing supply and housing bubbles." *Journal of urban Economics* 64 (2):198–217.

Glaeser, Edward L. and Charles G. Nathanson. 2017. "An extrapolative model of house price dynamics." *Journal of Financial Economics* 126 (1):147–170. URL https://ideas.repec.org/a/eee/jfinec/v126y2017i1p147-170.html.

Gohl, Niklas, Peter Haan, Claus Michelsen, and Felix Weinhardt. 2024. "House price expectations." *Journal of Economic Behavior & Organization* 218:379–398.

Guren, Adam M. 2018. "House price momentum and strategic complementarity." *Journal of Political Economy* 126 (3):1172–1218.

Hardin, James W, Henrik Schmiediche, and Raymond J Carroll. 2003. "The simulation extrapolation method for fitting generalized linear models with additive measurement error." *The Stata Journal* 3 (4):373–385.

Hastie, Trevor and Robert Tibshirani. 1993. "Varying-coefficient models." *Journal of the Royal Statistical Society Series B: Statistical Methodology* 55 (4):757–779.

Infante, Luigi, David Loschiavo, Andrea Neri, Matteo Spuri, and Francesco Vercelli. 2023. "The heterogeneous impact of inflation across the joint distribution of household income and wealth." Questioni di Economia e Finanza (Occasional Papers) 817, Bank of Italy, Economic Research and International Relations Area. URL https://ideas.repec.org/p/bdi/opques/qef_817_23.html.

Kuchler, Theresa, Monika Piazzesi, and Johannes Stroebel. 2023. "Chapter 6 - Housing market expectations." In *Handbook of Economic Expectations*, edited by Rüdiger Bachmann, Giorgio Topa, and Wilbert van der Klaauw. Academic Press, 163–191. URL https://www.sciencedirect.com/science/article/pii/B9780128229279000136.

Kuhnen, Camelia M. 2015. "Asymmetric learning from financial information." *The Journal of Finance* 70 (5):2029–2062.

Kuhnen, Camelia M and Andrei C Miu. 2017. "Socioeconomic status and learning from financial information." *Journal of Financial Economics* 124 (2):349–372.

Leombroni, Matteo, Monika Piazzesi, Martin Schneider, and Ciaran Rogers. 2020. "Inflation and the price of real assets." Tech. rep., National Bureau of Economic Research.

Li, Qi and Jeffrey S Racine. 2010. "Smooth varying-coefficient estimation and inference for qualitative and quantitative data." *Econometric Theory* 26 (6):1607–1637.

Li, Qi and Jeffrey Scott Racine. 2007. *Nonparametric econometrics: theory and practice*. Princeton University Press.

Loberto, Michele, Andrea Luciani, and Marco Pangallo. 2018. *The potential of big housing data: an application to the Italian real-estate market*. Banca d'Italia.

Loberto, Michele and Francesco Zollino. 2016. "Housing and credit markets in Italy in times of crisis." Temi di discussione (Economic working papers) 1087, Bank of Italy, Economic Research and International Relations Area. URL `https://ideas.repec.org/p/bdi/wptemi/td_1087_16.html`.

Malmendier, Ulrike and Stefan Nagel. 2011. "Depression babies: do macroeconomic experiences affect risk taking?" *The quarterly journal of economics* 126 (1):373–416.

———. 2016. "Learning from inflation experiences." *The Quarterly Journal of Economics* 131 (1):53–87.

Menz, Jan-Oliver and Philipp Poppitz. 2013. "Households' disagreement on inflation expectations and socioeconomic media exposure in Germany." Discussion Papers 27/2013, Deutsche Bundesbank. URL `https://ideas.repec.org/p/zbw/bubdps/272013.html`.

Mian, Atif, Kamalesh Rao, and Amir Sufi. 2013. "Household Balance Sheets, Consumption, and the Economic Slump." *The Quarterly Journal of Economics* 128 (4):1687–1726. URL `https://ideas.repec.org/a/oup/qjecon/v128y2013i4p1687-1726.html`.

Pangallo, Marco and Michele Loberto. 2018. "Home is where the ad is: online interest proxies housing demand." *EPJ Data science* 7 (1):47.

Piazzesi, Monika and Martin Schneider. 2009. "Momentum traders in the housing market: Survey evidence and a search model." *American Economic Review* 99 (2):406–411.

Rios-Avila, Fernando. 2020. "Smooth varying-coefficient models in Stata." *The Stata Journal* 20 (3):647–679.

Saiz, Albert. 2010. "The Geographic Determinants of Housing Supply*." *The Quarterly Journal of Economics* 125 (3):1253–1296. URL `https://doi.org/10.1162/qjec.2010.125.3.1253`.

