The University of Reading

THE BUSINESS SCHOOL
FOR FINANCIAL MARKETS

The Present and Future of Financial Risk Management

ISMA Centre Discussion Papers in Finance 2003-12
10 September 2003

Carol Alexander
Chair of Risk Management and Director of Research
ISMA Centre, University of Reading, Whiteknights, P.O. Box 242, Reading RG6 6BA, UK

Paper presented at the 1st International Derivatives and Financial Markets Conference

Organized by BM&F

Campos de Jordao, Brazil, August 20th – 23rd, 2003

The University of Reading • ISMA Centre • Whiteknights • PO Box 242 • Reading RG6 6BA • UK
Tel: +44 (0)118 931 8239 • Fax: +44 (0)118 931 4741
Email: research@ismacentre.rdg.ac.uk • Web: www.ismacentre.rdg.ac.uk

Abstract

As a result of recent global trends in financial markets, financial institutions face important challenges in their management of risks. In particular, to develop an intelligent way to aggregate risks, and to develop management processes that cover the new types of risks that are becoming increasingly important. These new types of risks include operational, business and systemic risks. We show that current trends towards more accurate and timely assessments of risks could in fact pose a threat to the stability in financial markets. The root of this threat is in the homogeneity of both risk assessments and the objectives of risk control. At the level of the economy, heterogeneity in risk modelling ('risk model risk') and in the decisions made to control financial risks, are desirable. With this in mind, classical statistical techniques should be less prevalent in both risk assessment and risk control. Currently we are learning much from the quantitative assessment of operational risks, where a Bayesian view is essential. In the future, we welcome the emergence of a Bayesian approach to risk assessment, and a behavioural view of risk management and control.

Contacting Author Details:

Carol Alexander
ISMA Centre, University of Reading, Whiteknights, Box 242, Reading, RG6 6BA,
Tel: +44–118–378–6134; fax: +44–118–378–4741.
E-mail address: c.alexander@ismacentre.rdg.ac.uk

Acknowledgements

I would like to thank Prof. Jose Carlos de Souza Santos of BM&F, Brazil, Dr. Mario Prado of Analitix, Brazil and Leonardo Nogueira of the ISMA Centre for providing the data on Brazilian equities and interest rates. Also many thanks to Anca Dimitriu of the ISMA Centre for optimising the hedge fund models on the Brazilian data, and to the Foundation for Managed Derivatives Research, for the research grant enabling the use of the HFR data set. Finally I would like to thank my husband, Dr. Jacques Pezier, also of the ISMA Centre, for his many insightful comments. Any errors or oversights are, of course, my own.

I The Present and Future of Risk Management

Although financial risk management has existed as a discipline in its own right for less than 20 years, it is already an enormous subject. A modern day risk manager requires much more than a detailed knowledge of financial markets. Risk assessment in particular has become a statistical science – and art – and model validation requires an understanding of the complex mathematical models that are now used to price financial derivatives. Risk management is a main concern for the front and middle office functions of banks, and is becoming increasingly important for fund managers in the volatile financial markets of today.

Given the comprehensive nature of the subject, I have been very selective in the topics covered here. The first part of this paper discusses the global trends in financial markets that have an impact on financial risk management at the level of the firm. I argue that the main *challenges* that financial institutions now face, as a result of these trends, are:

- the proper aggregation of economic capital over all lines of businesses and over the major categories of risks
- the development of risk management processes to cover new types of risk

The processes in risk management – identification, assessment, monitoring & reporting, and control – are then examined separately, to envision how these are likely to develop in response to these challenges over the next 10-20 years. More accurate and timely assessments of risks could pose a threat to the stability in financial markets and we conclude that, at the level of the economy, heterogeneity in the assessment and control of risks is desirable. Consequently we envision the future of risk management as one in which a more 'holistic' approach is adopted: where all types of financial risks are assessed using common risk factors, a common methodology and subjective, as well as objective data; and where the decisions made to control risks reflect the risk tolerance of the whole organisation.

I.1 Current Trends in Financial Risk Management

Three main global trends that can easily be identified in financial markets during the last few decades, and which have been a catalyst for change in risk management practices are: de-regulation of capital flows and financial operations, increasing banking supervision and regulation of firms, and technological advances.

a. De-regulation of Financial Markets: Limits on capital flows and operations have been raised, or removed. Capital flows have increased: for example, under the Bretton-Woods exchange system during the 1950s and 60s the convertibility of some major currencies such as Sterling was strictly limited. Also the scope of financial operations has widened: for example, some banks can now also offer insurance and insurance companies can, to some extent, write market and credit derivatives.

b. Increasing Banking Supervision and Regulation: There has been a gradual extension of capital adequacy requirements to cover more types of risks: First credit risks (1988), then market risks (1996) and now operational risks (2004). Before the Basel I Accord in 1988, regulators required only limited reporting of risks and imposed only some simple credit limits. The Basel I Accord introduced the first capital requirements for banks, but the requirements were product based – mainly for loans – with no offsets, netting or market sensitivities. The Basel I Amendment (1996) and the forthcoming Basel 2 Accord (2004) have introduced quantitative measures for capital adequacy that are risk sensitive, but not overly reactive to short term fluctuations.

c. Technological Advances: In particular, web and intranet based technology for improved communications, security and management of large databases (through Application Service Provider software), on-line trading, and standardised internet based order management.

What are the likely effects of these trends, and what can we deduce about the associated trends in current risk management practices?

<u>Risk Aggregation:</u>

De-regulation of markets has the effect of grouping all financial services (Insurance, Asset Management, Banking) into 'Universal' banks. The convergence of services to these large complex banking groups means that we now need to examine the risks of the organization as a whole. Following regulatory changes, consolidated risk reporting has moved away from 'product based' capital requirements to 'rules based' capital requirements that may be uniformly applied across all subsidiaries in a large complex group. Also, recent technological advances in firm wide risk management software for consolidated risk reporting now make it easier to take advantage of new diversification opportunities. But with the need to net risks across the whole enterprise, come aggregation difficulties and reporting ambiguities. In the face of these problems, many large complex groups are now moving towards changing their subsidiaries from independent legal entities to branches that fall under the jurisdiction of the regulator of the head office. This is to avoid any confusion between local and central regulators about the responsibility for regulation, and increases the viability of the proper aggregation of risks.[1]

<u>Increasing Systemic Risk:</u>

Systemic risk may be defined as the risk of increased volatility leading to mass insolvencies in the banking and other sectors. Increased capital flows (resulting from the lifting of capital limits, the rapid dissemination of information, the faster transfers of funds, and the increasing popularity of technical trading strategies) are increasing volatility, particularly in equity and commodity markets. Coupled with the trend towards 'real-time' risk monitoring, panic reactions now threaten to de-stabilize the whole economy. If all risk managers receive the same signals at the same time, and re-act in a similar fashion, there is a considerable increase in systemic risk.

Systemic risk is also affected by the concentration of key services (e.g. custody, or clearing and settlements) in the hands of very few firms. In the event of a crisis (e.g. 9/11, or a computer virus) an essential activity could be gravely affected, with catastrophic consequences. Primarily, this concentration of services is a result of greater competition, but increasing regulation of banking activities, and technological advances have also played an important role: until recently, some services such as agency and custody services, attracted no regulatory capital charges, but under the new Basel Accord this will change. When capital charges are imposed for these services, the best economic solution may be to out-source the service.

<u>Increasing Operational Risks:</u>

Operational risks have increased because of our increased reliance on technology, and to some extent because of the concentration of key services, and key individuals, in a few geographical locations. The increased complexity of financial instruments, with banks now

[1] If subsidiaries have to meet capital requirements on a solo basis, they must physically hold the necessary capital. Suppose risk is aggregated using correlations; then the total capital that must be held in the group that is sufficient to cover the firm-wide minimum capital can be much less than the sum of the capital in the subsidiaries.

offering highly structured products having access to wide range of asset classes across the world, has also influenced several types of operational risks.

With more complex instruments there is much less transparency in the trading, and an increase in: IT & systems risks because of the reliance on new and complex systems; products and business practice risks because of the danger of mis-pricing and mis-selling these products; and 'human' risks in general because now only a few experienced people understand the systems and the products.

