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

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June 2025

Abstract

We investigate how inflation expectations affect pricing decisions in the housing market. We leverage a randomized control trial embedded within an Italian survey of real estate agents and combine (for each agent) survey data with high-frequency listing prices observed on a large digital platform. Exploiting an exogenous shift in inflation expectations generated by an information treatment, we find that higher inflation expectations cause a one-to-one increase in housing listing prices, on average. The pass-through is weaker in more concentrated and low-demand markets, as well as for agents who are more pessimistic about housing and credit developments.

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

Keywords: Inflation Expectations, Randomized Control Trial, Housing Market, Market Concentration.

*We thank Olivier Coibion, Maarten De Ridder, Lena Dräger, Ester Faia, Giuseppe Ferrero, Mishel Ghassibe, Giacomo Mangiante, Claudio Michelacci, Joao Monteiro, Stefano Neri, Luigi Paciello, Tiziano Ropele, Alfonso Rosolia, Gabriele Rovigatti, Sergio Santoro, Andrea Tiseno, Basit Zafar and seminar participants at the conferences "Heterogeneous Households, firms and Financial Intermediaries" (Norges Bank, 2024), "Back to Basics and Beyond: New Insights for Monetary Policy Normalization" (Bank of Finland, 2024), "4th Macro-Monetary Workshop Bank of Italy - EIEF" (EIEF, 2025), and the "Spring Conference on Expectations of Households and Firms" (Bundesbank, 2025) for helpful comments and suggestions. We are extremely grateful to Immobiliare.it for providing the data and Andrea Luciani for his assistance. The opinions expressed are those of the authors and do not necessarily reflect the views of the Bank of Italy or the Eurosystem. All remaining errors are our own.

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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. Our understanding of the mechanisms and determinants of this pass-through is limited. Little is known, for example, about how changes in inflation expectations affect pricing decisions in the housing market or in other secondary markets for used goods. Existing literature has primarily focused on firms' pricing behavior, while the role of intermediaries and brokers in shaping price-setting decisions in response to inflation expectations has received virtually no attention.

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 investigate their impact 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 with substantial 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] Our findings reveal a novel channel through which central banks, by manipulating inflation expectations, can influence the housing market. More broadly, we shed light on the role of market microstructure and the characteristics of the price-setters in shaping the pass-through of inflation expectations, offering insights that may extend beyond the housing sector to other areas of the economy.

Real estate agents have a key role in setting listing prices due to their informational advantages in local housing markets (Levitt and Syverson, 2008; Agarwal et al., 2019; Cunningham et al., 2022; Gilbukh and Goldsmith-Pinkham, 2024). Agents are typically compensated through a commission based on a fixed percentage of the final sale price. This creates conflicting incentives in their pricing strategies. On the one hand, agents may prefer higher nominal listing prices to preserve the real value of homes or strengthen the seller's bargaining position, ultimately increasing their expected commission. On the other hand, setting higher asking prices can reduce the likelihood of a sale or prolong the time required to sell. In addition, a well-established stylized fact is the stickiness

[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.

of listing prices. Agents typically set an initial price and rarely revise it upward (Knight, 2002; Merlo and Ortalo-Magne, 2004; Merlo et al., 2015; Anenberg, 2016).[3] These two features – the critical role of individual real estate agents in price-setting and the upward rigidity of listing prices – make the housing market a particularly compelling context to examine how subjective inflation expectations influence pricing decisions.

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 use 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, this treatment allows us to study the causal relationship between inflation expectations and property pricing.

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, such as the number of markets they operate in and their average number of new ads per quarter. Moreover, we have access to all listings on the Immobiliare.it platform, which allows us to analyze various market (neighborhoods) characteristics, such as the number of competing agents, their behaviors, and 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.

In related works, firms' actual pricing decisions are unobserved, and the pass-through from inflation expectations to own prices is typically estimated based on the self-reported average planned change in own prices. In particular, survey respondents must first report their inflation expectations (subject to an information treatment) and then the planned change in their prices.[4] While informative, this approach has several limitations. Most notably, respondents must report an average planned change in prices, regardless of the number of products or services they offer and the diversity of markets in which they operate.[5]

[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.

[4] For example, the survey question exploited in Coibion et al. (2020) and Rosolia (2024) is: "For the next 12 months, what do you expect will be the average change in your firm's prices?".

[5] For multi-product firms, the average planned change in firms' prices is often a poor proxy for actual pricing

In contrast, our empirical strategy offers a significant advantage: we can directly observe the pricing decisions of individual real estate agents at the product level (i.e., a house) under different market conditions.[6] By including market fixed effects, we exploit the within-market heterogeneity between treated and untreated agents to estimate the causal impact of inflation expectations on listing prices. Moreover, in our setting, a market is clearly defined as a neighborhood, which enables us to exploit the precise observation of market microstructure and to investigate how the inflation expectations pass-through (IEPT) varies depending on the characteristics of the market.

