

Introduction to Finance and Econometrics in Complex Systems

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4 Article Outline

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13 Introduction

14 Economics and finance have slowly emerged from the
15 Walrasian, representative agent paradigm exemplified by
16 the research agenda in general equilibrium theory. This
17 program may have reached its pinnacle in the 1970s, with
18 a highly abstract treatment of the existence of a market
19 clearing mechanism. The normative foundation of this re-
20 search was provided by powerful welfare theorems that
21 demonstrated the optimality of the market allocations.
22 Unfortunately, this abstract world had little economics
23 in it. The models rarely provided empirical implications.
24 Lifetime consumption and portfolio allocation plans were
25 formed in infancy, unemployment was Pareto optimal,
26 and the role for government was largely limited to public
27 goods provision.

28 The demonstration by Benhabib, Brock, Day, Gale,
29 Grandmont, [1,4,8,9] and others, that even simple math-
30 ematical models could display highly complex dynamics
31 was the beginning of a new research program in eco-
32 nomics. This section on finance and econometrics surveys
33 some of the developments of the last 20 years that were
34 inspired by this research.

35 Econometrics

36 Time series econometrics was originally built on the rep-
37 resentation theorems for Euclidean spaces. The existence
38 of a Wold decomposition in linear time series led to the
39 widespread use of Box–Jenkins [3] style modeling as an al-
40 ternative to structural or reduced form models.

41 A number of stylized facts about the economy emerged
42 that simply could not be explained in this linear world.
43 Rob Engle [2] and Tim Bollerslev [5] showed that volatility

44 was quite persistent, even in markets that appeared to be
45 nearly random walks. In ► [GARCH modeling](#), Christian
46 Hafner surveys the extensive development in this area.

47 James Hamilton [10] and Salih Neftci [11] demon-
48 strated that the business cycle was asymmetric and could
49 be well described by a Markov switching model. James
50 Morley ► [Nonlinear time series in macroeconomics](#) and
51 Jeremy Piger ► [Models of regime changes](#) describe the de-
52 velopments in this area. Virtually all the moments, not just
53 the conditional mean, are now thought to be varying over
54 the business cycle. These models help us to understand
55 why recessions are shorter than expansions and why cer-
56 tain variables lead and lag the cycle.

57 Nearly all the business cycle models involve the use of
58 latent or unobservable state variables. This reflects a re-
59 ality that policy makers themselves face. We rarely know
60 whether we are in a recession until it is nearly over.
61 These latent variable models are often better described
62 in a Bayesian rather than a classical paradigm. Oleg Ko-
63 renok ► [Bayesian methods in nonlinear time series](#) pro-
64 vides an introduction to the frontier research in this area.

65 Markets are often drawn towards equilibrium states in
66 the absence of exogenous shocks, and, since the 1940s, this
67 simple idea was reflected in the building of macroecono-
68 metric models. In linear models, Engle and Granger [6]
69 formalized this notion in an error correction framework.
70 When the adjustment process is taking place between two
71 variables that are not stationary, we say that they are coin-
72 tegrated. Escanciano and Escibano extend the error cor-
73 rection framework and cointegration analysis to nonlinear
74 models in ► [Nonlinear cointegration](#).

75 Because we often know very little about the data gen-
76 erating mechanism for an economy, nonparametric meth-
77 ods have become increasingly popular in the analysis of
78 time series. Cees Diks discusses in ► [Nonparametric tests
79 for independence](#) methods to analyze both data and the
80 residuals from an econometric model.

81 Our last two entries look at the data generated by indi-
82 vidual consumers and households. Pravan Trivedi ► [Mi-
83 croeconometrics](#) surveys the microeconomic literature,
84 and Jeff Wooldridge ► [Panel data methods](#) examines the
85 tools and techniques useful for analyzing cross-sectional
86 data.

Agent Based Modeling

87 The neo-classical synthesis in economics was built upon
88 the abstraction of a single optimizing agent. This assump-
89 tion simplified the model building and allowed for an-
90 alytical solutions of the standard models. As computa-
91 tional power became cheaper, it became easier to relax
92

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93 these assumptions. Many economists underestimated the
94 complexity of a world in which multiple agents interact in
95 a dynamic setting. Econophysicists, as Bertrand Roehner
96 describes in ► [Observational econophysics](#), were not sur-
97 prised. Roehner is just one of scores of physicists who have
98 brought their tools and perspectives to economics.