Increasing Business Risks:

Business risk may be defined as the risk of insolvency due to inappropriate management decisions or external factors. Dis-intermediation has had a significant impact on business risk. Rather than relying on a bank for loans, many large companies now favour the direct insurance of debt by issuing bonds and equity. As the demand for loans declines but the need for corporate finance increases, banks now rely more on flow business – fees and commissions on services – for their income. This dis-intermediation has the effect of reducing market and credit risk for banks, but they now face more business risks. Mergers and acquisitions also affect business risk. The convergence of financial services into large, complex banking groups and the concentration of key services in the hands of a few firms have been a driving force behind the growing number of mergers and acquisitions.

A case in point is Abbey National, now the 6th largest British bank, but originally just a building society (issuing mortgages). Having obtained a license for retail banking, it rapidly expanded its services to treasury operations – writing complex derivatives products – and to corporate finance. This lasted only a few years, until large losses recently revealed how the management had over-extended itself with these particular decisions.

To summarize our main points, current trends in financial risk management are changing our perception of financial risks. In particular, operational, business and systemic risks are all becoming relatively more important, compared with the traditional market and credit risks. Furthermore, the move towards large complex global organizations and consolidated risk reporting has highlighted some important problems with current methods for risk aggregation.

I.2 The Future of Financial Risk Management

Financial risk management has been defined as a sequence of four processes: Identification; Assessment; Monitoring & Reporting; and Control.[2] Let us now consider each of these processes in turn, attempting to extrapolate the current trends identified above and hence envision some of the changes in financial risk management that are likely in the future.

a. Identification:

For the purpose of regulation, three broad categories of risks have been defined: market, credit and operational risks. But the coverage is uneven, with some important but less easily quantifiable risks simply ignored. Also, the boundaries between these categories are fuzzy (indeed some might even regard all risks as being operational risks!) and the industry has spent much time defining risks, and debating into which category a loss event falls. However, in the future, it is likely that these traditional boundaries will be relaxed, as large complex banking groups adopt a more ‘holistic approach’ to risk management.

One motivating factor for adopting a more holistic approach to risk management is that ‘other risks’ such as business and systemic risks – which are currently ignored by the regulators – are likely to be perceived as being important in the future. Also, operational risks, which are currently perceived as less important than market and credit risks, are likely to increase, for example, because of increased reliance on technology. On the other hand credit risks, one of the major risks that we face today because currently we are at a peak of the default cycle, are likely to decrease in relative importance. So, as new, or previously less important risks take the centre stage, the need for a clear distinction between market, credit, operational and other risks dissolves.

Current practice is to model the identified risks using completely different frameworks for different categories of risk. For example, we can employ a *statistical* analysis of short-term P&L distributions for market risks; an *option theoretic* models for credit risk; and an *actuarial* loss model for operational risks. But this is a great impediment to an important goal of enterprise wide risk management, that is, to ‘integrate’ market, credit and operational risks so that the net effect of a single scenario (such as a 200bp rise in an interest rate) can be assessed at the instrument level. Clearly, another factor which motivates the definition of all risks under one ‘umbrella’ for the purpose of capital allocation, is that when market, credit

[2] As in “Sound Practices for the Management and Supervision of Operational Risk”, the Basel Committee on Banking Supervision, December 2001, revised July 2002

and operational risks are assessed using diverse methodologies, it becomes extremely difficult to perform a consistent scenario risk analysis across all three models.

Even if market, credit and operational risks were assessed according to similar principles, the current methods used to aggregate distinct risk estimates are very imprecise. Simple summation provides a possible upper bound,[3] and an assumption of zero correlation provides a possible lower bound for total risk (where the total risk is the square root of the sum of the component risks squared). But in some activities, such as interest rate swaps trading, market and credit risks can be negatively correlated, so the net risk could be less than some of the component risks. In this case even the zero correlation assumption is far too conservative.

At present, risk assessment and aggregation methods do not properly account for the type of dependencies between risks that are known to exist. In searching for a better risk aggregation methodology, Alexander and Pezier (2003)[4] have proposed a factor model approach to risk assessment. Market, credit and operational risks are assumed to be driven by common risk factors such as interest rates, equity prices, the implied volatilities of both, credit spreads, expenses and the business activity level. This approach is very much in its infancy, and the residual market/credit/operational risks are large; the factor model explains only a fraction of the economic capital estimates from individual VaR models. However, in a recent report from the Basel Committee on Banking Supervision, the pressing need for a unified framework such as this has been highlighted.[5]

b. Assessment

Let us amuse ourselves here with a simple analogy. Risk management is like a cake. On the top we have a cherry – or several cherries – the risk assessment model(s); the icing on the cake represent the data used for model estimation and the substance of the cake itself represents the infra-structure – the systems and the management framework that are necessary to support the risk model.

Since the industry has long ago agreed on the 'best practice' for market risk assessment (by simulating VaR using Monte Carlo data and historic data)[6] we can regard market risk management as a cake with only one cherry. The market risk cake also has a relatively

[3] But not necessarily, since percentiles are not sub-additive

[4] Alexander, C. and J. Pezier (2003) "Assessment and Aggregation of Banking Risks" Presented to the 9th Annual IFCI Round Table, March 2003 (available from www.ifci.ch)

[5] Basel Committee for Banking Supervision (August 2003) "Trends in Risk Integration and Aggregation" available from www.bis.org

[6] If the portfolio is linear the Monte Carlo VaR should be equal to the 'RiskMetrics' or 'Covariance VaR.

smooth and complete icing, as the appropriate data are relatively easy to obtain, at least for most short-term market risks, compared with other risk types. Many powerful and sophisticated market risk systems are available, indeed, the cake itself is like a fine, English Christmas cake that has been matured in brandy wine for many years.

However, the industry has not agreed on a single 'best practice' model for credit risk capital assessment.[7] A bank will normally adopt one (or more) of the following three broad approaches: an option theoretic Merton model, an actuarial (loss model), or a macro-economic model. Within each broad approach, several variants might be available. In short, quite a few different 'cherries' are available for the credit risk cake and, without knowing which cherry is best, some banks decide to place them all upon the cake! The credit risk cake icing (the data) is also rather patchy in places – in particular, the marginal and joint distributions of default rates and recovery rates are extremely difficult to assess.

Operational risk assessment is at an early stage of development, and the operational risk 'cake' is far from complete. First, we potentially have 'one thousand' cherries, haphazardly placed all over the cake.[8] Secondly, the data are very incomplete, particularly for the important operational risks (the low frequency high impact risks) so there is hardly any icing for these cherries to stand upon. Finally, the substance of the operational risk cake itself is more or less non-existent: some banks have great difficulty obtaining the management 'buy-in' that they need for the self-assessment of operational risks, and the IT systems that are necessary to support the reporting and control of these risks are only just now being developed.

Perhaps the most challenging task of all is to provide appropriate data for assessing operational risks. And, in this respect, the industry has at least seen some benefit from the expensive task of implementing an operational risk management framework. That is because we have learned an important lesson about market and credit risk assessment: the need for operational risk quantification has forced the industry to consider using 'subjective' data for operational risks (in the form of self-assessments and/or expert opinions) and we now recognise that the problem of incomplete data extends to all types of risks, to a greater or lesser extent. With much historic data available for assessing market risks, risk managers have been lulled into a false sense of security, believing that it was possible to assess even long-term risks with some degree of accuracy. But now we are, quite rightly, beginning to

[7] Although a simple portfolio model is proposed in the Basel II 'Internal Rating Based' approach.
[8] The Basel working group on operational risk assessment have suggested that, for the Advanced Measurement Approaches, the industry should 'let one thousand flowers bloom'.

question the validity of historical data because it is not 'forward looking'. It has become increasingly clear that 'subjective' data will improve and enhance our assessments of credit and market risks, as well as operational risks.[9]

The use of data from different sources, based on both subjective beliefs and objective historical samples is not a new development. In fact, it is a very old science. Thomas Bayes, a seventeenth century English Presbyterian minister, laid the foundations for all modern statistical inference in his fanous essay 'A Doctrine towards the Theory of Chance'. From Bayes' ideas, the 'classical' statistics of today evolved as but a poor relative, a restricted form of Bayes' original doctrine, and it is only during the last few years that the Bayesian approach has witnessed a renaissance.

