Appendix

Contents

Haessel's R^2

As a service to readers who are not familiar with the measure, we provide a brief explanation. It is not meant to replace the complete description of the measure (see Haessel 1978) or to review how it has been often used in studies of market bubbles (see Stöckl et al. 2010).

Haessel's R^2 is measure of goodness of fit, which assess the quantum of variance explained in linear or nonlinear models. It is an extension of the familiar coefficient of determination (R^2), but it removes certain limitations, such as the requirement to use an OLS models with an intercept (Haessel 1978, pp. 648-9). Mathematically, it is equal to the square of Pearson's product-moment correlation coefficient between prices and true values. Relying on the same procedure used extensively in past research (Stöckl et al. 2010), we calculated Haessel's R^2 by regressing period-averaged market prices on true values, which are constant within periods. This procedure filters out idiosyncratic trading errors — only correlated errors lower Haessel's R^2.

Haessel's R^2 is often used for assessing the size of market bubbles because it can measure the extent to which prices fit true values, which are exogenously determined by the stream of cash flow that the asset produces. In contrast, the familiar R^2 measure assess goodness-of-fit between a set of data points and a regression line, which is *endogenously* generated from those points (Dufwenberg et al. 2005, p. 1733).

In this context, Haessel's R^2 is the (market-level) coefficient of determination from a regression of market prices on true values of assets. It expresses the goodness of fit between the data (traded prices) and what they should have been — true values — using the familiar 0–1 range, where higher values represent better fit between market prices and true values.

The Possibility of Negative Bubbles

In an impactful manuscript, Blanchard (1982, p. 300) theorized "there cannot be negative bubbles". Strictly speaking, he is correct: If a price of an asset is negative, then the owner is better off without it. But perhaps bubbles can be said to exist when market prices undervalue an asset?

The notion that bubbles are defined by overvaluation (but not undervaluation) is present in some seminal works: Porter and Smith (2003, p. 7) define a bubble as "trading at prices *above* the fundamental value of an asset" (all italics ours). More recently, Harras and Sornette (2011, p. 137) model bubbles as episodes of "unsustainable *high* value".

The notion of bubbles as episodes of overpricing is present outside economics. For example, Abolafia (2010, pp. 93-4) turns to Stiglitz (1990, p. 13) to define bubbles as "a condition in which *prices are high*…when "fundamental" factors do not seem to justify such a price". The popular use of the term suggests overpricing, as in a Forbes Magazine (Dreman 1993) article describing a "bubble time" in the market for initial public offerings (IPOs), where companies that were "mere concepts" with little or no revenue were offered for unjustifiably high prices.

But even if negative bubbles are impossible, it does not imply that assets cannot be undervalued. That it, they are traded below their true value. Although true value is hard to determine outside the behavioral laboratory (which is one reason to use market experiments), students of financial economics have investigated cases in which assets appear to be systematically underpriced. One of the best-known examples is the pricing of initial public offerings (IPOs). Stock prices often rise sharply on the first day of trading, suggesting that the IPO

price was below the true value. Scholars continue to debate the causes and whether such undervaluation fits the definition of a bubble (Altınkılıç and Hansen 2003; Ljungqvist and Wilhelm Jr. 2003).

Besides IPOs, episodes of "negative bubbles" (Siegel 2003) — or, more precisely, systematic undervaluation — are said to have occurred in oil prices (Fantazzini 2016), real estate investment trusts (Payne and Waters 2005), and cryptocurrency (Fry and Cheah 2016). But other definitions allow for systematic mispricing in both positive and negative directions. For instance, Siegel (2003) presents operational definitions of (positive) bubble and a negative price bubble, arguing that some low points in the stock market were examples of the latter.

Nothing in our theory prohibits the possibility of negative bubbles. Indeed, empirically, valuation errors in our data are not always positive (see Figure 4 in the manuscript). In fact, the average valuation in the first round of the high ambiguity conditions (Study 1) is below true values. It just so happens that subsequent errors are more likely to be positive, leading to inflated prices.

Future research may investigate when undervaluation becomes more likely, complementing recent archival evidence (Naumovska et al. Forthcoming).

