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Asset Markets**

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The Effect of Financial Selection in Experimental Asset Markets

Dmitry Gladyrev, Owen Powell and Natalia Shestakova¹

ABSTRACT

The *market selection hypothesis* posits that over time more successful traders will stay in the market, whereas those with trading losses will exit. If success is at least somewhat determined by behavior, then as a result of market selection traders who survive in markets behave differently than traders who are randomly drawn from the population to participate in markets. This effect has so far been ignored in the literature, therefore we design and carry out an experiment to study the effects of market selection on market outcomes. We find that markets populated by more extreme earners exhibit stronger mispricing, and that this is strongly related to the fact that more extreme earners experience higher bubbles in the past. This suggests that experience may not decrease bubbles in real markets as much as was previously thought. Furthermore, we find evidence of relationships between earnings, trading activity, portfolio risk and transaction risk. Mistakes are also associated with more extreme earnings, however this disappears over time.

JEL Codes: G02, C92, D4, D53

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“One general law, leading to the advancement of all organic beings, namely, multiply, vary, let the strongest live and the weakest die.”

-- Charles Darwin, 1859

On the Origin of Species

I. INTRODUCTION

The *market selection hypothesis*, dating back at least to Alchian (1950), posits that over time natural selection will happen in markets: more successful traders will stay in the market, whereas those with trading losses will exit. If success is at least somewhat determined by behavior, then as a result of market selection traders who survive in markets behave differently than traders who are randomly drawn from the population to participate in markets.

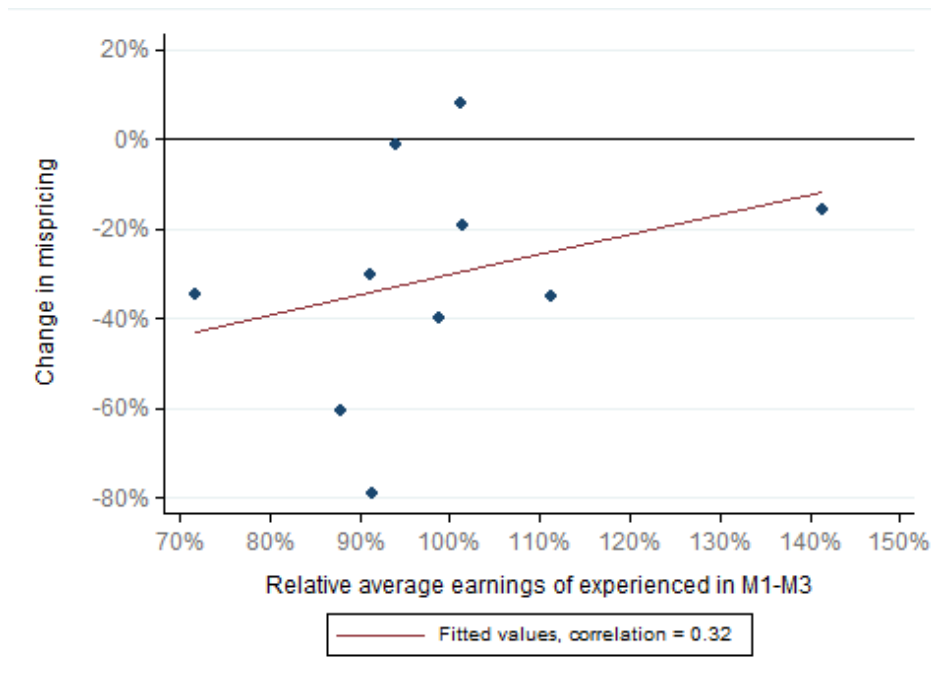
The effect of market selection on market outcomes is hard to evaluate empirically, since the counterfactual, i.e. the behavior of traders randomly drawn from the population, is not observable. One market outcome that is particularly important is market efficiency, as efficient markets produce prices that are accurate indicators of relative values. The actual efficiency of real markets has long been debated (Fama, 1970; Lim and Brooks, 2011) since underlying values, and hence efficiency, are not observable. This is one of the reasons for studying laboratory markets.

A common result of laboratory studies is that market efficiency improves with the experience of traders (King et. al, 1993; Noussair and Powell, 2010). Specifically, when all traders repeat the same market setting in the same group, markets display fewer bubbles, and bubble episodes

decrease with the amount of experience. Further work (Dufwenberg et. al, 2005; Xie and Zhang, 2012) relaxes the condition that all traders have the same level of experience and shows that bubbles in mixed-experience markets are as rare as in completely experienced markets. The summary of this line of research is an *experience effect*: markets populated by more experienced traders are more likely to be efficient².

However, all the studies that find the experience effect ignore market selection. Nevertheless, data from Dufwenberg et al. (2005) (DLM, hereafter, shown in Figure 1), while not designed to study the effect of market selection explicitly, are illustrative of the issue.

Figure 1: Change in mispricing vs. earnings of experienced



² Hussam et. al, 2008 argue that the experience effect depends on having a stationary environment.

The graph shows each of the 10 sessions reported in DLM. The experience effect, as measured on the vertical axis, is on average negative (as reported in DLM). It is plotted alongside the earnings of the experienced traders (earnings adjusted for random dividends, averaged over markets 1-3) on the horizontal axis. The limited number of observations preclude any definitive conclusions, however it does suggest that the experience effect may be sensitive to the previous market success of the experienced.

Therefore, the main focus of our study is the effect of market selection on market efficiency. Specifically, we vary the distribution of traders in the markets based on their previous success, and observe how the resulting markets differ in their efficiency. To understand the underlying forces behind the effect of market selection on market efficiency, we also look at the links between traders' behavior and their success.

The rest of the paper is structured as follows. Section II describes the experimental design and Section III presents the results. Section IV concludes.

II. DESIGN

The design follows DLM closely. Each session begins with all subjects reading a common set of instructions and answering a set of control questions. This is followed by participation in a series of markets. Immediately before entering the market for the first time, subjects receive training for the computerized *z-Tree* (Fischbacher, 2007) trading interface.

Markets consist of six traders who may trade units of an asset amongst one another. Each trader begins each market with an endowment of 3 asset units and 400 Euro cents cash. At two

minute intervals, all units of the asset pay a dividend of either 0 cents or 20 cents. Both values are equally likely, implying an average dividend payment of 10 cents. The market lasts for twenty minutes, meaning 10 dividends are paid over the life of the market. After $p-1$ dividend payments, the risk-neutral fundamental value of the asset is given by $fv(p) = (10-p)*10$ cents. Trading is done via a continuous double-auction with an open order book that resets after every dividend payment. Earnings from a market are equal to final cash holdings. Borrowing of cash and shares is not allowed.

The main part of the experiment consists of a set of markets. To begin with, a group of six subjects participates in a sequence of three identical markets. Afterwards, this original group of six (whom we refer to as *experienced*) are ranked and split into three new groups according to their previous earnings: the two highest earners form one group, the two middle earners form another, and the two lowest earners are assigned to the third. In order to control for the effect of random dividend draws, earnings are adjusted to use expected dividends rather than the actual dividend draws from the markets. Each of the new groups is then assigned four new inexperienced subjects to form a single mixed-experience market³. Thus each session consists of an initial set of three markets in which a single group becomes increasingly more experienced, followed by three additional markets where experienced and non-experienced traders are mixed together.

³ All subjects read the instructions and answered control questions together at the beginning of the experiment. While the first three markets took place, the inexperienced subjects completed a risk preference elicitation task. Training with the market interface was provided immediately before the subject participated in their first market. See the Instructions for full details.

The main difference between this design and DLM is the non-random assignment of experienced traders into groups⁴. This is done to increase the observed variation in previous earnings across groups.

III. ANALYSIS

Subjects were recruited for 7 sessions at the University of Vienna using ORSEE (Greiner, 2004). Sessions took two hours and thirty minutes and average earnings were €32 per subject.

Each session consists of six related markets: a sequence of three, each populated by the same group of six traders who become increasingly more experienced over time, followed by three separate yet simultaneous markets in which the now-experienced traders are combined with additional novice traders. In total, we get 42 (not independent) markets.

Mispricing in a market is measured as the deviation of prices from fundamentals. Markets are divided into *periods*, which coincide with the two-minute intervals between dividend payments.

The fundamental value within a period is constant, and the period price is the average of all

⁴ In addition to our main treatment difference, our design differs from the original DLM design in a few other ways: the instructions, training, user interface, and alternative activities. However, we argue that none of our changes are less realistic than the original design.

In designing the program, instructions and training phase, our main consideration was comprehension. We argue that in the real world, traders have a good understanding of both what they are doing and how they do it. Previous research has shown that confusion and misunderstanding are important drivers of bubbles (Kirchler and Huber, 2012; Kirchler et al., 2012).

Great care was taken in designing the trading interface. It included an on-screen tutorial and reminder text that explained how to complete various actions. DLM's instructions were changed in such a way as to improve comprehension, and the training period was extended to an entire market. In addition, control questions were added to verify subjects understanding.

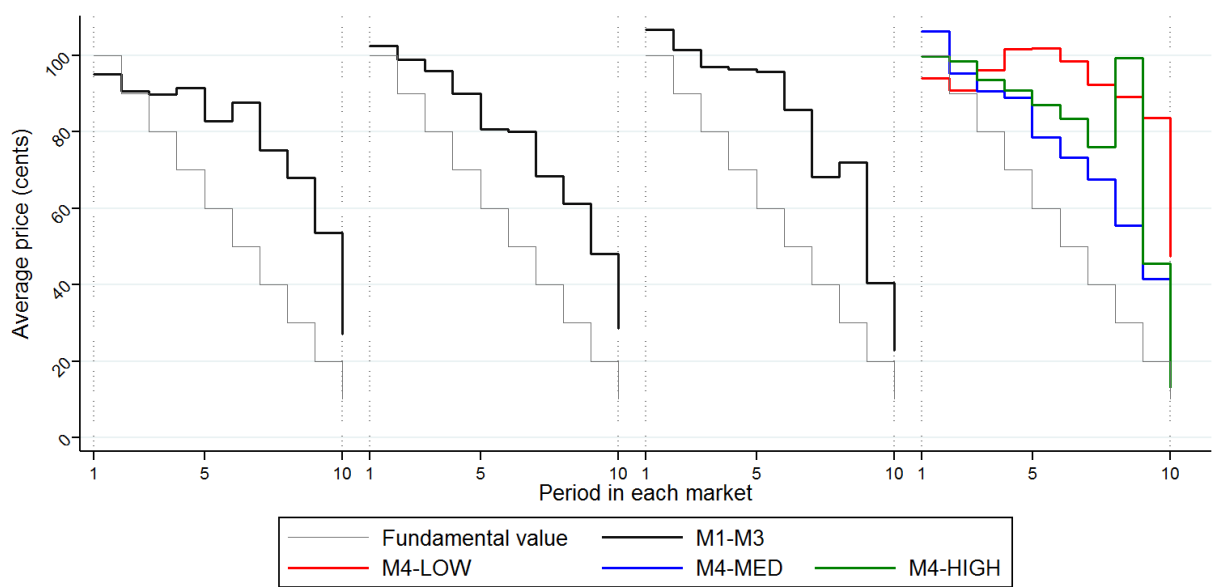
The individual task in DLM was not incentivized. We use incentivized tasks to keep subjects motivated in the experiment, while avoiding the use of a trading activity.

transaction prices that take place during the period. Deviation for the market as a whole is measured as the sum of deviations of period prices from fundamentals⁵.

