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Price Risk Intermediation in the Over-the-Counter Derivatives Markets: Interpretation of a Global Survey

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Since the early 1980s, the financial derivatives markets have increasingly been used by market participants to unbundle and trade their exposures to foreign exchange rate risk, interest rate risk, and other types of price risk.[1] The markets have given firms that wish to shed unwanted price risk the ability to hedge their exposures at low cost while offering investors flexibility in structuring their trading and investment positions.

Derivatives contracts are especially efficient vehicles for unbundling the price risks embodied in assets and liabilities.[2] The contracts allow users to trade away the risks they do not wish to be exposed to while retaining other risk exposures. For example, in a financing relationship between a lender and borrower, an interest rate swap can be used to strip out the interest rate risk from the credit risk. Such an unbundling of risk can resolve differences in the risk preferences of the lender and borrower by passing the unwanted interest rate risk to others in the derivatives markets who are more willing to bear it.

Drawing on the results of a recent central bank survey of these markets, this article looks to answer questions about the role of derivatives markets in the intermediation of price risks—specifically, their role in the transfer and trading of price risk exposures in the financial system. For example, what is the scale of potential price and credit shocks that could be transmitted through the derivatives markets? Are the price risk exposures traded by the end-users of derivatives concentrated among derivatives dealers? What is the relationship between the over-the-counter and the exchange-traded derivatives markets?

The Central Bank Survey of Derivatives Market Activity

To provide interested parties with consistent and comprehensive data about the size and structure of the financial derivatives markets, in April 1995 central banks in twenty-six countries conducted the "Central Bank Survey of Derivatives Market Activity." The Bank for International Settlements (BIS) coordinated the survey and aggregated the national survey data to produce global market statistics.[3] One of the most important contributions of the survey was the collection of global data on market values of derivatives contracts. These data, broken down by counterparty type and disaggregated by contracts with positive and negative values (from the perspective of reporting dealers), provided a unique view of the derivatives markets' intermediation of price risks.

Data were collected from banks and securities firms that trade in the over-the-counter derivatives markets. The reporting panel consisted of more than 2,000 reporters in twenty-six countries. However, most reporters were the local trading desks of large, internationally active parent companies. (Most parent companies had trading desks in many of the twenty-six countries.) The U.S. portion of the survey had fifty-one reporters with both domestic and foreign parents. The reporting panel in the United States was restricted to derivatives dealers, and affiliates of these firms were also reporters in other countries. The aggregation of market totals in the survey used an adjustment to avoid the double counting of transactions between reporters, both at the national and at the cross-border level.

One of the most important contributions of the survey was the collection of global data on market values of derivatives contracts.

The survey collected data on new transactions (turnover) during April 1995 and outstanding contracts at the end of March 1995 in terms of activity in each participating country. Outstanding contracts were reported on the basis of contracts booked in each country (book location), and turnover data were reported on the basis of new transactions executed in each country (trade location). The U.S. portion of the survey, for example, collected data on outstanding contracts booked in the United States and new transactions executed there.

The survey data were broken down by counterparty type and product category. Reporters were asked to assign all their derivatives contracts to the product categories used in the survey (Table 1). In addition to the products listed in Table 1, exchange-traded futures and exchange-traded options (by underlying asset class), other over-the-counter foreign exchange derivatives, and other over-the-counter interest rate derivatives were included.

Truly Global Markets

The central bank survey data underscore the global nature of the over-the-counter derivatives markets.[4] A high proportion of the contracts in the survey represented cross-border transactions. For contracts booked in the United States, these transactions accounted for 50 percent of outstanding interest rate contracts and 60 percent of currency or exchange-rate contracts. In the global totals, the cross-border share was 55 percent for both currency and interest rate contracts. For trades between customers and dealers, the cross-border share was 41 percent for contracts booked in the United States and 48 percent for all contracts worldwide.

Another indication of the markets' global nature is the dispersion of derivatives activity across countries. Turnover volume in the United Kingdom—the country with the largest share—amounted to only 30 percent of global turnover volume, with 64 percent of that amount representing cross-border transactions. The combined turnover of the United Kingdom, the United States, and Japan—the top three countries—amounted to only 56 percent of global turnover volume.

The survey showed that derivatives activity is not only dispersed across countries but also has a decentralized structure. For example, a firm's traders may enter into trades in one location that are then booked elsewhere. One indication of this decentralization is the higher U.S. share of outstanding contracts relative to the U.S. share of turnover. Over-the-counter contracts booked in the United States amounted to 20 percent of the global totals, while the U.S. share of global turnover was only 14 percent. For over-the-counter interest rate derivatives alone, contracts booked in the United States were 23 percent of the global totals, but the U.S. share of global turnover was only 15 percent.

The global nature of derivatives markets and firms' participation in them suggests that a disruption in these markets could have wide-ranging effects that would be transmitted across national boundaries. How concerned should policymakers be? We now consider what the central bank survey reveals about the scale of potential shocks in the over-the-counter derivatives markets.