Statistical Power and Sample Size

As discussed in the manuscript, the first study consisted of 10 markets (experimental sessions) of 6 participants each (n=62), and the second study consisted of 10 additional markets (n=60). To reduce the risk of false positives, we determined the sample size in advance, using an *apriori* power calculation, conducted before results were known (Simmons et al. 2011). Power analysis was conducted using G*Power (Faul et al. 2009; Faul et al. 2007) and verified in R (R Core Team 2020).

Perhaps thanks to the power analysis, the sample (n=122 in 20 markets) is larger than those of most prior studies. In their studies, Smith, Suchanek, and Williams (1988) relied on markets of 9 or 12 participants, with an average of 5 markets per treatment (n=45 and 60). Dufwenberg, Lindqvist and Moore (2005) had two studies, each with 5 markets of 6 participants each per treatment (n=30). Levine and associates (2014, pp.

SI10-1) sampled across conditions and countries, using an average of 7.5 markets per condition, each with six participants (n=45). Levine, Bernard and Nagel (2017) had two studies, one consisting of 16 markets of 6 participants each (n=96), and the second study consisted of 9 markets (n=54), like ours.

After the results were obtained, we conducted a *post-hoc* power analysis. It confirmed that the sample was sufficiently powered to detect the effect that was found. The statistical code, power analysis results, and graphs are all available in the online materials and data depository (https://j.mp/marketsanderrors).

Illustrative Evidence: Theory, Social Influence, and Performance

One of the participants (No. 6 in session A7) appears an excellent theoretician: He completed the Pricing Questionnaire flawlessly, without a single error. Most participants (over 86%) could not match this accomplishment. Yet the knowledge did not translate to cash earned: When trading began, this participant must have been astonished by the ballooning prices. He made a handful of offers to transact, offers that were not accepted, and then sat out the rest of the session. As a result, his earnings were just a little above average (about +0.20 SD), less than what one might expect by his theoretical prowess.

Compare his behavior to that of a top earner, whose earnings placed her more than +2 SD from the mean (Participant no. 3 in session A10). She performed below average in the Pricing Questionnaire (2.00 vs mean of 3.836, SD 3.493). Perhaps as a result, she transacted often, making 96 offers that resulted in 32 trades. Many of the trades were lucrative, even if she often overpaid for the assets. In one instance, she acquired an asset worth 90 for a price of 100 (11.1% premium), but two periods later, she managed to sell at a premium of 257.1%. A picante fact: Both transactions were with the same counterpart. Clearly, this participant came on top not because she followed economic theory, but perhaps because she followed market trends.

Individual Differences in Confidence

Our micro-institutionalization hypotheses addressed why individuals, in seeking the hoped-for benefits of conformity, may be biased in their choices towards favoring social information over private information, even when private information is more accurate (resulting, in our study context, in the propagation of asset

valuation errors). We also suggested that this conformity bias, which need not be conscious, is likely particularly strong when the source of social information is itself an institution (as is the case for market-based information). In other words, an individual's judgment will trend towards the group judgment based on an implicit or explicit expectation of an adaptive benefit accruing to the individual who conforms to the presumed superior group judgment.

Prior research on conformity, however, has sometimes distinguished between acts of conformity that reflect changes in an individual's beliefs (as discussed above) versus acts of conformity where the individual's underlying beliefs do not change (in this latter situation, conformity is sometimes referred to as compliance). In other words, the latter situation suggests that an individual's move towards conformity with a group judgment might be the result of a more calculatingly cognitive process whereby an individual maintains confidence in his/her belief about the relative superiority of his/her private information but also sees potential advantage in acting as if this were not the case. In our study context, this could involve a market participant with a relatively high degree of confidence in his/her sophistication and clarity of thought, such that s/he would *knowingly* acquire overpriced assets with the expectation of later selling that overpriced asset at an even higher price to those counterparts s/he views as either generally less discerning or more susceptible to typical social conformity pressures discussed above.[1] Taken to its (il)logical conclusion, a market bubble would appear.

