

Chapter 2

TOWARDS A HYBRID MODEL OF MICROECONOMIC AND FINANCIAL PRICE ADJUSTMENT PROCESSES: THE CASE OF A MARKET WITH CONTINUOUSLY REFRESHED SUPPLY AND DEMAND

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Abstract

Microeconomics and financial economics provide alternative models of market dynamics. A long history of laboratory results shows that market prices in the laboratory converge towards the static predictions of microeconomic theory with a resulting classical efficiency of allocation. Yet, the informational efficiency of market prices, often treated as a starting axiom for financial market theory, requires instead that current prices represent fair gambles over an unknown distribution of future prices: financial price processes are idealized as random walks with independent increments perhaps modified by some notion of heteroskedasticity such as stochastic volatility. Unlike prices following a Marshallian path, random walks do not generally converge towards an equilibrium price. The conflict between these two views of market processes is explored and a model that is a hybrid of the microeconomic and financial approaches is constructed and compared against data from laboratory markets involving continuously refreshed supply and demand.

1. INTRODUCTION

This chapter is a very rough first attempt to integrate some ideas from across microeconomics and finance about the price dynamics of competitive markets. The research is from the point of view of an experimental economist interested in laboratory market equilibration, not from the point of view of general asset pricing or finance in general. The goal is not to resolve all the questions one might have about the nature of price dynamics, convergence or the differing approaches or assumptions that may be involved across various fields.

Instead, the goal is more modest, to put forward the notion that the noisy equilibration of a fairly simple single market is still a subject worthy of study. There are no “states of the world” in the sense of classical finance and, correspondingly, no laboratory bets on securities whose values are based on coin tosses or dice rolls. Instead, there is a pair of markets, a private market and a public market. Buyers and sellers receive private, seemingly random opportunities to buy or sell a good from the “experimenter” in their private market and are able to trade with each other in the public market. Subjects are not told anything about the distribution of these opportunities. The supply and demand curves representing the aggregate of these private market opportunities are held stationary and the experimenter observes the time series of voluntary trading prices in the public market.

Since the market participants do not know *ex-ante* what the public market price should be, there is a kind of endogenous heterogeneity and complexity of beliefs and knowledge about market conditions more typical to the experimental economics literature than the classical finance literature. It is the general success of experimental economics in providing a means of studying this peculiar kind of complexity that is hoped to make such a laboratory approach worthwhile.

Although a broad view of some of the problems one encounters in merging ideas from different fields is important, ultimately the research reported here is much more narrowly focused upon a particular data set and a particular form of time-series analysis. One can then attempt to ask questions about the adequacy of simple, stationary models: Can price equilibration be described by a simple mathematical equation with fixed parameters or is a model with two or more regimes more appropriate? Does something happen when markets equilibrate that we can detect in the time-series properties of the data? The data reported here is an attempt to get at these questions, among others. The research is not expected to answer many questions at this stage, but instead it is an attempt to stimulate new questions and to begin a long process of obtaining answers made possible through the continued work of future researchers.

The remainder of this section will provide an overview of some literature, but does not pretend to be a guide to this subject for newcomers nor can it even hope to even briefly credit all those whose research formed the present understanding of markets. The introduction concludes with a brief road map organizing the research to be presented.

Early laboratory studies into market behavior, beginning with Smith (1962), were not designed merely to confirm or demonstrate known principles of economics. Early experimental environments by design violated three common assumptions once thought appropriate for the applicability of competitive models: (i) *perfect information* was violated as student subjects typically knew only their own costs and values when trading, not the costs or values of others, the aggregate supply and demand, or the distributions from which costs and values were drawn; (ii) *continuity* was violated at the unit level and the agent level because the units traded in the market are indivisible and because agents were not trading small quantities relative to the aggregate market; (iii) *perfect rationality* was probably violated because the

student subjects often had no previous exposure to trading and therefore could not be expected to trade as well as the perfectly rational *homo economicus*, and possibly not even as well as a businessman or professional trader.

High efficiencies of allocation and convergence of observed prices and traded quantities to the predictions of competitive theory nevertheless occurred in early laboratory markets. A critic who only saw the experiments as a misconception relative to the requirements of existing theories, inadequately “simulating” a larger market, or relying “too much” on data from students instead of experienced businessmen or professional traders would potentially miss an interesting result regarding the robustness of competitive processes. These early laboratory markets were real markets. The results showed that the details of trading institutions matter: the prices in the markets of Chamberlin (1948) did not converge nearly as well as Smith (1962) because Smith included specific kinds of trading structure – the publicly observable bids and asks recorded on a blackboard and the improvement requirement (bids go up, asks come down until a trade occurs) inherent to double auction rules – while Chamberlin’s completely unstructured approach left traders on their own to decide what to do as they walked around and searched out trades with others in the room. Charles Plott and a number of other researchers duplicated Smith’s early laboratory results, going on to laboratory investigations involving multiple markets, transformation and production, and other complex scenarios.

The broad pattern of these results demonstrated that markets could function fairly well – given the proper structure and a bit of learning by repetition – with lumpy goods and only a few inexperienced traders in a variety of situations and applications. Plott (2000) has argued that laboratory research on market processes and equilibration can support a modernization of Hayek’s view of the market. Hayek (1945) viewed markets as human institutions providing a means of imperfect, but self-correcting, coordination and solution to a demand/supply problem without having to convey all the information about market conditions to a single mind. Previous laboratory studies reveal market equilibration likened to a rational but almost mechanical process, possibly unrecognized by the market participants, attempting to find the solution of an equation balancing supply and demand. Even though no one (except the experimenters) knows the equations or has full knowledge of the parameter values needed to solve the equations, the rationality inherent in profit-seeking behavior would drive the process to equilibrium.

In contrast, the framework Gode and Sunder (1993) developed as an alternative explanation for market equilibration by way of their Zero Intelligence (ZI) robot algorithm demonstrated a strong potential for a mechanical, non-rational convergence processes based only on budget constraints and not on profit maximization. The ZI robot framework is still a popular environment for beginning a study of more complex phenomena (see Farmer, Patelli and Zovko (2004) for a recent example or Duffy (2004) for a review). Prices in markets populated by the ZI robots appear to converge towards competitive equilibria and exhibit negative autocorrelation of price changes. Cason and Friedman (1996) find negative autocorrelations of price changes in laboratory markets populated by inexperienced human traders,

with the autocorrelations moving towards zero and positive autocorrelation with more experienced subject pools. Both studies also show that large surplus trades would occur earlier in the market, with convergence being driven by the fact that this leaves the price-constrained low surplus trades to occur later in the market period.

While laboratory microeconomics has developed a body of empirical regularities surrounding imperfect – but functional – markets, standard financial theory generally begins with a set of axiomatically defined perfect markets and derives further properties under various conditions in an uncertain world using mathematical probability theory. Take, for example, the case of a popular and regularly traded stock on the NYSE or NASDAQ. Analysts follow the business closely. Therefore, at least among the major market participants setting prices, one might assume perfect information or at least homogeneous information. Millions of shares are traded, so continuity is virtually satisfied. The major market participants are generally expert traders, and so should be acting rationally. If one assumes that all known information has been fully processed by a perfect market, the prediction of finance in the short term is amazingly simple: the share price should represent a fair gamble based on the probability distribution of possible share prices in the near future.