1. General price patterns

The overall price patterns, averaged over session, are given in Figure 2 (data for individual sessions available in the appendix):

Figure 2: Average period prices



The first three panels plot the average period prices in the three repeated markets. In the first market, a typical bubble and crash pattern is observed. Prices move consistently further from fundamental value for much of the market, the gap disappearing only near the end of the market.

⁵ The deviations measure used here is equivalent to *Total Dispersion* defined in Haruvy and Noussair (2006) and proportional to *Relative Absolute Deviation* (RAD) defined in Stöck et al (2010).

This pattern continues to hold in the second and third markets. The fourth panel shows the average across the three treatment groups. All groups exhibit substantial mispricing. Low earners (red line) are furthest from fundamentals, median earners (blue line) are the closest to fundamentals, and high earners (green line) are roughly in between the other two groups.

The first three markets exhibit price patterns at odds with previous literature. Dispersion measures for the first market confirm that markets populated by inexperienced traders exhibit substantial mispricing. However, the data do not support the conjecture that mispricing goes away with experience ($p = 0.984$, Fisher-Pitman permutation test for paired replicates, $H_0: M1 = M3$, against two-sided alternative).

Result 1: Fail to reject hypothesis that bubbles do not decrease with experience.

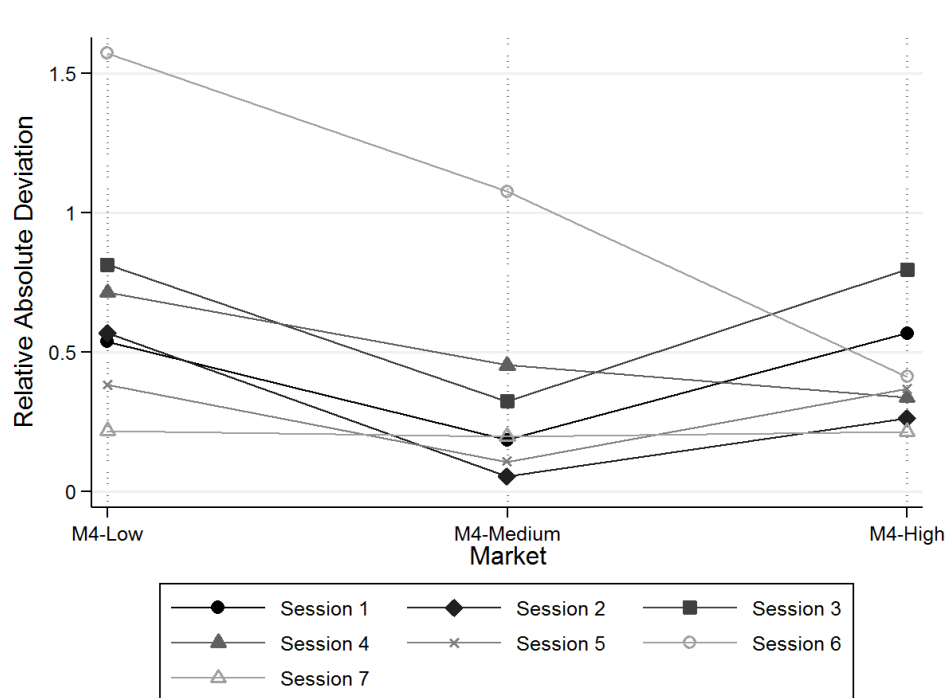
This finding is important since it is at odds with most of the literature on the topic (Smith et al., 1988; Haruvy et al., 2007)⁶. It would not be interesting if the changes in design compared to previous literature were already known to have such an effect, or if one could argue that the setting we study is less realistic than that studied in previous literature. However, for all of the differences in the setting we identify, we argue that the changes should (if anything) make it *more* likely to find an experience effect (see Footnote 4), and increase the realism of the setting. Therefore, we conclude that this finding is an important result for experimental asset markets generally.

2. Earnings and market behavior

⁶ Noussair and Powell (2010) report one of the few treatments where bubbles do not converge strongly over time. Hussam et al (2008) show that convergence to fundamentals is context-dependent.

Our main interest lies in studying how mispricing is affected by previous earnings of market participants. Specifically, we conjecture that higher earners may (consciously or not) produce different price patterns than their less successful peers. Figure 3 shows for each session how mispricing in the mixed-experience market varies according to the group type (LOW, MED or HIGH).

Figure 3: Mispricing vs. previous success

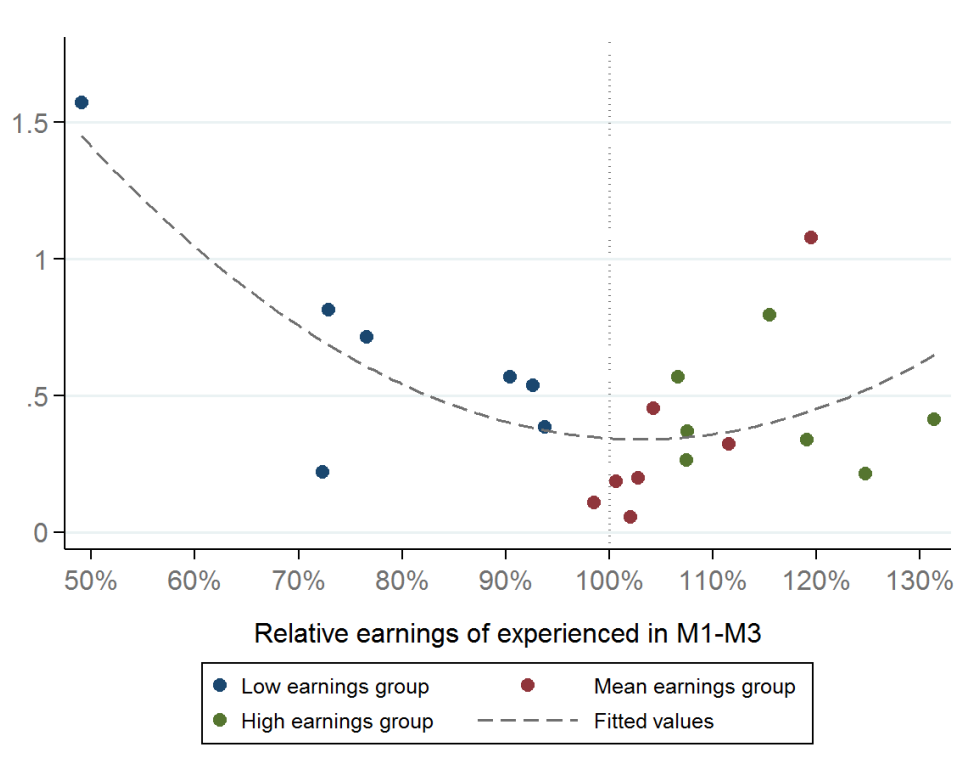


Recall that group types differ only in their previous success rankings. A paired replicates test rejects the hypothesis that price deviations in low and median markets are drawn from the same distribution ($p = 0.016$), but finds no significant difference between median and high markets ($p =$

0.609). This suggests that market behavior is not completely independent of previous success level.

However, subject rankings are based on actual earnings, and using the actual earnings variable allows for a cleaner test of the relationship between mispricing and earnings. Figure 4 compares the actual average earnings of each group of experienced traders to the mispricing in market 4.

Figure 4 - Mispricing vs. previous earnings measure



A regression of RAD in market 4 on the earnings of experienced traders from Markets 1-3 finds a statistically significant quadratic relationship between previous success and mispricing ($p < 0.01$, reported in the appendix): markets populated with more extreme earners have higher bubbles.

Result 2: Markets populated by more extreme earners exhibit stronger mispricing.

There are at least two potential channels through which extreme earnings may be associated with higher mispricing. The direct earnings effect is that traders with more extreme earnings may simply behave differently than those with modest earnings. Additionally, it could be that traders with more extreme earnings tend to have different past experiences than others. Previous bubble experiences may tend to skew the distribution of earnings, thus the indirect *history* effect is that traders with more extreme earnings simply be more likely to have experienced a bubble in the past.

The available evidence (reported in the appendix) suggests that this effect is summarized by the previous bubble experience of traders, rather than any specific behavioral activity. First, a regression of previous bubble size on earnings shows that more extreme earners did in fact experience higher bubbles in the past ($p < 0.01$). Secondly, we find that earnings from markets 1-3 do not explain any of the differences in bubble size in market 4 relative to the average bubble size in markets 1-3 ($p > 0.1$).

Result 3: Traders who experienced higher bubbles in the past are more likely to experience higher bubbles in the future.

Other studies have also found that earnings tend to be more dispersed in markets with higher bubbles (see, for example, Hirota and Sunder, 2007). This may not be surprising, since higher bubbles imply larger changes of portfolio values throughout the market. The second part of our

result simply confirms that controlling for aggregate experience, below-average earners experience the same increase in bubble as above-average earners.

3. Earnings and individual behavior

We look at a series of factors to see how they vary with current and past earnings. They are classified into the following strategic and non-strategic elements.

STRATEGIC

S1. Order volume: the number of orders placed by a trader.

S2. Transaction risk: the risk of a purchase is measured as the ratio of price to fundamental value. For sales, riskiness is measured as the inverse (fundamental value to price). A trader's risk measure is the geometric average of the risk measure for all trades they form a part of.

S3. Earnings variation over markets: the variation in adjusted earnings, and earnings rank, over the first three markets. This measure checks the consistency of a trader's performance over time.

S4. Portfolio composition: this measures the relative amount of a trader's portfolio that is invested in cash. Shares are valued at the current fundamental value in calculating portfolio value. To control for the dividends, which change the cash-to-asset ratio in the market over time, a trader's portfolio composition is taken relative to the aggregate market

portfolio. Finally, the trader's score is the average over the compositions they hold at each dividend payment.

