New results on household subjective probabilities of future house prices *

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Abstract:

I analyze new data on subjective probabilistic expectations on house prices collected in the Spanish Survey of Household Finances. Households are asked to distribute ten points among five different scenarios for the change in the price of their homes over the next 12 months. This paper is the first empirical study to document the beliefs of a representative sample of households about the future value of their homes. I model individual subjective probability densities using splines, construct quantiles from those densities, and analyze how the heterogeneity in the individual distributions relates to differences in housing and household characteristics. An important result of the paper is that women are more optimistic about the evolution of house prices than men. Location at the postal code level accounts for a large fraction of the variation in the subjective distributions across households. Finally, I provide some results on how subjective expectations matter for predicting spending behavior. Housing investment and car purchases are negatively associated with pessimistic expectations about future house price changes and with uncertainty about those expectations.

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1. Introduction

In this paper I analyze new data on subjective probabilistic expectations on house prices collected in the Spanish Survey of Household Finances (EFF) and provide some results on how subjective expectations matter for predicting consumption behavior.

The EFF is a representative survey of the Spanish population that contains detailed information on household assets, debts, income and consumption. Data have been collected every three years since 2002. Starting in 2011, the EFF introduced a new question to elicit household house price probabilistic expectations. Households were asked to distribute ten points among five different scenarios concerning the price change of their homes over the next 12 months. In this way respondents provide information not only about point expectations but also about the probabilities they assign to different future outcomes.

One motivation for introducing this question in the EFF is the importance of real estate assets in the wealth of Spanish households (80% of the value of household assets) all along the wealth distribution (88% for the bottom quartile and 67.5% for the top decile). Aside from a high proportion of owner occupier households (83%), 36% of Spanish households hold some other real estate property.

It is also a timely question due to the housing market collapse that shattered house price expectations after 2007 in Spain. The number of households buying housing dropped dramatically from an overall annual average rate of 2.3% between 2002 and 2005 to 1.1% in 2011. According to the data I analyze in this paper, in 2011 over 23% of households expected a large drop (of over 6%) in the future price of their homes. Moreover, among households expecting such large drops, the fraction who bought a car was half the fraction in the total population (4.5% instead of 9.4%).

This paper is one of the first empirical studies to document the beliefs of households about the future value of their homes, and the first one that uses a representative sample of households. Questions on probabilistic house price expectations have only recently been introduced in household surveys, as detailed in section 3. Niu and van Soest (2014) have independently obtained results that are complementary to ours using newly collected house price expectations data from the Rand American Life Panel.

I start by analyzing patterns of the answers provided by the EFF2011 respondents to the house price probabilistic expectation question to assess the coherency of responses. These include bunching, number of intervals used, and their association with the extent of non-response. Next I model individual probability densities and analyze how the heterogeneity in the individual distributions relates to differences in housing properties and in the characteristics of households.

An important result of the paper is that women are more optimistic about the evolution of house prices than men. Being a woman is associated with a positive shift in the median and the quartiles of the subjective distributions. I further examined potential differences in asset valuations by gender by considering self-assessed values of other assets reported in the EFF. I find that women tend to provide higher estimates for the value of their home compared to men but lower ones when it comes to value their financial assets.

Location at the postal code level accounts for a large fraction of the variation in the subjective distributions across households. Importantly, in the absence of postal code fixed effects the estimated effects of demographics on house price expectations would be biased. For example, the result on gender would not be found. Moreover, the location effects that emerge from the subjective probability data are meaningful and respond to economic fundamentals. In particular, estimated location fixed effects respond to past local house prices and unemployment rates.

Finally, I study whether reported household expectations predict household expenditure decisions. This is of substantive interest to understand household behavior and also a further step in the validation of the house price expectation responses. I exploit the availability in the EFF of information about purchases of secondary housing, cars, other big ticket items, and food. These data allow me to uncover some novel findings about correlations of house price expectations and their uncertainty with those purchases and expenditures. I find that housing investment and car purchases are negatively associated with pessimistic expectations about future house price changes and with uncertainty about those expectations. Moreover, these effects depend on household wealth. Specifically, the negative effects of holding very pessimistic house price expectations on secondary housing purchases are more pronounced at the top of the wealth distribution than at the median, while the opposite is true for car purchases.

The paper is structured as follows. Section 2 contains the analysis of the house price expectations data in the EFF. First I describe the formulation of the question and I examine the quality of the responses. Next I estimate a probability density for each respondent, which I use to document the extent of heterogeneity in beliefs. Based on these individual densities I compute various quantiles and measures of dispersion, and study their association with respondent and house characteristics. Section 3 reports the results on the relation between house price expectations and expenditure decisions. I present predictive results for the probabilities of purchasing secondary housing, an automobile, and other big ticket items. Finally, section 4 concludes.

2. Subjective house price expectations in the Spanish Survey of Household Finances

2.1. The EFF and its house price expectation question formulation

The Spanish Survey of Household Finances contains detailed information on household assets, debts, income and consumption and has now been conducted on five occasions (2002, 2005, 2008, 2011, and 2014).[1] The EFF was specially designed for the study of household wealth. While providing a representative picture of the structure of household assets and debt it incorporates an oversampling of wealthy households based on individual wealth tax files. In addition, there is an important panel component while the sample is being refreshed at each wave to maintain current population representativity. The sample size is around 6,000 households, the exact number depending on the wave. Questions on assets, debts, consumption refer to the household as a whole while demographics and labour income information is available for each of its members. The person answering the survey is the one who is most knowledgeable about the household finances although very often help is provided from other members to answer individual specific information. The survey is administered by a computer assisted face to face interview.

Starting in the EFF2011 a new question to elicit household house price expectations was introduced. The motivation behind is the importance of real estate assets in household wealth (80% of the value of household assets) all along the wealth distribution (88% for the bottom quartile and 67.5% for the top decile). Aside from a high proportion of owner occupier households (83%), 36% of Spanish households hold some other real estate property. Aggregate expectations about rates of return on housing have been found to be an important determinant of house purchase (see Bover, 2010). Moreover, uncertainty about that return has also been found to play a role. Learning about household house price expectations at the individual level may be therefore useful in understanding portfolio composition as well as consumption behavior.

Other surveys eliciting subjective expectations about house prices are the HRS and ELSA targeted to the over 50 years of age households, the NYFRB internet survey, and the Asset Price and Expectations module in the ALP. The introduction of this question is in all cases very recent: 2011 in the ALP module and 2010 in the case of the HRS and the NYFRB survey. This paper is one of the first attempt to analyze answers to this type of questions.[2]

The person answering the 2011 EFF questionnaire was asked the following:[3]

[1] Typically the fieldwork takes place during the last three months of the named year and the first four months of the next one with at least half of the interviews being conducted before the end of the named year.

[2] After writing and presenting the first version of this paper I learned of independent work in Niu and van Soest (2014).

[3] The original Spanish formulation is as follows:

"Estamos interesados en conocer cómo cree usted que evolucionará el valor de su vivienda en los próximos doce meses:

We are interested in knowing how you think the price of your home will evolve in the next 12 months: Distribute 10 points among the following 5 possibilities, assigning more points to the scenarios you think are more likely (assign 0 if a scenario looks impossible)

Large drop (more than 6%)

Moderate drop (around 3%)

Approximately stable

Moderate increase (around 3%)

Large increase (more than 6%)

Don't know

No answer

Several comments are in order. The question refers to the price of the household main residence because of the belief that households have more information about their own house than about prices of houses in the area or nationwide. Moreover, answers provide information about unobservables and heterogeneity in the housing market even if people were to have plenty of information about aggregates. A sentiment about house prices nationwide could be inferred by aggregating from a representative sample like the EFF although these are of course different questions. The question was posed to all households and not only to home owners. When eliciting the subjective distribution numerical answer options are provided together with verbal descriptions.[4] The number of intervals among which the probability mass is distributed is five and it was preferred to offer the respondent 10 points to distribute as opposed to 100 because it is cognitively less demanding.[5] For the same reason it was chosen to elicit the

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Reparta 10 puntos entre las cinco posibilidades siguientes, asignando más puntos a los escenarios que crea más probables (asigne cero puntos si alguno le parece imposible):

Caída grande (más de 6%)

Caída moderada (en torno a 3%)

Aproximadamente estable

Subida moderada (en torno a 3%)

Subida grande (más de 6%)

No sabe

No contesta"

[4] Juster (1966) proposed eliciting probabilistic expectations by linking verbal expressions with numerical probabilities.

[5] Delavande et al. (2011) compare distributing balls across bins to the percent chance approach in an Indian setting. Delavande and Rohwedder (2011) ask Internet respondents in the U.S. to allocate 20 balls across seven bins to express beliefs about their future Social Security benefits.

distribution using a density formulation rather than a cumulative distribution.[6] Respondents are also handed out a sheet of paper containing the question and the response options on which they could draft their answers. Explanations are provided by the interviewer when needed. Finally, an automatic prompt would appear on the screen whenever the answers entered in the computer by the interviewer do not add up to 10. In such cases the household and the interviewer are asked to revise the answers.