Over time, prices should exhibit the properties of a Martingale process, such as zero autocorrelation of price changes. Field tests on financial market data yield various non-zero results.¹ However, a careful theorist can still argue that the Martingale property is an *ex-ante* property related to *historical expectations* about future prices and therefore impossible to test *ex-post* based solely on observed prices alone without some additional assumptions – see for instance, Bossaerts (2002; pp. 42–43). Without certain simplifying assumptions, one would instead need to be able to somehow record what the “market was thinking” about future prices, and test whether the price at each moment in time equaled this expectation as beliefs evolve.

Of course, this *ex-ante* kind of Martingale theory is much more difficult to falsify, and also causes the fine details of beliefs to become important. Are beliefs actually homogeneous so that all market participants have the same expectations or is this merely a convenient approximation? If beliefs are homogeneous, are they correct or at least unbiased? Does it matter if homogeneous, correct beliefs do not initially exist but do form over time as the market converges? Or do the correct beliefs exist because the market participants exist in a world of stationary probabilities where the frequency of various kinds of events, and their effects on prices, are well known? Without evoking criticism of any microeconomic or financial theory and shying away for now from the technical details that make the approaches of microeconomics and finance to equilibration so different, it is interesting to note that the Hayekian view of market equilibration as a process of solving for prices without conveying all the necessary information to a single mind is in such stark contrast to the view of more widely studied theories in finance that assume that all market participants are indeed of a single mind in the sense of holding identical, correct beliefs. These questions are already well known but are tricky and quite technical to deal with, and are beyond the immediate scope of this work.

Several earlier laboratory experimental approaches to financial economics are reviewed by Sunder (1995). Information aggregation from insiders to the general market and belief formation were common areas for exploration. More recently, Bossaerts (2002) reviews many theoretical issues in finance and discusses laboratory experiments structured specifically to test asset-pricing models in a multi-asset risky environment. Bossaerts (2002; p. 129) notes that laboratory markets converge slowly, and this slow convergence in prices may require models with adjustments or biases of “market” beliefs away from the perfect beliefs assumed by the efficient market hypothesis.

Most previous work in finance-based laboratory experiments, including the work cited above, required experiments with many markets and many uncertain states of the world in order to fit the mold of the financial models. Instead, the research to be reported here focuses on equilibration of a single market. The connection to finance is in the efficient market hypothesis and its implication for Martingale or random walks in prices.

Irregardless of whether changes in financial market prices are due to random shocks to the profitability of an underlying business or random noise traders, if there is a pattern to the price changes then there is a potential for profit that should not exist in a perfect market. The Martingale or random walk hypothesis can be thought of as an axiomatic description of perfect market prices without reference to an underlying firm or asset or any specific requirement limiting the scope to only financial markets.

Does the notion of price as a Martingale process apply to laboratory markets? If prices do not follow a Martingale or random walk, is the notion of a random walk still useful somehow? Can the random walk somehow be reconciled with the notion of an imperfect market that is attaining competitive equilibrium over time? The answer to the first question will be no, both on principle and empirically prices in laboratory markets clearly do not follow a Martingale process. But the initial answer to the latter two questions will surprisingly be yes.

The process of reaching this result is as follows: Section 2 describes the Continuously Refreshed Supply and Demand (CRSD) Environment that is used to generate long data sets and disrupt the means by which ZI robot populated markets converge to equilibrium. Human-populated CRSD markets still appear to converge towards an equilibrium price, so something more is happening with the humans that do not happen with the ZI robots. Section 3 identifies the microeconomic and financial approaches to market convergence. Section 4 compares and contrasts these two approaches and identifies some issues that would appear to prevent the financial model from describing the behavior of laboratory markets. Section 5 shows how to use the random walk to design a new kind of trading robot that captures some of, but not all of, the dynamics of the human-populated market in the CRSD environment. Markets populated by the random walk robots show price dynamics that can be described fairly well as an AR(1) process. However, markets populated by humans also show a kind of outlier-correction whereby prices deviate from the convergence path and then pop back up to near the previous price. Outliers and corrections can be

modeled as a type of MA process so that the joint process becomes an ARMA process. Section 6 analyzes ARMA models of the price convergence of human-populated markets and summarizes the findings. Section 7 discusses conclusions.

2. THE CONTINUOUSLY REFRESHED SUPPLY AND DEMAND ENVIRONMENT

Figure 1 shows a set of instantaneous supply and demand curves that are held constant in the continuously refreshed supply and demand (CRSD) experimental study of Brewer, Huang, Nelson and Plott (2002). The environment is implemented by means of a set of java-based programs accessed from a standard web browser such as Microsoft Internet Explorer. Human traders sitting at a web browser see their screen divided into a public market, for trading within the group, and a private market, which displays a set of private trading opportunities (production costs or redemption values for a single unit of good) available only to that subject. Subjects complete trades and make money by arbitraging their private market prices available from the experimenter against the public market prices available from interaction with other experimental subjects. For example, if a subject can buy a

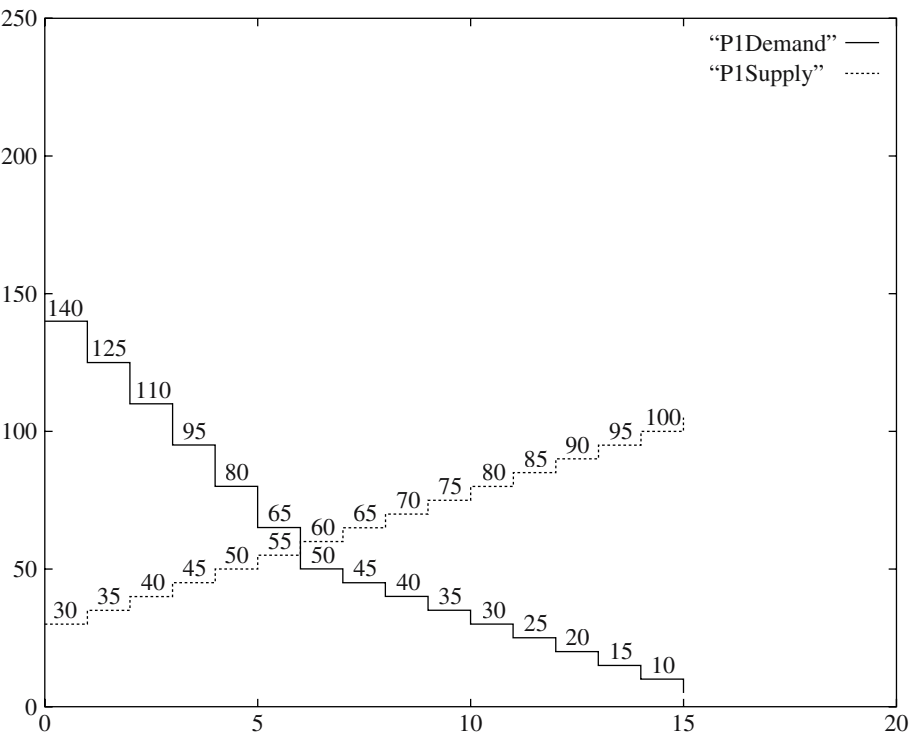


Figure 1. Sample Supply/Demand Environment.

unit in the public market for \$50 and sell it in the private market for \$70, they will earn a profit of $\$70 - \$50 = \$20$. Net profits are paid in cash at the end of the experiment.