THE SCALE OF POTENTIAL PRICE SHOCKS

The survey shows a high level of demand for products that are used to trade and hedge exposures to underlying financial risks, particularly those related to changes in foreign exchange and interest rates (Table 1).[5] For issues related to price risk, the notional amounts in Table 1 can be roughly compared to the principal amounts of cash market securities with similar maturities. For example, the interest rate risk

Table 1
OUTSTANDING OVER-THE-COUNTER DERIVATIVES CONTRACTS

	Global Totals		Contracts Booked in the United States[a]	
Product Category	Amount (Billions of U.S. Dollars)	Percentage[b]	Amount (Billions of U.S. Dollars)	Percentage[b]
PANEL A: NOTIONAL AMOUNTS				
Foreign exchange forwards and swaps	8,742	72	1,264	47
Currency swaps	1,974	11	258	10
Currency options	2,375	16	1,114	42
Forward rate agreements	4,597	17	874	11
Interest rate swaps	18,283	69	5,558	68
Interest rate options	3,548	13	1,595	20
Equity forwards and swaps	52	9	8	22
Equity options	547	91	28	78
Commodity forwards and swaps	208	66	127	64
Commodity options	109	34	72	36
Total[c]	40,714		11,044	
PANEL B: MARKET VALUES				
Foreign exchange forwards and swaps	602	70	94	59
Currency swaps	345	22	32	20
Currency options	69	7	32	20
Forward rate agreements	18	3	2.4	1
Interest rate swaps	560	87	130	85
Interest rate options	60	9	20	13
Equity forwards and swaps	7	14	1	37
Equity options	43	86	1.5	63
Commodity forwards and swaps	21	78	10	70
Commodity options	6	22	4	30
Total[c]	1,745		328	

Sources: Global totals were compiled by the Bank for International Settlements (1995c). Figures for contracts booked in the United States were compiled by the Federal Reserve Bank of New York (1995).

Notes: All figures in the table are as of the end of March 1995. The figures have been adjusted for double counting of trades between reporting dealers.

[a] The U.S. share in the global totals is smaller than the ratio of the two columns because of cross-border dealer trades.

[b] Percentage of each product within the corresponding product group.

[c] The totals include "other foreign exchange" and "other interest rate" products, which were a very small proportion of all currency and interest rate products (in terms of both notional amounts and market values). The global totals of foreign exchange forwards and swaps do not include contracts booked in the United Kingdom because data were not collected.

of a bond is comparable to that of an interest rate swap whose notional amount equals the principal amount of the bond (as long as both have equal maturities). The notional amounts in Table 1, however, are the gross trades in the markets and consequently overstate the amount of net price risk exchanged in the over-the-counter derivatives markets.[6]

The survey shows a high level of demand for products that are used to trade and hedge exposures to underlying financial risks, particularly those related to changes in foreign exchange and interest rates.

If we take these two factors into account, the notional amount of interest rate swaps and options worldwide, at $22 trillion, is comparable to the $24 trillion of outstanding *securities market* debt worldwide at year-end 1994.[7] Likewise, the $7 trillion notional amount of interest rate swaps and options contracts booked in the United States, though smaller, is of a comparable order of magnitude to the $17 trillion of outstanding *credit market* debt in the United States at the end of March 1995.[8] Although these are gross notional figures, their large size suggests that a significant amount of exposure to interest rate risk is being exchanged among derivatives market participants. Consequently, the role of the derivatives markets in transferring exposures to underlying price risks between market participants, between economic sectors, and between countries raises a question about the size of price and credit shocks (arising from changes in underlying exchange rates or interest rates) that could be transmitted through the derivatives markets.

From a market value perspective, the gross amount of wealth transferred between counterparties through outstanding over-the-counter contracts worldwide at the time of the survey amounted to $1,745 billion, as measured by the total market value of outstanding contracts in Table 1.[9] (The relationship between market values and notional amounts is explained in Box 1; Box 2 describes the aggregation of total market value in the survey.) Even though the market value is not a measure of price sensitivity to underlying risk factors, given the volatility of exchange rates and interest rates in the year preceding the survey, this sizable figure does provide some feel for the magnitude of the gross price shocks and wealth transfers that *could* be transmitted through the over-the-counter derivatives markets.[10]

Price Shocks

That having been said, the central bank survey in fact provides evidence that price shocks in the over-the-counter derivatives markets would *not* be inordinately large. To put the potential price shocks in perspective, we use data from the survey to compare the gross price sensitivity of outstanding over-the-counter interest rate derivatives with that of securities market debt (Box 3). Our estimates suggest that the price shocks transmitted through the interest rate derivatives markets, even on a gross basis, would be smaller than those in the debt securities markets. In addition, the combined effects of the shocks in the two markets would be smaller than their sum because some market participants have offsetting exposures in the two markets. (A large proportion of derivatives contracts are used for hedging and arbitrage; consequently, some of the price shocks in derivatives contracts and debt securities would be offsetting.)

Our estimates suggest that the price shocks transmitted through the interest rate derivatives markets, even on a gross basis, would be smaller than those in the debt securities markets.

While these estimates provide some reassurance about the scale of price shocks that might be transmitted through the derivatives markets, the manner in which a price shock is distributed across market participants is another important concern. About half of all interest rate derivatives contracts are between dealers and customers (Table 2). If customers are equally represented on both sides of the markets, the wealth transfer passing through the dealers from customers on one side of the markets to customers on the other side will be only one-quarter (the product of one-half of one-half) of the gross price shock estimate in Box 3 (or between $130 billion and $200 billion for a 1-percentage-point change in interest rates).

The net price shock or wealth transfer in the *interdealer* part of the market (which comprises the other half of outstanding interest rate contracts) is also likely to be significantly smaller than one-half the gross price shock estimate in Box 3. This difference is the result of offsetting trades between dealers in their market-making role. We cannot determine from the survey, however, just how much smaller the net exposure will be.

Table 2
DEALERS' CONTRACTS WITH CUSTOMERS AS A PERCENTAGE OF ALL CONTRACTS

Product Category	Financial Customers	Nonfinancial Customers	All Customers
Foreign exchange forwards and swaps	40	13	53
Currency swaps	33	33	66
Currency options	29	12	41
Forward rate agreements	41	0.3	41
Interest rate swaps	34	14	48
Interest rate options	39	19	58
All foreign exchange and interest rate contracts	37	15	52

Notes: The table reports outstanding contracts booked in the United States at the end of March 1995. The notional amount of dealers' trades with customers is relative to the total notional amounts outstanding in each product. The remaining contracts are interdealer transactions.