We 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). 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. 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 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. 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; under certain conditions, the pass-through can even exceed one (Werning, 2022). In our context, the combination of upward price rigidity and long-lived price spells in a period of rising inflation expectations provides a natural explanation for the strong pass-through that we uncover.

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. Then, these relatively higher prices are associated with a lower probability of delisting,

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 case of the IHMS, the survey questionnaire is sent to the head of the real estate agency. Thus, unlike in many firm-level studies, the person receiving the information treatment is also the one responsible for setting the listing prices.

suggesting an increase in the time-on-market.

In the second part of the paper, we investigate the heterogeneous impact of inflation expectations on current prices across markets' and agents' characteristics. We show that the pass-through is significantly weaker in more concentrated markets, where dominant agents may have greater pricing power and could sustain prices above their reservation values, allowing them to absorb the expected real losses associated with higher inflation. Conversely, the IEPT is stronger in high-demand markets, where we expect the trade-off between setting a higher listing price and experiencing a longer time-to-sale to be less pronounced.[7] In such markets, buyers are likely to be less sensitive to price changes, allowing real estate agents to adjust prices more aggressively without significantly reducing the likelihood of a sale.

Our unique dataset further allows us to study how individual characteristics of real estate agents influence the pass-through of inflation expectations. To our knowledge, this is a novel contribution to the literature, as establishing a clear link between survey respondents and those responsible for price-setting decisions is usually challenging.[8] In our case, this link is explicit: survey respondents are typically the owners of small real estate agencies and directly oversee the pricing of the properties. We find that the pass-through is higher for agents operating in multiple markets, likely reflecting a greater level of sophistication in their decision-making. Conversely, the pass-through is lower for agents with pessimistic expectations about housing price trends one year ahead in their reference market and for those reporting difficulties faced by potential buyers in securing mortgage loans.

Summing up, subjective inflation expectations influence pricing decisions in the housing market. The pass-through is complete on average, but its magnitude varies across markets and agents. The pass-through is more pronounced in competitive and high-demand markets and for more sophisticated agents. 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).

[7] Demand intensity in a neighborhood is measured as the average quarterly number of potential buyers' views per listing on the Immobiliare.it platform.

[8] Savignac et al. (2024) investigate how respondents' characteristics influence their inflation expectations. Here, we focus on how these characteristics interact with inflation expectations to shape price-setting decisions.

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).[9]

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. This work applies these methods to a novel setting, namely the price-setting strategies of real estate agents, finding a high pass-through. Moreover, our rich dataset enables us to study the impact of inflation expectations while controlling for many product and market-level characteristics, an approach that is usually unfeasible in most settings. 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 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). Moreover, we show that the extent of the pass-through depends on the market microstructure. In this respect, our paper contributes to the recent discussion on the role of market power in transmitting supply shocks to inflation (Acharya et al., 2023; Franzoni et al., 2023) as well as to the well-established literature on the pass-through of cost shocks to own prices (Gopinath and Itskhoki, 2010; Nakamura and Steinsson, 2013; Amiti et al., 2019; Wang and Werning, 2022). However, we focus on the role of inflation expectations, and we highlight an additional mechanism linking market concentration to price-setting behavior.

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

[9] 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.

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 investigates the heterogeneity in the pass-through and its determinants. 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.

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.[10]

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.

[10]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.

Real estate brokers who have taken part in the survey since 2022Q4 are also asked about their projections for inflation in consumer prices.[11] 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.

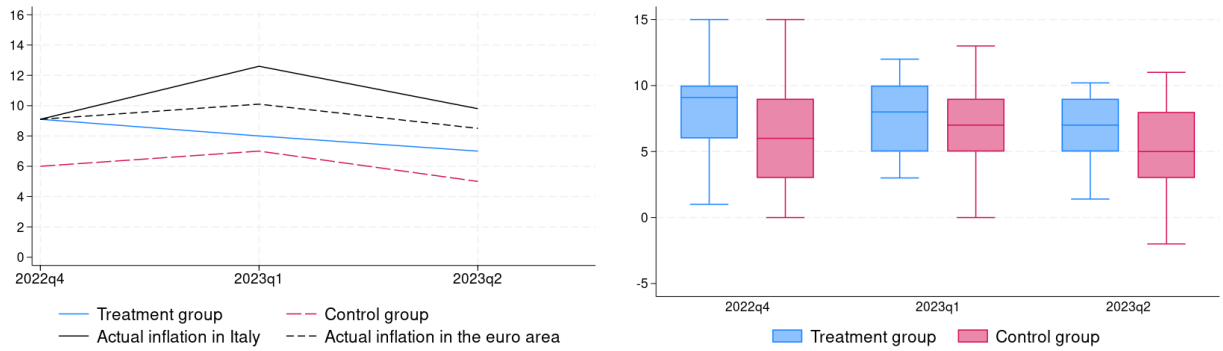
Hence, the treatment entails providing brokers with publicly available data about the latest inflation rates in Italy and the euro area. Because the inflation rate varies over time, the size of the treatment varies as well. In 2022Q4, participants were randomly assigned to treatment and control groups, and this assignment remained constant. The survey design was partially altered 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).[12]

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

[11] 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.

