Inflation Expectations and Price-Setting Decisions: Insights from the Housing Market *

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Abstract

We provide causal evidence on how inflation expectations shape pricing decisions in the housing market. Leveraging a randomized control trial embedded in a survey of Italian real estate agents, we generate exogenous variation in agents' inflation expectations and link survey responses to high-frequency listing-level data from the largest national real estate platform. We document economically large effects. Higher inflation expectations cause a one-to-one increase in housing listing prices and a lower market liquidity. Consistent with a stylized model of the seller's pricing problem, the pass-through is weaker among agents with more pessimistic beliefs about housing demand. Our results uncover a novel channel through which monetary policy authorities, by steering inflation expectations, affect the housing market.

JEL codes: D43, D84, E31, E52, R31

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1 Introduction

Well-anchored inflation expectations play a pivotal role in monetary policy decisions – in particular during high-inflation periods – because expectations of future inflation significantly influence current price dynamics. Yet, the link between the subjective inflation expectations of price-setters and their pricing strategies is still a matter of investigation. The existing literature has primarily focused on firms' pricing behavior in goods markets. By contrast, considerably less is known about how inflation expectations affect pricing decisions in other markets such as the housing market, or more broadly about the role of intermediaries and brokers in transmitting beliefs into actual prices.

We provide new insights into this debate by exploring the pass-through of inflation expectations to housing prices in the Italian real estate market. Specifically, we exploit a randomized control trial to instrument real estate agents' inflation expectations and we find a positive causal impact of the expectations on the observed listing prices of the properties they manage on a large digital platform.[1]

To our knowledge, this is the first study to analyze the impact of inflation expectations on price-setting behavior outside the domain of firms, focusing on a market of first-order macroeconomic relevance. Developments in the housing market can have spillovers on broader economic activity (Iacoviello and Neri, 2010; Piazzesi and Schneider, 2016) and affect the transmission of monetary policy interventions (Bluwestein et al., 2020, Adam and Woodford, 2021, Adam et al., 2024).[2] By documenting a positive and large effects of sellers' inflation expectations on housing prices, our findings reveal a novel channel through which central banks, by steering such expectations, can influence the housing market. This mechanism works independently of the conventional interest rate channel, which primarily operates by changing the cost of mortgage borrowing and thereby affecting housing demand. Instead, we document a supply-side channel: shifts in inflation expectations affect sellers' pricing behavior, thereby affecting equilibrium prices and liquidity in the housing market.

Two features of our setting make it particularly well suited to studying the inflation-expectations pass-through (IEPT). First, real estate agents play a key role in determining listing prices, reflecting their informational advantages in local housing markets (Levitt and Syverson, 2008; Agarwal et al., 2019; Cunningham et al., 2022; Gilbukh and Goldsmith-Pinkham, 2024). Second, our analysis exploits the central importance of initial listing prices in a market characterized by pronounced

[1] Middlemen are crucial in the housing market, with nearly 90% of U.S. buyers and sellers in 2023 relying on agents to complete home purchases (Gilbukh and Goldsmith-Pinkham, 2024). Similar trends are observed in Italy, where brokers mediate a substantial percentage of home purchases (Il Sole 24 Ore, 2023). During 2021-2023, agents posted 95% of all listings on Immobiliare.it, the largest Italian digital platform for house sales.

[2] In most countries, housing accounts for the largest share of household wealth. Variations in average house values, therefore, have an impact on macroeconomic dynamics – in particular through household spending and saving decisions – and redistributive consequences.

price stickiness. A well-established stylized fact is that agents typically choose an initial listing price and rarely revise it upward (Knight, 2002; Merlo and Ortalo-Magne, 2004; Merlo et al., 2015; Anenberg, 2016).[3] As a result, the initial pricing decision is pivotal for subsequent market dynamics.

Like for households and firms, real estate agents' expectations are seldom observable and must be elicited from surveys. Moreover, both expectations and current decisions are jointly influenced by unobserved factors, making it challenging to identify the causal impact of expectations on agents' choices. We overcome this issue by using a randomized control trial included in the Italian Housing Market Survey (IHMS) during the high-inflation period from 2022Q4 until 2023Q2. In this trial, half of the real estate agents received information about consumer price inflation in the month before the interview. We show that the agents who receive the information treatment exhibit significantly higher one-year-ahead inflation expectations. Thus, by identifying an exogenous upward shift in inflation expectations, we can employ an instrumental variable (IV) approach in a repeated cross-section setting, using the randomized information treatment as an instrument for inflation expectations as in Coibion et al. (2020) and Rosolia (2024).

Using record-linkage techniques, we match the agents interviewed in the IHMS with the housing ads they post on the largest online platform that offers real estate services in Italy, Immobiliare.it. This allows us to combine the agents' survey responses with detailed property information, including location, dwelling characteristics, and weekly listing prices, as well as agent-specific characteristics observed through the online platform. Moreover, we have access to all listings on the Immobiliare.it platform, which allows us to analyze various market (neighborhoods) characteristics, such as buyers' search activity. This wealth of data is crucial for understanding the factors that influence the pass-through of inflation expectations to current property prices.

We find that a one percentage point increase in inflation expectations causes a 0.8% to 1.1% rise in current listing prices, depending on the survey wave. Our estimated IEPT is substantially larger than what is typically found in firm-level studies, where estimates usually range from 0 to 0.3 (Coibion et al., 2020; Rosolia, 2024; Baumann et al., 2024). Several features of our setting plausibly contribute to this large IEPT. From a theoretical point of view, the magnitude of the IEPT depends on the hazard of future price adjustments and the expected duration of the price spell. When prices are sticky, the optimal individual-level pass-through can exceed one: a forward-looking price setter may optimally "overshoot" the current desired price because anticipated inflation will erode its real value over time (Werning, 2022). In our context, the conditions for a pass-through equal to or greater than one are clearly present. First, the housing market is characterized by upward rigidity in nominal listing prices, with real estate agents almost never revising prices upward once a listing

[3] Merlo and Ortalo-Magne (2004), exploiting one of the most comprehensive dataset tracking the selling process of real estate properties in the UK, report upward listing price revisions in only 0.4% of cases. Similarly, in the Immobiliare.it dataset of online listings in Italy (2022-2023), upward revisions occurred in just 0.7% of cases. Notably, most revisions occurred shortly after the listings were published, likely due to initial pricing errors.

is published. Second, homes typically remain on the market for several months before a sale occurs, which increases the importance of expectations at the time of initial price-setting. Third, our data cover a period of high – and initially rising – inflation.

We find that the transmission of inflation expectations to listing prices occurs through two channels. First, agents who receive the information treatment post new listings at a higher price than untreated agents. Focusing on newly listed properties, we estimate that a one percentage point increase in inflation expectations causes a 1.3% increase in the prices of new listings. Second, agents incorporate inflation expectations into the prices of their existing listings. Using a difference-in-difference (DiD) approach and exploiting the randomization in the information treatment in 2022Q4, we find a positive impact of the information treatment on the prices of properties that were on the market prior to the provision of the treatment. Since upward price revisions are unusual, this result suggests that treated agents are less likely to lower the prices of their old listings.

In the second part of the paper, we examine the determinants of real estate agents' pricing decisions following a positive shock to their inflation expectations. To guide the empirical analysis, we develop a stylized model of the seller's problem that formalizes the central trade-off. Real estate agents are typically compensated through a commission based on a fixed share of the transaction price. An increase in expected inflation therefore raises the incentive to increase nominal listing prices to preserve the real value of commissions. However, higher listing prices can reduce the likelihood of a sale or prolong the time required to sell. The model implies that the optimal pass-through of inflation expectations depends on agents' beliefs about demand conditions and market tightness. Even if agents hold pessimistic views about the overall impact of inflation on housing demand, as we find in survey evidence, they may still raise prices when the profit-preserving motive dominates.

The empirical evidence is consistent with this mechanism. We document a clear trade-off between higher listing prices and reduced sale probability. A one-percentage point increase in inflation expectations increases the average time a property remains on the market by approximately 4%. Moreover, agents' IEPT reflect their beliefs about the general equilibrium effects of inflation on housing demand. In line with the model's predictions, agents with a less optimistic assessment of inflation's impact on demand exhibit a lower pass-through. Similarly, agents operating in markets characterized by weak demand, or those reporting a more negative assessment of credit conditions, also display a lower degree of pass-through.

These findings highlight a supply-side mechanism through which inflation expectations propagate in the housing market. By raising listing prices to preserve the real value of their commissions, real estate agents slow transaction activity, thereby amplifying the demand-side contraction induced by rising borrowing costs. This supply-side response represents an important complement to the conventional interest rate channel and underscores the role of expectations in shaping housing

market dynamics.

A caveat for our analysis is that it focuses on a relatively short period characterized by high inflation in Italy and the euro area. While this raises concerns about external validity – specifically, to what extent these findings would hold in a low-inflation environment – high-inflation periods are precisely when understanding the effects of expectations on prices is most critical, and inflation dynamics attract heightened attention.

Related literature. This work is closely related to the literature studying the impact of macroeconomic expectations on the behavior of economic agents. Subjective inflation expectations impact business and household decisions and help explain why otherwise similar individuals react differently to the same business-cycle shocks and policy interventions (see Weber et al., 2022 for a recent summary of the main findings in this field and Candia et al., 2023 for a focus on firms' expectations). We are the first to analyze the impact of macroeconomic expectations on price-setting choices of intermediaries in a key market with spillovers on broader economic activity. Past works on the role of subjective beliefs in the housing market have focused only on households and their expectations about housing prices (Armona et al., 2018; Chopra et al., 2025; Bottan and Perez-Truglia, 2025).[4]

Our econometric strategy is inspired by recent studies examining the impact of inflation expectations on the decisions of Italian firms (Coibion et al., 2020; Ropele et al., 2024; Rosolia, 2024). In particular, this body of literature finds that the pass-through of firms' subjective inflation expectations to planned price changes is small or negligible. We instead focus on a novel setting, namely the housing market, and leverage granular data that arguably allows a better quantification of the IEPT. In most related studies, actual pricing decisions are unobserved and the pass-through is typically estimated based on self-reported measures of firms' planned average price changes, abstracting from product-level heterogeneity and cross-market differences.[5] By contrast, we can directly observe listing prices at the product level (i.e., for each individual housing unit) under different market conditions.[6] Doerrenberg et al. (2024) find a one-to-one correlation between inflation expectations and planned price changes for a sample of German firms surveyed in 2022. However, differently from us, their estimates cannot be interpreted in causal terms.

Werning (2022) provides a theoretical framework for understanding the pass-through of inflation expectations to current prices during periods of rising inflation expectations. The study shows that the magnitude of the pass-through varies across pricing mechanisms and that firms may overshoot

[4] Approaching this subject from the standpoint of real estate agents has the benefit of removing any potential subjective biases or idiosyncratic factors that might influence household decisions. Instead, the relationship between inflation expectations and properties' pricing strategies reflects the experts' assessment of the market's evolution.

[5] For multi-product firms, the average planned change in firms' prices is often a poor proxy for actual pricing behavior, because within-firm synchronization in price changes is limited (Bhattarai and Schoenle, 2014; Bonomo et al., 2023). Moreover, price revisions may differ across markets depending on differences in market microstructures.

[6] In the IHMS the survey questionnaire is sent to the head of the real estate agency, who is also responsible for setting listing prices. This feature mitigates concerns about a disconnect between measured expectations and actual price-setting decisions that often arise in firm-level surveys.

their optimal price, anticipating the possibility of being unable to revise prices in the future. Although we cannot claim that real estate agents' pricing strategies mirror those of firms, our findings reveal that the pass-through of inflation expectations to the prices of new listings exceeds one. This result may be attributed to the inability to revise listing prices upward, consistent with Werning (2022)'s theoretical framework and the empirical evidence on the upward rigidity in housing listing prices (Merlo and Ortalo-Magne, 2004).[7]

A recent literature documents that deviations of subjective housing price expectations from the full-information rational expectations benchmark impact not only aggregate housing price dynamics (Glaeser and Nathanson, 2017, Schmitt and Westerhoff, 2019) but also the propagation of economic shocks across the wider economy and the design of monetary policy (Adam and Woodford, 2021, Adam et al., 2024). Our work indicates that real estate agents' expectations significantly influence housing price dynamics and, therefore, may have implications beyond the housing market.

Finally, our paper contributes to the literature on the role of real estate agents in the housing markets. Levitt and Syverson (2008) and Agarwal et al. (2019) find that real estate agents have better information and secure better deals when they sell or buy a house for themselves. Cunningham et al. (2022) and Gilbukh and Goldsmith-Pinkham (2024) show that real estate agents differ in their abilities, and that affects housing prices and the probability of selling. Our work complements these insights by documenting that real estate agents adjust listing prices in response to new information about inflation, plausibly to preserve the real value of their remuneration from housing intermediation.

The remainder of the paper is organized as follows. Section 2 describes the data. Section 3 presents our econometric strategies and results. Section 4 proposes a stylized model of the seller's problem to interpret the empirical findings and tests its predictions by investigating the heterogeneity in the pass-through. Section 5 discusses the findings and potential future research directions. Section 6 concludes.

2 Data

The main data sources used in this work are the Italian Housing Market survey (IHMS) and the online housing ads posted on the platform Immobiliare.it. In the next Sections we describe each of them in detail and provide summary statistics for the merged sample.

[7]Notice that Werning (2022) focuses primarily on the pass-through of inflation expectations into *aggregate* prices, which depends both on individual pass-through and on the fraction of agents adjusting prices. In this paper we concentrate on the individual component, instead.

