Experimental assets markets and financial decision making.

Joe Seidel

Indiana University

June 28, 2022

Contents

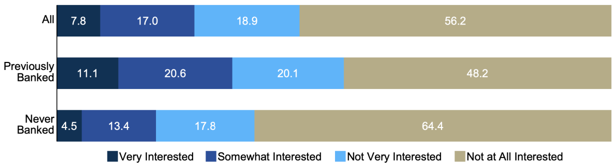
1. How the Internet Banks: Household Use of Banking and Financial Services
2. Heterogeneity and Bubbles in Large and Small Markets
3. Implementing an Infinite Horizon in Dynamic Asset Pricing Experiments

How the Internet Banks: Household Use of Banking and Financial Service

FDIC national estimate rate of unbanked household (2019): 5.4% or 7.1 million households

- Unbanked: no one in the household had a checking or savings account at a bank or credit union

Figure ES.2 Interest in Having a Bank Account, Among Unbanked Households, by Previous Bank Account Ownership, 2019 (Percent)



Source: How America Banks: Household Use of Banking and Financial Services (FDIC 2019)

Why should we care?

Financial Inclusion

- 33% of unbanked report family income less than $30k
- 29% have no high school diploma

A digital currency

- Potential to help in the design of digital currency run by the Federal Reserve
- ex: If people avoid banks because banks only care about profits

What do we do?

Contributions

1. Conduct FDIC survey
   - Dynata
2. Evaluate whether online samples are representative of population in terms of financial decisions and banking behavior.

Related

- Survey of Household Economics and Decisionmaking and Census Bureau survey results [Devlin-Foltz et al., 2015]

Primer on Surveys

Objective

Estimate some parameter about the population: e.g. banked and unbanked rates

Method

- Instrument (e.g. online, telephone, in-person questionnaires)
- Sample

Weighting

The problem

- Parameter of interest my be correlated with individual characteristics
- Unequal probabilities of selection when sampling

$\Rightarrow$ Potential for biased estimates

Solution

1. Adjust probabilities of being selected when sampling
2. Correct for different response rates post sampling (weighting) [Pasek et al., 2014]

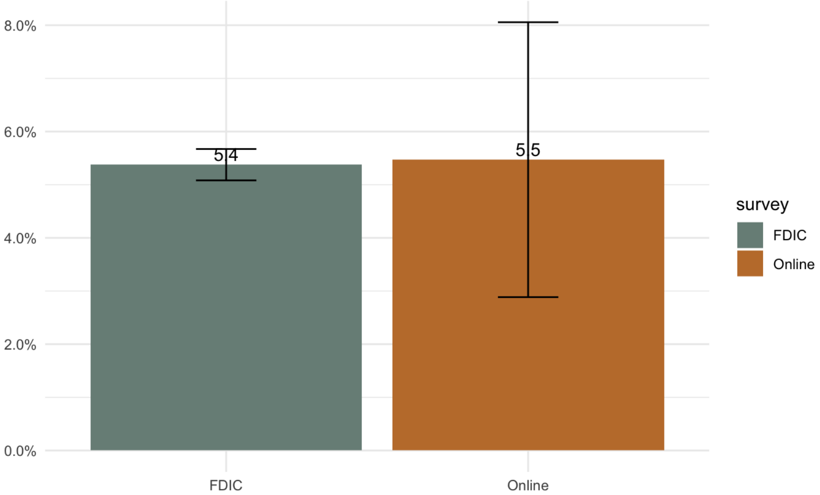
$\Rightarrow$ Respondents should mirror full population

Sampled Population

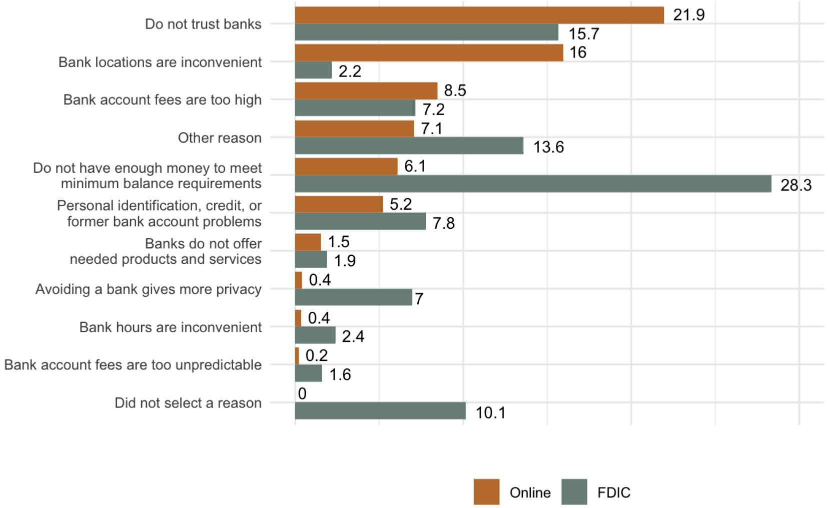
Characteristic	Unweighted	Online	FDIC
Gender			
Male	49.2%	52.4%	-
Female	50.8%	47.6%	-
Age Group			
15 to 24 years	16.73%	12.06%	4.805%
25 to 34 years	17.47%	15.91%	16.314%
35 to 44 years	20.63%	18.04%	17.028%
45 to 54 years	13.20%	21.74%	17.016%
55 to 64 years	12.64%	15.19%	18.628%
65 years or more	19.33%	17.06%	26.208%
Race/Ethnicity			
Black	20.8%	12.59%	12.74%
Hispanic	11.9%	10.46%	13.98%
Asian	17.1%	3.67%	5.34%
American Indian or Alaska Native	2.8%	0.35%	0.73%
Native Hawaiian or Other Pacific Islander	0.9%	0.14%	0.22%
White	39.8%	70.77%	65.64%
Family Income			
Less than $15,000	16.40%	9.900%	10.70%
$15,000 to $30,000	13.56%	17.100%	14.36%
$30,000 to $50,000	16.60%	12.000%	18.81%
$50,000 to $75,000	17.21%	17.200%	18.18%
At least $75,000	36.23%	43.800%	37.94%
Geographic Region			
Northeast	25.1%	17.0%	17.2%
Midwest	25.1%	21.0%	21.6%
South	27.1%	38.0%	38.3%
West	22.7%	24.0%	22.9%