Shiller, Robert J. 2015. *Irrational Exuberance*. No. 10421 in Economics Books. Princeton University Press. URL `https://ideas.repec.org/b/pup/pbooks/10421.html`.

Weber, Michael, Francesco D'Acunto, Yuriy Gorodnichenko, and Olivier Coibion. 2022. "The Subjective Inflation Expectations of Households and Firms: Measurement, Determinants, and Implications." *Journal of Economic Perspectives* 36 (3):157–184. URL `https://ideas.repec.org/a/aea/jecper/v36y2022i3p157-84.html`.

Appendix

A Additional results

Share of developable land in each OMI-zone in Rome

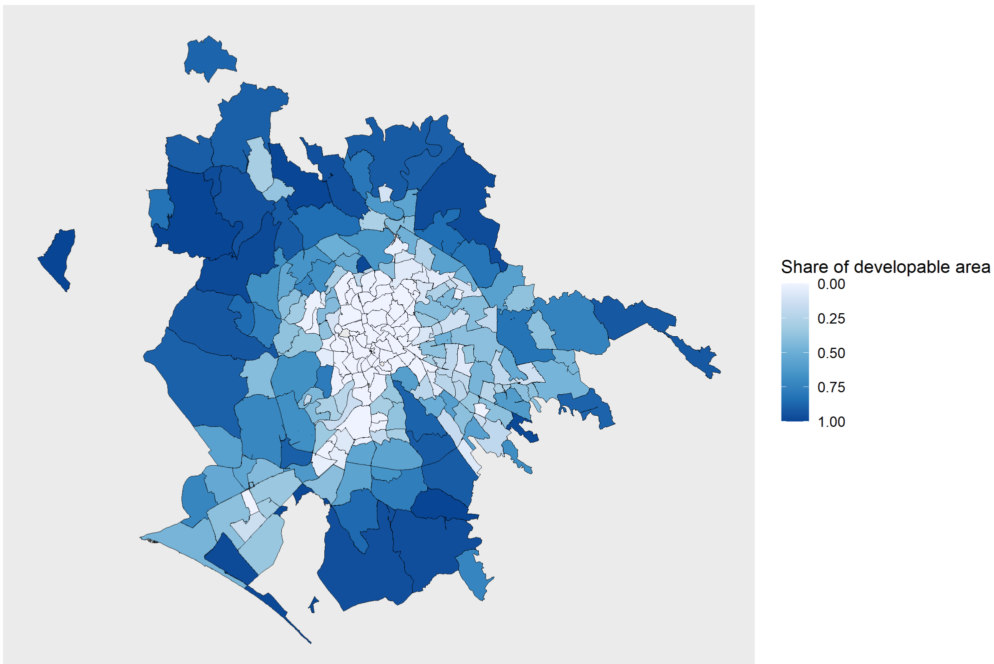


Figure A.1

Source: authors' elaboration on data from OMI-Revenue agency and Corine Land Cover 2018. Notes: the figure shows the share of developable land in each OMI-Zone in the municipality of Rome: darker areas mean a larger share of developable land in the zone. All land is considered developable except for artificial surfaces and water bodies.