The costs and values in Figure 1 are distributed among the subjects via the private markets visible on their individual trading screens and are recycled among the subjects as trade occurs. The details of this recycling will be explained below. The experimenter is not primarily concerned with this private market recycling, but instead the focus is on observing the trading between the humans in the public market.

Continuously refreshed supply and demand is a technique for recycling the costs and redemption values in a double auction experiment. In contrast to standard double auction experiments where gains from trading are finite and naturally exhausted as the trading period progresses (see, for instance, the classical experiments described by Smith (1962) or Plott (1982)), in the CRSD environment there is no natural end to trading.

Brewer, et al. (2002) describe the particulars of the CRSD environment as follows:

“... if buyer #3 used a private market offer (a redemption value) from the experimenter, this same offer would immediately be made to the *next* buyer (e.g., buyer #4). Similarly, offers to sell (costs) were recycled to the next seller. Subjects had no knowledge at all about this refreshing. Subjects knew only that new orders could appear in their private markets at any time.

Refreshing the private offers in this way keeps the instantaneous supply and demand curves constant at every moment in time. If an offer is used or expires, it does not vanish from the pool of supply and demand. Instead, it is recycled to someone else. Thus, the opportunities of gains from trade are never exhausted. The market demand and supply functions as represented by redemption values and costs are always constant – independent of the patterns of trade.”

Figure 2 shows the data set of public market trading prices produced from 2½ hours of trading in the environment of Figure 1. The data shown here has been ‘sanitized’ by removing possible outliers or errors – trades with large price movements – and will serve as the primary data source for this paper.

There are three primary benefits of the CRSD environment over other sources of data: (i) CRSD can produce long time series (there are 793 trades in the sample we will use vs. ~20 in the typical double auction period) useful when examining time series properties as the accuracy of some of the related estimators scales only as $1/\sqrt{N}$; (ii) because of the nature of the refreshing, the instantaneous supply and demand is held stationary; one does not have to consider the possibility of an equilibrium price that is changing as traders exit the market; (iii) stationary instantaneous supply and demand can be useful in separating models of market behavior and convergence. Certain price convergence processes – such as Marshallian path processes and noisy analogs like the Gode and Sunder (1993) ZI Robots – that operate

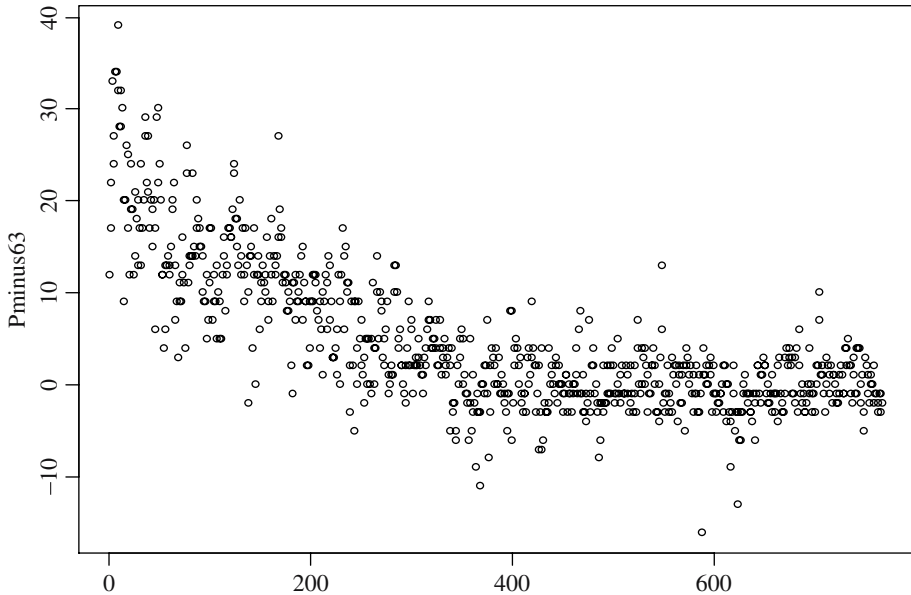


Figure 2. Price Time Series P1 from Brewer, Huang, Nelson, and Plott (sanitized).

in the ordinary double auction can not operate in the CRSD environment and therefore can not be an explanation for why human-populated CRSD markets are observed to converge to an equilibrium price.

3. STANDARD MODELS

Currently, fundamental models of market processes differ somewhat in both form and function between the fields of microeconomics and finance. The purpose of this section is to illustrate these basic models – much of which may be quite familiar to some readers. Section 4 will then consider how these models overlap in ways that might be compatible or incompatible.

3.1. The Microeconomics Approach – Law of Supply and Demand, Allocation Efficiency, and Dynamic Adjustment

The Law of Supply and Demand is a static theory of market equilibrium, and provides that the equilibrium of a competitive market occurs at the price and quantity given by the intersection of the demand and supply curves. For example, in Figure 1, the intersection of the demand and supply curves gives $Q = 6$ and $55 \leq P \leq 60$.

In an ordinary market experiment without the continuous refreshing described in section 2, the equilibrium $Q = 6$ and $55 \leq P \leq 60$ would be the predicted outcome

of microeconomic competitive theory. With continuous refreshing of the supply/demand curves, the correct equilibrium concept is less clear. First, there is no prediction for Q because refreshing allows trade to continue. Brewer, et al. (2002) maintained a hypothesis that competitive theory could possible still predict prices in these environments: the prediction for P from the Figure 1 of $55 \leq P \leq 60$ is the “instantaneous competitive equilibrium” of Brewer, et al. (2002), and there may also be a velocity-based equilibrium based on observed supply and demand curves that are calculated ex-post.

Allocation efficiency measures the ratio of the gains from trade achieved in a market versus the maximum possible gains from trade. Ordinarily, laboratory markets in the absence of externalities will equilibrate to prices near those predicted by the Law of Supply and Demand, supporting an allocation having nearly 100% allocation efficiency. In continuously refreshed markets, allocation efficiency is difficult to define because the proper definition of maximum possible gains from trade in the presence of refreshing is not obvious.

The Law of Supply and Demand is not a dynamic theory of price adjustment. Two early models of price adjustments are due to Marshall and Walras. Either could be expressed in the form of a differential equation, though there is no exact differential equation known to be accepted as an exact realization of either theory. The primary difference between the two adjustment models is whether adjustment occurs along the quantity axis or the price axis.

3.2. Marshallian Adjustment

The Marshallian adjustment process can be written as:

$$dQ/dt = F(P_D(Q) - P_S(Q))$$

where

$P_D(Q)$ = Demand Price (or Marginal Value) at Q

$P_S(Q)$ = Supply Price (or Marginal Cost) at Q

$F()$ is a sufficiently well-behaved unknown monotone function

3.3. Walrasian Adjustment

The Walrasian Adjustment Process can be written as:

$$dP/dt = G(Q_D(P) - Q_S(P))$$

where

$Q_D(P) - Q_S(P)$ gives the quantity of the excess demand at price P

and $G()$ is a sufficiently well behaved unknown monotone function.