BOX 1: NOTIONAL AMOUNTS AND MARKET VALUES

The notional amount of derivatives transactions is only a reference amount used to calculate the exchange of cash flows between counterparties. The market value of a derivatives contract is the net value of the cash flows to be exchanged between counterparties over the life of the contract. For a measure of the wealth transferred in the derivatives markets at a point in time, the market value of outstanding contracts is a better indicator than the notional amount because the relationship between notional amounts and cash flows varies across types of derivatives contracts. Nevertheless, notional amounts can be useful, as illustrated in Box 3. The market values of over-the-counter derivatives contracts are a small percentage of the notional amounts, at 3 percent for contracts booked in the United States and 4 percent for the global totals.

The market values as a percentage of notional amount are smaller for interest rate derivatives than for other products because of the lower volatility of interest rates relative to other underlying asset prices, such as exchange rates. As should be expected, products with longer maturities also have higher ratios of market value to notional amount. For contracts booked in the United States, the market value as a percentage of notional amount is smaller than it is for the global totals, in part because of the different currency and interest rate composition of the global totals and the contracts booked in the United States. For example, interest rate products tend to be booked in the United States to a greater degree than currency products, which have higher ratios of market value to notional amount.

TOTAL MARKET VALUE AS A PERCENTAGE OF NOTIONAL AMOUNT OF OVER-THE-COUNTER DERIVATIVES CONTRACTS

	Global Totals	Contracts Booked in the United States
Foreign exchange forwards and swaps	6.9	7.4
Currency swaps	17.5	12.5
Currency options	2.9	2.9
Forward rate agreements	0.4	0.3
Interest rate swaps	3.0	2.3
Interest rate options	1.7	1.2
Equity forwards and swaps	13.4	11.7
Equity options	7.8	5.7
Commodity forwards and swaps	10.1	8.1
Commodity options	5.5	6.1
All products	4.3	2.9

Sources: Global totals were compiled by the Bank for International Settlements (1995c). Figures for contracts booked in the United States were compiled by the Federal Reserve Bank of New York (1995).

Box 2: Total Market Value Aggregation

The total market value in the survey is the value of all contracts that had positive market values for the reporting dealers plus the absolute value of reporting dealers' contracts with nonreporters that had negative market values for the dealers (see table). This sum captures the market value of all contracts because all contracts in the market have a dealer on at least one side (end-users trade only with dealers, but not with each other). The sum of market values across all contracts is a measure of the gross amount of wealth transferred in the over-the-counter derivatives markets (the net wealth transfer may be smaller because of offsetting trades).

In the table, gross market value is defined as the market value of outstanding contracts before bilateral netting by counterparty. The positive and negative values are from the perspective of the reporting dealer. A typical dealer would have some contracts that have positive value and others that have negative value.

The amount *a* represents the value of contracts between reporting dealers. A contract between two dealers that has a positive value for one will have a negative value for the other (of equal amount), but that value should be included only once in the total market value. Hence, the amount *a* appears on both sides of the table but is included only once in the total market value.

While the reported values of *a* on both sides of the table should in principle be equal, in the survey they differed slightly (by less than 4 percent in the case of contracts booked in the United States). The discrepancy could be due to either differences between the valuation of the same contract by the two dealer counterparties or reporting errors in assigning contracts to the counterparty classes in the survey.

The amount *b* (*c*) represents the value of contracts between dealers and customers that have positive (negative) value for dealers. The market total should include both types of customer contracts.

Market Values of Contracts Held by Reporting Dealers by Counterparty Type

	Gross Positive Market Value	Gross Negative Market Value
Reporting dealers	*a*	*a*
Others/customers	*b*	*c*

Total market value = $a+b+c$
(All values reported in absolute value)

Combining the estimates of the net customer and interdealer wealth transfers in the derivatives markets might reduce the figures in the left-hand column of Table A2 in Box 3 to less than $300 billion (or less than $500 billion in the case of the larger estimate). In sum, these considerations suggest that the price shock or wealth transfer in the derivatives markets arising from a large interest rate change might not be excessively large, especially when compared with price risks in the debt securities markets. Note, however, that this interpretation applies only to the scale of aggregate shocks in the market as a whole. At the level of an individual market participant, the relative size of a change in value of its derivatives contracts could be quite significant.

Credit Exposures

Another potential channel for the transmission of shocks is the change in credit exposures between counterparties as a consequence of the change in value of their derivatives contracts. The derivatives markets' size and role as a conduit for price-risk transfers in the economy suggest that shocks that heighten settlement risks could have wide-ranging effects. These effects would include not only the higher credit risks themselves, but also market participants' elevated exposures to price risks if they faced settlement risks in contracts they had relied on as hedges. In addition, the markets' ability to intermediate price risks could also be disrupted if market liquidity were to be impaired by participants' reluctance to enter into new transactions for fear of settlement risk.

On these points, the central bank survey is again fairly reassuring. Although the survey did not collect data on credit exposures in derivatives contracts, the market value data do give some perspective on the scale of the credit exposures among all participants in the market.[11] If we start with the replacement value of dealers' contracts and then account for dealers' credit-risk-reduction practices (such as counterparty netting), we reach a global total for dealers' credit exposures of about $600 billion. However, customers also have credit exposures to dealers. Thus, total credit exposures globally, including customers' exposures, might amount to roughly $1 trillion. Before we assess the size of this figure, we offer a more detailed account of how it was calculated.