Gender for FDIC is not reported.
$n = 538$

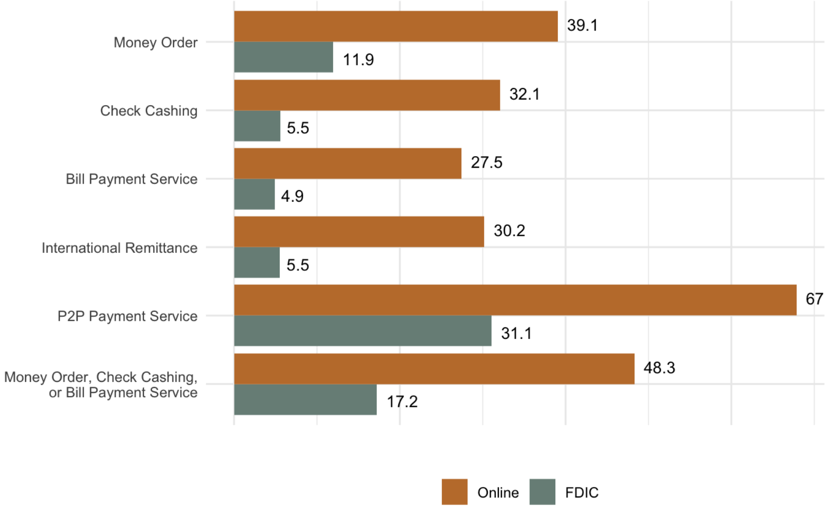
Unbanked Rates



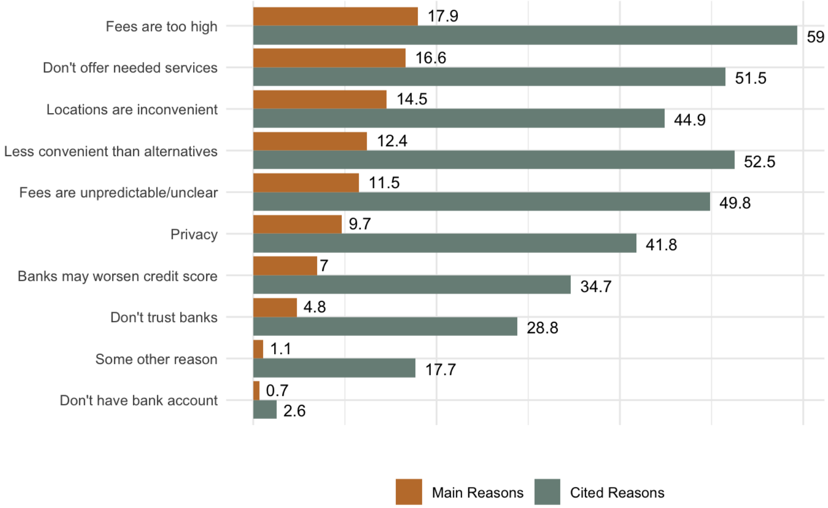
Reasons for being unbanked



Specific Nonbank Financial Transaction Service Use



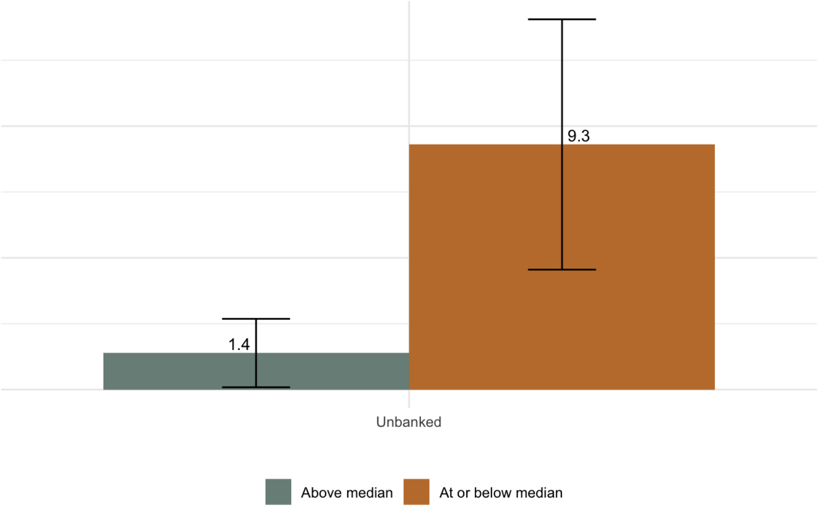
Reasons for using alternatives to banks



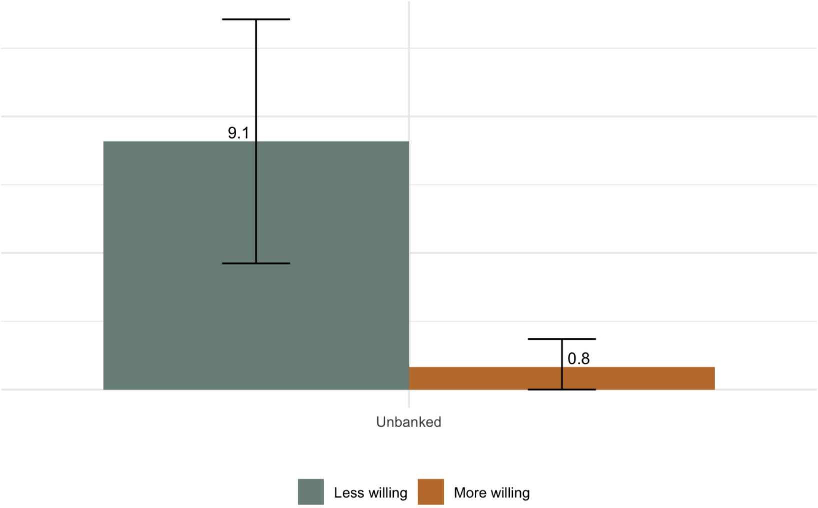
Additional Questions

- Financial literacy (scored test)
- Risk attitudes (scale on willingness to take risk)
- Saving habits (planned saving, unplanned saving, don't save)

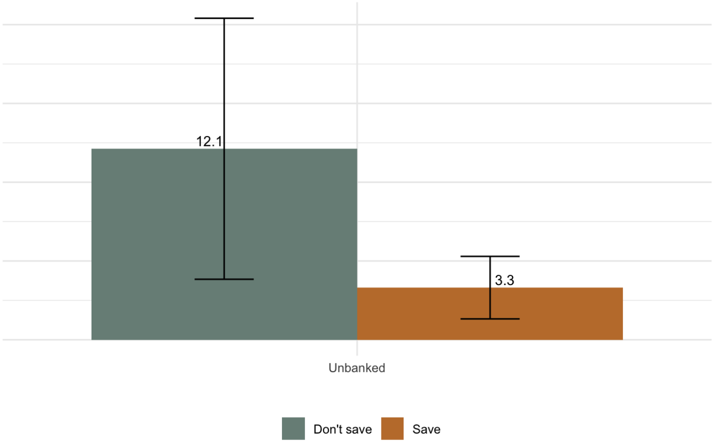
Unbanked Rates by Financial Literacy



Unbanked Rates by Willingness to take Financial Risks



Unbanked Rates by Saving Habits



$$p - value = .0432$$

Summary

Conclusions

- Reasonable estimate of the unbaked rate when compared FDIC/Census

$\Rightarrow$ 5.5% vs 5.4%

- Online reports larger proportion using non-bank financial services

$\Rightarrow$ Online panel suitable for reaching undeserved population

- Negative relationship between unbanked rates and financial literacy
- Negative relationship between unbanked rates and willingness to take financial risks
- Lower unbanked rate among those who save

Personal Characteristics, Traders' Performance and Bubbles in Small and Large Online Asset Markets

"Invisible hand wave" argument: individual biases do not matter in competitive markets (Thaler, 2015)