[12] 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 boxplot of agents' inflation expectations. Data are winsorized at the bottom and top 5%.

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 contains further information about the distribution of inflation expectations in the treatment and control groups. Compared to the treatment group, the latter's inflation expectations are noticeably more dispersed.

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.

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 size, and *(iii)* the bottom and the top 1% of ads by price/mq in each local housing market. Finally, we aggregate the data at the quarterly frequency.[13]

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

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.[14] 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

[13] 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.

[14] 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.

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 m2 and 860€/m2, respectively.

Our estimation sample includes about 74,000 observations (Table A2, Panel A). The average price/mq 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 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 A2, 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/mq2 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/mq2, 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. Considering the full specification in column (8), 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 posting a high number of ads tend to ask lower prices, while 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/mq2 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 square 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.[15] 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.[16]

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

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

[16] 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.

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 *** denote significance at the 10%, 5% and 1% levels, respectively.

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).[17] Indeed, 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

[17]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 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.

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 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.[18] 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).

There may also be other mechanisms at work. For example, real estate agents may anticipate that the central bank will tighten monetary policy to fight high inflation. Therefore, they may decrease housing prices to accelerate house sales in the face of future higher mortgage interest rates and lower housing demand. Then, how real estate agents solve all the trade-offs and how their choice is affected by market and agent characteristics is ultimately an empirical question.

[18] 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.

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:

$$p_{jt}^{i} = \beta F_t^i \pi + \zeta_j + \theta_t^i + \alpha_l + \gamma_t + \varepsilon_{jt} \tag{6}$$

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.

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.[19] 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

[19] 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.

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	-0.001	0.010***	0.010***	0.008***	0.010**	0.011***
	(0.000)	(0.002)	(0.002)	(0.003)	(0.004)	(0.003)
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		1915	2110	494	413	668
Panel B: New housing listings						
Inflation expectations	-0.000	0.013***	0.013***	0.010*	0.016**	0.014*
	(0.001)	(0.003)	(0.003)	(0.005)	(0.007)	(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		472	511	122	143	130

Note: The dependent variable is the log of the price/m2 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 average number of new ads posted each quarter, 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 and single-homes vs apartments). Inflation expectations are winsorized at the bottom and top 5%. All estimates use Huber-White robust standard errors. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

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.[20]

Mechanism. The transmission of inflation expectations to current listing prices can occur through

[20] 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, when inflation stood at 7.0% and was on a declining path.

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.[21]

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 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.

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.[22] 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:

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

where p^i_{jt} is the logarithm of the price/mq 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 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

[21] 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.

[22] 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)	(0.008)	(0.007)	(0.009)	(0.009)
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/m2 posted on Immobiliare.it; in column (2) the dependent variable is the quarterly number of price changes for any given ad; 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). All estimates use Huber-White robust standard errors. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

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.[23] 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.[24]

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:

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

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

[23] 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.

[24] 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.

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.

Interpreting the inflation expectations pass-through (IEPT). Inflation expectations can influence sellers' pricing decisions through several, potentially opposing, 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 margins, implying a positive IEPT. Second, agents might view inflation as associated with rising housing prices, expecting increased demand from households seeking inflation hedges. This general equilibrium mechanism would also suggest a positive IEPT. Third, agents may anticipate that higher inflation leads to rising interest rates, weakening buyers' mortgage access and dampening housing demand; this channel would thus imply a negative or null IEPT.

The positive IEPT we estimate suggests the dominance of the first and/or second mechanisms. To investigate further, we leverage an additional IHMS question, which asked agents about the expected impact of inflation on key housing market variables over the next 12 months (listings, buyer interest, and prices).[25] A majority expressed concern that inflation would depress prices and demand, thus indicating that real estate agents view high inflation periods as periods where the economic outlook worsens (Figure A4).[26] This implies that agents generally associate inflation with negative housing market outcomes, ruling out the second (optimistic) mechanism as the main driver of IEPT.

Finally, quantifying the offsetting impact of the third channel, operating through general equilibrium adjustments such as tighter credit conditions, is challenging. However, in Section 4 we will show that real estate agents who perceive credit conditions as tight also exhibit a lower IEPT. This suggests that some agents may associate higher inflation with rising mortgage interest rates. Nevertheless, this general equilibrium channel does not appear strong enough, on average, to offset the positive effect of the first, partial equilibrium channel, through which higher inflation expectations directly lead to higher listing prices.

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,

[25] 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.

[26] This supply-side perspective of the economy, whereby periods of high inflation are associated to worse economic conditions, is in line with survey evidence on households Coibion et al. (2023); Binetti et al. (2024).

