Financial
Econometrics
Research Centre

WORKING PAPERS SERIES

WP05-15

Phase coexistence in a forecasting game

Philippe Curty and Matteo Marsili

Phase coexistence in a forecasting game

Philippe Curty and Matteo Marsili
The Abdus Salam International Center of Theoretical Physics, Trieste, Italy
(Dated: February 2, 2008)

Individual choices are either based on personal experience or on information provided by peers. The latter case, causes individuals to conform to the majority in their neighborhood. Such herding behavior may be very efficient in aggregating disperse private information, thereby revealing the optimal choice. However if the majority relies on herding, this mechanism may dramatically fail to aggregate correctly the information, causing the majority adopting the wrong choice. We address these issues in a simple model of interacting agents who aim at giving a correct forecast of a public variable, either seeking private information or resorting to herding. As the fraction of herders increases, the model features a phase transition beyond which a state where most agents make the correct forecast coexists with one where most of them are wrong. Simple strategic considerations suggest that indeed such a system of agents self-organizes deep in the coexistence region. There, agents tend to agree much more among themselves than with what they aim at forecasting, as found in recent empirical studies.

Information affects in many subtle ways socio-economic behavior, giving rise to non-trivial collective phenomena. For example, a key function of markets is that of aggregating the information scattered among traders into prices. However, if traders rely on the information conveyed by prices, this same mechanism may lead to self-sustaining speculative bubbles. Likewise, we deduce the worth of a restaurant or the importance of a research subject from its crowdedness or popularity. However, popularity can consecrate even totally random choices [1].

Collective herding phenomena in general pose quite interesting problems in statistical physics. To name a few examples, anomalous fluctuations in financial markets [2, 5, 6], opinion dynamics [3, 4] and the way in which social changes take place [7] have been related to percolation and random field Ising models. It is natural to expect herding behavior when it is convenient for the individuals to follow the herd. For example, when the majority is buying in the stock market, prices go up, hence buying becomes the right thing to do (at least in the short run). If a technology (e.g. fax machine) is widely adopted, it becomes more convenient to adopt it. Herding takes place even in cases where agents' behavior does not influence the outcome, if agents try to infer information about the optimal choice from the actions of others. Ref. [1] discusses the relevance of these considerations for issues ranging from the prevalence of crime, marketing, fads and fashions to the onset of protests such as that leading to the collapse of the East German regime. Ref. [8] remarks that herding might explain why financial forecasters tend to make very similar predictions – whose diversity is much smaller than the prediction's error.

From the theoretical side, the onset of herding and the resulting failure of information aggregation has been shown to occur in models of *information cascades* [1]. The prototype example is that of a number of individuals choosing one of two restaurants on the basis of some private noisy information. If each of them follows the recommendation of his/her private signal, the majority will choose the best restaurant. However if an individual can observe what others have chosen before, he/she can infer their information from their choices and take advantage of this. This however leads him/her to follow the crowd disregarding private information. As a result, choices disclose no further information and there is a sizeable probability that all people enter the worse restaurant.

In this letter, we show that information herding can bring to non-trivial collective phenomena even when agents observe a finite number of peers and act in no particular order. In particular, a population of selfish agents fails to correctly aggregate information because herding brings the system into a coexistence region, where the vast majority of agents "agrees" on the same forecast, not necessarily the right one. A statistical mechanics approach gives a detailed account of the results in terms of a zero temperature spin model with asymmetric interaction. These insights extend to the case where agents have to forecast a variable in a continuous interval. Again we find a spinodal point beyond which forecasts tend to cluster, as observed in Ref. [8].

Let us consider a population of agents who have to forecast a binary event $E \in \{\pm 1\}$. Each agent $i = 1, \ldots, N$ faces the choice of either looking for information or herding. We shall denote by I and H, respectively, these two strategies, as well as the set of agents who follow them. In the former case agent $i \in I$ receives some private information $\theta_i \in \{\pm 1\}$ about E. We assume that θ_i is drawn independently $\forall i \in I$ with $P\{f_i = E\} = p > 1/2$, i.e. that private signals are informative about E. On the basis of this signal, agent i makes a forecast $f_i = \theta_i$. In the case of strategy H, agents receive a private information $\theta_i = \pm 1$ which is uncorrelated with E (i.e. $P\{\theta_i = \pm 1\} = 1/2$ i.i.d. for all $i \in H$). Each agent $i \in H$ information gathered by a sample group of other agents: He/she forms a sample group G_i by picking an odd number K of other agents at random, observes their forecasts f_j and sets his/her forecast to that of the majority of agents $j \in G_i$. Notice first that $j \in G_i$ – i.e.