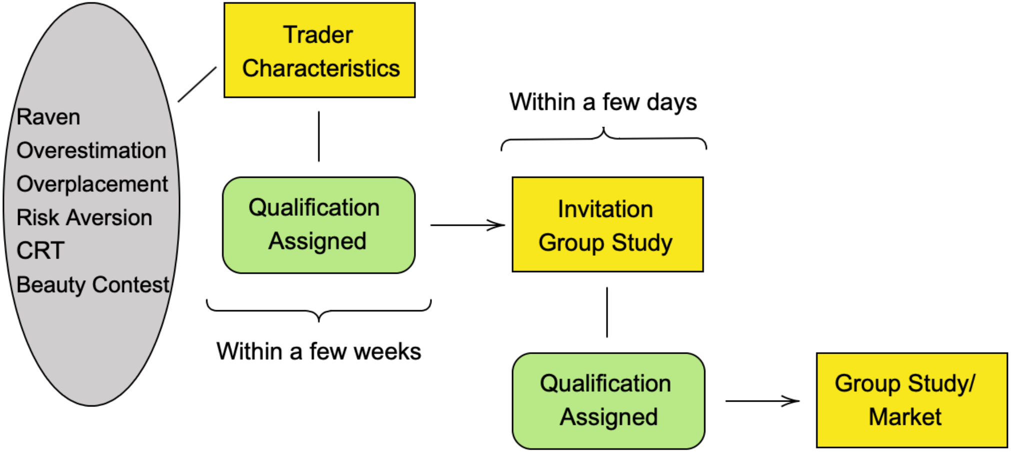
- Are bubbles robust to large markets?
- How robust are the laboratory markets results with student populations to other populations?
- Are traders' characteristics related to traders' performance and their strategies?

What do we do?

Contributions

- Methodological: implement online markets [Arechar et al., 2018]
- Compare individual and aggregate outcomes in small and large markets with different populations
  - [Hommes et al., 2021, Weitzel et al., 2019, Williams, 2008, Bossaerts and Plott, 2004]
- Study the relationship between trader's measures of intelligence (IQ, cognitive reflection and strategic)

MTurk Implementation



Session Summary

Market Sessions

Session	Treatment	No. of Markets	Subjects
Lg.1	Large Call Market	2	52
Lg.2	Large Call Market	2	33
Lg.3	Large Call Market	2	56
Lg.4	Large Call Market	2	40
Lg.5	Large Call Market	2	44
Sm.1	Small Call Market	2	19
Sm.2	Small Call Market	2	12
Sm.3	Small Call Market	2	19
Sm.4	Small Call Market	2	14
Sm.5	Small Call Market	2	10
Stu. 1-5	Student Markets	1	9

- Avg market earning: $10.05, Avg Trader Char. earning: $3.91
- total market subjects : 299 (MTurk), 45 (students)
- individual tasks from April 2021 to October 2021: 532

The environment

Smith, Suchanek and Williams, 1988

- Finite horizon
- Asset has a life of 10 periods
- At the end of each period asset yields $\{0, 8, 28, 60\}$ with equal probability, i.i.d. over time
- After final dividend realization, assets are worthless
- Sequence of two markets
- Total franc holdings at the end of the final period of a randomly selected market are converted to USD and paid to the subjects

Questions

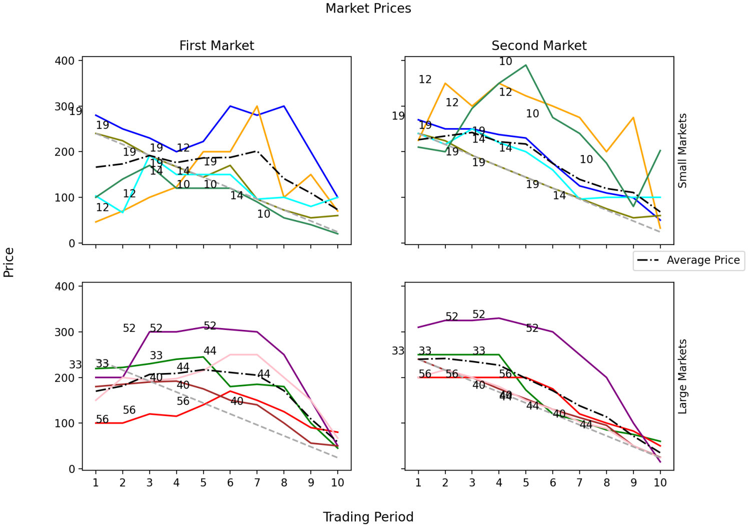
Aggregate Level

- Is mispricing smaller in large markets?
- Do markets consisting of traders recruited from MTurk (the general population) display less mispricing when compared to student populated markets?

Individual Level

- Is there any association between measures of intelligence and trading strategies?
- How are Raven's Standard Progressive Matrices scores, cognitive reflection scores (CRT), and strategic intelligence are related to earnings?

Small vs Large Overview (MTurk/Online)