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.[27] 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 The determinants of the pass-through rate

Our findings suggest that real estate agents, on average, adjust their listing prices one-to-one with their subjective inflation expectations. However, there are reasons to believe that the effects of inflation expectations vary across different markets and agent types. For instance, the degree to which inflation expectations translate into higher prices may depend on the seller's margin and their capacity and incentive to absorb a decline in real gains. On the agent side, the strength of the IEPT may depend on their degree of sophistication or their overall assessment of housing and mortgage market conditions. In the remainder of this Section, we investigate the heterogeneous effects of inflation expectations on actual prices along these two key dimensions: i) market characteristics' and ii) real estate agents' characteristics.

4.1 Price-setting and market characteristics

The first dimension of heterogeneity deserving investigation pertains to market characteristics, which may influence both the ability and the incentive of real estate agents to incorporate inflation expectations into listing prices. While a comprehensive theoretical treatment of the home-selling problem is beyond the scope of this paper, two general observations offer useful insights into understanding how market characteristics influence the IEPT. First, real estate agents face a

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

trade-off between setting a higher listing price and experiencing a longer time-to-sale. Then, the ability of real estate agents to set higher listing prices depends on the elasticity of the probability of selling to the listing price: the lower this elasticity, the higher the ability to increase the listing price. Second, any housing transaction must generate a non-negative net surplus for the parties involved. The IEPT may thus depend on how close market prices are, in equilibrium, to the reservation values of sellers or buyers. If listing prices closely align with sellers' reservation values – the minimum price at which they are willing to transact – then an upward revision in inflation expectations will likely be fully reflected in nominal prices, as sellers seek to preserve their real reservation values.

Although we lack direct data on reservation values and the elasticity of demand with respect to prices, we examine observable market features that plausibly correlate with these unobservables. First, we consider market concentration, which reflects the degree of competition among real estate agents. In highly concentrated markets, dominant agents may have greater pricing power and could sustain prices above their reservation values, resulting in a lower IEPT. To measure market concentration, we compute the Herfindahl-Hirschmann index based on agents' market shares, derived from the number of listings they manage.[28]

Second, we consider supply intensity, defined as the number of available homes for sale in the market, approximated here by the total number of listings. A higher volume of available homes increases buyers' choice and facilitates price comparisons, which tend to push prices closer to agents' reservation values (Giacoletti, 2021). In such settings, the ability of agents to absorb higher inflation expectations without adjusting prices might be more limited, implying a stronger IEPT.

Third, we compute a measure of demand intensity. 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 demand intensity 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. In high-demand markets, we expect the trade-off between setting a higher listing price and incurring a longer time-to-sale to be less severe. In other words, when demand is abundant, agents can raise prices without substantially increasing the probability that a listing remains on the market for an extended period.

To test these hypotheses empirically, we compute the aforementioned indicators utilizing the full sample of listings on the Immobiliare.it platform, and standardize these measures using the mean and standard deviation within each stratum to account for structural differences between

[28] The HHI is defined as $HHI_l = \sum_{i=1}^{I_l} (n_{il}/N_l)^2$, where n_{il} is the number of listings posted by agent i in market l and N_l is the total number of listings posted in that market. The index is computed on all listings available on the platform.

[29] We should remark that this measure of housing demand 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.

Table 4: Pass-through rate and market characteristics

	HHI	Supply	Demand	All
	(1)	(2)	(3)	(4)
Inflation expectations	0.006***	0.007***	0.009***	0.006***
	(0.002)	(0.002)	(0.002)	(0.002)
Infl. exp * Market concentration	-0.009***			-0.007***
	(0.002)			(0.002)
Market concentration	0.060***			0.047**
	(0.017)			(0.019)
Infl. exp * Supply intensity		0.003**		0.001
		(0.001)		(0.001)
Supply intensity		-0.037***		-0.022
		(0.014)		(0.015)
Infl. exp * Demand intensity			0.006***	0.004*
			(0.002)	(0.002)
Demand intensity			-0.031*	-0.022
			(0.016)	(0.016)
FE location-type	Yes	Yes	Yes	Yes
FE time	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes
Obs.	38470	38470	38470	38470
1st stage F stat	741	142	120	59

Note: The dependent variable is the log of the price/m2 posted on Immobiliare.it from 2022q4 to 2023q2. In any quarter, the Herfindahl-Hirschmann index, the supply of housing listings and demand intensity (clicks per ad) are defined at the local housing market level (OMI zones) are standardized using the mean and the standard deviation of the respective sample stratum. '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 average number of new ads posted each quarter, 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 and single-homes vs apartments). Inflation expectations are winsorized at the bottom and top 5%. All estimates use Huber-White robust standard errors. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

urban and suburban markets.

We run the IV regression specified in (6), interacting inflation expectations with each market indicator. Accordingly, we use the treatment status interacted with the respective market characteristic 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. Moreover, we restrict the sample to markets with variation in the information treatment, i.e., we exclude the markets in which all or none of the listings belong to agents that received the information treatment.[30] A crucial assumption is that the market structure is not directly affected by the shock to inflation expectations. This assumption would be violated if, for example, real estate agents sort across markets based on their inflation expectations. However, given that our analysis is focused on a short period, we believe that adjustments in market structure would be limited and would not dramatically affect our estimates.

