Double-question Survey Measures for the Analysis of Financial Bubbles and Crashes*

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Abstract

This paper proposes a new double-question survey whereby an individual is presented with two sets of questions; one on beliefs about current asset values and another on price expectations. A theoretical asset pricing model with heterogeneous agents is advanced and the existence of a negative relationship between price expectations and asset valuations is established, which is tested using survey results on equity, gold and house prices. Leading indicators of bubbles and crashes are proposed and their potential value is illustrated in the context of a dynamic panel regression of realized house price changes across key MSAs in the US.

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1 Introduction

Expectations formation is an integral part of the decision making process, yet little is known about the way individuals actually form expectations. At the theoretical level and in the context of representative agent models, the rational expectations hypothesis (REH) has gained general acceptance as the dominant model of expectations formation. But in reality markets are populated with agents that differ in *a priori* beliefs, information, knowledge, cognitive and processing abilities, and there is no reason to believe that such heterogeneities will be eliminated by market interactions alone. As argued in the seminal work of Grossman and Stiglitz (1980), the price revelation cannot be perfect and heterogeneity is likely to be a prevalent feature of expectations across individuals. Allowing for heterogeneity of expectations is particularly important for a better understanding of bubble and crashes in asset prices. This is apparent in the theoretical literature on price bubbles where most recent contributions consider different types of traders, variously refereed to as "fundamental" and "noise" traders, or "behavioral" traders. See, for example, Allen et al. (1993), Daniel et al. (1998), Hirshleifer (2001), Odean (1998), Thaler (1991), Shiller (2000), Shleifer (2000), and Abreu and Brunnermeier (2003). There is also a related literature on higher-order beliefs in asset pricing, inspired from Keynes's example of the beauty contest, that focus on the departure of asset prices from the average expectations of the fundamentals across agents. See, for example, Allen et al. (2006), Bacchetta and Van Wincoop (2006), and Bacchetta and Van Wincoop (2008). This literature provides a formal framework for the analysis of market psychology and the possibility of bubbles and crashes arising when market expectations of the fundamentals deviate from realized asset prices.

Furthermore, it has proved difficult to develop tests of bubbles/crashes based on representative agent models, as was recognized early on by Blanchard (1979), who concluded that "*...Detecting their [bubbles] presence or rejecting their existence is likely to prove very hard.*" There is also a large econometrics literature on tests of asset price bubbles based on long historical time series of asset returns.[1] But the outcomes of such tests are generally inconclusive. For example, Gürkaynak (2008) after surveying a large number of studies concludes that "We are still unable to distinguish bubbles from time-varying or regime switching fundamentals, while many small sample econometrics problems of bubble tests remain unresolved." Recent recursive time series tests proposed in a series of papers by Phillips and Yu provide more powerful tests, but these tests are purely statistical in nature and do not allow us to infer if structural breaks detected in the time series processes of asset prices are evidence of bubbles or are due to breaks in the underlying (unobserved) fundamentals. See Phillips et al. (2011) and Phillips et al. (2015). Also see Homm and Breitung (2012). Analysis of aggregate time series observations can provide historical information about price reversals and some of their proximate causes. But it is unlikely that such aggregate time series observations on their own could provide timely evidence of building up of bubbles and their subsequent collapse.

In this paper we consider an alternative survey-based strategy and propose indicators of bubbles and crashes that exploit the heterogeneity of expectations across individuals and the disparities that exist between individual subjective asset valuations and their expected price changes. We show that in a heterogeneous agent model with bubble-free equilibrium outcomes, we would expect a negative association between valuation and expected price changes, and use this theoretical result as a bench-mark for categorizing individual respondents as belonging to bubble, crash and normal states. The proportions of respondents in bubble and crash states can be used as leading indicators in forecasting or policy analysis.

The heterogeneity of expectations is a key feature of our analysis and has been well documented in the literature. For example, Ito (1990) considers expectations of foreign exchange rates in Japan, and finds that exporters tend to anticipate a yen depreciation while importers anticipate an appreciation, a kind

[1] There are a few empirical studies that use panel data regressions, but such studies face the additional challenge of allowing for bubbles at different times in different markets and possible bubble spill-overs across markets.

of ‘wishful thinking’. Dominitz and Manski (2011) and Branch (2004) study the heterogeneity of equity price expectations using the Michigan Surveys, and find that there is a large degree of heterogeneity in expectation formation. Similar patterns of expectations heterogeneity are documented for house prices. See, for example, Case and Shiller (1988), Case and Shiller (2003), Case et al. (2012), Niu and Van Soest (2014), Kuchler and Zafar (2015), and Bover (2015).[2]

However, all surveys of price expectations focus on individual expectations of future price movements either qualitatively (whether the prices are expected to rise, fall or stay the same) or quantitatively in the form of predictive densities. The outcomes of such surveys are used in disaggregated or aggregated forms in tests of rationality of expectations and for forecasting of aggregate trends. Typically, such survey questions are not placed in particular decision contexts. However, for the analysis of many economic problems more information about the nature of individual beliefs and expectations is required. This is particularly the case when individual decisions depend not only on their own expectations of future outcomes, but also on their beliefs about the expectations of other market participants.

But elicitation of individual expectations of others can be quite difficult. It is also likely to be unreliable since the reference group might not be known and could be changeable over time. In this paper we approach the problem indirectly and present an individual respondent with two sets of questions, one that asks about the individual's subjective belief regarding valuations (whether the prevailing asset price is "fairly valued"), and another regarding the individual's expectations of the future price of that asset.[3] Responses to these two questions are then used to measure the extent to which prices are likely to move towards or away from the subjectively perceived fundamental

[2] A review of the literature on survey expectations can be found in Pesaran and Weale (2006).

[3] The double-question surveys proposed in this paper are to be distinguished from other double-questions considered in the survey literature, such as the "double-barreled" questions that ask a respondent two questions but require one answer, and questions with anchoring vignettes, introduced by King et al. (2004), which are aimed at enhancing cross-respondent comparability of survey measures.

values. These questions do not require that the notation of a fundamental value is commonly understood or agreed upon.

We report the results of such double-question surveys for gold, equity and house prices conducted with US households using RAND American Life Panel (ALP).[4] The ALP covers over 6,000 members with ages 18 and over, and is nationally representative, drawing from respondents recruited from several sources, including University of Michigan Phone-Panel and Internet-Panel Cohorts, and National Survey Project Cohort. We started with two pilot surveys, and introduced the double-question surveys as a new module starting in January 2012 and ended January 2013 (13 waves altogether). The number of survey participants ranged form a low of 4,477 in January 2012, to a high of 5,911 in January 2013. All respondents provided demographic information, but were not compelled to respond to our questions. Nevertheless, as it turned out the response rate was around 72%, and we ended up with a panel of around 4,000 individuals who completed our survey questions over the period January 2012 to January 2013.

The survey responses provide information on individuals' price expectations as well as their valuation beliefs. It is the two questions together that allow us to construct bubble and crash indicators. To our knowledge this has not been done before. The paper also makes a theoretical contribution to the literature on asset pricing with heterogeneous agents. Under certain conditions on how individuals form expectations of others in the market place, it shows that individual expectations of price changes are negatively related to their market valuation. In the absence of price bubbles/crashes, individuals who believe market prices are too high tend to have lower price expectations, whilst those who believe market prices are too low tend to have higher price expectations. However, such an error-correcting process need not hold at times of bubbles (or crashes) when individuals could believe the prices to be too high (low), and yet expect higher (lower) prices. This pattern of expecta-

[4] For details of ALP see http://www.rand.org/pubs/corporate_pubs/CP508-2015-05.html. The survey questions have been designed jointly with Jeff Dominitz (Resolution Economics) and Charles Manski (Northwestern University).

tions formation is in line with theories of speculative behavior and bubbles and crashes, which argue that rational traders understand that market prices might be over-valued, but continue to expect higher prices as they believe they can ride the bubble and exit just before the crash. See, for example, Abreu and Brunnermeier (2003).

We provide estimates of the relationship between expected price changes and a valuation indicator using an unbalanced panel of responses from the double-question surveys. We find statistically significant relationships between expected price changes (at one, three and twelve months ahead) and asset valuations (under or over) for all the three asset classes. But these relationships are error correcting (in the sense discussed above) for equity price expectations at longer horizons and for house price expectations at all three horizons being considered. Gold price expectations do not seem to be equilibrating. The effects of demographic factors, such as sex, age, education, ethnicity, and income are also investigated. It is shown that for house price expectations such demographic factors cease to be statistically significant once we condition on the respondents' location and their asset valuation indicator.

Finally, using the double-question survey responses we propose bubble and crash indicators for use as early warning signals of bubbles and crashes in the economy as a whole or in a particular region. There is also the issue of how to evaluate the usefulness of such indicators. One approach would be to investigate their contribution in modeling and forecasting realized price changes in a given region or nationally. A pure time series approach would require sufficiently long time series data and is not possible in the case of the present survey (which covers a very short time period). But it is possible to exploit the panel dimension of our data and see if crash and bubble indicators can significantly contribute to the explanation of *realized* house price changes across different metropolitan statistical areas (MSAs). To this end we begin with a dynamic fixed effects panel data model in monthly realized house price changes and then add expected house price changes and crash and bubble indicators at different horizons to see if such survey based indicators can help in cross-sectional explanation of realized house price changes. We employ dynamic panel data models with fixed and time effects and include MSA-specific crash and bubble indicators together with similar indicators constructed for the neighboring MSAs. We find such indicators to have significant explanatory power for realized house price changes over and above past price changes. All estimated coefficients have the correct signs, predicting expected price changes to rise with bubble indicators and to fall with the crash indicators.

The remainder of the paper is organized as follows: Section 2 sets out the theoretical asset pricing model with heterogeneous agents and derives the relationship between individual expected price changes and their asset valuations at different horizons. Section 3 describes the survey design, provides summary statistics of survey responses, and presents some preliminary data analyses. Section 4 gives the panel regressions of respondents' expected price changes on their valuation indicator, and discusses the effects of location, socio-demographic characteristics and other factors on the expectations formation process. Section 5 introduces the bubble and crash leading indicators. Section 6 investigates the importance of such leading indicators for the analysis of realized house price changes across MSAs. Section 7 ends with some concluding remarks. The exact survey questions and the filtering rules used to clean the survey data for panel regression analyses are given in an Online Supplement. Additional results and descriptions are provided in the Online Supplement which is available from the authors on request.

