Quantitative Finance
Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/rquf20

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Version of record first published: 11 Feb 2009

To cite this article: Sun-Chong Wang, Sai-Ping Li, Chung-Ching Tai & Shu-Heng Che (2009): Statistical properties of an experimental political futures market, Quantitative Finance, 9:1, 9-16

To link to this article: http://dx.doi.org/10.1080/14697680701447482

Quantitative Finance, Vol. 9, No. 1, February 2009, 9–16

Routledge
Taylor & Francis Group

Statistical properties of an experimental political futures market

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(*Received 22 March 2005; in final form 18 September 2006*)

1. Introduction

Markets are complex systems that usually consist of the following different types of participants: (i) producers who provide goods, (ii) speculators or hedgers who, with beliefs in the trends of price movements, buy low and sell high for a profit or insurance, and (iii) arbitrageurs who buy products at a low price in one market and sell them at a high price in other markets for a riskless profit. A market is liquid if sufficient numbers of the different types of players exist in symbiosis. To study the system, successive movements in observables such as price are modeled as a stochastic process for the market's response to the random arrival of information. Fluctuations are predicted to be Gaussian (Bachelier 1900) or Lévy (Lévy 1937) distributed by the central limit theorem.

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Quantitative Finance
ISSN 1469–7688 print/ISSN 1469–7696 online © 2009 Taylor & Francis
http://www.informaworld.com
DOI: 10.1080/14697680701447482

The distributions of large price changes, those that exceed, say, five standard deviations, however, show characteristic power-law behaviour (Mandelbrot 1963, Fama 1965, Dacorogna *et al*. 1993, Loretan and Phillips 1994, Lux 1996, Pagan 1996, Arnéodo *et al*. 1998, Bouchaud and Potters 1998, Gopikrishnan *et al*. 1999, Plerou *et al*. 1999). Models to explain the power-law behaviour range from systems at the state of self-organized criticality exhibiting scale-free properties in the order parameters (Bak 1992), to evolutionary systems (Ponzi and Aizawa 2000) whose constituents interact through a social network (Lux and Marchesi 1999, Cont and Bouchaud 2000, Gabaix *et al*. 2003).

In an attempt to study market behaviour experimentally, we created an online marketplace that hosted the three types of market players mentioned above (Wang *et al*. 2004). In this market, a player, after free registration for an account on our exchange server†, was allocated a fixed (and common) amount of fictitious money to start with. We defined the so-called political futures contracts (Forsythe *et al*. 1992, Berg and Rietz 2003) and held trading tournaments that gave cash awards to those who fared well in their account wealth at the end of the tournament (Wang *et al*. 2004). A political futures contract, say *Bush–Cheney*, is a futures contract whose liquidation price is set by the percentage of (electoral college) votes the Bush–Cheney ticket receives on November 2, 2004, when the contract matures. A player who believes George W. Bush would win the election would buy in *Bush–Cheney* contracts when the market price of these contracts is low (e.g. below 50). In addition to *Bush–Cheney* and *Kerry–Edwards* futures contracts, we also issue *Others* to account for votes for independent candidates. The sum of the price of each contract of *Bush–Cheney*, *Kerry–Edwards*, and *Others* is 100 if the market is rational, deviations of the sum from 100 at any time providing opportunities for arbitrageurs. Players submit online bid or ask limit (or market) orders which are matched in real time on our server by the mechanism of continuous double auctions (Smith *et al*. 2003), which is widely used in real-world financial exchanges. The design of the tournament is to recruit serious participants, who are believed to make prudent decisions when they have a stake in the engagement.

Two tournaments were launched for anyone who had access to the Web. The first, between October 4 and November 3, 2004, was on the 2004 U.S. presidential election, while the second, between November 11 and December 12, 2004, was on the 2004 Taiwan parliamentary election‡. The exchange server, open 24 hours a day 7 days a week, recorded data including the transaction price, volume traded, highest bid, and lowest ask with the time of each contract. The result shows a scaling property in the probability densities of price returns over a range of time lags τ across two orders of magnitude (55 min $< \tau <$ 8103 min). The central region of the densities can be described by a Cauchy distribution (a stable Lévy distribution that decays slowly as a power law with an exponent equal to 2), while the tails can be described by a power law, the exponent of which depends on whether transaction prices or means of the bid–ask spread are used in obtaining the densities. The distribution of changes in trading volume was found to follow a Gaussian distribution, while that of large trading volumes can be fitted by a power law. The distribution of players' wealth, which started from a delta function, was found to be power law distributed when the tournament ended. The distribution of inter-transaction time intervals was also found to follow a power law. Despite the fact that the money is fictitious and the scale of the exchange is small in terms of the number of players and time span, the results reproduced many properties characteristic of real financial markets. If we consider a tournament as an experiment, by observing changes in the statistical properties of the market observables with changes in rules of the exchange, we expect the platform to shed light on the principles that govern socioeconomic behaviour.