The elicitation specificities in other surveys containing house price expectation questions are diverse. The HRS asks about own house price expectations (to owners only) using a cdf formulation with 4 cut-off points. The ALP module refers to house price in the area and has a pdf type of question with three intervals (two of them open ended). Finally the NYFRB survey asks about prices of a typical home in their zip code and follows their usual ten interval pdf formulation.

With the exception of the ALP, the previous surveys formulate their house price expectation question in terms of rates of change (as opposed to levels). In the EFF given that households provide a self-assessed current value for their home one could also derive the expected level of house price in twelve months time using the expected rate of change.

2.2. Item non-response

Only 4.1% of households who participated in the EFF2011 did not answer the house price expectation question.[7] Table 1 (columns 2 and 3) provides some breakdown by demographic characteristics of the respondent. Sample shares are discussed in the text but the corresponding estimated shares for the population are also contained in Table 1 columns 3 and 5.

This percentage is higher for non-owner occupiers (10.7%) than for owners of their main residence (3.2%). In any case it compares favorably with the 2006 HRS response rates to an expected stock returns question, to which 24% of households did not respond, suggesting how unfamiliar the stock market is for many households. Even among stockholders non response was 11% (and 29% for non-stock holders).[8]

Men are more prone to answering the question than women (2.8% vs. 6.2% non-response) and non-response rates decrease with education (7% for individuals with up to primary education, 2.3% for those with secondary education, and 1.4% in case of holding a university degree). By age, the non-response of the over 64 stands out. Table 2 (column 1) presents results from a multiple regression including income and wealth variables as well.

In the EFF I construct various measures to assess the amount of questions the household has provided an answer for. Among others, I calculate the percentage of monetary questions that have been answered with a point value (as opposed to an interval) as the ratio of exact

[6] Morgan and Henrion (1990) cite experimental evidence reporting that individuals find it easier to deal with pdfs that allow an easier vizualization of certain properties in the distribution like location and symmetry.

[7] Taking into account population weights the estimated percentage in the population is 5%.

[8] See Manski (2004) and van der Klaauw at al. (2008) for examples on the importance that the probabilistic questions concern well defined events that relate to the respondents' lives.

answers to total questions posed to the households. The correlation of this precise information ratio with not having answered the house price expectations question is -0.10 (-0.17 with a t-ratio of 8.2 in a simple regression). Not answering the house price expectation question also correlates significantly with not having been able to provide an estimate of the current value of their home (0.10; 0.05 with a t-ratio of 7.4 in a simple regression).[9]

2.3. Coherency analysis

Bunching in the middle of the scale. The percentage of respondents placing all ten points in the middle-of-the-scale option is 18.8%. For reference, in the 2006 HRS 23% of respondents chose the middle of the scale to the question on survival probability to age 75 and 30% chose it as a response to a question about the probability of stock market gains.[10]

There is certain heterogeneity by demographic groups (see Table 1, columns 4 and 5). Among home-owners 18.4% chose this answer while the share among non home owners is 21.1%. There is also some variation by education (varying from 19.5% for respondents with no secondary education to 17.8% in the case of University educated respondents). By gender there are some differences as well (18.2% in the case of men, 19.6% for women). Differences by age are less noticeable (ranging from 16.8% among the under 34 to 20% among the over 64). In a multiple regression (see Table 2, column 2) only being aged over 64 has a significant (positive) effect on bunching. All in all these are small differences across groups, which is suggestive of bunching driven by beliefs more than by ignorance, except may be for the older respondents.

The correlation between the constructed information ratio variable and choosing to put all ten points in the middle of the scale is not significant (0.004 and 0.01 with a t-ratio of 0.31 in a simple regression). Along the same lines, the correlation with not being able to provide a value of their home is not significant either (-0.002 and -0.002 with a t-ratio of 0.13 in a simple regression).

The effects of demographic variables do not work in the same direction as in the case of non-response and are much less significant in this case despite the sizeable number of such respondents (Table 2, column 2). This may indicate that there are different factors at work. Namely, while a fraction of individuals giving all ten points to the approximately no house price change option may do so because they are unable to express beliefs about the future path of house prices there are others who strongly believe (i.e. put all 10 points) that the price of their house will experience no change over the next 12 months (see more details on epistemic uncertainty in section 2.3). The absence of correlation with the information ratio and with not answering the current value of their house points in this direction as well. Unfortunately, I cannot separate the two types of answers because in the EFF the house price expectation question is not followed by one trying to disentangle ignorance from genuine belief of no change in house prices.

Number of intervals used. 61% of the respondents express uncertainty and put some probability mass in more than one interval while 28% of all respondents use more than two intervals (see Table 3). Only 6.32% use all five intervals.

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[9] Only homeowners are asked to provide an estimate of how much their house is worth.

[10] In the HRS survival probability question answering the middle of the scale corresponds to a 50% chance answer.

Using non-adjacent intervals. There is a very small fraction of respondents (1.6%) that assign non-zero probabilities to non-adjacent intervals. This may indicate non-coherent answers but also bimodal beliefs.

2.4. Preliminary analysis

Average histogram and most frequent answers. Figure 1 shows an average histogram showing the percentage probability mass in each of the 5 predefined intervals of the density function. The figure shows that respondents overwhelmingly put most of the probability mass in the expected drop-in-price region. Therefore, Spanish households at the end of 2011 were in general not expecting increases in the price of their homes over the next 12 months.[11] But importantly, around this average of distributions there is a large heterogeneity in individual subjective probability distributions. To provide more detail about the pattern of answers, Table 4 shows the most frequent answers up to 90% of the cumulative sample distribution. The ten most frequent answers collectively account for 60% of the sample.

Probability of a positive return. I calculate the respondent probability of a positive change in house prices as the sum of the number of points attributed to intervals 4 and 5 (i.e. to a moderate increase of around 3% and a large increase of over 6%). A fraction of 15.7% of respondents put some probability mass to an increase in house price and 3% (2.5% of men, 4.1% of women) believe this probability exceeds 50%.

The demographic characteristics behind the likelihood attributed to an increase are analyzed by reporting linear regression results for the probability of a positive return (Table 2, column 3).[12] The positive effect of having bought the main residence recently stands out. Other noticeable effects are the negative effects of age and having a University degree although these are not precisely estimated.

Probability of a negative return. The respondent's probability of a negative change in house prices is calculated as the sum of the number of points attributed to intervals 1 and 2 (i.e. to a moderate drop of around 3% and a large drop of over 6%). The results (Table 2 column 4) show no significant association of such beliefs with household characteristics, except for a not very precise positive effect of household income. Negative house price expectations were therefore widespread across groups of the population at the end of 2011.

No uncertainty. 32.7% of respondents believe the price of their homes will drop for sure during 2012 (i.e. they distribute all points between intervals 1 and 2 –large drop over 6%, moderate drop around 3%). Over half of them (57.2%) attribute all ten points to one of the two price drop alternatives and hence answer without uncertainty. The results in the fifth column of Table 2 are an attempt to uncover demographic differences associated with these "no uncertainty" answers. The only significant difference between these no-uncertainty respondents and the rest of respondents expecting a drop is gender and owning other housing.[13] According to

[11] Aggregate house prices had been falling in Spain since 2007.

[12] The sum of points is multiplied by 10 to provide results in percentage points.

[13] This analysis is conditioned on expecting a drop because I do not wish to mix determinants of certainty with determinants of expecting a rise. Given the macroeconomic scenario, respondents that are certain of a rise are few and probably with special characteristics. As for those putting all points to the "more or less the same" option we have already analyzed their characteristics above.

these results, women are less likely than men to give a 100% probability to one of the two drop-in-price scenarios (and hence more likely than men to distribute the chances among the two alternatives). Additionally, households owning other housing aside from their main residence are more likely to believe in a drop with no uncertainty about its magnitude.

Analyzing answers without uncertainty in the expected positive domain is not undertaken because it is hampered by the small number of observations.

2.5. Fitting subjective house price distributions

Calculating individual distributions. As seen above, subjects are asked to distribute 10 points among 5 possible changes to the price of their homes over the next year. I use the subject responses to fit a saturated probability distribution for each respondent. This is useful because it facilitates the calculation of comparable measures of position, uncertainty, and quantiles for all individuals. Using a saturated distribution avoids placing restrictions on the form of the distribution relative to the information in the data.

I assume that the probability distributions have a pre-specified support and a pre-specified neighborhood around zero for the no-change category. Having specified end-points and an interval around zero, to get a full cdf I connect the observed points using straight lines so that the cdf is piece-wise linear and the density is flat within segments. This allows calculating all quantiles by linear extrapolation.