2 Valuation and expected price changes

The importance of heterogeneity for speculative behavior and over-valuation has been emphasized by Miller (1977). Miller was the first to show that in markets with heterogeneous agents and short-sales constraints, security prices are likely to be over-valued, since short-sales restrictions deter the pessimists from trading without a commensurate effect on the optimists. The quantitative importance of this effect is investigated by Chen et al. (2002). Miller's result is obtained in a static framework, but similar outcomes are also obtained in a dynamic setting. Harrison and Kreps (1978) show that in the presence of short-sales restrictions, and when agents differ in their beliefs about the probability distributions of dividend streams, then over-valuation can arise since agents believe that in the future they will find a buyer willing to pay more than their asset's current worth. In a related paper, Scheinkman and Xiong (2003) argue that such speculative behavior can generate important bubble components even for small differences in beliefs. As noted earlier Allen et al. (2006), Bacchetta and Van Wincoop (2006), and Bacchetta and Van Wincoop (2008) have also emphasized the importance of high-order beliefs for under- and over-valuation of asset prices. In particular, Bacchetta and Van Wincoop (2008) investigate the impact of higher-order expectations on the equilibrium price and establish the existence of a gap between the equilibrium price and the average expectations of the fundamentals, which they refer to as the "higher order wedge". They show that such a non-zero wedge is compatible with rationality and arises purely due to persistent heterogeneity across agents.

These and other theoretical models of asset price over-valuation in the literature provide important insights into interactions of trader heterogeneity and other market features such as short-sales constraints. However, they are silent on the way over-valuation (or under-valuation) can affect price expectations. In what follows, building on the contributions of Allen et al. (2006), and Bacchetta and Van Wincoop (2008) we consider a multi-period asset pricing model with heterogeneous traders, and show that the model has a unique bubble-free solution when traders are anonymous and individual traders base their expectations of others only on publicly available information. Our model solution strategy differs from the one adopted in the literature on higher-order beliefs and does not aim to provide an explicit solution for the equilibrium asset price. Instead we make use anonamity of traders in the network to derive an explicit relationship between expected price changes and a valuation indicator. Specifically, we show that individual traders' expected price changes are related to their asset valuation, as measured by the gap between market prices and traders' own valuation. This relationship is shown to be error correcting in expectations formation, with traders who believe the market to be over-valued (under-valued) expecting prices to fall (rise). This result holds for expectations formed for longer horizons, with the weight attached to the asset valuation variable declining with the horizon. By implication, it also follows that the error correcting mechanism could become perverse if cross-agent expectations are likely to lead to indeterminate outcomes, possibly resulting in the build-up of forces for bubbles or crashes. In such situations, it is possible for traders to believe the market is over-valued (under-valued), and yet continue to expect prices to rise (fall).

More formally, suppose there are n traders with n sufficiently large. Let $\Omega_{it} = \Phi_{it} \cup \Psi_t$, $i = 1, 2, ..., n$, denote trader i^{th} information set composed of his/her private information, Φ_{it}, and the public information Ψ_t that contains at least current and past prices. Each trader decides on how many units, q_{it}, of a particular asset to hold by maximizing $E_i \left[U_i \left(W_{t+1,i} \right) | \Omega_{it} \right]$, where $U_i \left(W_{t+1,i} \right)$ represents the constant absolute risk aversion utility function with γ_i as the absolute risk aversion coefficient of the i^{th} trader, and $E_i \left(\cdot | \Omega_{it} \right)$ is the expectations operator for trader i conditional on his/her information set, Ω_{it}. Under this set up and assuming normally distributed asset returns and no transaction costs, it is easily established that asset demand for trader i is given by

$$P_t q_{it}^d = \frac{E_i \left(R_{t+1} | \Omega_{it} \right) - r_t}{\gamma_i Var_i \left(R_{t+1} | \Omega_{it} \right)},$$

where $R_{t+1} = \left(P_{t+1} - P_t + D_{t+1} \right) / P_t$, is the rate of return on holding the asset over the period t to $t+1$, P_t is the asset price at t, D_{t+1} is the dividend paid on holding the asset over period t to $t+1$, r_t is the risk free rate of return, and $Var_i \left(R_{t+1} | \Omega_{it} \right)$ is the i^{th} trader's conditional variance of asset returns. Assuming no new shares are issued, the market clearing condition is given by $\sum_{i=1}^n q_{it}^d = 0$, and we have[5]

$$P_t = \left(\frac{1}{1+r_t} \right) \left[\sum_{i=1}^n w_{it} E_i \left(P_{t+1} | \Omega_{it} \right) + \sum_{i=1}^n w_{it} E_i \left(D_{t+1} | \Omega_{it} \right) \right], \qquad (1)$$

[5]This assumption can be relaxed and replaced by $\sum_{i=1}^n q_{it}^d = Q$, where Q is the net addition to the supply of shares. In this case, our results hold if it is assumed that $Q/n \to 0$ as $n \to \infty$.

where $w_{it} = \left[\gamma_i Var_i\left(R_{t+1}\left|\Omega_{it}\right.\right)\right]^{-1} / \sum_{j=1}^{n}\left[\gamma_j Var_j\left(R_{t+1}\left|\Omega_{jt}\right.\right)\right]^{-1}$. This is a generalization of the standard asset pricing model and allows for the possible effects of information heterogeneity across traders on the determination of asset prices.[6] The weights w_{it} satisfy the adding up condition, $\sum_{i=1}^{N} w_{it} = 1$, and capture the relative importance of the traders in the market.

When information and priori beliefs are the same across traders, $E_i\left(P_{t+1}\left|\Omega_{it}\right.\right) = E\left(P_{t+1}\left|\Omega_t\right.\right)$ and $E_i\left(D_{t+1}\left|\Omega_{it}\right.\right) = E\left(D_{t+1}\left|\Omega_t\right.\right)$, and the price equation reduces to

$$P_t = \left(\frac{1}{1+r_t}\right)\left[E\left(P_{t+1}\left|\Omega_t\right.\right) + E\left(D_{t+1}\left|\Omega_t\right.\right)\right],$$

with homogeneous expected price changes given by

$$\pi_{i,t+h}^{e} = E\left(\pi_{t+h}|\Omega_t\right) = r_t - E\left(\frac{D_{t+1}}{P_t}\left|\Omega_t\right.\right), \text{ for all } i,$$

where $\pi_{t+h} = (P_{t+h} - P_t)/hP_t$. However, in the presence of information heterogeneity the solution will be subject to the "infinite regress" problem.[7] Each trader needs to form expectations of other traders' price and dividend expectations for all future dates, which is a multi-period version of Keynes' well known beauty contest. In general, the solution is indeterminate even if we impose transversality conditions on all traders, individually. There are many possible solutions. In what follows we consider a set of simplifying assumptions that allow for *heterogeneity but lead to a unique bubble-free market solution.* In this way we are able to model the cross section heterogeneity of expectations in an equilibrium context, so that bubble and crash states can be defined as deviations from the equilibrium benchmark. Specifically, we make the following assumptions:

Assumption 1 *(Risk free rate) Risk free rate, r_t, is time-invariant, namely $r_t = r$, $Var\left(R_{t+1}\left|\Omega_{it}\right.\right) = \sigma_i^2$ for all t, and $0 < c < \gamma_i\sigma_i^2 < C < \infty$, for some*

[6] See also Eq. (3) in Bacchetta and Van Wincoop (2008), and note that we allow for the effects of individual risk premia in the weights, whilst in Bacchetta and Van Wincoop (2008) average price and dividend expectations and risk premia are shown separately.

[7] For an early discussion of the infinite regress problem see Phelps (1983), Townsend (1983) and Pesaran (1987) Ch. 4.

strictly finite positive constants, $c < C$.

Assumption 2 *(Network anonymity) The traders $i = 1, 2, ..., n$ belong to an anonymous network and each trader i^{th} expectations of other traders' price expectations are given by*

$$E_i \left[E_j \left(\pi_{t+h} \left| \Omega_{j,t+h-1} \right. \right) \left| \Omega_{it} \right. \right] = E_i \left(\pi_{t+h} \left| \Omega_{it} \right. \right) + \xi_{it}^{(h)}, \tag{2}$$

for all i and $j = 1, 2, ..., n$, and $h = 1, 2, ...,$ where $\xi_{it}^{(h)}$ is the idiosyncratic part of trader i^{th} expectations of trader j^{th} price change expectations at horizon h, and satisfy the following

$$\begin{aligned} E_i \left(\xi_{jt}^{(h)} \left| \Omega_{it} \right. \right) &= \xi_{it}^{(h)}, \text{ for } j = i \\ &= 0, \text{ for } j \neq i. \end{aligned} \tag{3}$$

Assumption 3 *(Dividend processes) Traders commonly believe that the dividend process, $\{D_t\}$, follows a geometric random walk, but differ in their beliefs about the drift and volatility of the dividend process. Specifically, trader i^{th} dividend process is given by model M_i*

$$M_i : D_t = D_{t-1} \exp(\mu_i + \sigma_i \varepsilon_t), \text{ for } i = 1, 2, ..., n, \tag{4}$$

where ε_t is $i.i.d.N(0, 1)$. The true dividend process is given by

$$DGP : D_t = D_{t-1} \exp(\mu + \sigma \varepsilon_t), \tag{5}$$

Remark 1 *Conditional expectations taken under model M_i and under the DGP will be denoted by $E_i(\cdot\,|)$ and $E(\cdot\,|)$, respectively.*

Assumption 4 *(Market pooling condition) Market expectations of individual traders' price expectations are given by*

$$E \left[E_i \left(P_{t+1} \left| \Psi_t \right. \right) \left| \Psi_t \right. \right] = E \left(P_{t+1} \left| \Psi_t \right. \right), \tag{6}$$

the transversality condition $lim_{H \to \infty} (1 + r)^{-H} E \left(P_{t+H} \left| \Psi_t \right. \right) = 0$ holds, and

$\exp(g) < 1 + r$, *where* $g = \mu + (1/2)\sigma^2$, *with* μ *and* σ^2 *defined by (5).*

Remark 2 *Assumption 4 ensures the existence of a representative agent model associated with the underlying multi-agent set up.*