i observing j – does not imply that $i \in G_j$ – i.e. that j observes i. Secondly, the forecast of i may depend on the forecast of other agents who are themselves herding. Hence we assume that forecasts are formed by the following iterative process, mimiking a sort of information exchange: Forecasts are initialized to private signals $f_i = \theta_i$ for all i. Next, an agent $i \in H$ is chosen at random and its forecast is updated to that of the majority of $j \in G_i$

$$f_i \to f'_i = \text{sign} \sum_{j \in G_i} f_j. \qquad (1)$$

This process is repeated until it converges and we denote simply by f_j the fixed point values of the forecasts. It is important to stress that agents receive information on E and form their forecast only after they have chosen their strategy. In other words, agents have access to either type of information but not to both. This is natural if both strategies imply a fixed cost: then either agents invest in information seeking or in forming a sample group.

Before dealing with the game theoretic case where each agent chooses a strategy so as to maximize a payoff, let us focus on the case where a fixed fraction η of agents follow the H strategy and the rest follows the I strategy. By definition, the probability of a right forecast of $i \in I$ is $P\{f_i = E | i \in I\} = p$, whereas for $i \in H$ we define

$$q \equiv \frac{1}{\eta N} \sum_{i \in H} \delta_{f_i, E} \simeq P\{f_i = E | i \in H\}. \qquad (2)$$

The inset of Fig. 1 shows the behavior of q as a function of η in typical numerical simulations. The average $\langle q \rangle$ of q over different realizations is also reported in Fig. 1. When η is small, herding is quite efficient and it yields more accurate predictions than information seeking ($\langle q \rangle > p$). Actually the probability $\langle q \rangle$ that H-players end up with the correct forecast increases with η up to a maximum. This is because herders use the information of other herders who have themselves a higher performance than private information forecasters. However beyond a certain point, outcomes with a value $q < p$ start to appear, coexisting with outcomes with $q \approx 1$. Consequently the average $\langle q \rangle$ starts decreasing. The low q state becomes more and more probable as η increases, and for η close to one we find $\langle q \rangle < p$.

In order to shed light on the above results, let us notice that the probability of a randomly drawn agent to give the right forecast is

$$P\{f_i = E\} \equiv \pi = (1-\eta)p + \eta q. \qquad (3)$$

In order to derive an equation for q we observe that a herding agent adopts the point of view of the majority of his K randomly drawn agents, i.e.

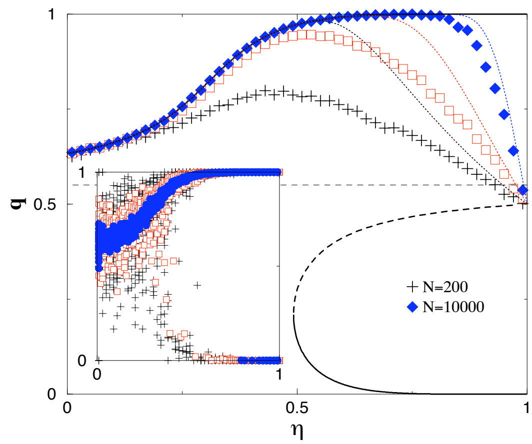

FIG. 1: The average success q of herding agents is shown, for simulations (symbols) and for the analytical solution (dotted lines) as a function of the herding probability η for $K = 11$, $p = 0.55$ (horizontal line) and $N = 200$ (+) 10^3 (□) and 10^4 (⋄) agents. The stable solutions $q_\pm$ are shown as full lines whereas the unstable one q_u is shown as a dashed line. Inset: individual realizations of q for the same systems above.

$$q = \Sigma_K(\pi) \equiv P\left\{ \text{sign} \sum_{j \in G_i} f_j = E | i \in H \right\} = \sum_{g=(K+1)/2}^{K} \binom{K}{g} \pi^g (1-\pi)^{K-g} \qquad (4)$$

These are two self consistent equations for q. For a given value of p, the solution is unique for $\eta < \eta_c(p, K)$ whereas for $\eta > \eta_c(p, K)$, as shown in Fig. 1, we find three solutions, which we denote by $q_+ > q_u > q_-$. The critical point η_c increases with p and with K.

A direct calculation shows that the average number of fixed points of Eqs. (1) is dominated by configurations $\{f_i\}$ for which q satisfies Eqs. (3,4). Interestingly, we find that the average number of fixed points $\mathcal{N} \simeq (K^K e^{-K}/K!)^{\eta N}$ is the same on all the solutions.

