

Manipulators Increase Information Market Accuracy

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July 2004 (First version March 2004)

Abstract

Information markets are low volume markets whose prices offer informative estimates on particular policy topics of interest. Observers have expressed concern that such prices might be less informative due to manipulators, i.e., traders who prefer that we see some policy estimates instead of others. We adapt a Kyle-style market microstructure model to the case of information markets, by assuming risk-neutrality and by allowing information effort and general trader irrationality. We add a trader who has an additional quadratic preference regarding the price, and we make ordinary traders uncertain about this manipulator's target price. We find that the mean target price has no effect on prices, but that increases in the variance of the target price *increase* average price accuracy, by increasing the returns to informed trading.

*For their comments, we thank Bryan Caplan, Dan Houser, John Ledyard, Kevin McCabe, Dave Porter, Emile Servan-Schreiber, Koleman Strumpf, Alex Tabarrok, Eric Zitzewitz, and several anonymous referees. For financial support we thank the Center for Study of Public Choice, the Mercatus Center, and the International Foundation for Research in Experimental Economics.

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Introduction

Observers have long been impressed by the ability of speculative markets to aggregate available information; it is hard to find information that is not already embodied in the prices of thick markets (Lo 1997). Recently some new markets, known as “information markets,” “prediction markets,” or “idea futures,” have been created in an attempt to harness this power on particular topics of interest (Chen and Plott 1998, Berg and Rietz 2003, Spann and Skiera 2003, Wolfers and Zitzewitz 2004). Such markets seem to hold great promise for better informing decisions in corporate governance and public policy (Hanson 1999).

Several concerns are often voiced about this approach. For example, during the recent furor over the DARPA Policy Analysis Markets (PAM), otherwise known as “terrorism futures,” critics complained that PAM might have allowed bets on the details of individual terrorist attacks.¹ In particular, critics feared that bad guys might do more bad things in order to win bets about those bad events, or that bad guys might intentionally lose bets in order to reduce market information.²

Since existing thick financial markets already respond to major terrorist attacks, it seems unlikely that new information markets, which are typically very thin, would offer substantial additional incentives for bad guys to do bad things. The typical thinness of information markets, however, does seem to make it cheap for bad guys to mislead markets with their trades. And at least one apparently successful attempt to manipulate political information markets has been reported (Hansen, Schmidt, and Strobel 2001).

Many others, however, have reported failed attempts to manipulate prices with trades, historically (Strumpf and Rhode 2004), in the field (Camerer 1998), and in the laboratory (Hanson, Oprea, and Porter 2004). A recent review article concludes that “none of these attempts at manipulation had much of a discernible effect on prices, except during a short transition phase” (Wolfers and Zitzewitz 2004). Why does this sort of manipulation³ seem

¹Actually, PAM would have focused on aggregate geopolitical trends, such as how the chance of political unrest in Saudi Arabia depends on whether US troops leave there (Polk, Hanson, Ledyard, and Ishikida 2003).

²Senators, reporters, and economists complained:

Terrorists themselves could drive up the market for an event they are planning and profit from an attack, or even make false bets to mislead intelligence authorities. *U.S. Senators Wyden and Dorgan (2003), Press Release, July 28, 2003.*

Would-be assassins and terrorists could easily use disinformation and clever trading strategies to profit from their planned misdeeds while distracting attention from their real target. *Steven Pearlstein (2003), Washington Post, July 30, 2003.*

Trading . . . could be subject to manipulation, particularly if the market has few participants – providing a false sense of security or . . . alarm. . . the lack of intellectual foundation or a firm grasp of economic principles - or the pursuit of other agendas - has led to a proposal that almost seems a mockery of itself. *Joseph Stiglitz (2003), Los Angeles Times, July 31, 2003.*

³Other kinds of “manipulation” not considered here include hidden actions that influence events, deceptive cheap talk intended to influence prices (Allen and Gale 1992), and strategic contrary trading made by an

to be less of a problem than many fear it should be?