99 Agent based modeling has had a large impact on fi-
100 nance. Financial economics had been led by a Chicago in-
101 fluenced school that saw markets as both rational and ef-
102 ficient. Behavioral finance has eroded the view that people
103 always make optimizing decisions even when large sums
104 of money are at stake. The boundedly rational agents in
105 Sebastiano Manzan's ► [Agent based modeling in finance](#)
106 are prone to speculative bubbles. Markets crash suddenly
107 in agent based computational models and in large scale ex-
108 perimental stock markets.

109 Finance

110 The foundation of financial economics is the theory of op-
111 timal consumption and saving. The goal of the empirical
112 literature was to identify a set of risk factors that would ex-
113 plain why certain assets have a higher return than others.
114 Ralitsa Petkova ► [The cross section of stock returns](#) sur-
115 veys the canonical model of Fama and French [7] and the
116 extensions to this model in the last decade.

117 With risk averse agents, asset returns are often pre-
118 dictable. Stijn van Nieuwerburgh and Ralph S.J. Koijen
119 ► [Return predictability and market efficiency](#) demonstrate
120 the robustness of this result in a structural model and show
121 that the dividend price ratio does predict future stock re-
122 turns.

123 Mototsugu Shintani addresses in ► [Sensitive depen-](#)
124 [dence](#) the concept of predictability from an information
125 theoretic perspective through the use of Lyapunov expo-
126 nents. The exponents not only tell us which systems dis-
127 play sensitive dependence on initial conditions ("chaos")
128 but also provide a predictive horizon for data generated by
129 the model. Shintani finds that financial data appear to not
130 be chaotic, even though they display local dependence on
131 initial conditions.

132 Mark Kamstra and Lisa Kramer's entry on ► [Time](#)
133 [variation in the market return](#) primarily focus on the eq-
134 uity premium, the substantially higher return in the US
135 and other countries on equities, over default free securi-
136 ties like Treasury bonds. They document its statistical sig-
137 nificance and discuss some behavioral explanations. They
138 demonstrate that behavioral moods can influence asset
139 prices.

140 Terence Mills' ► [Nonlinear time series in financial](#)
141 [economics](#) surveys the use of nonlinear time series tech-

142 niques in finance. Gloria Gonzalez-Rivera and Tae-Hwy
143 Lee look at the ability of nonlinear models to forecast
144 in ► [Financial forecasting in nonlinear time series](#). They
145 also cover the methodology for assessing forecast im-
146 provement. The best forecast may not be the one that pre-
147 dict the mean most accurately; it may instead be the one
148 that keeps you from large losses.

149 Our last two papers in this area focus on volatility.
150 Markus Haas and Christian Pigorsch discuss the ubiqui-
151 tous phenomenon of fat-tailed distributions in asset mar-
152 kets in ► [Fat-tailed distribution in financial economics](#).
153 They provide evidence on the frequency of extreme events
154 in many different markets, and develop the implications
155 for risk management when the world is not normally dis-
156 tributed. Torben Andersen and Luca Benzoni ► [Stochastic](#)
157 [volatility](#) introduce the standard volatility model from the
158 continuous time finance literature. They contrast it with
159 the GARCH model discussed earlier and develop econo-
160 metric methods for estimating volatility from discretely
161 sampled data.

Large Market Microstructure

162 Market microstructure examines the institutional mech-
163 anisms by which prices adjust to their fundamental val-
164 ues. The literature has grown with the availability of trans-
165 actions frequency databases. Clara Vega and Christian
166 Miller ► [Market microstructure](#) survey the topic largely
167 from a theoretical perspective. Because disparate markets
168 are likely to have different mechanisms and regulators, the
169 literature has evolved by instrument. Carol Osler ► [Mar-](#)
170 [ket microstructure of the foreign exchange market](#) exam-
171 ines the microstructure of the foreign currency market,
172 the largest and most liquid asset market. Bruce Mizrach
173 and Chris Neely ► [Market microstructure of the us trea-](#)
174 [sury market](#) look at the government bond market in the
175 US as it has evolved into an electronic market. Michael Pi-
176 wowar ► [US corporate and municipal bond market mi-](#)
177 [crostructure](#) looks at two bond markets with a large num-
178 ber of issues that trade only very infrequently. Both the
179 markets which he examines have become substantially
180 more transparent through recent government initiatives.
181

Conclusion

182 This section covers a wide range of material from theoret-
183 ical time series analysis to descriptive modeling of finan-
184 cial markets. The theme of complexity is a unifying one in
185 the sense that the models are generally nonlinear and can
186 produce a wide range of possible outcomes. There is com-
187 plexity in the data which now evolves at a millisecond fre-
188 quency. Readers should find a variety of perspectives and
189

190 directions for future research in a heterogenous but inter-
191 connected range of fields.

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