The Marshallian adjustment process was originally associated with adjustment of markets that are repeated over a series of days, months, or years. One general

argument is that if $P_D > P_S$ it will be easy for sellers to sell their goods in excess of their marginal cost, and production will expand. However, if $P_D < P_S$ trade will be difficult since buyers are willing to pay less than sellers require to meet production costs. Because some sellers will be producing at least part of their production at marginal costs that are higher than what buyers are willing to pay (P_D), sellers must necessarily take a loss on this excess production. Failure to sell at a price greater than marginal cost would rationally lead to a contraction of production over time as sellers learn to correct overproduction.

Walrasian adjustment can be thought of as either a virtual or real tatonnement process that occurs before trade to set a price, or it can be thought of as occurring within trade through shortages and surpluses. In this research, we are mainly concerned with the latter approach. The basic idea is that if prices are above equilibrium, there is excess supply, and prices will fall over time, and if prices are below equilibrium there is excess demand, and prices will rise over time. It is worth noting that the Walrasian adjustment process, as a first-order differential equation, implies an exponential approach to equilibrium. A first-order differential equation for price over time does not permit more advanced behavior seen in some physical (non-economic) systems: for example, the oscillation of a spring (with or without damping) is the result of a 2nd order differential equation of motion over time.

More recently, Easley and Ledyard (1993) provide a model of double auction price convergence that has both Marshallian and Walrasian aspects. However, this model applies to the standard double auction with finite periods, not the CRSD double auction.

Attempts at comparing the Walrasian and Marshallian adjustment processes in standard double auctions have been made by Plott and George (1992) and Jamison and Plott (1997). These studies involved the creation of externalities alternatively generating upward sloping demand or downward sloping supply (called “perverse-shaped” curves because normally demand is downward sloping and supply is upward sloping) to create particular regions of Walrasian instability/Marshallian stability or Marshallian instability/Walrasian stability. Plott (2001; Introduction p. xxv) summarizes these results as favoring a Marshallian theory when externalities cause perverse-shaped supply and demand curves but favoring Walrasian theory when income effects cause perverse-shaped curves.

One can see that there is no well-accepted choice between Marshallian and Walrasian dynamics. It is believed that the use of the Continuously Refreshed Supply and Demand in the research reported here will select against Marshallian dynamics because there will be no shortage of trading opportunities along the Q axis to force an outcome. This consequence of CRSD experiment design will be revisited again in the next section.

3.4. *The Financial Economics Approach – Informational Efficiency*

Market prices are said to be *informationally efficient* if prices summarize existing information to the extent that there is zero expected gain from buying or selling

based on existing information. Existing information includes all current and prior prices $\{P_t, P_{t-1}, P_{t-2}, \dots\}$ as well as any other commonly known information about the market.

More formally, given information I_t at time t , prices are a *Martingale process* whereby the expectation $E_t[P_{t+k}|I_t] = P_t$ for all $k > 0$.

3.5. Normal Random Walk

For the purpose of this paper, a normal random walk is an integrated time series P_t whose first differences $\Delta P_t = P_{t+1} - P_t$ are independently and identically distributed normal variables with $E(\Delta P_t) = 0$ and $\text{Var}(\Delta P_t) = \sigma^2$. Modeling prices in a market as a random walk necessarily satisfies the informational efficiency requirement: if the mean of the difference process is zero, then $E[P_{t+k}|P_t] = P_t + E(\Delta P_t) + E(\Delta P_{t+1}) + \dots = P_t + 0 + 0 + \dots = P_t$. Note that the normal random walk has linearly increasing prediction variance $\text{Var}[P_{t+k}|P_t] = k\sigma^2$ as the prediction horizon k is increased.

3.6. Heteroskedastic Martingales

A heteroskedastic Martingale is a time series that satisfies the informational efficiency hypothesis but is not a normal random walk due to changes over time in the variance parameter of price differences σ^2 . The variance could be time dependent or price dependent. Well known examples of this class of processes would include the ARCH and GARCH time-series models, which add a separate equation for variance that induces heteroskedasticity.

4. COMPARING AND CONTRASTING THE STANDARD MODELS

The financial and microeconomic theories appear to overlap only in the case of a perfect market that instantaneously finds the competitive equilibrium price. A constant price is trivially a Martingale and if this constant price is at the theoretical equilibrium then both kinds of theories can be satisfied. However, noisy prices are an empirical regularity common to both the lab and the field. The main tension between the two approaches of Section 3 is that the existence of a price adjustment process in Microeconomics converging towards the static prediction of the Law of Supply and Demand is incompatible with the notion that markets prices exhibit informational efficiency detectable through autocorrelation properties of price differences.

4.1. Random Walk destroys convergence

If prices were a random walk, the market would have informational efficiency but then prices would not converge towards any fixed level. Price increments are always independent and identically distributed and therefore do not tend to move price

towards the microeconomic competitive equilibrium given by the Law of Supply and Demand.

4.2. Convergence of prices towards competitive equilibrium implies non-Martingale behavior

Convergence of prices towards a competitive equilibrium price p^* would seem to suggest that $E_t[P_{t+k}|I_t] < P_t$ when $P_t > p^*$ and $E_t[P_{t+k}|I_t] > P_t$ when $P_t < p^*$. In contrast, a Martingale Process always has expectation $E_t[P_{t+k}|I_t] = P_t$ for all $k > 0$.

Voluntary trade within a set of supply and demand curves necessarily generates a price ceiling and a floor outside of which trade will never occur. This creates problems for random walk and Martingale models.

4.3. Voluntary Trade and The Support of Possible Prices

Nothing in a random walk theory prevents prices from wandering outside of the support of voluntary trade. For example, in Figure 1 the lowest seller's marginal cost is 30 and the highest buyer's marginal value is 140. Voluntary trades can only occur at prices greater than or equal to 30, and less than or equal to 140.

4.4. A Censored Normal Random Walk is no longer a Martingale process

Censoring the random walk above and below ceiling and floor values (P^H, P^L) would tend to violate the Martingale requirement that $E[P_{t+k}|P_t] = P_t$. To see this, consider a price ceiling P^H , then at $P_t = P^H$ we would necessarily have $E[P_{t+1}|P_t] < P_t$. Unless $P_{t+1} = P_t = P^H$ with certainty (which is never true for a censored iid normal random walk but could be true for a heteroskedastic censored random walk only for the unusual case that the variance falls to zero at the ceiling) the mean of the next price P_{t+1} must be less than the ceiling because the probability support does not include any prices above the ceiling. The argument for violation at a floor is similar.

4.5. Bounded Martingales seem to require various non-economic properties

A Bounded Martingale is a Martingale price process bounded between two limits $[P^L, P^H]$. From the previous paragraph we know that the first non-economic property that a Bounded Martingale must have is that the price bounds are sticky. If at some time t the price $P_t = P^H$ or $P_t = P^L$, it remains at P^H or P^L forever. If one considers exponentially decreasing, ever-tightening bounds on the variance of the Martingale process over time, one may obtain price convergence to an interior point, but there is no reason to believe that this interior point should always coincide with the economic notion of competitive equilibrium nor does classical economics provide a definitive source or model associated with this decrease in variance. Conditional

heteroskedasticity based upon the distance of the price P_i from equilibrium might be helpful, but once again there is no obvious economic source of this effect and one must still have a variance of 0 at P^L and P^H with the possibility of prices becoming stuck at or near these locations. In contrast, economic theory would seem to say that the forces pushing prices towards the equilibrium would be strongest at boundary prices P^L and P^H because it is at these prices that excess demand or excess supply will be greatest.