NON-STRATEGIC⁷

NS1. Stupidity: Given that market outcomes are endogenous to the trading strategies employed, it is difficult to pass judgement on the trading strategies. Nevertheless, we highlight one trading strategy dimension that we consider to be inherently weak. Specifically, purchasing (or attempting to purchase) at extra high prices, at selling (or attempting to sell) at extra low prices.

To capture this idea, orders are classified as “stupid” if, when created, they could have been fulfilled immediately at a better price for the creator by using a market order. An order's stupidity is the difference between the actual order price and the potentially improving market order price. A trader's stupidity index is the sum of the stupidity of all offers they executed.⁸

NS2. Luck: Shares pay dividends based on a stochastic dividend draw. This induces variation in actual earnings from the ex-ante expected values. Corrected earnings replace realized dividends with their expected values. Luck is then measured as the difference between actual and corrected earnings.

⁷ We also looked at the number of attempts required to successfully answer the control questions, however this was not related to earnings in any way.

⁸ For three sessions, we only have incomplete information on the order book. Specifically, the time that an order was cancelled is unknown. For these sessions, we ignore these orders when checking the stupidity of an order. We use the sessions for which full order book information is available to estimate the bias of this restricted measure, and to correct the restricted measure to arrive at our final measure.

We run a set of linear regressions to consider the correlation between earnings and each behavioral measure separately. Since the market-level analysis suggests that extreme earners may behave differently than their peers, we include a quadratic term in all regressions. Therefore each regression is a single behavioral measure as a function of earnings and earnings squared. For the analysis of contemporaneous relationships, we use data from all markets. For predicting future behavior with previous earnings, behavior in market 4 is predicted using average earnings from markets 1-3.

The correlations between strategic behavior and contemporaneous earnings are as one might expect. Traders with more extreme earnings also tend to have higher activity levels, and hold more of their portfolio in shares. This is to be expected, since trading and holding shares are inherently risky activities, and should be expected to generate more extreme earnings. It is also not surprising that there is a negative correlation between earnings and transaction risk in a market, since transaction risk measures how often you purchase above or sell below fundamentals, a (usually) poor strategy. All of these findings are the same when using earnings to predict future behavior, which suggests that earnings may be a consistent indicator of these behaviors.

Result 4: More extreme earners engage in more trading activity and hold riskier portfolios. Higher transaction risk is associated with lower earnings. Previous earnings also predict trading activity, portfolio risk and transaction risk in market 4.

The findings for non-strategic variables are a bit more puzzling. We find that higher stupidity is associated with contemporaneously more extreme earnings ($p = 0.030$). That is, not only those

with lower earnings have higher stupidity, but also with *higher* earnings(!). However, the effect may disappear with time, since the relationship is no longer significant when using earnings from markets 1-3 to predict stupidity in market 4.

Result 5: Stupidity is associated with more extreme earnings, but is not predicted by previous earnings in experienced markets.

As a final note, we report the correlations with luck, the difference between actual and adjusted earnings. We find that extreme earners also tend to have marginally higher luck. Since luck in this scenario is a combination of the exogenous determined dividend draws, and the endogenously chosen share holdings of a trader, this is not completely unexpected. The same relationship holds when looking at current earnings and luck in the future, which suggests that consistent share holdings may be an explanation for this result.

IV. CONCLUSION

This study examines the sensitivity of experienced markets to the previous success of the experienced traders. The results suggest that markets populated by experienced traders with more extreme previous earnings exhibit significantly higher mispricing than those with more modest earnings. We expect real world markets to display exactly these kinds of characteristics, and thus our results call into question the generalizability of previous results suggesting that experience always has a dampening effect on bubble size.

We find that earnings affect bubble size mainly through the different type of experience associated with more extreme earnings. In particular, more extreme earners are those who are also more likely to experience bubbles in the past, and this is what causes them to experience higher bubbles in the future. There is no evidence that, conditional on previous bubble size, earnings are otherwise related to increases to bubble size.

Earnings are shown to be contemporaneously correlated and predict several types of individual behavior. We identify strong patterns that show that more extreme earners behave differently from their peers. More extreme earnings are associated with higher trading activity and riskier portfolios, whereas higher transaction risk is associated with lower earnings. In terms of predicting future behavior, current earnings are shown to forecast aspects of trading activity, portfolio risk and transaction risk are predicted by previous earnings.

Finally, while not a central focus of our study, we fail to consistently replicate an important result regarding the presence of an experience effect in a repeated market setting. Due to the limited dataset of this study (7 sessions), for the moment we can only point out that this calls into question the consistency of this effect. More generally, the summary of this analysis is that earnings are a key indicator of both market and individual behavior. If, as we have argued above, the distribution of previous earnings in real markets is not uniform, then the findings reported here have important implications for the analysis of experimental markets. We suggest that additional research is merited on experience, earnings, and the interplay between the two in market settings.

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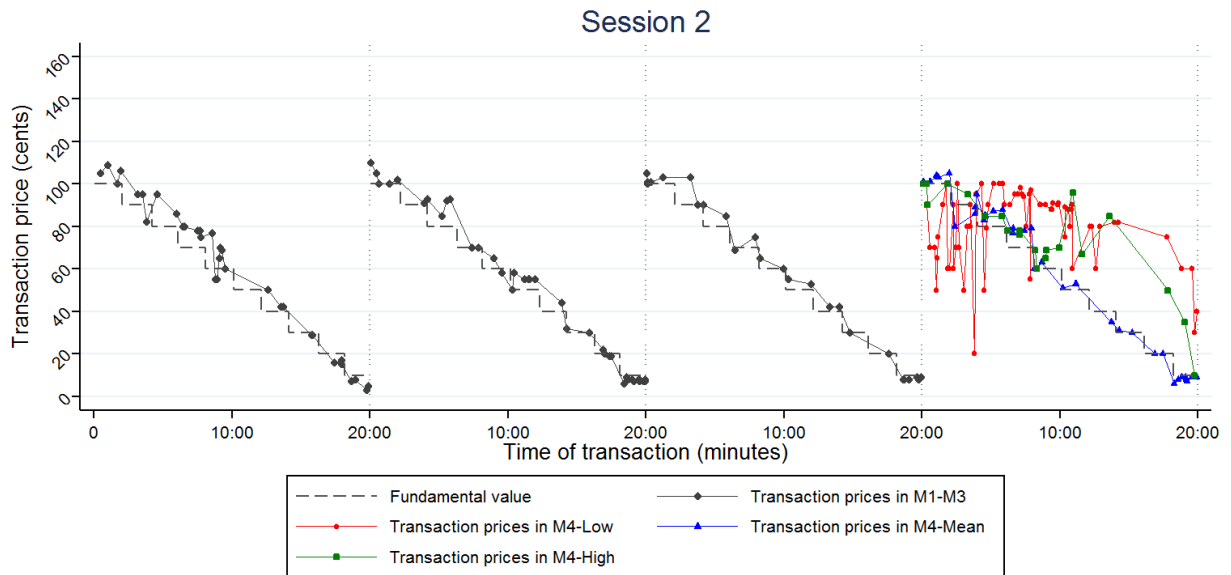
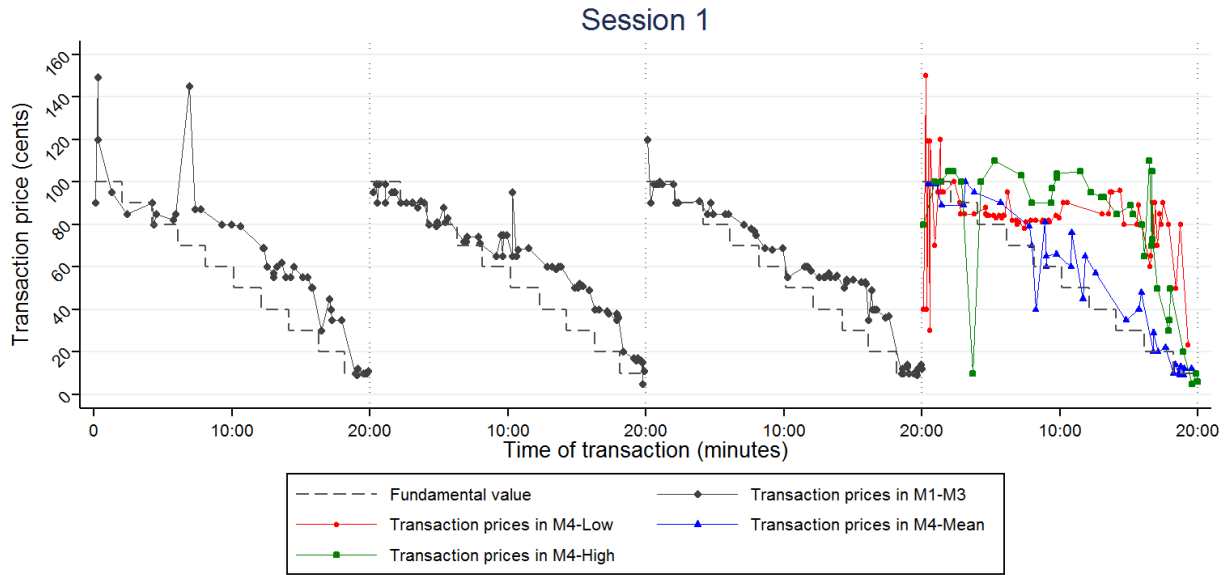
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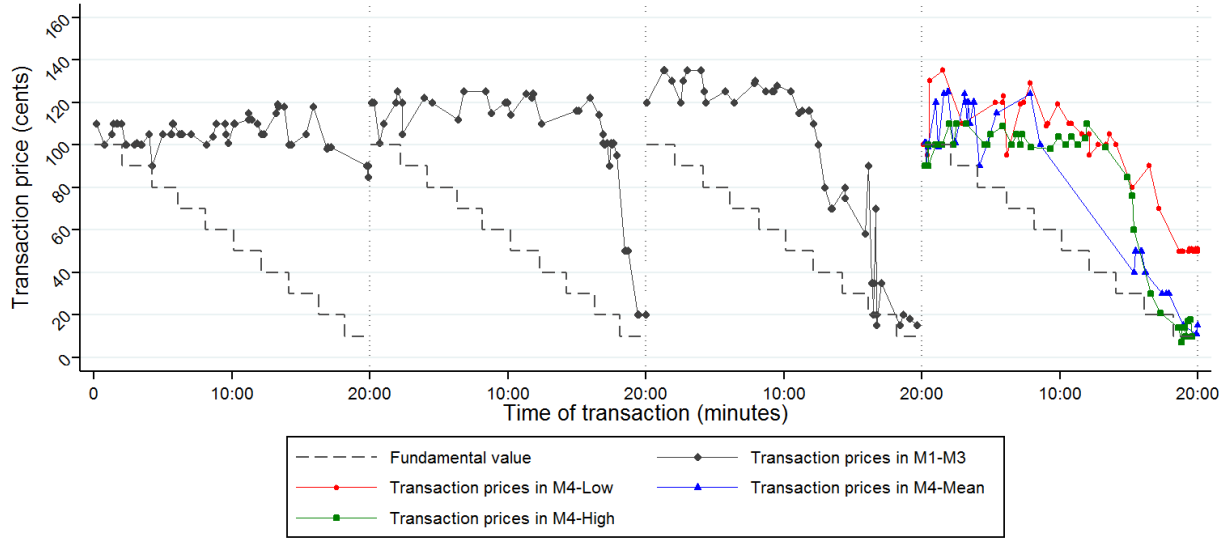
Xie and Zhang, 2012. "Bubbles and Experience: An Experiment with a Steady Inflow of New Traders". *Working paper*.