Dealers' Credit Exposures

The use of bilateral counterparty netting and collateral might reduce the credit exposures of a large derivatives dealer to less than half of the replacement value of its contracts.[12] The dealers' replacement value is the sum of all contracts that have positive values to dealers, which amounts to about $1.3 trillion in the global totals. Half

BOX 3: APPROXIMATE PRICE SENSITIVITY

The price sensitivity approximation for interest rate derivatives is based on the notional amounts in text Table 1 and the maturity distributions in Table A1. Depending on the distribution of contracts within the maturity bands in Table A1, the weighted average price sensitivity might range between 2 and 3 percent of notional amount for each 1-percentage-point change in interest rates. (The notional amount in Table A2 includes "other products" not broken out in Table 1, a difference of 1 percent. See Bank for International Settlements 1995c.)

Table A1
MATURITY DISTRIBUTIONS OF OVER-THE-COUNTER DERIVATIVES CONTRACTS

	Up to One Year	One to Five Years	Over Five Years
Foreign exchange forwards and swaps	77	21	2
Currency swaps	26	51	23
Currency options	89	8	3
Forward rate agreements	90	10	0
Interest rate swaps	34	48	18
Interest rate options	31	54	15
Equity forwards and swaps	67	29	4
Equity options	67	33	0.1
Commodity forwards and swaps	70	29	1
Commodity options	87	13	0.4

Notes: The table reports outstanding contracts booked in the United States at the end of March 1995. The figures represent notional amounts by maturity as a percentage of total notional amounts in each product.

The price sensitivity approximations in Table A2 do not reflect the nonlinearity of the price sensitivity of options and structured products (for options, these estimates are overestimates). However, as Table 1 shows, options account for only a small proportion of outstanding contracts. With regard to leveraged derivatives, the small ratio of market value to notional amount in Box 1 suggests that these products are not consequential for the markets as a whole.

Note that the estimate of the price sensitivity of outstanding interest rate derivatives is of a comparable order of magnitude to the market value of those contracts, which amounted to $646 billion (Bank for International Settlements 1995c). This figure differs slightly (by 1 percent) from the total for the interest rate products in Table 1 because of "other products" not broken out in Table 1. While this amount is not a measure of the potential change in value of over-the-counter derivatives contracts relative to a 1-percentage-point change in interest rates, the figure is of a comparable order of magnitude because of the path of interest rates prior to the survey. In the twelve to fifteen months before the survey, long-term interest rates rose by approximately 2 percentage points in four out of five major currencies (Bank for International Settlements 1995b).

The price sensitivity estimate for security market debt assumes that the average price sensitivity of outstanding debt is between 4 and 6 percent for each 1-percentage-point change in interest rates. This estimate is based on a maturity distribution of security market debt in Bank for International Settlements (1995b).

Table A2
APPROXIMATE PRICE SENSITIVITY
Billions of U.S. Dollars

	Global Total of Over-the-Counter Interest Rate Derivatives	Global Securities Market Debt
Notional amount	26,645	
Principal amount		24,428
Change in value relative to a 1-percentage-point change in interest rates:		
Small price sensitivity assumption	530	980
Large price sensitivity assumption	800	1,460

this amount is roughly $600 billion. The figure of $1.3 trillion, derived from the data in Table 3, is the sum of the $894 billion value of interdealer trades and roughly half of the $848 billion value of customer trades. The sum incorporates half of the gross value of customer trades because these trades are about evenly split between contracts with positive and negative values from the dealers' perspective.

All Credit Exposures in the Markets

The total or gross market value of contracts with customers amounts to $848 billion (Table 3). Approximately half this figure is customers' credit exposure to dealers; the remainder is the dealers' credit exposure to customers, which is already included in the $600 billion of dealers' credit exposures. The sum of customers' credit exposure (half of $848 billion) and the dealers' credit exposure ($600 billion) equals approximately $1 trillion. This calculation gives an upper bound on credit exposures because the aggregation ignores collateral posted by dealers that would reduce customers' credit exposure to them.

To put the estimate of over-the-counter derivatives credit exposures in perspective, the outstanding amount of gross international bank loans was $8.3 trillion, while outstanding net international bank loans amounted to $4.2 trillion at year-end 1994 (Bank for International Settlements 1995b). In addition, the world's seventy-five largest banks—from whose ranks the banks in the survey were drawn—had $700 billion of capital ("*The Banker* Top 1000" 1995).[13] In contrast, our estimate of dealers' over-the-counter derivatives credit exposures amounted to only $600 billion, and customers' credit exposures were another $400 billion.

Table 3
MARKET VALUE OF DEALERS' OUTSTANDING CONTRACTS BY COUNTERPARTY TYPE
Billions of U.S. Dollars as of End of March 1995

Contract	Global Totals	Contracts Booked in the United States
Interdealer	894	149
Customer	848	180

Sources: Global totals were compiled by the Bank for International Settlements (1995c). Figures for contracts booked in the United States were compiled by the Federal Reserve Bank of New York (1995).

While the estimated credit exposure in the derivatives markets is not excessively large compared with the total amount of other credit exposures, it is not insignificant. Clearly, practices that further reduce credit and settlement risk in the over-the-counter derivatives markets would contribute to the markets' resiliency.[14]

DERIVATIVES DEALERS' INTERMEDIATION OF PRICE RISKS

The survey data also shed light on derivatives dealers' intermediation of price risks. At the center of the financial derivatives markets are derivatives dealers who trade exposures to price risks among themselves and with customers. When a price risk exposure is exchanged between a dealer and customer through a derivatives contract, the contract transforms the customer's exposure and leaves the dealer with the mirror image of the change in the customer's exposure. For example, a customer with floating-rate debt can convert its obligations to fixed-rate payments with an interest rate swap in which the dealer receives a fixed interest rate and pays a floating interest rate to the customer. In this case, the customer's transformation of its floating-rate debt exposure to a fixed-rate obligation has left the dealer with an exposure to floating interest rates.