One possible explanation is the view that a manipulative trader is in essence a “noise” trader, in the sense that his trades are based on considerations other than his best estimate of asset value. Standard models of market microstructure find that when potentially informed traders have deep pockets relative to the volume of noise trading, increases in trading noise do not directly effect price accuracy. In addition, by inducing more traders to become better informed, an increase in noise trading indirectly *improves* the accuracy of market prices (Kyle 1989, Spiegel and Subrahmanyam 1992). If the presence of manipulative traders similarly induced more effort by informed traders, this could help explain the typical failure of manipulation attempts.

This paper presents a formal model which confirms this view of manipulative traders as noise traders. We start with one of the simplest standard models of market microstructure, the single-period simplification of Kyle (1989, 1985) as it appears in popular textbooks on market microstructure (O’Hara 1997, Brunnermeier 2001). This simplified Kyle model contains some noise traders, some potentially informed traders, and some competitive market makers. We adapt this standard model to the case of a thin information market, and then add a manipulator, i.e., a trader who has an additional preference over the market price, or equivalently over the beliefs of neutral observers.

We are interested in the case of a thin information market, where the quantity traded is small, where relevant information can be obtained with some effort, and where there may be no liquidity traders to attract rational speculators. We thus consider the case of risk neutral traders who can buy information, and who may be, but need not be mildly irrational. That is, each trader’s information depends on his choice of an information effort, and we allow trading choices to be made using a standard general model of irrational behavior, the quantal response noisy game theory equilibrium (McKelvey and Palfrey 1995, Goeree and Holt 2001).

Into this basic information market model we add a manipulator who, in addition to the usual profit-based payoff, has a quadratic preference for the market price to be close to a target price. (This generalizes a previous model which had a linear manipulator preference (Kumar and Seppi 1992).) Other traders know the strength of this quadratic preference, but have only a noisy clue about the manipulator’s target price. To study a best case for the possibility of manipulation, we consider a single fully-rational manipulator.

We find that the manipulator’s mean target price has no effect on the market price, and that variance in the manipulator’s target price has no direct effect on average price accuracy. However, by increasing the expected rewards to informed trading, a larger manipulator variance indirectly *increases* the accuracy of the market price as an estimate of fundamental asset value. Thus in a standard market microstructure model of thin information markets, with rational or irrational traders who can obtain information with effort, manipulator bias that is within the range of biases that traders suspect might exist will on average improve price accuracy.⁴

informed trader to control the rate at which his information is revealed (Chakrabortya and Ylmaz 2004).

⁴Of course it is possible for the average social harm from price errors to increase even as the average price errors decrease, if social harm varies in complex ways with price errors. As we lack a model of social harm

Model

The simplest standard model of market microstructure is arguably the one-period version of Kyle (1989, 1985) that appears in popular textbooks on market microstructure (O’Hara 1997, Brunnermeier 2001). In one version of this model, there is a single asset of uncertain value, and a single risk-neutral informed agent who has a noisy clue about this asset value. This informed agent chooses a quantity of the asset to buy or sell. A “noise” or “liquidity” trader asks to trade a random quantity at the same time, and these two orders are combined into a net market order, which is observed by a competitive risk-neutral market maker. This market maker then sets the price for these trades to be the expected value of the asset conditional on seeing this net market order.

Let us modify this standard model to describe a thin information market with a manipulative trader. That is, consider a single asset whose true value is drawn as $v \sim N(\bar{v}, S_v)$, i.e., from a normal distribution with mean \bar{v} and (finite) variance $S_v > 0$. We will allow for the possibility of a liquidity trade quantity l drawn as $l \sim N(\bar{l}, S_l)$, but all our results will hold when $S_l = 0$. (Unless specified otherwise, all parameters are drawn independently.)

There are T traders, labeled $i \in \{1, 2, \dots, T\}$, each gaining a trading profit

$$\pi_i(x_i) = x_i(v - P)$$

if he buys a quantity x_i when the asset price is P . We assume risk-neutrality because we are interested in thin, i.e., low volume, information markets, and it is already established that increased noise trading can reduce price accuracy when informed trader risk aversion makes the informed trade volume small compared to the noise trade volume (Kyle 1989).