B. APPENDIX

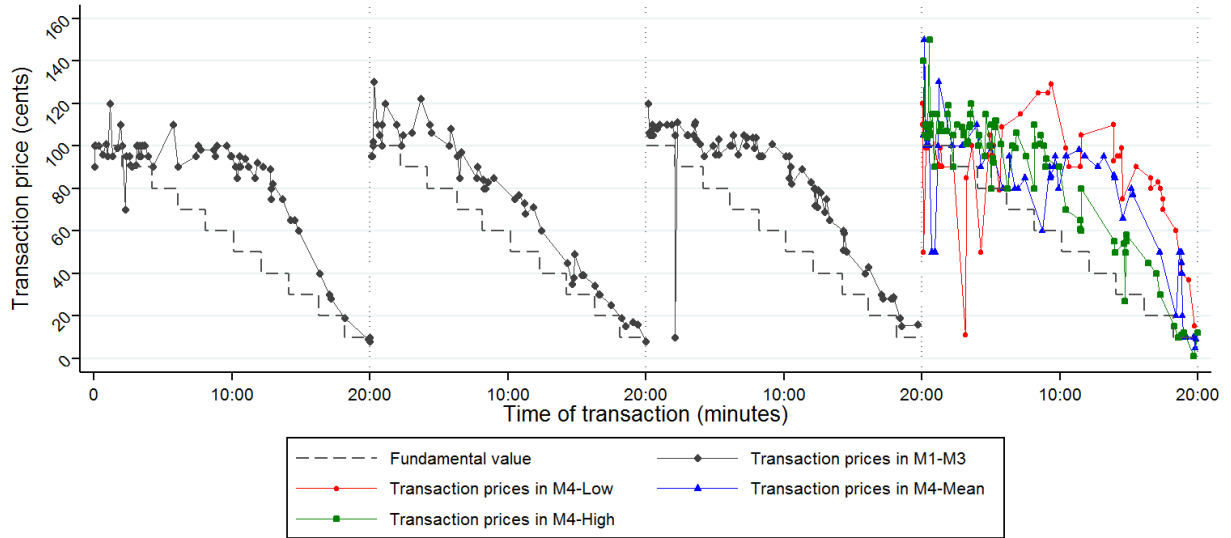
B.1 Session prices



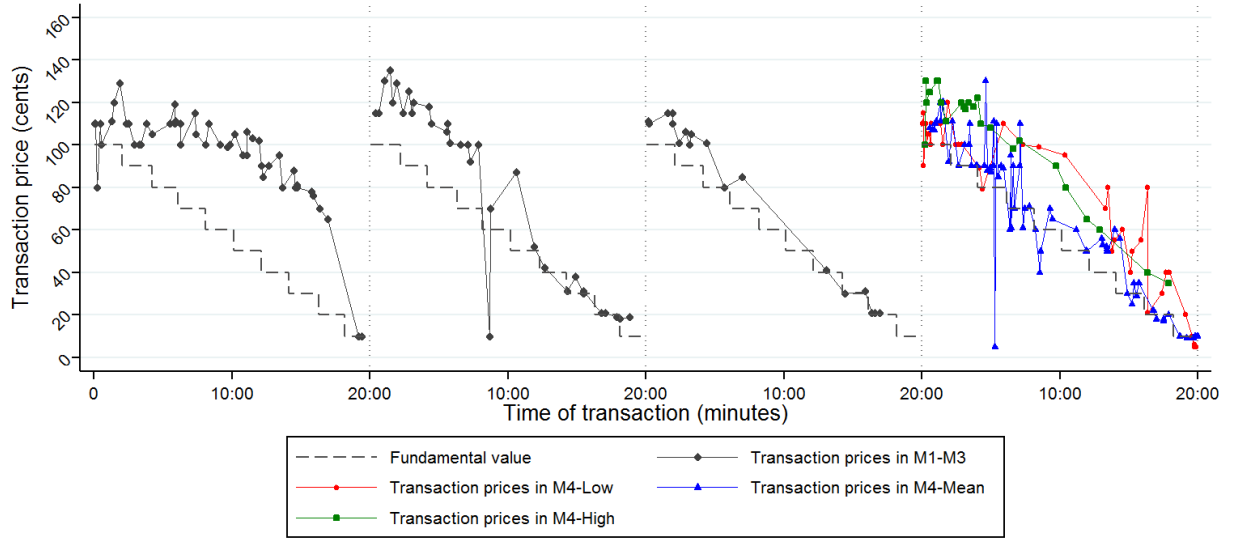
Session 3



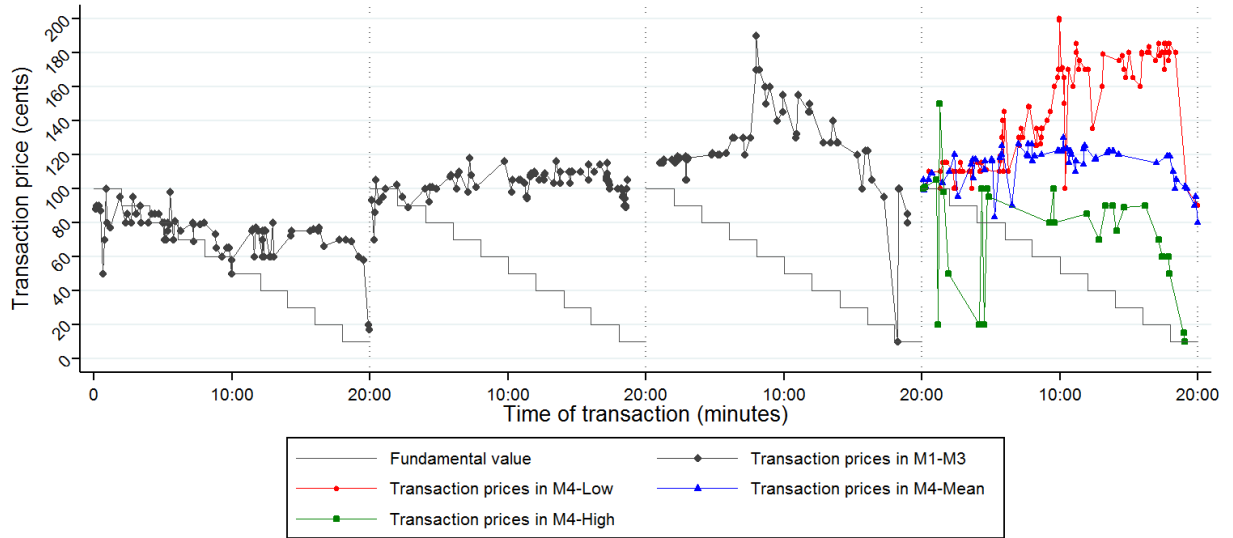
Session 4



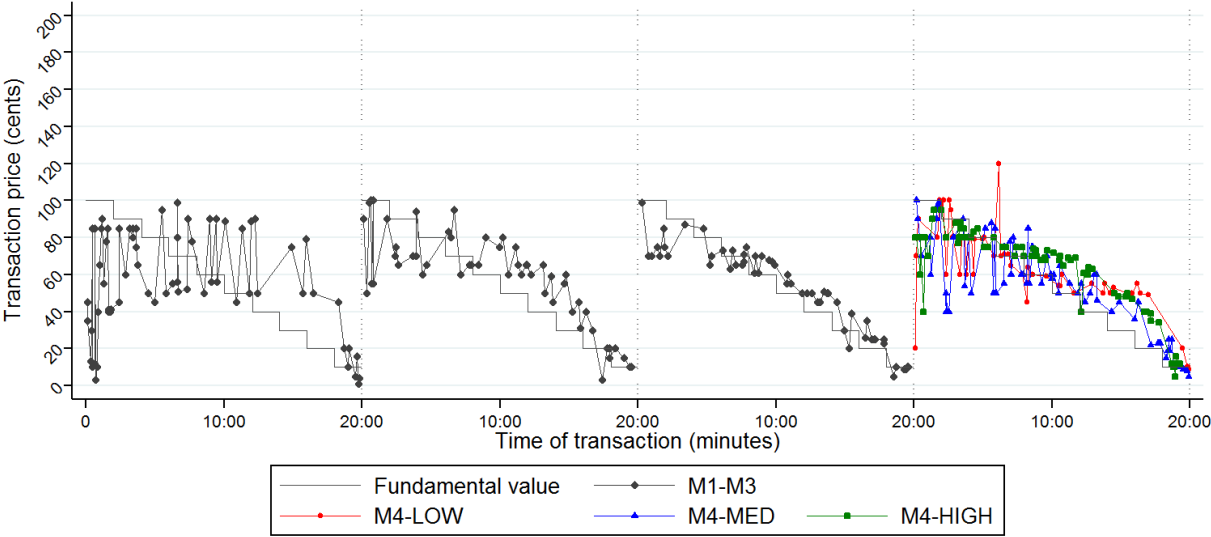
Session 5



Session 6



Session 7



B.2 Mispricing measures

Table 1 - Bubble measures, relative to M1

	M1	M2	M3		M4	
				LOW	MED	HIGH
HR2	100%	122%	114%	66%	132%	92%
nabpd	100%	78%	74%	135%	54%	104%
navpd	100%	78%	73%	133%	50%	103%
priceamp	100%	83%	114%	149%	75%	168%
RAD	100%	79%	73%	132%	49%	102%
RD	100%	76%	75%	124%	48%	102%

B.3 Instructions

This experiment lasts for two and a half hours and consists of several activities. Your earnings from each of these activities are paid to you at the end of the experiment. On the next screen, you are asked to answer a number of control questions to make sure you understand the instructions below. While doing the control questions, you may return to this screen at any time by pressing the "Instructions" button. Once you have correctly answered all of the questions, you will be able to proceed to the first activity. Please do not speak with any other participants during the experiment. If you have a question, raise your hand.