Dealers usually offer to assume the price risk exposures customers wish to trade regardless of whether they can immediately offset the exposure through a trade with another customer. While dealers' willingness to absorb the credit and price risk generated by such market making has facilitated the markets' growth and liquidity, the exposures traded in the markets do not disappear. Hence, the survey attempted to answer the question, Are the price risks traded by the users of derivatives concentrated among derivatives dealers?

The survey findings indicated that for over-the-counter derivatives contracts booked in the United States, dealers in the aggregate had a small net market value exposure to end-users (Table 4).[15] As a percentage of the total market value of customer trades, that exposure was only 3 percent for currency products and 4 percent for interest rate products.

The small net market value of the aggregate dealer exposure suggests that end-users were well represented on both sides of the market. Because U.S. dollar swap rates (three- and five-year rates) at the time of the survey were near their highest levels since 1991, the most likely explanation for the small net market value is that dealers as a group had roughly balanced long and short positions with respect to end-users. Thus, dealers in the aggregate were intermediaries between customers in the trading of price risks. Exposures from some end-users were ultimately passed through the market to other end-users, who demanded products with offsetting exposures. Therefore, at the time of the survey, dealers in the aggregate were taking relatively small price risk exposures to meet customer demand for over-the-counter derivatives.

The survey findings indicated that for over-the-counter derivatives contracts booked in the United States, dealers in the aggregate had a small net market value exposure to end-users.

However, this interpretation of dealers' intermediation of price risks should be considered with some caution. The conclusion applies only to dealers as a group, but not necessarily to an individual dealer. In addition, the market values were determined by the interest rate and exchange rate history at the time of the survey, and different paths of underlying asset prices might lead to different results. Moreover, market value does not reveal potential future exposure or price sensitivity. Definitive answers to questions about intermediation of price risks would require data on price sensitivity of exposures by counterparty class. Finally, the conclusions apply to the market for a risk factor as a whole (such as interest rate risk) and not necessarily to a particular product.

We have established that the trading in exposures to price risk between end-users and dealers in the over-the-counter derivatives markets has not led to a concentration of price risk among dealers in the aggregate. Still, for some dealers the net market value as a percentage of total market value of their contracts was significantly higher than for the market as a whole.[16] However, whether the higher net market value ratio of an individual firm's position represents significant price risk for that firm cannot be determined without taking into account the firm's offsetting cash market and exchange-traded futures positions. In any event, the net positive market values of some dealers were balanced by the net negative market values of others, resulting in the small net market value of the aggregate dealers' position.

The small net market value of the aggregate dealers' position suggests that demand for products that transfer price risk is sufficiently diverse to allow a dealer uncomfortable with its price risk exposure to trade that exposure back into the market. A dealer's exposure to price risk, therefore, would appear to be driven by its appetite for risk rather than by customer demand alone.

The survey data show that a large proportion of over-the-counter derivatives transactions (about 50 percent) are trades between dealers, suggesting that the intermediation of price risk in the derivatives markets occurs on two levels (Table 2).[17] First, a dealer serves as intermediary between its customers and, to the degree permitted by the

Table 4
NET MARKET VALUE STATISTICS OF DERIVATIVES CONTRACTS BOOKED IN THE UNITED STATES
As of End of March 1995

Contract	Total Market Value (Billions of U.S. Dollars)	Net Market Value as a Percentage of Total
PANEL A: DEALERS' OVER-THE-COUNTER DERIVATIVES CONTRACTS WITH CUSTOMERS		
Foreign exchange products	86	-2.7
Interest rate products	80	4.3
PANEL B: DEALERS' OVER-THE-COUNTER DERIVATIVES CONTRACTS WITH DEALERS OUTSIDE THE UNITED STATES		
Foreign exchange products	47	0.9
Interest rate products	48	-5.9
PANEL C: DEALERS' OVER-THE-COUNTER DERIVATIVES CONTRACTS WITH NONREPORTERS IN THE UNITED STATES[a]		
Foreign exchange products	133	-1.3
Interest rate products	128	0.5

[a] Nonreporters in the United States include dealers reporting in a foreign market center, financial customers, and nonfinancial customers.

balance in its customers' demands, the dealer offsets exposures to price risk taken from some customers with exposures from trades with other customers. However, the large proportion of interdealer trades implies that an individual dealer cannot perfectly offset its exposures from its customers internally. To manage its resulting residual exposure to price risk, the dealer may pass its net exposure from customer trades into the interdealer market. The exposure is then redistributed among dealers according to their risk appetites.

A feature of the survey data that supports this interpretation is the offsetting market values of trades with dealers located outside the United States and trades with customers (Table 4). In the case of interest rate products booked in the United States, transactions with customers had a positive net market value while transactions with dealers outside the United States had a negative net market value. This relationship suggests that derivatives dealers in the United States were transferring the price risk acquired from their customer business into the global interdealer market. The same relationship was also observed in the case of foreign exchange derivatives booked in the United States (except that the signs of the net market values were reversed).