Figure 2 illustrates the estimation of the probability distribution for a respondent having distributed his ten points as follows: 1 point to a drop of more than 6%, 6 points to a drop of around 3%, 1 point to more or less the same, 1 point to an increase of around 3% and 1 point to an increase larger than 6%. The limits of the support are defined to be -15% and +15% and the interval around zero for the non-change category to be between -1% and +1%. To obtain te $\boldsymbol{\tau}$-quantile $q_{\tau i}$ for some $\boldsymbol{\tau} \in (z_{li}\ , z_{(l+1)i})$ we use:

$$q_{\tau i} \ = \ q_{zli} \ + [(\boldsymbol{\tau} - z_{l\,i})/(z_{(l+1)i} - \ z_{l\,i})](q_{z(l+1)i} \ - \ q_{zli})$$

where the $z_{l\,i}$ are cumulative probabilities and q_{zli} the corresponding quantiles for $l = 0, 1, \ldots, 5$ which are given by (-15, -6, -1, 1, 6, 15).

Quantile regressions from subjective quantile variables. Measured quantiles $q_{\tau i}$ are to be interpreted as conditional quantiles given characteristics of the individual and the house, both observable and unobservable. To look at the variablility in these distributions, I estimate least squares regressions of individual quantiles on measured characteristics and postal code dummies (that is within postal code quantile estimates). These quantile regressions are very different from ordinary quantile regressions where one fits a quantile model to data that are sample draws from the distribution. Here the left hand side variable consists of direct measures of the conditional quantiles.

A factor model for unobserved heterogeneity in subjective quantiles. The quantile regression errors capture unobservable heterogeneity in the subjective probability distributions (except for functional form approximation errors). I estimate a random effects model for the errors of different quantiles to see to what extent a single factor captures the unobserved heterogeneity in the distributions.

Consider for example regressions for $q_{.25i}$, $q_{.50i}$, $q_{.75i}$

$q_{.25i} = x'\boldsymbol{\beta}_{.25} + u_{.25i}$

$q_{.50i} = x'\boldsymbol{\beta}_{.50} + u_{.50i}$

$q_{.75i} = x'\boldsymbol{\beta}_{.75} + u_{.75i}$

The factor model is:

$u_{\tau i} = \boldsymbol{\eta}_i + \boldsymbol{\varepsilon}_{\tau i} \quad \boldsymbol{\tau} = 0.25, 0.5, 0.75$

I estimate the variance of the common factor $\boldsymbol{\eta}_i$, the variances of the random errors $\boldsymbol{\varepsilon}_{\tau i}$ and the factor loadings $\boldsymbol{\delta}_{\tau}$ subject to $\boldsymbol{\delta}_{0.5} = 1$ and the assumption that $\boldsymbol{\eta}_i$ and the $\boldsymbol{\varepsilon}_{\tau i}$ are mutually independent.

2.6. Relating heterogeneity in expectations to housing and household characteristics

Individual density position measures and demographics. I examine the association between quantiles at various points of the estimated individual densities and demographics, within postal codes.[14] In particular I consider the individual median and the 10th, 25th, 75th, and 90th percentiles as distributional measures for each respondent. Multiple regression results for those variables on demographics may be found in Table 5.

The regression equations are of the form:

$q_{\tau i} = X_i \boldsymbol{\beta}_{\tau} + Z_i \gamma_{\tau} + u_{\tau i}$

where X_i is a vector of household characteristics such as age, education, gender, income and wealth. Moreover, Z_i is a vector of house characteristics, which includes postal code dummies, log (price/square meter) and in some cases also an indicator of age of the house.

The results include the household estimated price (per square meter) of their home. Interestingly, the self-assessed house price of a household is not a significant predictor of the expected evolution of the price of its home conditional on postal code dummies (and the rest of included controls).

We observe lower expected declines in the lower part of the distribution as age increases. This relates to the finding by Malmendier and Nagel (2013) that experience of older individuals draw on longer history of data when forming their expectations while expectations of younger ones are dominated by more recent data. In Spain in 2011 the house price drops experienced since 2007 came after decades of rising house prices.

Blue collar workers are associated with more optimistic expectations all over the distribution while for the self-employed there is a negative shift in the upper part of the distribution. Households in the middle-upper part of the wealth distribution have their expectation distribution shifted upwards (more pronounced in the lower part).

Interestingly, there is a positive effect for those households who bought their main residence recently (in the last six years). Moreover, this effect is quite uniform across the whole range of

[14] There are 1,094 postal codes in our data, 212 of them have only one household and 71 have 10 or more.

the distribution although more precise in the upper part of the distribution. Recent buyers may be more reluctant to accept a prospect of no house price increases as compared to non-recent buyers who have experienced sizeable house price returns. This effect may also reflect reverse causality, that is, buyers who expected higher house price changes than the rest were the ones who bought recently. Table A1 presents results omitting this variable and the results are unchanged (columns 1 and 2). The same result is obtained if instead a variable reflecting that the house was built in the last 6 years is included. These could be taken as suggesting that the previous result does not seem to be driven by reverse causality.

The results on gender stand up. Being a woman produces a positive shift that is particularly noticeable at the median and at the top quartile. This is difficult to explain in terms of differences in information as one may do with occupation or age. It does not seem to be related to risk aversion either. Indeed, I have also included a measure of risk aversion available in the EFF but the results are unchanged (see Table A1 columns 3 and 4).[15]

What these results say is that there is a difference by gender among the respondents to the survey (controlling for postal code and other covariates), who are meant to be the most knowledgeable about the household finances, as explained earlier. Whether these differences would still hold for randomly selected individuals cannot be answered on the current data.

To check the robustness of the gender result I estimated an Abadie-Imbens (2006) matching estimator of the gender average treatment effect which uses the control variables in a non-parametric way. This produces similar results both in magnitude and significance. The same result is also found estimating the gender average treatment effect by weighting on the propensity score. This is at odds with the generally accepted finding that women tend to be less optimistic than men (see for example Balasuriya et al., 2010).

To further assess potential differences in asset valuations by gender we regressed self-assessed values of different assets reported in the EFF on the same demographic and socio-economic characteristics. The results in Table A2 show that women tend to provide higher estimates for the value of their home compared to men but lower ones when it comes to value their financial assets.

An open research question in economic psychology is to what extent people's price perceptions and expectations are mediated by psychological variables like emotions and attitudes (see for example Ranyard et al., 2008). One hypothesis for further research that could explain our results would be that women positive affective feelings for their home (and its value) are stronger than for men and that these preferences affect the judgment of men and women. For a detailed description and evidence see Slovic et al. (2002).

[15] We classify as risk lover those individuals answering options 1 or 2 to the following question:

Which of the following statements do you feel best describes your household in terms of the amount of financial risk you are willing to run when you make an investment?

Take on a lot of risk in the expectation of obtaining a lot of profit	1
Take on a reasonable amount of risk in the expectation of obtaining an above-normal profit	2
Take on a medium level of risk in the expectation of obtaining an average profit	3
You are not willing to take on financial risk	4
Don't know	98
No answer	99

Are women more optimistic, or simply more realistic? A bold answer to this question can be based on the aggregate of counterfactual point predictions of house price changes across all households as if all were male respondents. Using the median as a point forecast measure, the estimation results inform us that the counterfactual female aggregate is 0.4 percentage points higher than the corresponding male aggregate. We can now look at the actual aggregate house price change between 2011 and 2012 to find out which one of the two genders was closer to the truth. The national house price change December 2011-December 2012 for second hand housing was around -10 percent. [16] The counterfactual aggregate male and female point forecasts are -3 and -2.6 percent respectively. Even if the position of the subjective probability distribution may be affected by framing, the distance between actual and predicted changes is sufficiently large to conclude that women were more optimistic rather than more realistic by comparison with men.

Uncertainty and demographics. As a first measure of individual forecast uncertainty I consider the inter-quartile range. I also analyze the range given by the difference between the 90th and the 10th percentiles. Heterogeneity in self-reported uncertainty is examined in Table 6. A distinct effect on uncertainty in a multiple correlation context is age. Older people express less uncertain expectations. Households in the middle-upper part of the wealth distribution are also less uncertain about their expectations. In line with other authors (see for example Bruine de Bruin et al., 2011) I also find that differences in uncertainty across demographic groups are smaller than those in central tendency forecasts.

Are people with more certain expectations more accurate? Since older people have more certain expectations, we can answer the question with relation to age. This is relevant because age is the main observable associated with differences in the degree of certainty in expectations. It turns out that age does not have a significant effect on point-forecasts as measured by the subjective median. Therefore, there is no evidence of differences in predictive accuracy according to the degree of certainty as captured by age.

As another indicator of the potential association between accuracy and certainty I calculated the correlation between the median and the inter-quartile range of the individual subjective distributions. It turns out to be -0.4. Therefore, more certain individuals tend to predict lower falls in house prices. Given the actual declines described above, such negative correlation would suggest that more certain expectations are less accurate. This result is consistent with recent evidence in psychology that superforecasters are more uncertain about their forecasts (Tetlock and Gardner, 2015).

Robustness to alternative cutting points and to bunching. As explained above, the individual densities required specifying values for various cutting points in the probability density. We analyzed the determinants of robustness of the analysis of beliefs and their uncertainty to alternative values of the cutting points. Table A1 (columns 5 and 6) presents results obtained increasing the minimum and maximum values of the support (from -+15 to -+20). As we can see the results are qualitatively robust to these alternative ways of fitting the distribution. The size of the effects varies depending on the cutting point but relative effects as well as significance are maintained. The conclusions hold for other changes in these values and in the interval chosen around zero.