Thanks to Thomas Bayes, in place of a single VaR estimate, we have a whole VaR distribution, where the uncertainty of VaR arises from our 'subjective beliefs' about risk model parameter values. As a consequence of the move towards using more subjective data for risk assessments, there will be increased reliance in the future on sophisticated individual models for assessing market, credit and operational risks. It is only progressing from there – possibly far into the future – that our aim should be towards unification of these models into one 'Universal VaR' model.

c. Monitoring and Reporting

Monitoring and reporting may be the most important part of the risk management process for some activities, such as fund management. Fund managers need to take risks, rather than control them, but it is their duty to inform clients *promptly* and *accurately* of the risks that they take. However, this is not necessarily a 'good thing' from the perspective of systemic risk. In fact, good risk management at the level of the firm, as we know it today, can actually increase systemic risk!

To see why, suppose good risk management means reducing exposure to risky assets and passing on the risk to others. Most pension funds, which have liabilities to current pensioners and risky assets comprising mainly bonds and equities, behave like this. If a market performs well, pension funds take more risk in that market, which produces an upwards price pressure; on the other hand, when a market under-performs, they sell off those risky assets. Suppose the price of some risky assets fall – let us say that equity prices go down. Those funds that have not performed well must maintain their solvency ratio and may therefore be forced to sell

[9] See Alexander, C. (ed) *Operational Risks: Regulation, Analysis and Management* FT-Prentice Hall (a division of Pearson Education), 2003.

risky assets. Assuming they sell the assets that are under-performing, the price of these assets will be depressed even further. But now the next level of funds – which were not originally concerned by their solvency ratio – will be forced into selling assets. The vicious circle continues and a downwards spiral in prices has been instigated.

In the past, this type of behaviour was observed in the 'portfolio insurance' strategies that were followed by pension funds during the late 1970's and 1980's. These strategies had a great run – until they contributed to the global equity market crash of 1987. More recently, a similar crisis happened to insurance companies after 09/11. However, this time the regulators relaxed solvency ratios and a global melt-down in equity markets was prevented.

The growing trend towards real-time risk monitoring and reporting also tends to increase systemic risk. With real-time monitoring we are immediately aware of variations in the solvency ratio. Even if there is no breach of the minimum, just knowing VaR in real-time could produce a panic reaction when traders use VaR-based limits in place of the traditional sensitivity based limits. A VaR limit could be easily be breached intermittently in a particular activity and, when previously we wouldn't know it, now with real-time VaR monitoring, we do. We may feel forced into selling, cutting down our positions in risky assets that have not performed well. We would have to take a capital loss, and of course this process will increase volatility in that asset. A vicious circle could be set in motion, where other risk managers now exceed their VaR limits and, if market participants all perceive the same danger at the same time and they all act in the same way, systemic risk will increase.[10]

d. Control

If all risk managers are aware of all risks, at all times, this does not necessarily imply that risks will be reduced. It all depends on the risk control strategies. Decisions about risk control are best taken at the senior management level in the organisation. Only in that case will the decision maker be able to take advantage of opportunities for diversification of risks. It is important that the monitoring and reporting of risks be independent of the decisions made to control the risk.

Efficient global hedging of risks should mean that the decision maker can choose to increase some risks, if it benefits the organization as a whole. However in the current system, junior managers normally 'own' risks at the same time as monitoring and reporting them, and

[10] In an attempt to prevent daily variation coming into play in this way, regulator introduced the rule that VaR = max(average of last 60 days VaR, or latest VaR * k). Economic capital calculations may not be calculated like this, in which case internal panic reactions can still be a problem.

having the power to make decisions about the control of these risks. These people are often rewarded on an individual basis, usually for reducing their 'own' risks, regardless of the effect on other risks within the organisation. It is therefore highly unlikely that efficient global hedging can be done for the enterprise as a whole. Risk control should be based on a business model, a decision theoretic framework that takes into account major costs and benefits to the global enterprise. In this sense, the role of risk control should be no different from the traditional management role.

II A Study of Risk Management in the Brazilian Markets

Market, credit and operational Value-at-Risk (VaR) models are being continuously refined and improved by academic research. In some cases these advances serve to make the risk model more complex, for example because they are based on more general assumptions; in other cases a risk model can be much simplified, for example because a unified framework, or new insights, have been developed.

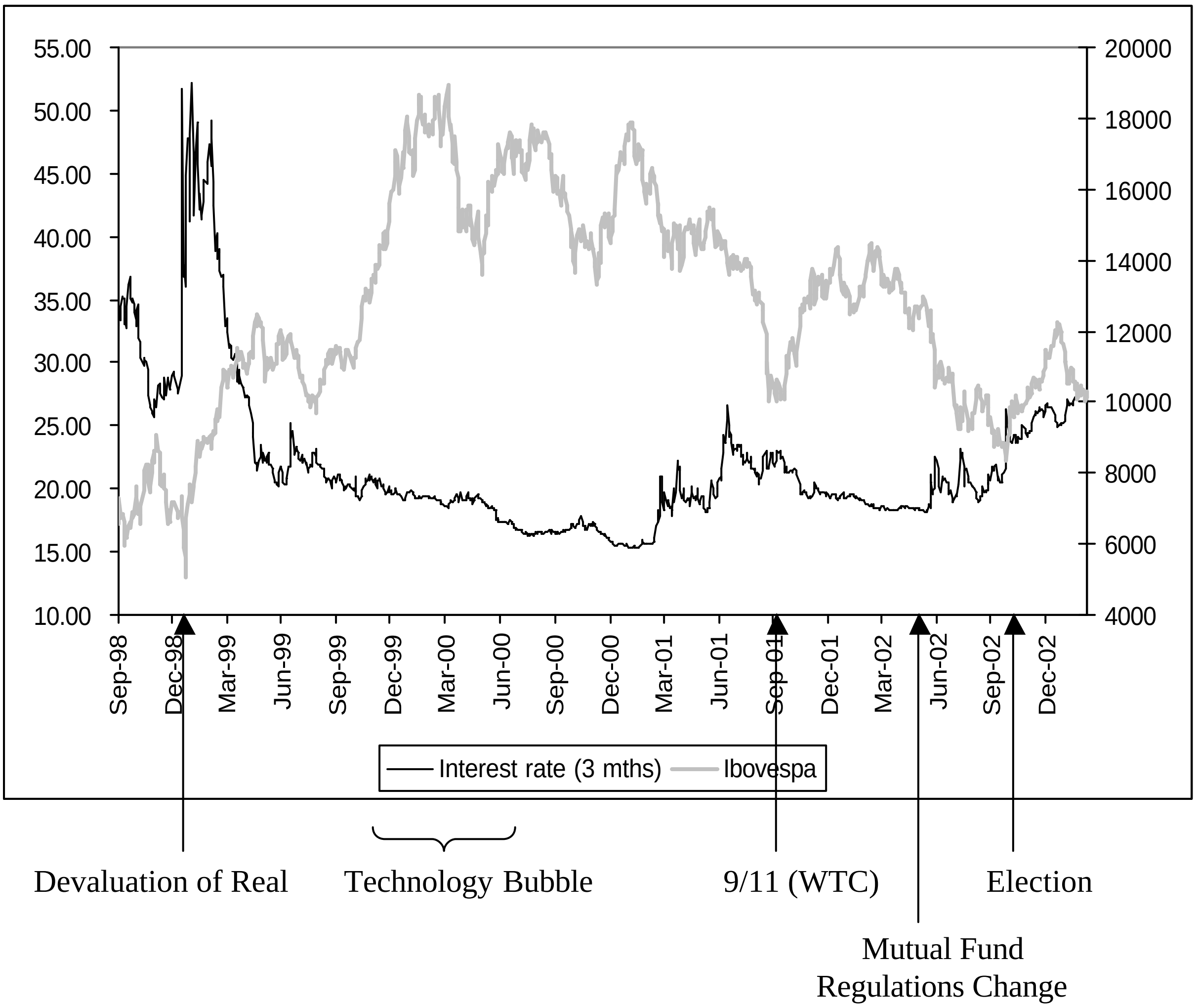
The second part of this paper examines the application of some new, advanced risk models to Brazilian equities and interest rates. Section II.1 simply introduces the data used in this study, then section II.2 will focus on model risk. Here we provide two examples of *model risk* in VaR models, based on our Brazilian market data. We ask whether VaR models are, in fact, appropriate for the assessment of market risks in Brazil. Section II.3 examines the dependencies between risks that need to be accounted for in portfolio models. We show that dependencies within Brazilian interest rates and within Brazilian equities are highly non-linear, so correlation is an inappropriate tool for the risk management of portfolios. Section II.4 successfully applies some new hedging models to Brazilian equities in the Ibovespa index, including a method that is based on 'cointegration' rather than correlation.

