

How manipulable are prediction markets? Evidence from sweepcash markets

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1 Overview

The goal of this experiment is to learn whether real-money prediction markets can be manipulated through random trades. To investigate this, we plan to make a series of random bets across different prediction markets on the Manifold platform. While these bets will automatically shift prices in the short run, our main goal is to learn whether these price effects persist in the long run or are instead ‘undone’ by the reactions of other traders.

2 Experimental design

Manifold. Manifold is a prediction market platform that allows users to bet on whether various events will occur. Prices are determined using an algorithm called ‘Maniswap’ and can be used to estimate the probability that the event will happen (see Manski, 2006, Gjerstad and Hall, 2005 and Wolfers and Zitzewitz, 2006 for discussion).

In a previous experiment (Rasooly and Rozzi, 2023), we tested the manipulability of Manifold markets that run on a website specific currency called ‘Mana’. However, Manifold has recently introduced markets that run on ‘sweepcash’, a currency that can currently be converted at (roughly) a 1 to 1 rate with USD. In this experiment, we will study Manifold’s sweepcash markets.

Exclusion criteria. We will only bet on binary markets, i.e. markets that must resolve as ‘Yes’ or ‘No’ (or N/A). We will exclude:

1. Markets that resolve after the end of 2026.
2. Markets which cost over \$500 to move in either direction by 4 percentage points.
3. Markets that end within 14 days of our trade.
4. Markets that are closely related to other markets in our sample (e.g. “Will Trump win?” vs “Will Trump lose?”).

Intervention. For each market, we will first randomly determine (with equal probabilities) whether we will bet on ‘Yes’ or bet on ‘No’. When making a yes bet, we will buy however many yes shares are necessary to increase the price by 4 percentage points. When making a no bet, we will buy however many no shares are necessary to decrease the price by 4 percentage points. Note that, although the instantaneous effect of the intervention is obvious, our main interest is in estimating the persistence of the effect on prices.

Data. For each market, we will collect data on:

1. The market question/topic
2. The treatment (‘Yes’ or ‘No’)
3. The size of our bet

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4. The time of the intervention
5. The market’s opening time
6. The market’s closing time
7. The total volume of trade in the last 24 hours
8. The total volume of trade
9. The number of traders
10. The amount of liquidity
11. The size of the ‘pool’
12. Whether the market is subsidised
13. The number of user comments on the market

Note that variables 4-13 are Manifold created and are defined on their website.

In addition to these variables, we also record daily market prices, starting from 24 hours before our trade and running until 168 hours after our trade. We will also record the price just before our trade.

Sample. We will bet on 110 markets (see power calculations below). If more markets are available than are required for our experimental sample, then we will choose the markets with the highest total trading volume.

3 Analysis plan

Specification. Our main regressions will take the form

$$p_{t,i} = \beta_0 + \beta_1 \mathbb{1}_i(\text{‘Yes’}) + \beta_2 p_{-1,i} + u_i \tag{1}$$

where $\mathbb{1}_i(\text{‘Yes’})$ is a dummy variable that equals 1 if market i is in ‘Yes’ group and $p_{-1,i}$ is the price in the market just before our bet. Thus, the ‘No’ group is the omitted category. We include the $p_{-1,i}$ variable to increase statistical power, and will also report regressions that include the full suite of controls that are available to us (see above). We will estimate this regression for all time periods available, i.e. for $t = 1, 2, \dots, 7$.

Power. To choose a sample size, we calibrated our assumed statistical model (1) using data from our previous experiment on Manifold. To do this, we considered markets in our existing dataset that had been assigned to the Yes or No groups and had positive 24 hour volume. This left us with 104 markets in our dataset. After running the regression (1) on this dataset for $t = 7$ (one week effects) and slightly altering the results to take account of the difference in designs (our current experiment shocks prices by 4 percentage points, not 5 percentage points), we estimated that:

$$\beta_0 = 0; \beta_1 = 0.04; \beta_2 = 1; p_{-1,i} \sim \mathcal{N}(0.5, 0.181); u_i \sim \mathcal{N}(0, 0.0074)$$

where $\mathcal{N}(\mu, \sigma)$ denotes a normally distributed random variable with mean μ and standard deviation σ . After calibrating our assumed data generating process, we then simulated a dataset generated by this process of different sizes n and repeated each simulation 10,000 times in order to estimate power. (See the code in the appendix.) These computations suggested that, in order to have 80% power (i.e. to find ‘statistically significant’ effects at the 5% level with probability 0.8), one would need a sample size of 110.

Appendix: Stata code

```
clear all
set seed 1

capture program drop sim

program sim
  clear
  set obs 110
  gen pm1 = rnormal(0.5, 0.181)
  gen pseudotreatment = runiform(0, 1)
  gen treatment = 0
  replace treatment = 1 if pseudotreatment > 0.5
  gen u = rnormal(0, 0.0740905)
  gen p168 = pm1 + 0.04*treatment + u
  reg p168 treatment pm1, robust
end

*Run the simulations

simulate _b _se, reps(10000): sim

*Generate the t-statistics

gen t = _b_treatment/_se_treatment

sum t if abs(t) >= 1.96
```

References

Steven Gjerstad and McClelland Hall. Risk aversion, beliefs, and prediction market equilibrium. *Economic Science Laboratory, University of Arizona*, 2005.

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