To allow for market pooling of traders' disparate beliefs regarding the dividend growth process, we introduce the following assumption:

Assumption 5 *(Distribution of trader disparities) Trader-specific belief regarding his/her steady state growth rate of dividends,* g_i*, defined by (8), are distributed independently across* i *as* $N(g, \omega_g^2)$*.*

Under Assumption 1 the price equation (1) simplifies to

$$P_t = \left(\frac{1}{1+r}\right)\left[\sum_{s=1}^{n} w_s E_s\left(P_{t+1}\left|\Omega_{st}\right.\right) + \sum_{s=1}^{n} w_s E_s\left(D_{t+1}\left|\Omega_{st}\right.\right)\right].$$

Also, under Assumption 3 it is easily seen that

$$E_s\left(D_{t+h}\left|\Omega_{st}\right.\right) = D_t \exp(h g_s), \tag{7}$$

where

$$g_s = \mu_s + (1/2)\sigma_s^2. \tag{8}$$

Hence

$$P_t = \left(\frac{1}{1+r}\right)\sum_{s=1}^{n} w_s E_s\left(P_{t+1}\left|\Omega_{st}\right.\right) + \frac{\theta_n}{1+r} D_t, \tag{9}$$

where

$$\theta_n = \sum_{s=1}^{n} w_s \exp(g_s). \tag{10}$$

Now suppose that the asset pricing equation (9) is common knowledge, and is therefore used by all traders to form their price expectations and asset price valuations. In cases where expectations are homogeneous across all traders or when differences in expectations are common knowledge then applying the conditional expectations operator for the i^{th} trader, $E_i\left(\cdot\left|\Omega_{it}\right.\right)$ to both sides of (9) will yield the same result, namely P_t. However, this is not the case in the more realistic scenario where differences in expectations are not common knowledge. Clearly, for the left hand side of (9) we have $E_i(P_t|\Omega_{it}) = P_t$ since P_t is included in Ω_{it}. But application of $E_i(\cdot|\Omega_{it})$ to the right hand side of (9) need not be equal to P_t since exact expressions for terms such as $E_i[E_s(P_{t+1}|\Omega_{st})|\Omega_{it}]$ are not known to trader i, and he/she has no choice but to use some form of an approximation, such as the one proposed in Assumption 2.

Accordingly, we define the i^{th} trader's asset valuation at time t, P^*_{it}, by applying $E_i(\cdot|\Omega_{it})$ to the right hand side of (9), namely

$$P^*_{it} = \left(\frac{1}{1+r}\right)\sum_{s=1}^{n} w_s E_i\left[E_s(P_{t+1}|\Omega_{st})|\Omega_{it}\right] + \frac{E_i(\theta_n)}{1+r}D_t.$$

Now under Assumption 2, and using the condition $E_i[E_s(P_{t+1}|\Omega_{st})|\Omega_{it}] = E_i(P_{t+1}|\Omega_{it}) + \xi^{(1)}_{it}P_t$, we have

$$P^*_{it} = \left(\frac{1}{1+r}\right)\left[E_i(P_{t+1}|\Omega_{it}) + \xi^{(1)}_{it}P_t\right] + \frac{E_i(\theta_n)}{1+r}D_t. \tag{11}$$

Subtracting P_t from both sides of (11) and after some re-arrangements we obtain

$$\frac{E_i(P_{t+1}|\Omega_{it}) - P_t}{P_t} = -(1+r)\left(\frac{P_t - P^*_{it}}{P_t}\right) + \left[r - \frac{E_i(\theta_n)}{1+r}\left(\frac{D_t}{P_t}\right)\right] - \xi^{(1)}_{it},$$

which we write as[8]

$$\pi^e_{i,t+1} = -(1+r)V_{it} + \left[r - \frac{E_i(\theta_n)}{1+r}\left(\frac{D_t}{P_t}\right)\right] - \xi^{(1)}_{it}, \tag{12}$$

where

$$\pi^e_{i,t+1} = E_i(\pi_{i,t+1}|\Omega_{it}), \text{ and } V_{it} = \frac{P_t - P^*_{it}}{P_t}. \tag{13}$$

[8]Note that θ_n is not known to trader i and $E_i(\theta_n)$ represents the i^{th} trader's expectations of θ_n.

Equation (12) relates the i^{th} trader's expected rate of price change to his/her over- or under-valuation as defined by V_{it}, which measures the degree to which trader i^{th} asset valuation, P^*_{it}, differs from the commonly observed prevail price, P_t.

In equilibrium the realized price dividend-ratio, P_t/D_t, is determined by taking expectations of the asset pricing equation (9) conditional on the publicly available information, Ψ_t, across all traders. Specifically, we have

$$\begin{aligned} E\left(P_t\left|\Psi_t\right.\right) &= P_t = \left(\frac{1}{1+r}\right)\sum_{i=1}^{n} w_i E\left[E_i\left(P_{t+1}\left|\Omega_{it}\right.\right)\left|\Psi_t\right.\right] + \frac{E\left(\theta_n\right)}{1+r}D_t, \\ &= \left(\frac{1}{1+r}\right)\sum_{i=1}^{n} w_i E\left[E_i\left(P_{t+1}\left|\Psi_t\right.\right)\left|\Psi_t\right.\right] + \frac{E\left(\theta_n\right)}{1+r}D_t. \end{aligned}$$

Further by Assumption 4 we have (recall that $\Sigma_{i=1}^n w_i = 1$)

$$P_t = \left(\frac{1}{1+r}\right) E\left(P_{t+1}\left|\Psi_t\right.\right) + \frac{E\left(\theta_n\right)}{1+r}D_t.$$

This is a standard asset pricing model for a representative risk neutral agent with the dividend process given by (5). Under thr standard transversality condition applied to P_t, it has the following unique solution:

$$P_t = \frac{E\left(\theta_n\right)}{1+r}\sum_{j=0}^{\infty}\left(\frac{1}{1+r}\right)^j E\left(D_{t+j}\left|\Psi_t\right.\right),$$

which in view of (5) yields (recall that $\exp(g) < 1+r$)

$$P_t/D_t = \frac{E\left(\theta_n\right)}{1+r-e^g} = \frac{\sum_{s=1}^n w_s E\left[\exp(g_s)\right]}{1+r-e^g}. \tag{14}$$

Using this result in (12) now gives the following relationship between expectations and valuations

$$\pi^e_{i,t+1} = \alpha_i - (1+r)V_{it} + u_{it}, \tag{15}$$

where $\pi^e_{i,t+1} = E_i(\pi_{t+1}|\Omega_{it})$, $V_{it} = (P_t - P^*_{it})/P_t$, and

$$\alpha_i = r - \frac{E_i(\theta_n)(1+r-e^g)}{E(\theta_n)}, \text{ and } u_{it} = -\xi^{(1)}_{it}. \tag{16}$$

It is easily seen that in the homogeneous information case where, $\Omega_{it} = \Psi_t$, and $g_i = g$, then we also have $P^*_{it} = P_t$, and $E_i(\theta_n) = E(\theta_n)/D_t$, for all i. Furthermore, (15) reduces to $\pi^e_{i,t+1} = e^g - 1$, for all i.

The above solution also relates to the over-valuation results obtained in the literature. We first note that the equilibrium price-dividend ratio under heterogeneous information, given by (14), tends to $e^{g+0.5\omega_g^2}/(1+r-e^g)$, as $n \to \infty$.[9] However, under homogeneity the equilibrium price-dividend ratio is given by $e^g D_t/(1+r-e^g)$ which is strictly less than the solution for the heterogenous case. This finding mirrors the over-valuation results due to Miller (1977) and Harrison and Kreps (1978), discussed above, but holds more generally even in the absence of short-sales constraints. The extent of over-valuation under heterogeneity depends on the degree of dispersion of opinion across traders about g_i. Our result is also consistent with that the existence of the higher-order wedge identified by Bacchetta and van Wincoop (2008). In terms of our simplified set up the first-order wedge is given by $E(D_{t+1}|\Psi_t) - \sum_{i=1}^n w_i E_i(D_{t+1}|\Omega_{it}) = (e^g - \theta_n) D_t$, which tends to $(1 - e^{0.5\omega_g^2})e^g D_t$, as $n \to \infty$. In this case the wedge is negative for $\omega_g^2 > 0$, which is consistent with asset over-valuation.

Finally, the error-correction specification (15) can be generalized to price expectations for higher-order horizons. In general, for a finite h we have

$$\pi^e_{i,t+h} = \alpha^{(h)}_i - \frac{(1+r)^h}{h} V_{it} + u^{(h)}_{it}, \tag{17}$$

where $\pi^e_{i,t+h} = E_i(\pi_{t+h}|\Omega_{it})$. Exact expressions for $\alpha^{(h)}_i$ and $u^{(h)}_{it}$ for $h = 2$ is given in Section S2 of the Online Supplement, and can be obtained similarly for a general h. But for the empirical analysis to follow, it is sufficient to note that the asset valuation coefficient, $(1+r)^h/h$, tends to fall with h for small

[9] Recall that under Assumption 5, g_i is $IIDN(g, \omega_g^2)$, with $1 + r > e^g$ and $\omega_g^2 > 0$.

values of r and so long as h is not too large. Empirically we model $\alpha_i^{(h)}$ as individual fixed effects and consider a general time series process for $u_{it}^{(h)}$. But first we need to provide further details of the double-question surveys.

3 Double-question surveys

To our knowledge the use of double-question surveys to elicit a respondent asset valuation along with her/his price expectations is new. Whilst there is a large and expanding literature on surveys of price expectations, there is no attempt at direct measurement of individual's subjective valuation of asset prices. We needed to carry out a fresh survey that simultaneously included both questions on expectations and valuations. With this in mind and in collaboration with Jeff Dominitz and Charles Manski, we designed survey questions on expectations and valuations for US households, using RAND American Life Panel (ALP).[10]

The ALP has a modular form, which allowed us to combine demographic, education and income data with the results from our double-question surveys. The double-question surveys on belief and expectations added to the ALP surveys covered equity, gold, and house prices. The two questions for equity prices were as follows:[11]

[10] We are particularly grateful to Arie Kapteyn for his generous support of this project. The sampling frame of ALP surveys, and other details can be found from the following link http://www.rand.org/pubs/corporate_pubs/CP508-2016-04.html.