II.1 Data

a. Ibovespa Index vs 3mth Interest Rate

Figure 1 shows time series of daily closing prices on the Ibovespa index and the 3mth interest rate from September 1998 to May 2003. The effect of the devaluation of the Brazilian real in January 1999, the technology crash in 2000, the World Trade Centre terrorist attack in September 2001 and the Brazilian election of President Lula in October 2002 are all clearly visible. There is a negative correlation between interest rates and equities, but more significant is the negative correlation between Brazilian equities and the US dollar - Brazilian real exchange rate, as flows into dollars normally increase with relatively bad news or uncertainty about the Brazilian economy.

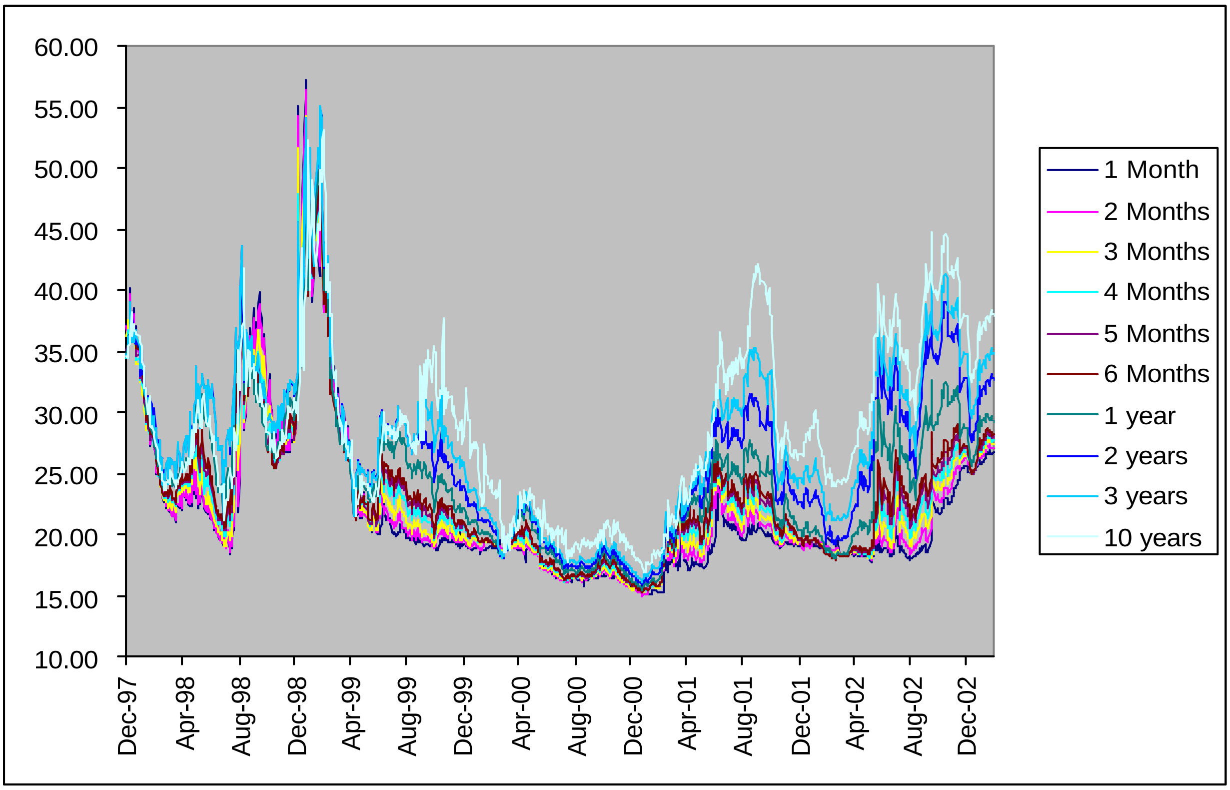
Figure 1: Equities and Interest Rates in Brazil



b. Term Structure of Interest Rates

Figure 2 shows the annual money market and swap rates, with maturities from 1 month to 10 years, recorded daily from the end of December 1997 to the end of February 2003. Around the time of the Brazilian real devaluation in January 1999, all interest rates were very high and variable, fluctuating between 40% and 55% over a period of 2 months. Following this, interest rates fell to 17-18% during a long a relatively calm period between April 2000 and March 2001, but higher volatility has returned to the interest rate markets, particularly in the longer maturity rates, during the last two years of the sample.

Figure 2: Money Market and Swap Rates in Brazil



c. Equities in the Ibovespa Index

We have daily closing prices on all 43 equities that are currently traded on the Bovespa stock index, from September 1998 to May 2003. Based on all these data, summary statistics for their returns distribution were examined and the results for six of the most liquid equities in the index are reported in Table 1.

The average annual return over the whole period is in the region of 25% for most of these stocks, except Embratel. However, the average annual volatility is high, at around 45% for Petrobras, Bradesco and Itaubianco, but ranging between 55% and 75% for the other stocks. From table 1a it is also clear that the daily returns distributions of Telemar, Petrobras, Embratel and Telesp cela are highly non-normal, and this is due to leptokurtosis (heavy-tails) rather than a significant skewness. Finally, table 1b. indicates that these most liquid equities in the Ibovespa are significantly positively correlated over the period of study.

Table 1: Distributions of Brazilian Equities:
Daily Data (September 1998 – May 2003)

Table 1a: Moments of Marginal Returns Distributions

Moments	TELEMAR	PETROBRAS	EMBRATEL	BRADESCO	TELESP CEL	ITAUBANCO
Mean	0.001	0.001	-0.001	0.001	0.000	0.001
Stdev	0.036	0.028	0.049	0.029	0.043	0.028
Skew	1.084	0.141	0.441	0.104	-0.057	0.183
XS Kurtosis	13.009	6.017	9.066	1.403	6.112	1.023

Table 1b: Historical Correlations

Correlations	TELEMAR	PETROBRAS	EMBRATEL	BRADESCO	TELESP CEL	ITAUBANCO
TELEMAR	1.000					
PETROBRAS	0.559	1.000				
EMBRATEL	0.531	0.385	1.000			
BRADESCO	0.538	0.452	0.384	1.000		
TELESP CEL	0.491	0.399	0.404	0.413	1.000	
ITAUBANCO	0.539	0.503	0.368	0.617	0.366	1.000

II.2 Model Risk in Risk Models

There is great deal of model risk in a risk model. It arises from inaccuracies in (a) the model assumptions and/or (b) the parameter estimates. Even if model assumptions are correct, model risk will arise from incomplete data, producing inaccuracies in parameter estimates. We now give an example of how each type of model risk affects a VaR model for estimating market risk in Brazil.

Consider first a Brazilian equity: let us estimate the 1% 10-day VaR from a long position on Petrobras on 21st May 2003, using historical daily closing prices. From the data used in Table 1a, the standard deviation of daily returns was 0.028. Hence an 'historical' forecast of the annual volatility for Petrobras is 45% and, based on the assumption that daily returns are normally distributed, the 1% 10-day normal VaR would be 21 cents per dollar invested.

However, we also know from Table 1a that the distribution of Petrobras is far from normal. An excess kurtosis of 6.07 indicates that Petrobras has a heavy-tailed distribution. Therefore the use of a normal assumption for the VaR estimate will be misleading: in fact it can seriously underestimate the risk. Using exactly the same data, but now making the more realistic assumption that Petrobras returns have a normal *mixture* distribution with an annual volatility of 45%, the 1% 10-day VaR is estimated as 29 cents per dollar invested.[11] That is, the VaR estimate is 40% larger when based on the (more realistic) assumption that Petrobras returns have a heavy-tailed distribution.