2.1 The Italian Housing Market Survey

The Italian Housing Market Survey (IHMS) has been conducted at quarterly frequency since 2009 by the Bank of Italy with the cooperation of Tecnoborsa and the Tax Revenue Agency on a rotating panel of about 1,500 real estate agents, representative of the reference universe consisting of about 32,000 estate agencies that work on behalf of third parties. The 15 most-populated towns in Italy and their hinterland are all covered in the sample.[8]

The survey is unique in Europe in that it obtains opinions about the housing market directly from intermediaries on a frequent basis. The survey gathers agents' opinions on the state of the housing market. The majority of the data collected is qualitative in nature and is intended to ascertain brokers' assessments regarding the recent changes in the housing market as well as future projections. Agents' opinions on house sales, price trends from the previous quarter, and the short- and medium-term outlook in the local and national markets are all extensively covered in the standard questionnaire.

Real estate brokers who have taken part in the survey since 2022Q4 are also asked about their projections for inflation in consumer prices.[9] The survey question resembles that included in the Bank of Italy's Survey on Inflation and Growth Expectations (SIGE), which is conducted on a sample of Italian businesses, and used in Coibion et al. (2020), Ropele et al. (2024) and Rosolia (2024). The question in the IHMS was created to treat firms randomly with regard to the information they receive about recent inflation, just like in SIGE. Two groups of real estate agents who take part in the survey are randomly assigned to receive two different variants of the same question. Half of the sample is given the following inflation-related (InflExp) question: "What do you think consumer price inflation in Italy, measured by the 12-month change in the Harmonized Index of Consumer Prices, will be one year ahead?" We refer to this group of respondents as the control group. The following query is posed to the other half of the panelists instead: "In the previous month, consumer price inflation measured by the 12-month change in the Harmonized Index of Consumer Prices was [X.X]% in Italy and [Y.Y]% in the euro area. What do you think it will be in Italy one year from now?" This question is asked at the end of the survey, and all other questions in the survey are identical.

Hence, the treatment entails providing brokers with publicly available data about the latest inflation rates in Italy and the euro area. Because the inflation rate varies over time, the size of the treatment varies as well. In 2022Q4, participants were randomly assigned to treatment and control groups, and this assignment remained constant. The survey design was partially altered

[8] The methodology of the survey is described in Bank of Italy (2019). A quarterly report describing the main results is made available on the Bank of Italy's website.

[9] The IHMS is conducted in the first month of each quarter, using the previous quarter as the reference period. Throughout the paper, the time period refers to the actual time when agents were surveyed. For instance, the question on inflation projections was introduced in the survey for 2022Q3 but we consider 2022Q4 as starting period because the survey was conducted in October.

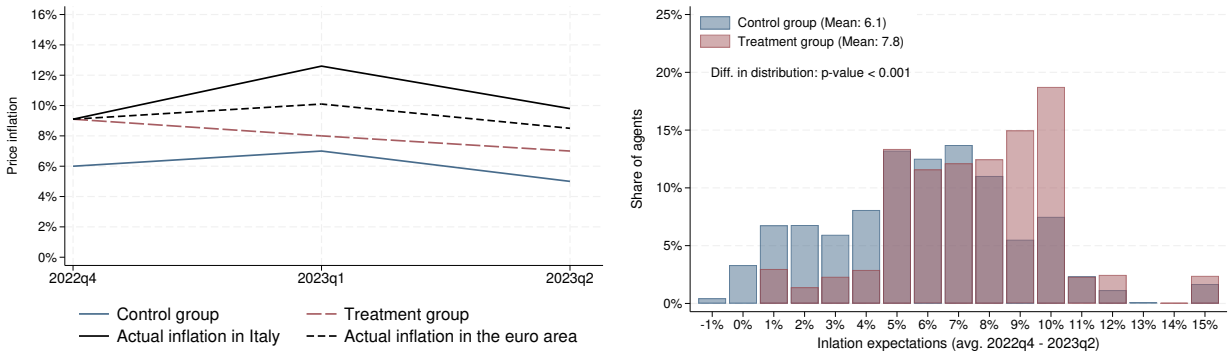
in 2023Q3, allowing respondents to choose not to answer the InflExp question. This caused a marked drop in the response rate and a concern about a potential selection bias for those agents who replied to the survey: for this reason, our analysis will focus on the three quarters of 2022Q4, 2023Q1, and 2023Q2. The interviews for these editions of the survey were conducted between 2022 September 21, 2022 and October 21, 2022 (for the 2022Q4 edition), between January 9, 2023 and February 8, 2023 (for the 2023Q1 edition), and between April 3, 2023 and May 4, 2023 (for the 2023Q2 edition).[10]

The InflExp question is asked at the end of the survey. Consequently, it is not possible to investigate the causal relationship between inflation expectations and other IHMS outcomes using the randomized control trial. However, we observe actual brokers' behavior through the online listings posted on Immobiliare.it, which we describe below.

We provide some summary statistics here, referring to section 3.2 for a deeper discussion of the effect of the treatment on inflation expectations. The answers to the InflExp question are shown in Figure 1. The solid black line is the actual value of the Italian consumer price inflation provided to the treatment group at the time of the interview; the dashed black line is the actual inflation rate in the euro area, also provided to the treatment group. The sample period includes the inflation spike registered at the end of 2022, when consumer prices grew at rates not seen in over two decades, which was communicated to the agents in the survey conducted in 2023Q1. Consumer price inflation fell throughout 2023. However, in the last survey we considered – conducted in 2023Q2 – the inflation rates that were communicated to the respondents in the treatment group were still high, at 9.8% for Italy and 8.5% for the euro area (inflation rates in February 2023).

Compared to agents in the control group, whose median expectations stay on lower values, agents in the treatment group expect inflation to be closer to the information they received (the black lines) for the entire sample period. The treatment group's inflation expectations decrease from roughly 9% in 2022Q4 to 7% in 2023Q2. On the other hand, the median control group's inflation expectations hover between 5 and 6.5%. Figure 1b reports the average distribution of inflation expectations in the control and treatment groups over the sample period. Relative to the control group, the distribution of treated agents is clearly shifted toward higher inflation expectations. We also provide a formal comparison using the Epps-Singleton two-sample test of equality of distributions. The resulting p-value < 0.001 indicates that the difference between the two distributions is statistically significant.

[10] In the rest of the paper, we align the timing of the analysis to that of the survey waves: for instance, the fourth quarter of 2022 is defined to start on September 21, 2022 (the first day of the interviews for the 2022Q4 edition) and to end on January 9, 2023 (the day before the start of the interviewing period for the 2023Q1 edition).



(a) Median

(b) Distribution

Figure 1: Inflation Expectations in IHMS

Note: Panel (a) represents the median of real estate agents' inflation expectations in IHMS; the solid (dashed) black line represents the actual value of the Italian (euro area) consumer price inflation provided to the treatment group at the moment of the interview. Panel (b) is the distribution of agents' inflation expectations over the sample period (2022q4–2023q2). The first and the last bins group observations with inflation expectations below 0 and above 14%, respectively. The difference in p-value refers to the Epps-Singleton test of the null hypothesis that the distribution of inflation expectations in the control and in the treatment group are identical. Data are winsorized at the bottom and top 5%.

2.2 Online listings

The other dataset we use comprises property listings from Italy's largest online real estate services portal, Immobiliare.it. We receive weekly screenshots from Immobiliare.it of all ads that are visible nationwide on the website every Monday. Comprehensive details regarding the geographical location, the physical attributes, and the asking price of a home are available. We also know the date on which the seller created and deleted the advertisement, but given the way the platform is organized, we cannot observe whether the house was sold or the precise transaction prices. This constitutes a limitation of our analysis, as we are unable to assess whether, and to what extent, the discount on asking prices varies in response to higher inflation expectations. If the discount tends to move positively with asking prices when inflation expectations rise, the effects we identify would only partially translate into transaction prices, as part of the adjustment would be offset by changes in the discount. At the same time, asking prices are fully under the seller's control, allowing us to capture a genuine behavioral response to inflation expectations, whereas the discount also reflects the attitudes and bargaining power of buyers.

Real estate agents use online platforms extensively to advertise homes for sale. Real estate agents polled in the IHMS in 2022Q4 were asked if they had placed their ads on at least one nationwide web portal in the preceding year (such as Immobiliare.it, Casa.it, or Idealista.it). In nearly 95% of the cases, the response was yes. With over 80% of agents using it, Immobiliare.it is the most popular of the main portals.

An examination of the universe of online listings posted on Immobiliare.it directly confirms the widespread use of the website by real estate agents. From 2022Q4 onwards, approximately 27,000 real estate agents posted one or more ads. This represents nearly 85% of the reference universe, which consists of approximately 32,000 estate agencies.

We merge this dataset with the IHMS by exploiting the name and the address of the agency. Unfortunately, the format of this information is heterogeneous across datasets, and we must resort to an approximate string-matching procedure that we describe in Appendix B. Following this procedure, we can match 1404 agencies in the sample period. We further clean the data by removing *(i)* the listings related to foreclosure procedures, *(ii)* the bottom and the top 1% of ads by floor area, and *(iii)* the bottom and the top 1% of ads by price/m^2 in each local housing market. Finally, we aggregate the data at the quarterly frequency.[11]

This unique dataset provides us with a rare chance to study how agents behave in various submarkets and contrast the pricing strategies of agents with varying inflation expectations. Selection is a key problem since agents can choose properties with varying *ex-ante* values and selling probabilities. To mitigate this issue, we can take advantage of the fact that each agent typically works in multiple markets, potentially exposing them to disparate housing market trends and controlling for a wide range of housing characteristics.

2.3 Summary statistics

Panel B of Table A1 reports some summary statistics on the characteristics of the agents using Immobiliare and participating in the IHMS who respect the selection criteria of the estimation sample. Our combined dataset comprises about 1,370 real estate agents. Every agent typically lists homes in a variety of markets, as defined by the OMI zones, which are homogeneous local housing markets corresponding to neighborhoods.[12] On average, agents are active in 14 neighborhoods, with a minimum of 1 and a maximum of more than 300. Every quarter, agents post an average of 11.5 new ads and 32.5 active ads. The average time on the market is 41 weeks. There are significant differences between the house types advertised by each agent. The average standard deviation of floor area and prices within the pool of ads posted by the same agent are approximately 70 square meters and €860/m^2, respectively.

Our estimation sample includes about 74,000 observations (Table A1, Panel A). The average price/m^2 of the ads in the sample is about €2,100, and the average size is 130 square meters, with sizable variations. The sample includes 26% of single-family homes, 12% of new buildings, 46% of

[11] We compute the quarterly average asking price in two ways, either considering the whole quarter or considering only the post-interview period. Our baseline estimates are based on the first definition and we provide robustness with respect to the second timing convention.

[12] OMI zones are defined by the Italian Tax Office. To provide an intuition about the size of a local housing market, they are comparable to the US Census tracts. The capital city of Rome, for instance, is divided into more than 200 OMI zones. The country is divided into about 28,000 zones.

houses with a garden, and 40% with a terrace. For each quarter and each local housing market including at least one treated and one control, we have on average 8 ads posted by about three distinct agents responding to the InflExp question in the IHMS (Table A1, Panel B).

In conclusion, the summary statistics of the merged sample of online listings and IHMS indicate that we can exploit the randomized information treatment within-neighborhood thanks to the significant number of real estate agents operating in each market and the amount of ads they post.

2.4 Determinants of asking prices

Before looking at the effects of inflation expectations, we consider other possible determinants of asking prices that we will use later on as controls in the main regressions. We estimate the following hedonic regression model:

$$p^i_{jt} = \zeta_j + \theta^i_t + \alpha_l + \gamma_t + \varepsilon_{jt} \tag{1}$$

where p^i_{jt}, is the log of the price/m^{2}2 of property j posted by agent i on Immobiliare.it at time t. α_l are location-type fixed effects referring to the local housing markets and the type of property (new vs existing properties and single-homes vs apartments). We interact the market dummies with the type of property to account for the plausible specialization of real estate agents on different market segments. Then, γ_t are quarter fixed effects, ζ_j are controls regarding the characteristics of the house for sale, and θ^i_t captures the characteristics of the agents from IHMS and their opinion about the current and future state of the local housing market.

The results are reported in Appendix Table A3. In column (1) we observe that the characteristics of the dwellings represented by ζ_j in equation (1) – derived from the ad content on Immobiliare.it – have the expected effect: larger properties have a lower price/m^2, while the presence of a garden, a terrace, a garage and an elevator have a positive impact; apartments on high floors and in better conditions sell at a premium. Including time fixed effects does not change the results (column 2). In columns (3) and (4) we add some controls from IHMS that capture agent-specific characteristics and opinions (θ^i_t in model 1). Notice that the number of observations halves because in each period only the ads posted by the agents interviewed in that specific survey wave are included. This notwithstanding, the coefficients of the hedonic regressions remain fairly stable. In columns (5) and (6) we further include some agent-specific variables derived from the overall sample of online housing ads in Immobiliare.it; column (6) further includes times fixed effects, which are instead absent in the specification reported in column (5). Considering the full specification in column (6), agencies with more employees tend to post higher prices but the magnitude of the coefficient is tiny. Assessment and expectations on local housing market conditions are not significant. Agents managing very different properties (as measured by the standard deviation of the size of properties on the market) tend to ask higher prices. Overall, the variables included in

the hedonic regression can explain a large part of the variability of house prices, with an adjusted R^2 around 0.88.

3 Inflation expectations and price-setting

We exploit the survey's RCT design to assess the impact of inflation expectations on real estate agents' pricing decisions. First, we illustrate the econometric strategy we adopt. Second, we analyze the effect of the information treatment on inflation expectations. Third, we assess the effect of inflation expectations on pricing strategies.

