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Value at Risk: Implementing a Risk Measurement Standard

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Value-at-Risk: Implementing a Risk Measurement Standard [1]

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Abstract: In the wake of recent failures of risk management, there has been a widespread call for improved quantification of the financial risks facing firms. At the forefront of this clamor has been Value at Risk. Previous research has identified differences in models, or Model Risk, as an important impediment to developing a Value at Risk standard. By contrast, this paper considers the divergence in a model's implementation in software and how it too, affects the establishment of a risk measurement standard. Different leading risk management systems' vendors were given identical portfolios of instruments of varying complexity, and were asked to assess the value at risk according to one common model, J.P. Morgan's RiskMetrics™. We analyzed the VaR results on a case by case basis, and in terms of prior expectations from the structure of financial instruments in the portfolio, as well as prior vendor expectations about the relative complexity of different asset classes. It follows that this research indicates the extent to which one particular model of risk can be effectively specified in advance, independent of the model's detailed implementation and use in practice.

Key words: Risk Management, Financial Services, Model Management.

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1. INTRODUCTION

In the wake of several high-profile failures of risk management (such as Barings Bank, Metallgesellschaft, and Orange County), there has been a widespread call for better quantification of the financial risks facing corporate and financial service firms. At the forefront of this clamor for a standardized risk measure has been Value at Risk, or VaR as it is commonly known. VaR is simply defined as the expected minimum loss of a portfolio over some time period for some level of probability. VaR's popularity is based on its ability to aggregate several components of firm wide market risk into a single number. Moreover, it focuses on a major concern of senior managers, the potential for significant loss in a firm's portfolio of assets. In its various forms, VaR has also gained strong support from industry and regulatory bodies such as the Group of Thirty (G30 1993), the Bank for International Settlements (Settlements 1994), and the European Union.[1] Proponents of VaR believe it will replace or at least complement less standardized techniques such as Asset/Liability Management and Stress testing, and as a result, it is hoped that regulators, auditors, shareholders and management, will finally be speaking a common language with respect to risk.

1.1 A Brief Description Of The Study

But while the concept of VaR is straightforward, it's implementation is not. There are a variety of models and model implementations that produce very different estimates of the risk for the same portfolio. While previous studies have focused on how differences between models[2] cause variation in VaR, this study considers how differences in the implementations of the same model produce variation in VaR. These issues are critical for practitioners; divergence in models and implementations leads to uncertainty in the mind

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[1] The European Union's Capital Adequacy Directive makes the VaR of the market risk in a bank's trading book one input to the calculation of their capital reserve requirement. For banks in the Group of Ten countries, the Basle committee on Banking supervision is proposing allocating risk capital according to banks' internal VaR models.

[2] In this paper, the term "model", denotes a system of postulates and data together with a means of drawing dynamic inferences from them. See for example, Derman (1996).

of the end user as to the meaning of the VaR estimates. This uncertainty translates to the real risk that the VaR estimates are used inappropriate y. To understand the importance of this risk in the estimation of VaR, we developed a test portfolio (see Appendix), which was given to a number of leading risk management software vendors, all of whom advertised that they used the same model of risk, J.P. Morgan's RiskMetrics™, and obtained their estimates for the portfolio's VaR. The results were analyzed and are discussed below.

1.2 Previous Research

This work builds on earlier research describing different models of VaR most notably, Tanya Beder's (1995) comparison of simulation and parametric models of VaR, and more recently, Daryll Hendricks (1996) comparison of random foreign exchange portfolios using different VaR models over multiple dates. Beder applied eight different approaches to three hypothetical portfolios and found VaR results varying by a factor of 14. She explained this by noting VaR's extreme sensitivity to the modeler's choice of parameters, data, assumptions and methodology. Hendricks compared twelve value-at-risk models to 1,000 randomly chosen FX portfolios. Using nine criteria to evaluate model performance, he found less variance than did Beder, noting that the different models generally capture the risk that they set out to assess and tend to produce risk estimates that are similar in average size. Our study differs from the previous research in two critical respects; first, our intent is not to compare different models, rather to understand the importance of the real world implementation and use of just one of these models. Secondly, our study focuses on different commercially available systems used by different individuals rather than specially constructed test systems used by the same individual. We suggest that this makes for a more realistic test of the use and interpretation of systems' results.

1.3 Models of VaR and Systems Risk

There are a variety of models that may be used to estimate Value at Risk. For instance, some risk management systems allow user-defined simulations, or use scenario-based models to calculate VaR. These techniques, and the circumstances in which they, and the tools that implement them, are most appropriate, are described elsewhere, e.g., Leong (1996). However, the most widely used technique to calculate VaR utilizes historical covariances between different risk factors to assess the effect of shocks on a portfolio whose positions can be mapped to those risk factors.[3] One such parametric model is J.P. Morgan's RiskMetrics™, and given its widespread use, we believe it is timely to ask to what extent this particular model provides a *lingua franca* for risk measurement. Updated daily across the Internet[4], RiskMetrics™ correlations and volatilities allow users to assess their aggregate financial market risks (in terms of VaR) over a given time period consistently across different asset classes. And, in an effort to make the use of the datasets more transparent, J.P. Morgan have also made public the detailed model by which these volatilities and correlations are calculated and the manner in which they should be used (Guldimann 1995). While this model has been criticized as making overly simplistic assumptions, we note that models are invariably compromises between usability on the one hand and accuracy on the other; RiskMetrics™ focuses on providing a relatively simple and transparent tool (Longerstaey and Zangari 1995).[6]

Despite RiskMetrics™' popularity, the question remains whether this or any other mode1[7], can constitute a standard independent of the details of the model's implementation and use. This is no new notion; it was Till Guldimann, one of the architects of RiskMetrics™, who observed that *"risk measurement and management continues to be as much a craft as it is a science"* and that *"no amount of sophisticated analytics will replace experience and professional judgment in managing risks"*.[8]

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[3]See Beckstrom's (1995) introductory guide to the meaning and use of VaR.

[4]Fromhttp://www.J.P.Morgan.com/RiskMetrics.

[5]Lawrence and Robinson (1995) criticize some of RiskMetrics' assumptions, such as its choice of 95% confidence interval, the assumption of normal markets, and its decision to ignore information in implied volatilities.

[6]It follows that our test of this model probably underestimates the extent of systems risk involved in more complex models.

[7]There are several other models of Value at Risk, such as Bankers Trust's RAROC 2020, and CS First Boston's PrimeRisk. From the perspective of this research however, RiskMetrics has the important advantage in that it is widely used, formally described and publicly available.

[8]See Guldimann (1995).