Our second example investigates the second source of risk model risk – the model risk arising from inaccurate parameter estimates. Consider the risk from exposure to a term structure of Brazilian interest rates, for example, for the risk management of a portfolio of loans. We shall apply a VaR model to the annual money market and swap rates, with maturities from 1 month to 10 years, shown in Figure 2. Suppose that we are unsure which is the most accurate covariance matrix, and that we have two possible covariance matrices at our disposal: (i) the RiskMetrics covariance matrix, based on an exponentially weighted moving average with smoothing constant 0.94 for all returns; and (ii) an orthogonal GARCH (O-GARCH) covariance matrix.[12] How different will our VaR estimates be?

---

[11] A mixture of two zero mean normal densities with volatility and excess kurtosis which match these moments of the empirical density, has a weight of 0.26 on one normal density with volatility 82%, and a weight of 0.74 on the other normal with volatility 17% p.a. For more information on VaR estimation based on normal mixture distributions, see Chapter 10 of Alexander, C. (2001) *Market Models: A Guide to Financial Data Analysis* John Wileys.

[12] An O-GARCH covariance matrix is obtained by applying a univariate GARCH model to the first few principal components of a system. For more details and further references to my work in this area,

Figure 3 compares the two types of model estimates, graphing a time series of volatilities from each covariance matrix. We see that whilst the O-GARCH volatility can be extremely high for short periods of time, there is little persistence in volatility following these times. In Brazilian markets volatility can be high, but it is also very variable. Indeed volatility in Brazilian markets is itself more 'volatile' that it is in most of the more developed markets in Europe and the US. The RiskMetrics volatility series are much smoother that the O-GARCH volatility series and, whilst they can seriously underestimate volatility during stressful markets, most of the time volatility is overestimated because the smoothing constant of 0.94 is simply too high for Brazilian markets.

Figure 4 shows how much higher the RiskMetrics VaR estimate will be than the O-GARCH VaR estimate for the 3 year swap rate. Over the entire period, RiskMetrics 1% 1-day VaR is, on average, 25% higher than the O-GARCH 1% 1-day VaR. At times, for example in late 1999 – early 2000, the RiskMetrics 1% 1-day VaR estimate was *double* that from the O-GARCH model.[13] One reason for this is huge difference is that the smoothing constant of 0.94 is far too high for Brazilian markets. Indeed, the exponentially weighted average covariance matrix with a smoothing constant of 0.9, or slightly less, would give estimates closer to the O-GARCH VaR estimates. But another problem with using exponentially weighted moving average methodology for covariance matrices is the need to use the 'square root of time rule'. The assumption of *constant volatility* on which this rule is based is clearly not appropriate in Brazil, even for relatively short holding periods.

The above examples cast some doubt on the wisdom of using VaR as the metric for risk capital calculation in Brazil. The figures above show that the volatility of Brazilian interest rates is very volatile: hence risk budgeting will be very difficult unless some robustness can be introduced to the risk metric. For this reason, the central bank of Brazil generates covariance matrices for use in VaR models that have an enhanced stability – even if they do overestimate the risk of short term interest rate positions. However, the BM&F risk models do not use covariance matrices – instead their risk estimates are based on scenario analysis.

---

see Chapter 7 of Alexander, C. (2001) *Market Models: A Guide to Financial Data Analysis* John Wileys.

[13] For other maturity interest rates, the RiskMetrics VaR was also found to be higher than the O-GARCH VaR , in general. For example for the 1 year rate the RiskMetrics VaR was, on average over the whole period, 14% higher than the O-GARCH VaR.

Figure 3:

RiskMetrics and O-GARCH 1-day Volatility Forecasts of 1 year Brazilian Swap Rate

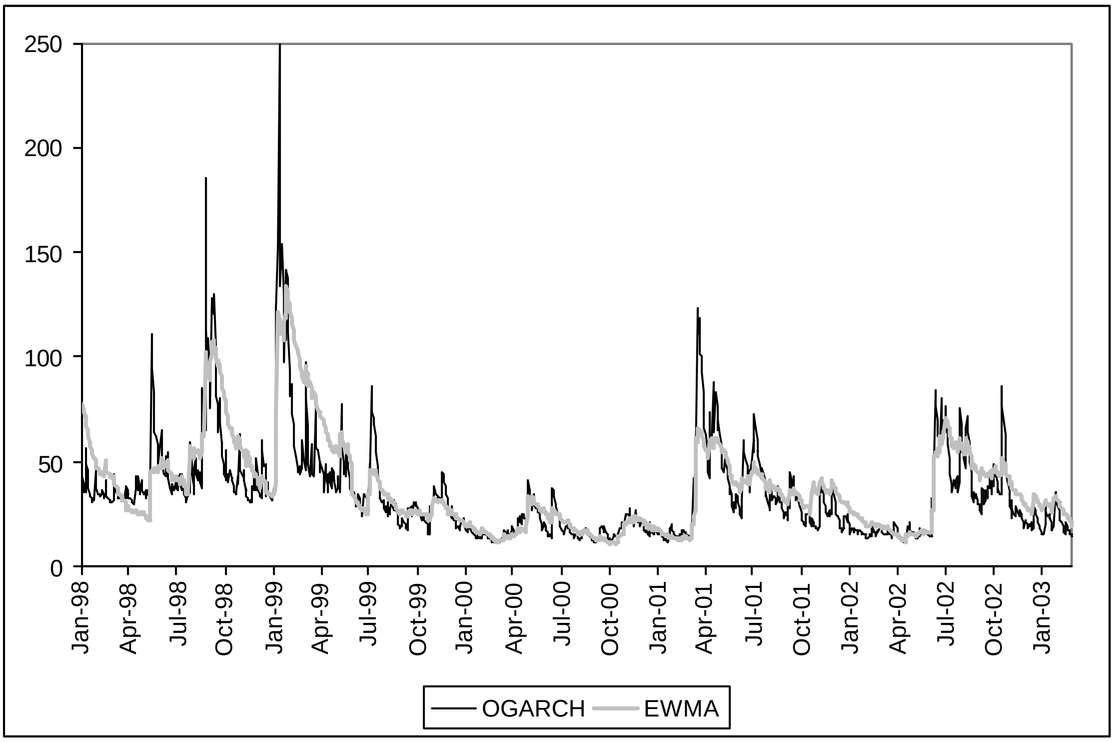
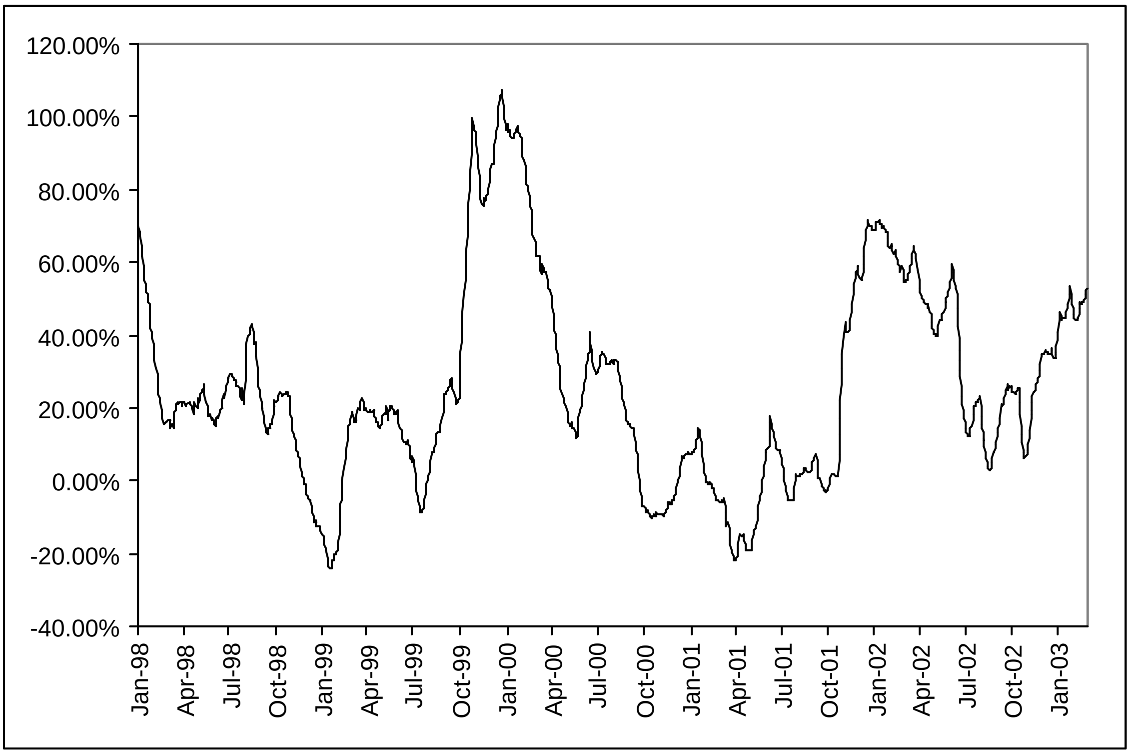


Figure 4:

How much larger is RiskMetrics VaR than O-GARCH VaR?