Inflation expectations and prior house price expectation

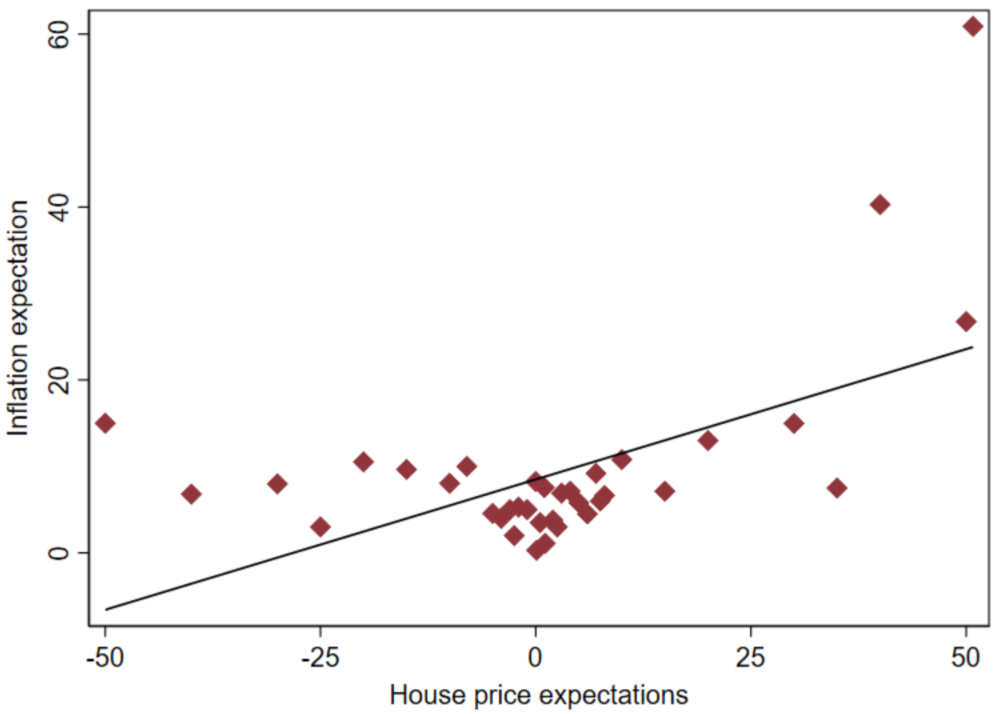


Figure A.2

Source: authors' elaboration on CSIH 2023-H2.
Notes: the figure shows the average of inflation expectations across percentiles of prior house price expectations. We exclude the units who were given the inflation treatment in order to measure correctly their prior expectations.

SVCM - Heterogeneous effect of perception gap on the treated - sample of homeowners

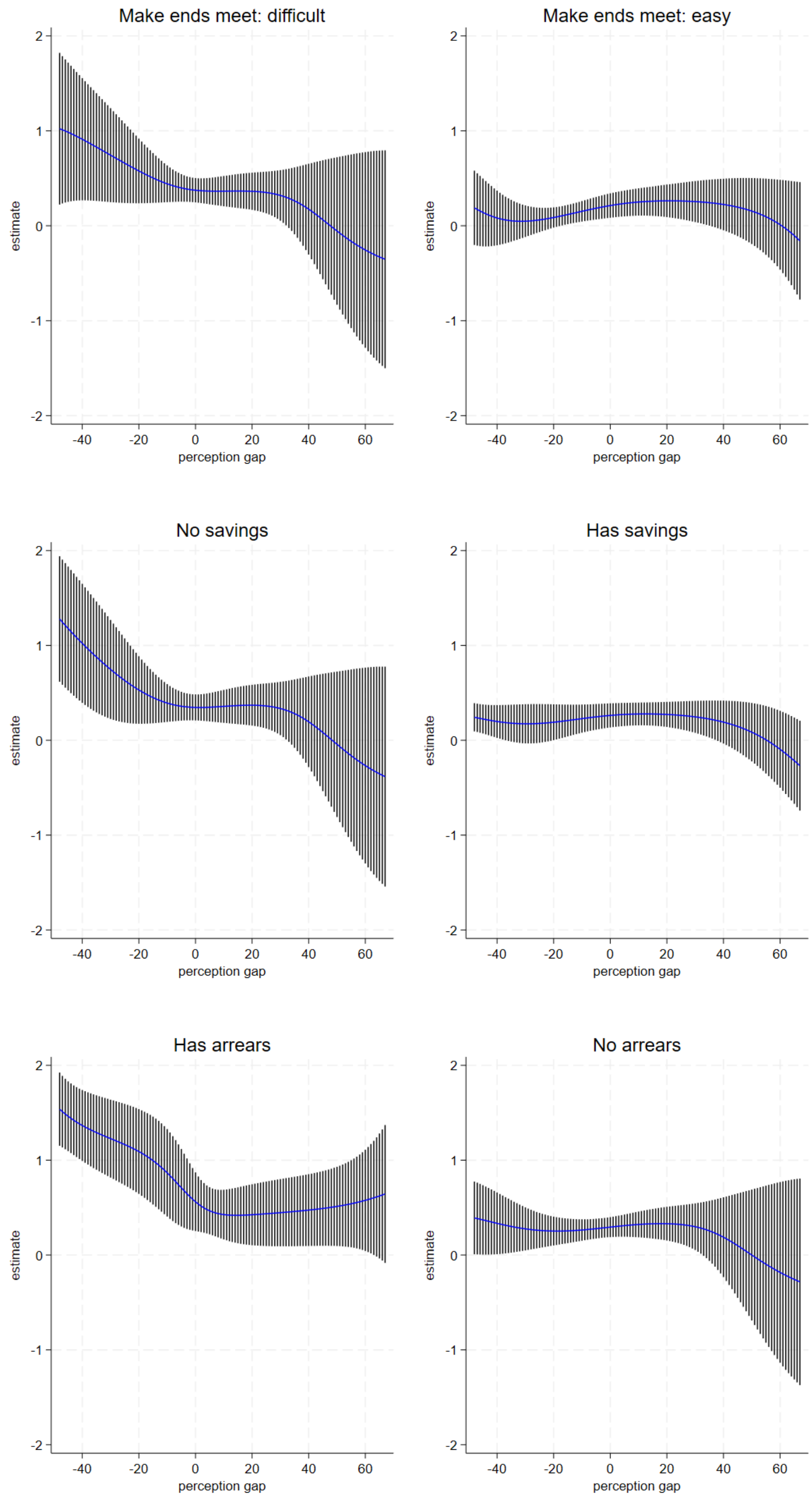


Figure A.3

Table A.1: Value of the main residence wrt wealth and intention to change the residence