We also add a special trader, $i = 0$, with an extra quadratic preference regarding the market price P .⁵ His profit can be written in two equivalent forms, either in terms of a target price t or in terms of a bias w , as

$$\begin{aligned} \pi_0(x_0) &= x_0(v - P) - k(t - P)^2 \\ &= x_0(v - P) - k(\bar{v} - P)^2 + wP - \hat{k}, \end{aligned} \tag{1}$$

assuming $k \geq 0$. One can translate between these forms using $w = 2k(t - \bar{v})$ and $\hat{k} = k(t^2 - \bar{v}^2)$. Since this additional preference gives this trader a special reason to manipulate the price, we call this trader⁶ the “manipulator.”

We will use the form shown in equation 1 because this explicitly includes the case of a linear manipulation preference, where $k = 0$ and $w \neq 0$. Such a linear preference has been considered previously, in a model where a trader seeks to manipulate a spot market in order to raise the value of assets previously acquired in a futures market (Kumar and Seppi 1992).

from price errors, we do not further consider this possibility here.

⁵This ends up being the same as having a preference over the beliefs of outside observers.

⁶We introduce only one manipulator in order to study a best case for manipulation. This single trader can represent a group of manipulators with maximal internal coordination.

We assume that k is common knowledge, but that “bias” w (or equivalently the target price t) is private information to the manipulator, and is only commonly known to have been drawn as $w \sim N(\bar{w}, S_w)$.

Of the T traders, let us assume that N of them can acquire information about the true asset value v , and about the manipulator’s bias w . Specifically, each informed trader i observes the clues $a_i = v + \epsilon_i$ and $b_i = w + \delta_i$, where $\epsilon_i \sim N(\bar{\epsilon}, S_i)$ and $\delta_i \sim N(\bar{\delta}, S_\delta)$. If we define relative clue accuracy as $\eta_i \equiv S_v/(S_v + S_i)$ and $\rho \equiv S_w/(S_w + S_\delta)$, then these clues give traders improved estimates $E[\Delta v|a_i] = \eta_i \Delta a_i$ and $E[\Delta w|b_i] = \rho \Delta b_i$, where for any variable f the deviation from its mean is $\Delta f \equiv f - E[f]$.

We assume that each informed trader can reduce the variance S_i of his asset value clue via costly effort $c(S_i)$, where $c'(S_i) < 0$, $c''(S_i) > 0$, and $c(\infty) = 0$. Full trader profit is thus

$$\pi_i(x_i, S_i) = x_i(v - P) - c(S_i).$$

The N informed traders can choose $S_i \in [0, \infty)$, and get $S_\delta < \infty$, while the other uninformed traders are stuck with $S_i = S_\delta = \infty$. For simplicity, we also assume $S_0 = \infty$, so that the manipulator has no private information on the asset value, though he does know w .

The order of actions is as follows. First, every informed trader chooses his clue noise S_i . Second, every trader observes his clues a_i, b_i . Third every trader chooses his market order x_i . No trader sees any other player choices before choosing S_i or x_i , and so informed trader effort $c(S_i)$ is hidden. Fourth, orders x_i are summed and added to the liquidity trade l to produce a total order

$$y = l + \sum_{i=0}^T x_i.$$

Finally, the market maker observes this total order y and sets the market price to be

$$P = E[v|y] + \theta,$$

where $\theta \sim N(0, S_\theta)$ describes error in the (unmodeled) price setting process.

The optimal actions, expressed in terms of expected profit, are thus

$$\begin{aligned} S_i^* &= \operatorname{argmax}_{S_i \in R^+} [\bar{\pi}_i(S_i) \equiv E[\pi_i(x_i^*(S_i), S_i)|S_i]], \\ x_i^*(S_i) &= \operatorname{argmax}_{x_i \in R} [\bar{\pi}_i(x_i) \equiv E[\pi_i(x_i, S_i)|a_i, b_i, x_i]], \\ x_0^* &= \operatorname{argmax}_{x_0 \in R} [\bar{\pi}_0(x_0) \equiv E[\pi_0(x_0)|w, x_0]]. \end{aligned}$$

While all our results will hold when all traders choose optimal quantities x_i^* , we also allow irrational choice given by the widely used noisy game theory, the quantal response equilibrium (McKelvey and Palfrey 1995, Goeree and Holt 2001). This gives a probability density of

$$\Pr[x_i] = \frac{\exp(\bar{\pi}_i(x_i)/r_i)}{\int_{-\infty}^{\infty} \exp(\bar{\pi}_i(x'_i)/r_i) dx'_i}, \quad (2)$$

where $r_i \geq 0$ is the irrationality of trader i . When $r_i = 0$, then $x_i = x_i^*$ for sure. To allow a best case for manipulation, we assume $r_0 = 0$.

