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BY

JOSHUA D. COVAL
AND
DAVID HIRSHLEIFER
UNIVERSITY OF MICHIGAN BUSINESS SCHOOL

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Joshua D. Coval† and David Hirshleifer‡

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†University of Michigan Business School, 701 Tappan Street, Ann Arbor, MI, 48109-1234. Ph:(734) 764-2313, Fax: (734) 936-0274, e-mail: coval@umich.edu
‡University of Michigan Business School, 701 Tappan Street, Ann Arbor, MI, 48109-1234. Ph:(734) 763-2170, Fax: (734) 936-0274, e-mail:david.hirshleifer@ccmail.bus.umich.edu

Trading-Generated News, Sidelined Investors, and Conditional Patterns in Security Returns

This paper provides a model of information aggregation in a security market with setup costs of trading. In this setting, informed investors may delay trading until price movements validate their private signals. Trading thereby internally generates the arrival of further news to the market. This leads to 1) negative skewness following price runups and positive skewness following price rundowns, 2) a lack of correspondence between large price changes and the arrival of external information, 3) increases in volatility following large price changes, and 4) more rapid market aggregation of information.

1 Introduction

A puzzle for theories of asset prices based on rational beliefs (or efficient markets) is that prices seem to change substantially without significant external news. Romer (1993) discusses the evidence of this phenomenon, and offers a model that addresses this puzzle by showing that price movements may result from learning that occurs through the trading process, rather than from external news.[1]

Romer offers two possible resolutions of this puzzle using models based on either differences in beliefs about information precision, or transaction costs of trading. At a broader level, Romer argues that "the fact that changes in stock prices are often unaccompanied by evident news is a major puzzle and that theories that attribute this fact to the revelation of information by the trading process offer a promising route to understanding it."

This paper pursues this route further in attempting to understanding several puzzling facts about the behavior of securities price which we argue may be related to the phenomenon of asset pricing movements without news. Romer applies his approach to the phenomenon of market crashes wherein stock prices suddenly drop, possibly without major external news. Recent empirical evidence discussed further below has shown that stock prices are more likely to have sudden large drops after recent price runups. In other words, stock prices become negatively skewed after price runups. Conversely, there is a tendency for positive skewness after conditioning on recent declines in stock prices. Furthermore, there is evidence of increasing in stock return volatility after market reversals. Volatility tends to cluster in asset returns, with large changes following large changes.

These patterns of path-dependent asymmetry in return distributions, and of path-dependent shifts in volatility, pose a challenge to rational theories of securities pricing. It is certainly far from clear why external news would arrive in a skewed pattern as a function of past external news. Nor is it obvious why external news should suddenly arrive more rapidly after a market reversal.

We argue in this paper that such patterns of conditional skewness and volatility can arise naturally in a setting in which information is only gradually revealed through the

[1]The crash of October 1987 provides a major example. Cutler et al. (1989) show that this is typical as they find large index changes to be seldomly associated with clear news announcements. Roll (1988) finds a similar phenomenon associated with firm-specific price changes. Finally, French and Roll (1986) find price volatility to depend more on when the market is open than on the rate of information arrival.

trading process. Central to our approach is that information in the hands of sidelined investors is not immediately aggregated into market price, and that events in the trading process trigger the arrival of such investors and the news they possess. Since trading events internally trigger the arrival of news, the distribution of future returns shifts predictably as a function of past price movements even when no new external news arrives. We offer a specific model that extends the models of Romer (1993) to show how such gradual revelation can generate the observed patterns in the conditional moments of security returns.

Several recent studies document remarkably strong variation in skewness of security returns as a function of past price movements. Following large price increases, return distributions become negatively skewed, with increased probability of a large downward correction. Likewise, following substantial price declines, returns become positively skewed, with little chance of further large declines, and an increased probability of what traders sometimes refer to as a 'dead-cat bounce.'[2]

Perhaps the most startling evidence of conditional shifts in skewness comes from Lo and Wang (1996). As summarized in Table 1, they find that stocks whose returns one week are in the top (bottom) 10% are much more likely to end the following week in the bottom (top) 10% than any other decile. Using transactions data, Ederington and Lee (1996) show a similar phenomenon exists at higher frequencies.[3] Furthermore, using monthly data, Harvey and Siddique (1995) document considerable time-variation in conditional skewness measures of the U.S. and world market portfolios.[4] Indeed, in an asset pricing framework in which investors have preference for skewness, they show that conditional skewness helps account for the time-series variation in the expected U.S. and world market risk premia as well as the cross-sectional variation in the expected returns of individual securities.

If a reversal does occur, however, there is additional evidence that it tends to be followed by a period of increased volatility. GARCH (Generalized Autoregressive Conditionally Heteroskedastic) models, with their ability to capture conditional volatility clustering in asset returns, have been successfully applied to modeling risk premia in foreign exchange markets

[2]These are conditional skewness effects, and hence are distinct from the conditional mean 'winner/loser' effects described by DeBondt and Thaler (1985) and (1987).

[3]They demonstrate that price changes of futures contracts on currency, bond, and stock indices become highly skewed following steady price rises or declines. For example, they show that if Treasury bond futures experience a sequence of four positive (negative) price changes, they are 4 times as likely to record a further price increase (decrease) (after adjusting for bid-ask bounce). Yet if the sequence is broken by a reversal, the price decline (rise) is 2.5 times as likely to be followed by further declines (rises).

[4]The null of no time-variation in skewness is consistently rejected at the 1% significance level.

(See Engle and Bollerslev (1986)) and other securities (see Bollerslev, Engle, and Wooldridge (1988)). GARCH models generally cannot distinguish between volatility increases which follow reversals of large run-ups (or run-downs) and those which simply follow periods of large changes in either direction. Whether reversals of past run-ups or run-downs give rise to larger volatility increases than price changes not conditioned on the sequence of past returns remains an open question. However, the success of exponential GARCH models (see Nelson (1991)), which allow volatility to be an exponential function of past shocks, does highlight the strong effect particularly large shocks have on future return volatility.

This paper constructs an information theoretic framework in which patterns of conditional skewness and heteroskedasticity in asset returns arise from the buildup and release of pockets of information temporarily hidden from most participants.[5] As such, the model places greater emphasis than most securities market theory on the distribution of information across informed individuals, rather than just the distinction between informed and uninformed.[6] Shiller (1995) has emphasized that limitations in the effectiveness of conversation in conveying information may be a source of stock market volatility. Our model lends itself to analysis of how conversation that transfers information between individuals can for long periods have no effect, yet in some circumstances can trigger large stock price movements.

The remainder of the paper is organized as follows. Section 2 describes the basic idea in relation to the literature. Section 3 presents a theoretical model in which conditional skewness arises endogenously in the presence of fixed transaction costs. Section 4 details some results and implications of this setup. The paper concludes with discussion in Section 5.

[5]There are alternative possible reasons for conditional skewness. Since limited liability equity is much like a call option on underlying firm value, a symmetric distribution for firm value changes would imply asymmetry in stock price changes. Such asymmetry should fluctuate over time as stock price and leverage changes (See Black (1972), Christie (1982), Nelson (1991)). Agency problems in portfolio management may induce asymmetries as well. If portfolio manager payoffs resemble call options with respect to the outcomes of their investment strategies, managers may prefer portfolio with high positive skewness (See Brennan (1993)).