	(1) HMR over gross wealth	(2) Past house change
Total	56.9	9.4
Make ends meet difficult	81.5	9.3
Make ends meet easy	42.2	9.5
Has arrears	90.5	11.5
No arrears	54.7	8.5
Has no savings	71.1	9.9
Has savings	43.8	8.5
High food and energy expenditure	80.7	9.7
Low food and energy expenditure	47.7	9.1

Source: authors' elaboration on CSIH 2023-H2 and SHIW2022.
Notes: Column 1 shows the share of the value of the main residence (HMR) of the household over gross wealth. Columns 2 shows the share of households reporting the intention to change their house in the years from 2020 to 2022, as elicited in SHIW 2022.

Table A.2: Home price revisions and house price treatment - by perception gap and make ends meet

	(1)
Treatment	0.682
	(1.033)
Perception gap	0.0136
	(0.0255)
Treatment*Perception Gap*$\mathbb{1}(1 PercGapQuintile)$*$\mathbb{1}(Easy)$	0.0673
	(0.0776)
Treatment*Perception Gap*$\mathbb{1}(1 PercGapQuintile)$*$\mathbb{1}(Difficult)$	0.759***
	(0.184)
Treatment*Perception Gap*$\mathbb{1}(2 PercGapQuintile)$*$\mathbb{1}(Easy)$	0.550**
	(0.271)
Treatment*Perception Gap*$\mathbb{1}(2 PercGapQuintile)$*$\mathbb{1}(Difficult)$	0.409*
	(0.233)
Treatment*Perception Gap*$\mathbb{1}(3 PercGapQuintile)$*$\mathbb{1}(Easy)$	1.040
	(1.502)
Treatment*Perception Gap*$\mathbb{1}(3 PercGapQuintile)$*$\mathbb{1}(Difficult)$	3.470
	(2.874)
Treatment*Perception Gap*$\mathbb{1}(4 PercGapQuintile)$*$\mathbb{1}(Easy)$	0.226
	(0.301)
Treatment*Perception Gap*$\mathbb{1}(4 PercGapQuintile)$*$\mathbb{1}(Difficult)$	0.00316
	(0.241)
Treatment*Perception Gap*$\mathbb{1}(5 PercGapQuintile)$*$\mathbb{1}(Easy)$	0.198*
	(0.109)
Treatment*Perception Gap*$\mathbb{1}(5 PercGapQuintile)$*$\mathbb{1}(Difficult)$	0.232**
	(0.118)
Constant	-0.304
	(0.448)
Observations	1,863
R-squared	0.327

Source: authors' calculation on data from CSIH 2023-H2.
Notes: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table A.3: Home price revisions and house price treatment - by perception gap and savings

	(1)
Treatment	1.137
	(1.056)
Perception gap	0.0136
	(0.0255)
Treatment*Perception Gap*$\mathbb{1}(1 PercGapQuintile)$*$\mathbb{1}(Savings)$	0.268**
	(0.110)
Treatment*Perception Gap*$\mathbb{1}(1 PercGapQuintile)$*$\mathbb{1}(NoSavings)$	0.758***
	(0.197)
Treatment*Perception Gap*$\mathbb{1}(2 PercGapQuintile)$*$\mathbb{1}(Savings)$	0.526*
	(0.296)
Treatment*Perception Gap*$\mathbb{1}(2 PercGapQuintile)$*$\mathbb{1}(NoSavings)$	0.593***
	(0.222)
Treatment*Perception Gap*$\mathbb{1}(3 PercGapQuintile)$*$\mathbb{1}(Savings)$	1.393
	(1.432)
Treatment*Perception Gap*$\mathbb{1}(3 PercGapQuintile)$*$\mathbb{1}(NoSavings)$	3.910
	(2.909)
Treatment*Perception Gap*$\mathbb{1}(4 PercGapQuintile)$*$\mathbb{1}(Savings)$	0.0892
	(0.321)
Treatment*Perception Gap*$\mathbb{1}(4 PercGapQuintile)$*$\mathbb{1}(NoSavings)$	-0.0775
	(0.251)
Treatment*Perception Gap*$\mathbb{1}(5 PercGapQuintile)$*$\mathbb{1}(Savings)$	0.208**
	(0.0910)
Treatment*Perception Gap*$\mathbb{1}(5 PercGapQuintile)$*$\mathbb{1}(NoSavings)$	0.208*
	(0.124)
Constant	-0.304
	(0.448)
Observations	1,863
R-squared	0.307