The formal model is not, and may never be a complete description of the precise implementation of the model in every circumstance, because of the potentially infinite variety of instruments and the large number of markets, whose institutional and statistical attributes are varying over time. This incompleteness of the model implies that decisions are left to the systems developer who chooses to implement the model and the systems user who interprets the inputs and outputs. It is these decisions that we suspect lead to variance in the outputs produced by the different systems, even though they utilize the same formal model. It follows, that unlike the earlier studies of Beder and Hendricks which focused on variance caused by a diversity of models, i.e., *Model Risk*, in this paper, we are concerned with that variance caused by a diversity of implementations of the same model, i.e., *Systems Risk.* We believe that a necessary condition for the use of any model as a potential standard is that it involves limited or at least quantifiable Systems Risk. This is especially important in the case of VaR, where the typical user of the VaR results, senior management, is often not a specialist in financial models and systems, and therefore tends to take the outputs from the models and systems at face value, partially oblivious of Model Risk and almost totally unaware of Systems Risk.

1.4 Research Goals

These goals are four-fold:

. To assess the variance in VaR estimates produced by different commercial implementations of the same model of Value at Risk.

. To assess how such variance is dependent on the nature of the asset class,

. To compare these results with the prior expectations of the vendors and those of the researchers, based on the portfolio's structure.

. Finally, to understand the extent of Systems Risk in the provision of any potential standard for risk measurement.

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[9] Note: That different model and system developers make different assumptions does not imply that they are in error. Rather, it should be inferred that an assumption's "correctness" is really an evolving social

2. RESEARCH DESIGN

2.1 Research Participants

As of the initial date of this study, twenty two vendors were known to have incorporated J.P. Morgan's RiskMetrics™ model into their assessments of Value at Risk, and all were asked to participate in the study. The following vendors completed VaR estimates for all or part of the test portfolio: Algorithmic, Brady, C-ATS Software, Dow Jones/Telerate, Financial Engineering Associates, Infinity, Price Waterhouse, Renaissance, Softek, True Risk, and Wall Street Systems.

2.2 **Research Process**

The extensive test portfolio is summarized in the appendix and was designed to assess the capabilities of all the tools and to produce a fair, but comprehensive and realistic test of their VaR capabilities, We also produced instructions describing the appropriate parameterizations to be used for the test. When the VaR estimates were returned, they were compared and analyzed, and feedback given to the vendors regarding any major discrepancies. [10] In many cases, vendors explained their need to change their results; the new results and the explanations for the changes were incorporated into the final report. When a sufficient number of results were gathered, they were analyzed on a case by case basis and also in terms of several prior hypotheses. A complete analysis was given to vendors describing all the results and made public in summary articles such as this. To encourage vendor participation, the details of which vendors gave particular results were not revealed.

2.3 **The Risk Assessment Task**

The task facing vendors involved several elements: First, **Inputs;** Most critical was the test portfolio describing positions in various asset classes, including Government Bonds,

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construct, based on accepted practice. Assumptions also differ from errors; in this paper, the term ***"Error"*** is limited to describing inconsistencies between assumptions within the same model or system.

Interest Rate Swaps, Money Market Deposits, FX Forwards, FRAs, FX Options and Interest Rate Options.[11] Vendors were also given identical RiskMetrics™ datasets. Second, vendors were asked to produce **Outputs** of one day, *95%* confidence, USD Daily Earnings at Risk (DEaR) estimates of interest rate, foreign exchange and total risk for the each asset class in the test portfolio as of 10.30 am EST, September 27, 1995. The final element of the risk assessment task was the following schedule of **Parameter Settings:**

[illegible]	[illegible]	[illegible]
Decision making Horizon	The time it is assumed to take to neutralize or liquidate a position.	1 day
Initial valuation of position	Marked-to-market value in USD. In the case of exchange-traded instruments, this is the last price on September 26.	Participants are strongly encouraged to use the end of day last prices provided in the enclosed spreadsheet.
Confidence Level	The probability associated with the occurrence of a given loss within the decision making horizon.	95%
Forward Rates and Prices	Describes the discounting of future cash flows.	For each market, a term structure of zero coupon yields is provided.
Diversification	Describes assumptions about diversification across assets.	Consistent with the RiskMetrics™ methodology recognizing complete diversification within and across different asset classes.
Volatilities and Correlations	Expected co-movement of different asset classes.	For this section, participants should use the enclosed RiskMetrics™ datasets and assume that these covariances are constant.
Instrument Mapping	Defines the equivalent portfolio in terms of RiskMetrics™ ' underlying asset classes.	Participants should perform the mapping in accordance with the RiskMetrics™ Methodology. If this is not possible, participants should define and make explicit what seems to them a reasonable mapping.
Derivative pricing	Assumed pricing relation between instrument and underlying assets.	Delta Valuation (not incorporating any higher order moments, such as gamma).
Estimation Technique	Describes the technique (e.g., User defined Simulation, RiskMetrics™ Parametric, Implied Volatilities, etc.) used to calculate the 95% percentile.	Parametric using the RiskMetrics™ datasets.

Table 1: Benchmark Parameterization

2.4 Research Issues

Gaining the cooperation of the vendors was a major challenge. Some vendors were busy with software releases, others reluctant to commit to a project that might reveal awkward discrepancies. One vendor reasoned that VaR was such a relatively small part of their system's total functionality, that any cross-tool survey based on VaR could not do them justice. In the light of these challenges, one of the more impressive aspects of the study, is that we obtained as extensive cooperation as we did—securing the involvement of a large proportion of the major risk management systems vendors. Nevertheless the size of

[10] Vendors were informed of the median and the standard deviation of the sample of VaR results by asset class. We also drew the vendor's attention to outliers.

the sample was clearly limited and limiting. To mitigate against this, we triangulated the quantitative results with prior structural analysis of the portfolio, and with vendor expectations regarding the complexity of different asset classes. Working through several iterations of estimates from vendors[12] also limited the importance of *User Risks* [13], *System Errors* and *User Errors* in the results. [14] Testing vendors' systems rather than end-users' systems allowed us to mitigate against User Risk and User Errors, since it is reasonable to assume that vendors know how to use their own systems better than do their customers. This follows because vendors are more likely to use their systems in the standard manner in which it was designed (mitigating User Risk), and are less likely to make inconsistent assumptions (mitigating User Errors). The variance remaining in the VaR results provides us with an estimate of the magnitude of Systems Risk. However these risk estimates are still subject to potential biases; first there is the tendency to underestimate Systems Risk. After all, we made it very clear to vendors that the results (and any discrepancies) would be made public in both academic and practitioner journals. We believe this meant that extra care was taken. On the other hand, as in any empirical test, Systems Risk may have been overestimated, since real money was not at stake, so many of the organizational safeguards (such as Back Office reconciliations, P&L, and Audit) were not in place.

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[11] The test portfolio is described in the appendix and is also available on the World Wide Web at: http://misdba.hbs.harvard.edu/cmarshall/mitstudy.

[12] One vendor gave us three different iterations of VaR results, several others gave us two iterations.

[13] ***User Risk is*** the risk of different users using the same model and tool to produce different results for the same task.

[14] ***System Errors*** or ***User Errors*** occur when developers or users make assumptions that are inconsistent with those made elsewhere in the model, the model's implementation in software, or its usage.