[16] It was -14 percent according to the index from the National Statistics Office (INE) and -10 percent according to the Ministry of Public Works and online search-sites based on asking price data.

As a further robustness check I estimate the models in Tables 5 and 6 dropping those respondents who put all ten points in the "more or less the same" alternative. The results (not shown) are similar except for the various effects of age that mostly disappear. This is not surprising given the estimates presented in Table 2 column 2 about the factors influencing the probability of assigning all 10 points to the middle interval.

Importance of detailed location of the house. Table 7 highlights the central importance of the detailed location of the house and in particular of introducing postal code information. Location at the postal code level accounts for 97% of the observed variation in the estimated median expectation and for 95% of the variation in uncertainty across households (as measured by the inter-quartile range). More aggregate location information like municipality or province do not do such a good job, as one would expect. Municipality dummies account for 66% of explained variation in the median (and 80% in the inter-quartile range).

Table A3 (columns 1 to 3) presents some of the regressions reported in Tables 5 and 6 but without location information. This shows how misleading the estimated effects of other variables could be in the absence of location information. In particular, the gender effect would not be found. Municipality dummies produce results more similar to estimates that control for postal code dummies but still quite different (Table A3 columns 4 to 6). As expected, it is location at a very disaggregate level that matters for house prices.

Relating expectations to local housing and labour markets. Inspection of the estimated postal code effects estimated in Tables 5 and 6 indicate that respondents expect the price of their home to grow more in areas where housing prices are already high. Figure 3 plots the estimated postal code effects for Barcelona and Madrid sorted in ascending order. The highest postal code effects in both cities correspond to sought-after areas. The opposite is true at the other end of the scale.

In Tables 8 and 9 estimated postal code fixed effects are regressed on housing and labour market variables, in particular rates of return on housing and unemployment rates at the province level. The results show that when forming expectations about the future price of their home respondents extrapolate the recent evolution of the province labour and housing markets. This is true both for the location of the distribution and for the measure of uncertainty. For example, an increase in the unemployment rate in the previous year of 1 percentage point leads to a decrease of 0.18 percentage point in expected median house price and to an increase of 0.1 point in uncertainty as measured by the inter-quartile range.

Quantile error structure. The first principal component of the (.1, .5, .9) quantile residuals explains 99% of total variation in a model with postal code dummies, and 98% with province dummies. When five residuals are used (.1, .25, .5, .75, .9) the variation captured by the first principal component is 91% with postal code dummies and 89% with province dummies. Estimation of the random effects model produces an estimated residual variance at the zero boundary (a Heywood case), which is not surprising given the high correlation among residuals. The estimated factor loadings for 0.25 and 0.75 in the 3 error specification are close to unity (0.94 and 0.95) with corresponding residual variances in the 0.10 range. Relative to those residuals the single common factor explains 97% of total variation.

3. House price expectations and consumption decisions

Expectations and decisions. One of the main purposes of collecting subjective expectation data is to help understand behavior. In this section I study whether house price expectations reported in the EFF predict household expenditure decisions. This is of substantial interest in its own right and also a further step in the validation of the information collected.

There were large unexpected shocks to house price expectations in Spain after 2007. The percentage of households buying second housing decreased dramatically since the bursting of the housing bubble. In the three year period between the 2002 and the 2005 EFFs, 5.2% of households bought a second house (an average of over 1.7% a year) while this percentage was only 0.6% for 2011. Also according to EFF data, 9.4% of the Spanish households bought a car in 2011. However, among the households who are very pessimistic about the future price of their house (i.e. those assigning all 10 points to the over 6% drop scenario) only 4.5% did so.[17] In this section I use information on expenditure outcomes on various items available in the EFF to see if house price expectations are predictive of purchase and expenditure decisions once a rich set of controls are taken into account.

Expenditure and purchases in the EFF. In the EFF households provide information on whether they bought a car in the last 12 months and the price paid for those who did. The same information is collected about other big ticket items (furniture, washing machines etc) as a whole. Amounts spent on food at home and outside as well as on other non-durables are also collected.

The EFF provides detailed information on purchases of secondary housing (for households owning their main residence). Housing purchases are both consumption and investment decisions. Bover (2010) provides evidence that aggregate predicted returns on housing have a large positive effect on the hazard of purchasing a house. However, aggregate returns are probably masking different individual expectations concerning future house prices, both in terms of differences in household characteristics and in terms of differences in house specific attributes like location. I therefore explore if individual household expectations about house prices help predict the probability of purchasing a house and, in case of purchase, the amount spent on it.

A word about the timing of subjective expectations and expenditure outcomes. Ideally, the interest is in how expectations held at *t* about the future influence decisions at *t*. The expectation data correspond to beliefs held at the time of the interview, while the expenditure data refer to purchases during the last 12 months, which is a good timing approximation, specially for durables.

Empirical model. First, probit estimates are presented for the probability of (i) buying secondary housing, (ii) buying a car, and (iii) buying other big ticket items (see Table 10). To analyze expenditure I present tobit estimates for the amounts spent on (i) other housing, (ii)

[17] At the end of 2011 23.3% of households expected a large decrease (over 6%) in the price of their home over the next 12 months. Among those, 30.7% expected this large drop without uncertainty that is 7.2% of the population of households.

cars, and (iii) other big ticket items, and multivariate regressions for the amount spent on (iv) food and other non durables (see Table 11A). As is well-known, tobit estimates rely on the assumption that the same relationship holds both for the decision to purchase and for the amount spent. To check how restrictive this assumption is here the implied tobit estimates for the various purchase probabilities are also be provided (see Table 11B) and compared with the probit estimates.

In the empirical models I include two variables measuring household beliefs about future house prices. To reflect the location of those expectations, a 0/1 dummy is defined taking the value 1 for people expecting a large certain drop with certainty (i.e. people who assign all 10 points to the option "more than 6%" drop). To capture uncertainty about the expectation location another 0/1 dummy is defined taking the value 1 for respondents assigning points to more than one option. Note that these indicators are constructed directly from the household responses, and not from fitted individual probability distributions.

A potential concern of reverse causality is that the uncertainty about the future price of the main residence may be reduced by investment in information associated with the purchase of other housing. However, the results in Table 6 indicate a lack of association between uncertainty and having bought the main residence recently, which suggests that endogenous reductions in uncertainty may not be very important.

Importantly, I am able to control for expectations about future household income and hence identify house price expectations net of income expectations. In the EFF2011 expectations about future household income are collected albeit in a qualitative way. Households are asked whether, compared to their current income, they believe their income in the future will be higher, lower, or approximately the same. Two indicators are constructed containing such that information.[18]

Additionally, the occurrence of positive or negative income shocks is controlled for by exploiting the information provided by a question in the EFF on whether current household income is higher than usual, lower than usual or as usual.

Other variables included in the estimated models are: log net household wealth and its interactions with the house price expectations dummies, respondent gender, age (six interval variables), number of persons in the household (six 0/1 dummies), couple dummy, children dummy, labour status dummies for respondent (four categories) and partner (if any).

Regarding location variables two sets of results are presented: controlling for municipality size (seven categories) or by postal code. However, probit estimates controlling for postal codes rely on a significantly reduced number of observations because of the requirement of observing households who buy and households who do not buy at postal code level (columns 2, 4, and 6 in Table 10). Those results therefore cannot be taken as representative of the population of households. This is not the case for the tobit estimates in Tables 11A and 11B.

[18] Starting from the 2014 wave the EFF includes a question on probabilistic expectations about future total household income.

Results. The results in Table 10 (column 1) show that the most pessimistic households have a significantly lower probability of buying a house than the rest. The reduction in probability is of 0.8 percentage point at the median level of wealth but higher (1.24 pp) at the 80th wealth percentile. Uncertainty about the evolution of future house prices is also associated with reductions in the probability of buying a house. The magnitude of this reduction is 0.63 pp at the median and 0.8 at the 80th percentile. Larger effects at the top of the wealth distribution appear sensible as those are the households most prone to buying second housing.

Expecting a large drop in house prices is also associated with a 4.5 pp smaller probability of buying a car at the median level of wealth but not for wealthier households. However, uncertain expectations are positively correlated with the probability of buying a car and, mostly, with other big ticket items. These results could reflect some substitution effects.

Table 11A shows the estimates for the various expenditures. Again, the larger and most significant effects are the reduction in the amounts spent when buying second housing for households expecting a large drop in the price of their house or for those being uncertain about the evolution of the value of their home. For these households the amounts spent when buying a car are also significantly lower (-13,000 € at median wealth). These conclusions hold when postal code dummies are included.

Similarly to the results on purchase probabilities, there seem to be some evidence of some substitution effects for expenditures on other big ticket items and on food and other non-durables among wealthy households uncertain about future house prices. However, these results do not hold when controlling for postal code.