Source: authors' calculation on data from CSIH 2023-H2.
Notes: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table A.4: Home price revisions and house price treatment - by perception gap and arrears

	(1)
Treatment	0.873
	(1.037)
Perception gap	0.0136
	(0.0255)
Treatment*Perception Gap*$\mathbb{1}(1 PercGapQuintile)$*$\mathbb{1}(NoArrears)$	0.508**
	(0.211)
Treatment*Perception Gap*$\mathbb{1}(1 PercGapQuintile)$*$\mathbb{1}(Arrears)$	0.869***
	(0.211)
Treatment*Perception Gap*$\mathbb{1}(2 PercGapQuintile)$*$\mathbb{1}(NoArrears)$	0.580**
	(0.226)
Treatment*Perception Gap*$\mathbb{1}(2 PercGapQuintile)$*$\mathbb{1}(Arrears)$	0.0747
	(0.150)
Treatment*Perception Gap*$\mathbb{1}(3 PercGapQuintile)$*$\mathbb{1}(NoArrears)$	3.097
	(2.389)
Treatment*Perception Gap*$\mathbb{1}(3 PercGapQuintile)$*$\mathbb{1}(Arrears)$	0.857
	(1.431)
Treatment*Perception Gap*$\mathbb{1}(4 PercGapQuintile)$*$\mathbb{1}(NoArrears)$	0.0537
	(0.261)
Treatment*Perception Gap*$\mathbb{1}(4 PercGapQuintile)$*$\mathbb{1}(Arrears)$	-0.0132
	(0.236)
Treatment*Perception Gap*$\mathbb{1}(5 PercGapQuintile)$*$\mathbb{1}(NoArrears)$	0.200*
	(0.118)
Treatment*Perception Gap*$\mathbb{1}(5 PercGapQuintile)$*$\mathbb{1}(Arrears)$	0.388***
	(0.145)
Constant	-0.304
	(0.448)
Observations	1,863
R-squared	0.302

Source: authors' calculation on data from CSIH 2023-H2.
Notes: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table A.5: Home price revisions and house price treatment - by perception gap and mood

	(1)
Treatment	0.740
	(0.976)
Perception gap	0.0136
	(0.0255)
Treatment*Perception Gap*$\mathbb{1}(1PercGapQuintile)$*$\mathbb{1}(Happy)$	0.346***
	(0.100)
Treatment*Perception Gap*$\mathbb{1}(2PercGapQuintile)$*$\mathbb{1}(Sad)$	0.980***
	(0.248)
Treatment*Perception Gap*$\mathbb{1}(2PercGapQuintile)$*$\mathbb{1}(Happy)$	0.541**
	(0.214)
Treatment*Perception Gap*$\mathbb{1}(2PercGapQuintile)$*$\mathbb{1}(Sad)$	0.130
	(0.233)
Treatment*Perception Gap*$\mathbb{1}(3PercGapQuintile)$*$\mathbb{1}(Happy)$	2.136
	(1.732)
Treatment*Perception Gap*$\mathbb{1}(3PercGapQuintile)$*$\mathbb{1}(Sad)$	3.778
	(3.881)
Treatment*Perception Gap*$\mathbb{1}(4PercGapQuintile)$*$\mathbb{1}(Happy)$	0.199
	(0.268)
Treatment*Perception Gap*$\mathbb{1}(4PercGapQuintile)$*$\mathbb{1}(Sad)$	-0.111
	(0.211)
Treatment*Perception Gap*$\mathbb{1}(5PercGapQuintile)$*$\mathbb{1}(Happy)$	0.274***
	(0.0904)
Treatment*Perception Gap*$\mathbb{1}(5PercGapQuintile)$*$\mathbb{1}(Sad)$	0.140
	(0.208)
Constant	-0.304
	(0.448)
Observations	1,863
R-squared	0.346

Source: authors' calculation on data from CSIH 2023-H2.
Notes: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

B Robustness checks

Table B.1: Home price revisions and house price treatment - Subsample

	(1)	(2)	(3)	(4)
Treatment	-1.375	-0.948	-0.948	-0.968
	(0.995)	(0.823)	(0.823)	(0.823)
Perception gap	0.022	0.021	0.021	0.026
	(0.043)	(0.039)	(0.039)	(0.039)
Treatment*perception gap	0.419**	0.381***	0.381***	0.380***
	(0.163)	(0.126)	(0.126)	(0.124)
Constant	-0.492	4.683	4.683	3.241
	(0.493)	(3.045)	(3.045)	(2.845)
Observations	904	904	904	904
R-squared	0.268	0.332	0.332	0.340
Geographic characteristics		Yes	Yes	Yes
Household characteristics			Yes	Yes
Local housing characteristics				Yes

Source: authors' calculation on data from CSIH 2023-H2.

