Testing for Granger Causality in the Stock Price-Volume Relation: A Perspective from the Agent-Based Model of Stock Markets *

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Abstract ***From the perspective of the agent-based model of stock markets, this paper examines the possible explanations for the presence of the causal relation between stock returns and trading volume. In addition, since the excess demand for the stock is an observable variable in our model, the causal relation between stock returns and the excess demand for the stock is also examined. Using a new version of the Granger causality test, which does not require an ad-hoc procedure of filtering, we found that the bi-directional causality between trading stock returns and trading volume ubiquitously exists in all our four artificial stock markets of different designs. The implication of this result is that the presence of the stock price-volume causal relation does not require any explicit assumptions like information asymmetry, reaction asymmetry, noise traders, or tax motives. In fact, it suggests that the causal relation may be a generic property in a market modeled as evolving decentralized system of autonomous interacting agents.***

Keywords: Agent-Based Stock Markets, Genetic Programming, Granger Causality, Stock Price-Volume Relation

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1 Motivation and Introduction

The stock price-volume relation has interested financial economists for many years. (See the survey article by [?].) While most of the earlier empirical work focused on the *contemporaneous* relation between trading volume and stock returns, some recent studies began to address the *dynamic relation*, i.e., *causality*, between daily stock returns and trading volume ([?], [?], [?]). In many cases, it was found that a bi-directional causality, or more precisely, *Granger causality* existed in the stock price-volume relation. In other words, not only did trading volume Granger cause stock returns, but stock returns also Granger cause trading volume. The implication of this finding is that trading volume can help predict stock returns. As an old Wall Street adage goes, "*It takes volume to make price move.*"

There are several explanations for the presence of a causal relation between stock returns and trading volume. ([?] gave their explanation based on the *asymmetric reaction* of investors ("bulls" and "bears") to the positive information and negative information. [?] and [?] used the *sequential information arrival* model to justify the causal relation, while [?] rested their explanation on the *noise trader models*. In light of these explanations, this paper attempts to see *whether we can replicate the causal relation between stock returns and the* *trading volume via the agent-based stock markets* (**ABSMs**).

We consider the agent-based model of stock markets highly relevant to this issue. First, the existing explanations mentioned above based their assumptions either on the information dissemination schemes or the traders' reaction styles to information arrival. Since both of these factors are well encapsulated in agent-based stock markets, it is interesting to see whether ABSMs are able to replicate the casual relation in a similar spirit. Secondly, information dissemination schemes and traders' behavior are known as the *emergent phenomenon* in ABSMs. In other words, these factors are endogenously generated rather than exogenously imposed. This feature can allows us to search for a fundamental explanation for the causal relation. For example, we can ask: *without the assumption of information asymmetry, reaction asymmetry, or noise traders, can we still have the causal relation?* In other words, is the causal relation a generic phenomenon? Finally, in agent-based stock markets, we can also test the causal relation between stock returns and other important, but unobservable, variables, such as the excess supply of or demand for shares of stocks.

The rest of the paper is organized as follows. Section 2 describes the agent-based stock markets considered in this paper. Section 3 introduces the version of the econometric tests for Granger causality used in this paper. Section 4 gives the testing results, followed by the concluding remarks in Section 5.

2 Experimental Designs and Data Description

The agent-based stock markets considered in this paper is from [**?**] and [**?**]. There are two agent-based stock markets studied in [**?**]. These two markets are distinguished by whether traders are *prudent* in the sense that they will *validate* any new ideas coming to them before actually put them into practice. The one with the validation step is coded as Market D in the paper, and the one without is coded as Market A in the paper.

Motivated by [**?**], who pointed out the traditional distinction between the phenotype and genotype in biology and doubted whether the adaptation can be directly operated on the genotype via the phenotype in the social process, [**?**] provided a new architecture to modeling agent-based stock markets. This architecture rests on a *mechanism* called " business school" which is a *procedure* to map the phenotype to the genotype or, in plain English, to uncover the secret of success. Within this new architecture, two markets were studies. These two markets are distinguished by the stochastic process of dividends. In the first market coded as Market B, the dividends are assumed to be iid (identically and independently) *uniform*, whereas in the second market coded as Market C, they are assumed to be iid normal.