3. PRE-EMPIRICAL ANALYSIS

3.1 Structural Analysis Of The Portfolio

One of the easiest ways to understand derivative instruments, is in terms of basic building blocks, such as money markets, forwards, and options (Smith 1993; Smithson 1987). Different instrument classes in the test portfolio are also structurally related, providing clues as to the source of the additional variance in the risk assessment caused as new building blocks are pieced together to form more complex instruments.

Instrument Class	Risk equivalence to other instruments	Description
Zero Coupon Bond	Z	A single payment at a specified future date. A single cash flow is mapped to one or two risk factors in the parametric model.
Government Bond	(Z_1, Z_2, Z_3,...)	A series of fixed coupon payments at periodic intervals, followed by a payment of the principal at the maturity. This can be represented as a series of zeros.
Money Market Note	MM=Z	Equivalent to a zero coupon bond with a near term maturity (within one year).
Floating Rate Note	FRN	A single floating coupon payment with a short-term maturity.
Interest Rate Swap	(MM_1, MM_2, MM_3,...,FRN_1, FRN_2, FRN_3,...)	The interest rate swap is an exchange of a series of floating rate payments and fixed rate payments.
Forward Rate Agreement (FRA)	(MM_1, MM_2)	An FRA can be thought of as a means of locking in a forward interest rate. It is equivalent to short a money market instrument and long a longer maturity money market instrument.
Spot Currency	SP	A spot position in a particular currency
Foreign Exchange Forward	FXF=(SP, MM_1)	An FX forward can be interpreted as a spot position plus a money market instrument in a different currency.
Foreign Exchange Option	(Delta, FXF)	Using delta mapping, the risk of an option is assessed as if the option were comprised a position of extent delta in the underlying. Assessing the delta requires a valuation model that relates the sensitivity of the value of the option to the underlying itself.
Interest Rate Caps and Floors	($Delta_1$, Z_1, $Delta_2$, Z_2, $Delta_3$, Z_3,...)	IR Caps and Floors effectively comprise a portfolio of options

Table 2: Instrument Structure

This structural model of the instruments suggests (but does not necessarily imply) a similar structure for the variance of the different instrument classes. According to elementary Error Analysis, when we combine two simple instrument types to produce a third, we expect the variance of the combination instrument estimates to be both greater than that of either of its components, and less than that of the components' sum of variances. This is a result of the uncertain y (reflected in the variance of the instrument samples) in estimating VaR for each of the component instruments, increasing the uncertainty in estimating VaR for the composite. This said, it should be noted that the composite instrument classes in the test portfolio, while structurally equivalent to combinations of other instrument classes, are not exactly equivalent, since each instrument class contains multiple instantiations of the instrument. Nevertheless, the structure of the instruments described above leads us to hypothesize the following relationships between instrument class' sample relative Standard Deviation (SDev).[15]

1) SDev (Money Market) < SDev (Government Bonds)
2) SDev (Money Market) < SDev (Interest Rate Swap)
3) SDev (Money Market) < SDev (FRAs)
4) SDev (FX Option) < SDev (Interest Rate Options)
5) SDev (FRAs) < SDev (Interest Rate Swap)
6) SDev (Money Market) < SDev (FXF)

3.2 Vendor Expectations

We also asked that vendors[16] express the degree of difficulty they had in evaluating the VaR of a particular asset class (1 -Low Effort though 7-High Effort).

Vendor	*Bonds*	*Swaps*	*MM Deposits*	*FX Forwards*	*FRAs*	*FX Options*	*IR Options*
B	3	5	2	1	4	6	7
D	3	5	2	2	2	4	7
F	5	4	1	3	3	7	6
G	4	5	1	2	3	6	7
J	6	4	6	5	4	3	6
Mean	**4.2**	**4.6**	**2.4**	**2.6**	**3.2**	**5.2**	**6.6**

Table 3: Perceived Complexity of the Asset Class

Non-linear instruments such as options, particularly Interest Rate Options, were perceived as the most complex. The simplest asset classes were those with the smallest

[15] In this study, because of the limited number of data points, we calculated relative standard deviation as sample standard deviation divided by the sample median.

[16] To preserve anonymity, throughout the rest of this document, vendors are identified by letters (A though H) and vendors' systems by letter. number combinations (e.g. A. 1 is one of vendor A's systems).

number of cash flows, such as money markets and FX forwards, and to some extent, FRAs. We hypothesized that the perceived difficulty of VaR estimation for an asset class would be positively related to the variance in the VaR estimates for that asset class.

4. RESULTS

Going from those asset classes least susceptible to Systems Risk to those most susceptible, we describe vendors' estimates of VaR. Then, we make use of the extensive feedback from the vendors, to suggest likely drivers for any variance in the results despite the obvious limitations imposed upon us by a small sample size.

4.1 FX Forwards

RiskMetrics™-based VaR	*Interest Rate Risk*	*FX Risk*	*Total DEAR*
B	48,446	442,524	426,288
D	N/A	N/A	437,379
E	47,000	441,000	426,000
F	48,817	441,988	425,677
G	46,605	440,845	425,189
J.1	47,352	441,729	425,363
Mean	**47,644**	**441,617**	**427,649**
Median	**47,352**	**441,729**	**425,839**
Std Dev.	**949**	**698**	**4,784**
Std Dev/Median (%)	**2%**	**0%**	**1%**

Table 4: VaR of FX Forward Portfolio

The first thing to note is the similarity of all the parametric results for FX forwards. There are no major outliers. This suggests the ease with which firms can map forward payments in different currencies to spot plus forward payments of the domestic currency. This was also confirmed by the ease with which users described the task estimating VaR for FX forwards.

Some of the variance in the VaR estimates can be accounted for by differences in the valuations upon which VaR is based. Conceptually we can see that the relation between variance in valuation and variance in risk assessment is approximately linear from the following fictional simplification of the VaR calculation.

VaR = 1.65 x Standard Deviation of Outcomes x $Value$

$$\therefore \frac{\partial VaR}{\partial Value} = 1.65 \times \text{Standard Deviation of Outcomes}$$

If the standard deviation of outcomes involves no uncertainty (i.e. is constant across implementations) then:

$$\delta VaR = \frac{\partial VaR}{\partial Value}\delta Value$$

$$\therefore \frac{\delta VaR}{|VaR|} = 1.65 \times \text{Standard Deviation of Outcomes} \times \frac{\delta Value}{|VaR|}$$

$$\therefore \frac{\delta VaR}{|VaR|} = 1.65 \times \text{Standard Deviation of Outcomes} \times \frac{|Value|}{|VaR|} \times \frac{\delta Value}{|Value|}$$

$$\therefore \frac{\delta VaR}{|VaR|} = \frac{\delta Value}{|Value|}$$

This suggests that the VaR calculation introduces systems risk beyond that introduced by valuation, to the extent that the ratio of the standard deviation to the mean of VaR exceeds that of the valuation.[17] This is tested in the following table:

FX Forwards	B	F	J	Stdv/Mean
Valuation	3,125,651	3,174,940	3,080,118	1.52%
VaR	426,288	425,677	425,363	0.11%
Implied Std dev. (%)	8.27%	8.13%	8.37%	1.46%

Table 5: FX Forward Valuations

This suggests that the VaR variation is almost certainly the result of variance in valuations.[18] This is consistent with the vendors' beliefs that FX forwards are the least sensitive of all the asset classes to the precise choice of assumptions made. Despite a small number of data points, this was strongly borne out by our results, with very small (although non-zero) discrepancies between systems. What variation there is, appears

[17] The difficulties in model-based valuation is discussed in earlier research by Tanya Beder (1994) and a recent Bank of England study on Valuation practices in banks (Weston and Cooper 1996).