Linear stability shows that the fixed points $q_\pm$ are stable whereas the one at q_u is unstable. To see this, imagine that at iteration t, the fraction of agents $i \in H$ with a correct forecast is $q(t) = q^* + \delta q(t)$, where q^* is a solution of $q^* = \Sigma_K[\eta q^* + (1-\eta)p]$. Then at time $t+1$ we have $\delta q(t+1) \simeq \Sigma'_K \eta \delta q(t)$, and it is easy to show that δq vanishes for $q^* = q_\pm$ whereas it diverges exponentially for $q^* = q_u$. The unstable solution q_u separates the basin of attraction of the fixed points $q_\pm$. This allows us to estimate the probability p_- that the system converges to the fixed point q_-, which is the probability that the initial value of $q(0)$ falls below q_u. Given that variables θ_i are assigned a random sign for $i \in H$, $q^{(0)}$ is well approximated by a gaussian variable of mean zero and variance

$1/(\eta N)$. Hence

$$p_- \equiv P\{q(0) < q_u\} \cong \frac{1}{2}\mathrm{erfc}\left(\sqrt{\eta N/2}(1-2q_u)\right). \quad (5)$$

The expected value of q is then given by

$$\langle q\rangle = p_- q_- + (1-p_-)q_+. \quad (6)$$

Fig. 1 shows that Eq. (6) agrees very well with numerical simulations for large N. The discrepancy for small N comes from the fact that indeed the dynamics of $q^{(\tau)}$ is subject to a noise term of order $1/\sqrt{N}$ which causes transitions across q_u in the early stages of the dynamics for small N. It is easy to show that, for $\eta \approx 1$,

$$q_u \simeq \frac{1}{2} - \frac{(p-1/2)k!!}{k!! - (k-1)!!}(1-\eta) + O(1-\eta)^2 \quad (7)$$

which shows that there is a window of size $1/\sqrt{N}$ close to $\eta = 1$ where p_- is sizeable. As a consequence, the fall of q in this region gets steeper and steeper as N increases.

This consideration is important if we analyze the behavior of selfish agents following game theory [9]. We assume for simplicity that agents aim at reaching a correct forecast, i.e. that their payoff is the probability that $f_i = E$. As long as $\langle q\rangle > p$ agents will find it more convenient to switch from the I to H strategy. Hence, the fraction η of herders increases when $\langle q\rangle > p$. The contrary is true when $\langle q\rangle < p$ and hence we expect that the population will self-organize to a state η^*, such that no agent has incentive to change strategy, i.e. where $\langle q\rangle = p$. Such a state is called a Nash equilibrium [9]. Its standard interpretation as the equilibrium of forward looking rational agents, who correctly anticipate the behavior of others, given the rules of the game, and respond optimally, requires agents to solve a rather complex statistical mechanical problem. We will however show below that adaptive agents with limited rationality can "learn" to converge to such a Nash equilibrium.

In light of the the results discussed above, the point where $\langle q\rangle = p$ – the Nash equilibrium – is attained when all but a fraction $1-\eta^* \sim N^{-1/2}$ of agents takes the H strategy. In addition, because in this region $q_+ \cong 1$ and $q_- \cong 0$, by Eq. (6)we have $p_- \cong 1-p$. This means that the whole population adopts the wrong forecast with probability $1-p$, as if it were a single individual forecasting on the basis of private information. Such a spectacular event is similar to the outcome of information cascades [1], but it takes place in a quite different setting.

Does this scenario changes when we introduce heterogeneity in agents' characteristics? Let us first consider the case where agent i, when using strategy H, can observe K_i peers. Naïvely one would expect that agents with larger K_i receive more precise information and hence should prefer the H strategy. However, because at the Nash equilibrium almost every agent is making the same prediction, either right or wrong, a larger "window" K_i does not help. The case where agents have different individual forecasting abilities, i.e. when p_i depends on i, is a bit more complex. It is reasonable to assume that "expert" agents with $p_i > \langle q\rangle$ will seek private information whereas those with $p_i < \langle q\rangle$ will herd. Again q is given by Eqs. (3,4) with

$$\eta = \int_0^{\langle q\rangle} dp\ \phi(p), \qquad (1-\eta)p = \int_{\langle q\rangle}^1 dp\ p\ \phi(p) \quad (8)$$

where $\phi(p)$ is the distribution of p_i. It is easy to show that a solution of Eqs. (3,4,8) with $q = \langle q\rangle$, i.e. where η and p do not fall in the coexistence region is not possible. Indeed the only solution of $\Sigma_K[q\int_0^q dp\phi(p) + \int_q^1 dpp\phi(p)] = q$ is at $q = 1$, which implies $\eta = 1$. The solution then lies in the coexistence region, where Eqs. (3,4) have three solutions, and it is found computing $\langle q\rangle$ as before from Eqs. (5,6) as a function of η and p, and then using Eq. (8) to compute η and p self-consistently. Again, the Nash equilibrium lies where $p_- \simeq 1 - \langle q\rangle$ is finite as $N \to \infty$, which, by Eqs. (5,7), implies that $\eta^* \to 1$ in this limit.