3.1 Econometric strategy

Our main goal is to estimate the impact of real estate agents' inflation expectations on the asking price of the houses sold through the Immobiliare.it platform. In particular, starting from (1), we assume the following linear relationship between house prices and a set of exogenous variables:

$$p^i_{j,l} = \beta F^i\pi + \zeta_j + \theta^i + \alpha_l + \varepsilon_j \tag{2}$$

where $p^i_{j,l}$, is the log of the price/m^{2}2 of property j, located in market l, posted by agent i. The main variable of interest is $F^i\pi$, i.e., the reported inflation forecast twelve months ahead of agent i.

The main strength of our specification is that we can observe the pricing decisions of each agent at the product level (i.e., a house) under different market conditions (a feature that we will explicitly exploit in Section 4). By including market fixed effects, we exploit within-market heterogeneity for estimating β. However, equation (2) cannot be estimated by ordinary least squares because the inflation forecast reported by the agents can be correlated with omitted variables also affecting the pricing decision. An example of these omitted variables is the personal experience of agents with inflation, which may simultaneously affect reported inflation expectations and price-setting decisions. Alternatively, inflation expectations may be correlated with expectations about economic growth or the path of household income, which we do not directly observe but that likely influence pricing decisions.

To overcome this issue, we take advantage of the randomized information treatment that IHMS has been incorporating since 2022Q4, and we estimate equation (2) in an instrumental variable setting, under the assumption that the assignment status affects pricing decisions only through inflation expectations. In particular, we follow two econometric approaches. As we will show later, the two approaches return similar results.

First, we use the econometric strategy proposed by Coibion et al. (2020), which exploits the time variation in the information treatment to build a time-varying instrument for inflation expectations.

In particular, we create a dummy variable equal to 1 if agents are treated and 0 otherwise (t_t^i, with i and t indexing agents and time). Next, we multiply that dummy by the treatment-related inflation rate ($\tilde{\pi}_t$). As a result, we get a time-varying measure of the treatment provided to an agent every quarter, which we call $T_t^i = t_t^i \times \tilde{\pi}_t$. Due to fluctuations in the rate of inflation, treated agents receive distinct treatments every period, which is reflected in the time variation. Finally, we estimate the following pooled version of equation (2) by 2SLS using T_t^i as an instrument for reported inflation forecasts over the 2022Q4-2023Q2 period:

$$p_{j,l,t}^i = \beta F_t^i \pi + \zeta_j + \theta_t^i + \alpha_l + \varepsilon_{j,t} \tag{3}$$

Exploiting the time variation of the information treatment for treated agents requires assuming that untreated agents do not change over time their assessments with the signal underlying the information treatment, i.e., untreated agents are inattentive to actual inflation (Rosolia, 2024). This assumption may be problematic during high-inflation periods, such as the one covered in our analysis, because people tend to become more attentive to price dynamics (Weber et al., 2025). Consequently, our second strategy involves estimating equation (3) separately for each survey wave. Different from Coibion et al. (2020), in a repeated cross-section setting the natural instrument for $F_t^i \pi$ is t_t^i, i.e., the indicator variable equal to 1 if agent i is exposed to the information treatment in period t.

Finally, agents' inflation expectations are a function of the information treatment and the *a priori* agents' beliefs, which are unobservable. Crucially, depending on the initial beliefs, the information treatment can be inflationary or deflationary for different real estate agents. As discussed by Rosolia (2024), we can interpret β as the average causal effect of expected inflation on listing prices only if the treatment satisfies a monotonicity condition (Angrist and Imbens, 1995; Angrist et al., 1996; Imbens, 2010). In particular, the instrument must shift the treatment variable – i.e., inflation expectations – in the same direction for all units. As we will discuss below, this condition will be verified by estimating quantile regressions and by looking at the cumulative density functions (CDFs) of inflation expectations across assignment status.

3.2 Information treatment and inflation expectations

As a first step in our analysis, we must assess the impact of the information treatment on inflation expectations, i.e., the validity of the first stage of our IV setting.

We start from the Coibion et al. (2020) approach. To quantify the effect of this time-varying treatment on the reported inflation forecast of agent i at time t, we regress their expectations that quarter on the treatment variable for that quarter:

$$F_t^i \pi = \alpha_l + \beta T_t^i + \varepsilon_t^i \tag{4}$$

We incorporate fixed effects for every stratum of the sample (the sample is stratified by 23 geographical areas) and use Driscoll-Kraay standard errors to account for cross-sectional and time correlation in the errors. We do not include time fixed effects as the treatment exploits time variation at the aggregate level.[13] Table 1 shows that real estate agents' average forecasts increase by 0.15 percentage points when they are informed that inflation has been one percentage point higher. The impact is statistically significant at the 1% level and remains unchanged when we incorporate other control variables derived from the IHMS (column 2). The magnitude, however, is relatively modest: it is three times smaller than the similar estimate on Italian firms that Coibion et al. (2020) obtain on the same one-year horizon.

Owing to some variation in the information treatment provided to the survey respondents over the sample period, we explore the possibility that the impact of the information treatment is not homogeneous over time. Our second identification strategy is similar to Rosolia (2024) and estimates the time-varying effect of the information treatment on the outcome of interest, using the dummy t_t^i:

$$F_t^i \pi = \alpha_l + \gamma_t + \beta t_t^i + \varepsilon_t^i \quad \forall t \in \{2022Q4, 2023Q1, 2023Q2\} \tag{5}$$

We find that the real estate agents who receive the information treatment have inflation expectations that are on average 1.6 percentage points higher than those reported by agents in the control group (column 3 of Table 1, which refers to a specification estimated on the full sample that includes time fixed effects). By considering each period separately, we find that the impact of the information treatment on inflation expectations ranges from 1.3 in 2023Q1 to 1.9 in 2022Q4.[14]

A simple and not rigorous back-of-the-envelope calculation suggests that the pass-through of the treatment on inflation expectations implied by the dummy identification strategy is higher than in the continuous treatment approach. The average inflation rate provided to treated agents over the sample is about 10%, i.e. 4 points higher than the median inflation expectations of the control group (6%). Therefore, the results obtained under the dummy treatment imply a pass-through of 0.41 (1.64/4).

Given that the treatment group's predictions are between one and two percentage points higher than the control group's in each of the three quarters included in the analysis, we can be fairly confident in interpreting the information treatment as an inflationary signal which exogenously shifts the real estate agents' inflation expectations upward. However, whether the signal provided by the information treatment is inflationary or deflationary cannot be ascertained if one relaxes the assumption of homogeneous and constant *a priori* distribution (Rosolia, 2024).[15] Indeed,

[13] Results are unchanged when we incorporate location-time fixed effects.

[14] We find the same results when estimating a single equation with a time-varying β: $F_t^i \pi = \alpha_l + \gamma_t + \beta_t t_t^i \times t + \varepsilon_t^i$. The results of this specification are shown in Appendix Figure A1.

[15] The IHMS, like the SIGE, does not elicit the pre-treatment inflation expectations of the respondents. Eliciting the pre- and post-treatment expectations in the same survey is complicated because it requires asking the same

Table 1: The effect of the information treatment on inflation expectations

	Time-varying treatment		Dummy treatment			
			2022q4-2023q2	2022q4	2023q1	2023q2
	(1)	(2)	(3)	(4)	(5)	(6)
Time-varying treatment	0.15***	0.15***				
	(0.01)	(0.01)				
Dummy treatment			1.64***	1.87***	1.27***	1.61***
			(0.15)	(0.28)	(0.24)	(0.25)
FE location	Yes	Yes	Yes	Yes	Yes	Yes
FE time	No	No	Yes	No	No	No
Other controls	No	Yes	Yes	Yes	Yes	Yes
Mean Y	6.93	6.94	6.94	7.30	7.31	6.13
SD Y	3.32	3.32	3.32	3.71	3.00	3.07
Obs.	2447	2386	2386	820	829	737

Note: Columns (1) and (2) show the estimates of equation (4). Columns (3) to (6) show the estimates of equation (5), where the specification in column (3) further includes time fixed effects. The dependent variable is real estate agents' inflation expectations. The sample period is 2022Q4–2023Q2. 'Other controls' include number of employees, the situation of the local housing in the current quarter compared to the previous one and the expectations on the local housing market in the next quarter. Location refers to 23 distinct geographical areas. Inflation expectations are winsorized at the bottom and top 5%. All estimates use Driscoll-Kraay standard errors and apply IHMS sample weights. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

our results show that *on average* the inflation treatment positively affects agents' expectations but does not rule out individual responses of opposite signs that, on average, cancel out. In other words, it could be that some agents, before receiving the treatment, projected one-year ahead inflation to reach levels above 10%: in this case, the information on realized data would shift expectations downward. This pattern would violate the monotonicity assumption previously discussed. Therefore, to verify that the random assignment shifts inflation expectations in the same direction for all units, we perform two additional exercises.

First, we look at the impact of the information treatment at different quantiles of the distribution. In particular, for each period we estimate quantile regressions for the ventiles (5^{th}, 10^{th}, 15^{th},..., 95^{th}) of inflation expectations conditioning on the assignment dummy, t_t^i, and sample stratum. Results are reported in Figure A2, including the 95% confidence interval (computed using Huber-White standard errors). We observe a strictly positive effect of the assignment along the entire distribution in each period.

Second, we inspect the differences between the CDFs of expected inflation of treated and untreated agents in each quarter. For the monotonicity assumption to be satisfied, the CDF of the treatment variable $F\pi$ conditional on being subject to the information treatment, $t_t^i = 1$, and the CDF of $F\pi$ conditional on not being treated, should not cross. In order to detect if potential differences in the empirical CDFs are statistically significant, we resort to the procedure introduced by Goldman and Kaplan (2018). Their methodology generalizes the classical Kolmogorov-Smirnov

question twice. See Haaland et al. (2023) for a general discussion of the main issues that a similar strategy can generate and Doerrenberg et al. (2024) for a specific application to inflation expectations.

test of equality between two distributions, identifying at which quantiles or values the distributions differ. Figure A3 shows that the CDF of the inflation expectations of the control group is always above the corresponding CDF for the treatment group in 2022Q4, and for the greatest part the difference is statistically significant at the 10% level. For 2023Q1 and 2023Q2, we observe a crossing in the empirical CDFs in the right tail of the distribution. However, these positive differences are in the far right tail of the distribution and, according to the Goldman and Kaplan (2018) test, they are not statistically significant.

Overall, the empirical evidence is consistent with the hypothesis that the information treatment – during the three quarters we consider – shifts the inflation expectations in the same direction for all agents. Therefore, our estimates have a causal interpretation.

3.3 Inflation expectations and property pricing

The next step of the analysis answers the following research question: "Do real estate agents' price-setting decisions change in response to inflation expectations?" As middlemen, they can impact the asking price of homes on sale. Real estate agents' revenues are the fees for selling homes, which in Italy are a fixed share of the sales price.[16] On the one hand, agents would like to adjust nominal prices to keep the real value of homes unchanged or at least strengthen the seller's bargaining position to increase their expected gain. On the other hand, higher asking prices decrease the probability of selling the home or at least lengthen the time to sell (Merlo and Ortalo-Magne, 2004).

In Section 4, we propose a model to explain this trade-off and discuss alternative mechanisms that may be involved. However, how agents resolve this trade-off remains an empirical question. Therefore, we will first examine the insights provided by the data, and only then will we use a model to interpret the findings.

Empirical analysis. We take advantage of the randomized information treatment that IHMS has been incorporating since 2022Q4. As demonstrated in Section 3.2, the information treatment is a valid instrument for inflation expectations because it provides a clear inflationary signal. We add the agent-specific inflation expectations in model (1), further considering all the controls in columns (5) and (6) of Table A3. Therefore, the model becomes:

$$p^i_{jt} = \beta F^i_t \pi + \zeta_j + \theta^i_t + \alpha_l + \gamma_t + \varepsilon_{jt} \tag{6}$$

Here, we assess the extent to which inflation expectations affect asking prices within the same quarter. If, however, real estate agents adjust their prices with a delay, our estimates would

[16] In Italy, the Chambers of Commerce provide guidelines about this fee, which vary by region and sometimes by individual Italian cities. The fee is generally comprised between 3% in suburban or rural areas and 5% in metropolitan areas. Both the buyer and the seller must pay this fee. There is no evidence of competition among agents on the fees charged.

Table 2: Impact of inflation expectations on asking prices

	OLS	IV time-varying treatment	IV dummy treatment			
			2022q4-2023q2	2022q4	2023q1	2023q2
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: All housing listings						
Inflation expectations	-0.000	0.010***	0.010***	0.008**	0.010*	0.011***
	(0.001)	(0.003)	(0.003)	(0.004)	(0.005)	(0.004)
FE location-type	Yes	Yes	Yes	Yes	Yes	Yes
FE time	No	No	Yes	No	No	No
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	65969	65969	65969	22216	19586	16636
1st stage F stat		266	280	74	82	173
Panel B: New housing listings						
Inflation expectations	-0.000	0.012***	0.013***	0.010	0.017*	0.013*
	(0.001)	(0.004)	(0.004)	(0.006)	(0.009)	(0.007)
FE location-type	Yes	Yes	Yes	Yes	Yes	Yes
FE time	No	No	Yes	No	No	No
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	15997	15997	15997	5916	5151	3091
1st stage F stat		134	134	35	49	80

Note: The dependent variable is the log of the price/m^2 posted on Immobiliare.it from 2022q4 to 2023q2. 'Other controls' include: i) dwelling characteristics: size, high floor, garden, terrace, garage, elevator, renovation status; ii) agent's characteristics and opinions from IHMS: number of employees, assessment and expectations on the local housing market; iii) agent-specific controls computed on the overall sample of online housing ads: the number of local housing markets where the agents operate and the standard deviation of the size of the properties posted by the agents. Location-type FE refer to local housing markets (OMI zones) interacted with the type of property (new vs. existing, single-family homes vs. apartments). Inflation expectations are winsorized at the bottom and top 5%. Standard errors are clustered at the OMI zone. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

understate the true impact of inflation expectations. The OLS estimate of equation (6) yields a coefficient very close to zero and not significant (column 1 of Table 2, panel A). This result is not surprising because our specification does not account for some relevant variables, such as expectations about future housing demand. As long as agents with higher expectations about future inflation are less optimistic about future housing demand – because, for example, these real estate agents expect an increase in the interest rates on mortgage loans – the coefficient on inflation expectations is downward biased. This further illustrates the need for an IV strategy to address the endogeneity of inflation expectations.