2. Experimental design

Due to the nature of the futures, tournaments were scheduled to start one month before election day and ended on election day when the futures matured. Recruiting as many players as possible presented a great challenge to researchers who lacked marketing channels. What was done was to post news about the tournament to college campus bulletin boards throughout Taiwan (Wang *et al*. 2004). The number of registrations increased with time and reached 364 and 498, respectively, for the U.S. presidential and the Taiwan parliamentary election near the end of the tournaments. There was a change in the rules between the two experiments§. In the U.S. case, submitted orders waited in the orderbook for matching orders until expiry otherwise. In the Taiwan case, orders could be canceled before they expired. Note that contracts could by no means be bought (sold) from (to) oneself. Figures 1 and 2 show the price time-series for each contract in the two experiments. Time is measured in minutes from the midnight of January 1, 1970 UTC (coordinated universal time). The higher frequency of trades in the second experiment reflects the change in the rules. Our data analysis thus focuses on the second experiment unless stated otherwise. Interpretation of the price movements and the accuracy and precision of the prediction of the time-series on election outcome are beyond the scope of this paper. We briefly mention

† http://socioecono.phys.sinica.edu.tw
‡ http://socioecono.phys.sinica.edu.tw/exchange/announce
§http://socioecono.phys.sinica.edu.tw/exchange/faq

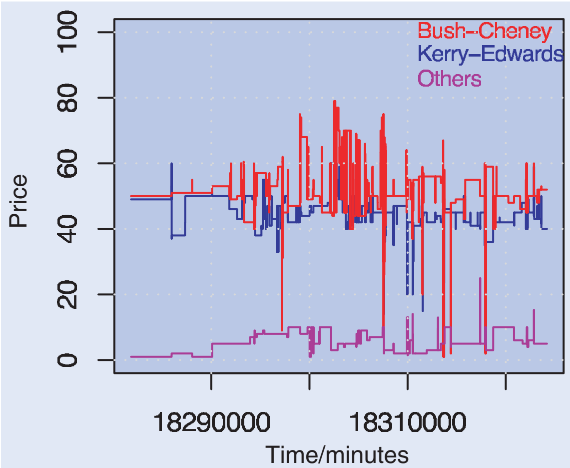

Figure 1. Price time-series for the futures in the 2004 US presidential election. 'Others' represents votes received by all candidates other than Bush–Cheney and Kerry–Edwards.

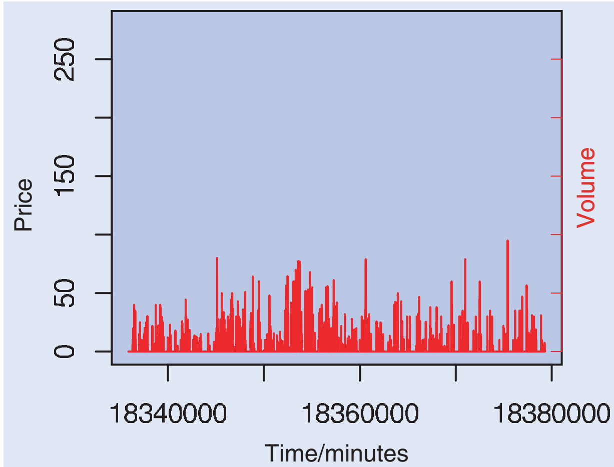

Figure 3. Time-series for the bundle price (black) and total volume (red) for the 2004 Taiwan parliamentary election.

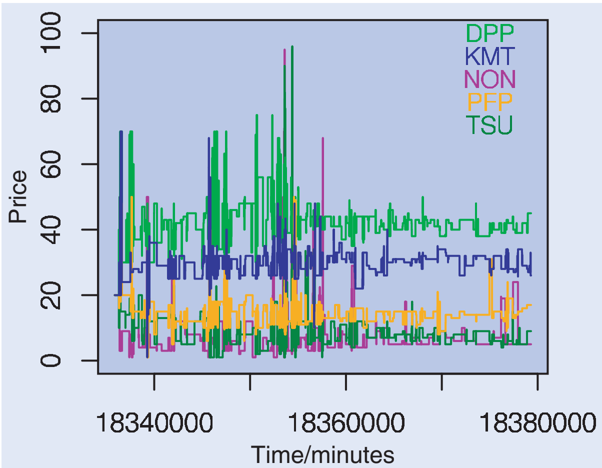

Figure 2. Price time-series for the futures in the 2004 Taiwan parliamentary election. The acronyms, with the exception of NON, are those of the major political parties participating in the election. NON indicates all candidates other than the four major parties.

here that vote–share rankings by the means of the price time-series correctly mirrored the election outcomes in both experiments, which is also true for our earlier experiment on the Taiwan presidential election in March 2004 (Wang *et al.* 2004).