A single run with 20,000 observations was conducted for Markets A and D in [**?**], and a single run with 14,000 observations was conducted for market B in [**?**]. In this paper, we conducted a single run with 20,000 observations for Market C. The time series plots of trading volume (V_t) observed in these four markets are given in Figures 1A-1D, and the time series plots of the stock price (P_t) are depicted in Figures 2A-2D. Moreover, the time series of "bids to buy" (B_t) and "offers to sell" (O_t) are also plotted in Figures 3A-3D and Figures 4A-4D respectively.

Given the time series P_t, V_t, and $D_t(\equiv B_t - O_t)$, we further conducted the difference transformation of them to make sure that all time series are stationary.

$$r_t = \ln(P_t) - \ln(P_{t-1}), v_t = V_t - V_{t-1} \quad (1)$$

and

$$d_t = D_t - D_{t-1} \quad (2)$$

Notice that r_t is the stock return. We then examined the causal relation between r_t and v_t and that between r_t and d_t. To test whether there is any unidirectional causality from one variable to the other, we followed the conventional approach in econometrics, i.e., *Granger causality*. While there are several different ways to conduct the Granger causality test,

Table 1: Unidirectional Causality from Trading Volume to Stock Returns: Q_1

N	Mkt A	Mkt B	Mkt C	Mkt D
1	10.831	2.590	1.677	9.014
2	10.881	3.408	2.624	8.787
3	12.105	2.411	2.262	8.967
4	11.540	3.253	2.117	8.884
5	11.712	1.882	2.290	9.083
6	11.661	2.692	2.414	8.986
7	11.261	1.828	2.060	9.283
8	11.831	N/A	2.025	9.505
9	11.371	N/A	1.813	8.351
10	11.593	N/A	2.729	7.782

The critical value for rejection of hypothesis of an unidirectional causality at the 0.05 (0.01) significance level is 2.241 (2.807). "N" refers to the Nth 2000-observation. For example, "1" refers to the period "1-2000", and "5" refers to the period "8000-10000".

some tests require an arbitrary choice of filtering processes, and others require an arbitrary choice of lags. The one which we followed in this paper is a new test developed by [?] which does not require these arbitrary choices. [?] called her tests Q_1 and Q_2 statistics. We shall briefly present this notion of causality tests in the next section.

3 Granger Causality Testing

The test employed in this paper is from [?]. Without losing generality, we shall illustrate Kau's test by showing how to test unidirectional causality from v_t to r_t. First, let $z_{tk} = r_{t+k}v_t$. Then [?] constructed the following two statistics.

$$Q_{1T} = \max_{1 \leq k \leq 30} \mid Z_T(\frac{T-k}{T-1}) \mid \quad (3)$$

$$Q_{2T} = \max_{1 \leq k \leq 30} Z_T(\frac{T-k}{T-1}) - \min_{1 \leq l \leq 30} Z_T(\frac{T-l}{T-1}) \quad (4)$$

where

$$Z_T(\frac{T-k}{T-1}) = \frac{1}{\hat{\sigma}_T(k)\sqrt{T-1}} \sum_{t=1}^{T-k} z_{tk}, \quad (5)$$

Table 2: Unidirectional Causality from Trading Volume to Stock Returns: Q_2

T	Mkt A	Mkt B	Mkt C	Mkt D
1	15.125	4.517	3.069	12.443
2	15.172	5.737	4.468	10.827
3	15.649	4.319	4.008	11.117
4	16.285	5.441	3.633	10.633
5	15.345	3.594	4.232	11.547
6	15.234	5.206	4.697	11.789
7	14.373	3.232	3.747	11.207
8	14.778	N/A	3.653	12.634
9	14.239	N/A	3.548	11.486
10	15.395	N/A	5.441	10.833

The critical value for rejection of hypothesis of an unidirectional causality at the 0.05 (0.01) significance level is 2.497 (3.023).