The survey data suggest that price risk intermediation in these markets could be resilient under stress. The small net market value of the aggregate dealers' exposure implies that market making in large part takes the form of price risk intermediation between end-users, rather than between end-users and dealers' cash market positions. Thus, market making is less likely to be vulnerable to the fragility of leveraged cash market hedging of large derivatives positions. Given the size of the markets, if dealers were to hedge the bulk of their derivatives in the cash markets, that hedging would take the form of large-scale use of leveraged cash market positions. These leveraged cash market hedging positions, however, could be vulnerable to disruptions caused by the scarcity of securities in repurchase markets or the difficulty of rolling over cash market positions. Consequently, the two-sided nature of end-user demands in the derivatives markets may make the markets more resilient because the use of leveraged cash market hedging positions would be limited to the hedging of net exposures. (Although derivatives dealers do use leveraged cash market positions to hedge derivatives positions, their use appears to be limited to the hedging of residual, or net, exposures of their portfolios.)

Over-the-Counter Derivatives Markets and Exchange-Traded Markets

The central bank survey also provides some information about the relationship between the over-the-counter derivatives markets and the exchange-traded derivatives markets. Campbell and Kracaw (1991) argued that dealers that intermediate price risks in large swaps portfolios will create economies of scale that make it more efficient for end-users to trade with dealers than to trade directly in exchange-traded futures markets. For example, a dealer that benefits from offsetting exposures in its swaps portfolio will need to hedge only the portfolio's residual exposure. The dealer's transaction costs from hedging this residual exposure in the futures markets would be much smaller than the total transaction costs expended by the dealer's customers in the aggregate had they separately traded in the futures markets.

An implication of this argument is that dealers will have offsetting over-the-counter derivatives positions and exchange-traded positions. For dealers in the aggregate, this relationship is apparent in the survey results. In other words, over-the-counter derivatives dealers in the aggregate appear to use futures markets to hedge their net over-the-counter exposures (cross-market hedging).

Interest Rate Contracts

For interest rate contracts booked in the United States, dealers' over-the-counter derivatives positions in the aggregate had net positive market values (both for U.S. dollar interest rate products and for the sum across all interest rate products). In addition, at the time of the survey, rates on U.S. dollar interest rate swaps were near their highest levels since 1991. These two observations suggest that dealers' over-the-counter derivatives positions benefited from the rise in interest rates.[18] In the futures markets, however, dealers in the aggregate were net buyers of U.S.

dollar interest rate futures, which decrease in value as interest rates rise. These apparently offsetting exposures are consistent with the cross-market hedging hypothesis.

Equity Contracts

For equity contracts booked in the United States, dealers in the aggregate predominantly had U.S. equity market exposure, and the net market value of their over-the-counter equity derivatives was positive. Hence, given that the U.S. stock market at the time of the survey was at its highest level in the two years up to that point, dealers in the aggregate most likely had net long over-the-counter exposures to the U.S. stock market. Dealers' net position in U.S. equity futures, however, was net short. This relationship is also consistent with the cross-market hedging hypothesis.

However, the survey results supporting the hypothesis are not strong. For example, the aggregate of dealers' over-the-counter positions is well balanced: the difference between the positive and negative market values is so small that reporting errors could reverse the sign of the net value. In addition, reliable inferences about dealers' hedging activity would require data on their cash market exposures, which were not addressed by the survey. Moreover, the futures market data in the survey are highly aggregated. Finally, the results apply to the market as a whole and not necessarily to individual firms. The cross-market hedging relationship appears in interest rate and equity products but is not apparent in currency products. This absence is probably due to the large daily turnover volume and liquidity of the foreign exchange spot and forward markets, which make it unnecessary to hedge residual currency exposures with exchange-traded products.

The survey suggests that the over-the-counter derivatives markets and the exchange-traded futures markets might not be entirely in competition.

The survey suggests that the over-the-counter derivatives markets and the exchange-traded futures markets might not be entirely in competition. The products of the two markets are also complementary to the extent that over-the-counter derivatives activity generates hedging demand on futures markets. The flexibility of over-the-counter contracts allows dealers to structure a contract's cash flows and maturities to meet the specific trading or hedging demands of a customer at relatively low cost, thus generating the trading of exposures to price risk on a scale that would not otherwise occur. This larger trading volume in the over-the-counter markets thus creates demand for standardized and liquid exchange-traded derivatives as dealers hedge their net exposures from meeting customer demand in the over-the-counter markets.

Policy Issues

The large scale of derivatives activity reported in the central bank survey and the role of dealers in intermediating price risks support the hypothesis that the derivatives markets are important price risk intermediation vehicles that contribute to a more efficient allocation of risks in the economy. However, despite this reassuring market-level interpretation, the situation of any single market participant could be quite different. Thus, although the markets appear to function well by some criteria, initiatives that could improve their ability to operate under stressful circumstances would be appropriate.

Areas where improvements have been and will continue to be useful include firms' internal risk management, accounting and disclosure, and market practices affecting credit and settlement risks. Improved market practices in these areas could address problems introduced by financial derivatives without depriving market participants of flexibility in managing their risks. By contrast, increased regulation of derivatives markets and products might undercut their ability to reallocate or disperse financial risks in the economy, especially when the absence of regulation in the over-the-counter markets has enabled them to intermediate price risks in innovative ways.

To be sure, the ability of derivatives instruments to transform risk profiles can be misused. Some market participants have used derivatives to evade investment guidelines or conceal risks from their principals, especially when risk management, reporting, and accounting practices are articulated in terms of product definitions and balance sheet concepts instead of in terms of risk exposures. Some market participants have also used the instruments to arbitrage inconsistencies in the accounting, tax, and regulatory treatment of different types of cash flows and risks.