The results are illustrated in Fig. 2 for the particular case $\phi(p) = \beta 2^\beta (1-p)^{\beta-1}$, $p \in [1/2, 1]$. When β is large, there is small heterogeneity and $p_i \simeq 1/2$: Almost all agents follow the H strategy ($\eta \approx 1$) and the probability of a wrong forecast $p_- \simeq 1/2$ is large. As β decreases, the number of "experts", i.e. agents with $p_i > \langle q\rangle$ increases, and correspondingly also the performance of the population as a whole improves (i.e. q increases and p_- decreases). In this region, asymptotic analysis shows that the fraction of "experts" $1-\eta \sim \sqrt{\log N/N}$.

The analytical results were tested against numerical simulations of adaptive agents who repeatedly play the game and learn, in the course of time, about their optimal choice. In order to do this, agents compute the cumulative payoff for both strategies and adopt the strategy with the largest score [10]. As expected, we find that in each run there is a value q such that all agents with $p_i > q$ play the I strategy whereas those with $p_i < q$ herd. Again some deviations occur for small N but the agreement improves as N increases. This shows that the type of equilibria we discuss are "learnable" by a population of not extremely sophisticated agents. It is well known that the type of reinforcement learning dynamics discussed above has close analogies with evolutionary dynamics [11]. Hence the above scenario, might as well describe social norms which are the result of evolutionary processes.

The insights of the discrete model hold also when agents have to forecast a continuous variable E. In order to show this, we adopt an asymmetric version of the continuous opinion model of Ref. [4], where a population of N agents submits forecasts $\{f_i\}$ of a continuous event $E \in [0,1]$. Again, forecasters may either seek private information (strategy I) or herd (strategy H). All I agents receive a signal $f_i \in [0,1]$ which, with probability p is "correct", i.e. is randomly drawn from the interval $[E-\epsilon, E+\epsilon]$, and with probability $1-p$ is uniformly distributed in $[0,1]$. If instead $i \in H$, we draw at random sample groups G_i

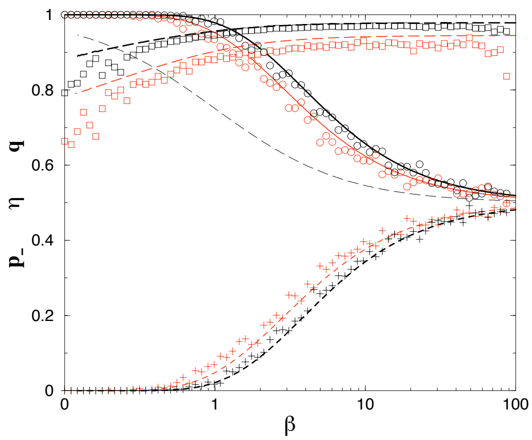

FIG. 2: Analytical results (lines) compared to numerical simulations (symbols) for systems of $N = 100$ and 800 agents with heterogeneous forecasting ability p_i drawn from the distribution $\phi(p) = \beta 2^\beta (1-p)^{\beta-1}$. The average success q (full line and ∘), the fraction η of herding agents (long dashed line and □) and the probability p_- that the majority forecasts the wrong outcome (short dashed line and +), as a function of β. For comparison, the thin dashed line shows the average success of agents with no herding ($\eta = 0$).