Table 4 summarizes the results. Consistent with the theoretical intuition, we find that higher

[30]Since we aim to assess the heterogeneity of the effect for different characteristics of the market, we exclude those markets for which we cannot estimate the impact of inflation expectations. Excluding these markets does not materially affect the baseline estimates, as shown in Table A6.

market concentration is associated with elevated prices and a lower pass-through rate (column 1). A one-standard-deviation increase in market concentration causes a 0.9 points reduction in the pass-through rate of a one percentage-point increase in inflation expectations. Given the baseline pass-through rate estimated in this regression (0.6), this suggests that in highly concentrated markets the pass-through of inflation expectations to current prices is null. In a similar vein, we find that higher supply is negatively correlated with housing prices and implies a slightly higher pass-through rate (column 2). However, this effect disappears when all market characteristics are included simultaneously in the regression (column 4), indicating that our measure of supply intensity does not convey additional information beyond that captured by HHI. Finally, as expected, higher demand intensity significantly amplifies the pass-through rate. A one-standard-deviation increase in demand intensity leads to a 0.6 point increase in the pass-through rate (column 3), and this effect remains significant even when tested against alternative channels (column 4).

Summing up, the pass-through of inflation expectations to listing prices increases with market competition and demand intensity. Both results are novel in the context of inflation expectations but are consistent with insights from related strands of the literature on firms' price-setting decisions.

4.2 Price-setting and real estate agents' characteristics

The second dimension of heterogeneity relates to the characteristics of real estate agents. This analysis leverages data from both the IHMS and Immobiliare.it datasets. The IHMS dataset contains information about agents' characteristics, such as the number of employees, and elicits their opinions on key market outcomes. Additionally, Immobiliare.it data allows us to determine whether agents operate in limited or diverse range of markets and to estimate the scale of their business activity.

We focus on four key features. First, we consider two measures of agents' sophistication: the number of listings managed and the number of distinct markets in which they operate. As for market indicators, we standardize these variables using the mean and the standard deviation of their respective sample stratum. Agents with larger business activities and broader geographic operations are presumed to be more sophisticated, likely paying greater attention to macroeconomic variables and incorporating these factors into their pricing strategies.

Furthermore, we exploit the heterogeneity in agents' beliefs about current and expected housing trends. To elicit beliefs about current housing demand, we exploit responses to a recurring IHMS survey question regarding the reasons for the non-renewal of sale mandates by property owners. Specifically, we identify cases where agents attribute non-renewal to buyers' difficulties in obtaining mortgage loans. This response is particularly relevant because credit supply, a critical determinant of housing demand, is largely exogenous to local real estate market conditions. We hypothesize that agents perceiving tighter credit supply conditions are more pessimistic about housing demand

Table 5: Pass-through rate and agents' characteristics

	(1)	(2)	(3)	(4)	(5)
Inflation expectations	0.008***	0.007***	0.013***	0.014***	0.013***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Infl. exp * Number of housing listings	0.001				-0.001
	(0.001)				(0.001)
Number of housing listings	-0.001				0.017
	(0.007)				(0.011)
Infl. exp * Number of markets		0.002**			0.003*
		(0.001)			(0.002)
Number of markets		-0.013**			-0.027**
		(0.007)			(0.011)
Infl. exp * Perceived tightness in the mortgage market			-0.008***		-0.009***
			(0.003)		(0.003)
Perceived tightness in the mortgage market			0.051***		0.055***
			(0.018)		(0.019)
Infl. exp * Expected decrease in prices				-0.006**	-0.005*
				(0.003)	(0.003)
Expected decrease in prices				0.033*	0.029
				(0.018)	(0.018)
FE location-type	Yes	Yes	Yes	Yes	Yes
FE time	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes
Obs.	65969	65969	65231	62557	61831
1st stage F stat	688	568	993	862	183

Note: The dependent variable is the log of the price/m2 posted on Immobiliare.it from 2022q4 to 2023q2. In any quarter, the number of listings managed by each agent and the number of markets in which they operate are standardized using the mean and the standard deviation of the respective sample stratum. '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 average number of new ads posted each quarter, 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 and single-homes vs apartments). Inflation expectations are winsorized at the bottom and top 5%. All estimates use Huber-White robust standard errors. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

and, thus, less likely to raise listing prices in response to increased inflation expectations.

For agents' beliefs about future housing market trends, we utilize responses to an IHMS question asking for their expectations of housing price variations in their reference market one year ahead. This question, like that on mortgage lending standards, is presented in the survey before the question on inflation expectations, ensuring that the information treatment does not affect these responses. We expect a lower IEPT for agents with pessimistic views on current and future housing demand.

We build four indicators to capture these dimensions. Two continuous indicators measure *(i)* the number of listings managed and *(ii)* the number of distinct markets in which the agent operates. Two dummy variables are equal to one if the agent: *(iii)* reports that buyers have difficulty in getting a mortgage loan or *(iv)* expects a decrease in housing prices in their reference market one year ahead. We then estimate a set of IV regressions interacting each of these variables with inflation expectations. Accordingly, we use the treatment status interacted with the respective agent characteristic as an additional instrument.