Finally, Table 11B reports the probabilities of purchase of the various items obtained from the tobit model. These are very much in line with those obtained with the probit model (see Table 10). Furthermore, in this case estimates of the probabilities controlling for postal code can be obtained for the whole sample and confirm the results in columns 1, 3, and 5 of Tables 10 and 11B.

4. Conclusions

In this paper I have first analyzed the answers to a question recently introduced in the EFF on probabilistic house price expectations. This analysis shows that asking such type of questions to Spanish households is feasible (as long as respondents are familiar with the subject matter), as shown by the high response rate and the results of a coherency analysis.

The results show significant heterogeneity in house price expectations across respondents. Heterogeneity is found to be significant both for the location of such expectations as well as for the amount of uncertainty around them. I find that women and blue collar workers are more optimistic about the evolution of house prices for 2012, and older respondents are more certain.

The results also provide valuable information about heterogeneity in the housing market. Location of the house at the postal code level is shown to explain most of the observed heterogeneity in expectations. Moreover, past returns to housing and unemployment rates are found to be strong determinants of the estimated effects of location.

Furthermore, the results show that in the absence of controlling for detailed location information about the house the estimated effects of demographic characteristics on house price expectations are biased and misleading.

I also exploit the availability of information about various durable and non-durable expenditures in the EFF and present some novel findings about the association between house price probabilistic expectations (location and uncertainty) and various durable expenditures. The results show that households holding pessimistic expectations have significantly lower probabilities of buying a house and of buying a car. Moreover, the amounts spent on those items by buyers are also smaller than in the absence of such negative expectations. However, I find no association between house price expectations and expenditure on other big ticket items, nor on food and other nondurable expenditure.

Finally, greater uncertainty in house price expectations is associated with a lower probability of buying a secondary house (as well as with smaller amounts spent) but not with the purchase or the amount spent in other goods.

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Figure 1. Average probability distribution of future HP

EFF 2011

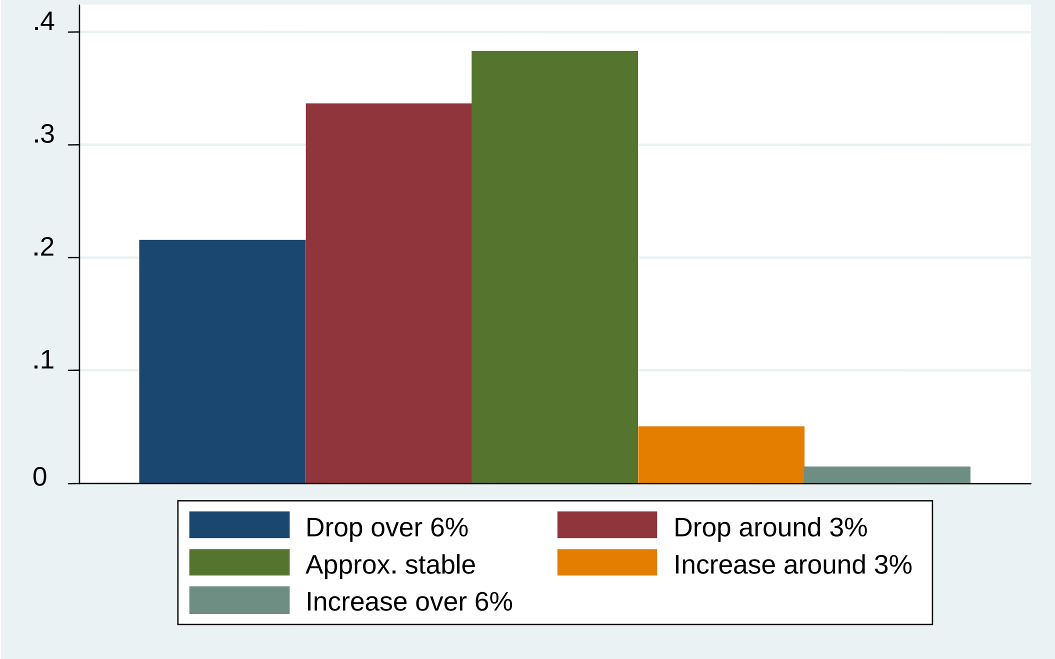


Figure 2. Fitting individual saturated distributions

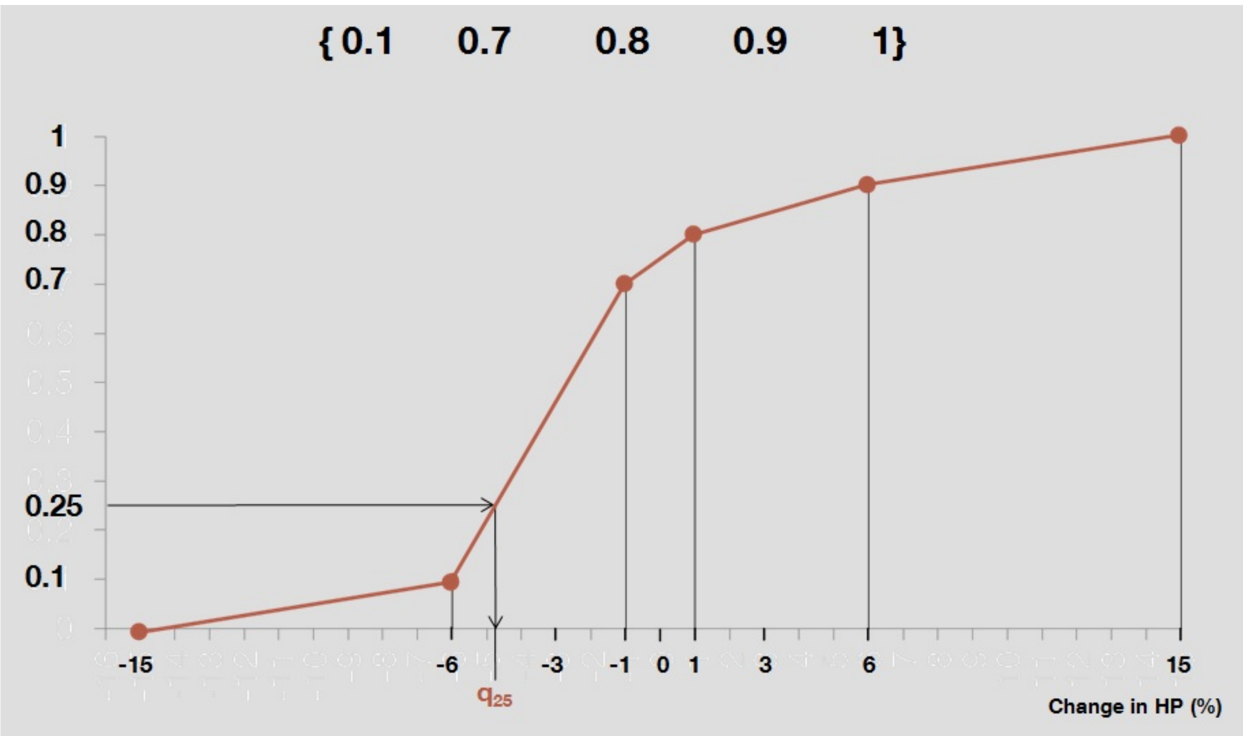
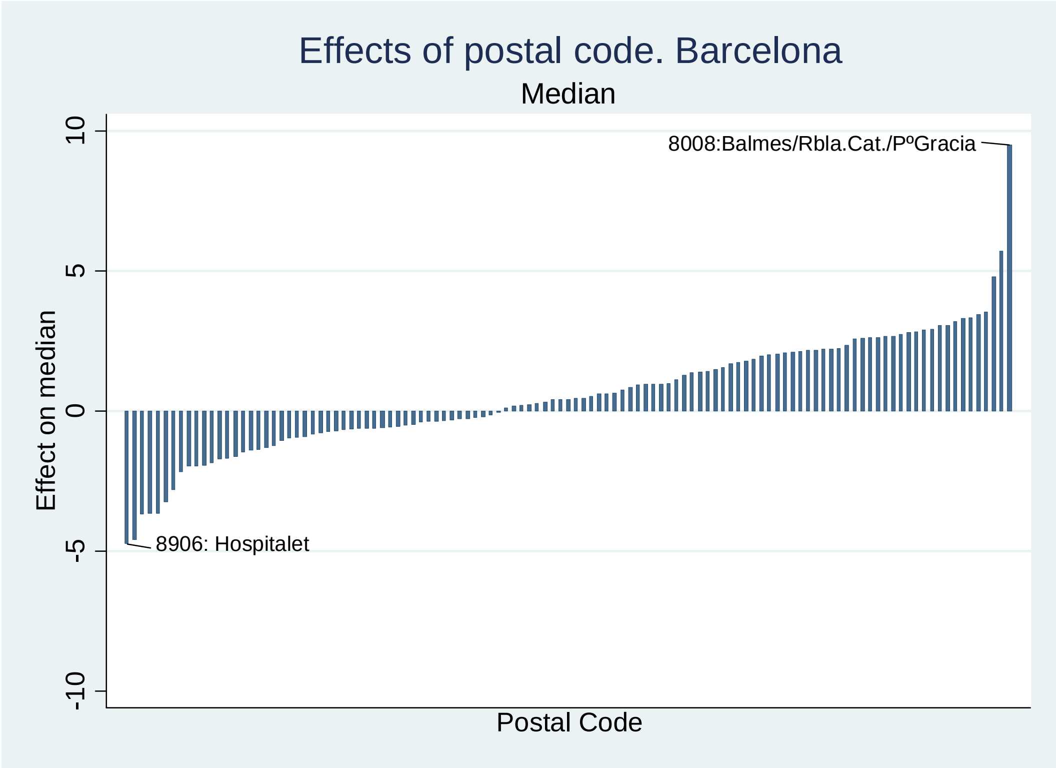