Ultimately, we want to know whether a stronger manipulator preference reduces or increases price accuracy. That is, how does the distribution of the error of the price as an estimate of value, $P - v$, including its mean $E[P - v]$ and mean square

$$\Phi = E[(P - v)^2],$$

respond to changes in the parameters \bar{w} and S_w describing the distribution of manipulator bias? (When we change the variance S_w we will assume that the clue error S_δ varies proportionally, so that the ratio S_w/S_δ remains constant.)

Analysis

As is standard in such a model, we seek equilibria where the price and quantities are linear in the various clues and parameters. Such linear equilibria are possible because we have assumed jointly normal distributions, which gives linear conditional expectations, such as

$$E[v|y] = \bar{v} + \Delta y \frac{E[\Delta v \Delta y]}{E[\Delta y \Delta y]}. \quad (3)$$

For clarity, we also focus on deviations from means. We thus we seek equilibria where

$$P = \mu + \lambda \Delta y + \theta, \quad (4)$$

$$x_i^* = \alpha_i + \beta_i \Delta a_i + \gamma_i \Delta b_i, \quad (5)$$

$$x_0^* = \tau + \gamma_0 \Delta w. \quad (6)$$

for certain values $\mu, \lambda, \alpha_i, \beta_i, \gamma_i, \tau, \gamma_0$. We furthermore seek equilibria which are symmetric within each class of traders. That is, for all informed traders $S_i = S_\epsilon$, $\eta_i = \eta$, $\alpha_i = \alpha$, $\beta_i = \beta$, and $\gamma_i = \gamma$, and for all other traders (besides the manipulator) $\alpha_i = \beta_i = \gamma_i = 0$.

Linear strategies make profit functions $\bar{\pi}_i(x_i)$ quadratic, and so quantal response behavior of equation 2 makes trading errors $e_i = x_i - x_i^*$ normally distributed. Thus $e_i \sim N(0, S_{e_i})$, with a variance of $S_{e_i} = -r_i/\bar{\pi}_i''$, expressed using the constant second derivative of $\bar{\pi}_i(x_i)$. We can combine these trading errors to obtain a total noise trade of $e \equiv \sum_{i=0}^T e_i$ with variance $S_E \equiv \sum_{i=0}^T S_{e_i}$. This allows us to redescribe the total order as

$$y = l + e + \sum_{i=0}^T x_i^*,$$

a form into which we can substitute our linear equations 4, 5, and 6.

Making such substitutions in our price error form gives

$$\Phi = S_\theta + S_v(1 - N\lambda\beta), \quad (7)$$

and in the market maker equations 3 and 4 gives $\mu = \bar{v}$, implying $E[P - v] = 0$, and

$$\frac{1}{\lambda} = \frac{S_E + S_X}{\beta N S_v} + \frac{\beta(N S_v + S_\epsilon)}{S_v}, \quad (8)$$

where non-error trading noise is

$$S_X \equiv S_l + N\gamma^2 S_\delta + (\gamma_0 + \gamma N)^2 S_w.$$

Substituting into the expected trader profit forms gives

$$\begin{aligned} \bar{\pi}_0(x_0) &= w\bar{v} - \lambda(x_0 - w)(\Delta x_0 + N\gamma\Delta w) - \hat{k} - kS_\theta - k\lambda^2(S_l + S_E) \\ &\quad - k\lambda^2(\Delta x_0^2 + 2\gamma N\Delta w\Delta x_0 + \beta^2 N(N S_v + S_\epsilon) + \gamma^2 N(N\Delta w^2 + S_\delta)) \\ \bar{\pi}_i(x_i) &= x_i[(1 - \lambda\beta(N - 1))\eta_i\Delta a_i - \lambda(\Delta x_i + (\gamma_0 + \gamma(N - 1))\rho\Delta b_i)] - c(S_i) \\ \bar{\bar{\pi}}_i(S_i) &= \beta_i(1 - \lambda(\beta + (N - 1)))S_v - \lambda(\beta_i^2(S_v + S_i) + \gamma^2 S_\delta + \gamma(\gamma_0 + N\gamma)S_w) - c(S_i) \end{aligned}$$

Note that when choosing S_i , agent i must distinguish the equilibrium value β from the value β_i that will describe his behavior if he makes an out of equilibrium choice of $S_i \neq S_\epsilon$.