[6]Supporting the importance of the distribution of information across individuals, a recent experimental study by Bloomfield and Libby (1996) found securities prices in an experimental market to be strongly influenced by the cross-sectional distribution of information holding constant the aggregate information available to market participants.

2 The Basic Idea and Related Literature

This paper extends the intuition of three important recent papers: Romer (1993), Avery and Zemsky (1997), and Lee (1997). We begin with Romer. Romer demonstrates that substantial price movements can occur during periods when there is relatively little arrival of new information. In Romer's first model, investors are uncertain about the relative quality of their private signal and look to prices to convey information about other investors' conviction. This results in price changes that sometimes insufficiently reflect changes in fundamentals and sometimes adjust too strongly. In his second model, Romer shows that with relatively small transaction costs, prices can also be highly sluggish in responding to changes in fundamentals.[7] If investors must pay a cost to trade immediately on private information or may opt to delay and then trade for free, Romer shows that the benefits of trading immediately can be quite small.

We examine a model that integrates the two elements examined by Romer separately: uncertainty about information signal precision, and transaction costs. In addition, in our model price is informative to an individual about his own precision, not just the precision of others. The combination of these features creates predictable patterns of path-dependent conditional skewness— returns become negatively skewed after a stock price runup, and positively skewed after a rundown.[8]

Avery and Zemsky (AZ) emphasize the importance of multidimensional uncertainty in the occurrence of market crashes and imperfect information aggregation. The first dimension of uncertainty, familiar from conventional models, is about underlying value. In a setting with only this single dimension of uncertainty, a price move in the direction implied by an investor's private signal tends to raise his cost of exploiting the information through speculative trading.

The second dimension of uncertainty, as modeled in Romer and AZ, is uncertainty about the precisions of own information and/or that of others. When there is a transaction cost (or, as in AZ, a bid-ask spread), AZ show that a price rise can encourage an investor to buy, because the price rise can persuade the investor that there is genuine positive information

[7]Throughout our paper, in referring to transaction costs, we have in mind fixed setup costs of trading, which could include costs of learning market mechanics and procedures, and costs of attention.

[8]Romer's focus main focus was on the possibility of slow impounding of information into price and the resulting possibility of crashes. Our focus is on the relation of skewness to preceding events.

supporting the move. The challenge for such a story is to explain why the investor updates about underlying value even more favorably than the uninformed market-maker who sets prices.

Avery and Zemsky provide the important insight that this can occur if the investor has an informational advantage over the market-maker along the second dimension of uncertainty. In their model, there is a low probability that a set of investors receive informative signals. The market-maker does not know whether a buy order comes from a liquidity trader (who trade for non-informational reasons) or from an informed trader. An investor who knows that he has received a signal will then place more weight than the market-maker on the possibility that the previous buy order came from an informed investor. Thus, even though the market-maker revises price upward, in the event that there are actually informed investors, an informed investor revises his assessment of fundamental value upward even higher.

Along a sample path where investors continue to buy in the face of rising prices, eventually investors with adverse signals infer that very likely a truly informative signal was observed, but that their own drawing of this signal was incorrect. As a result, they act in opposition to their personal signals and buy in the face of rising prices.[9] Once such 'herding' or 'cascading' occurs, purchases by informed traders will tend to drive up prices further even if their signals are actually opposed. Since informed traders understand that a cascade is occuring, the price rise is no longer accompanied by any favorable revisions by informed traders about underlying value. Eventually, locked-up adverse information will be released by sell orders. If the amount of such adverse information is greater than expected, a crash can result.

Like Romer and AZ, our approach is also based on the idea that fixed transaction costs affect trading strategies in a way that can conceal information. However, in contrast with AZ, in our model the prelude to a crash does not involve investors who trade in opposition to their own signals. In our model, there is a probability that some investors receive a

[9]The reason this can occur when prices are set rationally is that there is multidimensional uncertainty–about signal precision, not just about value. The market maker who sets prices believes the sequence of purchases or no-trades may be coming from noise traders. The trader with a signal, however, recognizes that the other trade was very likely an informed one. Hence, a trader who receives a signal - even if this signal is incorrect - has a significant advantage over the market maker in assessing whether observed trades are informed or uninformed. Under certain conditions, this advantage allows informed traders to profitably trade against their private signal.

common informative signal, and a probability that they observe mere independent noise. Observing price changes helps an individual infer whether his own signal is meaningful or noise. To be willing to trade an investor may sometimes need his information confirmed by other informed traders before he is confident that he can recover his fixed setup costs of trading.

As before, after a price increase an investor who is considering whether to buy faces a balance of effects. On the one hand it is more expensive to buy, but on the other hand, the validity of his information is confirmed. From the perspective of a favorably informed trader, the adverse price move is not severe enough to reduce the net gain from trading because the price is revised by an uninformed market maker. The informed investor concludes that the latest price move was probably a result of a similarly-informed informed trader rather than a noise trader. Thus, the price rise triggers trading on the part of the favorably informed investor. In contrast, adversely informed traders become less confident that they have received meaningful signals, and may thereby be sidelined.

In contrast with AZ, the 'information overhang' is not caused by investors becoming so persuaded by price moves that they trade in the opposite direction of their private signals. Instead, those investors whose signals are consistent with the price move trade in the direction of that move, while investors whose information opposes the price move choose not to trade. Because of this body of 'sidelined' investors, trading events can stimulate the arrival of news to the market. This leads to conditional patterns in volatility and skewness as a function of past returns. After an upward price trend, most likely there are only a few sidelined investors with opposing signals, in which case the price is likely to rise modestly further. But there is a modest probability that a large number of investors with adverse signals are on the sidelines, and whose eventual entry will prompt a major correction. Thus, security price changes will have path-dependent distributions, becoming negatively skewed following price rises, and positively skewed following declines. In this way, the combination of setup costs and uncertainty about the veracity of private signals produces highly uneven and asymmetric price responses to smooth arrival of new information. In particular, a stock's prospects will depend heavily on the extent to which preceding trading has allowed prices to reflect investors' aggregate information set.

Our model also makes different assumptions from AZ regarding what investors observe.

In AZ, investors can observe a failure to trade on the part of a market participant. For example, if the price rises and the next investor does not trade, others infer from this failure that this investor's signal could not have been strongly adverse. As a result, the market-maker revises bid and ask prices upward. As the market maker learns from the absence of orders about the underlying distribution of information, adjustments to the bid-ask spread and the price may trigger a subsequent trade and a large market movement.

In our model, there is always a trade at each point in time. Those who find it cheapest to trade will always be prepared to do so. Price movements are triggered by the direction of trades, not by whether trading occurs. Thus, our approach focuses on observation of price changes, rather than observation of volume of trade (or absence thereof) at each price. Individuals all receive their information at the start, and trading and price changes are driven by an endogenously shifting distribution of information across different informed individuals. Even though no new external information arrives in the market after the first period, a small trade can lead to a large sudden price movement.

Lee (1997) examines a setting in which transaction costs limit information aggregation, leading to possible market crashes. Our framework differs in allowing for heterogeneous setup costs and time-varying market participation. This permits the participation of informed traders to vary depending on how informative the market price is at a given time, which gives rise to conditional skewness. Even frictionless models are consistent with conditional skewness arising simply from the assumed discreteness of states. We explicitly compare the cases of positive and zero setup costs to show that setup costs can indeed increase conditional skewness. Also, in Lee's paper crashes are triggered by unusual realizations of a skewed signal distribution. In our paper the signal distribution is symmetric, and big market movements are triggered by normal signal values.