[18] Interestingly, it also suggests that the VaR estimation for FX forwards is relatively insensitive to valuation differences.

entirely the result of differences in valuations. We can conclude that for FX forwards, more than for any other asset class in the test portfolio, RiskMetrics™ VaR becomes an highly effective standard with strictly limited systems risk.

4.2 **Money Market Deposits**

RiskMetrics™-based VaR	*Interest Rate Risk*	*FX Risk*	*Total DEAR*
A	3,018	498,586	498,425
B	2,739	673,558	673,101
D	N/A	N/A	668,690
E	3,000	674,000	673,000
F	2,729	673,554	673,034
G	2,741	672,060	671,626
H.1	N/A	N/A	671,060
J.1	2,554	640,454	639,968
Mean	**2,797**	**638,702**	**646,113**
Median	**2,740**	**672,807**	**671,343**
Std Dev.	**179**	**69,891**	**60,720**
Std Dev/Median	**7%**	**10%**	**9%**

Table 6: VaR of Money Market Portfolio

Money markets were ranked by vendors to be like FX forwards in their relative complexity. Vendors also believed money market deposits to be among the least sensitive of the linear asset classes to the precise choice of assumptions made. Consequently, we would expect a standard model to have few difficulties in producing consistent results. And for the most part this is the case, with the only outlier of note, that of system A; it's estimate, while consistent with some simulation-based results obtained for the same portfolio, is lower that that of all the other parametric estimates. While we have no evidence concerning A's valuation, we suspect that it's VaR and that of J (also lower than most of other estimates) were caused by lower valuations. This was also suggested by the large importance of the FX risk as a component of the total DEaR.

Some of the vendors provided the following valuations of the money market positions:

Money Market Deposits	B	F	H.1	J	Stdv/Mean
Valuation	48,758,258	48,750,860	48,750,575	46,408,239	**2.43%**
VaR	673,101	673,034	671,060	639,968	**2.45%**
Implied Std Dev. (%)	0.84%	0.84%	0.80%	0.84%	**2.41%**

Table 7: Money Market Valuations

The similarity of the relative standard deviation of the valuations to that of the VaR estimates suggests that amongst these systems, most, if not all the variance in the VaR estimate comes from variance in the valuations. Although, as with the bonds, these vendors had less variance in their estimates than did many of the others in the sample. So while valuation may have been the predominant source of variance in VaR for these vendors, other VaR-specific factors may have been responsible for some of the variance in the rest of the vendors' estimates of VaR. To summarize, money markets were well suited to the RiskMetrics™ model, although not to the same extent as FX forwards. Money markets thus involved a small but significant systems risk, greater than that for forwards, but less than all other asset classes.

4.3 Forward Rate Agreements (FRAs)

RiskMetrics™-based VaR	Interest Rate Risk	FX Risk	Total DEAR
B	93,485	15,527	88,452
D	N/A	N/A	81,099
E	91,000	16,000	86,000
F	73,411	18,225	71,706
G	72,430	17,956	69,934
J.1	83,301	17,610	76,612
Mean	**82,725**	**17,064**	**78,967**
Median	**83,301**	**17,610**	**78,856**
Std Dev.	**9,712**	**1,218**	**7,534**
Std Dev/Median	**12%**	**7%**	**10%**

Table 8: VaR of FRA Portfolio

For FRAs, like the structurally similar money markets, we saw a fairly wide range (10%) in the VaR estimates. This variance was also reflected in the relatively high complexity ranking vendors gave to the asset class. Although there were no outliers, there was also no clear clustering around a particular estimate. Like FX forwards, as there are only two cash flows to map, there should be a limit to the effect of different assumptions regarding mapping.

FRAs	F	J	Stdv/Mean
Valuation	1,212,273	1,242,093	2.43%
VaR	71,706	76,612	6.62%
Implied Std Dev. (%)	3.58%	3.74%	4.37%

Table 9: FRA Valuations

The two valuations available to us suggested marginally that valuation was only partly responsible for variance in the VaR estimates. To summarize, FRAs look much like money market deposits in the ease of VaR estimation. Unlike money markets, there are some indications that valuation is less the driving factor in the variance of VaR estimation. Hence, Systems Risk appears greater for FRAs than for forwards and money markets but less than that for bonds and swaps.

4.4 Government Bonds

RiskMetrics™-based VaR	Interest Rate Risk	FX Risk	Total DEAR
B	1,171,322	4,191,516	3,808,750
C	N/A	N/A	5,490,568
D	N/A	N/A	3,802,820
E	1,158,000	4,127,000	3,754,000
F	1,190,421	4,211,048	3,824,799
G	1,175,013	4,192,618	3,809,410
H.1	N/A	N/A	4,823,042
J.1	1,174,177	4,191,972	3,806,757
Mean	**1,173,787**	**4,182,831**	**4,140,018**
Median	**1,174,177**	**4,191,972**	**3,809,080**
Std Dev.	**11,550**	**32,280**	**652,762**
Std Dev/Median (%)	**1%**	**1%**	**17%**

Table 10: VaR of Bond Portfolio

First, note that there is little difference in the components of risk, but there is significant variance in the aggregate Daily Earnings at Risk (DEaR) assessment. Second, most of this variance in the aggregate results comes from two outliers (vendors C and H. 1) both of whom did not break down their VaR into FX and interest rate components. The narrow range of VaR estimates is not surprising as bonds are relatively simple instruments (See sections 4.10 and 4.11). Although we were unable to ascertain why these systems results were outliers compared with the others, we do note that these results were compatible with the results from simulations[19], and that one of the tools, C was a pre-release piece of software. When these outliers are removed, the standard deviation/median estimate decreases to less than one percent. This was in spite of different assumptions made by this reduced sample of vendors regarding a number of issues, such as:

- Vendor E and J's keeping basis point sensitivities across mapped vertices rather than the RiskMetrics™ approach of maintaining variance.
- Use of different daycount schemes: We suggested that vendors use the day count conventions in place in the exchanges where the products are traded. In some cases however the systems had not implemented these options. The choice of day count was thought to be most likely to make a difference for very short term bonds and money market deposits. Nevertheless, we have evidence that the magnitude of the effect was usually of the order of a fraction of a percentage point in the VaR estimate.
- Interest rate calculations: Different exchanges and markets have slightly different conventions regarding yield calculation. Unlike the daycount effect, this effect seems to cause greater discrepancies as the maturity of the instrument increases.
- Small differences in valuation dates: E's numbers were calculated as of October 2, 1995 and not September 27.
- Holidays and weekend adjustments: Theoretically, settlement and reset dates should be adjusted if they fall on weekends or holidays. To do this requires significant calculation as it implies keeping record of holidays in multiple markets as well as relatively simple adjustments for leap years etc. Most of the vendors believed this to

[19] While not the focus of this paper, we also compared parametric results with those obtained from non-

have little effect and since there was a range of implementations on this issue, the data largely confirms this.