[11] We also asked the respondents a third question regarding the chance of $1,000 investment to fall in three different ranges. Further details can be found in the Online Supplement. A similar set of questions was asked about gold prices.

Question 1 (equity)
We have some questions about the price of publicly traded stocks. Do you believe the US stock market (as measured by S&P 500 index) to be currently:
1 Overvalued
2 Fairly valued (in the sense that the general level of stock prices is in line with what you personally regard to be fair)
3 Undervalued

Note: The S&P 500 is an index of 500 common stocks actively traded in the United States. It provides one measure of the general level of stock prices.

Question 2 (equity)
Bearing in mind your response to the previous question, suppose now that today someone were to invest 1000 dollars in a mutual fund that tracks the movement of S&P 500 very closely. That is, this "index fund" invests in shares of the companies that comprise the S&P 500 Index. What do you expect the $1000 investment in the fund to be worth
- in one month from now,
- in three months from now,
- in one year from now.

For house prices respondents were also provided with the median price of a single family home in the area close to their place of residence. We used quarterly house prices disaggregated by 180 MSAs from the National Association of Realtors.[12] This turned out to be an important consideration given the large disparity of house prices across the US. Although, due to privacy considerations APL does not provide ZIP code information on respondents, we were able to match respondents to MSAs using their self-reported city and state of residence. Respondents who resided further than 500 miles away from a major metropolitan area were instead asked about the median US house price. The survey questions on house prices for respondents who resided closer than 500 miles away from a major metropolitan area are presented below. The exact wording of the survey questions can be found in the Online Supplement.

[12] All areas are metropolitan statistical areas (MSA) as defined by the US Office of Management and Budget though in some areas an exact match is not possible from the available data. For further details see http://www.realtor.org/topics/existing-home-sales.

Question 1 (house prices)
We now have some questions about housing prices. The median price of a single family home in the [*fill for city nearest to R zip code*] cosmopolitan area is currently around [*converted fill for median housing price in R zip code area*] (Half of all single family homes in the area cost less than the median, and the other half cost more than the median.). Do you believe that current housing prices are:
1 just right (in the sense that housing prices are in line with what you personally regard to be fair),
2 too high,
3 too low as compared to the fair value?

Question 2 (house prices)
Bearing in mind your response to the previous question, suppose now that someone were to purchase a single family home in [*fill for city nearest to R zip code*] area for the price of [...] What do you expect the house to be worth (Please enter a numeric answer only, with no commas or punctuation)
- 1 month from now,
- 3 months from now,
- 1 year from now.

It is important to note that the survey design does not require that the notion of "fairly valued" to be commonly agreed on. What is important is the consistency in measurement of what a respondent considers an asset to be fairly valued and his/her expectations of future price change. Also, we do not ask respondents about percentage price changes but about future price itself, and we ask no direct questions on inflation expectations.

3.1 Survey waves and respondent characteristics

The American Life Panel (ALP) consists of over 6,000 panel members aged 18 and older. Participants are recruited from various sources, such as the University of Michigan phone-panel and internet-panel and cohorts, mailing experiments, phone experiments and vulnerable population cohorts. The panel is representative of the nation, and panel members are provided with equipment that allows them to respond any survey programmed by RAND. The attrition rate of ALP participants is relatively low, between 2006 and 2013 the annual attrition rates were between 6 and 13 per cent. Panel members who have answered a non-household information survey within the last year are considered active and are invited to surveys. Each survey, in addition to the specific survey questions, contains a "Demographics" module, which elicits demographic and socio-economic information about the respondent.

The double-question (DQ) surveys were carried out over the period January 2012 to January 2013. But the first two waves were dropped due to incomplete house price information provided to respondents residing more than 500 miles from major metropolitan areas. For the remaining survey waves (March 2012 to January 2013), we ended up with 5,480 respondents. ALP members were offered the opportunity to respond to our DQ surveys, but their participation was not made mandatory. Table 1 provides the number of ALP members who participated in the surveys and the fraction of those who completed the DQ surveys. The response rates were quite high and averaged around 72 per cent of the survey participants, and varied little across the 13 survey waves. This is a very high response rate as compared to other surveys of house prices conducted in the literature. For example, the average response rate of the home-buyers surveys conducted by Case and Shiller was around 22.7% over the years 1988, and 2003-2012. See Table 1 in Case et al. (2012). We found no significant demographic differences between the respondents and non-respondents of our DQ surveys.

3.2 Filters applied to survey responses

To reduce the impact of extreme outlier responses on our analysis a number of filters were applied to the responses. We also dropped waves 1 and 2 since, as was noted above, in the case of these waves respondents residing more than 500 miles from major metropolitan areas were not provided with house price data. This shortcoming was rectified in the subsequent waves (3-11), by providing such respondents with US median house prices. For these remaining survey waves (March 2012 to January 2013), we ended up with 5,480 respondents. We applied the following truncation filters to the data. First, we dropped

Table 1: **Survey waves and response rates**

Waves	**Months**	**All ALP participants**	**Completed DQ Surveys**		**Filtered Samples**	
				per cent[(1)]		per cent[(2)]
1	January 2012	4477	3371	75	2707	80
2	February 2012	4864	3685	75	2727	74
3	March 2012	5015	3721	74	2991	80
4	April 2012	5260	3723	71	2967	80
5	May 2012	5464	3706	68	2982	80
6	June 2012	5568	4179	75	3379	81
7	July 2012	5674	4135	73	3363	81
8	August 2012	5713	4208	74	3445	82
9	September 2012	5762	4162	72	3425	82
10	October 2012	5772	4180	72	3421	82
11	November 2012	5847	3926	67	3169	81
12	December 2012	5894	4083	69	3404	83
13	January 2013	5911	4209	71	3415	81

The surveys were fielded on the third Monday of the month
[(1)] - Respondents who completed the DQ Surveys as a percentage of all ALP participants
[(2)] - Filtered respondents as percentage of all respondents who completed the DQ Surveys

all respondents with missing responses to the survey questions or missing demographic characteristics. We also dropped respondents whose demographic characteristics were incomplete or contained inconsistent entries over time.[13] Finally, for all expectations horizons (one month, three months and one year) and for all asset prices (equity, gold, housing) we remove respondents from our analysis if they report an expected price equal to zero for any of the survey questions, or report any expected price rises for equity or gold which are in excess of 400 per cent, or report expected price rises for equity or gold for all horizons in excess of 200 per cent, or report expected price falls of more than 90 per cent for all expectations horizons, or report expected house price rises in excess of 200 per cent, or if they report expected house price falls of more than 50 per cent for any expectation horizon.

Around 20 per cent of the responses were filtered in any given survey wave, leaving us with 35,961 responses and 4,971 respondents. A comparison of the

[13]Detailed descriptions are provided in Section S8 of the Online Supplement.

demographic characteristics of the filtered and unfiltered samples is provided in Table S1 in the Online Supplement and shows only minor differences between the two. The frequency distribution of monthly participation of the respondents in the filtered sample is shown in Table 2. Just over a quarter of respondents (1,268) answered the DQ surveys for all the 11 waves (3 to 13), 50 per cent (2,453) answered 9 waves, suggesting a high degree of over-time participation of the respondents in the DQ surveys.

Table 2: **Empirical frequency distribution of participants by months**

Months	11	10	9	8	7	6	5	4	3	2	1
No.	1268	1933	2453	2779	3088	3331	3597	3860	4161	4520	4971
Per cent	25.51	38.89	49.35	55.90	62.12	67.01	72.36	77.65	83.71	90.93	100

The average and median number of months participated are 7.23 and 6, respectively.
The distribution is based on respondents who remained in the sample after the truncation filter is applied.

3.3 Socio-demographic characteristics of respondents:

For the purposes of the econometric analysis, we calculate respondent-specific time averages of the variables age, income and education. A summary of selected socio-demographic characteristics of the respondent sample is presented in Table 3. A detailed comparison of the socio-demographic characteristics of the respondents remaining in our sample and the US population are provided in the Online Supplement. The main differences are as follows:

- Female respondents are over-represented at 59 per cent as compared to 51 per cent for the entire US population.
- The age group 50 to 70 years old constitute a higher fraction of the ALP respondent sample compared to the US population.
- Roughly 2 per cent of the respondents identify as Asian or Pacific Islanders, the corresponding number for the entire US population is 5.4 per cent.
- ALP respondents have a higher educational level than the US population.

Table 3: **Summary statistics of respondent-specific time invariant characteristics**

Statistic	Mean	St. Dev.	Min	Median	Max
Age	47.80	15.50	16	49	94
Family income[1] ($)	52,470	36,627	5,000	45,000	200,000
Female (%)	0.59	0.49	0	1	1
Asian (%)	0.02	0.14	0	0	1
Black (%)	0.11	0.31	0	0	1
Hispanic/Latino (%)	0.19	0.39	0	0	1
Education Index[2]	1.33	0.57	0	1	2

All statistics are based on the sample of 4,971 respondents.
[1] - note that incomes higher than 200,000 were coded as equal to 200,000
[2] - respondent's education averaged over the time period the respondent participated in the survey, where education is equal to 0 if the respondent has no high school diploma, 1 if the respondent is a high school graduate with a diploma, some college but no degree, an associate degree in college occupational/vocational or academic program, and 2 if the respondent has a Bachelor's degree or higher.

- Households with an annual income higher than $125,000 are under-represented in the ALP respondent sample.

3.4 Geographic location of respondents

Around 20 per cent of the respondents in any given survey wave resided further than 500 miles away from a major metropolitan area, and were thus given the median US house price instead of the local house price in the survey section on house prices. From the sample of 4,971 respondents, we could match exactly 4,000 to a Metropolitan Statistical Area. We achieved this using the information about the respondent's city and state of residence, provided in the survey. Information on the geographical distribution of the respondents as compared to the population density of the US are provided in the Online Supplement. Overall, we find that the geographical distribution of the respondents over time is relatively stable and match closely the national distribution for the six out of the eight regions. The exceptions are South East and South West. Survey respondents are underrepresented in the South East region and over-represented in the South West region.

Overall, the above comparative analysis suggests that the DQ sample of respondents are fairly typical of the US population and provide a reasonable mix of individuals with different demographic and location characteristics. Furthermore, to allow for unobserved characteristics of individual respondents (such as their optimistic or pessimistic disposition) we focus primarily on the fixed effects estimates and report the full set of random effect estimates in the Online Supplement.