At the same time, however, many other market participants have used the instruments effectively for hedging purposes. For those who have benefited from the appropriate use of derivatives, regulatory restrictions could be costly and counterproductive. Moreover, the central role of risk management failures in the occasional instances of dramatic losses suffered by market participants (spanning both cash market and derivatives products) suggests that efforts to strengthen firms' risk management practices would be more effective in reducing risk than regulatory prohibitions on the use of particular products.[19]

Practices that reduce credit risks will also improve the markets' ability to intermediate price risks, especially during periods of stress, because market liquidity would not be impaired by traders' reluctance to enter into new transactions for fear of settlement risk. In this regard, improvements in disclosure and accounting practices would be helpful.

The large-scale use of derivatives indicated by the survey reveals that the exposure to underlying price risks of a large set of firms and institutions cannot be known without also taking into account exposures embodied in their derivatives contracts. By the same token, however, focusing on derivatives apart from cash market exposures would also be misleading. Consequently, disclosures by firms about their exposure to financial risks should be articulated in terms of underlying risks instead of according to traditional product definitions and balance sheet concepts, which may have little relationship to risk.[20]

Other credit-risk-reduction techniques could include the use of adequate capital ratios, collateral, and robust netting arrangements. Practices that clarify the relationship between dealers and customers and make the risk and return of a derivatives contract more transparent to customers would also enhance the markets' ability to operate under stressful circumstances.

Conclusions

The large volume of activity apparent in the central bank survey results underscores the over-the-counter derivatives markets' importance and resiliency. The year leading up to the survey was a period of stress, with numerous anecdotal reports of market participants' reassessment of their derivatives usage and a scaling back of activity in highly structured products. Despite the concerns about these products, the over-the-counter derivatives markets are now a permanent feature of the global financial system. The markets have withstood the test of several interest rate cycles and episodes of large changes in exchange rates. Market volumes have remained high regardless of particular market circumstances, specialized product offerings, or other transitory factors.

Another indication of the markets' resiliency is the role of dealers in the aggregate as intermediaries. The survey data suggest that exposures to price risk from some end-users are ultimately passed through the markets to other end-users. The markets bring together diverse end-users with offsetting demands; therefore, dealers in the aggregate assume only small exposures to price risks in meeting customer demands.

Thus, dealers' price risk intermediation takes the form of intermediation between end-users themselves, rather than between end-users and dealers' cash market positions. This market structure suggests that the overall effect of the derivatives markets may be to modify and redistribute exposures to price risks in the financial system, rather than to leverage those exposures.

In addition, the survey data indicate that price shocks in the over-the-counter derivatives markets (even on a gross basis) will be smaller than price shocks in the cash markets. At the level of an individual market participant, however, the change in value of a derivatives contract could be relatively large because of the implicit leverage of derivatives contracts. The ability of derivatives contracts to leverage exposures and transform exposures from one risk category to another underscores the importance of market participants' adoption of risk management and accounting and disclosure practices that can deal with such issues.

The analysis of the market value data from the survey provides only rough answers to questions about the role of derivatives in the intermediation of price risks in the economy. More precise answers require data on the price sensitivity of dealer positions by counterparty class. However, the production of such data in ways that would allow aggregation across dealers to produce market statistics may be too costly an exercise. Such statistics will not be feasible until dealers' internal risk management models are flexible enough to analyze exposures by type of counterparty.

Finally, we have not addressed the question of the ultimate impact of derivatives on the financial system. The large volume of activity apparent in the survey shows that a significant amount of price risk is being traded in the derivatives markets. But is this activity leading to a more efficient distribution of risks in the financial system and thereby contributing to the resiliency of financial markets? The survey data showing that dealers in the aggregate are intermediaries and that the market is two-sided (so that price risks are dispersed, rather than concentrated) lend support to an affirmative answer.

While inferences drawn from the survey provide some reassurance about the impact of derivatives on the financial system, other issues relating to the effects of the derivatives markets were not addressed. For example, the survey shed no light on the role of positive feedback in asset prices arising from dynamic risk management strategies (such as dynamic hedging and stop-loss limits). An issue here is whether a risk limit or stop-loss limit that is risk-reducing at the level of an individual firm has different general equilibrium properties for the markets as a whole. This and other issues regarding the general equilibrium effects of financial derivatives remain to be explored.

ENDNOTES

1. For additional discussion, see Chapter 2 of Bank for International Settlements (1995a) and Remolona (1992-93).

2. Their efficiency is due to their leveraged nature. In particular, the price risk exposure of a derivatives contract can be replicated by a position in a cash market asset (or assets) financed by a loan. Hence, the user of a derivatives contract can acquire exposure to underlying assets without investment of principal in those assets.

3. The U.S. part of the survey was conducted by the Federal Reserve. For additional details and results, see Bank for International Settlements (1995c) and Federal Reserve Bank of New York (1995).

4. The global figures in this section are from Bank for International Settlements (1995c).

5. The market size figures in the survey are larger than some other estimates. One reason for the difference is the comprehensive coverage of the survey. Another is the survey's inclusion of internal arm's-length transactions between affiliates, which are internal trades between affiliates that would otherwise have been made with an unrelated party. To the extent that some reporters experienced difficulty separating arm's-length interaffiliate trades from other trades with affiliates, the market totals in the survey could be larger than they should have been. Despite the differences among the various estimates of the markets' size, all estimates point to large markets.

6. For instance, some market participants will have contracts that offset their exposures in other contracts. Consequently, the total amount of all contracts, as in Table 1, will overstate the actual exposures in the markets. In the over-the-counter markets, a trader's offsetting contracts are not always extinguished, especially when each has been transacted with different counterparties. By contrast, for products traded on a futures exchange, two offsetting contracts of a trader are extinguished.