Vendors' valuations are shown in the following table:

Government Bonds	*B*	*F*	*H.1*	*J*	*Stdv/Mean*
Valuation	357,008,500	357,823,842	344,739,857	357,284,825	**1.79%**
VaR	$3,808,750	$3,824,799	4,823,042	$3,806,757	**12.42%**
Implied Std dev. (%)	0.65%	0.65%	0.85%	0.65%	**14.15%**

Table 11: Bond Valuations

Although not all the valuations were available, the fact that the VaR estimates vary much more than do the valuations suggests that valuations are a only partial driver of variance in VaR. However, even when the H.1 outlier is taken out, although valuation becomes much more important as a driver of variance in the VaR estimates, it still only drives half the variance in the VaR results. The variance not accounted for by valuations is probably due to a combination of the factors discussed above. To summarize, system risk is generally small for bonds using the RiskMetrics™ model, but significant outliers do exist. Valuation accounts for at most half of the variance in the VaR results with the remaining variance believed to be caused by differences in mapping and other factors. Bonds appear to become more complex and thus more likely to produce outliers in VaR as the number of coupons increases.

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parametric models, such as Monte Carlo and Historical Simulation,

4.5 Interest Rate Swaps

RiskMetrics™-based VaR	*Interest Rate Risk*	*FX Risk*	*Total DEAR*
A	398,519	221,048	438,680
B	326,574	133,688	315,177
D	N/A	N/A	303,502
E	304,000	129,000	307,000
F	327,133	128,595	315,322
G	40,503	218,050	205,770
H.1	N/A	N/A	250,058
J.1	328,278	152,008	317,796
Mean	**287,501**	**163,732**	**306,663**
Median	**326,854**	**142,848**	**311,089**
Std Dev.	**125,192**	**44,083**	**66,648**
Std Dev/Median (%)	**38%**	**31%**	**21%**

Table 12: VaR of Swap Portfolio

The Swap results present a major contrast with those of the bonds. For swaps there is much greater variation in the VaR estimates, i.e., Systems risk appears to be greater for swaps than it was for bonds. Systems A and G are outliers, but their removal from the sample does not eliminate the relative standard deviation which decreases to about 8°/0. G's estimates are based on their assumption that all the fixed legs and all the floating legs of the swap should contribute to the interest rate risk component of the swap, whereas other vendors assumed that all the fixed legs but only the first floating leg should contribute to interest rate risk. All the vendors had widely different allocations to FX risk. We believe that this was due to differences in valuation, as spot FX risk is a direct function of the instruments net present value. Several vendors believed the VaR of the swap was especially (i.e. more than the other linear instruments) sensitive to the swap's valuation.

The following table shows the vendors' valuations:

Interest Rate swaps	B	F	H.1	J	Stdv/Mean
Valuation	14,021,377	13,638,989	13,915,596	15,416,977	**5.58%**
VaR	315,177	315,322	250,058	317,796	**11.03%**
Implied Std dev. (%)	1.36%	1.40%	1.09%	1.25%	**10.91%**

Table 13: Swap VaR and Valuations

Here we see much greater variance in the valuations of swaps than were seen in the bond valuations, but a similar variance in the VaR estimates. This suggests that while estimation of VaR for swaps is similarly difficult to VaR estimation of bonds, swap valuation poses greater difficulties. In both swaps and bonds, it appears that about half the variance in VaR estimates is the result of variance in the valuations. To summarize, the choice of whether to map one or multiple floating legs contributes most to variance in the swap VaR, with much of the remaining variance driven by discrepancies in the valuations. Presumably, like bonds, some swaps' large number of cash flows means that mapping differences may also responsible for some additional variance.

4.6 Foreign Exchange Options

RiskMetrics™-based VaR		Interest Rate Risk	FX Risk	Total DEAR
B		30,127	873,329	889,609
E		29,000	927,000	943,000
G		160	501,770	501,811
J.1		21,730	725,883	718,846
Mean		**20,254**	**756,996**	**763,317**
Median		**25,365**	**799,606**	**804,228**
Std Dev.		**13,903**	**190,213**	**198,829**
Std Dev/Median		**55%**	**24%**	**25%**
Simulation-based VaR				
F	Full Valuation	576	2,111,045	2,111,349
H.3[20]	MC 1mth	26,010	575,033	577,059
H.3	MC 3mth	21,019	670,837	672,422
H.3	MC 6mth	19,807	850,223	848,537
H.3	MC 1 yr	15,966	767,962	709,081
H.3	MC 2 yr	16,164	753,054	759,248
H.3	MC 5 yr	13,943	936,381	951,471
J.2	RM Strct MC %	29,865	706,973	N/A
J.3	RM Strct MCSD	31,560	764,556	N/A
	Mean	**20,028**	**893,567**	**929,174**
	Median	**20,413**	**766,259**	**781,738**
	Std Dev.	**9,079**	**438,792**	**490,972**
	Std Dev/Median	**44%**	**57%**	**63%**

Table 14: VaR of the FX Option Portfolio

For the non-linear instruments, we include a number of non-parametric results obtained from various vendors. Vendors used a range of non-parametric models including full-valuation (F), Monte Carlo simulation (H.3), Historical Simulation (H.2), Structured Monte Carlo Simulation based on the 95th percentile (J.2), and Structured Monte Carlo Simulation based on a multiple (1.65) of the standard deviation (J.3).

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20 In one case, a vendor (H.3) provided us with different results estimated using the same methodology (e.g. historical simulation) but using different datasets. In accordance with our earlier definition of a model, i.e., "a system of postulates **and data", these are considered distinct models.**

Obviously these do not tell us anything about Systems Risk but as with the studies by Hendricks and Beder mentioned earlier, they do reveal the relative magnitude of systems risk compared to model risk. The first thing to notice about the option results, is that even using the parametric model of RiskMetrics™ is no guarantee to producing consistent results. The parametric results obtained had significant variation. This should be seen as reiterating many vendors' concerns about using a parametric model for the assessment of the risk of non-linear instruments, because of the parametric model assumption that the sensitivity of the derivative value with respect to the underlying rates (delta) is constant. For far out of the money options this might be a reasonable assumption, but a more general portfolio such as we have here, the assumption breaks down. The choice of a different risk model such as Full Valuation or Simulation incorporating vega and gamma risks can have a massive impact on the VaR estimation. Because of their non-linear nature, options also appear sensitive to the detailed assumptions regarding day counts, interest calculations and holiday assumptions. However, in general, FX options appear less sensitive to these assumptions than do the interest rate options discussed in the next section. FX options were however highly sensitive to the precise choice of risk model (full vs. delta valuation) used. Like all options, FX options were highly sensitive to the choice of volatilities used.