II.3 Modelling Dependencies for Portfolio Risk Management

Dependencies between different assets, or different risk factors, are commonly found to be higher in extreme market conditions than they are in 'normal' market circumstances. For example, during an equity market crash, or an exchange rate devaluation, correlations that are normally low, or even negative, can become very high and positive.

To see that this is indeed the case in Brazilian markets, table 2 reports the 'core' and 'tail' correlation coefficients for some different maturity Brazilian interest rates, and table 3 reports the same for six most liquid equities in the Ibovespa index.[14] Table 2 shows that – with the exception of the 10 year interest rate – the 'tail' correlations are much higher than the 'core' correlations, and this remain true whether we use points within the 1% or the 5% tails. The same is true for equities, although since the equity data sample contains fewer 'extreme' market conditions, table 3 gives less remarkable results than table 2.

Thus, if we distinguish between the correlation in the 'tails' and the 'core' of these risk factor and asset distributions, it is higher in the tails than core. Consequently, the application of a single, overall correlation to measure dependency in these markets can give some misleading results. This type of non-linear dependency, which is typical in financial markets, is not well captured by the standard linear correlation coefficients that have become a cornerstone of portfolio risk models. Instead, *copulas* can provide general method of modelling joint distributions that have powerful applications to all risk models.[15] Alternatively, and depending on the application, measures of dependency other than correlation (or, more generally, copulas) are available. The next section will employ just such a new measure of dependency, which is based on prices rather than returns.

[14] Equally weighted correlation estimates were calculated, using (a) all data; (b) only data from the upper and lower 1% tails of the empirical distributions; and (c) only data from the inner 98% core of the distributions. To be more precise, for case (b) we have excluded all data points that lie within the rectangular area $\{X_L < X < X_U$ and $Y_L < Y < Y_U\}$ where X and Y are daily returns and the subscripts "L" and "U" refer to the lower and upper 99%-iles of the empirical density. The remaining points are used to estimate the tail correlations. For case (c) the points $\{X_L < X < X_U$ and $Y_L < Y < Y_U\}$ are the only points used to estimate correlations. In this way we gain some idea of the overall correlation and how this is related to the points that lie in the tails of the distributions.

[15] The concept of a copula is not new in statistics, indeed it goes back at least to Schweizer, B. and A. Sklar (1958) 'Espaces metriques aleatoires' *Comptes Rendyes de l'Academie des Sciences de Paris*, 247, pp2092-2094

Table 2: 'Core' and 'Tail' Correlations between Interest Rates

Table 2a: Overall Correlations

Overall	1 Month	3 Months	6 Months	1 year	3 years	10 years
1 Month	1.000					
3 Months	0.699	1.000				
6 Months	0.612	0.906	1.000			
1 year	0.556	0.841	0.926	1.000		
3 years	0.434	0.670	0.718	0.782	1.000	
10 years	0.030	0.013	0.052	0.079	0.035	1.000

Table 2b: 'Tail' Correlations

5% Tails	1 Month	3 Months	6 Months	1 year	3 years	10 years
1 Month	1.000					
3 Months	0.772	1.000				
6 Months	0.699	0.920	1.000			
1 year	0.648	0.870	0.935	1.000		
3 years	0.514	0.703	0.735	0.797	1.000	
10 years	-0.012	-0.026	0.006	0.027	-0.049	1.000

1% Tails	1 Month	3 Months	6 Months	1 year	3 years	10 years
1 Month	1.000					
3 Months	0.887	1.000				
6 Months	0.815	0.931	1.000			
1 year	0.808	0.935	0.965	1.000		
3 years	0.652	0.764	0.791	0.876	1.000	
10 years	-0.128	-0.139	-0.149	-0.105	-0.186	1.000

Table 2c: 'Core' Correlations

90% Core	1 Month	3 Months	6 Months	1 year	3 years	10 years
1 Month	1.000					
3 Months	0.271	1.000				
6 Months	0.237	0.855	1.000			
1 year	0.196	0.743	0.901	1.000		
3 years	0.123	0.548	0.660	0.736	1.000	
10 years	0.190	0.157	0.197	0.237	0.284	1.000

98% Core	1 Month	3 Months	6 Months	1 year	3 years	10 years
1 Month	1.000					
3 Months	0.476	1.000				
6 Months	0.411	0.892	1.000			
1 year	0.336	0.774	0.899	1.000		
3 years	0.252	0.598	0.663	0.713	1.000	
10 years	0.161	0.149	0.196	0.205	0.184	1.000

Table 3: 'Core' and 'Tail' Correlations between Brazilian Equities

Table 3a: Overall Correlations

Overall	TELEMAR	PETROBRAS	EMBRATEL	BRADESCO	TELESP CEL	ITAUBANCO
TELEMAR	1.000					
PETROBRAS	0.559	1.000				
EMBRATEL	0.531	0.385	1.000			
BRADESCO	0.538	0.452	0.384	1.000		
TELESP CEL	0.491	0.399	0.404	0.413	1.000	
ITAUBANCO	0.539	0.503	0.368	0.617	0.366	1.000

Table 3b: 'Tail' Correlations

1% Tails	TELEMAR	PETROBRAS	EMBRATEL	BRADESCO	TELESP CEL	ITAUBANCO
TELEMAR	1.000					
PETROBRAS	0.694	1.000				
EMBRATEL	0.521	0.442	1.000			
BRADESCO	0.655	0.600	0.371	1.000		
TELESP CEL	0.462	0.501	0.389	0.496	1.000	
ITAUBANCO	0.730	0.699	0.459	0.836	0.534	1.000

Table 3c: 'Core' Correlations

98% Core	TELEMAR	PETROBRAS	EMBRATEL	BRADESCO	TELESP CEL	ITAUBANCO
TELEMAR	1.000					
PETROBRAS	0.491	1.000				
EMBRATEL	0.539	0.354	1.000			
BRADESCO	0.489	0.392	0.395	1.000		
TELESP CEL	0.489	0.341	0.414	0.382	1.000	
ITAUBANCO	0.467	0.428	0.340	0.549	0.303	1.000

II.4 The Risk Management of Brazilian Equities

a. Hedge Funds in Latin America

In general, Ibovespa stocks have not performed well during the last few years. Table 4 shows that the average annual return on the Ibovespa index has been a mere 5% since January 1997 – hardly a compensation for the index volatility of 42% per annum. Not surprisingly, there has been a significant growth in quantitative asset management strategies during past five years, and in hedge funds in particular. Such funds are now becoming more attractive investments for institutions.