Notes: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Geographic characteristics include geographic area and municipality size indicators; household characteristics include socio-demographic variables of the respondent (sex, age, education, occupation) economic variables of the household (having difficulties in making ends meet, main residence ownership, inflation treatment); local housing characteristics refer to indicators for high demand tightness and high supply elasticity. The estimation uses only the subsample that did not receive the inflation treatment.

Table B.2: Home price revisions and house price and inflation treatments

	(1)	(2)	(3)	(4)
House price treatment only	-1.193	-1.258	-1.328	-1.344
	(0.929)	(0.931)	(0.908)	(0.911)
Inflation treatment only	0.265	0.144	0.205	0.264
	(0.906)	(0.933)	(0.932)	(0.891)
House price and inflation treatments	-0.673	-0.648	-0.566	-0.535
	(1.281)	(1.253)	(1.158)	(1.143)
House price treatment*Perception gap	0.407***	0.389***	0.395***	0.393***
	(0.148)	(0.140)	(0.135)	(0.134)
Inflation treatment*Perception gap	-0.0187	-0.0150	-0.0237	-0.0215
	(0.0476)	(0.0495)	(0.0499)	(0.0505)
House price and inflation treatments*Perception gap	0.450***	0.442***	0.447***	0.447***
	(0.134)	(0.127)	(0.125)	(0.124)
Perception gap	0.0164	0.0197	0.0102	0.0127
	(0.0428)	(0.0411)	(0.0412)	(0.0415)
Constant	0.229	1.069	0.895	1.012
	(0.807)	(1.164)	(2.254)	(2.340)
Observations	1,863	1,863	1,863	1,863
R-squared	0.259	0.271	0.291	0.294
Geographic characteristics		Yes	Yes	Yes
Household characteristics			Yes	Yes
Local housing characteristics				Yes

Source: authors' calculation on data from CSIH 2023-H2.
Notes: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Geographic characteristics include geographic area and municipality size indicators; household characteristics include socio-demographic variables of the respondent (sex, age, education, occupation) economic variables of the household (having difficulties in making ends meet, main residence ownership, inflation treatment); local housing characteristics refer to indicators for high demand tightness and high supply elasticity.

Table B.3: Home price revisions - Robustness check: measurement error

	Trimmed sample	Winsorized sample	Difficult interview	Easy interview
	(1)	(2)	(3)	(4)
Treatment	-1.175	-1.167	-0.330	-1.932*
	(0.865)	(0.859)	(1.368)	(1.063)
Perception gap	0.014	0.028	0.058	-0.019
	(0.026)	(0.028)	(0.044)	(0.028)
Treatment*perception gap	0.449***	0.428***	0.406***	0.461***
	(0.108)	(0.102)	(0.135)	(0.161)
Constant	-0.306	-0.281	-0.772	0.142
	(0.448)	(0.448)	(0.879)	(0.319)
Observations	1,855	1,863	875	988
R-squared	0.252	0.280	0.261	0.242

Source: authors' calculation on data from CSIH 2023-H2.
Notes: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