The second observation from the results is that the non-parametric results varied more widely than the parametric results, suggesting that model risk is greater than system risk for this asset class.

FX Options	*F*	*H.3*	*J*	*Stdv/Mean*
Valuation	-1,261,177	-873,053	-1,578,703	29%
VaR	2,111,349	734,165	718,846	67%
Implied Std Dev. (%)	-101.46%	-50.96%	-27.60%	63%

Table 15: FX Option Valuations

It appears the wide variation in valuation only partly explains the variation in VaR results. To summarize, FX options are non-linear in their dependence on the underlying risk factors used in RiskMetrics™. Consequently, they are very sensitive to the precise assumptions made in the system and the model. Both systems and model risks are higher than for any linear instrument. This said, it appears the least likely of the two non-linear asset classes considered in the test portfolio to be mis-specified, since mapping is a minor issue, and valuation relatively straightforward.

4.7 Interest Rate Caps and Floors

RiskMetrics™-based VaR		*Interest Rate Risk*	*FX Risk*	*Total DEAR*
B		286,411	274,505	416,722
G		288,393	512,586	616,145
J.1		292,223	263,864	416,523
Mean		**289,009**	**350,318**	**483,130**
Median		**288,393**	**274,505**	**416,722**
Std Dev.		**2,954**	**140,628**	**115,194**
Std Dev/Median		**1%**	**51%**	**28%**
Simulation-based VaR				
F	Full Valuation	4,429	300,128	296,890
H.2	Hist. Simuln.	438,426	181,996	455,960
H.3	MC 1mth	255,996	229,227	347,301
H.3	MC 3mth	354,898	192,398	401,068
H.3	MC 6mth	332,272	205,440	387,729
H.3	MC 1 yr	253,044	163,249	297,497
H.3	MC 2 yr	219,222	143,821	263,300
H.3	MC 5 yr	163,818	135,485	212,941
J.2	RM Strct MC %	615,177	269,237	N/A
J.3	RM Strct MCSD	618,431	266,218	N/A
	Mean	**322,191**	**214,700**	**342,156**
	Median	**288,393**	**205,440**	**347,301**
	Std Dev.	**183,097**	**56,844**	**79,878**
	Std Dev/Median	**63%**	**28%**	**23%**

Table 16: VaR of the IR Option Portfolio

All of the three parametric estimates were very close in their interest rate risks. Two of the three were close in the FX risks and total DEaR. Neither we, nor vendor G, know why G's results were so different. There was also extensive model variation. For interest rate options, most of the discrepancies seem to be due to the choice of model, followed by variation in the valuation of the portfolio. Repeatedly, vendors were dubious about the effectiveness of parametric methods for interest rate options because of the significance of their non-delta risks. The added complexity of the interest rate options is also seen in their use of additional models of interest rate term structure. Combining these models itself increases the complexity and increases the likelihood of user and implementation error. Despite the very small number of data points, but consistent with these concerns, interest rate options appear to have the highest model and systems risk of all the instruments considered in this test portfolio.

IR Options	B	F	H.1 & H.2	H.3	J	Stdv/Mean
Valuation	14,404,289	15,295,900	13,915,596	13,458,349	13,370,796	**6%**
VaR	416,722	296,890	455,960	322,399	416,523	**18%**
Implied Std Dev %	1.75%	1.18%	1.99%	1.45%	1.89%	**20%**

Table 17: Valuations of the IR Option Portfolio

Variation in valuations appears responsible for a smaller part of the variation in VaR than it was for FX options. This suggests that the risk assessment of interest rate options is more complex than that of FX options even though the valuation appears easier. To summarize, model and systems risks were more similar for interest rate options, and generally larger than for any other asset class in the portfolio. Valuation is less obviously a driver of variance in VaR than it was for FX options.

4.8 Comparative Analysis of Aggregate Tool Results

The vendors also produced assessments of VaR for the complete portfolio using RiskMetrics™ Parametric techniques. In our portfolio, we asked that vendors assume complete diversification of risks both across, and within, different asset classes. These are the aggregate results obtained:

RiskMetrics™-based VaR		*Linear Portfolio*	*Non Linear Portfolio*	*Entire Portfolio*
B		4,246,678	786,767	3,848,254
C		5,410,794	N/A	N/A
D		4,236,783	N/A	N/A
E		2,989,000	N/A	N/A
F		4,225,722	2,071,517	6,141,525
G		4,327,583	906,713	4,764,070
J.1		4,092,468	747,521	3,832,917
Mean		**4,218,433**	**1,128,130**	**4,646,692**
Median		**4,236,783**	**846,740**	**4,306,162**
Std Dev.		**702,638**	**632,560**	**1,087,510**
Std Dev/Median		**17%**	**75%**	**25%**
Simulation-based VaR				
H.2	Hist. Simuln.	4,824,224	N/A	N/A
H.3	MC 1mth	3,707,069	578,636	3,491,719
H.3	MC 3mth	3,698,294	742,004	3,344,544
H.3	MC 6mth	4,293,514	896,789	3,799,679
H.3	MC 1 yr	3,811,267	786,138	3,296,188
H.3	MC 2 yr	3,546,585	790,756	3,018,817
H.3	MC 5 yr	4,097,556	969,585	3,338,785
	Mean	**4,026,912**	**801,521**	**3,513,699**
	Median	**3,954,412**	**790,756**	**3,344,544**
	Std Dev.	**421,447**	**124,458**	**420,653**
	Std Dev/Median	**11%**	**16%**	**12%**

Table 18: Aggregate VaR Estimates

Note the wide range of results even for the RiskMetrics™-based results. Surprisingly variation at the aggregate level is greater than that at asset class level. This suggests that Systems Risk may be a systematic risk, since diversification has little effect on the total variance. It is also interesting to note that in the case of the aggregate portfolio, we see greater variation in the RiskMetrics™ based VaR results than we do using various non-parametric models. This said, most of the variation reflects the importance of the bonds in the aggregate portfolio and thus probably underestimates the inaccuracies in estimating the aggregate VaR. Also, less surprisingly, non linear instruments showed much greater model and systems risks than did linear instruments.

4.9 **Corroboration of Researcher Expectations**

The expectations of the researchers discussed in sections 3.1 and 3.2 with one exception were corroborated in the results:

1) SDev (Money Market)	(9%) <	SDev (Government Bonds)	(17%)	TRUE
2) SDev (Money Market)	(9%) <	SDev (Interest Rate Swap)	(21%)	TRUE
3) SDev (Money Market)	(9%) <	SDev (FRAs)	(10%)	TRUE
4) SDev (FX Option)	(25%) <	SDev (Interest Rate Options)	(28%)	TRUE
5) SDev (FRAs)	(10%) <	SDev (Interest Rate Swap)	(21%)	TRUE
6) SDev (Money Market)	(9%) <	SDev (FX Forwards)	(l%)	FALSE

Obviously with such small samples, there is also a large confidence interval around these estimates of variance. This error also prevents us from definitively expecting the structural relation being reflected in the variance of the estimates, nevertheless, the results are suggestive.