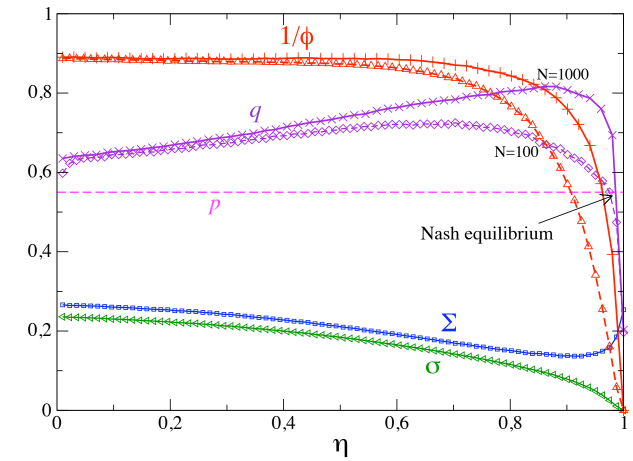

FIG. 3: Continuous forecasting model for $K = 11, d = \mu = 0.5, \varepsilon = 0.1$. The inverse herding parameter ϕ^{-1} is only of the order of 0.1 for a strong herding regime near the Nash equilibrium $\eta \approx 0.98$. The dispersion σ and the error Σ are only shown for $N = 100$. Note that η_{Nash} increases with N whereas ϕ_{Nash} decreases.

of K agents and assign initial random values $f_i^{(0)} \in [0,1]$ to herding agents. Then we iterate the dynamics over agents j of the the group G_i

$$f_i^{(\tau+1)} = f_i^{(\tau)} + \mu(f_j^{(\tau)} - f_i^{(\tau)})\ \theta\left(d - |f_j^{(\tau)} - f_i^{(\tau)}|\right)$$

until $|f_i^{(\tau+1)} - f_i^{(\tau)}| < \epsilon$. We denote simply by f_i the limit value of $f_i^{(\tau)}$ in this process. Note that agent i is influenced by $j \in G_i$ only if their opinion are not too far, i.e. if $|f_j^{(\tau)} - f_i^{(\tau)}| < d$. Forecasts are considered to be correct if $|f_i - E| < \epsilon$.

As in Ref. [8], we introduce the forecast error $\Sigma = \sqrt{\langle(\bar{f} - E)^2\rangle}$ and the forecast dispersion $\sigma = \sqrt{\langle\overline{(f_i - \bar{f})^2}\rangle}$ where $\bar{\cdot}$ denotes the average over agents whereas the average $\langle \ldots \rangle$ is taken over different realizations of the process. The ratio $\phi = \Sigma/\sigma$ called the empirical herding coefficient, is a measure of herding as explained in Ref. [8]. Fig. 3 shows the results of numerical simulations of the model as a function of the fraction η of herders, for a typical choice of the parameters. As in the discrete model, we find that for small values of η the probability $q = P\{|f_i - E| < \epsilon | i \in H\}$ of a correct forecast for herders is larger than that of information seeking agents (p) and it increases because herding agents aggregate the information of other agents who are also herding. Upon increasing η further, q reaches a maximum and then it decreases as the information entering in the system diminishes. In this region, we find coexsuccessful ($\langle q \rangle = p$), is precisely in this region and the herding coefficient attains values $\phi \simeq 5 \div 10$, which are comparable to those found in Ref. [8] on a survey of earning forecasters of US, EU, UK and JP stocks during the period 1987-2004. The fact that analysts agree with each other five to ten times more than with the actual result, was claimed to be related to herding effects in Ref. [8], a conclusion fully supported by our results. Furthermore, as in the discrete model, the Nash equilibrium moves towards $\eta = 1$ as N increases, thus making herd behavior more pronounced.

In conclusion, we introduced a simple model capturing the tension between private information seeking and exploiting information gathered by others (herding) in a population. When few agents herd, information aggregation is very efficient. This makes herding the choice taken by nearly the whole population, thus setting the system deep in a "coexistence" region where the population as a whole adopts either the right or the wrong forecast. This scenario is rather robust and applies both to a discrete and a continuum model and it compares well with empirical findings [8]. The model and the statistical mechanics analysis can serve as a basis to address a wide range of related issues.

We are grateful to J.-P. Bouchaud, S. Goyal and F. Vega-Redondo for useful discussions. We acknowledge financial support from Swiss National Science Foundation and from EU grant HPRN-CT-2002-00319, STIPCO and EU-NEST project COMPLEXMARKETS.

[1] S. Bikhchandani, D. Hirshleifer and I. Welch, J. Pol. Econ. **100** (1992).
[2] R. Cont and J. Bouchaud, Macroeconomic Dynamics **4**, 170 (2000).
[3] D. Stauffer, Adv. Complex Syst. **4** (2001).
[4] G. Weisbuch and *alter*, Complexity **7**, 55 (2002).
[5] V. Eguíluz and M. Zimmermann, Phys. Rev. Lett. **85**, 5659 (2003).
[6] W.-X. Zhou and D. Sornette, e-print physics **0503230** (2005).
[7] Q. Michard and J.-P. Bouchaud, cond-mat **0504079** (2005).
[8] O. Guedj and J.-P. Bouchaud, cond-mat **0410079** (2004).
[9] F. Vega-Redondo, *Economics and the theory of games* (Cambridge Univ. Press, 2004).
[10] D. Challet, M. Marsili and Y.-C. Zhang, *The Minority Game* (Oxford Univ. Press, 2004).
[11] T. Borgers and R. Sarin, J. Econ. Th. **77** (1997).