4 Price change expectations and valuation indicators

We are now in a position to provide empirical evidence on the importance of individual asset valuations, V_{it}, on expected prices changes, as set out in (17). Bearing in mind the survey questions, for equity and gold prices the expected rate of price change is defined by $\hat{\pi}^e_{i,t+h|t} = 100(P^e_{i,t+h|t} - 1000)/(1000h)$, and for house prices it is computed as $\hat{\pi}^e_{i,t+h|t} = 100(P^e_{i,t+h|t} - P^0_{it})/(hP^0_{it})$, where $P^e_{i,t+h|t}$ is the i^{th} respondent's price expectation formed at time t for h months ahead, and P^0_{it} is the house price provided to the respondent i at time t. We assume that

$$\pi^e_{i,t+h|t} = \hat{\pi}^e_{i,t+h|t} + \eta_{i,t+h}, \tag{18}$$

where $\eta_{i,t+h}$ is the error associated with the measurement of $\pi^e_{i,t+h|t}$. Using responses to the first question of the surveys we measure $sign\,(V_{it})$, by x_{it} with $x_{it} = 1$ if respondent i at time t believes the asset is over-valued (*i.e.* $V_{it} > 0$), $x_{it} = -1$ if respondent i at time t believes the asset is under-valued ($V_{it} < 0$), and $x_{it} = 0$, otherwise. We then approximate V_{it} by $\phi_i x_{it}$, with $\phi_i > 0$, is a scalar constant. Using (18) in (17) and setting $V_{it} = \phi_i x_{it}$ we obtain the following interactive fixed-effects panel data model with individual effects, $\alpha_i^{(h)}$, heterogeneous slopes, $\beta_i^{(h)} = h^{-1}\,(1+r)^h\,\phi_i$

$$\hat{\pi}^e_{i,t+h|t} = \alpha_i^{(h)} - \beta_i^{(h)} x_{it} + u_{it}^{(h)} - \eta_{i,t+h}. \tag{19}$$

Since the time dimension of the panel is short we can not identify the individual slope effects, $\beta_i^{(h)}$. Instead we focus on estimation of the mean effect of x_{it} on $\hat{\pi}^e_{i,t+h|t}$ by assuming the following random effects specification for ϕ_i

$$\phi_i = \phi + \zeta_i, \tag{20}$$

where ζ_i is assumed to be distributed independently of x_{it} and the composite error $u_{it}^{(h)} - \eta_{i,t+h}$. Substituting (20) in (19) we now obtain

$$\hat{\pi}^e_{i,t+h|t} = \alpha_i^{(h)} + \beta^{(h)} x_{it} + \varepsilon_{i,t+h}, \tag{21}$$

where

$$\beta^{(h)} = -\frac{\phi\,(1+r)^h}{h}, \text{ and } \varepsilon_{i,t+h} = u_{it}^{(h)} - \frac{(1+r)^h}{h}\zeta_i x_{it} - \eta_{i,t+h}. \tag{22}$$

Under the above assumptions x_{it} and $\varepsilon_{i,t+h}$ are uncorrelated, and $\beta^{(h)}$ can be estimated consistently using fixed effects estimation that allows for arbitrary correlations between the individual effects, $\alpha_i^{(h)}$, x_{it} and the error term, $\varepsilon_{i,t+h}$. We also allow for common (economy-wide) effects on individual expectations by including a time effect in (21), which gives the following fixed-effects, time-effects (FE-TE) panel regression

$$\hat{\pi}^e_{i,t+h|t} = \alpha_i^{(h)} + \delta_t^{(h)} + \beta^{(h)} x_{it} + \varepsilon_{i,t+h}. \tag{23}$$

This is a reasonably general framework that allows for random errors in measurement of expectations, random heterogeneity in the scale parameters ϕ_i, and possible time effects. We also use robust standard errors for the FE-TE estimates of $\beta^{(h)}$, that allow for serial correlation in the errors, $\varepsilon_{i,t+h}$, and cross-sectional heteroskedasticity

We provide estimates of $\beta^{(h)}$ for the three different asset classes, and for all the three horizons, $h = 1, 3$, and 12, separately. We use the full set of responses which yields an unbalanced panel and estimate (23) with and without time effects, allowing the individual effects, $\alpha_i^{(h)}$, to be correlated with $\varepsilon_{i,t+h}$ (and hence with its components, $\zeta_i x_{it}$, $u_{it}^{(h)}$, and $\eta_{i,t+h}$). We report FE and FE-TE estimates of $\beta^{(h)}$, together with standard errors robust to serially correlated and heteroskedastic errors in Table 4.

Table 4: **Estimates of $\beta^{(h)}$ in the panel regressions of individual expected price changes on their belief valuation indicators for different assets (equation (23))**

	Equity		Gold		Housing	
Horizons	FE	FE-TE	FE	FE-TE	FE	FE-TE
One Month	-0.0991	-0.126	0.602***	0.581***	-0.292***	-0.303***
Ahead ($h = 1$)	(0.127)	(0.128)	(0.197)	(0.198)	(0.0643)	(0.0642)
Three Months	-0.0905	-0.0995	0.222**	0.203*	-0.106***	-0.109***
Ahead ($h = 3$)	(0.0760)	(0.0760)	(0.108)	(0.109)	(0.0273)	(0.0274)
One Year	-0.115***	-0.117***	-0.0226	-0.0316	-0.0481***	-0.0479***
Ahead ($h = 12$)	(0.0365)	(0.0364)	(0.0488)	(0.0489)	(0.0102)	(0.0102)

Dependent variable: $\hat{\pi}^e_{i,t+h|t}$. FE and FE-TE estimates are computed based on equation $\hat{\pi}^e_{i,t+h|t} = \alpha_i^{(h)} + \beta^{(h)} x_{it} + u_{it}^{(h)}$ with an unbalanced panel of 4,971 respondents over 11 months, March 2012 to January 2013. $N = 35,961$, $T_{min} = 1$, $\bar{T} = 7.23$, $T_{max} = 11$ Standard errors are in parentheses, *, ** and *** denote statistical significance at 10%, 5% and 1% levels, respectively. Standard errors are robust to heteroskedasticity and residual serial correlation.

The FE estimates of $\beta^{(h)}$ for equity price expectations are statistically insignificant for $h = 1$ and 3, but become statistically significant and negative for $h = 12$. These results are in line with our theoretical findings and suggest that over the sample under consideration equity price expectations and belief valuations are consistently related. However, the same is not true of the results for gold prices, where $\beta^{(h)}$ is estimated to be positive and statistically significant for $h = 1$ and 3, and suggest that respondents might view gold prices to be over-valued and still expect gold prices to rise. Interestingly enough, even for gold prices $\beta^{(h)}$ stops being statistically significant for $h = 12$, suggesting the short term nature of the misalignment between expectations and valuations. By contrast, the estimates of $\beta^{(h)}$ for house prices are much more coherent across h and are all negative and statistically highly significant. Also, FE estimates of $\beta^{(h)}$ for house prices fall with h, as predicted by the theory. Similar conclusions are obtained if the FE-TE estimates are considered.

Although, the scaling parameter ϕ is not identified, an estimate of r, the discount rate can be obtained using any two of the estimates $\hat{\beta}^{(h_1)}$ and $\hat{\beta}^{(h_2)}$, so long as $|\hat{\beta}^{(h_1)}| > |\hat{\beta}^{(h_2)}|$.[14] For example, using the FE-TE estimates for one and three months ahead expectations, $\hat{\beta}^{(1)}$ and $\hat{\beta}^{(3)}$, we obtain $\hat{r} = 3.9\%$, which seems quite reasonable. Estimates of r based on other combinations of $\hat{\beta}^{(h_1)}$ and $\hat{\beta}^{(h_2)}$ yield similar but higher estimates of r.[15]

Overall, the panel estimates support the predictions of the heterogeneous agent model developed in Section 2, and suggest a strong relationship between respondent's housing price expectations and their valuations which is shown to be equilibrating, at least over the period under consideration. The same cannot, however, be said about the gold price expectations. This could be due to the fact that respondents are likely to have more first hand knowledge and experience about house prices as compared to international gold prices. The results for equity prices are ambiguous; there are no statistically significant relationship between equity price expectations and valuations at one month and three months horizons, which is in line with the prediction of a representative agent model. Nevertheless, for one year horizons asset valuations seem to play a significant role in respondent's price expectations formation process.[16]

4.1 Effects of individual-specific characteristics on price expectations

So far we have focused on the effects of valuations on price expectations, and by using interactive fixed effects panel data set up, we have shown our results to be robust to individual-specific heterogeneity. But it is also of interest to investigate possible effects of individual-specific characteristics of respondents on their price expectations. For example, Niu and Van Soest (2014) explore

[14] Specifically, using $\beta^{(h)} = -h^{-1}\phi\,(1+r)^h$ we have $\hat{r}(h_1, h_2) = \left(\frac{h_1}{h_2}\frac{\hat{\beta}^{(h_1)}}{\hat{\beta}^{(h_2)}}\right)^{\frac{1}{h_1-h_2}} - 1.$.

[15] See Table S21 in the Online Supplement for further details.

[16] In the Online Supplement we also provide estimates of $\beta^{(h)}$ across different sub-groups such as male and female, home-owners and renters, and find that our main conclusion continues to hold. See Sections S14 and S19 of the Online Supplement.

the relationship between house price expectations, local economic conditions, and individual household characteristics. Bover (2015) uses house price expectations data from the Spanish Survey of Household Finances, and finds important differences in expectations across gender and occupation. Kuchler and Zafar (2015) use data from Survey of Consumer Expectations and focus on how personal experiences affect expectations at the national level. They find that experiencing a house price fall leads respondents to be more pessimistic about future US house prices.