4.10 Corroboration Of Vendor Expectations

We plotted vendors' prior perceptions of the difficulty of performing the risk assessment of a particular asset class against the standard deviation (as a % of the mean) of the VaR estimates of the sample to see if there was any relationship. There was a clear correlation; not that this can be misinterpreted to infer causation between these variables, since both variables are actually proxies for a more fundamental metric of complexity associated with each asset class. Nevertheless, the validation of both the researchers' and the vendors' prior expectations does increase confidence in the general validity of the data, despite understandable concerns over the small size of the sample.

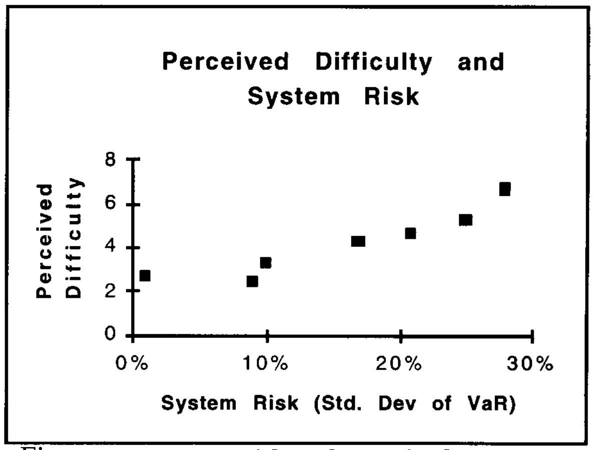

Figure **1: Systems Risk and Perceived** Complexity

5. CONCLUSIONS

The extent to which different vendors produced similar estimates was closely tied to the nature of the instrument.[21] The importance of systems risks for each asset class is shown graphically and in tabular form below:

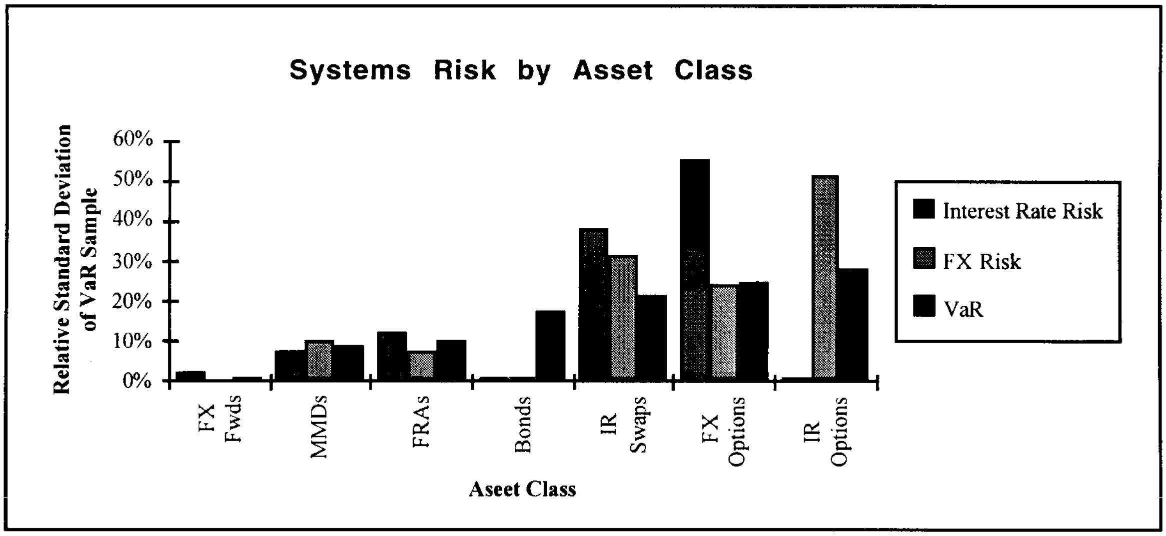

Figure 2: Systems Risk by Asset Class

Asset Class	Standard Deviation as Percentage of Median		
	Interest Rate Risk	FX Risk	Total VaR
Government Bonds	1%	1%	17%
Interest Rate Swaps	38%	31%	21%
Money Market Deposits	7%	10%	9%
FX Forwards	2%	0%	1%
FRAs	12%	7%	10%
FX Options	55%	24%	25%
Interest Rate Options	1%	51%	28%

Table 19: Variance in the VaR Results

Implicit in this study is our assumption that a necessary condition for a model to be a potential standard is that it involves limited or quantifiable systems risk. Therefore from

[21] To some extent this clashes with the work of Beder (1995), who found little systematic behavior in the errors according to different methodologies. She however compared across models rather than implementation, which presumably introduced a great deal of additional variance in the results.

the data, it appears that RiskMetrics™ provides a useful benchmark for FX forwards, money markets, and FRAs, somewhat less useful for bonds and swaps, and has major weaknesses dealing with non-linear instruments such as FX options and interest rate caps and floors. Divergence in FX risk seems to be driven by variations in valuation, but there also appears to be other significant factors driving variation in interest rate risk assessment. The authors note that criticism of any model can be over done; the decision to use the RiskMetrics™ model must be made in the context of alternative models. For FX options, model risk appears much greater than Systems Risk; for interest rate options, model risk is similar in magnitude to Systems Risk. In addition, Systems and Model Risks are not necessarily a threat to the accurate measurement of the total financial risk of a portfolio, provided users can obtain reasonable estimates of the magnitude of Systems and Model Risks. Given these estimates, we can then adjust the market risk-based VaR estimate to include Model and Systems Risks. The details of just how to do this are explained in a forthcoming paper by the authors.

Finally, our results suggest that Systems Risk should be an important concern of any user of a Value at Risk model. We found wide variation in VaR results produced even using the same model, and variation that was related to increasing complexity of asset class. We note the extreme sensitivity of the results on the detailed assumptions embedded in the models and the systems by highly skilled professionals. This is all too often forgotten by firms' senior management who may assume that formal models (such as that provided by J.P. Morgan's RiskMetrics™) specifies algorithms, and therefore results completely.

6. **FUTURE RESEARCH**

While this study provides research methods and a framework for understanding Model and System Risk, we believe the most effective way to estimate the Systems and Model Risk is through a large-scale regulator-mandated survey of Risk/Valuation models and their implementations. The Bank of England survey (Weston and Cooper 1996) is an early attempt to do for banks' internal valuation models. What is also needed, we suspect, is a battery of rigorous tests set by an independent body that systems vendors must perform in order to obtain some industry-wide seal of approval. The development of such a series of test would have other effects. Because of the secrecy and the competitiveness of the member firms, there are few resources available in the financial services industry for a relatively unbiased assessment and comparison of model and systems. We hope that this research builds the foundation of a more detailed research program geared to the detailed cataloging, sensitivity analysis and comparative analysis of such complex financial models as well as pointing the way towards a more systematic management of firms' financial models, their implementations, and their use.