and

$$\hat{\sigma}_T^2(k) = \frac{1}{T-k}\{\sum_{t=1}^{T-k} z_{tk}^2 + \sum_{\tau=1}^{T-k-1} (w_{n(T)}(\tau) \times \sum_{t=\tau+1}^{T-k} z_{tk} z_{(t-\tau)k})\}. \quad (6)$$

The $w_{n(T)}(\tau)$ appearing in $\hat{\sigma}_T^2(k)$ was the *Barlett kernel*. By the *Barlett kernel*, $n(2000)$ is 13.6. As a result,

$$w_9(\tau) = \begin{cases} 1 - \frac{\tau}{13.6}, & \text{if } 0 \leq \frac{\tau}{13.6} \leq 1 \\ 0, & \text{otherwise.} \end{cases} \quad (7)$$

By the *functional central limit theorem* and *continuous mapping theorem*, [?] was able to show that the 0.05 (0.01) significance level of Q_1 and Q_2 is 2.241 (2.807) and 2.497 (3.023) respectively. By these critical values, we tested unidirectional Granger causality from v_t to r_t. Following a similar procedure, we also tested unidirectional Granger causality from r_t to v_t, d_t to r_t and r_t to d_t.

4 Experimental Results

We divided the time series $\{r_t\}$, $\{v_t\}$, and $\{d_t\}$ into several non-overlapping subseries with 2,000 observations for each. We then applied Kau's test to each of this subseries, and the results are given in Tables 1 to 8.

Table 3: Unidirectional Causality from Stock Returns to Trading Volume: Q_1

T	Mkt A	Mkt B	Mkt C	Mkt D
1	12.869	2.057	3.442	10.731
2	11.325	2.609	2.740	11.042
3	8.218	2.192	3.307	9.740
4	9.237	2.017	2.272	10.275
5	12.224	2.084	2.401	9.281
6	12.387	2.597	3.232	10.527
7	12.076	1.636	2.378	10.007
8	8.318	N/A	2.853	10.658
9	12.163	N/A	3.450	10.525
10	12.292	N/A	2.842	9.374

Table 4: Unidirectional Causality from Stock Returns to Trading Volume: Q_2

T	Mkt A	Mkt B	Mkt C	Mkt D
1	22.640	3.350	5.175	17.427
2	14.571	5.006	5.425	16.079
3	14.539	4.046	4.973	14.945
4	17.709	3.788	4.157	13.632
5	22.561	3.514	4.148	14.518
6	21.747	4.666	5.141	16.770
7	17.602	3.263	4.541	15.449
8	13.888	N/A	5.005	17.449
9	19.952	N/A	6.552	15.603
10	18.529	N/A	4.587	14.452

Tables 1 and 2 are the results for testing "$H_{vr} : v_t \to r_t$." We find that the results are quite different between the market with the business school (Markets B,C) and the market without (Markets A,D). For the latter, no matter which statistics or which significance level we use, the hypothesis " H_{vr}:v_t fails to Granger cause r_t" is always rejected. However, for the former, if we conduct the Q_1 test at the 0.01 significance level, then we fail to reject the null hypothesis H_{vr} in most subseries. Leaving the testing results aside, by just looking at the values of Q_1 and Q_2, we can be convinced that the unidirectional causality from v_t to r_t is much weaker in the market with business school.

Similar patterns are also found in tests for "$H_{rv} : r_t \to v_t$" (Tables 3, 4), "$H_{dr} : d_t \to r_t$" (Tables 5, 6), and $H_{rd} : r_t \to d_t$" (Tables 7, 8).