Some of the activities consist of trading. You begin trading with an endowment of shares and cash. Then for 20 minutes you may buy and sell shares for cash. Whenever you buy a share, your shares increase by one and your cash decreases by the price you pay. Whenever you sell a share, your shares decrease by one and your cash increases by the price you receive.

Every two minutes, each share pays a dividend to its current owner. This implies that there are 10 dividend payments altogether. Each dividend is equally likely to be 0 or 20 cents, is randomly decided by the computer, and is the same for all shares. This implies that the expected dividend per share is 10 cents. Dividends are added immediately to the share owner's cash.

The software automatically keeps track of your holdings of cash and shares using these two formulas:

ENDOWMENT OF CASH
+ CASH RECEIVED FROM SHARES SOLD

- CASH SPENT ON SHARES BOUGHT

+ DIVIDENDS RECEIVED

= CASH HOLDINGS

ENDOWMENT OF SHARES

- SHARES SOLD

+ SHARES BOUGHT

= SHARE HOLDINGS

Your earnings from the trading are equal to your cash after the last dividend has been paid.

Shares have no value once the trading has finished.

The holding value of a share shows how much you can expect to receive in terms of dividends if you hold one share from a given point in time until the end of trading. This is summarized in the table below.

Time	Dividends remaining	Holding value
0:01 - 2:00	10	100
2:01 - 4:00	9	90
4:01 - 6:00	8	80
6:01 - 8:00	7	70
8:01 - 10:00	6	60

10:01 - 12:00	5	50
12:01 - 14:00	4	40
14:01 - 16:00	3	30
16:01 - 18:00	2	20
18:01 - 20:00	1	10

[1] The current time, measured in minutes and seconds (mm:ss).

[2] The number of remaining dividend payments, given that payments occur every two minutes.

[3] The holding value per share, measured in cents. This is the number of remaining dividend payments multiplied by the expected dividend per share (10 cents).

B.4 Regression results

Market-level

Number of obs = 21

Robust Std. Err. adjusted for 7 clusters in session

Market 4 Bubble

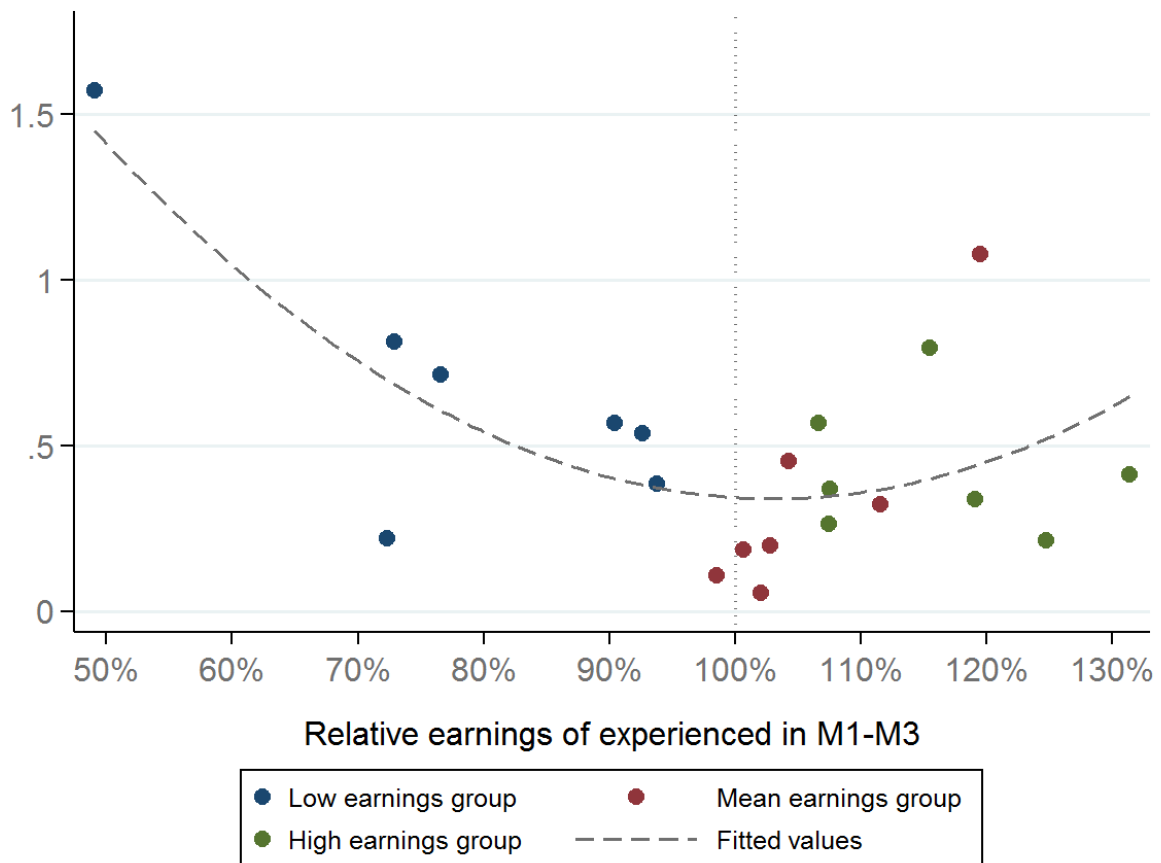
F(2, 6) = 43.68

Prob > F = 0.0003

R-squared = 0.4953

Root MSE = .26874

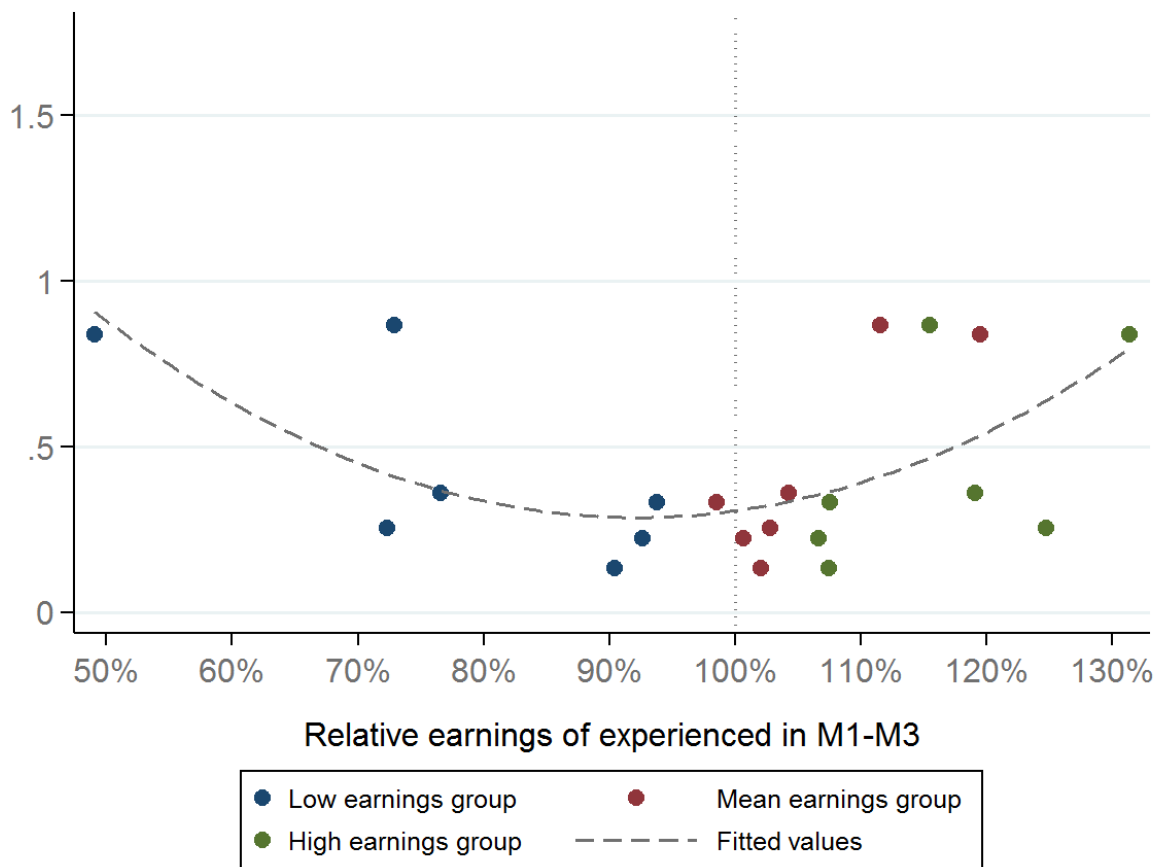
RAD	Coef.	Std. Err.	t	P> t	[95% CI]
ravgearn	-7.859273	.9523181	-8.25	0.000	-10.18951 -5.529035
ravgearn_sq	3.81535	.4951248	7.71	0.000	2.603823 5.026876
_cons	4.387843	.4892265	8.97	0.000	3.190749 5.584937