The next note about conflicts among the models has more to do with the specific choice of a CRSD environment for generating the experimental data.

4.6. CRSD environment selects against Marshallian Price Adjustment Processes

Brewer, et al. (2002) considered an alternative interpretation of the Marshallian adjustment process acting within a single trading period: the *Marshallian Path*. The idea is simply that the sequence of trades in a market will be from left to right along the supply and demand curves at any series of prices P_n where $P_s(n) \leq P_n \leq P_d(n)$. For example, for the market of Figure 1, the Marshallian Path theory would imply the following sequence of trade: (buyer with value 140/seller with cost 30), (buyer with value 125/seller with cost 35), (buyer with value 110/seller with cost 40), (buyer with value 95/seller with cost 45), (buyer with value 80/seller with cost 50), (buyer with value 65/seller with cost 55). The equilibrium quantity of trades would be $Q^* = 6$. No further trades will be possible since $P_d < P_s$ at $Q = 7$.

Gode and Sunder (1993) advanced the idea that fully human rationality suggested in the adjustment processes above was not necessary because markets populated by so-called “Zero Intelligence” robots, which patiently bid/ask randomly within their budget constraint, converged to market equilibrium prices. ZI robots effectively follow a noisy Marshallian path, because at any time the robots with the greatest probability of trading are the high value buyer and the low cost seller. By removing the high-value and low-cost traders early, prices are stochastically forced towards the competitive equilibrium at the supply-demand intersection. Cason and Friedman (1996) provide additional evidence that suggests markets populated by humans follow such a noisy Marshallian path.

The continuously-refreshed environment of Brewer, et al. (2002) removes the Marshallian path as a possible mechanism for adjustment because the high-value and low-cost units are recycled back into the market. Prices are still seen to converge. This might be seen as lending support towards a Walrasian adjustment model at least for the CRSD class of environments.²

5. A HYBRID MODEL – ROBOT SIMULATIONS

Figure 3 shows market prices generated by three groups of specially designed trading robots. These prices are seen to converge towards a kind of equilibrium, similar to the convergence of the humans. The robots, which we will call constrained random walkers, use a pricing algorithm based partially upon a random-walk. The purpose of



Figure 3. Prices from Constrained Random Walkers attain equilibrium over time.

this section is to explain the algorithm of these robots, compare this algorithm to the Zero Intelligence algorithm of Gode and Sunder (1993), and compare and contrast the behavior of markets populated by the robots. The potential significance of these robot simulations for a combined microeconomic/financial theory of markets is explored.

5.1. Constrained Random Walkers

Constrained Random Walkers obey the following algorithm: at each moment in time one robot representing a particular buyer or seller is selected to act. This robot will then (1) fetch the previous transaction price p_{t-1} . This transaction price is the price of the last completed trade, not the advertised price of a previous bid or ask. (2) add an independent, identically distributed deviate $\varepsilon \sim N(0, \sigma^2)$ to obtain the potential price $p^* = p_{t-1} + \varepsilon$, and (3) submit a bid or ask at price p^* if and only if p^* is within the robot's budget constraint – that is, $p^* > \text{cost}$ for a seller, or $p^* < \text{value}$ for a buyer. Potential prices that fail step (3) are discarded.

5.2. Gode and Sunder (1993) ZI Robots

The ZI Robots obey the following algorithm: at each moment in time one robot representing a particular buyer or seller is selected to act. This robot will then randomly bid over the budget constraint without regard to previous prices. A Buyer robot will bid a price b^* from a uniform random distribution over $0 \leq b^* \leq v$, where v is the redemption value. A Seller robot will ask a price a^* from a uniform random

distribution over $c \leq a^* \leq H$, where c is the cost of the unit to the seller and H is an arbitrary ceiling price chosen to be higher than the highest buyers' value.

5.3. Double Auction Trading Rules

As bids and asks arrive, they are interpreted under the two rules of the double auction. The first rule is an improvement rule that discards bids and asks if they are not better than any previous standing bid or ask. The second rule is a trading rule that specifies that a trade occurs when a new bid is greater than the ask price, or a new ask is less than the bid price. When a trade occurs, the earlier bid or ask of the pair determines the trading price.

5.4. Effect of Individual Budget Constraints

The effect of individual budget constraints manifesting the supply and demand curves must be significant for any organized trend of prices towards an equilibrium price predicted by the Law of Supply and Demand. Gode and Sunder (1993) demonstrate that without the individual budget constraint and the double auction improvement rule requiring bids to be ascending and asks to be descending, the ZI robots do not converge to an equilibrium price but instead generate independent, identically distributed prices over the interval $[0, H]$. Brewer, et al. (2002) demonstrated the additional requirement of scarcity or finiteness of supply and demand for the ZI robots to reach equilibrium prices. In the CRSD environment, ZI robots fail to reach an equilibrium price, instead generating an iid sequence of prices. However, the exact shape of the iid distribution is affected by the particulars of the supply and demand curves.

Without individual budget constraints, the Constrained Random Walkers would generate prices that are a Martingale process. The individual budget constraints are imposed at step (3). Without step (3), each proposed bid or ask price is simply a normal based around the previous price. But with step (3) added, prices appear to converge. It is clear from Figure 3 that the rate of convergence depends on the deviation parameter σ^2 of the Normal distribution generating successive bids and asks. Over a range of small σ^2 , higher σ^2 appears to allow convergence to proceed at a faster pace.

5.5. Effect of Double Auction Trading Rules

The effect of the double auction trading rules is to impose a type of order on the competitive process that converts streams of bids and asks into transaction prices. The importance of these rules, and of changes to them, is borne out by the rich literature of double auction processes. Chamberlin's (1948) experiments showing the apparent non-convergence of market prices did not impose the formalities of double auction trading, but instead had subjects circulate the room to find partners. In contrast, Smith (1962) showed that when the rules of the double auction were applied to trading, prices converged after a series of repetitions to match the predictions of the Law of Supply and Demand.

5.6. Price Convergence in CRSD markets populated by Constrained Random Walk Robots

Brewer, et al. (2003) showed that with a CRSD environment, the ordering effect of the double auction market lacks sufficient strength to tame the aggregate pricing behavior of the ZI robots. However, because prices of markets populated by humans converge in the CRSD double auction environment, it was hypothesized that some additional element of human rationality, absent in the ZI robots, was responsible. With the demonstrated convergence of market prices in double auctions populated by the Constrained Random Walkers, the element of behavior required may have been identified: basing of bid and asks upon the previous price, while still censoring bids and asks against the budget constraint, causes the market prices to converge.

Notice what happens as the robots compete in Figure 3. Prices drift towards equilibrium at a rate that rises with increasing innovation σ^2 . After noting the pattern, σ^2 was varied in an attempt to generate time series comparable to the human traders. But why should prices converge at all? The key is to recognize the combined effect of budget constraints, double auction rules, and anchoring bids and asks to the previous transaction price.