3. Results and data analysis

The 2004 Taiwan parliamentary election took place a month after the 2004 U.S. presidential election. The higher frequency of trades in the Taiwan experiment could have resulted from our continued marketing effort which had begun since the U.S. election experiment started. Another explanation is that players were more interested in local elections. In the following, we focus the analysis on the high-frequency time-series data from the experiment on the Taiwan election unless stated otherwise.

3.1. Preparation of the time-series data

During the tournament, information arrives stochastically and the time intervals between successive transactions are irregular. To generate a time-series at a constant time interval of 1 minute, we bin time into discrete values with a resolution of 1 minute. Prices in a time bin are then averaged. A value of zero, meaning no transactions in that time bin, is replaced with the non-zero price in the most recent time bin. There are thus a total of 43 430 data points in such price time-series, corresponding to the duration of the tournament in minutes. For volume time-series, no such replacement with non-zero is performed, however.

We call the portfolio consisting of a contract of DPP, KMT, PFP, TSU, and NON a *bundle*. The acronyms come from the Democratic Progressive Party, Kuomintang (i.e. Nationalist Party), the People First Party, and the Taiwan Solidarity Union, which represent the major political parties in Taiwan. NON stands for non-partisan candidates. Similar to a stock index which is a (weighted) sum of the stock prices of the representative companies, we sum the five price time-series of the individual futures contracts to obtain the price time-series of a bundle. Figure 3 shows the time-series of the summed prices and summed trading volumes. Only 8340 data points in the summed volume time-series are non-zero. The ratio of 8340 to 43 430 indicates that the market was active 19% of the time. Hereafter, the analysis will be on such summed observables unless stated otherwise.

3.2. Price returns

There are many large fluctuations in figure 3. To study the occurrence of the fluctuations, we calculate the difference in the logarithmic price $\log S(t)$ between time $t+\tau$ and time t,

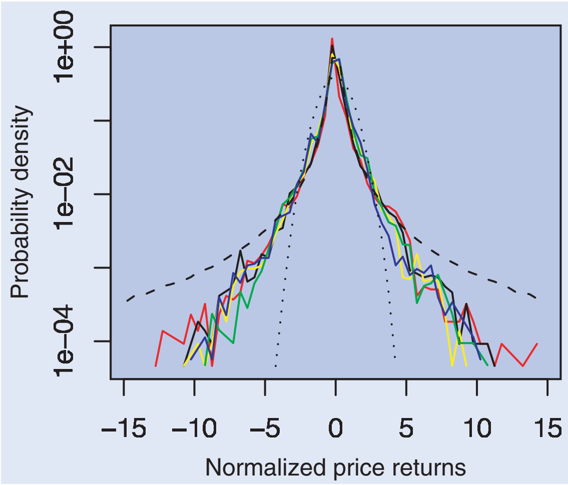

Figure 4. Probability density of normalized price returns with time lag equal to 55 (red), 148 (black), 403 (yellow), 1097 (green) and 8103 (blue) minutes. The dashed line was obtained from a Cauchy distribution and the dotted line is a Gaussian distribution of unit variance. Data are from figure 3.

$$G_\tau(t) = \log S(t+\tau) - \log S(t), \tag{1}$$

and the normalized price return,

$$g_\tau(t) = \frac{G_\tau(t) - \mu_\tau}{\sigma_\tau}, \tag{2}$$

where μ_τ and σ_τ are the mean and standard deviation of $G_\tau(t)$. Figure 4 superposes the probability densities of the returns g_τ at five different time lags: $\tau = 55$, 148, 403, 1097 and 8103 minutes, which are roughly evenly spaced in the logarithmic scale. The scaling behaviour of price returns over time lags spanning over two decades has been well documented (Mandelbrot 1963, Fama 1965, Dacorogna *et al.* 1993, Loretan and Phillips 1994, Lux 1996, Pagan 1996, Arnéodo *et al.* 1998, Bouchaud and Potters 1998, Gopikrishnan *et al.* 1999, Plerou *et al.* 1999) and is reminiscent of the phenomenon of self-organized criticality in some physical systems (Bak *et al.* 1987, Field *et al.* 1995).