Markets 1-3 Bubble

F(2, 6) = 15.60
 Prob > F = 0.0042
 R-squared = 0.3567
 Root MSE = .23941

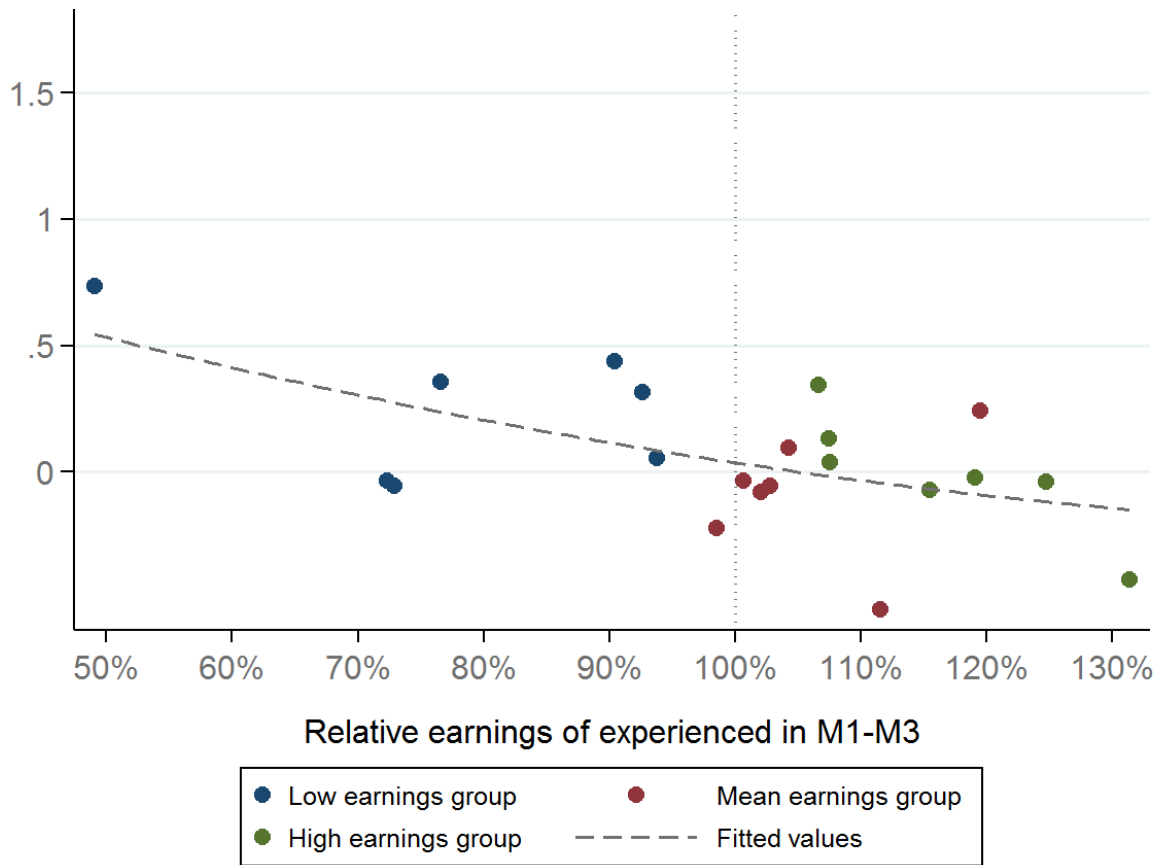
avgRAD	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
ravgearn	-6.135673	1.148414	-5.34	0.002	-8.945742 -3.325604
ravgearn_sq	3.326635	.6580375	5.06	0.002	1.716475 4.936794
_cons	3.115979	.4851923	6.42	0.001	1.928756 4.303202



Market 4 Bubble - Markets 1-3 Bubble

F(2, 6) = 6.59
 Prob > F = 0.0306
 R-squared = 0.3249
 Root MSE = .24865

RAD_B4vsAVG	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
ravgearn	-1.7236	1.051633	-1.64	0.152	-4.296854 .8496536
ravgearn_sq	.4887148	.5697955	0.86	0.424	-.9055244 1.882954
_cons	1.271864	.4743044	2.68	0.036	.111283 2.432445



Individual level - Current earnings and current behavior

Number of obs = 252

Robust Std. Err. adjusted for 42 clusters in market

STUPIDITY

F(2, 41) = 3.83
 Prob > F = 0.0298
 R-squared = 0.1768
 Root MSE = 63.211

sum_stupid~y	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
adjeearn	-218.4198	90.69521	-2.41	0.021	-401.5825	-35.25714
adjeearn_sq	82.00706	37.06694	2.21	0.033	7.148856	156.8653
_cons	151.507	54.80737	2.76	0.009	40.82127	262.1927



ACTIVITY

F(2, 41) = 12.57
 Prob > F = 0.0001
 R-squared = 0.0855
 Root MSE = 26.062

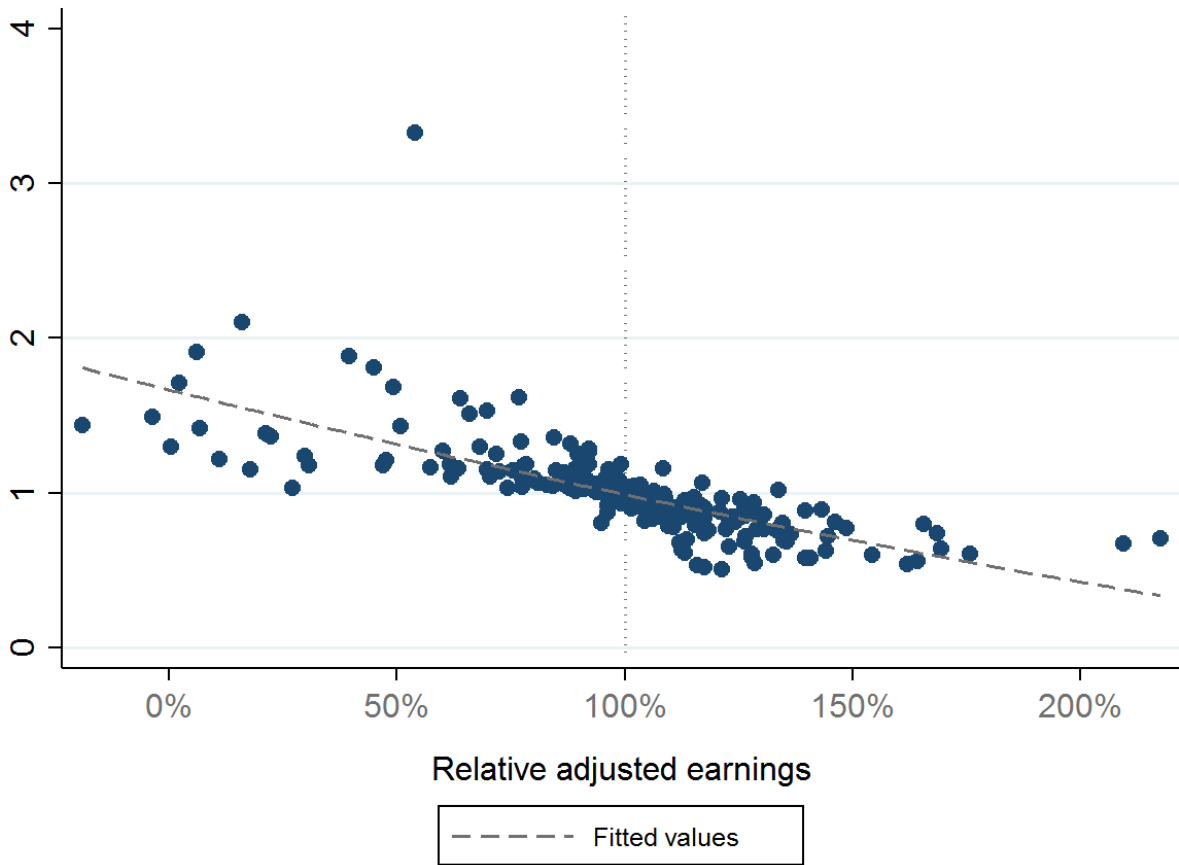
sum_act	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
adjearn	-64.20465	12.85339	-5.00	0.000	-90.16261 -38.2467
adjearn_sq	26.37478	6.328389	4.17	0.000	13.59434 39.15522
_cons	82.42873	7.506932	10.98	0.000	67.26817 97.58928



TRANSACTION RISK

F(2, 41) = 44.81
 Prob > F = 0.0000
 R-squared = 0.5255
 Root MSE = .19492

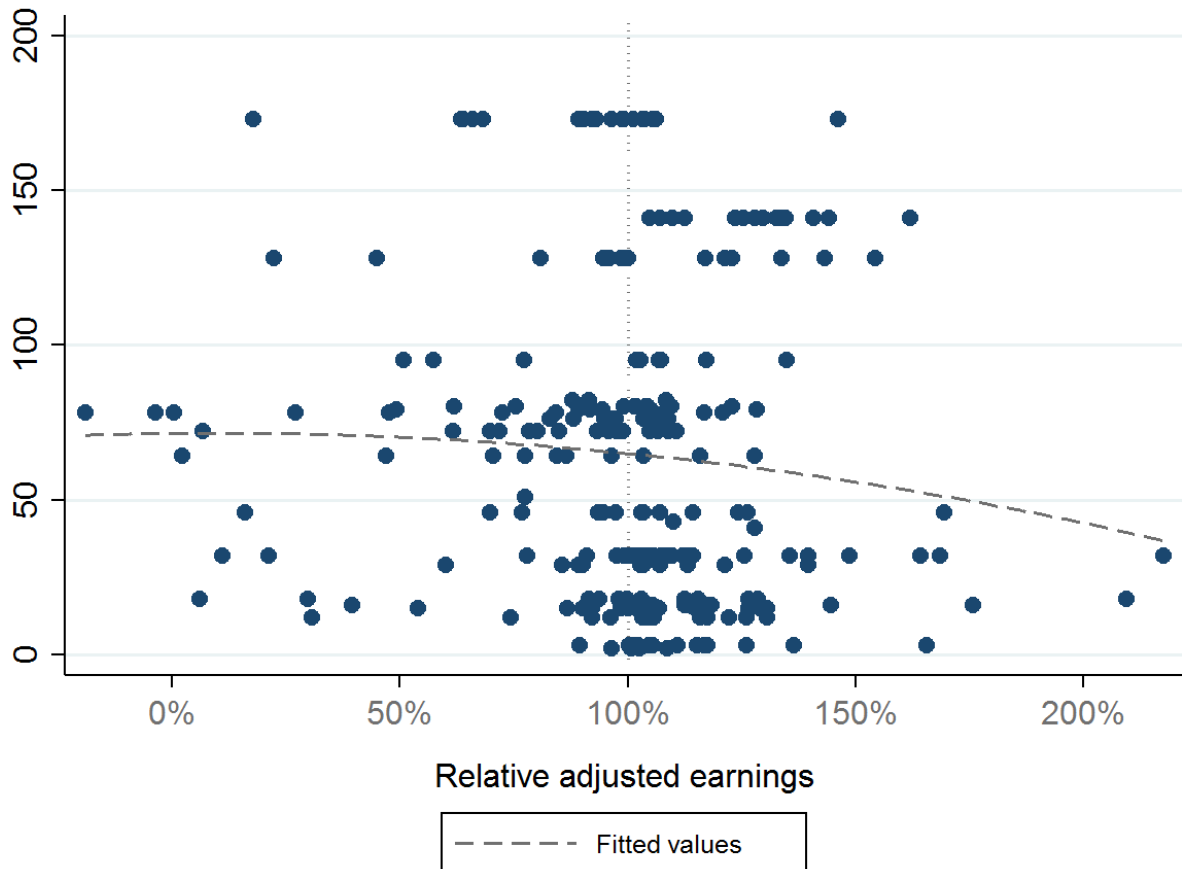
mean_risk	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
adjearn	-.7315028	.1208752	-6.05	0.000	-.9756152 - .4873904
adjearn_sq	.0554377	.0625282	0.89	0.380	-.0708406 .181716
_cons	1.665166	.0815574	20.42	0.000	1.500458 1.829875