If the previous price is low compared to competitive equilibrium, then the budget constraints imply a larger pool of buyers submitting bids than sellers submitting asks. The double auction rules require bids to be ascending and asks to be descending. Suppose prices are so low that it is likely that 2 buyers will submit bids before the next seller will submit an ask. Then the double auction rules will filter out the highest of these two bids, which has a 75% probability of being higher than the previous transaction price. While the bid price will likely move up, it is unlikely it moves up by much more than σ because of the anchoring effect of the bid generation process where $b \sim p_{t-1} + N(0, \sigma^2)$. When the seller robot generates an ask, with about 50% probability the ask price will be below the previous transaction price and a trade will occur at the earlier, and higher, bid price. Therefore the trade price will tend to move slowly towards the equilibrium, with the strength of the drift decreasing as prices move towards the equilibrium. When the prices are too high, there are more potential sellers than potential buyers, and a similar process occurs to lower the price.

This type of slow convergence suggests an AR(1) process might reasonably fit prices converging towards competitive equilibrium, compatible with the notion of Walrasian adjustment processes:

$$(P_{t+1} - P_{eq}) = a_1(P_t - P_{eq}) + \varepsilon_t; |a_1| < 1, \varepsilon_t \text{ iid } N(0, \sigma^{*2})$$

The market prices of the Constrained Random Walkers fit an AR(1) process fairly well. It is possible that there could be some price-based heteroskedasticity that does not fit the standard AR(1) model, or the residuals may be non-normal. These effects were not tested formally. When we look at the data of the human populated markets, there is also an additional effect that does not fit a AR(1) process: correction of outlier prices. The analysis of markets populated by humans will be the focus of the next section.

6. ARMA BEHAVIOR OF MARKETS POPULATED BY HUMANS

The purpose of this section is to examine ARMA models of the CRSD double auction market populated by humans. The impetus for using ARMA models is based in part upon the hypothesis that markets populated by Constrained Random Walker robots of section 5, which demonstrate convergence towards competitive equilibrium, appear to fit an AR model in prices.

However, with the humans, the visual evidence suggests a handling of outliers inconsistent with a simple AR(1) model. In an AR(1) model, an outlier in price would generate a new slow drift towards the equilibrium price. But in this data, the observed effect is that the price corrects to a price near the previous prices. This is a property of a moving average or MA model where the error terms follow a linear process and allow for such self-correction. An ARMA(1, 1) model incorporates both effects.

$$(P_{t+1} - P_{eq}) = a_1(P_t - P_{eq}) + \varepsilon_t;$$

$$\varepsilon_t \sim b_1 \varepsilon_{t-1} + \text{iid } N(0, \sigma^{*2})$$

In this model, the a_1 term is typically denoted the AR(1) or autoregressive term and the b_1 term is typically denoted the MA(1) or moving-average term. Slow convergence towards equilibrium is described by a near unity $a_1 \sim 1 - \phi$, with the speed of convergence increasing with ϕ . The b_1 term indicates “memory” in the shocks. A positive b_1 may indicate a run-on effect in large shocks being followed by a run of smaller and smaller shocks. A negative b_1 may indicate that shocks tend to partially self-correcting in successive trades. From a visual inspection of the human trading data, we expect b_1 to be negative in human populated markets.

The analysis of the data yields six results. Result 1 states that neither a fixed random process nor a random-walk unit-root process adequately describes the human market data. Result 2 identifies the drift in the pricing process and identifies a large source of variance from outliers, or large movements in price that are almost immediately corrected³. Based on this, we removed large movements in price to “sanitize” the time series. The goal is to separate the effects of these self-correcting price movements from other features of the time series. Result 3 finds a curious relationship between price variance and price in the sanitized time series. Results 4–6 characterize features of ARMA models fitted to the time series.

Result 1: Neither an iid fixed random process nor a unit-root process – such as a random walk – adequately describes the price data.

Support: Visually, it is unlikely that the data could be independent and identical draws from a fixed random distribution because the mean and variance of the process are changing. Visually, a unit-root process is unlikely because shocks to a unit-root process are persistent. This means, for instance, that large changes in the price should not be followed by reversals. Two formal tests were performed to examine

the possibility of a unit-root. Both the Dickey-Fuller test and the Philips-Perron test for a unit-root yield p-values of less than 0.01 for this data, indicating rejection of the null hypothesis of a unit-root at 99% certainty.

Trades	1–100	101–200	201–300	301–400	401–500	501–600	601–700	701–end
Raw Data								
Mean	81.22	75.86	69.89	64.83	63.44	63.39	61.91	63.40
Var	87.11	26.53	21.49	18.06	18.03	13.78	9.62	6.61
ΔP > 15 removed (26 trades)								
Mean	80.69	74.82	68.88	64.14	62.85	63.18	62.05	63.47
Var	57.87	24.96	22.51	15.03	9.85	9.93	8.03	6.58

Result 2: The price data shows a slow drift in mean from $T = 1$ to $T = 300\text{--}400$. The variance also changes over time, and is generally decreasing. A large portion of the variance in trades 1–100, 401–500 and 501–600 can be attributed to price changes where $|P_{t+1} - P_t| > 15$.

Result 3: The variance of the price process appears to be exponentially decreasing, once certain outliers are removed.

Support: A naïve OLS regression of $\log(\text{var})$ on the group midpoints $T_{\text{mid}} = (50, 150, \dots)$ of groups of 100 observations yields

$\log(\text{var}_{100}(p_t)) \sim 3.8379$
 (± 0.159)

$-0.00283 T_{\text{mid}};$
 (± 0.00034)

(standard errors)

The adjusted R^2 of this model is 0.9041 indicates a fairly close match as can also be seen visually in Figure 4.

The price data exhibits some features of an ARMA(1, 1) model, provided one is willing to ignore the heteroskedasticity and the possibility of higher order terms.

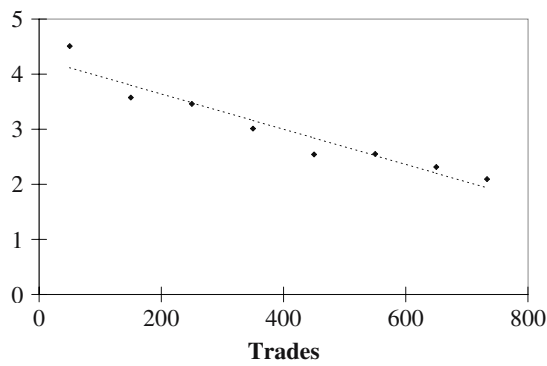


Figure 4. $\log(\text{Var}[P])$ for Groups of 100 trades with Log-linear Fit.

ARMA (1, 1) model	AR(1)	MA(1)	σ^2	Log(Likelihood)
Raw $P[t]$ no filtering	0.9952	-0.8043	23.73	-2382
(se)	0.0041	0.036		
$ \Delta P > 15$ removed	0.9877	-0.6429	15.95	-2151.6
(se)	0.0067	0.0419		
AR only	0.8726	-	19.80	-2234.0
MA only	-	0.6567	42.44	-2526.0

Result 4: The ARMA(1,1) fits reveal (i) an AR coefficient compatible with a very slow Walrasian dynamic together with (ii) a stronger MA coefficient compatible with short-term corrections of remaining outliers against the slowly moving mean. Sanitizing the data enables better detection of the slow Walrasian dynamic.