The variation in market participation rates which prompts the conditional skewness in our model has two important additional effects. First, large corrections give rise to an increase in price volatility which lingers for several periods. Consider the case where prices have increased for several periods, successfully aggregating positive market sentiment. At this point, there will exist an 'information overhang' of unaggregated negative sentiment in the market. If a correction occurs, the market becomes highly uncertain as to how many 'bears' will be prompted to enter the market – that is, how large the overhang is that correction will release.

Second, although setup costs induce conditional patterns of skewness and volatility, we show that, on average, they *improve* the market's aggregation of private information. This is because the setup costs act as a filter on market participation in a way that allows price movements to accurately test the market's information set. Recall that informed investor participation rates respond sharply to price changes, with more purchasers participating as prices begin to rise and more sellers entering when prices begin to decline. This gives rise to significant imbalances in the participation rates of informed buyers and sellers and brings about the conditional patterns of skewness mentioned above. But since noise traders purchase and sell with equal probabilities, it is precisely imbalances in informed trader participation which allow the market maker to rapidly determine whether he is trading against informed or uninformed investors, and to determine whether fundamentals have actually changed. The occasional corrections brought about by setup costs are simply the flip-side to this improved information aggregation - occasionally the imbalance is in the wrong direction, as investors with accurate signals have been scared to the sidelines by early price moves in opposition to their signals.

3 The Model

Consider a model in which risk-neutral investors submit buy and sell orders for a single risky security. The orders are completed in a market of competitive risk-neutral market-makers. Investors receive noisy signals about the security's true value. The market-makers quote prices at which they are willing to purchase or sell the security. Market-makers receive no signals but trade with no setup costs. Investors face setup costs.

3.1 Payoff and Signal Structure

Formally, the asset has a terminal payoff, V, equal to 1 or 0 with probabilities a and $1-a$, respectively. With probability γ no information is received. With probability $1-\gamma$, a subset of investors receive signals about the terminal value. We label the state in which the terminal value is 1 and signals are sent as state h. The state where the terminal value is 0 and signals are sent is labeled state l. Only a small fraction of the trading population receives the signal σ about the true value of V.[10] The signal conveyed to a given investor is either 0 or 1. The signal conveyed is either conclusive or entirely uninformative - the investor does not know which is the case. If the signal is conclusive, the signal is equal to the true value V. If the signal is uninformative, it is equal to 1 with probability a or 0 with probability $1-a$, and is independent of V. The probability that a signal is conclusive is β, where $0 < \beta \leq 1$. Hence, the probability that a given signal reflects the true payoff is

$$\pi(\sigma = V|V) = \beta + (1-\beta)[Va + (1-V)(1-a)]. \tag{1}$$

3.2 Market Structure

Investors wishing to trade on their signals must pay a fixed setup cost to do so. These costs vary uniformly across the population, $c \sim U(1-\tau, 1)$, so that $f(c) = 1/\tau$, and the fraction of investors with a trading cost less than c is $F(c) = 1-\tau+\tau c$, where $0 \leq \tau \leq 1$. The higher is τ, the greater the proportion of investors faced with high costs of transacting.

Before trading takes place, the terminal payoff is determined and any signals are sent to investors. The security is then traded for T rounds. Each round of trade consists of four stages. First, a representative competitive market maker announce the price at which they are willing to purchase or sell a single share of the security. Since everyone in this model is risk neutral, the announced price will simply be the market maker's expected terminal payoff. Second, investors decide whether to submit a buy or sell order for a share of the security. Third, a market maker draws a single order from the pool of all submitted orders. Fourth, traders and the market maker observe the executed order and update their beliefs accordingly.

3.3 Equilibrium Trade and Prices

Define π_{st} as the market-maker's view of the probability that the state is s at the beginning of round t. Hence, the price P_t announced at the beginning of round t will be:

$$P_t = \pi_{ht} + a(1 - \pi_{ht} - \pi_{lt}). \tag{2}$$

[10]We require that the proportion of those traders who can receive signals who actually do so in a given state is sufficiently small that traders who do not receive signals remain no better informed than the market maker.

With probability π_{ht} the terminal payoff is 1 and with probability $(1 - \pi_{ht}$ no signals have been sent and thus the terminal payoff is equal to its unconditional value a.

Next, define π^{σ}_{ht} as the probability that the state is h at the beginning of round t from the perspective of an investor who has received signal σ. Since the asset pays either 1 or 0, an investor's expected terminal value will be his perceived probability of state h — i.e., π^{σ}_{ht}.

When faced with a fixed setup cost c, a risk-neutral investor with signal σ will place a buy order if $c \leq \pi^{\sigma}_{ht} - P_t$ and sell if $c \leq P_t - \pi^{\sigma}_{ht}$. The proportion of investors having received signal σ who place orders in round t is defined as θ^{σ}_t. Since the fraction of traders with trading costs less than c is $1 - \tau + \tau c$, the proportions of investors receiving signals who participate in trading can be expressed as:

$$\theta^1_t = 1 - \tau + \tau\left(\pi^1_{ht} - P_t\right) \tag{3}$$

$$\theta^0_t = 1 - \tau + \tau\left(P_t - \pi^0_{ht}\right). \tag{4}$$

Next, define q_{st} as the probability that the market-maker receives a buy order in round t if the state is s. In other words, q_{st} is the fraction of total submitted orders that are buy orders. Finally, we assume that there exist a small number of liquidity traders, defined as $2N$, who always participate in the market and place buy and sell orders with equal probability. Thus, the fraction of buy orders in the market at any given time is

$$q_{ht} = \frac{\theta^1_t[\beta + (1-\beta)a] + N}{\theta^1_t(\beta + (1-\beta)a) + \theta^0_t(1-\beta)(1-a) + 2N} \tag{5}$$

$$q_{lt} = \frac{\theta^1_t(1-\beta)a + N}{\theta^1_t(1-\beta)a + \theta^0_t(\beta + (1-\beta)(1-a)) + 2N}. \tag{6}$$

Since no information traders exist in states h' and l', $q_{h't}$ and $q_{l't}$ are both 0.5, as the only market participants are liquidity traders who purchase or sell with equal probability.[11]

The remaining calculation is to determine how investors and arbitrageurs update assessments of state probabilities. At the end of each round of trade the only new information being revealed to market participants is whether the executed trade was a buy or sell order. Hence, participants will use Bayes' Rule to update their beliefs. If the period-t trade is a buy, the updated probabilities will be:

$$\pi_{ht+1} = \frac{\pi_{ht}q_{ht}}{\pi_{ht}q_{ht} + \pi_{lt}q_{lt} + (1 - \pi_{ht} - \pi_{lt})0.5}$$

[11]The fraction of liquidity traders can be made arbitrarily small, as long as the buy probabilities remain 0.5 and the market maker remains unable to distinguish between the signal and the non-signal states.

$$\pi_{lt+1} = \frac{\pi_{lt}q_{lt}}{\pi_{ht}q_{ht}+\pi_{lt}q_{lt}+(1-\pi_{ht}-\pi_{lt})0.5}$$
$$\pi^{\sigma}_{ht+1} = \frac{\pi^{\sigma}_{ht}q_{ht}}{\pi^{\sigma}_{ht}q_{ht}+(1-\pi^{\sigma}_{ht})q_{lt}}.$$

If the period-t trade is a sell, the updated probabilities are:

$$\pi_{ht+1} = \frac{\pi_{ht}(1-q_{ht})}{\pi_{ht}(1-q_{ht})+\pi_{lt}(1-q_{lt})+(1-\pi_{ht}-\pi_{lt})0.5}$$
$$\pi_{lt+1} = \frac{\pi_{lt}(1-q_{lt})}{\pi_{ht}(1-q_{ht})+\pi_{lt}(1-q_{lt})+(1-\pi_{ht}-\pi_{lt})0.5}$$
$$\pi^{\sigma}_{ht+1} = \frac{\pi^{\sigma}_{ht}(1-q_{ht})}{\pi^{\sigma}_{ht}(1-q_{ht})+(1-\pi^{\sigma}_{ht})(1-q_{lt})}.$$

Hence, the above updating rules, in conjunction with the expressions for prices, (2), participation rates, (3) and (4), and buy probabilities, (5) and (6), uniquely determine how the market evolves in response to a sequence of orders.