Table 5: Unidirectional Causality from Excess Bids to Stock Returns: Q_1

T	Mkt A	Mkt B	Mkt C	Mkt D
1	8.946	2.471	2.748	7.297
2	10.619	1.711	1.716	8.421
3	11.256	2.254	1.747	8.829
4	11.565	3.822	2.261	8.361
5	11.144	3.196	1.887	8.251
6	11.228	2.474	2.210	9.135
7	11.105	2.926	2.327	8.554
8	11.203	N/A	2.057	9.007
9	10.908	N/A	1.775	8.564
10	11.604	N/A	3.199	7.896

Table 6: Unidirectional Causality from Excess Bids to Stock Returns: Q_2

T	Mkt A	Mkt B	Mkt C	Mkt D
1	14.217	4.880	4.398	11.636
2	14.431	3.036	3.135	12.036
3	16.187	3.887	3.371	12.256
4	15.603	5.893	4.229	11.021
5	16.338	6.298	3.596	11.497
6	15.814	4.461	3.985	13.288
7	15.067	5.208	4.486	11.658
8	15.443	N/A	3.856	13.619
9	15.574	N/A	3.386	11.948
10	17.032	N/A	5.474	10.855

5 Conclusions

The operation of the business school in the artificial stock market has an impact on the information flows. When traders' trading strategies are not observable and are kept as secret, direct imitation is infeasible, and it is only through the channel of the business school that traders get to imitate their competitors. However, regardless of the change in information flow, bidirectional Granger causality did ubiquitously exist in all our four artificial stock markets at the 5% significance level. The implication of this result is that the presence of the stock price-volume causal relation does not require any explicit assumptions like information asymmetry, reaction asymmetry, noise traders, or tax motives. In fact, it suggests that the causal relation may be a generic property in a market modeled as an evolving decentralized system of autonomous interacting agents.

Table 7: Unidirectional Causality from Stock Returns to Excess Bids: Q_1

T	Mkt A	Mkt B	Mkt C	Mkt D
1	10.308	9.770	8.363	7.863
2	9.731	9.698	5.537	9.448
3	7.402	8.181	5.813	6.156
4	9.567	8.091	8.674	8.837
5	11.530	7.839	7.580	7.289
6	9.974	5.305	6.409	9.123
7	11.806	7.856	5.948	8.914
8	9.925	N/A	5.008	9.193
9	11.567	N/A	8.400	9.529
10	7.353	N/A	8.735	8.405

Table 8: Unidirectional Causality from Stock Returns to Excess Bids: Q_2

T	Mkt A	Mkt B	Mkt C	Mkt D
1	18.093	11.762	9.910	13.586
2	13.369	11.707	7.346	15.010
3	13.766	9.809	7.796	11.447
4	16.564	10.488	10.502	12.755
5	13.692	10.243	9.689	12.939
6	18.084	7.716	8.624	15.057
7	18.443	9.896	8.708	12.015
8	13.175	N/A	7.736	15.804
9	18.224	N/A	10.919	14.253
10	14.232	N/A	12.294	13.401

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Figure 1.A : Time Series Plot of Trading Volume: Market A