List of other working papers:

2005

1. Shaun Bond and Soosung Hwang, Smoothing, Nonsynchronous Appraisal and Cross-Sectional Aggreagation in Real Estate Price Indices, WP05-17
2. Mark Salmon, Gordon Gemmill and Soosung Hwang, Performance Measurement with Loss Aversion, WP05-16
3. Philippe Curty and Matteo Marsili, Phase coexistence in a forecasting game, WP05-15
4. Matthew Hurd, Mark Salmon and Christoph Schleicher, Using Copulas to Construct Bivariate Foreign Exchange Distributions with an Application to the Sterling Exchange Rate Index (Revised), WP05-14
5. Lucio Sarno, Daniel Thornton and Giorgio Valente, The Empirical Failure of the Expectations Hypothesis of the Term Structure of Bond Yields, WP05-13
6. Lucio Sarno, Ashoka Mody and Mark Taylor, A Cross-Country Financial Accelorator: Evidence from North America and Europe, WP05-12
7. Lucio Sarno, Towards a Solution to the Puzzles in Exchange Rate Economics: Where Do We Stand?, WP05-11
8. James Hodder and Jens Carsten Jackwerth, Incentive Contracts and Hedge Fund Management, WP05-10
9. James Hodder and Jens Carsten Jackwerth, Employee Stock Options: Much More Valuable Than You Thought, WP05-09
10. Gordon Gemmill, Soosung Hwang and Mark Salmon, Performance Measurement with Loss Aversion, WP05-08
11. George Constantinides, Jens Carsten Jackwerth and Stylianos Perrakis, Mispricing of S&P 500 Index Options, WP05-07
12. Elisa Luciano and Wim Schoutens, A Multivariate Jump-Driven Financial Asset Model, WP05-06
13. Cees Diks and Florian Wagener, Equivalence and bifurcations of finite order stochastic processes, WP05-05
14. Devraj Basu and Alexander Stremme, CAY Revisited: Can Optimal Scaling Resurrect the (C)CAPM?, WP05-04
15. Ginwestra Bianconi and Matteo Marsili, Emergence of large cliques in random scale-free networks, WP05-03
16. Simone Alfarano, Thomas Lux and Friedrich Wagner, Time-Variation of Higher Moments in a Financial Market with Heterogeneous Agents: An Analytical Approach, WP05-02
17. Abhay Abhayankar, Devraj Basu and Alexander Stremme, Portfolio Efficiency and Discount Factor Bounds with Conditioning Information: A Unified Approach, WP05-01

2004

1. Xiaohong Chen, Yanqin Fan and Andrew Patton, Simple Tests for Models of Dependence Between Multiple Financial Time Series, with Applications to U.S. Equity Returns and Exchange Rates, WP04-19
2. Valentina Corradi and Walter Distaso, Testing for One-Factor Models versus Stochastic Volatility Models, WP04-18
3. Valentina Corradi and Walter Distaso, Estimating and Testing Sochastic Volatility Models using Realized Measures, WP04-17
4. Valentina Corradi and Norman Swanson, Predictive Density Accuracy Tests, WP04-16
5. Roel Oomen, Properties of Bias Corrected Realized Variance Under Alternative Sampling Schemes, WP04-15
6. Roel Oomen, Properties of Realized Variance for a Pure Jump Process: Calendar Time Sampling versus Business Time Sampling, WP04-14