The above studies all point to important systematic differences in price expectations across respondents. Similar disparities in expectations are also present in our surveys. Using the information in demographic modules of ALP, we considered the effects of sex, age, income, ethnicity and education on price expectations. Given the time-invariant nature of the demographic variables, there are two ways that this can be done. One possibility would be to augment the panel regressions in (23) with the observed individual-specific effects, and then treat $\alpha_i^{(h)}$ as random effects, distributed independently of x_{it}. Setting $\alpha_i^{(h)} = \alpha^{(h)} + \mathbf{z}_i'\boldsymbol{\gamma}^{(h)} + \psi_i^{(h)}$, where $\mathbf{z}_i$ is the vector of time-invariant observed characteristics of the i^{th} respondent, $\psi_i^{(h)}$ is the unobserved random component of $\alpha_i^{(h)}$ assumed to be distributed independently of $\mathbf{z}_i$ and x_{it}. The associated random effects panel data model can now be written as

$$\hat{\pi}^e_{i,t+h|t} = \alpha^{(h)} + \delta_t^{(h)} + \mathbf{z}_i'\boldsymbol{\gamma}^{(h)} + \beta^{(h)}x_{it} + \varepsilon_{i,t+h} + \psi_i^{(h)}. \tag{24}$$

We consider model (24) both with and without time effects $\delta_t^{(h)}$. For the elements of $\mathbf{z}_i = (z_{i1}, z_{i2}, ..., z_{i7})'$, we consider $z_{i1} = 1$ if the respondent identifies as female, and 0 otherwise, $z_{i2} = \ln age_i$, z_{i3} measures the education level of respondent i, $z_{i4} = \ln \text{income}_i$, and z_{i5} to z_{i7} are dummy variables that take the value of 1 if the respondent identifies her/himself as Asian, Black and Hispanic/Latino, respectively. For a detailed description of how the time-invariant variables are constructed see the Online Supplement. We allow $\varepsilon_{i,t+h} + \psi_i^{(h)}$ to be serially correlated and heteroskedastic.

An alternative approach, that does not require $\psi_i^{(h)}$ and x_{it} to be independently distributed, is to employ the two-stage approach proposed recently in Pesaran and Zhou (2016), whereby in the first stage FE (or FE-TE) estimates of $\beta^{(h)}$ are used to filter out the effects of x_{it}, and in the second stage a pure cross section regression of $\bar{\hat{u}}_i$ is run on an intercept and z_i, for $i = 1, 2, ..., N$, where

$$\bar{\hat{u}}_i = \frac{\sum_{t=1}^{T} s_{it}\left(\hat{\pi}^e_{i,t+h|t} - \hat{\beta}^{(h)}_{FE-TE} x_{it}\right)}{\sum_{t=1}^{T} s_{it}},$$

and s_{it} is an indicator variable which takes the value of 1 if respondent i is included in wave t of the survey and 0 otherwise. This estimator is referred to as the FE filtered estimator and denoted by $\hat{\boldsymbol{\gamma}}^{(h)}_{FEF}$ (or $\hat{\boldsymbol{\gamma}}^{(h)}_{FEF-TE}$). Pesaran and Zhou (2016) provide standard errors for $\hat{\boldsymbol{\gamma}}^{(h)}_{FEF}$ that allow for the sampling uncertainty of $\hat{\beta}^{(h)}_{FE}$ (or $\hat{\beta}^{(h)}_{FE-TE}$), and possible error heteroskedasticity.

The FE filtered and RE estimates of $\boldsymbol{\gamma}^{(h)}$ and their robust standard errors are summarized for equity, gold and house price expectations in the Online Supplement in Tables S12, S13 and S14, respectively. For completeness we also report the estimates of $\beta^{(h)}$, although, as noted earlier, the RE estimates are not robust to possible correlations between η_i and x_{it}. The FE estimates of $\beta^{(h)}$ in Tables S12-S14 are the same as those already reported in Table 4. Inclusion of time dummies had little impact on the RE or FE estimates (the FE-TE estimates are reported in the Online Supplement). But we find it matters a great deal, particularly to the regressions for house price expectations, if we did include a location (MSA) dummy in the regressions. As noted earlier, we have been able to identify the MSA within which a respondent resides from the demographic module of the survey and the house price information that was provided to the respondents. This additional information (often absent in other survey expectations) allows us to separate the location-specific nature of house price changes from respondent-specific characteristics.

Comparing RE and FE estimates of $\beta^{(h)}$ we note that they are generally quite close, although the RE estimates tend to be larger in absolute magnitude, and more statistically significant. Judging by the implied estimates of r, and the fact that FE estimates are robust to possible correlations between x_{it} and η_i, the FE estimates are clearly to be preferred. But it is worth noting that our main conclusion that the valuation indicator plays a significant role in price expectations formation holds irrespective of whether RE or FE estimates are used. Also, RE estimates of $\beta^{(h)}$ are robust to the inclusion of location dummies.[17]

Regarding the effects of individual-specific characteristics on price expectations, we find important differences across assets. For equity prices sex, age and education are statistically significant at all three horizons and irrespective of whether RE or FE filtered estimates are considered. Ethnicity also features significantly for 3 and 12 months horizons. Females tend to have higher equity price expectations, whilst older respondents, and those with a higher level of income, tend to have lower equity price expectations. But it is interesting that the estimates and their statistical significance are hardly affected by the inclusion of location and/or time dummies (the latter results reported in the Online Supplement). Similar results are obtained for gold price expectations where in addition to sex, age, income and ethnicity, education is also statistically significant, with higher educated respondents having lower price expectations of gold prices.

The picture is very different when we consider regressions for house price expectations (in Table S14). Generally speaking, the respondent-specific characteristics are not as significant as compared to the equity and gold price regressions, and the test outcomes critically depend on the estimator and whether the regressions include location dummies. Using the preferred FE filtered estimates and considering the regressions with MSA dummies, we find that only income is statistically significant (with a positive sign) in the case of regressions for one month ahead, and ethnicity for the one year expectations. The heterogeneity of house price expectations across respondents seem to be largely explained by the location dummy once we condition on the valuation indicator, and all other respondent-specific characteristics loose their

[17] Note that the FE estimates are unaffected by respondent-specific characteristics, including their location.

statistical significance.[18]

5 Constructing leading indicators of bubbles and crashes from DQ surveys

The equilibrium relation between expected price changes and the valuation indicator in (17) can also be used to construct time series indicators of bubbles and crashes at the level of individual respondents, that can then be aggregated at regional or national levels. Such indicators are likely to provide valuable information about the possibility of bubbles or crashes building up, and could prove useful as predictors of realized price changes. In what follows we suggest such indicators.

We begin with respondent-specific indicators and for each horizon h consider individual i^{th} responses to the DQ surveys that contradict the theoretical relations between $\hat{\pi}^{e}_{i,t+h|t}$ and x_{it}, namely when respondent's valuation belief and price change expectations do not match the pattern predicted by (17), which is derived assuming an equilibrating mechanism. Accordingly, we define the bubble indicator for respondent i at time t for h periods ahead by $B_{i,t+h|t} = I[(x_{it} > 0) \cup (\hat{\pi}^{e}_{i,t+h|t} \geq 0)]$, and the crash indicator by $C_{i,t+h|t} = I[(x_{it} < 0) \cup (\hat{\pi}^{e}_{i,t+h|t} \leq 0)]$. Specifically, a respondent is said to be in a bubble (crash) state if he/she believes the asset under consideration is overvalued (undervalued) but at the same time expects prices to rise (fall) or stay the same. Therefore, $B_{i,t+h|t} = 1$ (or $C_{i,t+h|t} = 1$) if respondent i is in bubble (crash) state and 0 otherwise.

The proportion of respondents with non-zero bubble and crash indicators are summarized in Table 5. The results are summarized for all respondents and by gender. The proportion of respondents in bubble and crash states are relatively small for equity and house prices, but not for gold. The proportion of respondents who believe gold prices are over-valued and nevertheless expect

[18] A similar result is also reported in Bover (2015) who shows that most of the observed heterogeneity in house price expectations can be explained by a location dummy at the postal code level.

gold prices to rise over the next month is around 47 per cent, as compared to 24 per cent for equity prices and 16 per cent for house prices. In all cases the proportion of respondents in bubble state falls with horizon, and beliefs and expectations are more likely to be aligned with our theoretical prediction when expectations are considered over longer horizons. These results are in line with the regression estimates reported in Table 4, where we find positive and statistically significant estimates of $\beta^{(h)}$ only for gold prices and only at one month and three months horizons. Finally, the proportion of respondents in bubble and crash states do not differ much by gender, which is interesting considering the statistically significant gender effect observed on expectations in the case of equity and gold prices.[19]

The time profiles of bubble and crash indicators can be aggregated across respondents and related to realized price changes. But since the survey results are available only over a very short time period, a time series evaluation of the usefulness of such indicators is not possible. Instead we consider a related question of whether spatially disaggregated bubble and crash indicators can help explain the cross-section variations of realized house price changes across five US regions, and more formally across 48 Metropolitan Statistical Areas (MSAs). We begin by illustrating the evolution of the bubble and crash indicators along with realized house price changes across the US mainland regions Northeast, Southeast, Midwest, Southwest and West, as defined by the National Geographic Society.[20] Region-specific bubble and crash indicators are defined by simple averages of the individual responses averaged over the respondents that reside in region r, namely

$$B_{r,t+h|t} = \frac{\sum_{i\in\Theta_{rt}} B_{i,t+h|t}}{\#\Theta_{rt}},\ C_{r,t+h|r} = \frac{\sum_{i\in\Theta_{rt}} C_{i,t+h|t}}{\#\Theta_{rt}} \tag{25}$$

where Θ_{rt} denotes the set of respondents in region r at time t. The regional bubble and crash indicators can then be related to realized house prices

[19] Females tend to have higher price expectations as compared to male respondents. See the estimates reported in Section S17 of the Online Supplement.

[20] https://www.nationalgeographic.org/maps/united-states-regions/ See Section S10 in the Online Supplement for an exact specification of the regions.