4 Results

The introduction of fixed setup costs to a setting where investors are uncertain about signal precisions will have three main effects. First, as noted in the introduction, price changes will exhibit path-dependent, conditional skewness. Price movements which confirm only one set of investors' signals create another group of sidelined investors. Sidelined investors remain deterred by the setup costs and await the possibility of subsequent confirming price moves before returning to the market. As a result, future price changes become highly skewed. The potential for these sidelined investors to return to the market at some point requires that prices retain the possibility of a large correction. The question facing market participants is not so much *whether* there are 'bears' out there (or 'bulls' if the market has been declining) but more *how many* 'bears' are sitting on the sidelines.

Figure 1 shows how this happens. Each tree node shows the price P, the state probabilities π_h and π_l, and market participation rates θ^0 and θ^1 which follow a particular sequence of buy and sell orders. The first tree depicts the case with fixed setup costs; in the second they are absent. To see the conditional skewness of price changes that arises in the presence of setup costs, compare the sequence {BUY, BUY, BUY} to that of the sequence {BUY, BUY, SELL}. At $t = 2$, after two BUY orders, the price has increased to .5483. At this point, traders having received a signal of 1 are more than 40 times as likely to participate in the market as those receiving a signal of 0 (.365 versus .008). Hence, the probability of a subsequent increase in price is above 58% [.317/(.317+.227)]. On the other hand, if a SELL order arrives, the decline in price will be substantial – the asset price will drop below its unconditional mean to .4983. Moreover, further declines now become likely, as sellers are over 6 times as likely as buyers to participate at this point. Because of the discrete state-space, even in the zero setup cost case the market exhibits some conditional skewness, but it is much less. The probability of a BUY after two previous BUY orders is only 52.5% [.269/(.269+.243)].

The second main effect of introducing fixed setup costs is that prices become more volatile in earlier trading rounds, meaning that the market aggregates information *more* rapidly. This is surprising since the setup costs are locking some pockets of informed traders out of the market. To see why, consider the order sequence {BUY, SELL, BUY}. In the zero-transaction cost setting, this sequence of orders does little to resolve uncertainty. State probabilities remain similar to their unconditional levels. In contrast, with fixed setup costs, uncertainty is largely resolved following such an order flow. The probability of a non-signal state is now 99.7%, and the probability of states h or l has fallen from 10% to 0.3%. Setup costs advance resolution and volatility to earlier periods, and, surprisingly, improve the market's aggregation of information.

The reason for this is that setup costs filter market participation in way that allows for accurate tests of the market information set.[12] Following a BUY order, investors receiving signals of 1 are 15 times as likely to participate as those receiving signals of 0. Hence, the subsequent order acts as an excellent test to see whether the true state is indeed 1. If the true state is h, the probability that the next order is a BUY is 97.8% [(.75)(.375)/((.75)(.375)+(.25)(.025))]. Hence, when a SELL occurs in period 2, market participants become fairly certain that the true state is not state h. As a result, investors who possess a signal of 1 move to the side-lines, while investors with signals of 0 re-enter the market. Now, the test becomes whether the true state is l, as the possibility of seeing a BUY in state l is 3.6% [(.25)(.043)/((.25)(.043)+(.75)(.382))]. Thus, when the order is indeed a BUY, the probability that the state is l becomes small. As a result, in period 4, after observing the sequence {BUY SELL BUY}, the market maker become highly certain

[12] See Fishman and Hagerty (1992) for a model that involves a somewhat analogous filter benefit from restrictions on disclosure.

(99.7%) that he is not facing informed investors and that signals have not been sent.

The final effect of time-varying market participation is to create conditional heteroskedasticity. Figure 2 depicts the price paths that follow a sequence of five BUY orders and then a SELL. Note that with setup costs, the SELL order prompts a market crash from .7088 down to .4981, whereas the no-transaction cost decline is from .6476 to .5858. At this point, in the no-transaction cost setting, the price only reflects a reduction of probability of state h from .296 to .174. The probability of state l remains low, and further price declines are of limited size and probability. With setup costs, the crash is larger, as the price decline reflects not only a lowering of the probability of state h but also an increase in likelihood of state l. At this point, there is considerable uncertainty regarding the true state. In fact, even though only one SELL has been observed in the first six rounds, state l is now more likely than state h. Investors with a signal of 1 are asking how many 'bears' the SELL order will attract into the market from the sidelines. Indeed, the probability of two further SELL orders is high [.295] and the price decline these would bring is substantial (from .4981 to .3963). It is precisely this uncertainty about how many side-lined investors had contrarian signals which prompts the increase in variance following a crash.

To see that these results generalize, Figures 3, 4, and 5 graph the conditional skewness, early variance, and conditional variance that accompany different levels of setup costs in a market with 100 rounds of trade. For each parameterization, the market is simulated 1000 times. Each of the graphs plot the changes relative to the zero-transaction cost case. In all cases, the expected terminal value, a, is set to 0.5.

In Figure 3, the change in conditional skewness is conditional on the prior price change being positive. The y-axis (left axis) of the graphs measure the probability of a non-signal state - that no signals have been sent and the terminal payoff is either 1 or 0 with expected value a. The x-axis (right axis) reflects the probability of receiving an accurate signal when signals have been sent (β). Under setup costs, asset returns uniformly exhibit increased negative skewness following a price rise. The increase in skewness is most pronounced when β is large and γ is small.

This is because conditional skewness requires that correction probabilities are low. If investors expect signals seldom to be informative, participation rates will not respond as drastically to price changes. This is because investors are not surprised when orders arrive which are inconsistent with their signals. When investor signals are highly accurate, an order which is inconsistent with the prior price history is highly unlikely, and therefore its placement prompts a significant correction. When γ is small, the imbalance between buyers and sellers at any given time can be large. Because market maker view the order flow to be far less informative than the informed traders, they do not update prices aggressively. As a result, investors with signals that were confirmed by price moves participate extensively, since the price move is not so great as to increase severely the cost of their trade. Likewise, investors with unconfirmed contrarian signals move to the sidelines even if their setup costs are fairly modest. Hence, when informative signals arrive, orders become highly autocorrelated. When the market maker finally adjusts prices sufficiently to bring about some contrarian participation, the decline in price that a contrarian order brings is substantial.