The results are reported in Table 5. We find that the number of listings managed by each agent does not significantly affect the pass-through rate (column 1). However, the number of markets in which the agents operate does matter: a one-standard-deviation increase in market diversity causes a 0.2 point increase in the IEPT (column 2). Agents' beliefs about current and prospective market conditions also affect their price-setting decisions in response to inflation expectations (columns 3-4). The IEPT is 0.8 points lower for agents reporting that buyers face difficulties obtaining a mortgage loan, and 0.6 points lower for agents expecting a decline in housing prices one year ahead. These effects remain significant when all four agent characteristics are included in the regression simultaneously (column 5).

In summary, the degree of agents' sophistication, as proxied by the number of distinct markets in which they operate, modestly increases the pass-through of inflation expectations to listing prices. More importantly, agents' views on current and future market conditions significantly shape their pricing decisions. Specifically, agents concerned about tighter mortgage lending standards or anticipating a decline in housing prices exhibit lower pass-through rates.

5 Discussion

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 and varies with market and agents' characteristics. 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.

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.

The role of market microstructure. Our results shed light on the critical role played by the market microstructure in mediating the pass-through of inflation expectations to housing listing prices set by real estate agents. This raises the question of whether these results can be generalized to other contexts, such as firms' price-setting decisions. To the best of our knowledge, there is no empirical evidence examining how the pass-through of firms' inflation expectations into actual prices varies across different market characteristics. Nevertheless, our results align with existing empirical evidence and the implications of theoretical models on the transmission of cost shocks to firms' pricing (Gopinath and Itskhoki, 2010; Amiti et al., 2019; Wang and Werning, 2022). In particular, in models with imperfect competition with variable markups, higher concentration lead to higher mark-up elasticity and smaller price adjustments.

Implications for monetary policy. Our findings indicate that real estate agents with high inflation expectations set higher housing listing prices, at least in a high-inflation environment. While we cannot currently determine whether this behavior translates into higher transaction prices or a deterioration in market liquidity, 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.[31]

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 competition among real estate agents, which are typically associated with lower prices (Table 4, column 1). Consequently, if elevated inflation expectations lead to a stronger appreciation of relatively cheaper properties, this could reduce 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

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

policy, by affecting inflation expectations, could have distributional consequences.[32]

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 in competitive and high-demand markets and among more sophisticated agents. 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] For a recent discussion on the consequences of monetary policy for wealth inequality, see McKay and Wolf (2023).

A Additional Figures and Tables

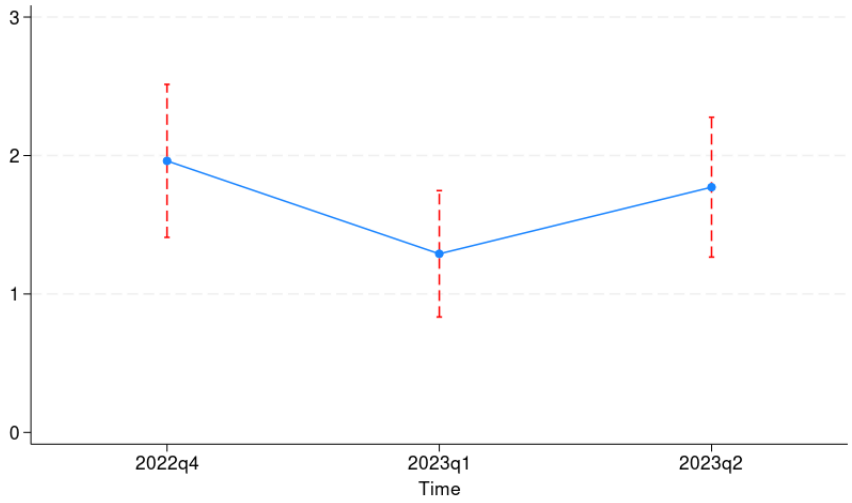


Figure A1: The time-varying effect of the information treatment on inflation expectations

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. The vertical bars are 95% confidence intervals.