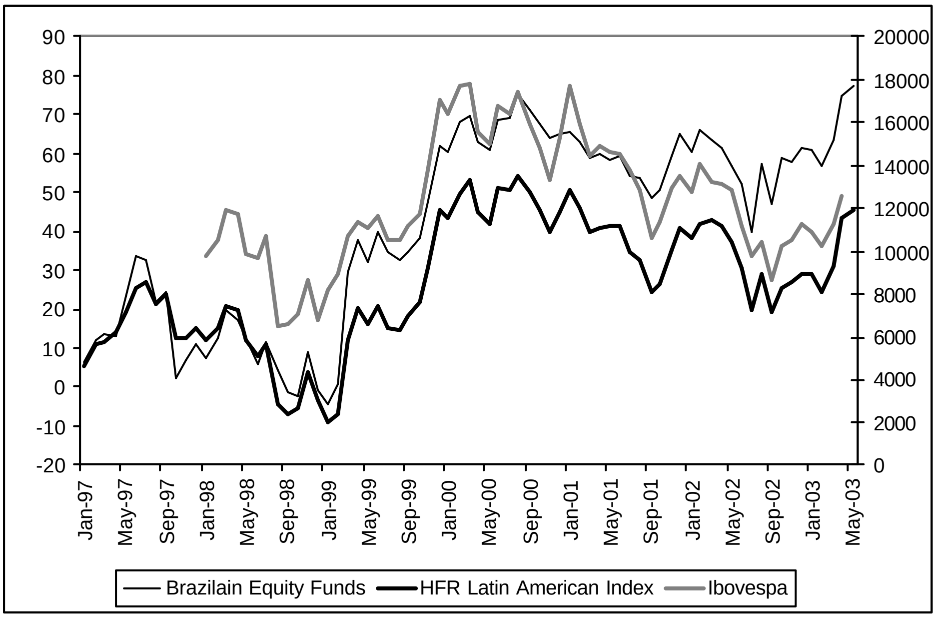
Table 4: Returns on Ibovespa and Hedge Funds in Latin America

Jan 1997 – May 2003	Av. Annual Return	Av. Annual Volatility	Information Ratio
Ibovespa Index	5%	42%	0.11
HFR Latin America Hedge Fund Index	7%	21%	0.33
Brazilian Hedge Funds (Average)	12%	26%	0.46

The Hedge Fund Return (HFR) database reports the performance of several indexes relating to emerging markets. Table 4 shows that the HFR Latin American index (a sample of funds domiciled in Central and Southern America with assets including equities and sovereign debt) has returned an average of 7% p.a. with an annual volatility of just 21% since January 1997. Also, there are currently six Brazilian hedge funds reporting to the HFR database, with total funds under management of approximately 160m$. On average, their returns are highly correlated with the HFR Latin American index and the Ibovespa (see Figure 5), but their performance has surpassed both: average annual returns of 12%, with a volatility of 26% imply an average annual information ratio of 0.47 since January 1997.

Some of these funds appear to be heavily invested in equities and others appear to be holding a substantial portion of sovereign debt. In fact, although specific details of each funds investments are not disclosed, it is clear that the over-performance apparent in table 4 has only been achieved by switching out of equity into sovereign debt and money markets, especially during the last few years. In fact, due to transaction costs and administration fees, active management has been shown to under-perform its passive alternative. Moreover, in the Brazilian markets, where lack of liquidity can give rise to very high bid-ask spreads for many stocks, a passive investment strategy that requires only a minimum amount of rebalancing is particularly attractive.

Figure 5: Average Cumulative Returns on Six Brazilian Long-Short Equity Hedge Funds, the HFR Latin America Hedge Fund Index and the Ibovespa



b. New, Quantitative Hedge Fund Strategies for Brazilian Equities

We shall now investigate the application of some new, quantitative long-short equity hedge funds strategies to the stocks traded on the Bovespa exchange. On average, during the last 3 years, the annual information ratio from this strategy was 0.74. This is net of (approximate) transactions costs, and is obtained with a self-financing long-short equity strategy, so its Sharpe ratio is much higher.

Active management has been shown to under-perform its passive alternative due to transaction costs and administration fees, mostly in bull, but also in bear markets. For example, the S&P active/passive scorecard for the last quarter of 2002 shows that the majority of active funds have failed to beat their relevant index even in the bear market of the last few years. Moreover, in the Brazilian markets, where lack of liquidity can give rise to very high bid-ask spreads for many stocks, a passive investment strategy that requires only a minimum amount of rebalancing is particularly attractive.

However, traditional optimization models, which are usually based on tracking error or on correlation estimates, have significant drawbacks which limit their applicability to a passive investment framework. First, the attempt to minimize the in-sample tracking error with respect to an index which, as a linear combination of stock prices, comprises a significant amount of noise, may result in large out-of-sample tracking errors. This is a result of the well-known trade off between the in-sample fit and the out-of-sample performance of a model. An optimization based on tracking error will attempt to over-fit the data in-sample, but this is done at the expense of additional out-of-sample tracking error. Moreover, the in-sample over-fitting will result in a very unstable portfolio structure, which implies frequent re-balancing and significant transaction costs.

In addition to these problems, any optimization based on correlation has additional weaknesses arising from the fact that correlation is an inappropriate and misleading measure of dependency: it is linear, and therefore unable to adequately capture the type of non-linear dependencies that are known to exist between financial assets or risk factors; it is only applicable to stationary variables, such as stock returns, and so prices require prior de-trending and this has the disadvantage of loosing valuable information (e.g.. the *common* trends in prices); it is a short-term statistic, which lacks stability over time, indeed its estimation is very sensitive to the presence of outliers, non-stationarity or volatility clustering, which limit the use of a long data history. All these exacerbate the general problems created by optimization and small sample over-fitting.

These limitations are well known and are usually dealt with, in an active management setting, through fine-tuning of model parameters such as the length and quality of the data used to calibrate the portfolio, the choice of optimization target, implementation of filtered re-balancing, etc. However, stability in the portfolio structure and transaction costs are central issues for passive investment. In our view, these can only be dealt with properly by changing the optimization model so that we accommodate directly the objectives and limitations of passive investment.

To this end, we have proposed two models that are designed to suit a passive investment framework: a cointegration-based index tracking (Alexander, 1999; Alexander and Dimitriu, 2002; Alexander and Dimitriu, 2003a) and a common trend replication (Alexander and Dimitriu, 2003b).[16] Both models produce stable portfolios having strong relationships with

---

[16] Alexander, C., (1999) "Optimal Hedging Using Cointegration", *Philosophical Transactions of the Royal Society*, A 357, p. 2039-2058

Alexander, C. and A. Dimitriu. (2002) "The Cointegration Alpha: Enhanced Index and Long-Short Equity Market Neutral Strategies", ISMA Centre Discussion Paper Series in Finance DP2002-08

Alexander, C. and A. Dimitriu. (2003a) "Regimes of Index Out-Performance: A Markov Switching Model of Index Dispersion", ISMA Centre Discussion Paper Series in Finance DP2003-02

Alexander, C. and A. Dimitriu. (2003b) "Optimizing Passive Investments", ISMA Centre Discussion Paper Series in Finance DP2003-08

All discussion papers are downloadable from www.ismacentre.rdg.ac.uk/dp either the benchmark itself, or with only one of its components, i.e. the common trend of the stocks included in the benchmark. Their enhanced stability results in a low amount of re-balancing and, consequently, reduced transaction costs.

By constructing well-diversified portfolios, each of which has a stable relationship with a benchmark, and by considering several benchmarks, a statistical arbitrage arises from the spread between the benchmarks tracked. We name these two strategies the ‘cointegration arbitrage’ and the ‘principal component arbitrage’ respectively.

For illustration of the power of this approach, a simple, combined long-short equity strategy, comprising equal weights on the cointegration arbitrage and the principal component arbitrage, has been applied to the Ibovespa stocks. Figure 6 shows the cumulative out-of-sample returns (net of transaction costs at 50bp per trade) to this statistical arbitrage strategy over period Sept 2000 to May 2003, and the Ibovespa index over the same period. Re-balancings amount to 100% turnover approximately every two months and transactions costs amount to between 1.2% and 3% of the amount invested in the tracking part of the portfolio at any particular time.