Figure 3. Estimated postal code effects for the two major cities:



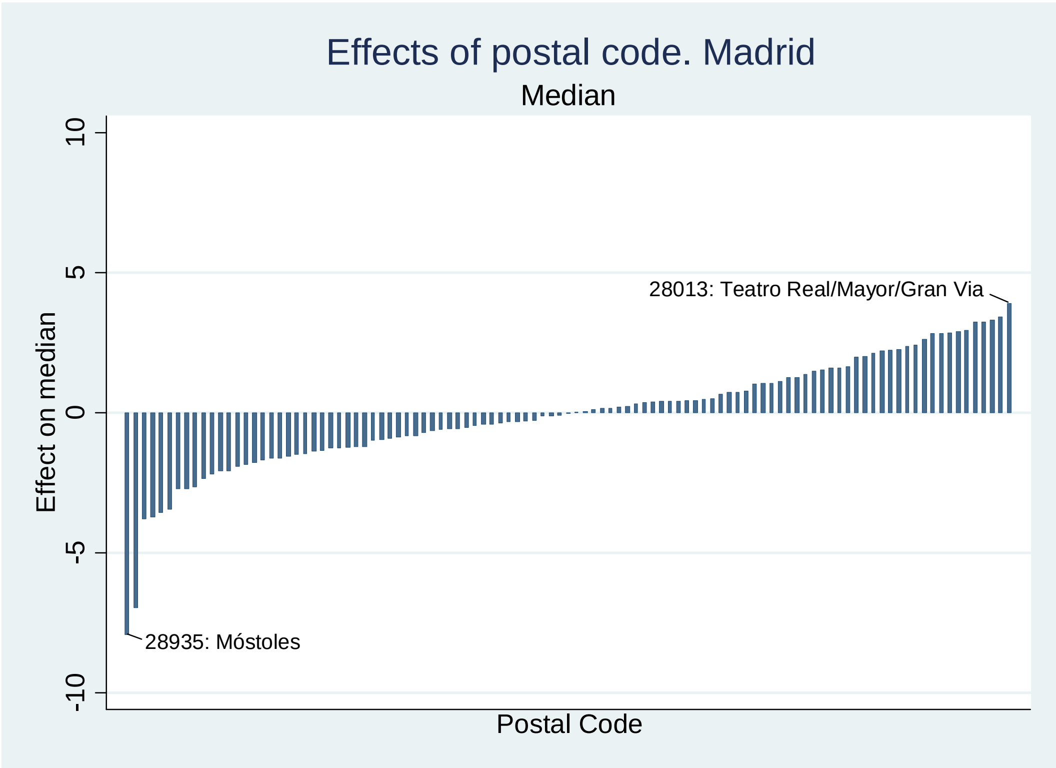


Table 1. Don’t know/No answer and bunching in the middle: demographic characteristics

VARIABLES	(1) Number of respondents	DK/NA (%)		Bunching in the middle (%)	
		(2) sample	(3) population	(4) sample	(5) population
Women	2,442	6.18	6.93	19.57	20.53
Men	3,664	2.78	3.44	18.23	17.86
Primary educ.	2,767	6.98	7.46	19.48	19.48
Secondary educ.	1,466	2.32	2.47	18.62	17.99
University educ.	1,851	1.40	1.67	17.83	19.47
Age under 35	279	2.87	2.26	16.85	20.48
Age 35 to 44	763	3.01	3.55	18.48	16.26
Age 45 to 54	1,177	2.97	3.86	17.33	16.41
Age 55 to 64	1,274	2.20	3.72	18.13	20.26
Age over 64	2,613	6.08	8.85	20.02	21.97
Owner occupiers	5,326	3.22	3.56	18.42	18.71
Non-owner occupiers	780	10.70	12.21	21.14	20.77
Total	6,106	4.14	5.02	18.77	19.06

Table 2. Observed answers and characteristics: multiple regressions

VARIABLES	(1) dk/na	(2) + or - same	(3) points to increase (x10)	(4) points to drop (x10)	(5) all points to one drop interval
Woman	0.025**	-0.010	0.959	-1.785	-0.032**
Secondary educ.	-0.010	0.019	-0.661	0.638	0.017
University educ.	-0.005	0.052	-1.938	-2.218	-0.028
Age 35 to 44	0.001	-0.009	-1.148	6.966	0.053
Age 45 to 54	0.043***	0.028	-0.694	-0.171	0.034
Age 55 to 64	0.034*	0.086*	-1.906	-3.583	0.042
Age over 64	0.061***	0.081*	-3.105	-3.703	0.036
Blue collar	0.005	0.026	-0.223	-2.910	-0.018
Self-employed	-0.008	0.021	-1.463	1.785	-0.015
Log(hh income)	-0.020**	0.002	-0.461	2.608*	0.013
Wealth percentiles					
25-50	-0.003	0.009	-0.512	-1.857	0.041
50-75	-0.024	0.041	0.034	-3.903	0.021
75-90	-0.005	0.017	0.265	-1.987	0.024
90-100	-0.010	0.002	-0.520	-0.845	-0.011
Bought main recently	-0.004	0.010	2.858**	-4.256	-0.008
Own other housing	-0.004	-0.014	-0.402	2.609	0.064***
Constant	0.233**	0.142	11.323	27.260	-0.050
Observations	5,326	5,326	5,326	5,326	5,326

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

All specifications include postal dummies and have been estimated taking into account population weights and the five imputed datasets

Table 3. Bins used (%)

Nº of bins used	Sample	Population
1	38.55	36.17
2	33.62	35.01
3	17.13	16.26
4	4.37	5.31
5	6.32	7.24
Using non-adjacent bins	1.59	1.66

Table 4. Most frequent answers to probabilistic expectations of future house prices

	- > 6%	- around 3%	+or- same	+ around 3%	+ > 6%	frequency	percent	cumpercent
1.	0	0	10	0	0	1146	19.58	19.58
2.	0	10	0	0	0	583	9.96	29.54
3.	10	0	0	0	0	558	9.53	39.07
4.	0	5	5	0	0	382	6.53	45.60
5.	5	5	0	0	0	323	5.52	51.12
6.	8	2	0	0	0	125	2.14	53.25
7.	0	3	7	0	0	116	1.98	55.24
8.	0	2	8	0	0	111	1.90	57.13
9.	6	4	0	0	0	91	1.55	58.69
10.	0	8	2	0	0	79	1.35	60.04
11.	3	7	0	0	0	79	1.35	61.39
12.	2	8	0	0	0	73	1.25	62.63
13.	0	0	5	5	0	73	1.25	63.88
14.	7	3	0	0	0	70	1.20	65.08
15.	0	6	4	0	0	70	1.20	66.27
16.	0	4	6	0	0	65	1.11	67.38
17.	0	7	3	0	0	64	1.09	68.48
18.	4	6	0	0	0	64	1.09	69.57
19.	2	6	2	0	0	57	0.97	70.55
20.	5	3	2	0	0	56	0.96	71.50
21.	4	4	2	0	0	55	0.94	72.44
22.	0	0	0	10	0	54	0.92	73.36
23.	3	5	2	0	0	52	0.89	74.25
24.	2	3	5	0	0	52	0.89	75.14
25.	2	5	3	0	0	51	0.87	76.01
26.	6	3	1	0	0	47	0.80	76.82
27.	2	4	4	0	0	36	0.62	77.43
28.	0	0	8	2	0	35	0.60	78.03
29.	3	3	4	0	0	32	0.55	78.58
30.	2	2	6	0	0	31	0.53	79.10
31.	0	1	9	0	0	31	0.53	79.63
32.	0	2	6	2	0	28	0.48	80.11
33.	4	3	3	0	0	27	0.46	80.57
34.	5	4	1	0	0	26	0.44	81.02
35.	9	1	0	0	0	26	0.44	81.46
36.	2	7	1	0	0	23	0.39	81.86
37.	3	4	3	0	0	23	0.39	82.25
38.	6	2	2	0	0	22	0.38	82.62
39.	3	6	1	0	0	21	0.36	82.98
40.	1	2	7	0	0	21	0.36	83.34
41.	0	0	7	3	0	20	0.34	83.68
42.	0	3	5	2	0	20	0.34	84.03
43.	1	7	2	0	0	20	0.34	84.37
44.	7	2	1	0	0	20	0.34	84.71
45.	0	3	4	3	0	18	0.31	85.02
46.	0	5	3	2	0	18	0.31	85.32
47.	4	5	1	0	0	18	0.31	85.63
48.	0	0	0	5	5	17	0.29	85.92
49.	0	3	6	1	0	16	0.27	86.20
50.	1	8	1	0	0	16	0.27	86.47
51.	1	2	5	2	0	16	0.27	86.74
52.	2	3	4	1	0	16	0.27	87.02
53.	8	1	1	0	0	14	0.24	87.25
54.	0	0	0	0	10	13	0.22	87.48
55.	3	2	5	0	0	13	0.22	87.70
56.	1	6	3	0	0	13	0.22	87.92
57.	0	9	1	0	0	13	0.22	88.14
58.	1	4	5	0	0	12	0.21	88.35
59.	1	3	5	1	0	12	0.21	88.55
60.	0	0	4	6	0	12	0.21	88.76
61.	0	1	8	1	0	12	0.21	88.96
62.	0	2	7	1	0	11	0.19	89.15
63.	2	4	3	1	0	11	0.19	89.34
64.	0	2	5	3	0	11	0.19	89.53
65.	0	0	5	3	2	11	0.19	89.71
66.	3	4	2	1	0	11	0.19	89.90
67.	3	3	3	1	0	10	0.17	90.07