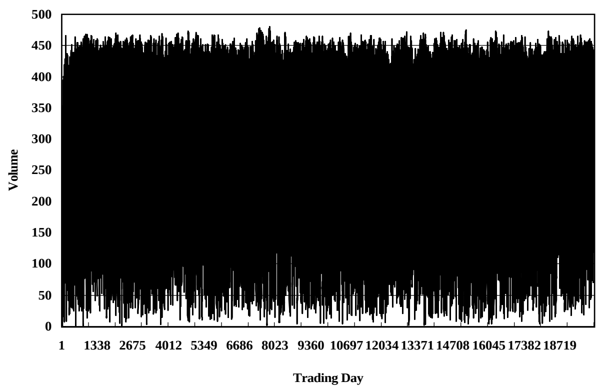

Figure 2.A : Time Series Plot of the Stock Price: Market A

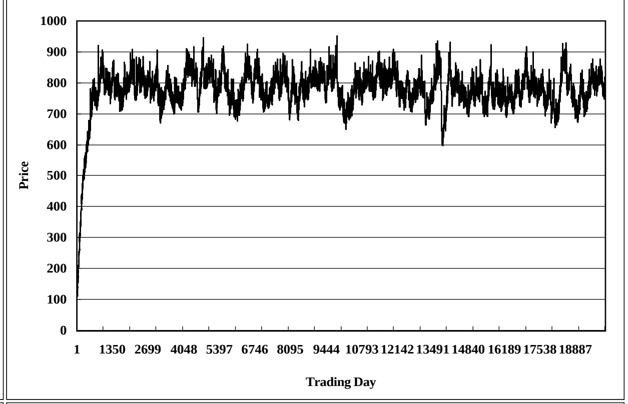

Figure 1.B : Time Series Plot of Trading Volume: Market B

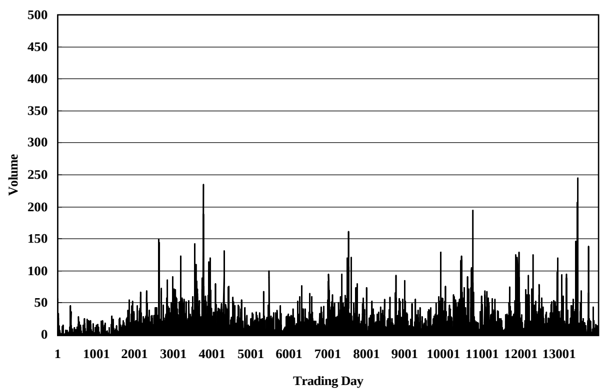

Figure 2.B : Time Series Plot of the Stock Price: Market B

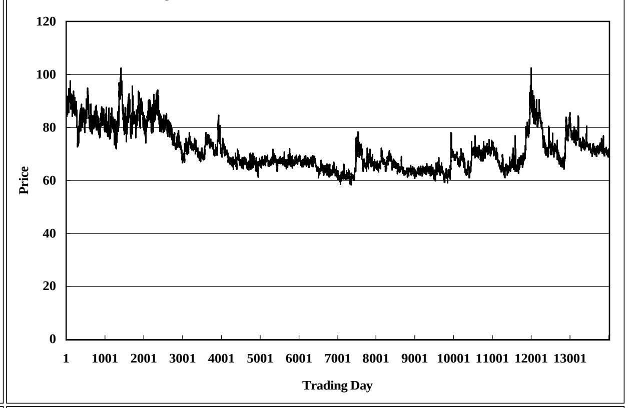

Figure 1.C : Time Series Plot of Trading Volume: Market C

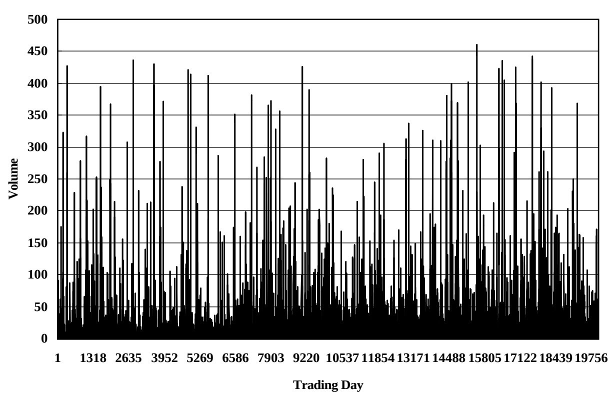

Figure 2.C : Time Series Plot of the Stock Price: Market C