Figure 6: Cumulative Returns on a Statistical Arbitrage Long-Short Equity Market Neutral Hedge Fund Strategy, and the Ibovespa Index

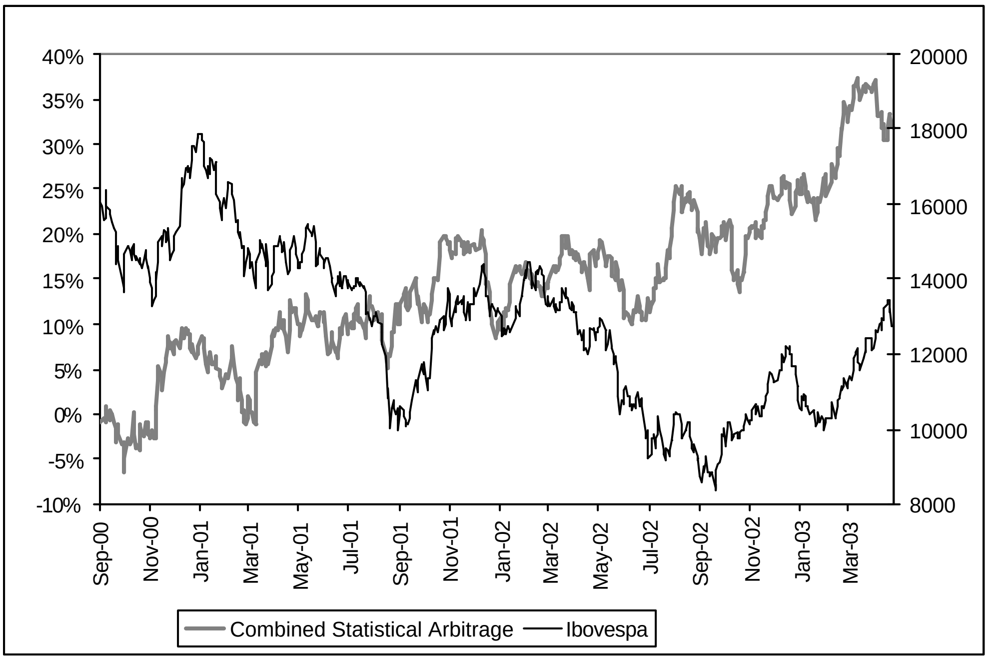


Table 5: Performance of the Statistical Arbitrage Strategy Compared with HFR Funds

Average Annual Statistics	Fund 1	Fund 2	Fund 3	Fund 4	Fund 5	Fund 6	IBOV	Our Fund
Return	-15%	8%	5%	-1%	2%	-1%	-6%	13%
Volatility	46%	6%	4%	72%	7%	7%	34%	17%
Information Ratio	-0.33	1.25	1.37	-0.01	0.23	-0.10	-0.19	0.74
Market Correlation	0.82	0.32	0.28	0.71	0.60	0.54	N/A	0.46

Table 5 compares the performance of this strategy with the performance of the six Brazilian hedge funds that currently report to the HFR database, during the period Sept 2000 to May 2003. Based on an average annual return of 13% and an average annual volatility of 17%, the average annual information ratio from our statistical arbitrage strategy is 0.74, which is less than the information ratio of both fund 2 and fund 3. However, when the returns series for these two funds are examined more closely, it is clear that they are mostly investing in fixed income side of the market, not in equities. The other four funds which, by their higher market correlations, *are* investing in equities, have not performed well during the last three years.

To summarize, there are clear disadvantages with the use of standard, correlation based models to determine the holdings of active investments in Brazilian equities. Rather than hedging the market risks, the returns to this type of fund remain highly correlated with the market, and have not performed well during the last few years. This standard type of model has its roots in modern portfolio theory, where the basic framework is one of *returns* analysis. The two new hedging models we have applied here have departed from the traditional approach: one aims to identify common trends in stocks, the other examines co-movements of *prices* rather than returns. Both are shown to have interesting new applications to Brazilian markets.

III Concluding Remarks

We have seen that current trends in risk management may lead to dangers in the road ahead. If risk assessors are all using the same 'best practice' risk model based on the same, quantifiable factors, they will all perceive exactly the same risks at the same time. With the trend towards 'real-time' risk monitoring and reporting, panic reactions could spread very quickly through the markets, leading to increased volatility leading and mass insolvencies in the banking and other sectors. But this will only happen if the risk controllers, the decision makers, all re-act in a similar way. In short, a major threat to the stability of the financial system lies in the homogeneity of both risk assessors and decision makers and the trend towards 'real-time' risk monitoring and reporting.

Current trends are all working towards increasing the accuracy and frequency of risk monitoring. Of course one must aim for the accurate and timely assessment of risks, but a certain amount of fuzziness, or even ignorance, at least has the advantage of reducing systemic risks.

The model risk arising from inappropriate assumptions about the behaviour of assets and risk factors should certainly be avoided. However, the model risk arising from differences in parameter estimates is something that we should accept, indeed welcome, rather than attempt to eradicate. An important lesson to learn from our early experiences with operational risks, is that 'historical' profit and loss data are not enough; it is absolutely necessary to admit *subjective* assessments into the risk modelling process. Risk managers may, quite justifiably, have very different prior views about important parameters such as default rates, or long-term volatilities. There will always be differences between model parameter estimates when risk managers employ subjective, forward-looking assessments.

In this light, and somewhat paradoxically, incomplete data should be viewed as a desirable thing for financial risk management at the level of the economy – but not at the level of the firm. It creates an heterogeneity in risk assessments, an heterogeneity that is induced by incomplete or inaccurate information.

For the same reason, heterogeneity in risk control is also desirable. Even if all risk managers do perceive the same threats at the same time, markets may not be de-stabilized if different managers re-act in quite different ways. But – in my view – there is too much emphasis on classical statistics in risk control. Consider the typical risk control objective 'minimize the variance of a hedged portfolio'. In the absence of subjective parameter assessments, all such hedgers would re-act in a similar fashion. On the other hand, if different 'types' of risk controllers exist in the market, for example, because their objectives are derived using different utility functions – or at least, they have different levels of risk tolerance – then risk control would be more heterogeneous.

Indeed there is too much emphasis on classical statistics in other financial risk management processes, and in risk assessment in particular. We have already argued the case for Bayesian risk assessment methods based on subjective data.

In the future we should regard risk control as a *behavioural* rather than a statistical science. We must learn from our cousins in economics and in other management disciplines, to broaden our view. In portfolio management, to take a simple case, the existence of different types of investors in a market[17] may be necessary to prevent asset price bubbles and crashes.[18] So it may also be that, in a world where risks can be assessed as accurately and as rapidly as prices are quoted, different 'types' of risk managers may be essential for the future stability of the financial system.

Over time, when we have learned more from management scientists and economists, 'good risk management' will evolve towards, simply, 'good management'. Risk control will be based on a business model which focuses on the *net* costs and benefits to the entire organization; risk management decisions will be based on utility functions that properly reflect the risk tolerance of the organization – and, assuming risk tolerance differs across organizations, an heterogeneous population of risk managers may co-exist in stable equilibrium.

This paper has highlighted a number of issues, some of which have been illustrated using data from the Brazilian markets:

- Global trends in financial markets are changing our perception of financial risks. Some risks, such as operational, business and systemic risks are now becoming relatively more important

[17] Traders may be classified into *hedgers* who aim to pass on the risk to others, *arbitrageurs* who trade on their perception of mean-reversion (and this can be self-fulfilling) and *speculators*, which can be of two main types, 'trend followers' who increase volatility, and 'contrarians' who decrease volatility.

[18] See Alexander, C. and A. Katsaris (2003) "Intrinsic Time Trading and Stock Market Bubbles: An Evolutionary Model" *Forthcoming as an ISMA Centre Discussion Paper in Finance, 2003.*

- As institutions change in response to these trends, the need for consolidated risk reporting in large complex banking organisations introduces a new challenge – risk aggregation that properly accounts for dependencies between risk factors.
- The inadequate modelling of dependencies between financial assets also affects our ability to risk manage portfolios (e.g. it undermines the performance of hedge funds)
- Incomplete data presents a problem for risk management at the level of the firm. This applies to all risk types, not just operational and other risks. The use of subjective, forward looking, data should be encouraged.
- However, incomplete data, and risk model risk in general, is not necessarily a 'bad thing' for financial risk management at the level of the economy – it can play an important role in reducing systemic risk.
- In the absence of risk model risk, and with 'real-time' risk monitoring, all risk managers would perceive the same risks at the same time; consequently, it is a 'good thing' for the stability of the financial system if there is an heterogeneity between the decision makers who attempt to control risks.
- To this end, a new branch of research – in behavioural financial risk management – will benefit from knowledge already gained in both micro-economic theory and management science.