To assess whether setup costs cause uncertainty to be resolved more quickly, early variance in Figure 4 is measured as variance over the first 20 periods of trade. Figure 4 verifies that setup costs uniformly shift variance to earlier trading rounds. The shift is more pronounced as the accuracy of signals (β) declines. This is because when orders arrive and prices move, investors with contrarian signals wait on the sidelines, and the market maker can more easily see the composition of buyers and sellers. In the absence of setup costs, all investors remain in the market, regardless of how confident they are in their signals. Hence, when only a small fraction of investors have informative signals (low β), the imbalance between buyers and sellers is slight, and the market maker has great difficulty extracting information from the order flow. As a result, prices take much longer to reflect private information when setup costs are absent than when they are present.

Finally in Figure 5 we see that after corrections price changes tend to be much more volatile in the presence of transaction costs. The change in variance is measured conditional on the prior 5 price changes being of identical sign. This increase in volatility is also most pronounced for low β. When few investors have received informative signals, there exists considerable potential for a large number of 'bears' to re-enter the market following a crash. This possibility creates an uncertainty which follows corrections and lingers several periods.

Figure 6 plots price paths and participation rates for simulations of the market. In all four panels the state is h and the fraction of accurate signals sent (β) is set to 0.5. In the first two panels, the probability of non-signal states (γ) is set to 0.9, while in the latter two it is set to 0.999. The first panel plots a price path which is common when the state is h. The initial buy order prompts sellers to leave the market and buyers to enter. Further purchase orders arrive, as the price begins to rise, and the fraction of buyers remains high. At a certain point buyers begin to leave the market, rather than purchase at an increasingly expensive price. Some sellers re-enter during periods 4-10, in order to short the asset at a high price that retains some possibility of correcting. After a while, they become convinced that the market has correctly aggregated information, and they exit the market along with the buyers.

The second panel demonstrates how corrections, and their induced shifts in market participation rates, can prompt wide swings in the asset price. In period 5, when a sell order arrives, the price not only corrects, but it prompts a dramatic shift in the composition of market participants from buyers to sellers. This leads to a period of sustained selling and a continued decline in the price. This pattern repeats every few periods, until a sustained sequence of purchases begins to move the price towards the terminal value.

The third panel depicts the situation where a sell order is initially executed even though the true state is h and therefore sellers only comprise 25% $((1-\beta)/2)$ of market participants. What this prompts, however, is a massive exit of buyers and entry of sellers. As a result, many subsequent sell orders are executed, and the price declines to below 10% of its terminal value. Eventually, when the price drops so far that sufficient sellers have exited the market and the pool of orders has become more balanced, a buy order is executed. This brings about a sustained period of rising prices and buyers returning to the market. After 15 purchases, the price has converged to the terminal value.

The final panel shows that even when prices have neared the terminal value, unexpected orders can bring about sustained periods of divergence. Subsequent to period 28, a sequence of sell orders causes the price to drop from over 0.95 to below 0.4. This is because the initial sell orders were so unexpected that they brought on a sustained period of re-entry on the part of sellers.

5 Discussion and Conclusion

This paper examines a setting in which fixed setup costs of trading cause investors' market participation to vary through time depending on the past history of prices. Sidelined investors optimally wait for confirming price changes before they are sufficiently confident in their information to enter the market. Thus, the trading process itself endogenously triggers the arrival of further news. As a result, limited participation and trading-generated news affects whose information is aggregated into price in a way that is related to past price movements. This leads to returns distributions which exhibit conditional skewness, becoming negatively skewed following positively-trending prices and positively skewed following downward-sloping prices. Time-varying market participation also generates a period of increased volatility following corrections, and results in a market that is actually highly-efficient at aggregating private information.

A market in which conditional skewness arises from hidden information will have a number of interesting features, several of which merit further research. In our framework, individuals do not receive any new private information after initial signals are sent. Price changes are driven by market participants' gradual learning of each others' information, rather than by the observation of new signals. Such a process makes price movements highly sensitive to communication among traders. What if the 'silent majority' of sidelined investors is not so silent? The introduction of oral communication among a subset of market participants may have large effects on the equilibrium. A sidelined investor who is told that another sidelined investor shares a similar signal may participate. Such participation may trigger rapid emptying of the sideline, and thereby large sudden price moves.[13]

Similarly, if for example a market 'guru' such as Abbie Cohen receives a private signal, it will not be her immediate trading on this signal which moves the price so much as the subsequent announcement of the signal in her market forecast. Hence, gurus or investment newsletters may have effects that seem disproportionate to the accuracy or timeliness of the information they contain. More broadly, consider a setting where agency problems in delegated portfolio management are important. Suppose that portfolio managers' compensation takes the form of a call option on the portfolios' return. Then even if the market is

[13]DeMarzo, Vayanos, and Zwiebel (1998) provide an analysis of verbal communication and influence and its effects on financial markets when individuals are 'near-rational.'

efficient, from the manager's perspective technical trading rules of buying winners, stocks with good 'charts', or stocks that 'break-out', may have merit. 'Chartist' money managers may prosper by identifying strategies which skew the distribution of their portfolio's return, thereby increasing the value of their options.

Finally, suppose that some 'overconfident' investors are irrationally inclined to trade even when the expected profits from doing so do not justify the costs. (Some recent models that allow for trading by overconfident investors include Kyle and Wang (1997), Hirshleifer, Subrahmanyam and Titman (1994), Odean (1998), and Daniel, Hirshleifer and Subrahmanyam (1998).) Bernardo and Welch (1997) describe some social benefits of overconfidence in managerial project decisions arising from the willingness of overconfident managers to take informative actions which rational managers would avoid. In a similar fashion, overconfident investors in our model would trade more actively. This may in some cases improve welfare and improve the extent to which the security market aggregates diverse investor information.

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Table 1

Weekly Return Transition Probabilities: Based on Lo and Wang (1996)

this week's decile	next week's decile	0-10%	90-100%
	0-10%	12.55 (0.09)	19.52 (0.11)
	90-100%	20.56 (0.12)	12.50 (0.08)

The above table is modified from Lo and Wang (1996). T-stats are in parenthesis. Transition probabilities reflect the probability that a stock which finishes one week in a given return decile will finish the following week in a second given return decile.

Figure 1: Order Flow Tree Diagram; $\gamma = 0.9$; $\delta = 0.5$; $\beta = 0.5$; $a = 0.5$