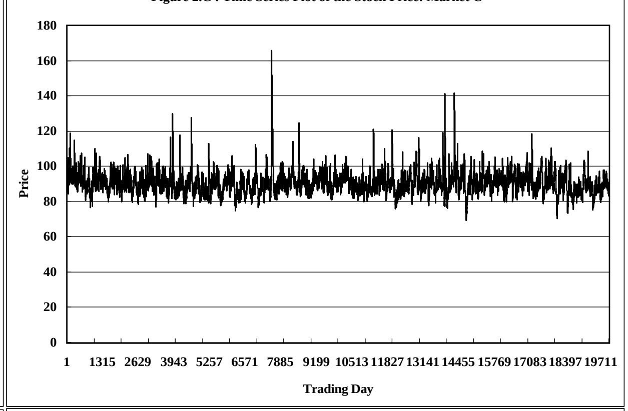

Figure 1.D : Time Series Plot of Trading Volume: Market D

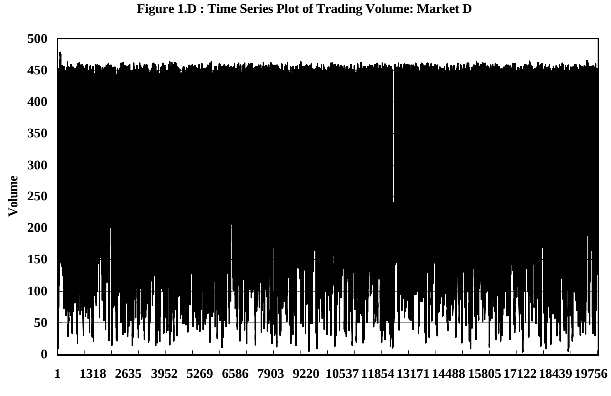

Figure 2.D : Time Series Plot of the Stock Price: Market D

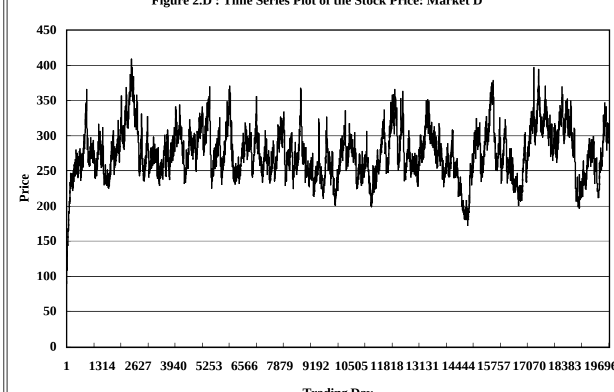

Figure 3.A : Time Series Plot of Bids: Market A

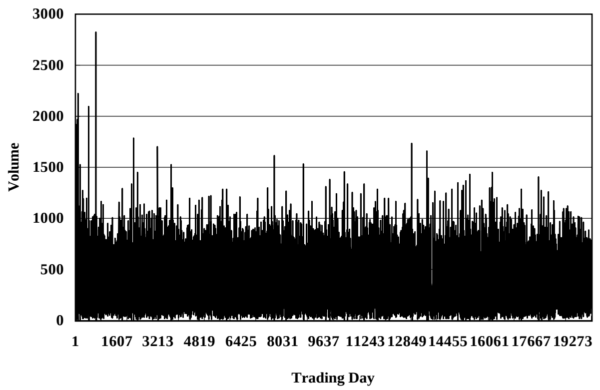

Figure 4.A : Time Series Plot of Offers: Market A

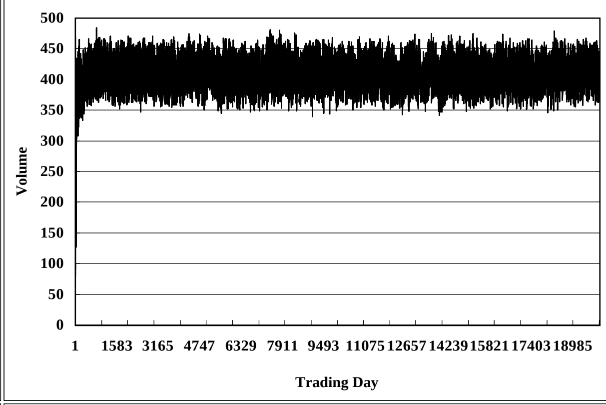

Figure 3.B : Time Series Plot of Bids: Market B