Table 5: **Respondents in bubble and crash states by gender**

	(a) Equity								
	One Month			Three Months			One Year		
	Total	Female	Male	Total	Female	Male	Total	Female	Male
Bubble	8700	4804	3896	8084	4542	3542	7949	4519	3430
(%)	*24.19*	*23.32*	*25.37*	*22.48*	*22.05*	*23.06*	*22.10*	*21.93*	*22.33*
Crash	3549	2422	1127	2168	1523	645	1177	836	341
(%)	*9.87*	*11.76*	*7.34*	*6.03*	*7.39*	*4.20*	*3.27*	*4.06*	*2.22*
Neither	23712	13376	10336	25709	14537	11172	26835	15247	11588
(%)	*65.94*	*64.93*	*67.30*	*71.49*	*70.56*	*72.74*	*74.62*	*74.01*	*75.45*
	(b) Gold								
	One Month			Three Months			One Year		
	Total	Female	Male	Total	Female	Male	Total	Female	Male
Bubble	16891	9561	7330	15437	8884	6553	13971	8224	5747
(%)	*46.97*	*46.41*	*47.72*	*42.93*	*43.12*	*42.67*	*38.85*	*39.92*	*37.42*
Crash	1116	799	317	699	533	166	473	369	104
(%)	*3.10*	*3.88*	*2.06*	*1.94*	*2.59*	*1.08*	*1.32*	*1.79*	*0.68*
Neither	17954	10242	7712	19825	11185	8640	21517	12009	9508
(%)	*49.93*	*49.71*	*50.21*	*55.13*	*54.29*	*56.25*	*59.83*	*58.29*	*61.91*
	(c) Housing								
	One Month			Three Months			One Year		
	Total	Female	Male	Total	Female	Male	Total	Female	Male
Bubble	5720	3370	2350	5147	3037	2110	5189	3077	2112
(%)	*15.91*	*16.36*	*15.30*	*14.31*	*14.74*	*13.74*	*14.43*	*14.94*	*13.75*
Crash	6322	3954	2368	4861	3053	1808	3000	1896	1104
(%)	*17.58*	*19.19*	*15.42*	*13.52*	*14.82*	*11.77*	*8.34*	*9.20*	*7.19*
Neither	23919	13278	10641	25953	14512	11441	27772	15629	12143
(%)	*66.51*	*64.45*	*69.28*	*72.17*	*70.44*	*74.49*	*77.23*	*75.86*	*79.06*

The statistics are calculated using a sample of 35,961 responses, with 15,359 male and 20,602 female responses. Male and female responses represent 43% and 57% of the sample, respectively. The percentages in the table are column percentages and sum to 100 % for each column.

changes in these regions. In what follows we first show how the balance of these regional indicators lagged three months, defined by $BC_{r,t+h-3|t-3} = B_{r,t+h-3|t-3} - C_{r,t+h-3|t-3}$, can be viewed as leading indicators of future realized house price changes, π_{rt}. For illustrative purposes we also average the balance statistics over the horizons $h = 1, 3$ and 12, and focus on the relationship between $\overline{BC}_{r,t-3} = (1/3)\sum_{h=1,3,12}\left(B_{r,t+h-3|t-3} - C_{r,t+h-3|t-3}\right)$ and realized house price changes π_{rt} for the US as a whole and the five regions. Figure 1 shows the plots of $\overline{BC}_{r,t-3}$ and π_{rt} over the 11 months from July 2012 to May 2013 for the US as a whole and the five regions. As can be seen the balance statistics, $\overline{BC}_{r,t-3}$, track reasonably well the evolution of house price changes three months ahead for all five regions.

6 Bubble and crash indicators and realized house price changes across MSAs

Given the promising graphical results in the previous section, we develop a dynamic panel data model of realized house price changes and bubble and crash indicators across 48 MSAs. Specifically, we define thee bubble and crash indicators for MSA s at time t for h periods ahead as

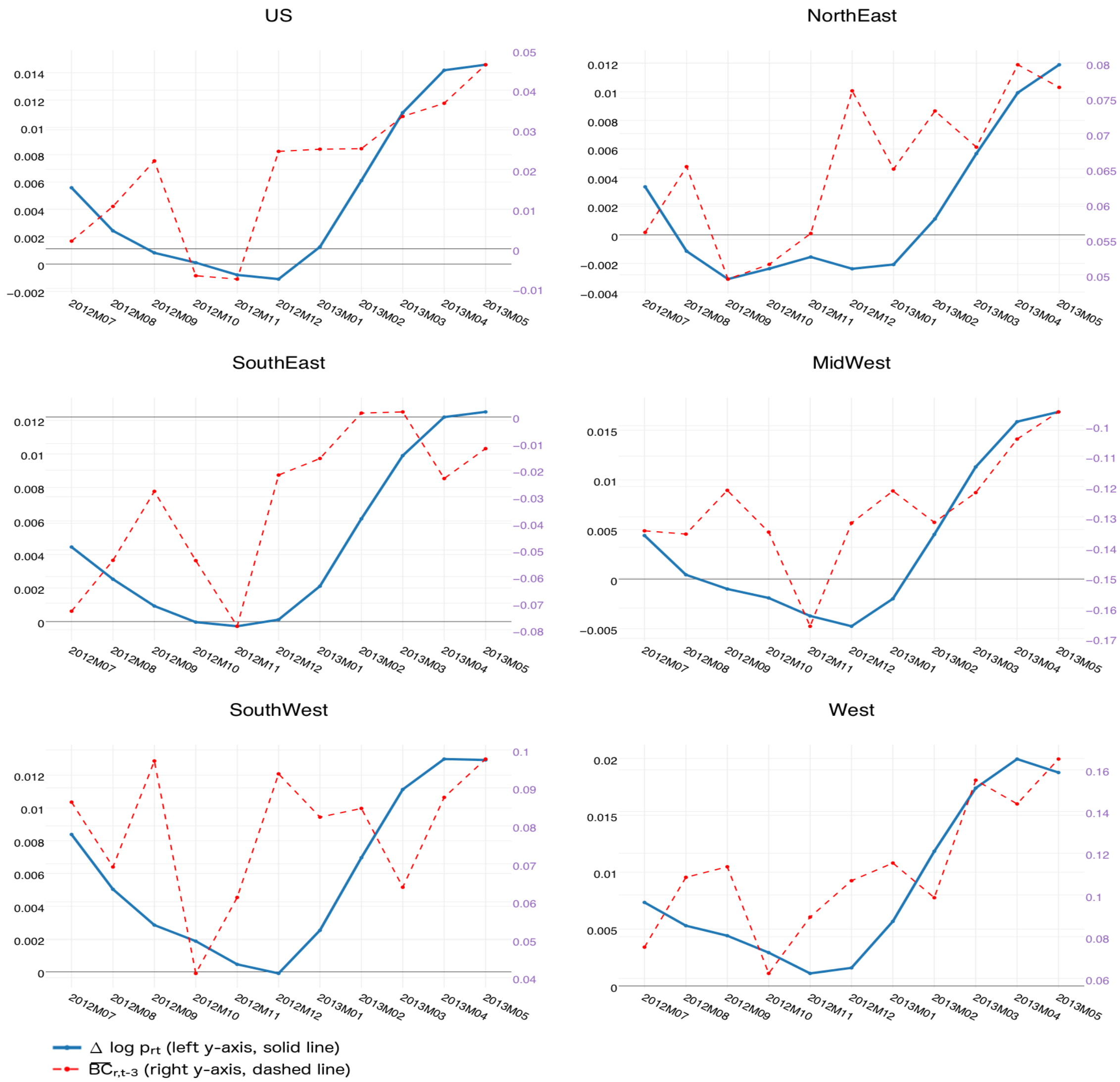
$$B_{s,t+h|t} = \frac{\sum_{i_t \in \Theta_{st}} B_{i,t+h|t}}{\#\Theta_{st}}, \text{ and } C_{s,t+h|t} = \frac{\sum_{i_t \in \Theta_{st}} C_{i,t+h|t}}{\#\Theta_{st}}.$$

where Θ_{st} denotes the set of respondents in MSA s at time t. For each MSA s, we also define bubble and crash indicators of neighboring areas as follows. Let $\mathbf{W} = \{w_{ss'}\}_{s,s'=1,2,\ldots,N}$ denote an $N \times N$ matrix with $w_{ss'} = 1$ if MSAs s and s' lie in neighboring areas, and $w_{ss'} = 0$, otherwise. $w_{ss'}$ is determined based on the Haversine distance between the geographic centers of MSAs s and s'. See Section S11 in the Online Supplement for further details. The neighboring area bubble and crash indicators for MSA s in month t are defined by

$$B^*_{s,t+h|t} = \frac{\sum_{s'=1}^{N} w_{ss'} B_{s,t+h|t}}{\sum_{s'=1}^{N} w_{ss'}}, \text{ and } C^*_{s,t+h|t} = \frac{\sum_{s'=1}^{N} w_{ss'} C_{s,t+h|t}}{\sum_{s'=1}^{N} w_{ss'}}.$$

We now consider the statistical significance of the above indicators for explanation of realized house price changes across the 48 MSAs over the 11 survey waves. As a bench mark model we consider the following standard

Figure 1: Realized house price changes and three months lagged values of balanced bubble-crash indicators by regions



dynamic panel regression model for expectation horizons $h = 1, 3, 12$ months.

$$M_1 : \pi_{s,t+1} = \alpha_s^{(h)} + \lambda_0^{(h)} \pi_{st} + \lambda_1^{(h)} \hat{\pi}^e_{s,t+h|t} + u_{s,t+1,h}, \text{ for } h = 1, 3, 12, \tag{26}$$

where $\pi_{s,t+1} = 300 \left[\ln(P_{s,t+1}) - \ln(P_{st}) \right]$ is the one month ahead realized house price change in MSA s (expressed in per cent per quarter), and $\hat{\pi}^e_{s,t+h|t}$ is the expected house price change formed in month t for h months ahead, and averaged across the respondents in MSA s. Specifically

$$\hat{\pi}^e_{s,t+h|t} = \frac{\sum_{i_t \in \Theta_{st}} \hat{\pi}^e_{i,t+h|t}}{\#\Theta_{st}}.$$

Given the importance of location in the formation of house price expectations discussed above, we also allow for MSA-specific fixed effects, $\alpha_s^{(h)}$, in the benchmark model. We then augment the benchmark model (26), with the MSA-specific bubble and crash indicators. We consider the following specification

$$\begin{aligned} M_2 \quad : \quad \pi_{s,t+1} &= \alpha_s^{(h)} + \lambda_0^{(h)} \pi_{st} + \lambda_1^{(h)} \hat{\pi}^e_{s,t+h|t} + \delta_1^{(h)} B_{s,t+h|t} + \delta_2^{(h)} C_{s,t+h|t} \\ &\quad + \gamma_1^{(h)} B^*_{s,t+h|t} + \gamma_2^{(h)} C^*_{s,t+h|t} + u_{s,t+1,h}. \end{aligned} \tag{27}$$

To isolate the importance of the bubble and crash indicators from the price expectations we also estimate (27), without the expectations variable, $\hat{\pi}^e_{s,t+h|t}$, which we denote as model M_3.