For the uninformed traders $\bar{\pi}_i(x_i) = -\lambda x_i \Delta x_i$, making the first order condition (FOC) on x_i be $x_i^* = 0$, which gives $\alpha_i = \beta_i = \gamma_i = 0$ as we had assumed. The FOC on x_i for informed traders and manipulators give $\alpha_i = 0$, $\tau = \bar{w}$ and

$$\begin{aligned} \beta_i &= (1/\lambda + \beta(N - 1))\eta_i/2, & (9) \\ \gamma_i &= \frac{-\rho}{N\rho + 2(2 - \rho)(1 + k\lambda)}, \\ \gamma_0 &= \frac{N\rho + 2 - \rho}{N\rho + 2(2 - \rho)(1 + k\lambda)}, \\ 1/\lambda\beta &= N + 1 + 2S_\epsilon/S_v & (10) \end{aligned}$$

The second order condition (SOC) for manipulators is $0 \geq \bar{\pi}_0'' = -2\lambda(1 + k\lambda)$, and for all other traders is $0 \geq \bar{\pi}_i'' = -2\lambda$. If we assume a strict interior optimum of x_i^* , then $\lambda > 0$. And since $r_0 = 0$, we have $S_E = r/2\lambda$, for $r \equiv \sum_{i=1}^T r_i \geq 0$.

Equation 10 can be substituted into equation 7 to give our first result.

Theorem 1 *Given a fixed number of informed traders N and price setting error S_θ , the error $P - v$ of price as an estimate of asset value is distributed with mean zero, and variance*

$$\Phi = S_\theta + S_v \left(1 - \frac{N}{N + 1 + 2S_\epsilon/S_v} \right),$$

which depends only on (and is increasing in) the equilibrium asset value clue variance S_ϵ .

Thus there is on average no net bias, and the manipulator bias distribution $w \sim N(\bar{w}, S_w)$ can only effect price accuracy by effecting the informed trader's choices of clue variance S_ϵ .

The FOC and SOC for the choice of S_i are $\bar{\pi}'_i(S_i) = 0$ and $\bar{\pi}''_i(S_i) \leq 0$, where these expressions hold constant $\beta, \eta, S_\epsilon, \lambda, \gamma, \gamma_0$, while allowing β_i, η_i to vary with S_i . We assume that $c''(S_i)$ is large enough to induce a strict interior optimum, so that $\bar{\pi}''_i(S_\epsilon) < 0$, $S_\epsilon < \infty$.

Solving equations 8, 9, and 10 gives a quadratic equation, whose solution is

$$\beta = \beta_0 \pm \sqrt{\beta_0^2 + S_X/N(S_v + S_\epsilon)} \quad (11)$$

where

$$\beta_0 = \frac{r(N + 1 + 2S_\epsilon/S_v)}{2N(S_v + S_\epsilon)}.$$

The negative solution violates the SOC on x_i^* ($\lambda > 0$), so only the positive solution is valid.

Equations 10 and 11 show that an equilibrium exists, with λ and β finite and non-zero, when any one of S_l, S_w , or r is non-zero (and all are finite). Thus liquidity trading is not required to produce an information market equilibrium; a manipulator with unknown bias or any trader irrationality can substitute as a source of noise trading.

We are interested in how the price error Φ changes as we change the parameters ($k, \bar{w}, S_w, S_\delta$) that describe the manipulator. We already know that \bar{w} has no effect on prices. Let us now consider a proportional variation of S_w and S_δ together. That is, let us hold ρ constant while we increase S_w , keeping a proportional $S_\delta = S_w(1 - \rho)/\rho$. This variation plausibly describes a change to situation with “more” manipulation and similar clues about such manipulation.

We can show that as S_w and S_δ increase together in this way, the equilibrium trader clue error S_ϵ will decrease, lowering average price error Φ .