Aggregate Measures

Measure
Turnover $= \frac{1}{10}\sum_{t=1}^{10} q_t/\mathrm{TSU}$
Amplitude $= \max_t \left\{\frac{\mathrm{P}_t - \mathrm{FV}_t}{\mathrm{FV}_1}\right\} - \min_t \left\{\frac{\mathrm{P}_t - \mathrm{FV}_t}{\mathrm{FV}_1}\right\}$
Norm. Dev. $= \frac{1}{\mathrm{TSU}}\frac{1}{10}\sum_{t=1}^{10} q_t \lvert \mathrm{P}_t - \mathrm{FV}_t \rvert$
RD $= \frac{1}{10}\sum_{t=1}^{10} \frac{(\mathrm{P}_t - \mathrm{FV}_t)}{\bar{\mathrm{FV}}}$
RD+ $= \frac{1}{10}\sum_{t=1}^{10} \frac{(\mathrm{P}_t - \mathrm{FV}_t)}{\bar{\mathrm{FV}}}$ where $p_t > \mathrm{FV}_t$
RD- $= \frac{1}{10}\sum_{t=1}^{10} \frac{(\mathrm{P}_t - \mathrm{FV}_t)}{\bar{\mathrm{FV}}}$ where $p_t < \mathrm{FV}_t$
RND $= \frac{1}{\mathrm{TSU}}\frac{1}{10}\sum_{t=1}^{10} q_t \frac{\mathrm{P}_t - \mathrm{FV}_t}{\mathrm{FV}_t}$
RND+ $= \frac{1}{\mathrm{TSU}}\frac{1}{10}\sum_{t=1}^{10} q_t \frac{\mathrm{P}_t - \mathrm{FV}_t}{\mathrm{FV}_t}$ where $p_t > \mathrm{FV}_t$
RND- $= \frac{1}{\mathrm{TSU}}\frac{1}{10}\sum_{t=1}^{10} q_t \frac{\mathrm{P}_t - \mathrm{FV}_t}{\mathrm{FV}_t}$ where $p_t < \mathrm{FV}_t$
RAD $= \frac{1}{10}\sum_{t=1}^{10} \frac{\lvert \mathrm{P}_t - \mathrm{FV}_t \rvert}{\bar{\mathrm{FV}}}$
RPAD $= \frac{1}{10}\sum_{t=1}^{10} \frac{\lvert \mathrm{P}_t - \mathrm{FV}_t \rvert}{\mathrm{FV}_t}$

Finding 1

Table 1: Comparing Bubble Measures across Market Size

Session	Treatment	Market	TR	Amp	ND	RD	RD+	RD-	RND	RND+	RND-	RAD	RPAD
Average	Small		0.062	0.709	3.871	0.303	0.463	-0.067	0.037	0.041	-0.004	0.484	0.765
Average	Large		0.090	0.568	4.905	0.291	0.403	-0.040	0.041	0.044	-0.004	0.407	0.566
p-value			0.002	0.705	0.385	0.850	0.850	0.515	0.970	0.734	0.619	0.571	0.521

Two-way tests

No detectable differences between large and small markets in terms of price amplitude and deviations from fundamental value.

Finding II

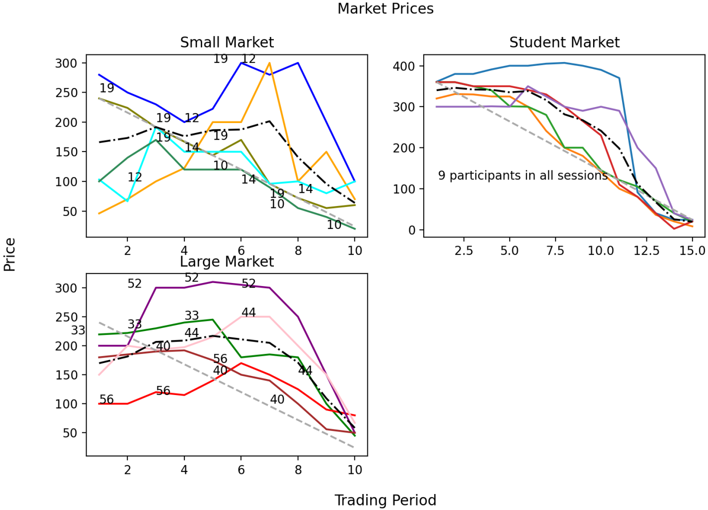
Table 2: Comparing Bubble Measures by Experience and Market Size

Session	Treatment	Market	TR	Amp	ND	RD	RD+	RD-	RND	RND+	RND-	RAD	RPAD
Average	Small	First	0.067	0.842	4.301	0.106	0.343	-0.128	0.033	0.040	-0.007	0.449	0.683
Average	Small	Second	0.058	0.575	3.440	0.500	0.583	-0.005	0.042	0.043	-0.001	0.519	0.848
p-value			0.312	0.188	0.812	0.438	0.438	**0.068**	0.812	1.000	**0.068**	1.000	0.812
Average	Large	First	0.097	0.764	6.311	0.317	0.528	-0.065	0.051	0.058	-0.007	0.517	0.756
Average	Large	Second	0.084	0.372	3.499	0.266	0.278	-0.016	0.030	0.031	-0.001	0.297	0.376
p-value			0.125	**0.062**	**0.062**	0.812	**0.062**	0.188	0.188	**0.062**	**0.062**	0.125	**0.062**

Two-way tests

Bubble measures tend to decrease with experience in larger markets more so than smaller markets.

Comparison with student markets



Finding III

Table 3: Comparing Bubble Measures with Student Markets

Session	Treatment	Market	TR	Amp	ND	RD	RD+	RD-	RND	RND+	RND-	RAD	RPAD
Average	Online	First	0.082	0.803	5.306	0.212	0.435	-0.096	0.042	0.049	-0.007	0.483	0.719
Average	Student		0.083	0.469	4.909	0.240	0.238	-0.056	0.015	0.024	-0.009	0.304	0.370
p-value			0.859	**0.098**	0.859	0.679	0.310	1.000	0.165	0.310	0.254	0.310	**0.099**

Two-way tests

Very marginal differences in measures when comparing our online markets with Student Markets. We detect no difference in the distribution of observed market measures in small markets. In large markets we observe differences (10% level) in Normalized Deviation and Relative Proportional Absolute Deviation.