The other feature of figure 4 is the heavy tails relative to the log normal distribution. Fat tails in the distribution of price returns have long been observed and are suggested to be power-law distributed (Mandelbrot 1963, Fama 1965, Dacorogna *et al.* 1993, Loretan and Phillips 1994, Lux 1996, Pagan 1996, Arnéodo *et al.* 1998, Bouchaud and Potters 1998, Gopikrishnan *et al.* 1999, Plerou *et al.* 1999). We performed a linear fit to the log transformed probability density of g_{148} in figure 4 for $g_{148} > 4$ and obtained an asymptotic density p_{g148} for the normalized returns g_{148},

$$p_{g_{148}} \sim \frac{1}{g_{148}^{1+\alpha}} = \frac{1}{g_{148}^{4.9}}. \tag{3}$$

Estimation of the exponent $1+\alpha$ from the log–log plot may depend on the histogram bin size. A workaround that is popular in extreme value studies is the Hill estimator, which calculates the difference between the average of the k most extreme observations and the

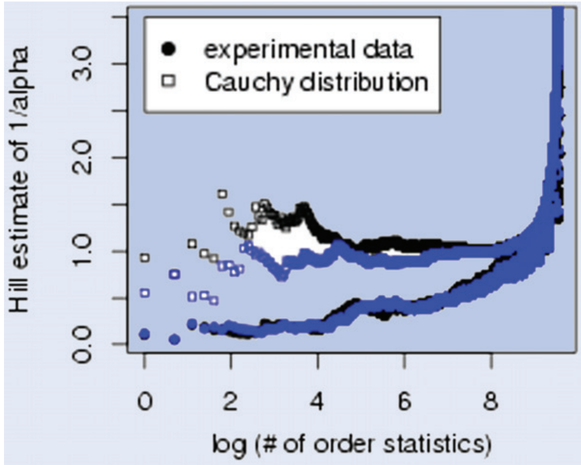

Figure 5. Hill plot of the normalized price returns g_{148} of the Taiwan experiment and Cauchy distribution from simulation. Positive returns are in black and negative returns in blue.

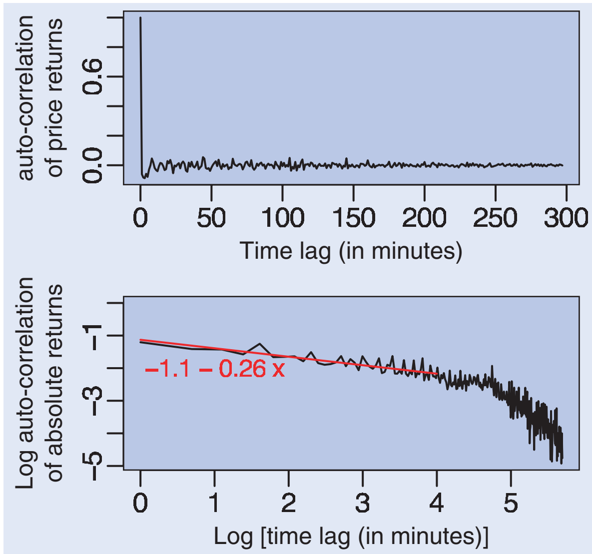

Figure 6. Autocorrelation function of $G_1(t)$ (top) and $|G_1(t)|$ (bottom). A slope of − 0.26 results from the linear regression fit.

kth most extreme observation (Hill 1975). The Hill plot (Drees *et al.* 2000) of g_{148} is shown in figure 5, which also includes a Hill plot for the data drawn from a Cauchy density. The number of draws was made equal to the number of observed price returns. If we consider only the first 1097 Hill estimates, the exponents $1+\alpha$ are found to be 1.93 (2.08) and 3.50 (3.46) for the positive (negative) tails of the Cauchy and price returns g_{148}.