Table 5. Quantiles of subjective probability distributions of house prices
(within postal code estimates)

VARIABLES	(1) q10	(2) q25	(3) q50	(4) q75	(5) q90
Log(price/m2)	0.014	0.131	0.147	0.121	0.116
Age 45 to 64	0.608*	0.504*	0.379	0.150	-0.087
Age over 64	1.052***	0.728**	0.432	0.100	-0.241
Blue collar	0.676**	0.604**	0.523**	0.406**	0.364**
Self-employed	-0.563	-0.363	-0.327	-0.385	-0.412*
Secondary education	0.221	0.041	0.030	-0.025	-0.082
University education	0.595	0.506	0.382	0.268	0.137
Woman	0.228	0.367*	0.401**	0.323**	0.206
Own other housing	-0.141	-0.225	-0.310	-0.331*	-0.358**
Bought main residence recently	0.609	0.621*	0.578**	0.551**	0.508**
Log(household income)	-0.103	-0.103	-0.125	-0.125	-0.131
Wealth percentiles 25-50	0.455	0.322	0.223	0.091	-0.181
Wealth percentiles 50-75	1.054**	0.765*	0.520	0.328	-0.010
Wealth percentiles 75-90	0.758	0.638	0.555	0.389	0.049
Wealth percentiles 90-100	0.258	0.246	0.212	0.139	-0.102
Constant	-7.230**	-5.811**	-3.405*	-1.279	0.643
Observations	5,023	5,023	5,023	5,023	5,023
Adjusted R2	0.366	0.345	0.353	0.382	0.400

*** p<0.01, ** p<0.05, * p<0.1

All specifications include postal dummies and have been estimated taking into account population weights and the five imputed datasets

Table 6. Uncertainty in subjective probability distributions of house prices (within postal code estimates)

VARIABLES	(1) q75-q25	(2) q90-q10
Log(price/m2)	-0.010	0.102
Age 45 to 64	-0.354**	-0.694***
Age over 64	-0.628***	-1.293***
Blue collar	-0.198	-0.312
Self-employed	-0.023	0.151
Secondary education	-0.066	-0.303
University education	-0.237	-0.458
Woman	-0.044	-0.023
Own other housing	-0.107	-0.217
Bought main residence recently	-0.070	-0.101
Log(household income)	-0.022	-0.029
Wealth percentiles 25-50	-0.231	-0.636*
Wealth percentiles 50-75	-0.437**	-1.064***
Wealth percentiles 75-90	-0.249	-0.709*
Wealth percentiles 90-100	-0.107	-0.360
Constant	4.533***	7.873***
Observations	5,023	5,023
Adjusted R2	0.432	0.456

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

All specifications include postal dummies and have been estimated taking into account population weights and the five imputed datasets

Table 7. Importance of the location of the house

	(1)	(2)
	On q50	On q75-q25
% of explained variation due to postal code dummies[1]	96.6	94.7
% of postal code variation explained:		
• by municipality dummies	63.7	75.4
• by province dummies	29.2	29.3

1. The reference for these calculations are Table 5 (column 3) in the case of the first column and Table 6 (column 1) in the case of column 2.

Table 8. Postal code dummies on housing and labour market variables [1, 2]

	(1)	(2)	(3)	(4)	(5)
VARIABLES	q10	q25	q50	q75	q90
Rate of return on housing 2010	0.005	0.044	0.078	0.098**	0.102*
Rate of return on housing 2009	0.150**	0.185***	0.174***	0.153***	0.123***
Change in unemployment rate 2010	-0.278***	-0.234***	-0.179***	-0.143**	-0.085
Constant	1.680**	2.095***	2.124***	2.034***	1.784***
Observations	1,093	1,093	1,093	1,093	1,093
Adjusted R-squared	0.009	0.012	0.014	0.013	0.007

*** p<0.01, ** p<0.05, * p<0.1

1. Housing and labour market variables are available at the province level
2. Postal code dummies estimated in Table 5

Table 9. Postal code dummies on housing and labour market variables [1, 2]

VARIABLES	(1) q75-q25	(2) q90-q10
Change in rate of return on housing 2010	0.042*	0.029
Change in unemployment rate 2010	0.097**	0.114***
Constant	-0.210*	-3.307***
Observations	1,093	1,093
Adjusted R-squared	0.006	0.006

*** p<0.01, ** p<0.05, * p<0.1

1. Housing and labour market variables are available at the province level
2. Postal code dummies estimated in Table 6

Table 10. Effects of house price expectations on average probabilities of purchase
(at various points of the wealth distribution; probit estimates)

	Other housing		Car purchase		Other big ticket items	
Memo: % of households buying	0.57%		9.42%		41.99%	
Expectation variables[1]	(1) Full sample Weights	(2) Within postal codes No weights	(3) Full sample Weights	(4) Within postal codes No weights	(5) Full sample Weights	(6) Within postal codes No weights
Large certain drop in HP[2]						
at median net wealth	-0.826**	-4.06	-4.46**	-11.7***	2.80	-7.26**
at 80th percentile of net wealth	-1.24***	-4.31	-2.83	-11.3***	2.07	-6.46**
Uncertainty in HP[3]						
at median net wealth	-0.629*	-5.88**	2.67*	0.296	8.09***	0.461
at 80th percentile of net wealth	-0.803**	-8.27***	2.64	-0.334	12.5***	1.59
Income higher than current[4]	-0.145	11.8*	2.14	1.56	0.724	4.95**
Income lower than current	0.656	-4.43	1.77	1.83	-0.007	-1.91
Observations[5]	5,019	381	5,019	2,158	5,019	4,189

*** p<0.01, ** p<0.05, * p<0.1

1. Control variables include: interactions of expectation dummies with log net wealth, gender, age brackets, number of persons in the household dummies, children dummy, couple dummy, labour status dummies for respondent and partner (if any), positive and negative income shocks dummies and in columns 1, 3 and 5 municipality size dummies instead of postal code dummies.
2. Large certain drop = 1 if respondent assigns all 10 points to "large drop (more tan 6%)"
   Large certain drop = 0 if respondent assigns all 10 points to any other of the 4 other options.
3. Uncertainty = 1 if respondent assigns points to more than one option
   Uncertainty = 0 if respondent assigns 10 points to any of the 4 options different from "large drop (>6%)".
4. Income higher (lower) than current=1 if future expected income higher(lower) than current, 0 otherwise.
5. Sample sizes vary slightly across imputations. The numbers shown correspond to the smaller sample size.
6. Probabilities are shown in percentage terms.