Theorem 2 *Changes in the mean manipulator bias \bar{w} have no effect whatsoever on prices. When the variance of manipulator bias S_w and bias clue error S_δ increase in the same proportion, trader asset clue variance S_ϵ and price error Φ both decrease.*

Proof The first claim follows trivially because \bar{w} only effects τ , which does not effect price P . Regarding the second claim, if we define $\hat{\pi}(S_i) \equiv \bar{\pi}_i(S_i) + c(S_i)$, then the FOC for S_i can be written $c' = \hat{\pi}' = -\lambda\beta_i^2$ and the SOC can be written $c'' \geq \hat{\pi}''$, where only β_i, η_i vary with S_i . If we differentiate this FOC with respect to S_w and collect terms appropriately, we find

$$(\hat{\pi}'' - c'') \frac{dS_\epsilon}{dS_w} = - \left. \frac{\partial}{\partial S_w} \right|_{S_\epsilon} \hat{\pi}' = \left. \frac{\partial}{\partial S_w} \right|_{S_\epsilon} \left(\frac{\beta_0 + \sqrt{\beta_0^2 + \frac{S_X}{N(S_v + S_\epsilon)}}}{N - 1 + 2/\eta} \right). \quad (12)$$

In the far right term, when S_ϵ is held constant then only S_X depends on S_w . So if we assume a strict interior optimum of S_i , with the SOC holding strictly ($\hat{\pi}'' - c'' > 0$), we must have

$$-\text{sign} \left[\frac{dS_\epsilon}{dS_w} \right] = \text{sign} \left[\left. \frac{\partial S_X}{\partial S_w} \right|_{S_\epsilon} \right]$$

Substituting proportional variation of S_w and S_δ into our expression for S_X , and differentiating, we find

$$\frac{\partial S_X}{\partial S_w} \Big|_{S_\epsilon} \left(1 + 4kS_w(2-\rho) \frac{N\rho(1-\rho) + (2-\rho)^2}{(N\rho + 2(2-\rho)(1+k\lambda))^3} \frac{\partial \lambda}{\partial S_X} \Big|_{S_\epsilon} \right) = \frac{N\rho(1-\rho) + (2-\rho)^2}{(N\rho + 2(2-\rho)(1+k\lambda))^2}.$$

If we take the derivative of λ with respect to S_X , we can rearrange and find that S_X increases in S_w , and hence S_ϵ and Φ decrease in S_w , when

$$1 > \frac{\beta - 2\beta_0}{\beta - \beta_0} \times \frac{2(2-\rho)k\lambda}{N\rho + 2(2-\rho)(1+k\lambda)} \times \frac{S_w}{S_w + S_l \frac{(N\rho + 2(2-\rho)(1+k\lambda))^2}{N\rho(1-\rho) + (2-\rho)^2}}.$$

The right hand side here is a product of three non-negative terms, each of which is no greater than one, and one of which (the middle) is strictly less than one. QED.

Conclusion

It is natural for people to fear that a complex social institution that they do not understand will be used by their enemies to hurt them. Thus people might naturally fear that information markets on the topic of their enemies, such as the Policy Analysis Market might have been, would be used by those enemies to hurt them. And while the low volume of such markets limits the profits that such enemies might realize from trading, that low volume seems to make it cheap for enemies to manipulate perceptions with their trades. This has led to fears that manipulators may decrease price accuracy.

Historical, field, and laboratory data, however, have failed to find substantial effects of such manipulation on average price accuracy. Since previous models have found that increases in noise trading can increase the accuracy of thin markets, by increasing the rewards to informed trading, we might hypothesize that manipulators are like noise traders, in that both make trades based on considerations other than their best estimate of the asset value.

This paper has presented a standard Kyle-style market microstructure model that confirms this basic hypothesis. Adapting this standard model to the case of an information market, and adding in a manipulator, we find that a manipulator can substitute for a liquidity trader or for trader irrationality to produce an information market equilibrium. A manipulator with a known target price preference has no effect on the market price, but one whose target price is unknown is much like a noise trader with an unknown trading quantity. The prospect of trading against someone who trades on non-asset-value considerations can entice other traders to become better informed, increasing average price accuracy.

While the social desirability of information markets remains an open question, this model suggests that concerns about manipulators reducing average price accuracy are misplaced.

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