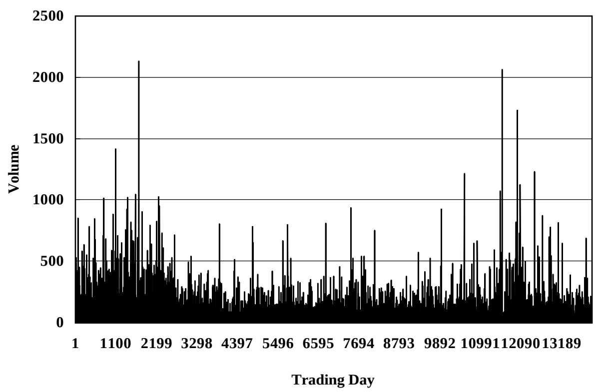

Figure 4.B : Time Series Plot of Offers: Market B

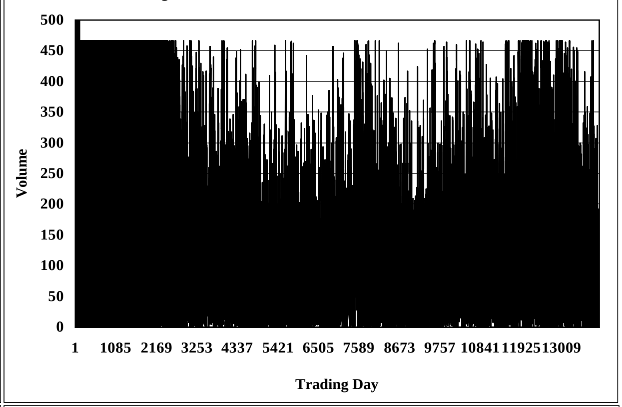

Figure 3.C : Time Series Plot of Bids: Market C

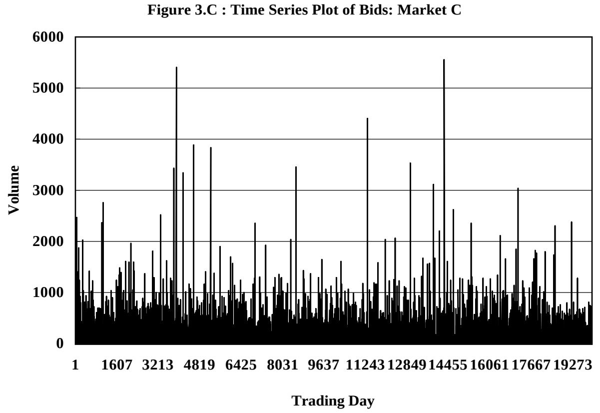

Figure 4.C : Time Series Plot of Offers: Market C

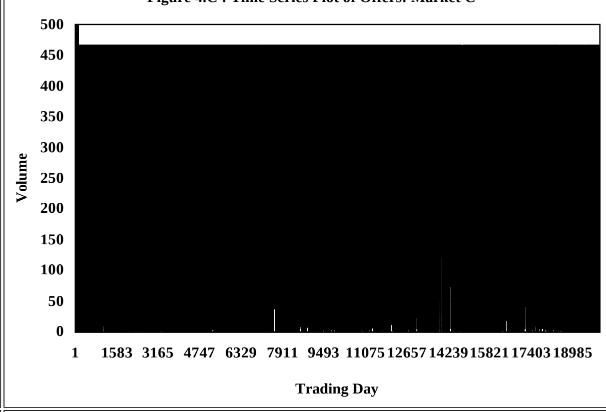

Figure 3.D : Time Series Plot of Bids: Market D

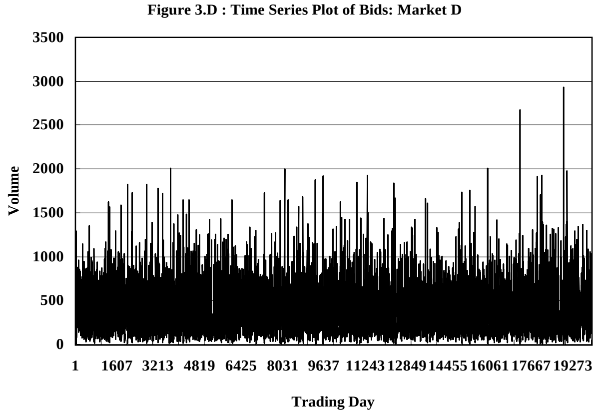

Figure 4.D : Time Series Plot of Offers: Market D