Trading Activity

Is there any association between measures of intelligence and trading strategies?

We consider buying and selling activity under 3 market conditions

1. Prices below fundamental value
2. Before price peak
3. After price peak

Table 4: Trader Activity – Prices Below FV

	Dependent variable:	
	Contracts to Buy	Contracts to Sell
	(1)	(2)
Raven (IQ)	0.058	-0.025
	(0.046)	(0.035)
CRT	0.419**	-0.126
	(0.183)	(0.143)
Strategic Int.	0.006	-0.011
	(0.021)	(0.008)
Overestimation	-0.059	0.0004
	(0.059)	(0.045)
Overplacement	0.046	-0.015
	(0.042)	(0.018)
Risk Aversion	0.001	0.051
	(0.080)	(0.058)
Constant	-0.013	2.034***
	(0.676)	(0.568)
Observations	550	550
R^2	0.012	0.007
Adjusted R^2	0.001	-0.004
Residual Std. Error (df = 543)	5.558	3.189
F Statistic (df = 6; 543)	1.103	0.676

Note: *p<0.1; **p<0.05; ***p<0.01
Clustered standard errors at session level

Table 5: Trader Activity – Before Price Peak

	Dependent variable:	
	Contracts to Buy	Contracts to Sell
	(1)	(2)
Raven (IQ)	0.123**	0.083
	(0.061)	(0.081)
CRT	0.551***	1.752***
	(0.104)	(0.218)
Strategic Int.	0.006	-0.018**
	(0.018)	(0.009)
Overestimation	-0.011	-0.378***
	(0.036)	(0.093)
Overplacement	0.067	0.276***
	(0.068)	(0.036)
Risk Aversion	0.022	-0.323***
	(0.067)	(0.065)
Constant	-0.541	4.268***
	(0.845)	(0.900)
Observations	550	550
R^2	0.017	0.035
Adjusted R^2	0.007	0.025
Residual Std. Error (df = 543)	6.366	14.335
F Statistic (df = 6; 543)	1.603	3.312***
Note:	*p<0.1; **p<0.05; ***p<0.01	
	Clustered standard errors at session level	

Table 6: Trader Activity – After Price Peak

	Dependent variable:	
	Contracts to Buy	Contracts to Sell
	(1)	(2)
Raven (IQ)	-0.014	0.190*
	(0.121)	(0.112)
CRT	-0.256	0.989***
	(0.299)	(0.285)
Strategic Int.	0.012	-0.015
	(0.017)	(0.009)
Overestimation	-0.114	-0.027
	(0.206)	(0.089)
Overplacement	0.107	0.120
	(0.138)	(0.079)
Risk Aversion	-0.077	-0.072
	(0.132)	(0.116)
Constant	3.816**	0.045
	(1.934)	(2.015)
Observations	550	550
R^2	0.007	0.051
Adjusted R^2	-0.004	0.040
Residual Std. Error (df = 543)	8.253	6.821
F Statistic (df = 6; 543)	0.674	4.831***

Note: *p<0.1; **p<0.05; ***p<0.01
Clustered standard errors at session level

Trader Earnings

	Dependent variable:		
	All	Small	Large
	(1)	(2)	(3)
Raven (IQ)	0.001	-0.015	0.011
	(0.013)	(0.026)	(0.011)
CRT	0.157**	0.037	0.190**
	(0.061)	(0.069)	(0.077)
Strategic Int.	0.001	0.007	-0.0004
	(0.002)	(0.007)	(0.003)
Overestimation	0.002	0.029	-0.005
	(0.025)	(0.030)	(0.033)
Overplacement	-0.004	-0.027	0.006
	(0.015)	(0.030)	(0.016)
Risk Aversion	-0.004	-0.023	0.008
	(0.025)	(0.035)	(0.038)
Constant	9.859***	10.024***	9.669***
	(0.280)	(0.291)	(0.363)
Observations	550	124	426
R^2	0.017	0.039	0.027
Adjusted R^2	0.006	-0.010	0.013
Residual Std. Error	1.296 (df = 543)	1.022 (df = 117)	1.358 (df = 419)
F Statistic	1.559 (df = 6; 543)	0.800 (df = 6; 117)	1.967* (df = 6; 419)
Note:			*p<0.1; **p<0.05; ***p<0.01 Clustered SE at session level.

Summary of Findings

Trader Activity and Performance

- Cognitive Reflection Scores predict trading behavior coinciding with market bubbles
- CRT scores predict individual earning

Summary of Findings

Aggregate

- Bubbles are robust to market size
- Outcomes are similar to markets populated by students

$\Rightarrow$ Advantages: cheaper, easier to address external validity criticisms and to reach different populations; Disadvantage: less control than in the lab

Implementing an Infinite Horizon in Dynamic Asset Pricing Experiments

General Idea

Investigate different approaches to implementing an infinite horizon in laboratory markets: a random stopping rule and definite + discounting.