Support: The strength of the convergence process depends on $(1 - a_1)$. As the a_1 coefficient is almost 1.0, the convergence process is very slow and furthermore does not have good statistical significance given the standard error of the a_1 coefficient. The MA(1) coefficient b_1 is negative and is picking up the bounce or correction of large movements in price. Removing the large price changes from the time series improves the log likelihood by over 200 and shows a slightly stronger convergence dynamic now safely above the noise. The AR(1) and MA(1) process estimated separately show that both terms are significant. A log-likelihood χ^2 test would reject removing either term at well above the 0.999 level.

Result 5: A structural change in the ARMA process may occur roughly corresponding to the attainment of equilibrium.

Support: Figure 5 shows a standard log-likelihood test for detecting the breakpoint for a single structural change in a time series model. Figure 5 suggests, based on log-likelihood, a structural break around $T \sim 290$. When we look at the time series of prices this does correspond to a rough visual assessment of where equilibrium appears to have been attained ($T \sim 300-400$).

		Coefficients			Log(Likelihood)
ARMA 1, 1 models		AR(1)	MA(1)	σ^2	
$ \Delta P > 15$ removed					
$T \leq 290$		0.9882	-0.5918	26.02	-885.25
s.e.		0.0088	0.0631		
$T > 290$		0.7368	-0.4615	9.05	-1204.7
		0.0846	0.1138		
				Combined	-2089.95

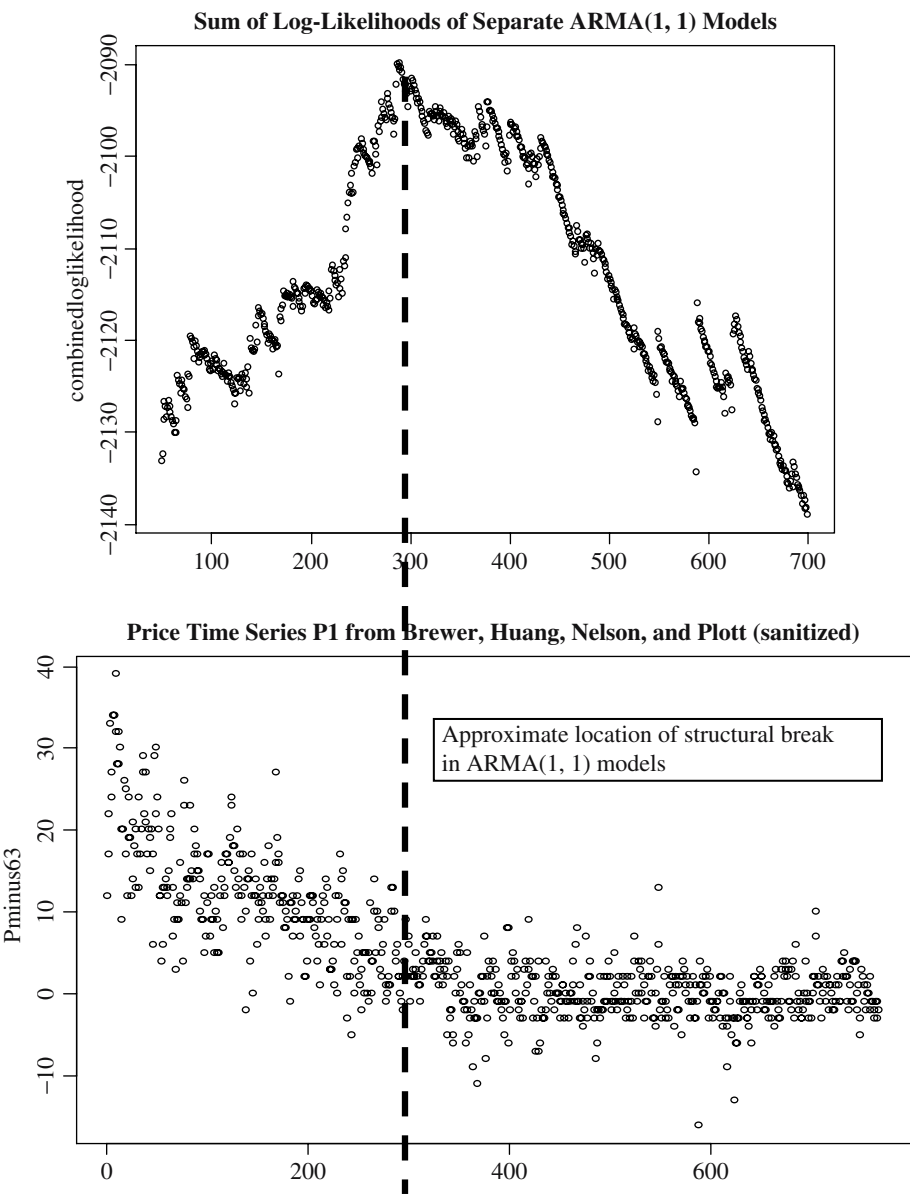


Figure 5.

With the caveat that smaller data sets yield less accurate fits, it is possible to break up the time series into groups of 100 trades.

		Coefficients			
ARMA 1, 1 models		AR(1)	MA(1)	σ^2	Log(Likelihood)
Data					
all data, no filtering					
trades	1–100	0.9954	−0.9085	78.98	–
	101–200	0.996	−0.7463	24.65	–
	201–300	0.9789	−0.6892	20.11	–
	301–400	0.857	−0.4291	12.35	–
	401–500	0.2489	−0.1507	22.6	–
	501–600	0.1925	0.0329	8.53	–
	601–700	0.8711	−0.6732	9.23	–
	701–792	0.4172	−0.099	5.99	–
ΔP > 15 removed					
trades	1–100	0.983	−0.4676	35.44	−321.97
	101–200	0.9907	−0.676	20.33	−293.68
	201–300	0.962	−0.5767	19.84	−291.97
	301–400	0.9058	−0.6693	12.23	−267.30
	401–500	0.674	−0.4279	8.49	−248.91
	501–600	0.0083	0.1263	9.68	−255.42
	601–700	0.7797	−0.422	6.68	−237.00
	701–767	0.5295	−0.179	5.68	−153.34
Combined					−2069.59

The pattern is given as Result 6.

Result 6: The price convergence process is not purely stationary but there is (i) a slow trend towards lower variance, and (ii) a shift in behavior around attainment of price equilibrium toward stronger price-related effects and away from outlier effects.

Support: The variance effect is clearly shown in the table above, and is also expected given Result 3. There are large changes in the coefficients beginning with $T = 301\text{--}400$. Figure 6 (constructed from the unfiltered data) suggests that the AR(1) coefficient drops, indicating a stronger strength of the price convergence process. At the same time, the MA(1) coefficient drops in absolute value, indicating that less of the price movements seem to be corrections of previous shocks.

Note also that the coefficients begin to wander after $T > 500$. This wandering may involve effects of discreteness in prices, given that prices are constrained to unit values and the observed price variance is very low.