The exponents of the price returns are outside the stable Lévy regime. Figure 6 shows plots of the autocorrelation functions of the price returns and the absolute value of the price returns. Note that the data are truncated at a time lag equal to 298 minutes, where the first negative autocorrelation of $|G_1(t)|$ occurs. It can be seen that the autocorrelation of price returns drops to the noise level in about half an hour, after which the market is considered efficient. Higher-order correlations, however, persist

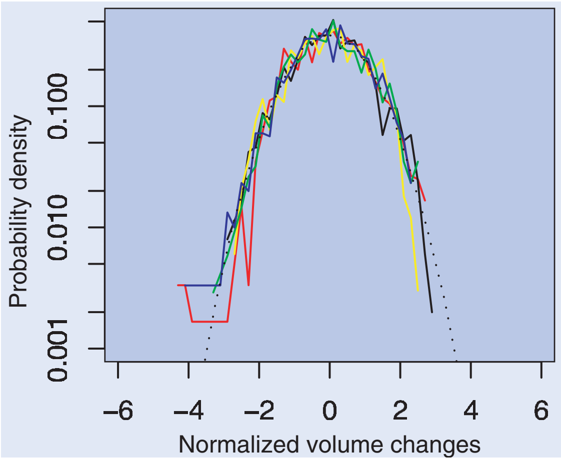

Figure 7. Probability density of normalized logarithmic volume changes with time lag equal to 55 (red), 148 (black), 403 (yellow), 1097 (green) and 8103 (blue) minutes. The dotted line was obtained from a standardized Gaussian distribution. Data are from figure 3.

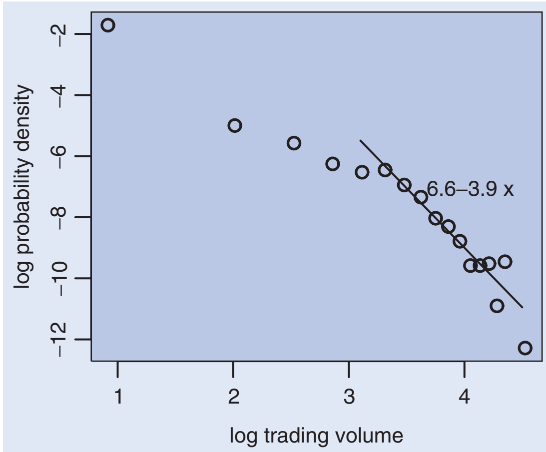

Figure 8. Probability density of the trading volume (log transformed) from figure 3. The straight line results from a linear regression fit to the large volume data points, giving a slope of −3.9.

Table 1. Numbers of valid logarithmic volume differences from the volume time-series and their standard deviations at different time lags.

	Time lag (min)				
	55	148	403	1097	8103
Number of differences	3001	2506	1660	1722	1506
Standard deviation	1.62	1.58	1.64	1.52	1.55

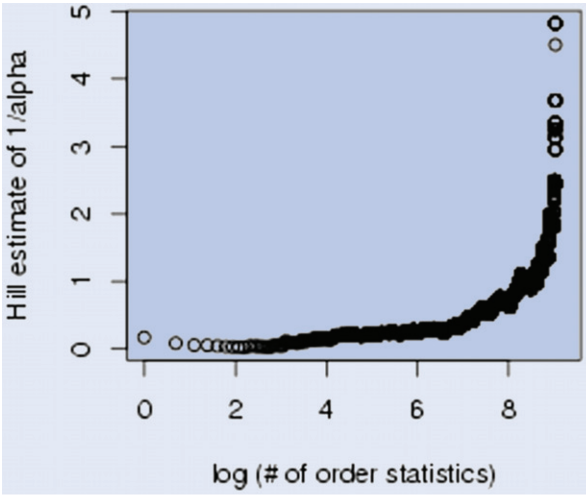

Figure 9. Hill plot of the trading volumes in the 2004 Taiwan parliamentary election experiment.

longer, as can be seen by the slow decay of the autocorrelation of the absolute value of the price returns in the bottom panel of figure 6, suggesting that traders have long-range memory of the magnitude of price changes (Dacorogna *et al.* 1993, Ding *et al.* 1993, Liu *et al.* 1999).

3.3. *Trading volume*

In parallel to changes in price, we calculated normalized logarithmic volume changes and plot the probability densities in figure 7, which, unlike the fat tails in figure 4, coincides with a standardized normal distribution. Note that the differences were calculated from non-vanishing volumes $V(t+\tau)$ and $V(t)$ in the time-series because log(0) would diverge. Table 1 shows the available numbers of differences from the volume time-series. Normality seems to suggest Brownian motions (or Wiener processes) which are Markovian (Bachelier 1900). However, the standard deviations of the distributions of differences listed in table 1 do not increase with the square root of the time lag. Changes in trading volume are therefore not independent over the range of time lags tested.