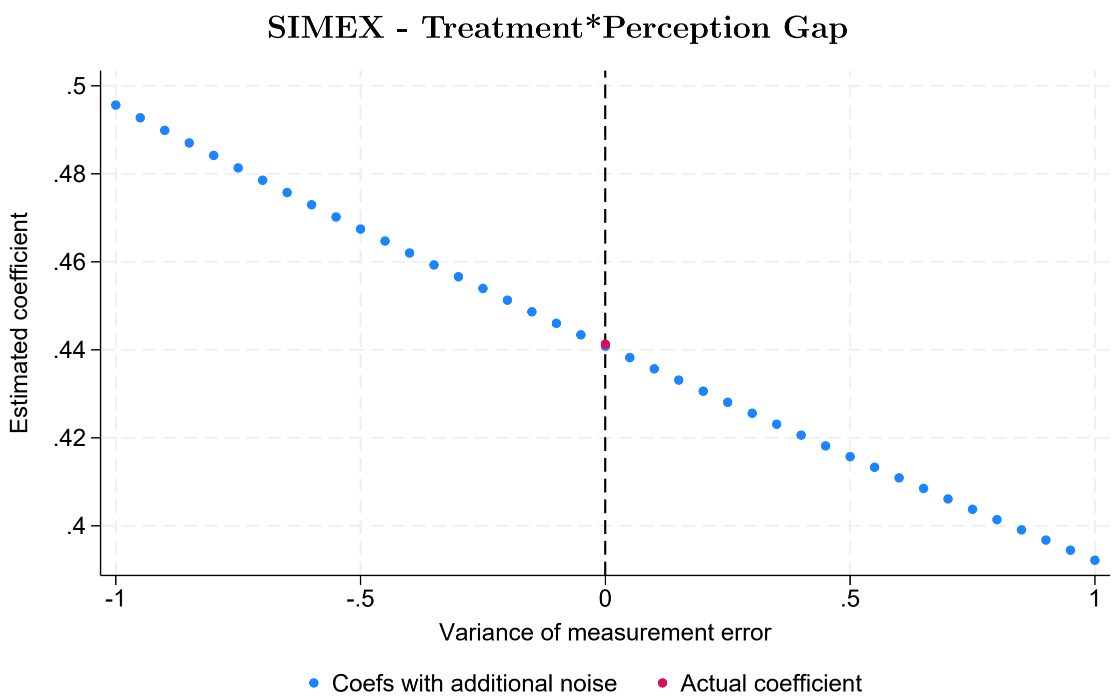


Figure B.1

Source: authors' calculation on data from CSIH 2023-H2.

SVCM - Estimated effect of perception gap on the treated - Robustness checks

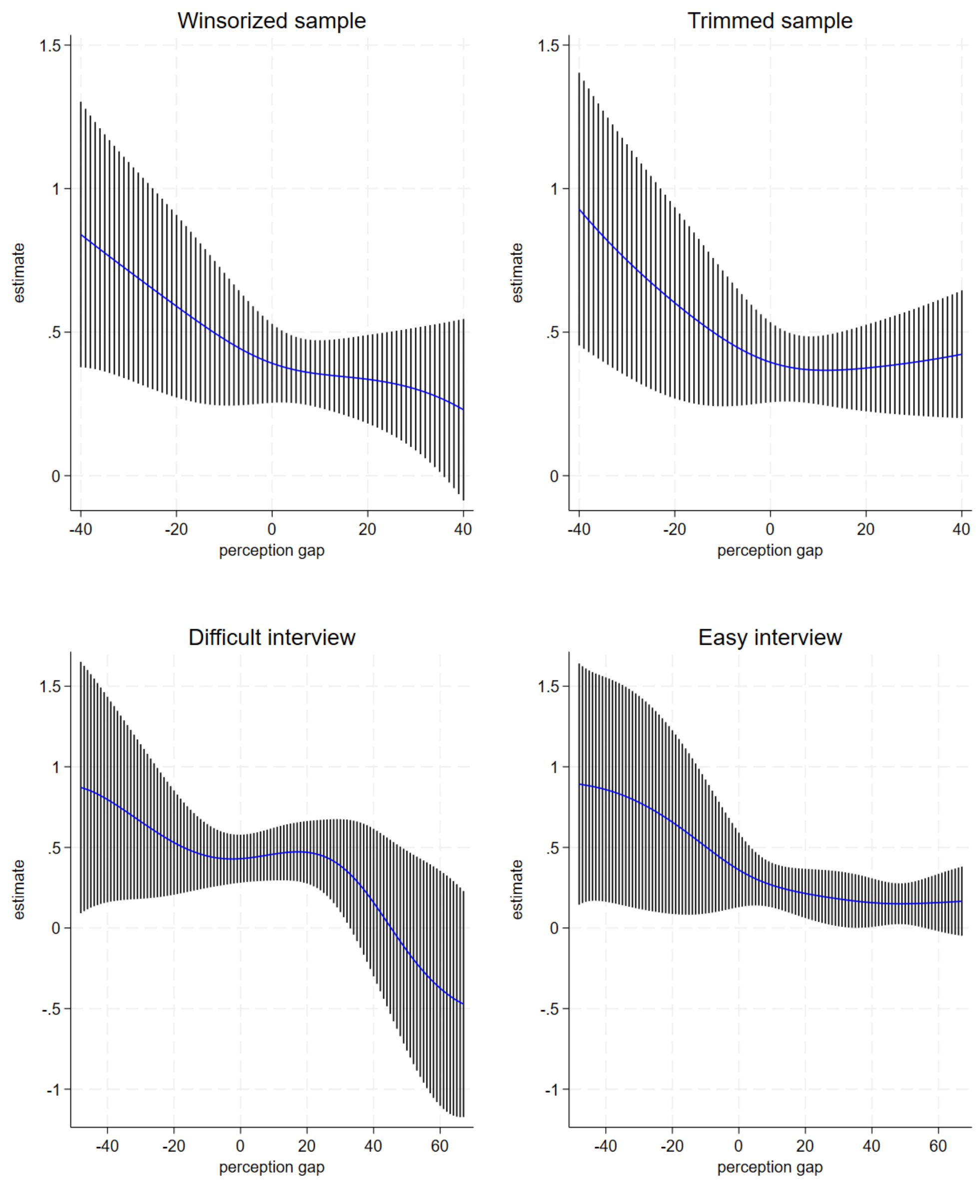
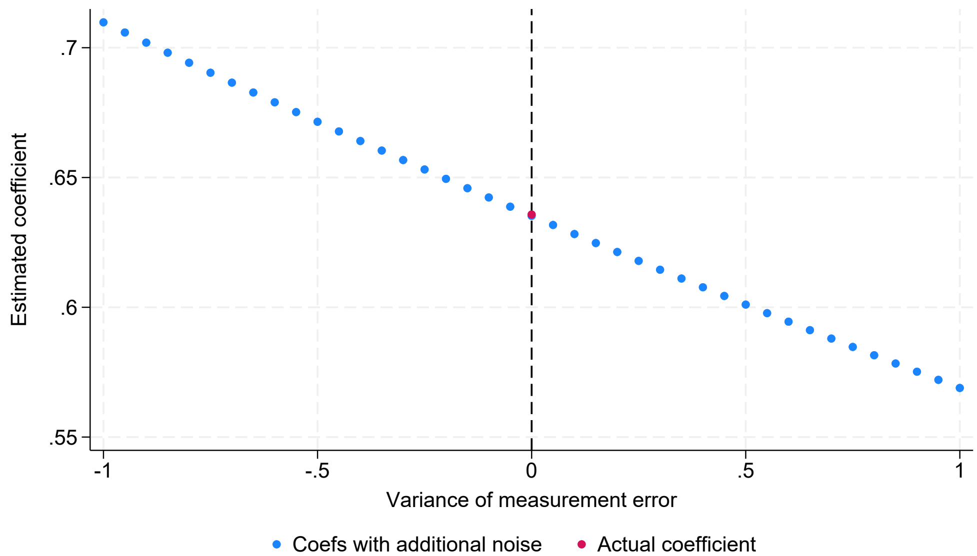