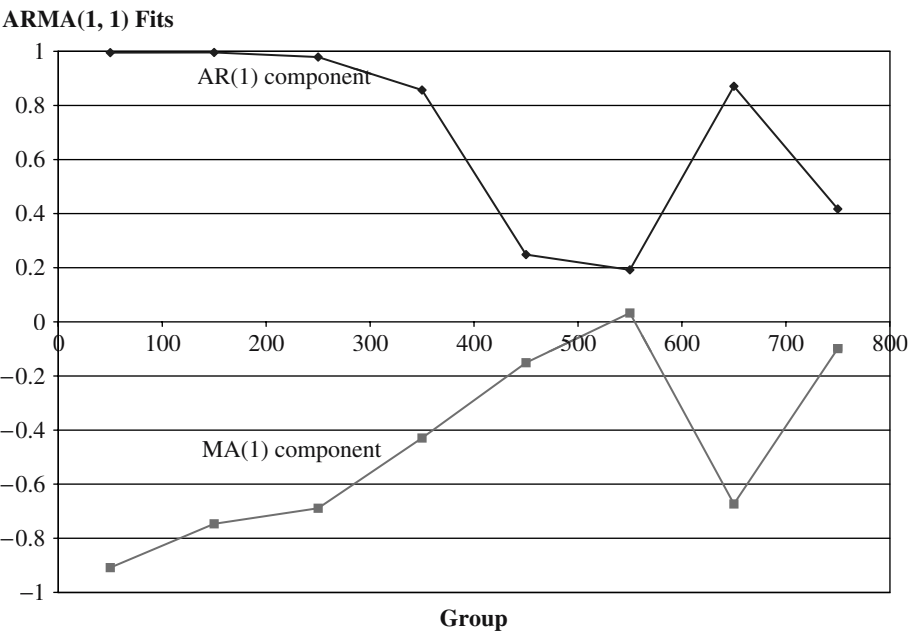


Figure 6. ARMA(1, 1) fits to raw subsamples.

An alternative, but perhaps important, interpretation for Result 6 is that as the market equilibrates, there is initially an advantage for subjects who pay attention to the trend in market prices and whether a price offer is an outlier and this generates the near unity values for the time-series coefficients that we see. But as the market equilibrates, there is less and less variance in price and therefore less and less money that could be earned by careful timing of, or attention to, market activities. The changes and variability in the time-series properties that occur upon, or just after equilibrium, could be simply due to the fact that there is almost nothing to be gained by trading in the previous manner.

7. CONCLUSIONS

This paper began with the question of whether it might be possible to integrate or reconcile ideas of market dynamics found in microeconomics with those found in the random walk or Martingale theory of finance. The use of long time series generated by a CRSD laboratory market provided a practical framework for an initial study of these questions.

Two conclusions can be found in the present research. The first conclusion is that something like a random walk process can be useful in modeling the slow convergence component of prices found in CRSD markets. When a random walk in bids and asks is censored against individual budget constraints the resulting market

prices appear to slowly converge towards the predictions of supply and demand. The innovative step in this model is that the random walk is not in transaction prices, but instead is a component involved in the process generating bids and asks.

The second conclusion is that the price dynamics of human-populated markets contain a number of different kinds of effects that seem to be operating simultaneously. Smoothing shows a AR(1) process similar to that seen in the constrained random walk robots. However, prices in the human-populated markets also show a complex outlier generation and correction process. A large move in prices at one trade is often corrected back towards the average with the next trade. This type of “memory” of the process is not captured by an AR(1) statistical process or a constrained random walk of bids/asks. Removing many of the large outliers and adding an MA(1) component to absorb the remaining outlier/correction process yields an ARMA(1, 1) model that varies as the market converges towards equilibrium.

A structural break in the ARMA parameters seems to occur as equilibrium is reached. The nature of this structural break is left for further research. It may suggest the use of models with multiple regimes for price discovery and equilibrium behavior rather than a simple stationary model.

Hope for a combined theory of microeconomic and financial adjustment suggested in this work possibly relies on classifying markets along what is for now a somewhat speculative grouping: (i) Markets with finite ending times and finite trade can be roughly modeled as a noisy Marshallian process and it is possible that scarcity and the likelihood of large surplus traders trading early are all that is necessary for the appearance of prices converging to the competitive equilibrium. Prices following a noisy Marshallian process will not be Martingales but instead will exhibit negative autocorrelation of price changes. (ii) Markets with no fixed ending time and continuously refreshed supply and demand, such as the CRSD market presented here, exhibit price convergence when populated by humans that can not be explained as a Marshallian process, but only as either a Walrasian class of adjustment process or some other type of process yet to be defined. Within the Walrasian class of adjustment processes is the possibility that a random-walk approach to submitting bids and asks can explain market price convergence when the random walk generating bids and asks is censored, at the individual level, against an individual seller’s supply costs or buyer’s redemption values making up the supply and demand. This convergence also relies upon the details of trading, e.g., the improvement rules of the double auction.

It is this second grouping of markets involves a hybrid model of CRSD market price convergence incorporating both ideas from finance (the random walk) and microeconomics.

In addition, the hybrid model can yield back a purely financial model, when the microeconomic constraints of supply and demand are removed. Suppose a financial market is modeled as being like the CRSD environment, but without the individual constraints on traders’ costs and values typically associated with supply and demand. If individual behavior based on (possibly faulty) future expectations turns out to be quite different from behavior based on a known arbitrage opportunity, this may be

a sensible rough model. In the absence of individual budget constraints associated with supply and demand curves, a random walk generating bids and asks would be uncensored, depending only on the previous transaction price. Thus, when the rules of double auction trading are applied, the random walk process in bids and asks would generate a random walk in prices, which is the expected result in an informational efficiency model of a price adjustment.

As warned in the introduction, this approach may be seen by some as overly broad or raising more questions than it answers. However, as pointed out in section 4, there are a number of apparent conflicts between microeconomic price processes as confirmed by laboratory experiments and the standard assumptions of finance. Rather than simply assume that the latter do not apply to the former, it is hoped that the search for a combined theory of price adjustment may – with continued contribution by theorists and empiricists in both fields – yield further insights into the behavior of markets not discernable with the tools of one field alone.

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NOTES

¹ Fama [1965] finds positive autocorrelations of returns on 75% of the Dow 30 stocks. Solnik [1973], Lawrence [1986], and Butler and Malaikah [1992] find many examples of negative autocorrelations of daily returns in the stock markets. Hawawini and Keim [1995] provide a survey of this literature in their introduction. Dacorogna, Gençay, Müller, Olsen and Pictet [2001; pp. 123–4] briefly discuss negative autocorrelations found in the price formation process of foreign exchange markets that are strong for very short time horizons but vanish over the course of 30 minutes or so.

² The argument is that in a CRSD environment, the Marshallian dynamic is precluded. Nothing precludes Marshallian or multiple adjustment models from acting in the ordinary classical environment or other domains not studied here.

³ The interface for trading was a graphical screen rather than numeric input of bids and asks, and so it is also possible that these outliers are caused by subjects recklessly sending in asks that are too low (or bids that are too high) in an attempt to quickly accept a desirable bid (ask). Priority for input from multiple subjects that would cause acceptance of a bid/ask was based on time only not on price. A tendency for some subjects to send in outlier prices can also be seen as a human/computer interface design flaw because subjects could have been warned and given a pop-up box to confirm questionable behavior. The design used did not involve any such handholding, settling for simplicity and minimal interaction or guidance of the subject.

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