Summary

- Absent behavioral biases, implementation should not matter
- Biases are introduced into the model to generate differences
- Design an experiment with a treatment that should shut down risk channel.

Characteristic	Unweighted	Online	FDIC
All	8.0%	5.5%	5.4%
Family Income			
Less than $15,000	17.3%	10.4%	23.3%
$15,000 to $30,000	11.9%	12.2%	10.4%
$30,000 to $50,000	6.1%	4.1%	4.6%
$50,000 to $75,000	8.2%	8.3%	1.7%
At least $75,000	1.7%	0.9%	0.6%
Education			
No high school diploma	42.1%	14.3%	21.4%
High school diploma	12.5%	10.8%	8.1%
Some college	5.1%	3.6%	4.3%
College degree	4.9%	2.9%	0.8%
Age Group			
15 to 24 years	12.2%	7.1%	8.8%
25 to 34 years	12.8%	6.5%	6.9%
35 to 44 years	6.3%	3.6%	6.3%
45 to 54 years	11.3%	10.0%	5.1%
55 to 64 years	4.4%	2.9%	5.5%
65 years or more	1.9%	1.9%	3.3%
Race/Ethnicity			
Black	11.6%	14.5%	13.8%
Hispanic	10.9%	2.3%	12.2%
Asian	4.3%	3.4%	1.7%
American Indian or Alaska Native	20.0%	13.0%	16.3%
Native Hawaiian or Other Pacific Islander	40.0%	64.2%	5.4%
White	3.7%	4.0%	2.5%
Two or More Races	16.7%	15.3%	4.9%
Disability Status			
Disabled, aged 25 to 64	14.1%	8.0%	16.2%
Not disabled, aged 25 to 64	7.4%	3.9%	4.5%
Not applicable (not aged 25 to 64)	6.1%	5.4%	4.2%
Monthly Income Volatility			
Income was about the same each month	5.7%	3.7%	4.9%
Income varied somewhat from month to month	11.0%	8.1%	6.4%
Income varied a lot from month to month	17.9%	16.2%	10.7%

Session	Market	Avg. Rounds Submitting
Lg. 1	1	8.56
Lg. 1	2	8.13
Lg. 2	1	8.73
Lg. 2	2	7.12
Lg. 3	1	8.61
Lg. 3	2	8.98
Lg. 4	1	8.50
Lg. 4	2	7.65
Lg. 5	1	8.25
Lg. 5	2	7.75
Sm. 1	1	9.00
Sm. 1	2	8.63
Sm. 2	1	9.67
Sm. 2	2	9.42
Sm. 3	1	9.11
Sm. 3	2	8.84
Sm. 4	1	8.43
Sm. 4	2	7.43
Sm. 5	1	8.20
Sm. 5	2	8.70

Table 7: Average number of rounds a participant submitted non-zero offers

Related Literature

The indefinite horizon

- Prisoners dilemma: Dal Bó and Fréchette [2018], Fréchette and Yuksel [2017]
- SSW: Jiang et al. [2020]
- Lucas Asset Markets: Duffy et al. [2020], Crockett et al. [2018]

Experimental Setting

General

- Market with N traders (including yourself)
- You will start with k_0^i of an item that produces d francs at the start of every trading period.
- You will receive y^i francs in even periods and 0 in odd periods.
- Any amount of francs left in your trading account will be converted to cash and stored in your payment account.
- Earnings from one of the trading sequences will be randomly determined to be paid to you in cash.

Decision Screen

Market -- Period 1 of 3

Your Francs

From dividends: 1.00
From endowment: 101
Total: 102.00 francs

Allocation to Payment Account

0 — 102.00

Amount: 51	Remaining Balance: 51.00	
Value: $0.93	Endowment next period: 5	Weighted Value: $0.93

Your Assets: 1.00 asset(s)

Buy Order

Max total cost: 0

Number of assets you want to buy: 0.00

The highest price at which to buy: 0.00 francs

Sell Order

Min total value: 0

Number of assets you want to sell: 0.00

The lowest price at which to sell: 0.00 francs

Submit

Prediction Screen

Making Predictions -- Period 1 of 3

Price forecast for the upcoming period:

francs

Next

Price History

Period	Trading Price

Instructions

In addition to the money you earn from your trading activity, you can make money by accurately forecasting the trading price of the upcoming period. You will indicate your forecast in the text input above.