Indeed, some have taken this perspective (sometimes referred to as the "greater fool theory") and used it not only as an *ex post* explanation for market bubbles, but actually as a definition of market bubbles. The New Palgrave Dictionary of Economics adopts this viewpoint: Bubbles emerge "because current owners believe they can resell the asset at an even higher price" (Brunnermeier 2008). Others have argued similarly, suggesting that market participants "realize that there is the possibility of irrational behavior on the part of other traders. This realization promotes speculation" (Lei et al. 2001, p. 858). It is also popular among

[1] We use "he" as a shorthand. The same is true for female traders, even if males are known to be more overconfident on average (e.g., Barber and Odean 2001; Huang and Kisgen 2013).

practitioners, as exemplified by a Forbes Magazine article describing a "bubble time" in the market for initial public offerings (IPOs), where companies that were "mere concepts" with little or no revenue were offered for unjustifiably high prices: "Many people who know the IPOs are phonies play the game, hoping to take advantage of dumber people" (Dreman 1993; also see The Economist 2003).

It is noteworthy that this perspective can be *partially* reconciled with our earlier micro-institutionalization predictions, with both perspectives sharing a directional prediction towards conformity, with market participants generally favoring group judgments over personal judgments (even when personal judgments are superior). The difference is in the mechanism: in the greater fool theory, the high confidence market participant may share our micro-institutionalization expectation that a conformity bias will likely emerge among other interacting participants, but sees such as process as only affecting others, but not him/her, and seeks to exploit this difference! Such high levels of confidence has been shown to be prevalent among sophisticated market participants: professional traders (Cheng 2007), stock analysts (Stotz and Nitzsch 2005), corporate acquirers (Billett and Qian 2008) as well as among ordinary investors (Barber and Odean 2001; Bhandari and Deaves 2006). However, empirical tests have provided only mixed support for the suggestion that overconfidence begets price bubbles. The oft-cited study of Lei, Noussair, and Plott (2001) examined whether bubbles appear when arbitrage was prohibited by design, making it impossible to profit from "greater fools". For that, they designed an experimental market where buying low and selling high was not an option: Participants could either buy or sell, but not both. They found that even in such a restricted environment, valuation errors, price bubbles, and eventual crashes were all still prevalent. The contrast between popular appeal and mixed empirical findings suggests that our study should at least consider the possibility that individual differences in the confidence levels of market participants may also play a role in the propagation of valuation errors. An advantage of our experimental approach is our ability to assess such individual differences in advance and test whether greater market participants' level of confidence generates greater collective valuation errors and resulting price bubbles.

Measures and analysis of confidence. After the Valuation Questionnaires were collected, we asked the participants to complete a self-assessment questionnaire, designed to measure confidence. In it, each

participant was asked to assess her (or his) valuation skills in comparison to those of the other participants. We were interested in participants' perception that one's skills are superior to others' (Goethals et al. 1991; Larrick et al. 2007; Moore and Healy 2008). According to the Greater Fool argument, relative confidence is the source of valuation errors. But we find no correlation between relative overconfidence and bubble magnitude (Spearman's Rho = -0.1164; p>0.4021). Confidence is also uncorrelated with any other measure of bubbliness: common error, total error, or average error. Thus, we see no evidence that individual confidence is inflating bubbles.

To understand the mechanism (or lack thereof), we scrutinized the measures of confidence. The measure itself displays high levels of Cronbach's alpha, an indicator of reliability (Cronbach 1951). We had also asked about the respondent's view of others' perception of self, and when we compared how participants assessed their skills vis-à-vis others', we found that on average, participants did not perceive their valuation skills to be superior to others' (

Table **A1**). The two measures, self-assessment of skill and assessment of the skills possessed by other market participants, are highly correlated (Pearson's=0.66), suggesting that participants tended to view themselves about as skilled as the others. The small difference between average self- and other-assessment shows low statistical significance, which is robust to alternative specifications, whether t-test (two-sample two-tailed heteroscedastic test, t=1.986, p>0.3170) or the nonparametric two-sample Wilcoxon rank-sum (Mann-Whitney) test (z=0.402; p>0.3121). We verified by testing with the nonparametric Wilcoxon signed-rank test, which does not require assumptions of independence between measures (z=0.380; p>0.2960). So, because relative overconfidence is absent, it naturally cannot be correlated with valuation errors or bubble magnitude.