In column (2) of Table 2, panel A, inflation expectations are instrumented with the continuous treatment $T_t^i = t_t^i \times \tilde{\pi}_t$. Since T_t^i exploits the time-variation in the information treatment, we exclude time fixed effect from the regression. We find that a one percentage point higher inflation expectations induce real estate agents to post 1% higher prices. The impact of inflation expectations is the same when we use the dummy treatment on the full sample ranging from 2022Q4 till 2023Q2 and include year-quarter fixed effects (column 3). From columns (4) to (6), we run the same

regression quarter by quarter and find significant results for all three quarters; the point estimates are quite similar, ranging from 0.8% in 2022Q4 to 1.1% in 2023Q2, suggesting a full pass-through.

Our estimates for 2022Q4 are informative about the effects of first-time treatment. Survey participation may shape subsequent responses – for example, by inducing information acquisition between waves – so that agents exposed repeatedly to the survey could behave differently from those participating only once (Kim and Binder, 2023). The survey design, however, precludes leveraging later waves to test this hypothesis more directly. Although we observe some variation in participation across quarters, some agents may appear as non-participants because they failed to complete the questionnaire properly, even though they almost certainly received it. For the same reason, these agents cannot be used as controls in quarters in which they are recorded as non-respondents.

The magnitude of the inflation expectations pass-through that we find is high, 4 to 5 times higher than that estimated by Coibion et al. (2020) and Baumann et al. (2024), while the pass-through is null in Rosolia (2024). In general, the transmission channels and the agents involved are different, so we do not necessarily expect the same impact. However, there are additional factors that may explain this discrepancy. First, according to theory, the pass-through of inflation expectations on firms' prices may be even larger than one and depends on the hazard of future price adjustments and the duration of ongoing price spells (Werning, 2022). Real estate agents never revise upward the listing prices, and homes usually remain on the market for several months before a sale occurs.[17] The upward rigidity of listing prices, together with a long duration of the price spells, plausibly explains the significant pass-through in a period of rising inflation expectations. In contrast, firms can adjust the frequency of price changes depending on the size of the inflation shock, revising their prices more frequently in a high-inflation period (Cavallo et al., 2024). Second, our estimates are based on observed price changes at a highly granular product-market level, whereas the findings of Coibion et al. (2020), Baumann et al. (2024), and Rosolia (2024) rely on self-reported price changes at the firm level without distinguishing between selling markets and products. If the IEPT varies across markets and products – as we demonstrate in the next Section – then relying on firm-level averages may mask this heterogeneity and, in some cases, lead to an underestimation of the true impact of inflation expectations. Third, the impact of inflation expectations might be state-dependent, with agents reacting more forcefully during a high inflation period, like the one considered in our analysis, compared to a normal period as in Coibion et al. (2020) and Rosolia (2024). However, our results are also stronger than those reported by Baumann et al. (2024), which are based on a sample of European firms surveyed in early 2023.[18]

[17] Focusing on 2021-2023, the average time on market in Italy was about 6 months. In addition, about three months elapse (on average) from the time of the agreement between the seller and the buyer for the final transaction.

[18] A key difference between our work and Baumann et al. (2024) is the timing of the survey. Our sample includes the peak of inflation in Italy and the euro area, recorded in 2022Q4. Specifically, the euro area inflation rate communicated to real estate agents was 9.1% for the first wave, 10.1% for the second wave, and 8.5% for the third wave. In contrast, the study by Baumann et al. (2024) is based on an information treatment referring to April 2023,

Mechanism. The transmission of inflation expectations to current listing prices can occur through two channels. First, real estate agents who receive the information treatment may post new listings at a higher price than the other agents. Second, they can incorporate their inflation expectations into the prices of their old listings by changing their propensity to revise the listing price downward.[19]

Regarding the first channel, we can easily test the role of inflation expectations by running the baseline specifications only on new listings. Panel B in Table 2 shows that point estimate of the impact of inflation expectations is stronger on new listings compared to the effect on the whole stock of listings (panel A). On average, a one percentage point increase in inflation expectations causes a 1.3% increase in the prices of new listings (columns 2 and 3). The impact on new listings is consistently higher also by looking at each survey wave separately (columns 4-6). However, the estimates are less stable than in panel A because of the much smaller number of observations and we lack statistical power to conclude that the effect on new listings differs significantly from that on the full stock of homes for sale.

This methodology is not suited to test the relevance of the second channel for two reasons. First, in the baseline regression the dependent variable is the average price during each quarter, and this does not allow tracking the price revisions. Second, some of the real estate agents interviewed during the second and third waves had already received the information treatment during the first wave.[20] Therefore, we may not detect any adjustment in the propensity to revise their listing prices because the initial listing price already incorporates the updated inflation expectations.

To address these issues, we resort to a different approach. First, we focus on the 2022Q4 wave because it was the first time that we included the information treatment in the IHMS. Second, we exploit the random assignment to the treatment in a two-period difference-in-difference (DiD) setup. In particular, we restrict the sample to listings online both in 2022Q3 and 2022Q4 posted by real estate agents involved in the 2022Q4 survey. Then, we estimate the following regression:

$$p_{jt}^{i} = \xi_j + \beta\, 2022Q4_t + \gamma\, 2022Q4_t \times t^i + \varepsilon_{kt} \tag{7}$$

where p_{jt}^{i} is the logarithm of the price/m^2 in period t for listing j posted by agent i, ξ_j are listing fixed effects, $2022Q4$ is a dummy equal to one in the period of the survey, and t^i is a dummy equal to one if agent i received the information treatment.

The parameter of interest is γ, which measures the average impact of the information treatment on the prices of existing listings. Column 1 in Table 3 shows that the listing prices of treated agents

when inflation stood at 7.0% and was on a declining path.

[19] As reported in the Introduction, real estate agents usually do not revise their listing prices upward. However, they might incorporate their revised inflation expectations by not decreasing the listing prices previously set.

[20] We do not observe which agents were reached to participate in the survey, only those who responded. Thus, the real estate agents participating in the second and third waves may have received the information treatment in the first wave.

Table 3: Impact of inflation expectations on asking prices: Mechanism

	Existing ads			New ads	
	Log(price)	Price change	Delisting	Log(price)	Log(price)
	(1)	(2)	(3)	(4)	(5)
Post * Treated	0.002***	-0.008	-0.032***	0.021*	0.028***
	(0.001)	(0.009)	(0.011)	(0.010)	(0.010)
FE location-type	No	No	No	Yes	Yes
FE time	Yes	Yes	Yes	Yes	Yes
FE agency	No	No	No	No	Yes
FE ad	Yes	Yes	Yes	No	No
Obs.	34776	34776	34776	14140	14088

Note: Columns (1)-(3) report the results of equation (7) estimated over the period 2022q3–2022q4. Columns (4) and (5) report the results of equation (8) estimated over the period 2022q1–2022q4. In columns (1), (4), and (5) the dependent variable is the log of the price/m^2 posted on Immobiliare.it; in column (2) the dependent variable is the quarterly number of price changes for any given listing; in column (3) the dependent variable is a dummy equal to one if the listing has been removed from the website during 2022q4. Location-type FE refer to local housing markets (OMI zones) interacted with the type of property (new vs existing and single-homes vs apartments). Standard errors are clustered at the OMI zone. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

are 0.2% higher after providing the information treatment. Column 2 reports the estimate of γ when the dependent variable is the number of price revisions for each listing. Although the estimate is not statistically significant, its sign is negative and is consistent with the hypothesis that the information treatment lowered the propensity of the real estate agents to revise the prices of old listings downward. To put these estimates into perspective, it is worth considering that price revisions are relatively infrequent events. Considering all listings on the Immobiliare.it during 2022Q1-2023Q2, about 10% of listings have their price revised during a quarter.

This strategy implies that the agents trade off higher prices for a higher time-on-market or a lower probability of selling the house. Therefore, we test this hypothesis by estimating a version of (7) where the dependent variable is a dummy equal to one if a house is delisted in 2022Q4.[21] We find that the estimated γ is negative and statistically significant at the 1% level, consistent with our hypothesis. The probability that a house is delisted is 3.2 percentage points lower if the real estate agent received the information treatment.[22]

Finally, we exploit the DiD framework to assess the robustness of the results on the prices of new listings. Since the number of new listings is small, particularly during the third quarter of the year, we include in the pre-treatment period the new listings posted since January 2022 by the real estate agents involved in the 2022Q4 survey. Then, we estimate the following equation:

$$p^i_{jt} = \alpha_l + \delta_i + \zeta_j + \beta\, 2022Q4_t + \gamma\, 2022Q4_t \times t^i + \varepsilon_{jt} \tag{8}$$

[21] Testing for the effect on time-on-market is difficult because selling a house takes several months (on average). Therefore, there is naturally a long time span between the timing of the treatment and the outcome of interest, which would make our identification strategy less credible.

[22] We remark that we do not observe if a house is sold or withdrawn from the market. However, this is not an issue because we are interested only in how long a house remains on the market.

where α_l are location-type fixed effects, δ_i are agent fixed effects and the other variables are defined as above. Column 4 in Table 3 shows that real estate agents receiving the information treatment set 2.1% higher prices on new listings compared to the other agents. Including real estate agent fixed effects, this estimate increases to 2.8%.

Summing up, following an upward revision in inflation expectations, real estate agents set higher prices on new listings and have a lower propensity to revise the prices of existing listings downward. This further results in a lower probability of delisting, suggesting a longer time to sell the property.

Robustness. We conduct two types of robustness checks. The first addresses the timing of information provision, which could occur on any day within the interview period. Specifically, respondents may read the questionnaire – thereby receiving the information treatment – on the first day of the survey or at any later point before the response deadline. In our baseline regressions, we assumed that the information treatment occurred on the survey's first day. We replicate our main results (Table 2) by restricting the sample to listings that remained online after the interview period concluded. For these listings, we calculate the average price using data only from the post-interview period.[23] The results are highly consistent with those derived from the full dataset (Table A4). We thus conclude that our estimates are robust to uncertainties regarding the exact timing of the information provision.

The second robustness check evaluates the validity of the randomization design. This design is intended to rule out preexisting differences in the price-setting behavior of real estate agents who received the information treatment compared to those who did not. To verify this, we conduct the following exercise: we estimate the IV regression (6) using the listing data from the period 2022Q1-2022Q3, under the assumption that the treatment status and agents' expectations correspond to those observed in 2022Q4, 2023Q1, or 2023Q2. Specifically, we replicate the pooled specification presented in column 3 of Table 2, where the treatment status serves as an instrument and time-fixed effects are included. The results indicate that the information treatment has no significant impact prior to its actual introduction (Table A5).

4 Interpretation of the inflation-expectations pass-through

Inflation expectations can influence real estate agents' pricing decisions through several, potentially offsetting, channels. First, higher expected inflation reduces the real value of real estate agents' fees (provided that fees are fixed in the short term). To preserve their real profits, agents may raise nominal listing prices. This is a partial equilibrium response based solely on protecting individual

[23] For the 2022Q4 wave, this period starts on October 22; for 2023Q1, on February 9; for 2023Q2, on May 5.

margins that implies a positive IEPT.[24] Second, agents may associate inflation with rising housing prices, anticipating stronger demand from households seeking an inflation hedge. This general equilibrium mechanism likewise suggests a positive IEPT. Third, agents may expect inflation to trigger higher interest rates, weakening buyers' mortgage access and dampening housing demand; this channel would imply a negative or null IEPT.

The OLS coefficient reported in Table 2 reflects the endogenous co-movement between inflation expectations and other beliefs. Consistent with the presence of offsetting channels, the estimated coefficient is close to zero and statistically insignificant. By contrast, our information treatment provides exogenous variation in inflation expectations. The IV strategy is therefore better suited to isolate the partial equilibrium effect of higher expected inflation on listing prices. That said, we cannot fully rule out cross-learning effects whereby the treatment also shifts other beliefs, such as expectations about housing demand.

To rationalize how these mechanisms should affect the IEPT, we build a stylized model of a seller's price choice. In the model, we allow the treatment (i.e. an exogenous increase in inflation expectations) to shift agents' beliefs in a manner that may encompass both partial equilibrium responses and agents' perceptions of the associated general equilibrium implications. Then, we compare the model's predictions with the empirical evidence.

4.1 A stylized model

In this section we sketch a stylized model of the seller's problem: additional details are contained in Appendix C. A broker is entrusted with selling a housing property. In period 0, he sets a nominal price p which cannot be subsequently revised.[25] In period 1, the broker sells the house at the nominal price p with probability q and incurs a real cost κ for the activities required to close the deal. If the property remains unsold, the broker retains the asset until period 2, when the asset perishes. Preferences are linear in consumption with no intertemporal discounting, so the timing of consumption is irrelevant.