The money you receive from your forecasts will be calculated in the following manner

Accuracy	Your earnings
Within 10% of actual trading price	$0.07
Within 25% of actual trading price	$0.02
Within 50% of actual trading price	$0.01

Treatment

Random Termination

- A random draw determines if the trading sequence will continue
- Probability π to continue

Definite + Discounting

- The current trading sequence will last $\frac{1}{1-\pi}$ periods.
- Each period your francs to be converted to cash will be multiplied by a factor $\pi^t < 1$
- After the final period, payoffs for subsequent rounds will be simulated based on your previous actions

Hypothesis

Theory

The environment can be modeled using Lucas Asset Pricing Model with one tree

Hypothesis

- Agents smooth consumption by trading in every period
- If agents have no behavioral biases, no difference in prices across treatments
- If agents are risk averse prices will be lower in RT treatments
- If subjects predictions are consistent with rational expectations, forecasts should be equal to the predicted prices (table in appendix)

Predictions

Discount Factor	P_{DD} (FV)	$P_{1,RT}$	$P_{2,RT}$	$P_{17,RT}$		k_o	k_e	c
0.7	2.33	1.35	1.93	2.27	Type I	17.94	1	87.47
					Type II	0.06	17	86.53
0.9	9	7.33	8.15	8.8	Type I	6.05	1	81.53
					Type II	11.95	17	92.47
0.94	15.67	13.71	14.59	15.37	Type I	3.97	1	80.48
					Type II	14.03	17	93.52

Predictions $p_{t,\mathrm{RT}}$ assume homegrown utility is CRRA with risk aversion parameter .5.
Allocation and consumption prediction assume linear homegrown utility U.

Table 8: Prices and Allocations

Summary

The probability is taken to be equivalent to the discount factor in the lab setting.

- Introduce behavioral bias to the model to generate differences in predictions.
- Design an experiment with a treatment that should shut down risk aversion in the model.

References I

Antonio A. Arechar, Simon Gächter, and Lucas Molleman. Conducting interactive experiments online. *Experimental Economics*, 21(1):99–131, 2018. doi: 10.1007/s10683-017-9527-2. URL https://doi.org/10.1007/s10683-017-9527-2.

Peter Bossaerts and Charles Plott. Basic Principles of Asset Pricing Theory: Evidence from Large-Scale Experimental Financial Markets. *Review of Finance*, 8(2):135–169, 2004. URL https://ideas.repec.org/a/kap/eurfin/v8y2004i2p135-169.html.

Sean Crockett, John Duffy, and Yehuda Izhakian. An Experimental Test of the Lucas Asset Pricing Model. *The Review of Economic Studies*, 86(2):627–667, 07 2018. ISSN 0034-6527. doi: 10.1093/restud/rdy035. URL https://doi.org/10.1093/restud/rdy035.

References II

Pedro Dal Bó and Guillaume R. Fréchette. On the determinants of cooperation in infinitely repeated games: A survey. *Journal of Economic Literature*, 56(1): 60–114, March 2018. doi: 10.1257/jel.20160980. URL https://www.aeaweb.org/articles?id=10.1257/jel.20160980.

Sebastian Devlin-Foltz, Jeff Larrimore, and Maximilian D. Schmeiser. Should You Trust Things You Hear Online? Comparing SHED and Census Bureau Survey Results. FEDS Notes 2015-10-15, Board of Governors of the Federal Reserve System (U.S.), October 2015. URL https://ideas.repec.org/p/fip/fedgfn/2015-10-15.html.

References III

John Duffy, Janet Hua Jiang, and Huan Xie. Experimental Asset Markets with an Indefinite Horizon. Cahiers de recherche 08-2019, Centre interuniversitaire de recherche en économie quantitative, CIREQ, July 2020. URL https://ideas.repec.org/p/mtl/montec/08-2019.html.

Guillaume R. Fréchette and Sevgi Yuksel. Infinitely repeated games in the laboratory: four perspectives on discounting and random termination. *Experimental Economics*, 20(2):279–308, 2017. URL https://EconPapers.repec.org/RePEc:kap:expeco:v:20:y:2017:i:2:d:10.1007_s10683-016-9494-z.

References IV

Cars Hommes, Anita Kopányi-Peuker, and Joep Sonnemans. Bubbles, crashes and information contagion in large-group asset market experiments. *Experimental Economics*, 24(2):414–433, 2021. doi: 10.1007/s10683-020-09664-w. URL https://doi.org/10.1007/s10683-020-09664-w.

Janet Hua Jiang, Daniela Puzzello, and Cathy Zhang. How long is forever in the laboratory? three implementations of an infinite-horizon monetary economy. *Working paper*, 2020.

Josh Pasek, Matthew DeBell, and Jon A. Krosnick. Standardizing and democratizing survey weights: The anes weighting system and anesrake. 2014.

References V

Utz Weitzel, Christoph Huber, JÃ¼rgen Huber, Michael Kirchler, Florian Lindner, and Julia Rose. Bubbles and Financial Professionals. *The Review of Financial Studies*, 33(6):2659–2696, 08 2019. ISSN 0893-9454. doi: 10.1093/rfs/hhz093. URL `https://doi.org/10.1093/rfs/hhz093`.

Arlington W. Williams. *Price Bubbles in Large Financial Asset Markets*, volume 1 of *Handbook of Experimental Economics Results*, chapter 29, pages 242–246. Elsevier, 2008. URL `https://ideas.repec.org/h/eee/expchp/1-29.html`.