Construct	No. of Items	Mean	S.D.	Cronbach's Alpha
Participant's self-assessment	3	2.901	1.041	0.79
Participant's assessment of the other market participants	6	3.002	0.790	0.69
Participant's assessment of the other participants' perception of him/her	3	2.954	0.773	0.83

Table A1. Items measured in the self-assessment questionnaire

Trading Activity by Period and Condition

Period	1	2	3	4	5	6	7	8	9	10
Study 1 (high ambiguity)										
Offers	223	264	312	342	383	360	342	366	345	431
Acceptance Rate	0.2601	0.2992	0.2308	0.1959	0.1201	0.1111	0.1608	0.1475	0.1275	0.1230
SD	0.4397	0.4588	0.422	0.3975	0.3255	0.3147	0.3679	0.3551	0.3441	0.3288
No. of Accepted Offers	58	79	72	67	46	40	55	54	44	53
Study 2 (low ambiguity)										
Offers	189	207	219	208	267	284	286	295	304	401
Acceptance Rate	0.2857	0.1546	0.2329	0.1875	0.1573	0.1268	0.1923	0.1525	0.1743	0.152
SD	0.453	0.3624	0.4236	0.3913	0.3648	0.3332	0.3948	0.3602	0.38	0.3596
No. of Accepted Offers	54	32	51	39	42	36	55	45	53	61

Table A2. Trading Activity, Averaged Across Markets, by Period and Condition.

Measures of Price Bubbles by Market and Condition

Session Code	Study	Ex-Ante-Price Amplitude	Ex-Ante-Normalized Absolute Price Deviation	Ex-Ante-Haessel R2	Ex-Post-Price Amplitude	Ex-Post-Normalized Absolute Price Deviation	Ex-Post-Haessel R2	Change-Price Amplitude	Change-Normalized Absolute Price Deviation	Change-Haessel R2
A1	1	0.119	0.016	0.927	0.678	0.142	0.552	0.559	0.126	-0.375
A2	1	0.123	0.036	0.903	0.149	0.040	0.962	0.026	0.004	0.059
A3	1	0.317	0.083	0.859	0.560	0.120	0.691	0.243	0.037	-0.168
A4	1	0.367	0.067	0.916	0.443	0.131	0.698	0.076	0.064	-0.218
A5	1	0.195	0.044	0.888	0.786	0.162	0.069	0.591	0.118	-0.819
A6	1	0.133	0.041	0.906	0.479	0.092	0.747	0.346	0.051	-0.159
A7	1	0.142	0.083	0.969	0.186	0.034	0.896	0.044	-0.049	-0.073
A8	1	0.602	0.113	0.004	0.785	0.204	0.000	0.183	0.091	-0.004
A9	1	0.200	0.057	0.927	0.395	0.039	0.810	0.195	-0.018	-0.117
A10	1	0.398	0.052	0.758	1.329	0.295	0.525	0.931	0.243	-0.233
E2	2	0.267	0.520	0.898	0.476	0.315	0.915	0.210	-0.205	0.017
E3	2	0.833	0.581	0.688	1.303	0.271	0.504	0.469	-0.310	-0.184
E5	2	0.263	0.290	0.930	0.359	0.264	0.920	0.096	-0.026	-0.009
E7	2	0.383	0.559	0.890	0.503	0.991	0.667	0.120	0.432	-0.222
E10	2	0.758	1.738	0.511	0.675	0.830	0.778	-0.083	-0.908	0.267
F1	2	0.115	0.424	0.986	0.412	0.296	0.842	0.297	-0.128	-0.144
F2	2	0.253	0.451	0.922	0.432	0.225	0.904	0.178	-0.225	-0.018
F3	2	0.242	0.463	0.968	0.329	0.292	0.930	0.087	-0.171	-0.039
F4	2	1.475	0.845	0.679	0.205	0.038	0.952	-1.270	-0.808	0.273
F5	2	0.110	0.125	0.856	0.152	0.095	0.986	0.042	-0.029	0.130

Table A3. Measures of Price Bubbles, Before Trading, During Trading, and the Resulting Difference, by Market and Condition

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