The broker's value function is:

$$V = \max_{p} \quad q \times \left[\frac{p}{P_0(1+\pi^e)} - \kappa \right] \tag{9}$$

where P_0 is the price level of consumption goods in period 0, and π^e is the broker's expected change

[24] Italian real estate agents associate housing market downturns with a larger discount to the asking price (Figure A6). Therefore, pessimistic agents expecting lower selling prices and housing demand are plausibly predicting an increase in the average discount buyers request. This is another reason why real estate agents may raise listing prices to preserve their real profits.

[25] Without loss of generality, we abstract from price revisions: as long as listing prices exhibit some rigidity, the model's intuition remains intact. In our data, upward revisions are virtually nonexistent, and downward revisions are infrequent. We also abstract from the buyer-seller bargaining stage, which typically results in a selling price below the listing price.

in the price level between period 0 and 1.

To study the trade-off faced by the broker, we assume that the selling probability depends on the nominal listing price p and expected inflation π^e: $q \equiv q\left(p, \pi^e\right)$. The dependence of q on expected inflation is a reduced-form device to account for the broker's beliefs about the general-equilibrium effect of inflation on housing demand. Regarding the first argument, the likelihood of selling the house decreases with the nominal listing price, $q_p \equiv \frac{\partial q}{\partial p} < 0$. Hence, the broker trades off a higher net real payoff against a lower probability of sale. The problem becomes less interesting if the probability of sale depends on the real listing price and brokers believe that buyers share their inflation expectations. In that case, an exogenous increase in expected inflation would translate one-for-one into higher nominal listing prices. The broker would face exactly the same real trade-off as before, simply evaluated at a higher nominal price level, implying full pass-through of inflation expectations by construction.[26] Finally, to simplify the problem and focus on the impact of inflation on housing demand, we assume that the selling probability is concave in p: $q_{pp} \equiv \frac{\partial^2 q}{\partial^2 p^2} \leq 0$.

This setup yields an intuitive expression for the IEPT:

$$IEPT = \frac{dp^*}{d\pi^e} = -\frac{-q_p \kappa P_0 + q_{p\pi^e}\left[p^* - \kappa P_0(1+\pi^e)\right] + q_{\pi^e}}{q_{pp}\left[p^* - \kappa P_0(1+\pi^e)\right] + 2q_p} \tag{10}$$

Equation (10) implies that the IEPT is unambiguously positive when brokers believe inflation has no direct effect on housing demand (i.e., $q_\pi = q_{p\pi} = 0$). In this case, higher expected inflation induces brokers to raise the housing listing price to preserve real commissions. Moreover, it is straightforward to show that the strength of this profit-preserving motive increases with the expected duration of the price spell. If the property is sold not in the following period but h periods after the listing price is set, inflation erodes the real value of commissions over a longer horizon. Anticipating this effect, the broker optimally raises the initial nominal price by a larger amount, implying a higher IEPT.

A more interesting case arises when brokers believe inflation reduces housing demand either directly ($q_{\pi^e} < 0$) and/or indirectly by increasing the sensitivity of demand to the listing price ($q_{p\pi^e} \leq 0$). Here the profit-preserving motive that pushes p^* upward is counterbalanced by the demand channel, making the sign of the IEPT *a priori* ambiguous. The model, however, predicts unambiguously that the IEPT should be smaller, and potentially negative, for agents with more pessimistic beliefs about the impact of inflation on housing demand. We test this prediction empirically below.

[26] Through the lens of the model, assuming the sale probability depends on the nominal rather than real listing price implies that buyers exhibit money illusion, i.e., they respond to nominal values without fully internalizing inflation. This assumption is consistent with empirical evidence (Brunnermeier and Julliard, 2008; Andersen et al., 2022). In the context of our empirical analysis, this assumption has a more operational interpretation: holding buyers' inflation expectations constant, a seller who posts a higher nominal price relative to comparable listings faces a systematically lower probability of sale.

4.2 Empirical validation of model predictions

Our empirical validation of the model proceeds as follows. First, we examine whether the data provide evidence of the fundamental trade-off between higher listing prices and a lower probability of sale. Establishing this relationship is critical for validating the core framework of our model and for ruling out the alternative explanation that higher observed prices are simply the result of increased housing demand (as would be the case if households perceive housing as a hedge against inflation). By confirming that higher inflation expectations lead to higher prices and a lower sale probability, we demonstrate that market dynamics align with the model's core predictions. Second, we analyze whether real estate agents who hold more pessimistic beliefs about the future evolution of housing demand exhibit lower IEPT, consistent with the model's implications. This analysis further validates that heterogeneous expectations among market participants translate into observable differences in listing behavior, reinforcing the link between inflation expectations and housing price formation.

Inflation expectations and probability to sell. To empirically assess the trade-off between setting higher listing prices and incurring a lower sale probability, we estimate a series of pooled instrumental-variable (IV) regressions based on the specification in equation (6), replacing prices with alternative measures of time-on-market (TOM) – which we use as a proxy for the sale probability – as the dependent variables. The results indicate that a one-percentage point increase in inflation expectations is associated with roughly a four-percentage point increase in TOM (Table 4, columns 2-3), that is about 2 weeks if we consider the average time on market.[27] These findings confirm that higher inflation expectations are associated with both higher prices and longer times to sale, a pattern consistent with the mechanism highlighted in our theoretical framework.

Agents' beliefs and IEPT. To elicit real estate agents' beliefs about the general equilibrium feedback of inflation on housing demand (hence, about q_{π^e}), we leverage an additional IHMS question that asked agents about the expected impact of inflation on key housing market variables over the subsequent 12 months (listings, buyer interest, and selling prices).[28] Most agents expressed concern that inflation would depress transaction prices and demand (Figure A4). Therefore, the empirical evidence supports the hypothesis that for most agents $q_{\pi^e} < 0$.

As discussed earlier, such pessimism can be consistent with the positive average IEPT estimated in Section 3 if the profit-preservation motive dominates on average. However, the IEPT should be

[27] We consider two measures of time on the market. First, we restrict the sample to listings that are terminated within the quarter and compute the number of weeks between initial publication and their disappearance from the website (column 2). Second, we use all active listings in each quarter and compute the average number of weeks since publication (column 3).

[28] The question was asked in the same survey waves considered in the analysis. The question was as follows: "In your opinion, what will be the impact of inflation on the following national housing market variables over the next 12 months?", with the housing market variables being *(i)* sale listings, *(ii)* number of potential buyers, and *(iii)* selling prices.

Table 4: The impact of inflation-expectations on the selling probability

	Log(price) (1)	Log(TOM) (2)	Log(TOM) (3)
Inflation expectations	0.010***	0.044*	0.039**
	(0.003)	(0.023)	(0.016)
FE location-type	Yes	Yes	Yes
FE time	Yes	Yes	Yes
Other controls	Yes	Yes	Yes
Obs.	65969	20788	65969
1st stage F stat	280	209	280

Note: Column (1) reproduces the coefficient from column (3) of Panel A of Table 2 for ease of comparison. In column (2), the dependent variable is the log of time-on-market (TOM), calculated by restricting the sample to listings that terminate within the quarter and measuring the number of weeks between initial publication and disappearance from the website. Column (3) uses an alternative TOM measure, defined for all active listings in a given quarter as the average number of weeks since publication. 'Other controls' include: i) dwelling characteristics: size, high floor, garden, terrace, garage, elevator, renovation status; ii) agent's characteristics and opinions from IHMS: number of employees, assessment and expectations on the local housing market; iii) agent-specific controls computed on the overall sample of online housing ads: the number of local housing markets where the agents operate and the standard deviation of the size of the properties posted by the agents. Location-type FE refer to local housing markets (OMI zones) interacted with the type of property (new vs. existing, single-family homes vs. apartments). Inflation expectations are winsorized at the bottom and top 5%. Standard errors are clustered at the OMI zone. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

higher among agents who are less pessimistic about the impact of inflation on housing demand. To test this prediction, we construct four proxies for agents' beliefs about near-term demand conditions, which capture both direct and indirect channels through which inflation may affect demand. First, we use the qualitative question on the expected impact of inflation on the number of potential buyers. We define a dummy equal to one for agents who expect inflation to *increase* buyer interest, that is, those who believe households view real estate as an inflation hedge. This measure provides the most direct test of the model's mechanism.

Then, we elicit agents' expectations about one-year-ahead changes in housing prices in their local market, and we define a dummy variable equal to one if they expect a decrease in housing prices. We also exploit heterogeneity in perceptions of credit conditions, drawing on a recurring IHMS question asking agents to identify reasons why property owners do not renew sale mandates. We construct a dummy equal to one for agents who attribute non-renewals to buyers' difficulties in obtaining mortgage loans. This measure is particularly relevant because credit supply, a critical determinant of housing demand, is largely exogenous to local real estate market conditions. Agents who perceive tighter credit constraints should be more pessimistic about demand and thus exhibit a *lower* IEPT. In the Appendix we show that the agents expecting a negative impact of inflation on housing demand are significantly more likely to report pessimistic expectations about future housing prices and current credit conditions.

Finally, we construct a measure of market tightness: agents experiencing a stronger demand in their reference markets are plausibly more optimistic about future demand conditions despite high inflation. To capture market tightness, we exploit the weekly number of views per listing on the Immobiliare.it platform. We aggregate this variable quarterly at the market level, and we define

Table 5: Heterogeneity in the inflation-expectations pass-through on prices

	(1)	(2)	(3)	
Inflation expectations	0.010***	0.015***	0.013***	0.008***
	(0.003)	(0.003)	(0.003)	(0.003)
Infl. exp * Exp. positive effect of inflation on potential buyers	0.004			
	(0.006)			
Infl. exp * Exp. decrease in prices		-0.006*		
		(0.003)		
Infl. exp * Perceived tightness in the mortgage market			-0.009**	
			(0.004)	
Infl. exp * Demand intensity (clicks per ad)				0.008**
				(0.003)
FE location-type	Yes	Yes	Yes	Yes
FE time	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes
Obs.	64962	62581	65253	65993
1st stage F stat	38	116	132	17

Note: The dependent variable is the log of the price/m^2 posted on Immobiliare.it from 2022q4 to 2023q2. In column (1), inflation expectations are interacted with a dummy equal to 1 for agents expecting inflation to increase housing demand. In column (2), the interacted variable is a dummy variable equal to one for agents expecting a decrease in housing prices in their local market one year ahead. In column (3), the interacted variable is a dummy equal to one for agents who attribute non-renewals to buyers' difficulties in obtaining mortgage loans. In column (4), inflation expectations are interacted with the average number of views per listing at the market level, standardized using the mean and standard deviation within each stratum to account for structural differences between urban and suburban markets. 'Other controls' include dwelling characteristics: size, high floor, garden, terrace, garage, elevator, and renovation status. Location-type FE refer to local housing markets (OMI zones) interacted with the type of property (new vs. existing, single-family homes vs. apartments). Inflation expectations are winsorized at the bottom and top 5%. Standard errors are clustered at the OMI zone. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

market tightness as the average number of views per listing.[29] This direct measure of demand outperforms indirect proxies, such as past housing price growth, which may be affected by other factors. Consistent with the model, in high-demand markets we expect the IEPT to be stronger.[30]

To bring these cross-sectional predictions to the data, we estimate the IV specification of equation (6), interacting inflation expectations with each of the indicators described above. Accordingly, we use the interaction between treatment status and each indicator as an additional instrument. To maintain statistical power, we pool observations from 2022Q4 to 2023Q2, including year-quarter fixed effects as in the specification reported in column 3 of Table 2.[31]

Our findings are broadly consistent with theoretical predictions. The impact of agents' beliefs about the impact of inflation on housing demand on the IEPT is positive but it is not statistically significant (Table 5, column 1). This may be due to a lack of meaningful variation in this variable, as only 15% of real estate agents expect a positive effect of inflation on the number of potential buyers.

[29] We should remark that this measure conflates the extensive margin – i.e., the number of buyers searching for a house – and the intensive margin – i.e., the search intensity of the buyers. Therefore, we must be careful in providing structural interpretations to the elasticities we estimate.

[30] We compute market tightness using the full sample of listings on the Immobiliare.it platform, and standardize this indicator using the mean and standard deviation within each stratum to account for structural differences between urban and suburban markets.

[31] Differently from equation (6), we do not control for other agents' opinions about the housing market or their level of activity, because these variables are correlated with the four indicators studied here.

Current and prospective market conditions affect the IEPT in the expected direction (columns 2-4). The IEPT is lower for agents expecting a decrease in housing prices (by 0.6 percentage points) and for those reporting that buyers face difficulties obtaining a mortgage loan (by 0.9 points). Finally, as expected, higher demand intensity significantly amplifies the pass-through rate. A one-standard-deviation increase in market tightness is associated with a 0.8 point higher pass-through rate (column 4).

Alternative mechanisms. We acknowledge that our evidence is not definitive, and conclusive validation of the mechanisms at work would require information on transaction prices. Nonetheless, alternative explanations for our findings appear implausible. For instance, if agents were primarily concerned about the negative impact of inflation on future housing demand, they would have an incentive to sell more quickly; yet this runs counter to the negative effect on times to sale. Our econometric strategy also mitigates concerns that agents with higher inflation expectations may selectively operate in higher-value market segments. The identification relies on within-local market heterogeneity in inflation expectations, i.e., within markets that display limited variation in the quality of the housing stock, and includes an extensive set of dwelling controls, including maintenance status. Finally, we do not have evidence of significant adjustments in agents' intermediation fees that could affect the interpretation of our results. Roughly 70% of real estate agents interviewed in June 2025 reported that their commission rate had remained unchanged since 2021, before the inflation surge. The remaining agents were almost evenly split between those reporting an increase and those reporting a decrease.