Another distribution of interest is that of trading volumes (Gopikrishnan *et al.* 2000), which we show in figure 8. A straight line fit of the distribution p_V for large trading volumes V gives

$$p_V \sim \frac{1}{V^{1+\alpha}} = \frac{1}{V^{3.9}}. \tag{4}$$

Figure 9 shows the Hill plot for the trading volume data from the 2004 Taiwan parliamentary election experiment. If we truncate the log(order statistics) at 7, i.e. consider only the largest $1097 = \exp(7)$ trading volumes among the total of 43 1430 observations, we obtain an averaged exponent $1+\alpha$ of 4.7.

3.4. *Transaction time intervals*

Our exchange server, which was open 24 hours a day 7 days a week, received orders from online players who submitted their orders in response to the random arrival of information on campaign activities. An order was carried out only when it intersected with a matching order

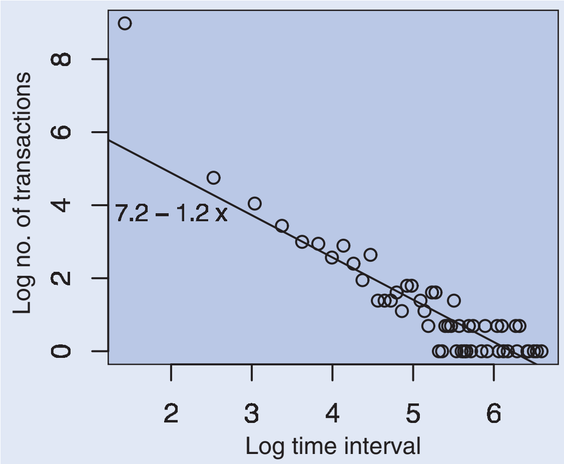

Figure 10. Distribution of inter-transaction time intervals (log transformed). The straight line is from a linear regression fit to the data points, with the exception of the first, with a slope of −1.2.

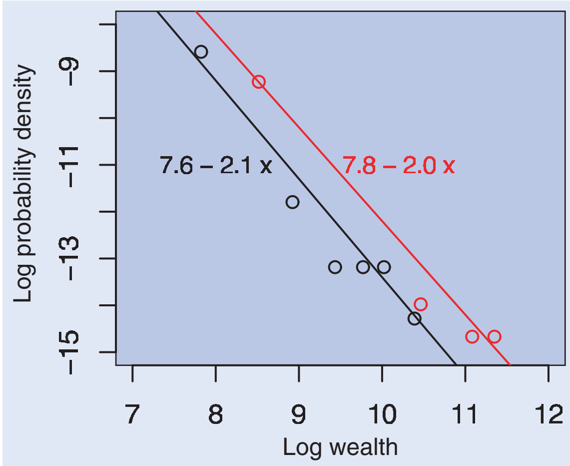

Figure 11. Probability density of wealth (log transformed). The straight lines result from linear regression fits to the whole wealth range, giving a slope of about 2. Black and red are, respectively, for the 2004 Taiwan parliamentary and the 2004 U.S. presidential elections.

before it expired in the order-book. When orders were matched, a transaction took place. We calculated the time intervals between successive transactions. Figure 10 shows a plot of the number of transactions versus the inter-transaction time intervals measured in minutes. It can be seen that the numbers decay asymptotically in a power-law fashion with an exponent of 1.2. The non-exponentiality of the distribution indicates that transactions do not take place randomly in time, even though orders are assumed to be submitted randomly in time.

3.5. *Wealth*

At the end of the tournament we liquidated the futures contracts left in the players' accounts, the wealth of which could then be calculated. Recall that every player was allocated an equal amount of 3100 units of fictitious money when his account was created. If the account wealth remained 3100 after liquidation, the account was deemed inactive. To obtain the distribution of wealth we removed inactive accounts, leaving 319 active accounts in the Taiwan election experiment and 235 in the US election experiment. The wealth distribution pw of the active accounts is shown in figure 11, a linear fit to which suggests a power law distribution (Pareto 1897, Zipf 1965),

$$pw \sim \frac{1}{W^{2.1}}. \tag{5}$$

The exponent from the average of the first $148 = \exp(5)$ Hill estimates in the Hill plot of figure 12 gives a value of $1 + \alpha = 3.2$.