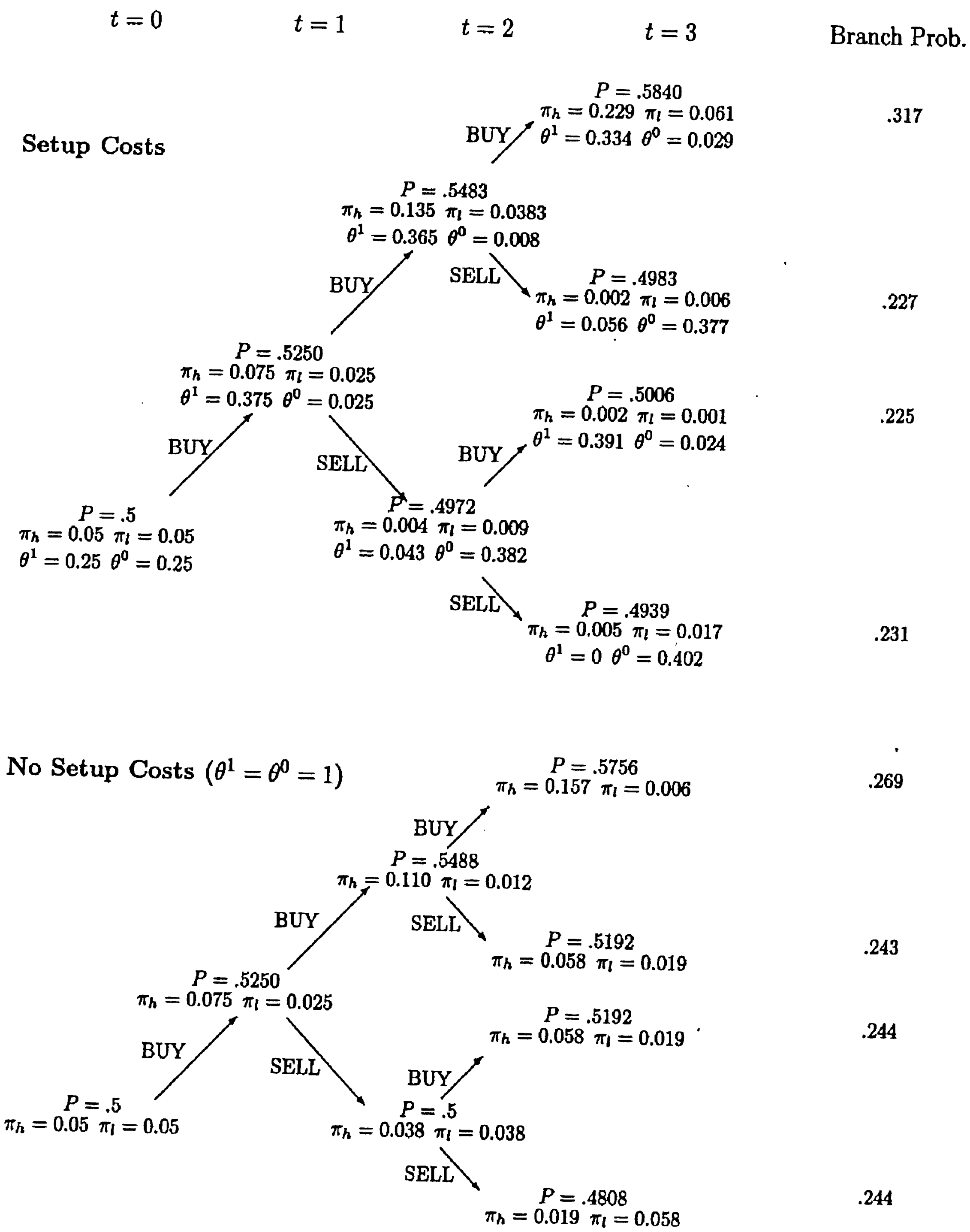


Figure 2: Order Flow Tree Diagram following 5 Buys; $\gamma = 0.9$; $\beta = 0.5$; $a = 0.5$