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APPENDIX A: Test Portfolio given to Vendors

Exchange rates versus USD	
DEM	**1.4413002**
FRF	**4.9718098**
ITL	**1605.1364**
JPY	**101.10201**
USD	**1**

Government Bonds

Currency	Instrument	Price - Clean	Maturity	Coupon	Amount (LC)	Amount (USD)
FRF	BTAN	101.88	12-Aug-97	7.25%	300,000,000	**60,340,200**
FRF	BTAN	103.88	12-Apr-00	7.75%	450,000,000	**90,510,300**
FRF	OAT	102.33	25-Oct-05	7.75%	-165,000,000	**-33,187,110**
FRF	OAT	77.29	25-Oct-25	6.00%	172,000,000	**34,595,048**
DEM	Schatz	103.18	20-May-97	6.38%	125,000,000	**86,727,250**
DEM	Bobl	104.16	15-Mar-00	6.50%	75,000,000	**52,036,350**
DEM	Bund	109.53	22-Jul-02	8.00%	48,000,000	**33,303,264**
DEM	Bund	87.18	4-Jan-24	6.25%	25,000,000	**17,345,450**
ITL	BTP	98.8	1-Oct-96	9.00%	-5,000,000,000	**-3,115,000**
ITL	BTP	98.08	1-Apr-00	10.50%	10,000,000,000	**6,230,000**
JPY	JGB	114.303	20-Sep-04	4.60%	-2,500,000,000	**-24,727,500**
USD	Treasury	99.95317	31-Jul-97	5.88%	-10,000,000	**-10,000,000**
USD	Treasury	100.03125	31-Jul-00	6.13%	15,000,000	**15,000,000**
USD	Treasury	101.54688	15-May-05	6.50%	25,000,000	**25,000,000**

Interest Rate Swaps

Currency	Receive	Value (Local curr) Includes acc. int	roll Freq	Maturity	Next Settle	current fixed	Fixed rate	Floating rate	Amount (LC)	Amount (USD)
FRF	Floating	-2,256,800	6M	30-Jun-97	31-Dec-95	6.29	7.40%	7.00%	125,000,000	**25,141,750**
FRF	Fixed	11,412,000	6M	30-Sep-99	30-Sep-95	6.825	8.00%	6.75%	225,000,000	**45,255,150**
DEM	Fixed	5,247,000	6M	15-Jun-00	15-Dec-95	6.04	7.50%	5.63%	75,000,000	**52,036,350**
DEM	Floating	55,000	3M	1-Apr-05	1-Oct-95	7.015	6.75%	5.85%	52,500,000	**36,425,445**
ITL	Fixed	1,203,000,000	6M	1-Jun-97	3-Dec-95	10.905	12.50%	10.50%	55,000,000,000	**34,265,000**
JPY	Fixed	309,332,000	6M	1-Jul-99	3-Jan-96	1.87	3.50%	2.25%	5,000,000,000	**49,455,000**
USD	Fixed	4,073,000	3M	30-Mar-00	29-Sep-95	6.385	8.02%	5.25%	55,000,000	**55,000,000**
USD	Floating	45,000	3M	30-Mar-96	29-Sep-95	5.809	5.25%	4.60%	15,000,000	**15,000,000**

FX Forwards

Buy	Sold	Value (Buy currency)	Value date	fwd rate	Contract Rate	Buy Amount (LC)	Sell Amount (LC)
USD	FRF	0	29-Dec-95	4.92	4.92	30,000,000	147,600,000
DEM	BEF	-180,000	28-Jun-96	20.594	20.7	35,000,000	724,500,000
DEM	USD	-69,000	30-Sep-95	1.4255	1.43	45,000,000	31,468,531
USD	JPY	3,058,000	29-Dec-95	99.1	89	30,000,000	2,670,000,000
USD	ITL	-11,000	29-Mar-96	1,643.75	1650	3,000,000	4,950,000,000

Money Market Deposits

Currency	Instrument	Value (LC)	Maturity	basis	current yield	Contract Rate	Amount (LC)	Amount (USD)
DEM	Demand Deposit	55,077,000	30-Oct-95	30/360	4.06	5.75%	55,000,000	**38,159,990**
ITL	Demand Deposit	5,002,071,000	31-Dec-95	30/360	10.43	10.60%	5,000,000,000	**3,115,000**
JPY	Demand Deposit	512,075,000	31-Mar-96	30/360	0.46875	5.31%	500,000,000	**4,945,500**

Forward Rate Agreements (FRAs)

Currency	Instrument	Value(LC)	Maturity	Value date	current yield	Contract Rate	Amount (LC)	Amount (USD)
FRF	Bought	583,000	30-Mar-96	28-Sep-95	6.40%	6.92%	225,000,000	**45,255,150**
DEM	Sold	56,000	15-Mar-96	15-Dec-95	4.00%	4.30%	75,000,000	**52,036,350**
DEM	Sold	62,000	3-Aug-96	3-May-96	4.00%	4.60%	42,000,000	**29,140,356**
JPY	Bought	80,881,000	15-Mar-96	15-Dec-95	0.59%	2.75%	15,000,000,000	**148,365,000**
USD	Sold	237,000	1-Jun-96	2-Jan-96	5.77%	6.25%	100,000,000	**100,000,000**

FX Options

Instrument	Base	**premium as %**		Maturity	**volatility**	Optioned	Strike		Amount (LC)	Amount (USD)
Buy Call	USD	3.57%	per usd	30-Dec-95	**15%**	JPY	100	JPY/USD	45,000,000	**45,000,000**
Buy Put	USD	0.44%	per usd	16-Oct-95	**15%**	DEM	1.46	DEM/USD	55,500,000	**55,500,000**
Sell Call	USD	6.18%	per usd	30-Nov-95	**15%**	DEM	1.5	DEM/USD	77,500,000	**77,500,000**
Buy Call	DEM	2.50%	per yen	30-Mar-96	**15%**	JPY	68	JPY/DEM	95,000,000	**65,912,710**
Sell Put	DEM	0.20%	per dm	17-Feb-96	**15%**	FRF	3.6	FRF/DEM	85,000,000	**58,974,530**

Interest rate caps and floors

Currency	Instrument	premium in bp's	volatility	Maturity	Value date	Strike	Amount (LC)	Amount (USD)
DEM	Buy Cap 6M	0.07	17.00%	8-Jul-96	8-Jan-96	5%	75,000,000	**52,036,350**
DEM	Sell Floor 6M	173	16.70%	5-Jan-04	8-Jan-96	5%	110,000,000	**76,319,980**
FRF	Sell Floor 6M	14.8	23.00%	3-Sep-98	3-Mar-96	4.50%	250,000,000	**50,283,500**
FRF	Sell Cap 6M	36.9	22.60%	3-Sep-98	3-Mar-96	8.75%	250,000,000	**50,283,500**
JPY	Buy Floor 6M	1,521.30	41.60%	11-Apr-00	11-Oct-95	5.25%	10,000,000,000	**98,910,000**