CONTROL QUESTION ATTEMPTS

F(2, 41) = 0.93
 Prob > F = 0.4023
 R-squared = 0.0080
 Root MSE = 49.935

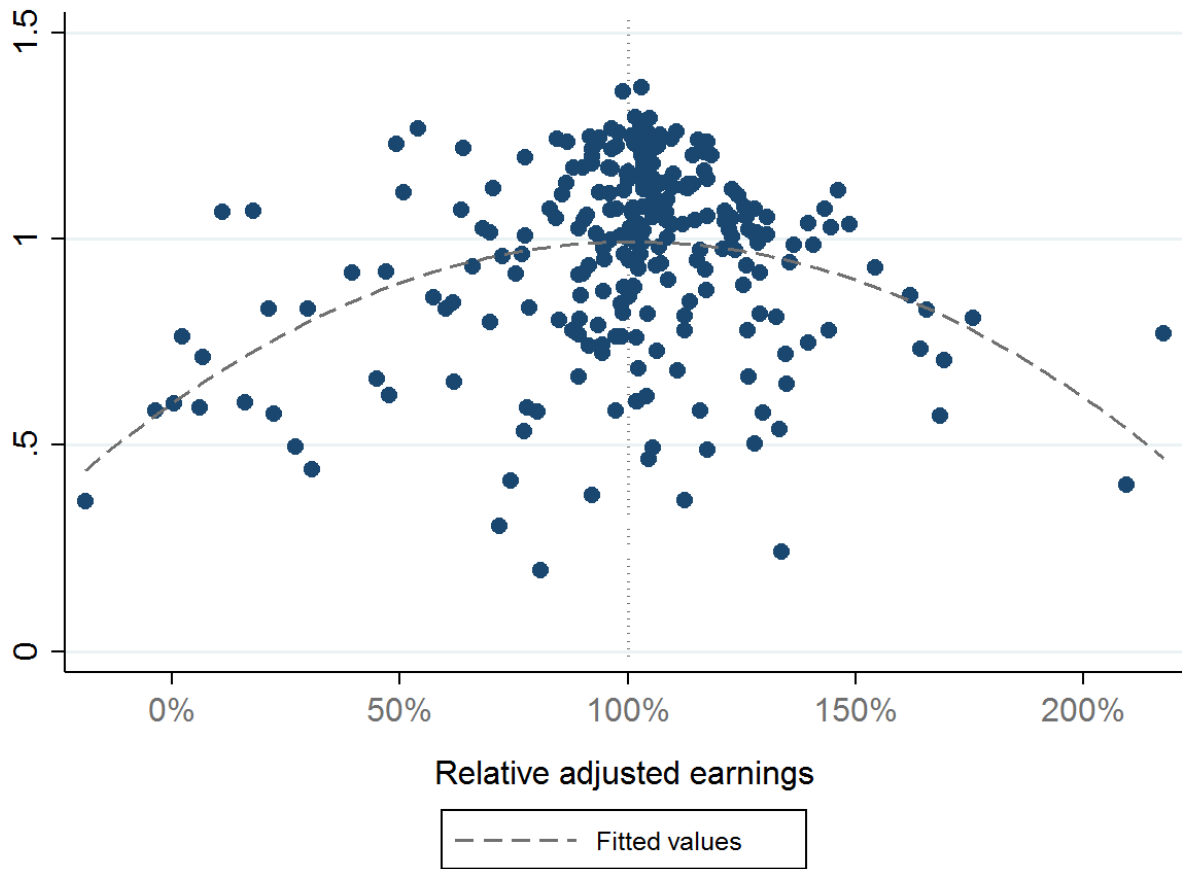
attempts	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
adjeearn	1.524935	18.92883	0.08	0.936	-36.70262 39.75249
adjeearn_sq	-7.998921	9.561461	-0.84	0.408	-27.30868 11.31084
_cons	71.49413	11.51169	6.21	0.000	48.24581 94.74246



PORTFOLIO IN CASH

F(2, 41) = 32.67
 Prob > F = 0.0000
 R-squared = 0.1434
 Root MSE = .21678

mean_portf~o	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
adjearn	.7751704	.0964541	8.04	0.000	.5803775 .9699633
adjearn_sq	-.3840655	.0549687	-6.99	0.000	-.495077 -.2730539
_cons	.6020594	.0506105	11.90	0.000	.4998493 .7042695



LUCK

F(2, 41) = 2.53
Prob > F = 0.0917
R-squared = 0.0638
Root MSE = 120.44

luck	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
adjeearn	-259.868	118.3637	-2.20	0.034	-498.9083 -20.82779
adjeearn_sq	143.7031	63.82749	2.25	0.030	14.80083 272.6053
_cons	107.0453	57.259	1.87	0.069	-8.591616 222.6822



Individual level - Average earnings in M1-M3 and behavior in M4

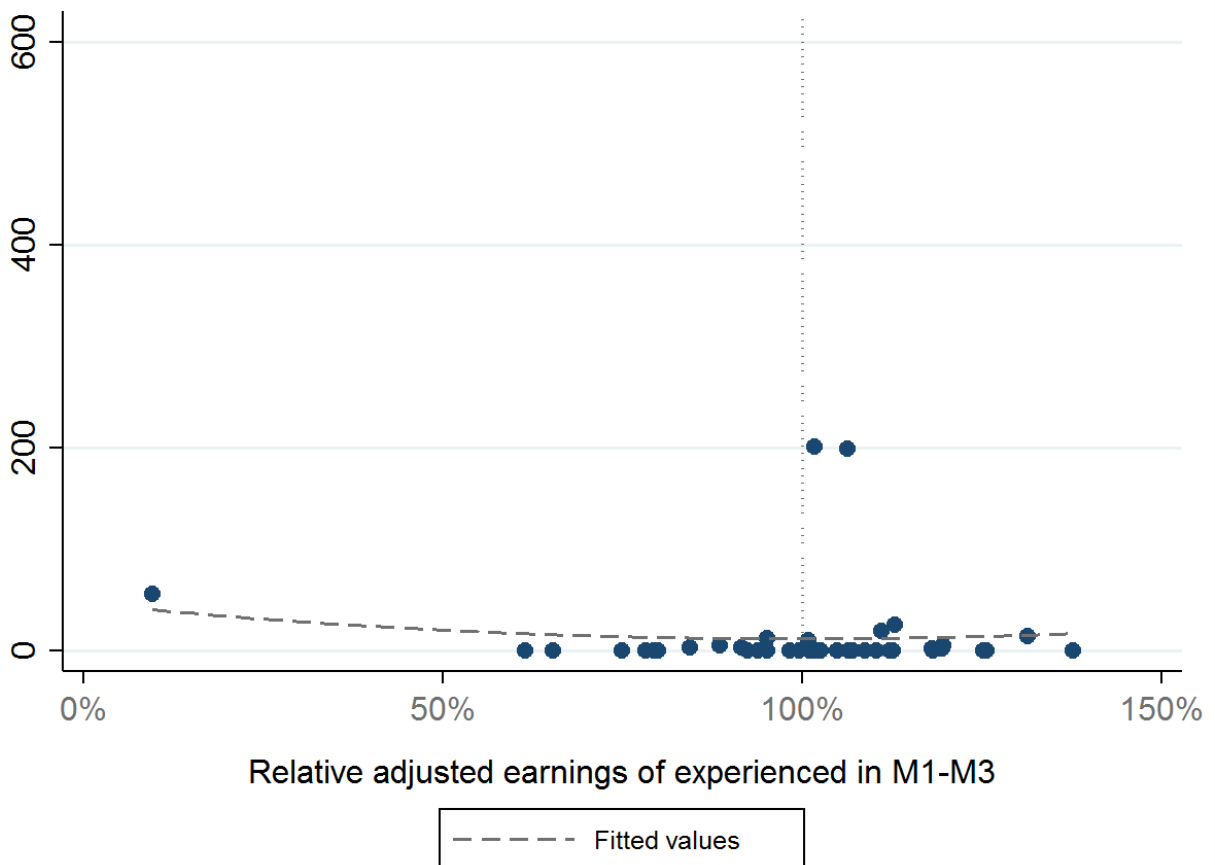
Number of obs = 42

Robust Std. Err. adjusted for 7 clusters in session

STUPIDITY

F(2, 6) = 0.81
 Prob > F = 0.4873
 R-squared = 0.0104
 Root MSE = 44.282

sum_stupidity~4	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
adjeearn_M123	-70.01847	56.12621	-1.25	0.259	-207.3544 67.31741
adjeearn_M123_sq	35.22636	27.74589	1.27	0.251	-32.66538 103.1181
_cons	46.38641	22.0439	2.10	0.080	-7.553077 100.3259