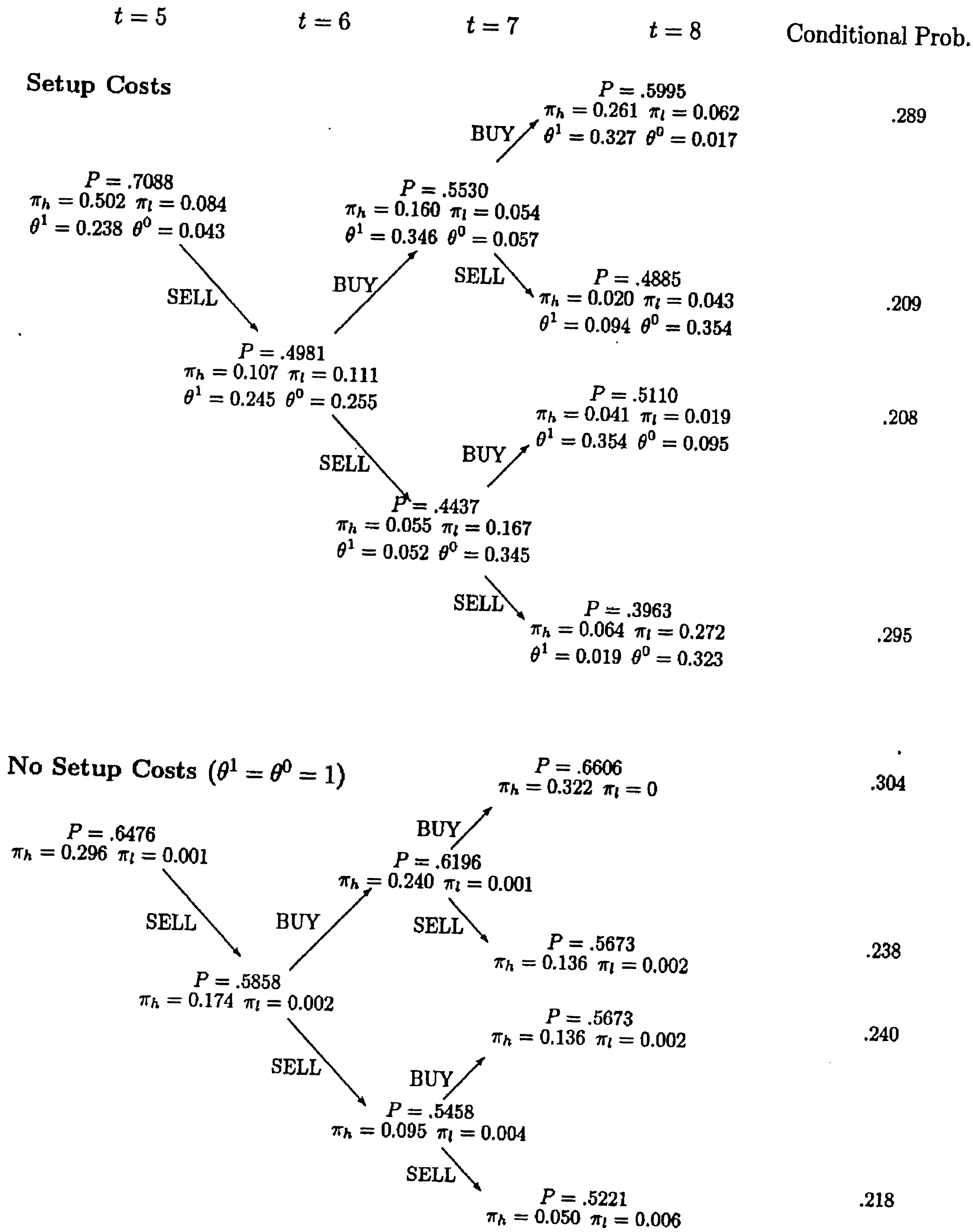
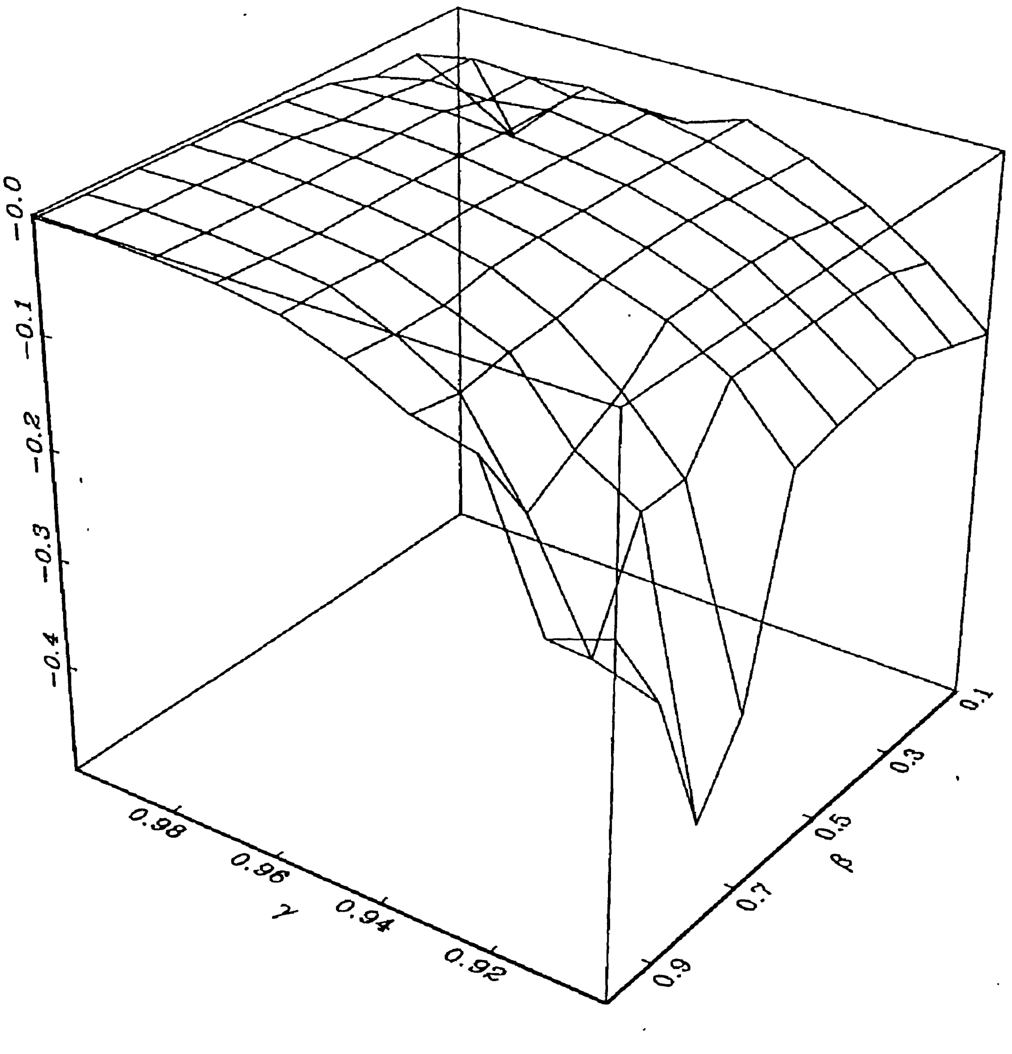
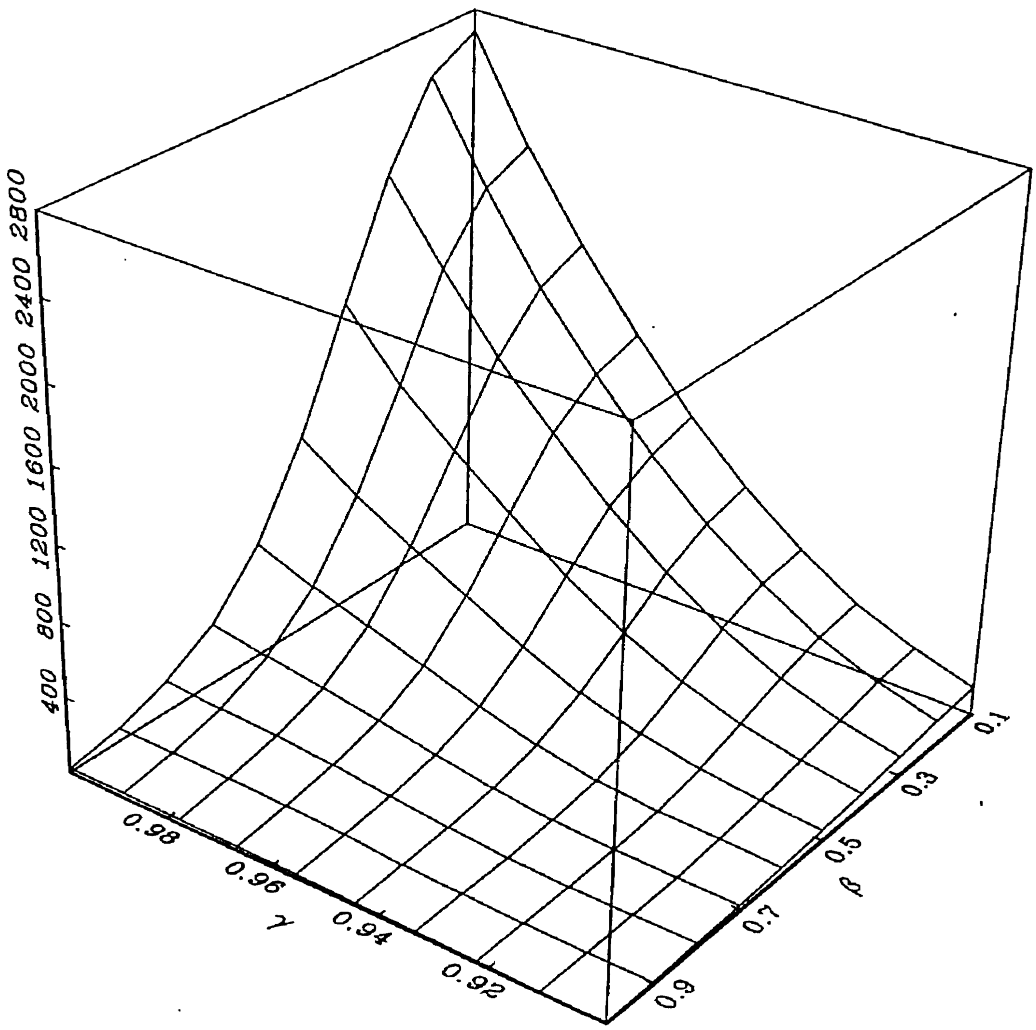