4. Discussion

The exponent can differ if different time-series constructions are used. In the above we padded missing prices using the last transaction price. (Note that futures

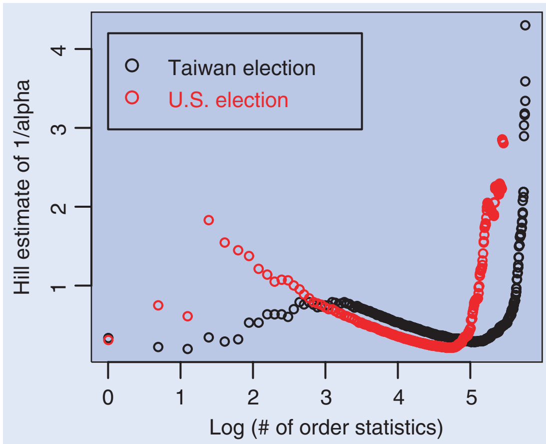

Figure 12. Hill plot of wealth. The black and red plots are for the 319 and 235 observations in the 2004 Taiwan parliamentary and the 2004 U.S. presidential election, respectively.

contracts cannot be traded at zero price in our experiment.) The interpolation is valid under the assumption that players consider the price fair and thus do not bother to buy or sell. However, one can argue that the lack of transactions only reflects the fact that no one is online during the time bin, rather than a consensus on the price among players. We therefore also analysed the data without padding. In this case, the difference between prices at $t+\tau$ and t can only be found when both prices exist, resulting in a drop in statistics as in table 1. Nevertheless, figure 13 shows the scaling behaviour of the normalized price returns (from the Taiwan experiment) thus formed, g'_τ.

The exponent of the positive tail of the density of g'_{148} is now 3.1 from the log–log plot,

$$p_{g'_{148}} \sim \frac{1}{{g'_{148}}^{3.1}}, \tag{6}$$

and again it is outside the stable Lévy regime.

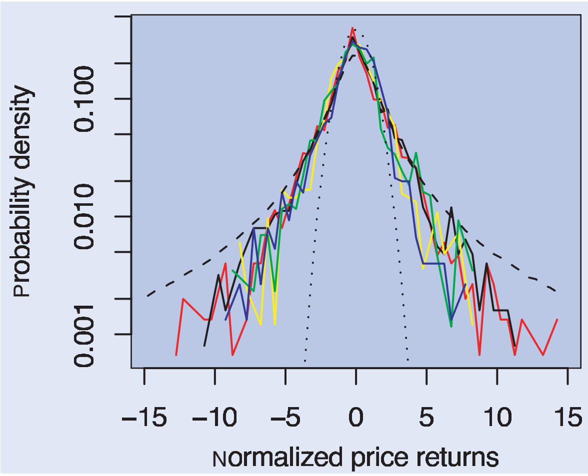

Figure 13. Probability density of normalized returns with time lag equal to 55 (red), 148 (black), 403 (yellow), 1097 (green) and 8103 (blue) minutes. Returns are calculated from the transaction prices. The dashed line was obtained from a Cauchy distribution and the dotted line is a Gaussian distribution of unit variance. Data are from figure 3.

The large value of the exponent of pV in equation (4) compared with $1+\alpha=2.7$–3.1 from the four actively traded companies on the NYSE between 1994 and 1995 (Gopikrishnan *et al.* 2000) may be due to the fact that, in our experiment, the start-up cash for each player was limited to 3100. The maximum trading volume was limited to 31 as a result. In real financial markets, the resources of the investors, who consist of individuals as well as large investment houses, can vary greatly, giving rise to a fatter tail in the volume distribution. Moreover, shares of a company stock that are traded over an extended period of time, such as the two-year period studied by Gopikrishnan *et al.* (2000), have a high chance of changing hands at large volumes relative to the one-month period in our experiment.

A limit order is placed with an upper bound for buying (or lower bound for selling) a volume of contracts, expiring in a period of time specified by the bidder (seller). A market order, on the other hand, buys (or sells) from (to) the existing orders in the orderbook, and is executed immediately after it is received on our server. We can therefore say that cautious traders tend to use limit orders while impatient traders use more market orders. The effect of the limit order–limit order interactions and limit order–market order interactions on the price is interesting. Our server recorded the lowest ask and highest bid in the orderbook of each futures contract throughout the experiment. We summed these five time-series to form the lowest ask and highest bid time-series of the bundle in the Taiwan experiment. Figure 14 plots the time-series, which are seen to flank the transaction price time-series of figure 3. We calculate the arithmetic mean of the lowest ask and highest bid at any time and obtain a time-series, the scaling property of which is shown in figure 15. The spread of the tails, compared with that in figure 4, does not seem to support the exacerbating effect of market orders. However, since the market was thin, players might have learned quickly to avoid placing