7. Richard Clarida, Lucio Sarno, Mark Taylor and Giorgio Valente, The Role of Asymmetries and Regime Shifts in the Term Structure of Interest Rates, WP04-13
8. Lucio Sarno, Daniel Thornton and Giorgio Valente, Federal Funds Rate Prediction, WP04-12
9. Lucio Sarno and Giorgio Valente, Modeling and Forecasting Stock Returns: Exploiting the Futures Market, Regime Shifts and International Spillovers, WP04-11
10. Lucio Sarno and Giorgio Valente, Empirical Exchange Rate Models and Currency Risk: Some Evidence from Density Forecasts, WP04-10
11. Ilias Tsiakas, Periodic Stochastic Volatility and Fat Tails, WP04-09
12. Ilias Tsiakas, Is Seasonal Heteroscedasticity Real? An International Perspective, WP04-08
13. Damin Challet, Andrea De Martino, Matteo Marsili and Isaac Castillo, Minority games with finite score memory, WP04-07
14. Basel Awartani, Valentina Corradi and Walter Distaso, Testing and Modelling Market Microstructure Effects with an Application to the Dow Jones Industrial Average, WP04-06
15. Andrew Patton and Allan Timmermann, Properties of Optimal Forecasts under Asymmetric Loss and Nonlinearity, WP04-05
16. Andrew Patton, Modelling Asymmetric Exchange Rate Dependence, WP04-04
17. Alessio Sancetta, Decoupling and Convergence to Independence with Applications to Functional Limit Theorems, WP04-03
18. Alessio Sancetta, Copula Based Monte Carlo Integration in Financial Problems, WP04-02
19. Abhay Abhayankar, Lucio Sarno and Giorgio Valente, Exchange Rates and Fundamentals: Evidence on the Economic Value of Predictability, WP04-01

2002

1. Paolo Zaffaroni, Gaussian inference on Certain Long-Range Dependent Volatility Models, WP02-12
2. Paolo Zaffaroni, Aggregation and Memory of Models of Changing Volatility, WP02-11
3. Jerry Coakley, Ana-Maria Fuertes and Andrew Wood, Reinterpreting the Real Exchange Rate - Yield Diffential Nexus, WP02-10
4. Gordon Gemmill and Dylan Thomas , Noise Training, Costly Arbitrage and Asset Prices: evidence from closed-end funds, WP02-09
5. Gordon Gemmill, Testing Merton's Model for Credit Spreads on Zero-Coupon Bonds, WP02-08
6. George Christodoulakis and Steve Satchell, On th Evolution of Global Style Factors in the MSCI Universe of Assets, WP02-07
7. George Christodoulakis, Sharp Style Analysis in the MSCI Sector Portfolios: A Monte Caro Integration Approach, WP02-06
8. George Christodoulakis, Generating Composite Volatility Forecasts with Random Factor Betas, WP02-05
9. Claudia Riveiro and Nick Webber, Valuing Path Dependent Options in the Variance-Gamma Model by Monte Carlo with a Gamma Bridge, WP02-04
10. Christian Pedersen and Soosung Hwang, On Empirical Risk Measurement with Asymmetric Returns Data, WP02-03
11. Roy Batchelor and Ismail Orgakcioglu, Event-related GARCH: the impact of stock dividends in Turkey, WP02-02
12. George Albanis and Roy Batchelor, Combining Heterogeneous Classifiers for Stock Selection, WP02-01

2001

1. Soosung Hwang and Steve Satchell , GARCH Model with Cross-sectional Volatility; GARCHX Models, WP01-16
2. Soosung Hwang and Steve Satchell, Tracking Error: Ex-Ante versus Ex-Post Measures, WP01-15
3. Soosung Hwang and Steve Satchell, The Asset Allocation Decision in a Loss Aversion World, WP01-14
4. Soosung Hwang and Mark Salmon, An Analysis of Performance Measures Using Copulae, WP01-13
5. Soosung Hwang and Mark Salmon, A New Measure of Herding and Empirical Evidence, WP01-12

6. Richard Lewin and Steve Satchell, The Derivation of New Model of Equity Duration, WP01-11
7. Massimiliano Marcellino and Mark Salmon, Robust Decision Theory and the Lucas Critique, WP01-10
8. Jerry Coakley, Ana-Maria Fuertes and Maria-Teresa Perez, Numerical Issues in Threshold Autoregressive Modelling of Time Series, WP01-09
9. Jerry Coakley, Ana-Maria Fuertes and Ron Smith, Small Sample Properties of Panel Time-series Estimators with I(1) Errors, WP01-08
10. Jerry Coakley and Ana-Maria Fuertes, The Felsdtein-Horioka Puzzle is Not as Bad as You Think, WP01-07
11. Jerry Coakley and Ana-Maria Fuertes, Rethinking the Forward Premium Puzzle in a Non-linear Framework, WP01-06
12. George Christodoulakis, Co-Volatility and Correlation Clustering: A Multivariate Correlated ARCH Framework, WP01-05
13. Frank Critchley, Paul Marriott and Mark Salmon, On Preferred Point Geometry in Statistics, WP01-04
14. Eric Bouyé and Nicolas Gaussel and Mark Salmon, Investigating Dynamic Dependence Using Copulae, WP01-03
15. Eric Bouyé, Multivariate Extremes at Work for Portfolio Risk Measurement, WP01-02
16. Erick Bouyé, Vado Durrleman, Ashkan Nikeghbali, Gael Riboulet and Thierry Roncalli, Copulas: an Open Field for Risk Management, WP01-01