Figure 3: Conditional Skewness



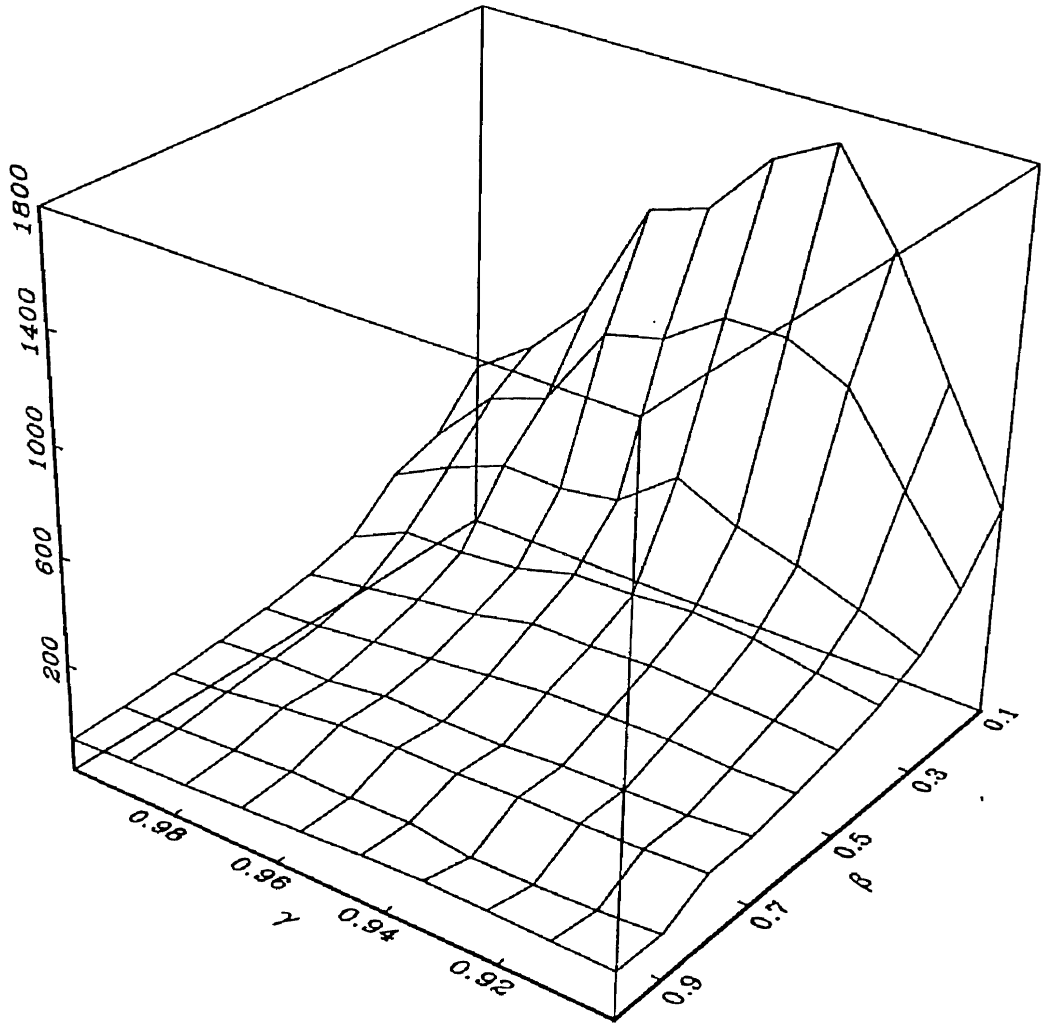
The probability of receiving an accurate signal in state h or l is graphed on the x-axis as β and the probability of non-signal states is graphed on the y-axis as γ. The z-axis graphs the change in skewness of returns conditional on an increase in price during the prior trading round (less the change in the no-transaction cost state). The variance of liquidity trades is arbitrarily small.

Figure 4: Early Variance



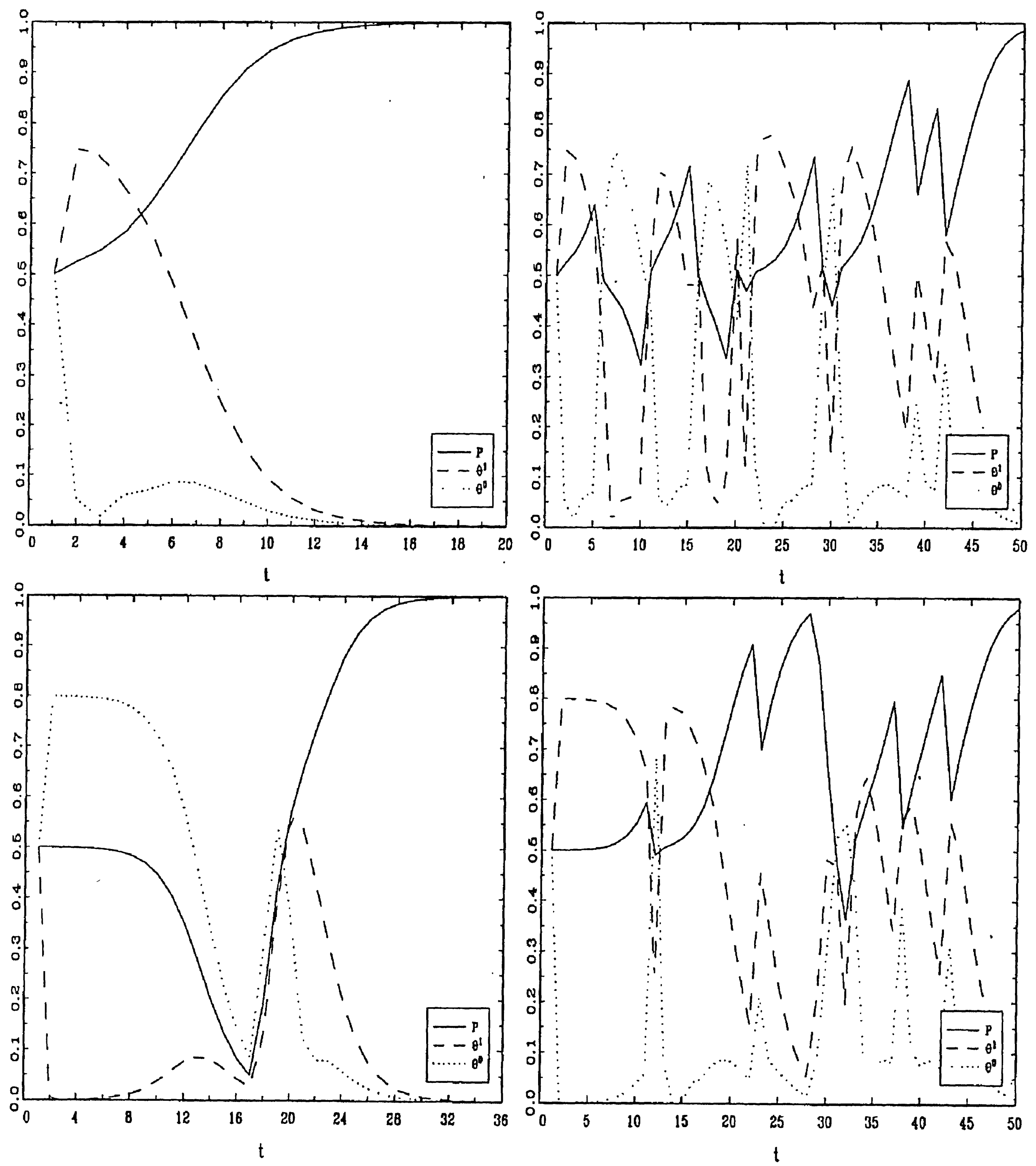
The probability of receiving an accurate signal in state h or l is graphed on the x-axis as β and the probability of non-signal states is graphed on the y-axis as γ. The z-axis graphs the variance of price changes over the first 20 trading rounds, expressed as a percentage of that of the no-transaction cost case. The variance of liquidity trades is arbitrarily small.

Figure 5: Conditional Variance



The probability of receiving an accurate signal in state h or l is graphed on the x-axis as β and the probability of non-signal states is graphed on the y-axis as γ. The z-axis graphs the change in variance, expressed as a percentage of that of the no-transaction cost case, that is conditional on 5 like price changes followed by a reversal. The variance of liquidity trades is arbitrarily small.

Figure 6: Simulations of Price Paths and Participation Rates



The above panels simulate prices and participation rates in the market when the state is h. Participation rates are scaled $(\times 2)$ to match the price scale. Noise traders are arbitrarily small; $\beta = 0.5$; In the first two panels $\gamma = 0.9$ and in the second two $\gamma = 0.999$.