Table A1: Summary statistics on real estate agents in the estimation sample

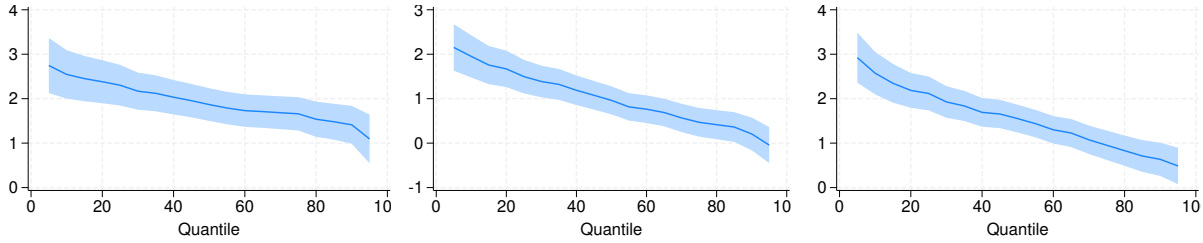
	Observations	Mean	Std. Dev.	Min	1th perc.	Median	99th perc.	Max
Number of local housing markets covered by each agent	1,368	14.2	16.9	1.0	1.0	10.0	77.0	337.0
Avg. number of new ads posted by each agent every quarter	1,368	11.5	32.2	0.0	0.0	6.0	90.0	847.0
Avg. number of active ads by each agent every quarter	1,368	32.5	72.5	1.0	1.0	20.0	218.0	2,191.0
Avg. time-on-market (weeks) of the ads posted by each agent	1,368	41.3	23.6	0.0	3.2	37.9	114.2	160.0
Standard deviation of floor area of homes advertised by each agent	1,348	69.4	34.7	0.0	14.5	64.0	170.2	302.6
Standard deviation of prices (€/m2) of homes advertised by each agent	1,348	861.4	580.7	33.3	217.0	685.1	2,946.7	5,279.1

Note: Statistics based on ads posted on the web portal Immobiliare.it merged with IHMS from 2022Q4 until 2023Q2.

Table A2: Summary statistics on the estimation sample of housing ads

	Observations	Mean	Std. Dev.	Minimum	1th perc.	Median	99th perc.	Maximum
Panel A: Housing characteristics								
Price/mq2	74,039	2,119.22	1,562.77	203.01	343.14	1,697.74	7,943.93	14,806.38
Size	74,039	131.60	86.09	35.00	40.00	107.00	488.00	648.00
Floor	65,714	1.61	1.66	-1.00	0.00	1.00	7.00	21.00
Single-family homes (share)	74,039	0.26	0.44					
New buildings (share)	72,130	0.12	0.33					
Garden (share)	74,039	0.46	0.50					
Terrace (share)	74,039	0.40	0.49					
Garage (share)	74,039	0.46	0.50					
Elevator (share)	74,039	0.37	0.48					
Panel B: Agents' characteristics by market and time								
Number of active ads	4,435	7.69	11.55	1.00	1.00	4.00	55.00	151.00
Number of real estate agents	4,435	2.64	2.14	1.00	1.00	2.00	12.00	21.00
Share of agents receiving the information treatment	4,435	0.70	0.26	0.00	0.20	0.67	1.00	1.00

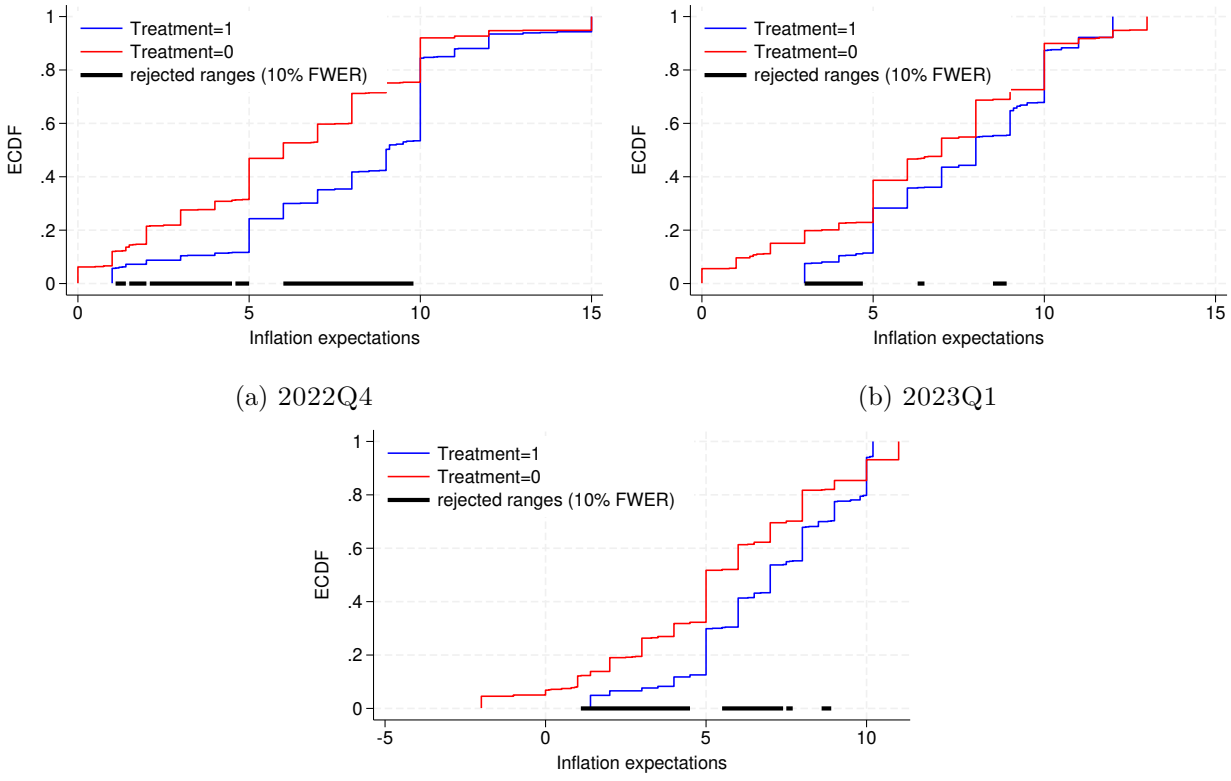
Note: Statistics based on the matched sample of Immobiliare.it and IHMS from 2022Q4 until 2023Q2. Panel B provides summary statistics on the restricted sample of markets including at least one treated and one control.