All three specifications are estimated using a balanced panel of observations over $N = 48$ MSAs, and $T = 9$ months, namely for $s = 1, 2, \ldots, 48$, and $t =$ June 2012 - February 2013. First-differencing is applied to eliminate the MSA-specific effects. Note that standard FE estimation of dynamic panel regressions will not be appropriate since T is small relative to N, and FE estimates can lead to significant bias due to the presence of the lagged dependent variable in the panel regressions. After first-differencing we estimate the parameters by the two-step Generalized Method of Moments (GMM) method due to Arellano and Bond (1991), using the following moment conditions:[21]

$$E\left(\Delta u_{s,t+1,h}\mathbf{z}_{s,j}\right)=\mathbf{0}, \text{ for } j=t-2,t-1; t=5(\text{June } 2012),6,...,13(\text{February } 2013); \tag{28}$$

where we set $\mathbf{z}_{s,j}=\left(\pi_{s,j},\hat{\pi}^e_{s,j+h|j}\right)'$, for the baseline model M_1,

$$\mathbf{z}_{s,j}=\left(\pi_{s,j},\hat{\pi}^e_{s,j+h|j},B_{s,j+h|j},C_{s,j+h|j},B^*_{s,j+h|j},C^*_{s,j+h|j}\right)', \text{ for model } M_2,$$

and

$$\mathbf{z}_{s,j}=\left(\pi_{s,j},B_{s,j+h|j},C_{s,j+h|j},B^*_{s,j+h|j},C^*_{s,j+h|j}\right)', \text{ for model } M_3.$$

The estimation results are summarized in Table 6. Note that we are primarily interested in the explanatory power of house price inflation expectations, $\hat{\pi}^e_{s,t+h|t}$, and the crash and bubble indicators $B_{s,t+h|t}$, $C_{s,t+h|t}$, $B^*_{s,t+h|t}$, and $C^*_{s,t+h|t}$. The lagged value of realized house price changes, π_{st}, is included in the analysis to take account of the high degree of known persistence in realized price changes. Consider first the estimates for the baseline model, M_1. As expected, $\lambda_0^{(h)}$ which measure the degree of persistence in the rate of house price changes, is estimated to be quite high and lies in the range $0.70-0.80$, and is statistically significant at all horizons. The coefficient of house price expectations formed at t, $\lambda_1^{(h)}$, is also statistically significant but its magnitude is disappointingly low, and in fact becomes negative for $h=12$. In contrast, the bubble and crash indicators, included in model M_2, are statistically significant and have the correct signs for all horizons, $h=1,3$, and 12. For $h=1$, the panel regressions predict that MSAs with a higher bubble indicator tend to experience a higher degree of house price changes, and MSAs with a higher crash indicator tend to experience a lower degree of house price changes.[22] It

[21] Note that we do not use all available moment conditions suggested by Arellano and Bond (1991), to avoid the weak instrument problem.

[22] It is also interesting to note that estimated coefficients of crash indicators tend to be larger than those of the bubble indicators. But this could partly reflect the fact that over the survey period the proportion of respondents in the crash state is generally smaller than the proportion of respondents in the bubble state.

is also most interesting that similar effects are observed from spillover bubble and crash indicators, in the sense that MSAs that are surrounded by neighboring MSAs with a high (low) value of the bubble (crash) indicator also tend to show a higher (lower) degree of house price changes. The effects of changes in bubble and crash indicators on future house price changes get accentuated due to the fact that in general the bubble and crash indicators move in opposite directions. Finally, these results continue to hold even if the price expectations variable is dropped from the analysis. See the estimates under columns M_2 and M_3 in Table 6

Table 6: **Dynamic panel regressions of realized house prices by MSAs (Across 48 MSAs and months June 2012 to February 2013)**

	One Month ($h = 1$)			**Three Months** ($h = 3$)			**One Year** ($h = 12$)		
	M_1	M_2	M_3	M_1	M_2	M_3	M_1	M_2	M_3
π_{st}	0.712***	0.765***	0.771***	0.704***	0.736***	0.741***	0.721***	0.792***	0.798***
	(0.00872)	(0.00555)	(0.00564)	(0.00772)	(0.00732)	(0.00346)	(0.00528)	(0.00521)	(0.00675)
$\hat{\pi}^e_{s,t+h\|t}$	0.0159***	-0.0118**		0.0513***	-0.0115		-0.0924***	-0.247***	
	(0.00231)	(0.00521)		(0.00697)	(0.0123)		(0.0217)	(0.0490)	
$B_{s,t+h\|t}$		2.018***	1.669***		2.921***	2.841***		1.825	2.174***
		(0.637)	(0.504)		(1.020)	(0.971)		(1.158)	(0.663)
$C_{s,t+h\|t}$		-8.623***	-8.836***		-8.395***	-8.638***		-14.36***	-13.02***
		(0.736)	(0.680)		(0.622)	(0.593)		(1.659)	(1.583)
$B^*_{s,t+h\|t}$		3.529***	3.742***		8.410***	8.401***		3.452***	3.564***
		(0.650)	(0.874)		(0.991)	(0.927)		(0.543)	(0.696)
$C^*_{s,t+h\|t}$		-11.84***	-11.99***		-9.669***	-10.04***		-16.83***	-18.84***
		(0.874)	(0.656)		(1.245)	(1.198)		(1.470)	(2.270)

Dependent variable: $\pi_{s,t+1}$ (in per cent per quarter). The panel regression is estimated using a two-step GMM estimator (Arellano and Bond (1991)) using the moment conditions specified in Section S5 with heteroskedasticity-robust standard errors. Observations from the first two survey waves April to May 2012 are used to initialize moment conditions. The estimates are based on a balanced panel with $N = 48$ and $T = 9$. Standard errors are in parentheses, *, ** and *** denote statistical significance at 10%, 5% and 1% levels.

The estimates clearly show that bubble and crash indicators and the associated neighboring indicators play an important role in future movements of realized house price changes across MSAs. For example, the estimates of model M_2 for the one month expectation horizon imply that an increase in the bubble indicator from 0.2 to 0.5 leads to a 0.87 percentage point increase in the quarterly growth rate of house prices. A rise in crash indicators has the opposite effect and depresses future house prices.

Finally, the explanatory value of bubble and crash indicators seems to be robust to averaging the indicators across the three horizons and/or introducing a longer lag between when the indicators are observed and the target date of house price changes. Table 7 provides estimates based on the following dynamic panel regressions

$$\begin{aligned} M_4 \quad : \quad \pi_{s,t+1} &= \alpha_s^{(h)} + \lambda_0^{(h)}\pi_{st} + \lambda_1^{(h)}\hat{\bar{\pi}}_{st}^e + \delta_1^{(h)}\bar{B}_{s,t-2} + \delta_2^{(h)}\bar{C}_{s,t-2} \\ &+\gamma_1^{(h)}\bar{B}_{s,t-2}^* + \gamma_2^{(h)}\bar{C}_{s,t-2}^* + u_{s,t+1,h}, \end{aligned} \tag{29}$$

where $\hat{\bar{\pi}}_{st}^e = \frac{1}{3}(\hat{\pi}_{s,t+1|t}^e + \hat{\pi}_{s,t+3|t}^e + \hat{\pi}_{s,t+12|t}^e)$, $\bar{B}_{st} = \frac{1}{3}(B_{s,t+1|t} + B_{s,t+3|t} + B_{s,t+12|t})$, $\bar{C}_{st} = \frac{1}{3}(C_{s,t+1|t} + C_{s,t+3|t} + C_{s,t+12|t})$, and so on.[23] The results are in fact stronger and more robust as compared to those reported in Table 6. The coefficients of the average indicator variables are all statistically significant with the *a priori* expected signs. Most importantly, lagging the indicators by two months has not reduced their explanatory power for future changes in house prices across MSAs.

Table 7: **Dynamic panel regressions of realized house prices by MSAs (Across 48 MSAs and months August 2012 to February 2013)**

π_{st}	0.765***	0.923***	0.913***
	(0.0141)	(0.0168)	(0.0124)
$\hat{\bar{\pi}}_{st}^e$	0.0318***	0.0904***	
	(0.00723)	(0.00664)	
$\bar{B}_{s,t-2}$		4.088***	4.071***
		(1.239)	(0.527)
$\bar{C}_{s,t-2}$		-11.51***	-11.36***
		(1.128)	(0.864)
$\bar{B}_{s,t-2}^*$		10.64***	11.73***
		(1.146)	(0.578)
$\bar{C}_{s,t-2}^*$		-9.897***	-10.54***
		(1.425)	(1.138)

Dependent variable: $\pi_{s,t+1}$ (in per cent per quarter).
See notes to Table 6 and Section S5 in the Online Supplement.

[23] See Section S5 in the Online Supplement for further details.

7 Concluding remarks

In this paper we have introduced a new type of survey which combines standard surveys of price expectations with questions regarding the respondents' subjective belief about asset values. Using a theoretical asset pricing model with heterogenous agents we show that there exists a negative relationship between the agents expectations of price changes and their asset valuation, a relationship that holds under different horizons. DQ surveys provide evidence in support of such relationships, particularly for house prices for which survey respondents are more likely to have a first-hand knowledge as compared to other assets such as equities or gold prices which might not be of concern to many respondents in the survey. We also investigate the effects of demographic factors, such as sex, age, education, ethnicity, and income on price expectations, and find important differences in price expectations. But, interestingly enough, for house price expectations demographic factors stop being statistically significant once we condition on the respondent's location and his/her valuation indicator. Finally, we show how the results of the DQ surveys can be used to construct leading bubble and crash indicators for use in forecasting and policy analyses. The potential value of such indicators is illustrated in a dynamic panel regression of realized house price changes across a number of key MSAs in the US.

We consider the DQ surveys carried out so far, and the analysis of the survey results that we have provided, as a prototype study which needs to be pursued further by government and international agencies, particularly central banks. It is only by further critical analysis and the conduct of similar surveys in the US and elsewhere that the true worth of results from DQ surveys as leading indicators of bubbles and crashes can be ascertained.

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