2000

1. Soosung Hwang and Steve Satchell , Valuing Information Using Utility Functions, WP00-06
2. Soosung Hwang, Properties of Cross-sectional Volatility, WP00-05
3. Soosung Hwang and Steve Satchell, Calculating the Miss-specification in Beta from Using a Proxy for the Market Portfolio, WP00-04
4. Laun Middleton and Stephen Satchell, Deriving the APT when the Number of Factors is Unknown, WP00-03
5. George A. Christodoulakis and Steve Satchell, Evolving Systems of Financial Returns: Auto-Regressive Conditional Beta, WP00-02
6. Christian S. Pedersen and Stephen Satchell, Evaluating the Performance of Nearest Neighbour Algorithms when Forecasting US Industry Returns, WP00-01

1999

1. Yin-Wong Cheung, Menzie Chinn and Ian Marsh, How do UK-Based Foreign Exchange Dealers Think Their Market Operates?, WP99-21
2. Soosung Hwang, John Knight and Stephen Satchell, Forecasting Volatility using LINEX Loss Functions, WP99-20
3. Soosung Hwang and Steve Satchell, Improved Testing for the Efficiency of Asset Pricing Theories in Linear Factor Models, WP99-19
4. Soosung Hwang and Stephen Satchell, The Disappearance of Style in the US Equity Market, WP99-18
5. Soosung Hwang and Stephen Satchell, Modelling Emerging Market Risk Premia Using Higher Moments, WP99-17
6. Soosung Hwang and Stephen Satchell, Market Risk and the Concept of Fundamental Volatility: Measuring Volatility Across Asset and Derivative Markets and Testing for the Impact of Derivatives Markets on Financial Markets, WP99-16
7. Soosung Hwang, The Effects of Systematic Sampling and Temporal Aggregation on Discrete Time Long Memory Processes and their Finite Sample Properties, WP99-15
8. Ronald MacDonald and Ian Marsh, Currency Spillovers and Tri-Polarity: a Simultaneous Model of the US Dollar, German Mark and Japanese Yen, WP99-14
9. Robert Hillman, Forecasting Inflation with a Non-linear Output Gap Model, WP99-13
10. Robert Hillman and Mark Salmon , From Market Micro-structure to Macro Fundamentals: is there Predictability in the Dollar-Deutsche Mark Exchange Rate?, WP99-12
11. Renzo Avesani, Giampiero Gallo and Mark Salmon, On the Evolution of Credibility and Flexible Exchange Rate Target Zones, WP99-11
12. Paul Marriott and Mark Salmon, An Introduction to Differential Geometry in Econometrics, WP99-10

13. Mark Dixon, Anthony Ledford and Paul Marriott, Finite Sample Inference for Extreme Value Distributions, WP99-09
14. Ian Marsh and David Power, A Panel-Based Investigation into the Relationship Between Stock Prices and Dividends, WP99-08
15. Ian Marsh, An Analysis of the Performance of European Foreign Exchange Forecasters, WP99-07
16. Frank Critchley, Paul Marriott and Mark Salmon, An Elementary Account of Amari's Expected Geometry, WP99-06
17. Demos Tambakis and Anne-Sophie Van Royen, Bootstrap Predictability of Daily Exchange Rates in ARMA Models, WP99-05
18. Christopher Neely and Paul Weller, Technical Analysis and Central Bank Intervention, WP99-04
19. Christopher Neely and Paul Weller, Predictability in International Asset Returns: A Re-examination, WP99-03
20. Christopher Neely and Paul Weller, Intraday Technical Trading in the Foreign Exchange Market, WP99-02
21. Anthony Hall, Soosung Hwang and Stephen Satchell, Using Bayesian Variable Selection Methods to Choose Style Factors in Global Stock Return Models, WP99-01

1998

1. Soosung Hwang and Stephen Satchell, Implied Volatility Forecasting: A Compaison of Different Procedures Including Fractionally Integrated Models with Applications to UK Equity Options, WP98-05
2. Roy Batchelor and David Peel, Rationality Testing under Asymmetric Loss, WP98-04
3. Roy Batchelor, Forecasting T-Bill Yields: Accuracy versus Profitability, WP98-03
4. Adam Kurpiel and Thierry Roncalli , Option Hedging with Stochastic Volatility, WP98-02
5. Adam Kurpiel and Thierry Roncalli, Hopscotch Methods for Two State Financial Models, WP98-01