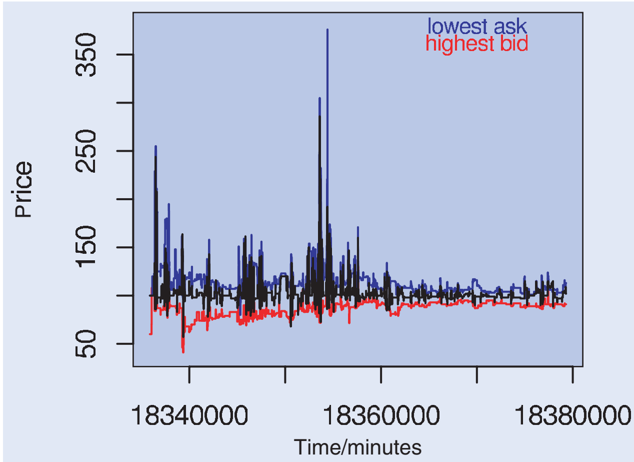

Figure 14. Lowest ask and highest bid time-series of the 2004 Taiwan parliamentary election.

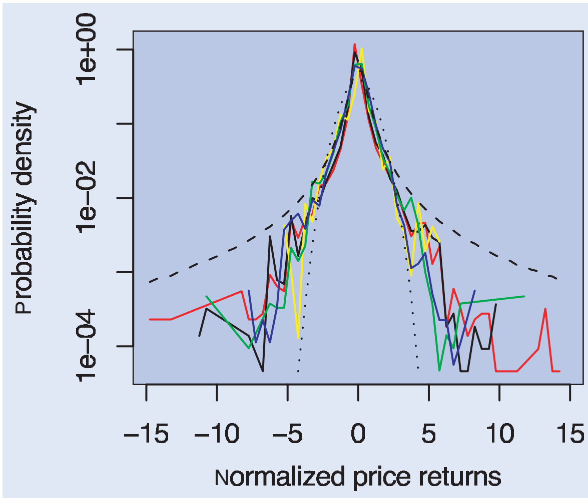

Figure 15. Probability density of normalized price returns with time lag equal to 55 (red), 148 (black), 403 (yellow), 1097 (green) and 8103 (blue) minutes. Returns are calculated from the arithmetic means of the lowest asks and highest bids. The dashed line was obtained from a Cauchy distribution and the dotted line is a Gaussian distribution of unit variance.

market orders. More studies are needed to understand the impact of market orders.

In our experiment, an equal amount of money was made available to the market whenever a new player joined the tournament. Players' money was redistributed through trading as the tournament proceeded (a player was found to own, on average, 11 contracts of each futures contract in the Taiwan experiment). Figures 11 and 12 show that the distribution of wealth after the 2004 Taiwan parliamentary election appears to be power-law distributed. In the independent experiment on the 2004 US presidential election, we also examined the wealth distribution of the active players (235 in this case). The exponent $1+\alpha$ from the average of the first $122=\exp(4.8)$ Hill estimates in the Hill plot (in red) of figure 12 was found to be 3.1. The two experiments gave similar exponents using the method of either figure 11 or figure 12. The Pareto-like property appears robust considering the lower changeover rate of the futures contracts in the 2004 US presidential tournament than in the 2004 Taiwan parliamentary tournament (see figures 1 and 2). An asymptotic fat-tailed distribution of price fluctuations also appeared in the 2004 US presidential tournament (figures not shown) as we carried out a similar analysis on the time-series despite their lower statistics. The formation of the Paretian wealth distributions could be attributed to the large price fluctuations, not the frequency of trades, according to our experiment.

Furthermore, a simple survey of the geographical and occupational information on the top 20 players indicates that they do not know one another in person, suggesting that social networks are not necessary to explain the power-law property of the price returns and wealth.

The decay times in the autocorrelation functions of individual prices differ. In particular, the decay time of the DPP price autocorrelation function is found to be the longest, suggesting that there were more DPP supporters in the tournament or that the DPP supporters were more loyal. The dependencies of the price changes could be caused by the collective actions of segments (coalitions) of participants of different genres, contributing to the large fluctuations.

In summary, we have presented an approach to studying the principles underlying complex and strongly fluctuating socioeconomic systems. Futures contracts corresponding to a social event were designed. Futures trading experiments with well-defined initial conditions were then set up. Participants were recruited and contributed to the study via the Internet. Market observables such as transaction price, trading volume, and bid ask price were recorded in real time. Scaling behaviour similar to that observed in real financial markets was found in the distributions of price returns and trading volume. Power-law behaviour was also found in the distributions of inter-transaction time intervals as well as participants' wealth. To study the effect of different trading rules (social insurance policies) on wealth redistribution, we can, for example, charge a fee (tax) on every transaction (income). We also plan to study the dynamics by sampling the wealth distribution throughout the tournament in future experiments.

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