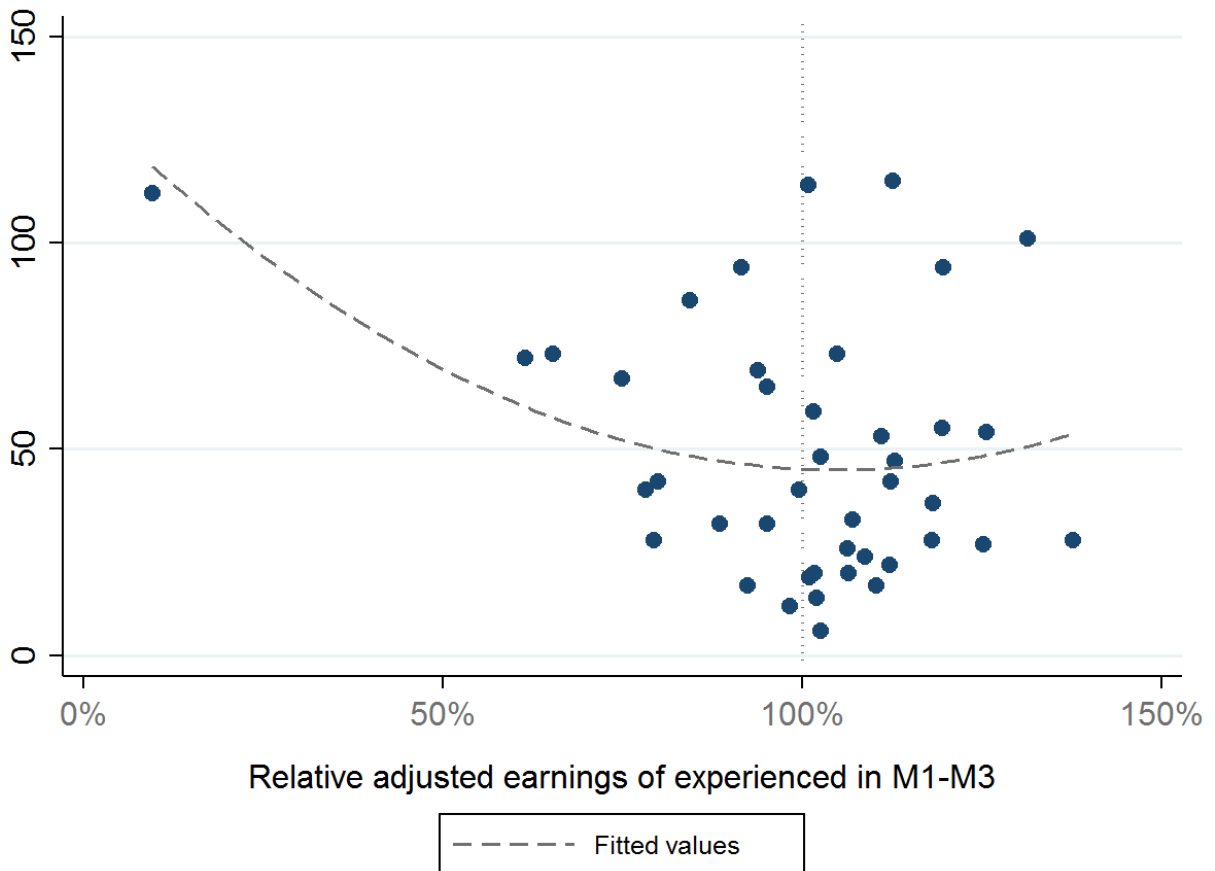


sum_stupidi ty_M4	Freq.	Percent	Cum.
0	28	66.67	66.67
2	2	4.76	71.43
3	2	4.76	76.19
5	2	4.76	80.95
10	1	2.38	83.33
12	1	2.38	85.71
14	1	2.38	88.10
19	1	2.38	90.48
25	1	2.38	92.86
56	1	2.38	95.24
199	1	2.38	97.62
201	1	2.38	100.00
Total	42	100.00	

ACTIVITY

F(2, 6) = 17.78
 Prob > F = 0.0030
 R-squared = 0.1453
 Root MSE = 28.674

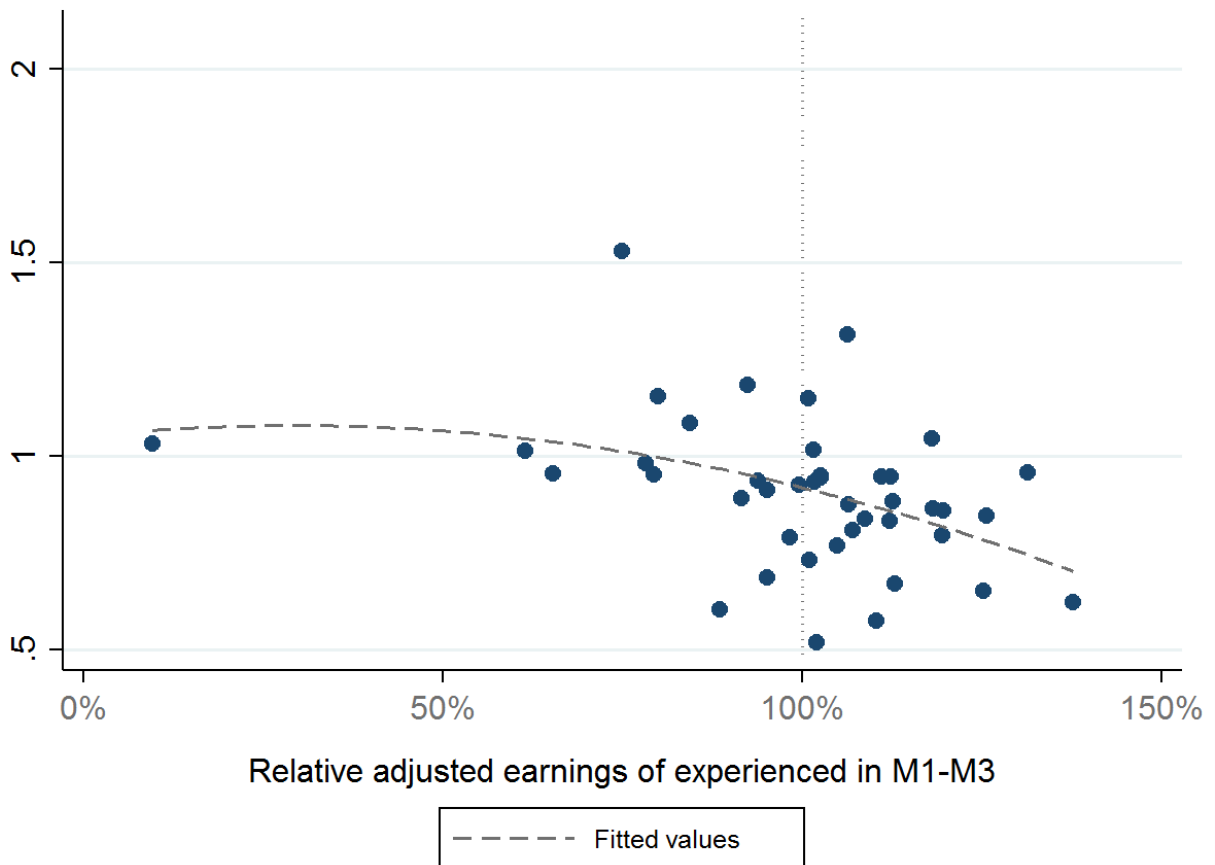
sum_act_M4	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
adjeearn_M123	-170.1805	45.13235	-3.77	0.009	-280.6154 -59.74565
adjeearn_M123_sq	81.15277	32.04418	2.53	0.045	2.743483 159.5621
_cons	134.217	14.43545	9.30	0.000	98.89476 169.5393



TRANSACTION RISK

F(2, 6) = 5.78
 Prob > F = 0.0398
 R-squared = 0.1655
 Root MSE = .1834

mean_risk_M4	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
adjearn_M123	.1892883	.1890113	1.00	0.355	-.2732058 .6517824
adjearn_M123_sq	-.3219278	.15302	-2.10	0.080	-.6963542 .0524985
_cons	1.051334	.0753879	13.95	0.000	.8668664 1.235802



CONTROL QUESTION ATTEMPTS

F(2, 6) = 2.01
 Prob > F = 0.2147
 R-squared = 0.0215
 Root MSE = 54.833

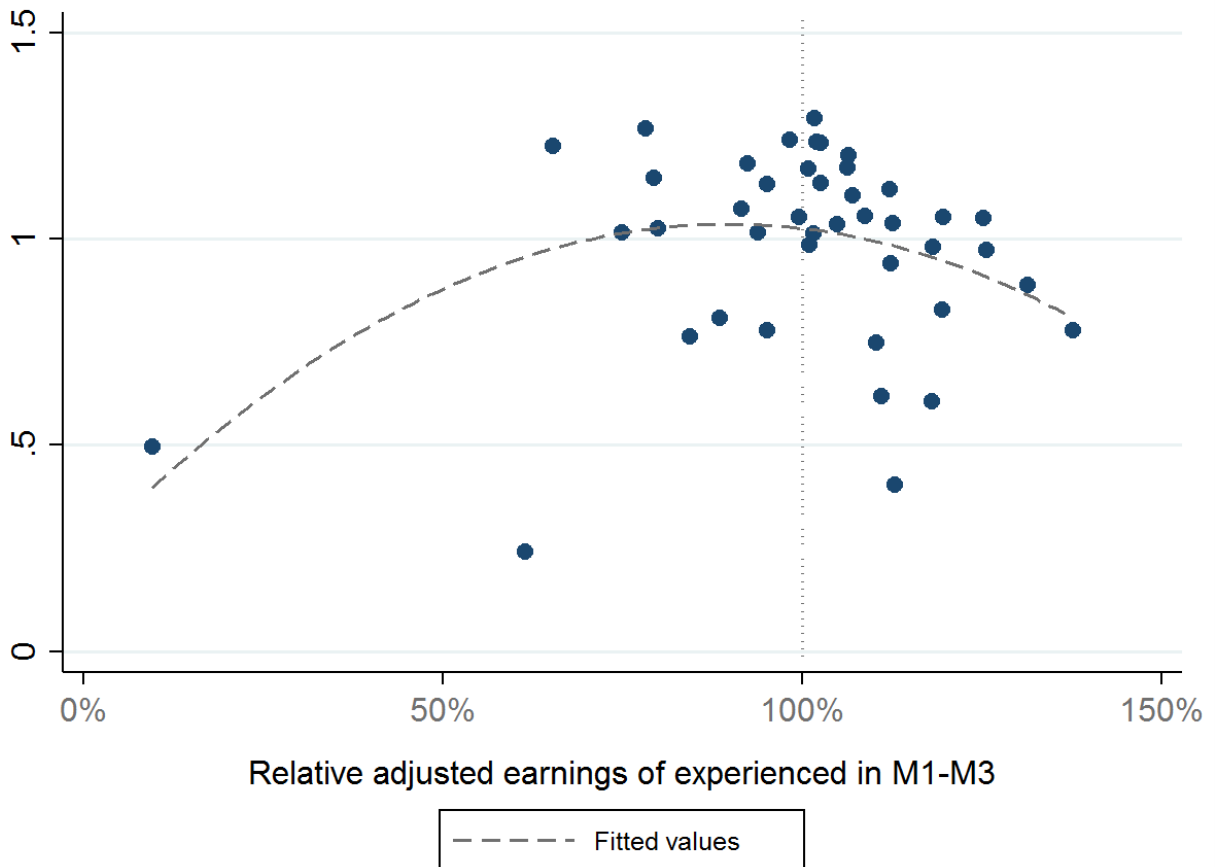
attempts_M4	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
adjearn_M123	-135.2831	79.21114	-1.71	0.139	-329.1058 58.53958
adjearn_M123_sq	79.98859	66.60044	1.20	0.275	-82.97681 242.954
_cons	119.0381	28.51247	4.17	0.006	49.27059 188.8056



PORTFOLIO IN CASH

F(2, 6) = 12.55
 Prob > F = 0.0072
 R-squared = 0.1872
 Root MSE = .22281

mean_portfoli~4	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
adjearn_M123	1.78696	.3669458	4.87	0.003	.8890757
2.684844					
adjearn_M123_sq	-.9956072	.2316076	-4.30	0.005	-1.56233
-.4288839					
_cons	.2343799	.1768998	1.32	0.233	-.1984782
.6672381					



LUCK

F(2, 6) = 4.87
 Prob > F = 0.0555
 R-squared = 0.1266
 Root MSE = 87.195

luck_M4	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
adjearn_M123	-381.3714	141.3782	-2.70	0.036	-727.3113 -35.43147
adjearn_M123_sq	281.8511	101.2963	2.78	0.032	33.98813 529.7141
_cons	74.93934	47.547	1.58	0.166	-41.40397 191.2826