5 Discussion and macroeconomic implications

Our estimates reveal an average full pass-through of real estate agents' inflation expectations on listing prices. This finding has several important implications: *(i)* real estate agents play a key role in determining property listing prices; *(ii)* real estate agents are not fully informed on publicly available information (past consumer price inflation), hinting to a violation of the full-information paradigm; *(iii)* higher inflation expectations lead to higher housing prices, revealing an additional channel through which monetary policy interventions and communication impact the economy; *(iv)* the pass-through rate is heterogeneous, being stronger for more optimistic agents and in thicker markets. The first result aligns with the literature on the significant influence of real estate agents (Cunningham et al. (2022), Gilbukh and Goldsmith-Pinkham, 2024). However, the other implications are, to our knowledge, novel to our setting.

In this section, we discuss some potential implications of our results and several open questions we aim to address in future research.

Inflation and the housing market. While our micro-level estimates do not capture the full

extent of inflation's impact on the housing market, they provide qualitative insights into the underlying mechanisms. The prevailing view holds that inflation depresses the housing market primarily because the central bank, in response to an inflationary shock, raises interest rates, thereby increasing the cost of mortgage borrowing. Higher borrowing costs reduce mortgage demand and, in turn, lead to a decline in housing transactions and prices.

Our analysis identifies a complementary supply-side mechanism. In an inflationary environment, real estate agents, aiming to preserve the real value of their commissions, tend to raise listing prices even if this reduces the probability of sale, and sales volumes decline. This behavior is consistent with the patterns we observe in the data. Between 2023Q2 and 2022Q2, housing sales decreased by 16.1%, but asking prices (hedonic-adjusted) increased by 2.4% (Figure A7). This opposite pattern would be more difficult to rationalize solely by a housing demand shock. Instead, higher listing prices further suppress transactions, compounding the contraction in housing sales triggered by weaker demand. This supply-side response thus amplifies the initial downturn originating on the demand side. Quantifying the relative importance of this channel in the overall decline of housing sales remains an open question and represents a promising direction for future research.

Expectations formation and extrapolation to low-inflation periods. While a thorough exploration of how real estate agents form expectations is beyond the scope of this paper, our results align with the pervasive evidence of information rigidities among households, firms and professional forecasters (Coibion and Gorodnichenko, 2012, 2015). Real estate agents react in a significant way to publicly available information on consumer price inflation, although they should be attentive to price developments that affect their business.

The magnitude of this response, however, is relatively modest (ranging from 0.2 to 0.4), suggesting that the degree of information rigidity may be state-dependent, diminishing when inflation becomes more salient. This is consistent with Weber et al. (2025), who use a similar randomized control trial across various countries and periods, and find that information treatments are more effective in low-inflation environments, when inflation is typically less salient and new information more revelatory. Nonetheless, we cannot rule out the hypothesis that real estate agents are generally better informed than firms, which could explain why they react less to new information.

At the same time, we find an average full pass-through of inflation expectations to housing prices. It remains unclear whether such a high pass-through would also be confirmed in a low-inflation environment. In our view, however, this does not undermine the importance of our findings: high-inflation periods are the times when it is most important to understand how expectations affect current prices, and the focus on inflation is maximal.

Implications for monetary policy. Our findings indicate that inflation expectations matters even for a crucial market such as the housing market. These results underscore the importance of firmly anchoring inflation expectations. In this regard, central bank communication could play

a pivotal role. Therefore, it is crucial to explore how monetary authorities can effectively reach these agents, who are likely to be not sophisticated and scarcely attentive to macroeconomic developments.[32]

The heterogeneous impact of inflation expectations across markets is relevant because adjustments in relative housing prices influence wealth inequality. Specifically, we find that the pass-through is more pronounced in markets characterized by higher tightness of the demand (Table 5, column 3). Consequently, if higher inflation expectations lead to a stronger appreciation of some properties compared to others, this could reduce or increase inequality among homeowners. However, it may simultaneously exacerbate housing affordability challenges for renters and movers. Although addressing this issue lies beyond the scope of this paper, this scenario would represent an additional channel through which monetary policy, by affecting inflation expectations, could have distributional consequences.[33]

6 Conclusions

This paper investigates the impact of real estate agents' inflation expectations on housing listing prices during a high-inflation period. Using a novel dataset that combines survey-based inflation expectations with granular activity data from Italy's largest digital housing sales platform, we present two main findings. First, we find that the pass-through of inflation expectations to housing listing prices is, on average, full. Second, we show that the pass-through is more pronounced for more optimistic agents and high-demand markets. Therefore, higher inflation expectations lead to higher housing prices, revealing an additional channel through which monetary policy interventions and communication impact the economy.

We believe that the extent and heterogeneity of the inflation expectations pass-through to current prices warrant further research, as they carry critical policy implications. Although our analysis is limited to a specific market, it provides a first step in this direction, showing that the causal impact of inflation expectations on prices may be substantial. This highlights the need for central banks to effectively anchor inflation expectations through clear and targeted communication, especially given that key intermediaries in the real estate market appear to be inattentive to macroeconomic developments.

[32] See Coibion et al. (2022) for a study on how different forms of communication influence households' inflation expectations.

[33] For a recent discussion on the consequences of monetary policy for wealth inequality, see McKay and Wolf (2023).

A Additional Figures and Tables

Table A1: Summary statistics on estimation sample

	Obs.	Mean	Std. Dev.	Min.	1th perc.	Median	99th perc.	Max.
Panel A: Housing characteristics								
Price/m^2	54,922	2,150.44	1,573.20	203.01	352.94	1,729.73	8,000.00	14,806.38
Time-on-market (weeks)	54,922	49.20	64.31	0.00	0.00	30.00	318.14	832.43
Quarterly price revisions	54,922	0.11	0.36	0.00	0.00	0.00	2.00	7.00
Quarterly probability of delisting	54,922	0.41	0.49	0.00	0.00	0.00	1.00	1.00
Property size	54,922	130.31	85.29	35.00	40.00	105.00	488.00	648.00
Floor	48,825	1.62	1.66	-1.00	0.00	1.00	7.00	21.00
Single-family homes (share)	54,922	0.25	0.43	0.00	0.00	0.00	1.00	1.00
New buildings (share)	53,480	0.12	0.33	0.00	0.00	0.00	1.00	1.00
Garden (share)	54,922	0.46	0.50	0.00	0.00	0.00	1.00	1.00
Terrace (share)	54,922	0.40	0.49	0.00	0.00	0.00	1.00	1.00
Garage (share)	54,922	0.46	0.50	0.00	0.00	0.00	1.00	1.00
Elevator (share)	54,922	0.38	0.48	0.00	0.00	0.00	1.00	1.00
Panel B: Agent characteristics								
Number of markets served	1,368	14.16	16.95	1.00	1.00	10.00	77.00	337.00
Quarterly number of new listings	1,368	11.41	31.62	0.00	0.00	6.00	90.00	847.00
Quarterly number of active listings	1,368	32.43	72.54	1.00	1.00	20.00	227.00	2,191.00
Std. dev. of property size	1,348	69.41	34.66	0.00	14.51	64.03	170.21	302.64
Std. dev.of prices (€/m^2)	1,348	861.43	580.65	33.26	216.97	685.10	2,946.72	5,279.08
Panel C: Market-level statistics								
Quarterly number of active ads	2,763	10.05	12.89	1.00	1.00	5.00	70.00	138.00
Quarterly number of agents	2,763	3.41	2.29	1.00	1.00	3.00	13.00	21.00
Share of treated agents	2,763	0.52	0.15	0.00	0.00	0.50	1.00	1.00

Note: Statistics based on the matched sample of Immobiliare.it and IHMS from 2022Q4 until 2023Q2. Panel C provides summary statistics on the restricted sample of markets including at least one treated observation and one control observation.

Table A2: Randomization balance on pre-sample characteristics

	All (1)	Control (2)	Treatment (3)	p-value (4)
Property size (m^2)	131.610	132.211	130.921	0.793
	(2.224)	(3.253)	(2.975)	
Garage (%)	0.430	0.433	0.427	0.815
	(0.012)	(0.016)	(0.018)	
Garden (%)	0.464	0.459	0.469	0.694
	(0.011)	(0.015)	(0.016)	
Elevator (%)	0.376	0.358	0.397	0.132
	(0.012)	(0.016)	(0.018)	
Terrace (%)	0.386	0.379	0.393	0.543
	(0.011)	(0.014)	(0.016)	
Floor > 3 (%)	0.216	0.211	0.222	0.557
	(0.009)	(0.012)	(0.013)	
New buildings (%)	0.104	0.095	0.114	0.245
	(0.007)	(0.009)	(0.012)	
Single-family homes (%)	0.235	0.235	0.234	0.945
	(0.009)	(0.013)	(0.013)	
Number of employees	1.854	1.941	1.754	0.171
	(0.113)	(0.185)	(0.117)	
Assessment of better local housing mkt (%)	0.242	0.240	0.244	0.914
	(0.017)	(0.023)	(0.026)	
Expectation of improving local housing mkt (%)	0.098	0.107	0.088	0.476
	(0.012)	(0.017)	(0.017)	
Number of markets served	-0.086	-0.094	-0.076	0.754
	(0.028)	(0.040)	(0.038)	
Std. dev. of the size of managed properties	0.012	-0.016	0.043	0.532
	(0.043)	(0.060)	(0.060)	
Observations	1,320	764	556	

Note: Statistics based on the matched sample of Immobiliare.it and IHMS from 2022Q4 until 2022Q3 (before treatment provision). Statistics are averaged within agents and weighted with sample weights. Standard errors in parenthesis.

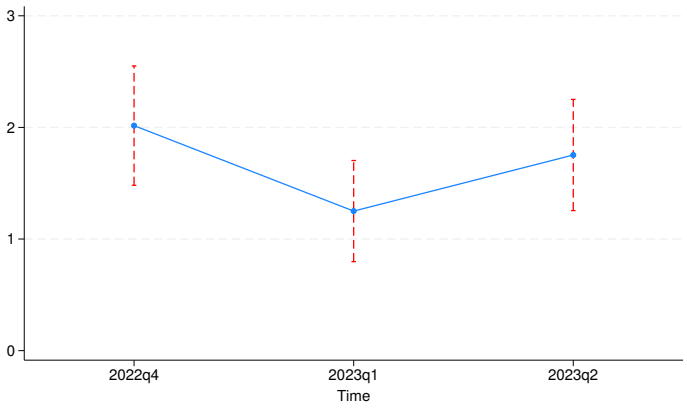
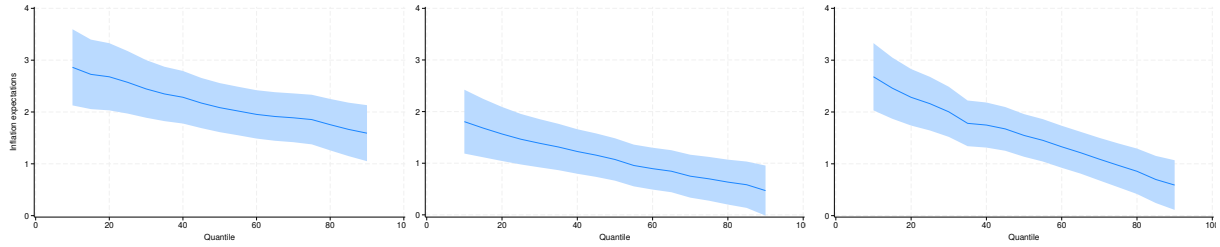


Figure A1: The time-varying effect of the information treatment on inflation expectations

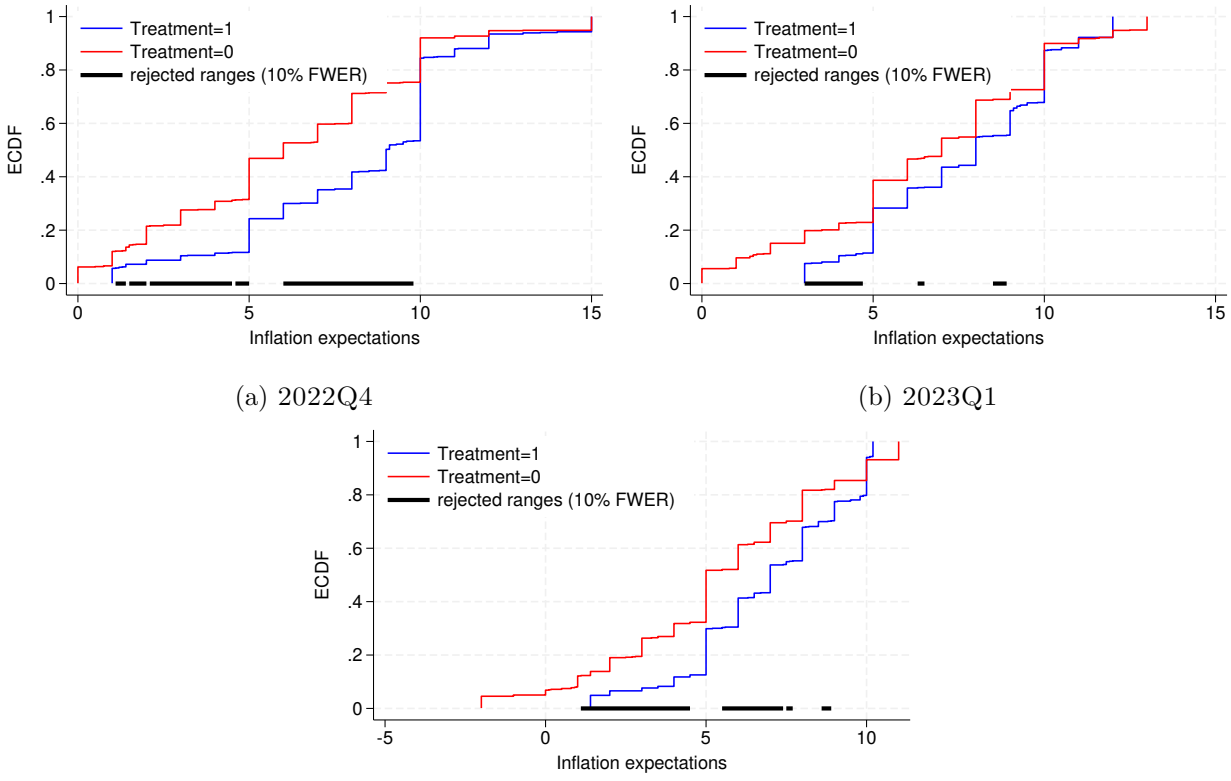
Note: The Figure shows the estimates of coefficient β_t in the equation: $F_t^i\pi = \alpha_l + \gamma_t + \beta_t t_t^i \times t + \varepsilon_t^i$. The sample period is 2022Q4–2023Q2. The model includes location and time fixed effects (where location refers to 23 distinct geographical areas) and other controls, namely: number of employees, situation of the local housing market in the current quarter and expected situation of the local housing market in the following quarter. Inflation expectations are winsorized at the bottom and top 5%. All estimates use Huber-White standard errors and IHMS sample weights are applied. The vertical bars are 95% confidence intervals.