Figure B.2

Source: authors' calculation on data from CSIH 2023-H2.

SIMEX - Asymmetric updating

Treatment*Perception Gap*$\mathbb{1}(PercGap < 0)$



Treatment*Perception Gap*$\mathbb{1}(PercGap \geq 0)$

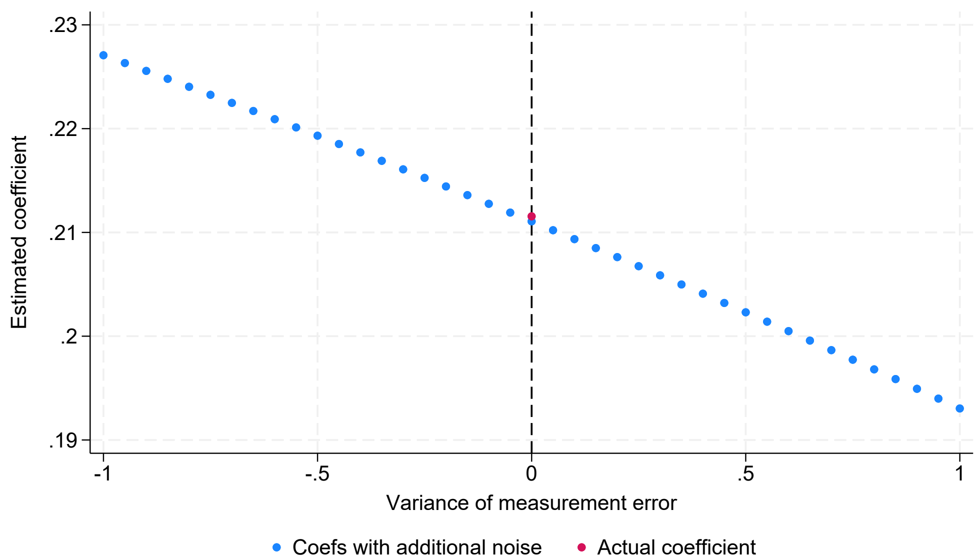


Figure B.3

Source: authors' calculation on data from CSIH 2023-H2.