Table 11A. Effects of house price expectations on expenditures
(at various points of the wealth distribution)

	Other Housing (Tobit)		Car purchase (Tobit)		Other big ticket items (Tobit)		Food and other non-durables (log)	
Expectation variables[1]	(1)	(2) Within postal codes[7]	(3)	(4) Within postal codes	(5)	(6) Within postal codes	(7)	(8) Within postal codes
Large certain drop in HP[2]								
at median net wealth	-876,501**	-811,159***	-11,580*	-12,975**	260.1	-705.2	0.0319	0.0402
at 80th percentile of net wealth	-676,699**	-483,728***	-4,995	-5,105	652.0	-667.8	0.0431	0.0566
Uncertainty in HP[3]								
at median net wealth	-229,984**	-507,576***	3,761	1,871	646.9	69.92	0.0255	0.0102
at 80th percentile of net wealth	-180,981**	-380,539***	4,063	2,793	1,497**	626.2	0.0486*	0.0295
Income higher than current[4]	-47,607	50,864	2,694	-843.1	-315.5	222.3	0.0769***	-0.106***
Income lower than current	155,664*	-143,444	2,137	2,104	-282.4	-669.6	-0.0140	0.00542
Observations[5]	5,019	5019	5,019	5019	5,019	5019	5,019	5,019
of which uncensored[6]	40	40	412	412	1,959	1,959	5,019	5,019

*** p<0.01, ** p<0.05, * p<0.1

1. Control variables include: interactions of expectation dummies with log net wealth, gender, age brackets, number of persons in the household dummies, children dummy, couple dummy, labour status dummies for respondent and partner (if any), positive and negative income shocks dummies and in columns 1, 3 and 5 municipality size dummies instead of postal code dummies.
2. Large certain drop = 1 if respondent assigns all 10 points to "large drop (more tan 6%)"
   Large certain drop = 0 if respondent assigns all 10 points to any other of the 4 other options.
3. Uncertainty = 1 if respondent assigns points to more than one option
   Uncertainty = 0 if respondent assigns 10 points to any of the 4 options different from "large drop (>6%)".
4. Income higher (lower) than current=1 if future expected income higher(lower) than current, 0 otherwise.
5. Sample sizes vary slightly across imputations. The numbers shown correspond to the smaller sample size.
6. Sample sizes vary slightly across imputations. The numbers shown correspond to the smaller number of uncensored observations.
7. Population weights are used in all columns (both in parameter estimation and in the computation of the effects).

Table 11 B. Effects of house price expectations on average probabilities of purchase from tobit model
(at various points of the wealth distribution)

	Other Housing (Tobit)		Car purchase (Tobit)		Other big ticket items (Tobit)	
Expectation variables[1]	(1)	(2) Within postal codes[7]	(3)	(4) Within postal codes	(5)	(6) Within postal codes
Large certain drop in HP[2]						
at median net wealth	-0.771**	-0.753***	-5.64**	-5.95***	1.35	-3.55
at 80th percentile of net wealth	-1.22***	-0.935***	-3.05	-2.87	3.48	-3.45
Uncertainty in HP[3]						
at median net wealth	-0.535*	-0.600***	2.51	1.02	3.41	0.360
at 80th percentile of net wealth	-0.729**	-0.709***	2.96	1.66	8.18***	3.34
Income higher than current[4]	-0.124	0.0841	1.93	-0.477	-1.65	1.15
Income lower than current	0.570	-0.231	1.51	1.21	-1.48	-3.40
Observations[5]	5,019	5019	5,019	5019	5,019	5019
of which uncensored[6]	40	40	412	412	1,959	1,959

*** p<0.01, ** p<0.05, * p<0.1

1. Control variables include: interactions of expectation dummies with log net wealth, gender, age brackets, number of persons in the household dummies, children dummy, couple dummy, labour status dummies for respondent and partner (if any), positive and negative income shocks dummies and in columns 1, 3 and 5 municipality size dummies instead of postal code dummies.
2. Large certain drop = 1 if respondent assigns all 10 points to "large drop (more tan 6%)"
   Large certain drop = 0 if respondent assigns all 10 points to any other of the 4 other options.
3. Uncertainty = 1 if respondent assigns points to more than one option
   Uncertainty = 0 if respondent assigns 10 points to any of the 4 options different from "large drop (>6%)".
4. Income higher (lower) than current=1 if future expected income higher(lower) than current, 0 otherwise.
5. Sample sizes vary slightly across imputations. The numbers shown correspond to the smaller sample size.
6. Sample sizes vary slightly across imputations. The numbers shown correspond to the smaller number of uncensored observations.
7. Population weights are used in all columns (both in parameter estimation and in the computation of the effects).

Table A1. Various robustness checks

	(1)	(2)	(3)	(4)	(5)	(6)
	No recent buyer variable		Risk aversion		Wider support	
VARIABLES	q50	q75-q25	q50	q75-q25	q50	q75-q25
Log(price/m2)	0.182	-0.014	0.145	-0.012	0.179	-0.045
Age 45 to 64	0.325	-0.347**	0.326	-0.301*	0.424	-0.491**
Age over 64	0.378	0.621***	0.321	0.514***	0.493	0.792***
Blue collar	0.530**	-0.199	0.554***	-0.227*	0.639***	-0.327*
Self-employed	-0.340	-0.021	-0.362	0.007	-0.379	0.037
Secondary education	0.050	-0.068	0.022	-0.055	0.015	-0.052
University education	0.417	-0.242	0.353	-0.197	0.479	-0.369
Woman	0.381**	-0.041	0.422**	-0.050	0.500**	-0.141
Own other housing	-0.295	-0.109	-0.273	-0.153	-0.410*	-0.054
Bought main residence recently	--	--	0.501*	0.004	0.677**	-0.176
Risk lover	--	--	-0.189	0.676	--	--
Log(household income)	-0.113	-0.024	-0.133	-0.008	-0.146	-0.030
Wealth percentiles 25-50	0.129	-0.220	0.212	-0.205	0.261	-0.364
Wealth percentiles 50-75	0.410	-0.423**	0.522	-0.430**	0.623*	-0.635**
Wealth percentiles 75-90	0.430	-0.233	0.574	-0.265	0.720*	-0.457
Wealth percentiles 90-100	0.090	-0.092	0.252	-0.143	0.310	-0.167
Constant	-3.392*	4.531***	-3.256	4.338***	-3.860*	5.801***
Observations	5,023	5,023	5,004	5,004	5,023	5,023
Adjusted R2	0.351	0.432	0.354	0.437	0.359	0.407

*** p<0.01, ** p<0.05, * p<0.1

All specifications include postal dummies and have been estimated taking into account population weights and the five imputed datasets

Table A2. Self-assessed value of different assets (for those owning each asset)

VARIABLES	(1) Log(home price/m2)	(2) Log(current accounts)	(3) Log(stocks)	(4) Log(pension funds)
Age 45 to 64	-0.149***	-0.082	0.281	0.565***
Age over 64	-0.211***	0.473***	0.009	0.296
Blue collar	0.008	-0.176**	-0.954***	-0.057
Self-employed	-0.151***	-0.023	0.552	0.164
Secondary education	0.017	-0.011	-0.494	0.043
University education	-0.008	0.588***	-0.393	0.108
Woman	0.054***	-0.266***	-0.611*	-0.256
Log(household income)	0.028*	0.534***	-0.010	0.187
Wealth percentiles 25-50	0.250***	0.669***	-0.030	0.235
Wealth percentiles 50-75	0.457***	1.081***	0.485	0.604*
Wealth percentiles 75-90	0.520***	1.403***	0.285	1.117***
Wealth percentiles 90-100	0.635***	1.461***	1.025*	1.866***
Constant	6.905***	1.776**	9.047***	5.707***
Observations	5,190	5,717	1,631	1,858
Adjusted R-squared	0.663	0.447	0.673	0.584

*** p<0.01, ** p<0.05, ** p<0.1

All specifications include postal dummies and have been estimated taking into account population weights and the five imputed datasets

Table A3. Some quantile measures of subjective probability distributions of house prices: (i) no location information, (ii) municipality dummies

	(1)	(2)	(3)	(4)	(5)	(6)
	No location information			Municipality dummies		
VARIABLES	q25	q50	q75-q25	q25	q50	q75-q25
Log(price/m2)	-0.237	-0.074	0.256***	-0.142	-0.019	0.148
Age 45 to 64	0.079	0.113	-0.061	0.281	0.272	-0.157
Age over 64	0.398	0.114	-0.621***	0.645**	0.481*	-0.473***
Blue collar	0.423	0.387*	-0.118	0.464*	0.412*	-0.188
Self-employed	-0.395	-0.444	-0.171	-0.315	-0.217	0.032
Secondary education	-0.295	-0.286	-0.009	-0.124	-0.102	-0.028
University education	0.421	0.345	-0.199	0.454	0.396	-0.177
Woman	0.294	0.226	-0.161	0.269	0.313*	-0.001
Own other housing	-0.102	-0.236	-0.174	-0.123	-0.217	-0.116
Bought main residence recently	0.878**	0.605*	-0.437**	0.753**	0.639**	-0.166
Log(household income)	-0.071	-0.144	-0.108	-0.121	-0.132	-0.021
Wealth percentiles 25-50	0.635	0.221	-0.650***	0.652*	0.316	-0.471**
Wealth percentiles 50-75	1.024**	0.474	-0.833***	1.056***	0.583*	-0.642***
Wealth percentiles 75-90	0.954**	0.425	-0.764***	0.891**	0.474	-0.531**
Wealth percentiles 90-100	0.719	0.304	-0.537*	0.546	0.178	-0.396
Constant	-3.939*	-1.508	4.314***	0.723	0.777	0.736
Observations	5,023	5,023	5,023	5,023	5,023	5,023
Adjusted R2	0.0116	0.00988	0.0218	0.208	0.209	0.318

*** p<0.01, ** p<0.05, * p<0.1

All specifications have been estimated taking into account population weights and the five imputed datasets. Columns 1 to 3 include no location dummies and columns 4 to 6 include municipality dummies.