(a) 2022Q4 (b) 2023Q1 (c) 2023Q2

Figure A2: Information treatment and inflation expectations: quantile regressions

Note: The Figure shows the impact of the information treatment on inflation expectations in the IHMS at different quantiles of the distribution, including fixed effects for the strata (23 geographical areas).



(a) 2022Q4

(b) 2023Q1

(c) 2023Q2

Figure A3: Inflation expectations CDFs and information treatment

Note: Empirical CDFs of inflation expectations for agents in the treatment and control group in the IHMS. The black horizontal lines denote the portion of the distribution where the test proposed by Goldman and Kaplan (2018) detects statistically significant differences in the two CDFs.

Table A3: Determinants of asking prices

	(1)	(2)	(3)	(4)	(5)	(6)
Floor area	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Garage	0.092***	0.092***	0.092***	0.091***	0.092***	0.092***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Garden	0.060***	0.054***	0.054***	0.054***	0.054***	0.054***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Elevator	0.113***	0.115***	0.115***	0.115***	0.115***	0.115***
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Terrace	0.062***	0.065***	0.065***	0.065***	0.065***	0.065***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
High floor (> 3)	0.005	0.009**	0.009**	0.009**	0.009**	0.009**
	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)
Status: good conditions	0.206***	0.195***	0.195***	0.195***	0.194***	0.195***
	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Status: renovated	0.384***	0.373***	0.372***	0.373***	0.372***	0.372***
	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Number of employees			0.000	0.000	0.000**	0.000***
			(0.000)	(0.000)	(0.000)	(0.000)
Local housing market situation: same			-0.001	0.001	-0.001	0.001
			(0.002)	(0.002)	(0.002)	(0.002)
Local housing market situation: better			-0.004	-0.001	-0.002	0.003
			(0.003)	(0.003)	(0.003)	(0.003)
Local housing market in the next quarter: same			-0.005**	-0.003	-0.005*	-0.003
			(0.003)	(0.003)	(0.003)	(0.003)
Local housing market in the next quarter: better			-0.001	0.001	-0.004	-0.001
			(0.004)	(0.004)	(0.004)	(0.004)
Number of quarterly new ads posted by the agent					-0.003	-0.003
					(0.002)	(0.002)
Number of housing markets covered by the agent					-0.001	-0.001
					(0.002)	(0.002)
St. dev. of the size of the properties posted by the agent					0.022***	0.022***
					(0.003)	(0.003)
Constant	7.175***	7.211***	7.213***	7.210***	7.216***	7.213***
	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
FE location	Yes	Yes	Yes	Yes	Yes	Yes
FE time	No	Yes	No	Yes	No	Yes
Adj-R2	0.874	0.875	0.875	0.875	0.876	0.876
Obs.	251240	130133	126119	126119	125415	125415

Note: The dependent variable is the log of the price/m^2 posted on Immobiliare.it from 2022q1 to 2023q1. Base outcome for status is'to be renovated'. Base outcome for the assessment and expectations on the local housing market is 'worse'. Location-type FE refer to local housing markets (OMI zones) interacted with the type of property (new vs existing and single-homes vs apartments). Standard errors are clustered at the OMI zone. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

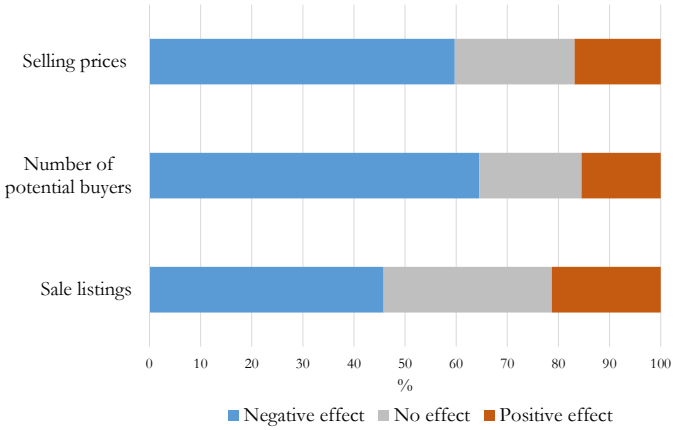


Figure A4: Real estate agents' assessment of the impact of high inflation on the housing market

Note: Data are taken from the IHMS waves of 2022Q3, 2022Q4 and 2023Q1. The graph represents the average responses of real estate agents to the question: "In your opinion, what will be the impact of inflation on the following national housing market variables over the next 12 months?".

Table A4: Impact of inflation expectations on asking prices: post-interview period

	OLS	IV time-varying treatment	IV dummy treatment			
			2022q4-2023q2	2022q4	2023q1	2023q2
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: All housing listings						
Inflation expectations	-0.000	0.010***	0.010***	0.010**	0.009*	0.011***
	(0.001)	(0.003)	(0.003)	(0.004)	(0.005)	(0.004)
FE location-type	Yes	Yes	Yes	Yes	Yes	Yes
FE time	No	No	Yes	No	No	No
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	56325	56325	56325	19260	15993	13869
1st stage F stat		252	267	71	80	159
Panel B: New housing listings						
Inflation expectations	-0.000	0.012***	0.013***	0.011*	0.018**	0.013*
	(0.001)	(0.004)	(0.004)	(0.006)	(0.009)	(0.007)
FE location-type	Yes	Yes	Yes	Yes	Yes	Yes
FE time	No	No	Yes	No	No	No
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	15237	15237	15237	5684	4821	2909
1st stage F stat		138	135	32	52	76

Note: The dependent variable is the log of the price/m^2 posted on Immobiliare.it from 2022q4 to 2023q2. Only observations after the interview period concluded are considered. For the 2022Q4 wave, this period starts on October 22; for 2023Q1, on February 9; for 2023Q2, on May 5. 'Other controls' include: i) dwelling characteristics: size, high floor, garden, terrace, garage, elevator, renovation status; ii) agent's characteristics and opinions from IHMS: number of employees, assessment and expectations on the local housing market; iii) agent-specific controls computed on the overall sample of online housing ads: the number of local housing markets where the agents operate and the standard deviation of the size of the properties posted by the agents. Location-type FE refer to local housing markets (OMI zones) interacted with the type of property (new vs. existing, single-family homes vs. apartments). Inflation expectations are winsorized at the bottom and top 5%. Standard errors are clustered at the OMI zone. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

Table A5: Impact of inflation expectations on asking prices: placebo on pre-treatment period

	Treated in 2022q4	Treated in 2023q1	Treated in 2023q2
	(1)	(2)	(3)
Inflation expectations in 2022q4	-0.004		
	(0.004)		
Inflation expectations in 2023q1		0.002	
		(0.005)	
Inflation expectations in 2023q2			-0.003
			(0.004)
FE location-type	Yes	Yes	Yes
FE time	Yes	Yes	Yes
Other controls	Yes	Yes	Yes
Obs.	36323	33273	31591
1st stage F stat	47	73	126

Note: The dependent variable is the log of the price/m^2 posted on Immobiliare.it from 2022q1 to 2022q3, prior to the introduction of the informations treatment. We assume that the treatment status and agents' expectations correspond to those observed in 2022Q4 (column 1), 2023Q1 (column 2), or 2023Q2 (column 3). 'Other controls' include: i) dwelling characteristics: size, high floor, garden, terrace, garage, elevator, renovation status; ii) agent's characteristics and opinions from IHMS: number of employees, assessment and expectations on the local housing market; iii) agent-specific controls computed on the overall sample of online housing ads: the number of local housing markets where the agents operate and the standard deviation of the size of the properties posted by the agents. Location-type FE refer to local housing markets (OMI zones) interacted with the type of property (new vs. existing, single-family homes vs apartments). Inflation expectations are winsorized at the bottom and top 5%. Standard errors are clustered at the OMI zone. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

Table A6: Impact of inflation expectations on asking prices: locations with treatment heterogeneity

	OLS	IV time-varying treatment	IV dummy treatment			
			2022q4-2023q2	2022q4	2023q1	2023q2
	(1)	(2)	(3)	(4)	(5)	(6)
Inflation expectations	-0.000	0.009***	0.009***	0.009**	0.010*	0.011***
	(0.001)	(0.003)	(0.003)	(0.004)	(0.005)	(0.004)
FE location	Yes	Yes	Yes	Yes	Yes	Yes
FE time	No	No	Yes	No	No	No
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	26280	26280	26280	9911	9471	5602
1st stage F stat		225	226	66	82	160

Note: The dependent variable is the log of the price/m^2 posted on Immobiliare.it from 2022q4 to 2023q2. The Table reports estimates based on a restricted sample including, for any period, only the neighborhoods (OMI zones) where there is at least one control and one treated agent. 'Other controls' include: i) dwelling characteristics: size, high floor, garden, terrace, garage, elevator, renovation status; ii) agent's characteristics and opinions from IHMS: number of employees, assessment and expectations on the local housing market; iii) agent-specific controls computed on the overall sample of online housing ads: the number of local housing markets where the agents operate and the standard deviation of the size of the properties posted by the agents. Location-type FE refer to local housing markets (OMI zones) interacted with the type of property (new vs. existing, single-family homes vs. apartments). Inflation expectations are winsorized at the bottom and top 5%. Standard errors are clustered at the OMI zone. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

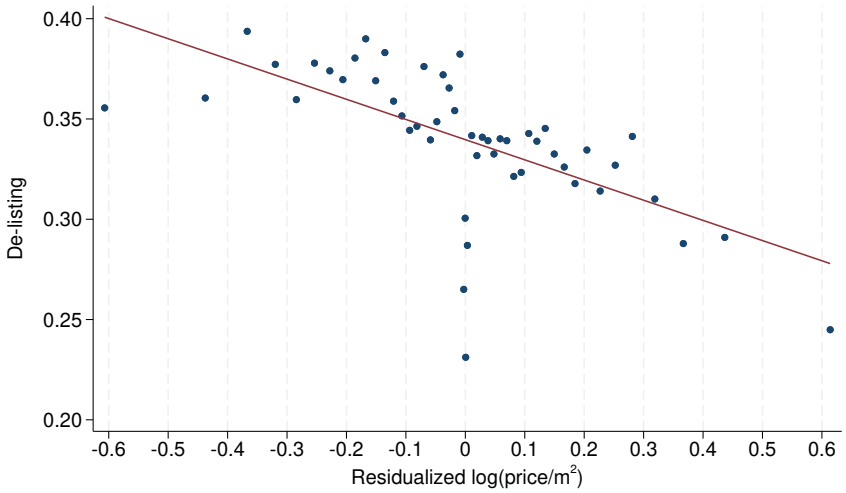


Figure A5: De-listing and property prices

Note: The Figure shows the binscatter of de-listing (a dummy equal to 1 if the listing disappears from the website during the quarter and 0 otherwise) and the residuals of the regression of log(price/m^2) on property and agents' characteristics (column 6 of Table A3).

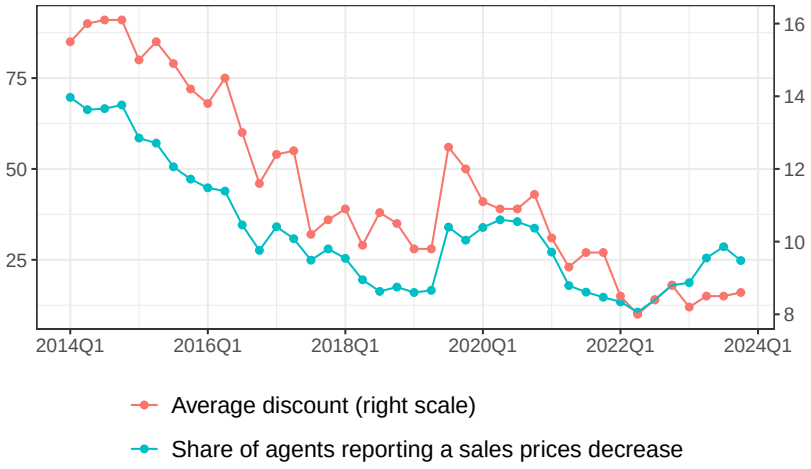


Figure A6: Real estate agents' assessments on sale prices and average discount

Note: This chart shows the evolution of the share of real estate agents reporting a decrease in housing transaction prices in their market and the average discount obtained by the buyers compared to the listing price. Data are taken from the IHMS waves of the 2014-2023 period.