(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***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Garden	0.060***	0.060***	0.054***	0.054***	0.054***	0.054***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Elevator	0.113***	0.113***	0.115***	0.115***	0.115***	0.115***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Terrace	0.062***	0.062***	0.065***	0.065***	0.065***	0.065***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
High floor (> 3)	0.005***	0.005***	0.009***	0.009***	0.009***	0.009***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Status: good conditions	0.206***	0.206***	0.195***	0.195***	0.194***	0.195***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Status: renovated	0.384***	0.384***	0.372***	0.373***	0.372***	0.372***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
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
			(0.002)	(0.002)	(0.002)	(0.002)
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***
					(0.001)	(0.001)
Number of housing markets covered by the agent					-0.001	-0.001
					(0.001)	(0.001)
St. dev. of the size of the properties posted by the agent					0.022***	0.022***
					(0.002)	(0.002)
Constant	7.175***	7.175***	7.213***	7.210***	7.216***	7.213***
	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)
FE location-type	Yes	Yes	Yes	Yes	Yes	Yes
FE time	No	Yes	No	Yes	No	Yes
Adj-R2	0.874	0.874	0.875	0.875	0.876	0.876
Obs.	251240	251240	126119	126119	125415	125415

Note: The dependent variable is the log of the price/m2 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). All estimates use Huber-White standard errors. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

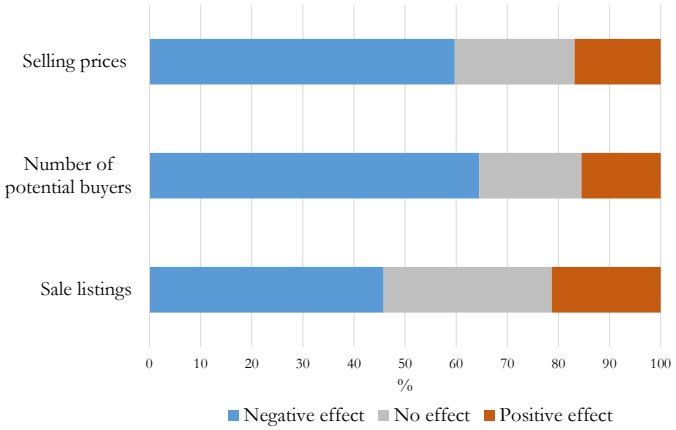


Figure A4: Real estate agents' assessment of the impact of high inflation on the housing market

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*	0.012***
	(0.000)	(0.002)	(0.002)	(0.003)	(0.004)	(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		1577	1756	443	337	528
Panel B: New housing listings						
Inflation expectations	-0.000	0.012***	0.013***	0.011**	0.017***	0.013*
	(0.001)	(0.003)	(0.003)	(0.006)	(0.007)	(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		448	482	108	141	123

Note: The dependent variable is the log of the price/m2 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 average number of new ads posted each quarter, 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 and single-homes vs apartments). Inflation expectations are winsorized at the bottom and top 5%. All estimates use Huber-White robust standard errors. *, **, 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

	(1)	(2)	(3)
Inflation expectations in 2022q4	-0.004		
	(0.003)		
Inflation expectations in 2023q1		0.001	
		(0.003)	
Inflation expectations in 2023q2			-0.003
			(0.003)
FE location-type	Yes	Yes	Yes
FE time	Yes	Yes	Yes
Other controls	Yes	Yes	Yes
Obs.	36323	33273	31591
1st stage F stat	725	568	987

Note: The dependent variable is the log of the price/m2 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 average number of new ads posted each quarter, 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 and single-homes vs apartments). Inflation expectations are winsorized at the bottom and top 5%. All estimates use Huber-White robust standard errors. *, **, 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	-0.001	0.009***	0.008***	0.008***	0.009**	0.011***
	(0.001)	(0.002)	(0.002)	(0.003)	(0.004)	(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.	31800	31800	31800	11481	11219	6964
1st stage F stat		1821	2014	477	437	564

Note: The dependent variable is the log of the price/m2 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 average number of new ads posted each quarter, 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 and single-homes vs apartments). Inflation expectations are winsorized at the bottom and top 5%. All estimates use Huber-White robust standard errors. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

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 name, and the address of the agency. We should find the corresponding identifier for each real estate agent in the Immobiliare.it dataset. This second dataset includes about 36,000 thousand real estate agents, their names, and their 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 $M = F$.[33] 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.

[33] 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.

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