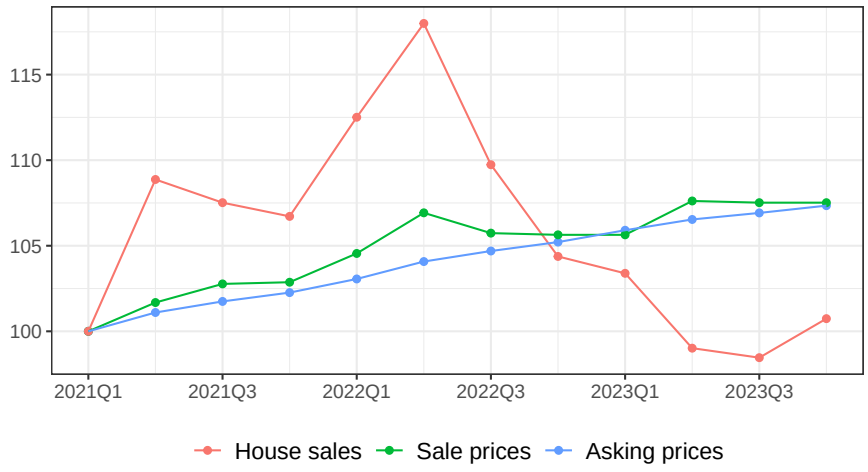


Figure A7: Housing prices and transactions

Note: This chart illustrates the main trends in the Italian housing market in 2021-2023. House sales data are provided by the Italian Tax Office and are not seasonally adjusted. Sale prices refer to the national residential property prices produced by ISTAT. Asking prices are quality-adjusted and based on all advertisements on Immobiliare.it. Quarterly data. All variables are rescaled to their 2021Q1 values and multiplied by 100.

B Matching the IHMS with Immobiliare.it

During the period 2019-2023, the Italian Housing Market Survey (IHMS) was based on interviews with 5,172 real estate agents. For these agents, we have access to the unique identifier in the survey, the agency's name, and the agency's address. We should find the corresponding identifier for each real estate agent in the Immobiliare.it dataset. This second dataset includes about 36,000 real estate agents, along with their names and addresses.

Unfortunately, the format of this information is heterogeneous across the two datasets, and we must resort to an approximate string-matching procedure to match the unique identifier in the survey, ID_S, with the unique identifier in the Immobiliare.it dataset, ID_I.

The record-linkage procedure involves the following steps:

Step 1. We perform a standard pre-processing of the strings to increase their comparability. In particular, we remove the franchising affiliation from the name of the agency, as this is not regularly reported by all agents. We also remove all acronyms.

Step 2. We match each entry of the survey with all entries in the Immobiliare.it within the same zip code. This step generates a table where each row corresponds to a unique combination of ID_S and ID_I.

Step 3. For each combination of ID_S and ID_I, we compute different measures of name and address string distance. The distance measures used are the Damerau-Levenshtein, Hamming, Levenshtein, q-gram, Jaccard, Jaro, and Jaro-Winkle. Moreover, we also include the lengths of the strings and the difference in the number of characters between the names and the addresses as variables.

Step 4. To decide whether an agency pair is a match, we use three supervised machine learning models: logit, random forest, and stochastic gradient boosting. With these models, we predict if a couple (ID_S, ID_I) corresponds to the same agency ($M = T$) or not ($M = F$).

Step 5. For the agencies left unmatched after step 4, we search for potential matches based on the location and manually validate the output.

Since the list of potential matches created in step 2 is very large and cannot be checked manually, we must use some algorithms to filter out only the potential true matches.

We trained the models used in step 4 on a random sample of 2000 agency pairs manually labeled. The 80% of sample observations are used to train the models, and the remaining 20% for testing. The performance of these models is similar and is reported in Table B1. The accuracy is defined as $\frac{TP+TN}{TP+TN+FP+FN}$, where TP is the number of true positives, TN is the number of true negatives, FP is the number of false positives, and FN is the number of false negatives. The recall

is defined as $\frac{TP}{TP+FN}$, while the precision is $\frac{TP}{TP+FP}$. A recall lower than the precision implies that all models are conservative in considering a couple (ID_S, ID_I) as a true match.

Table B1: Performance of the classification models

Model	Performance		
	Accuracy	Recall	Precision
Random forest	0.9182	0.8786	0.8978
Logistic regression	0.9103	0.8643	0.8897
Stochastic gradient boosting	0.9103	0.8500	0.9015

Note: This table reports the performance indicators of the three models considered for the record linkage.

We use the models to find the true matches for about 2,800 agencies interviewed in the IHMS since 2022Q3. We find 1,464 true matches ($M = T$). For 1,334 cases, all three models classify the couple (ID_S, ID_I) as a true match. For 115 cases, only two models predict a true match. In the remaining 15 cases, only one model predicts a true match. For the remaining agencies in the survey, we identified the most likely match in Immobiliare.it, and we manually checked if $M = T$ or $M = F$.[34] This operation allows us to find an additional 116 true matches.

To find additional true matches, we geocoded the addresses of all unmatched agencies (using the TomTom API), and we computed the distance of the location for each couple (ID_S, ID_I). We manually inspected all couples within a 25-meter radius, and we identified 382 true matches.

Therefore, we match 1,962 out of 2,800 agencies. Those interviewed during the period 2022Q3-2023Q1 were 1,432.

[34] The three models selected for the classification return a score in the interval $[0, 1]$ that proxies the likelihood that $M = T$. For each couple (ID_S, ID_I), we computed the average score among the three models. Then, for each ID_S we selected the ID_I with the higher score.

C A stylized model of the seller's problem

Here we describe more extensively the stylized model of the seller's problem sketched in Section 4.1. A broker is entrusted with selling a housing property. In period 0, he sets a nominal price p which cannot be subsequently revised. Without loss of generality, we abstract from price revisions: as long as listing prices exhibit some rigidity, the model's intuition remains intact. We also abstract from the buyer-seller bargaining stage, which usually leads to a selling price below the listing price. As long as the probability of selling a property remains decreasing in the nominal listing price p, the main intuition goes through.[35] The broker's fee is a fixed share of p; we therefore ignore this scaling factor without loss of generality. In period 1, the broker sells the house at the nominal price p with probability q. At this stage, q summarizes both the probability of meeting a potential buyer and the likelihood of closing the deal conditional on the buyer visiting the property. In his activity, the broker incurs a real cost κ. This cost proxies for all activities undertaken by the broker and is incurred only upon finding a buyer and completing the sale. If the property remains unsold, the broker retains the asset until period 2, when the asset perishes.[36] Preferences are linear in consumption with no intertemporal discounting, so the timing of consumption is irrelevant.

The broker's value function is:

$$V = \max_{p} \quad q(p, \pi^e) \times \left[\frac{p}{P_0(1+\pi^e)} - \kappa \right] \tag{11}$$

where P_0 is the price level of consumption goods in period 0, and π^e is the broker's expected change in the price level between period 0 and 1.

To study the trade-off faced by the broker, we assume that the selling probability depends on the nominal listing price p and expected inflation π^e: $q \equiv q\left(p, \pi^e\right)$. The dependence of q on expected inflation reflects the broker's beliefs about the general-equilibrium effect of inflation on housing demand. The likelihood of selling the house decreases with the nominal listing price, $q_p \equiv \frac{\partial q}{\partial p} < 0$.[37]

The first-order condition yields:

$$F(p^*, \pi^e) = q_p(p^*, \pi) \left[p^* - \kappa P_0(1+\pi^e) \right] + q(p^*, \pi^e) = 0 \tag{12}$$

At the optimum listing price p^*, brokers equate the marginal revenue – equal to the probability of selling the house and thus obtaining the intermediation fee – with the marginal cost, i.e. a lower

[35] We rule out that properties exhibiting higher listing prices are always discounted more than comparable properties with lower listing prices, such that they end up being sold systematically at a lower transaction price.

[36] Allowing the asset to yield a payoff $w > 0$ in period 2 would not affect the model's key insights.

[37] Assuming the sale probability depends on the nominal rather than real listing price implies that buyers exhibit money illusion, i.e., they respond to nominal values without fully internalizing inflation. This assumption is consistent with empirical evidence (Brunnermeier and Julliard, 2008; Andersen et al., 2022).

selling probability q_p times the expected surplus from the transaction.

The second order condition reads as:

$$\frac{\partial F(p^*, \pi^e)}{\partial p^*} = F_{p^*} \leq 0 \tag{13}$$

$$q_{pp}\left[p^* - \kappa P_0(1+\pi^e)\right] + 2q_p \leq 0 \tag{14}$$

Notice that $q_{pp} < 0$ (the selling probability is a concave function of the listing price) is a sufficient, though not necessary, condition for p^* to be a maximum (assuming that $(p^* - \kappa P_0(1+\pi^e)) > 0$, which ensures positive profits). For simplicity, from here onwards we assume that this condition holds.

To derive an expression for the inflation-expectations pass-through (IEPT) – i.e., how the optimal price p^* varies with π^e, we apply the implicit function theorem:

$$IEPT = \frac{dp^*}{d\pi^e} = -\frac{F_{\pi^e}}{F_{p^*}} = -\frac{-q_p\kappa P_0 + q_{p\pi^e}\left[p^* - \kappa P_0(1+\pi^e)\right] + q_{\pi^e}}{q_{pp}\left[p^* - \kappa P_0(1+\pi^e)\right] + 2q_p} \tag{15}$$

For the second-order condition, we know that $F_{p^*} < 0$, so the sign of equation (15) is the same as the sign of F_{π^e}, i.e. the numerator of equation (15). If the selling probability does not depend on inflation (i.e., $q_\pi = q_{p\pi} = 0$), F_{π^e} simplifies to:

$$F_{\pi^e} = -q_p\kappa P_0 > 0 \tag{16}$$

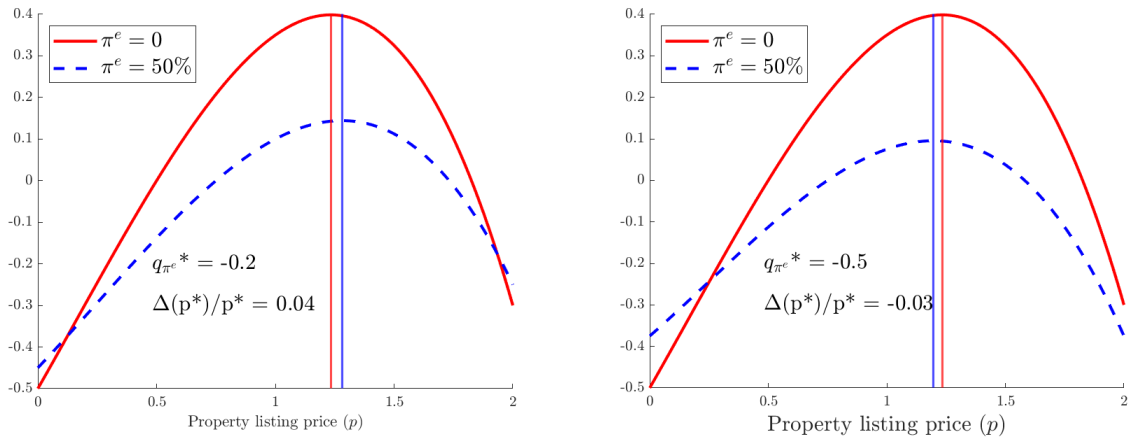
Equation (16) implies that the IEPT is unambiguously positive when brokers believe inflation has no direct effect on housing demand. In this case, higher expected inflation induces brokers to raise the housing listing price to preserve real profits.

A more interesting case arises when brokers believe inflation reduces housing demand either directly ($q_{\pi^e} < 0$) and/or indirectly by increasing the sensitivity of demand to the listing price ($q_{p\pi^e} \leq 0$). Here the profit-preserving motive that pushes p^* upward is counterbalanced by the demand channel, making the sign of the IEPT *a priori* ambiguous. From equation (15) we can immediately see that more pessimistic agents ($q_{p\pi^e} \ll 0$ and/or $q_{\pi^e} \ll 0$) are less likely to increase prices in response to a rise in inflation expectations. We confirm empirically this prediction in Section 4.2.

Here we provide a qualitative illustration in Figure C1. Panel a shows that, even when brokers factor in a negative impact of inflation on demand and overall prices (i.e., in this reduced-form context, on the selling probability), they may still find it profitable to raise the listing price in response to higher inflation expectations. However, when the perceived negative impact of inflation on the selling probability is sufficiently strong, a rise in expected inflation may trigger a decrease in own listing prices (Figure C1, panel b).

Figure C1: Sellers' profit and optimal listing prices when the selling probability is negatively affected by inflation

(a) Low q_π (b) High q_π



Notes: We assume that the selling probability has this functional form: $q(p_h, \pi^e) = \theta_1 + \theta_2 p_h^{\theta_3} + \theta_4 \pi^e$. In both panels we have: $\theta_1 = 1$, $\theta_2 = -0.3$ and $\theta_3 = 2$. In panel (a) we assume $\theta_4 = -0.5$, while in panel (b) we assume $\theta_4 = -1$.

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Conflict-of-interest disclosure statement

The author declares that they have no relevant or material financial interests that relate to the research described in this paper.