7. These figures are from Table 1 and Bank for International Settlements (1995b).

8. Credit market debt includes both securities market debt and bank loans. These figures are from Table 1 and Board of Governors of the Federal Reserve System (1995).

9. The replacement value of contracts with customers as reported by dealers is less than the market value of those trades as reported here because dealers typically focus on their own credit exposure (credit extended to customers). From a market perspective, however, the replacement value from the customer's view is also relevant. Consequently, the market value aggregation in the survey (Box 2), which also includes contracts that have positive value to customers, will be larger than the replacement value as reported by dealers.

10. The market value of outstanding over-the-counter derivatives contracts in large part reflects the change in the value of the contracts caused by changes in underlying risk factors, principally interest rates and exchange rates, since the contracts were originated. This relationship applies only "in large part" for two reasons. First, as is apparent from Table 1, equity and commodity derivatives represent only a small proportion of the over-the-counter derivatives markets. Second, some products, such as options, have an initial market value at origination, and the current market value would reflect but not equal the change in value since origination. Nevertheless, options represent only a small share of outstanding contracts.

11. The estimate of credit exposure here accounts for only the current credit exposure or replacement value of derivatives contracts (the amount at risk if default occurred today). The credit exposure in a derivatives contract also includes potential credit exposure, which is a measure of the potential increase in the current credit exposure caused by changes in the underlying asset price or risk factor over the remaining life of the contract.

12. See "Banks Are Succeeding" (1995) and year-end 1994 annual reports of derivatives dealers.

13. In addition to commercial banks, some securities firms were included in the survey.

14. While collateral can reduce credit exposures, the collateralization of all derivatives exposures could generate large demands for securities and funds for use as collateral. To the extent that some of the liquidity supporting collateral might be supplied by bank credit lines, some credit exposure would merely be shifted from one place to another.

15. Net market value of outstanding contracts is defined as the gross positive market value minus the gross negative market value of contracts, from the perspective of reporting dealers.

16. The variability of exposures at the level of individual firms is apparent in the dispersion of firms' net market value ratios. These ratios are the net market value of a firm's contracts as a proportion of the value of either the positive or the negative market value contracts, whichever is smaller in absolute value. For over-the-counter interest rate contracts booked in the United States, one-quarter of the reporting firms had a net market value ratio of 4 percent or less; at the other extreme, one-quarter of the firms had a net market value ratio of 50 percent or higher. The degree of balance in a firm's position was related to its size. For the

ENDNOTES (*Continued*)

Note 16 continued
25 percent of reporting firms with the largest books, the net market value ratio was 15 percent on average. However, for the 25 percent of reporting firms with the smallest books, the net market value ratio averaged 42 percent (after dismissing one outlier).

17. This proportion, however, seems large even after consideration of intermediation issues. Other explanations for the large interdealer share would include the dealers' own use of derivatives for hedging in their nondealer or traditional banking activities and proprietary trading.

18. This line of argument assumes that maturity differences between long and short positions were not significant. This assumption is consistent with the maturity data that were available in the survey.

19. See, for example, Group of Thirty (1993), Board of Governors of the Federal Reserve System (1993), and Basle Committee on Banking Supervision (1994).

20. See, for example, Bank for International Settlements (1994) and Federal Reserve Bank of New York (1994).

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Risk Management by Structured Derivative Product Companies

Eli M. Remolona, William Bassett, and In Sun Geoum

The phenomenal growth of the derivatives markets in the last decade and the spate of huge losses there have highlighted the importance of risk management.[1] To respond to customers' concerns about the credit risk of intermediaries in these markets, some U.S. securities firms and non-U.S. banks have created subsidiary derivative product companies (DPCs) that are specially structured to function as intermediaries with triple-A credit ratings. These "structured" DPCs obtain these ratings because of the way in which they manage risk.

The structured DPCs have developed approaches to managing two basic types of risk—market risk and credit risk—in an effort to minimize capital while maintaining triple-A ratings. In particular, the DPCs hedge market risk as fully as they can, typically by means of mirror transactions with their parents. To manage credit risk, DPCs use quantitative models so that they can measure credit exposures precisely and allocate capital to cover just the risks measured in a given day. In addition, the DPCs have a contingency mechanism in place that would limit the risk that would arise should their regular risk management structure break down.

As subsidiaries of securities or banking firms, structured DPCs are organized to secure credit ratings that substantially exceed those of their parents. The nine such DPCs currently operating around the world are rated Aaa by Moody's Investors Service and AAA or AAAt by Standard and Poor's, the highest ratings of these agencies, despite parents with no rating above single-A (Table 1). The first such DPCs were designed to achieve triple-A ratings because it was thought that many customers would insist on dealing only with the most highly rated intermediaries.[2] In 1995, however, four years after they first emerged, the structured DPCs still accounted for a relatively small share of markets in which the major intermediaries generally had substantially lower credit ratings. Are the DPCs getting off to a slow start or are they structurally inhibited from more significant market expansion?

In this article, we explore the DPCs' approaches to risk management and the extent to which these approaches provide competitive advantage. We begin by characterizing the major intermediaries in the derivatives markets and describing how they manage risk. We then discuss the emergence of structured DPCs and their approaches to managing risk, and explain how the approaches minimize the capital required for triple-A ratings. Finally, we discuss the possible reasons why, despite these ratings, DPCs have not succeeded in taking a larger share of the derivatives markets.

In 1995, four years after they first emerged, the structured DPCs still accounted for a relatively small share of markets in which the major intermediaries generally had substantially lower credit ratings.

Table 1
CREDIT RATINGS OF STRUCTURED DPCS AND THEIR PARENTS/SPONSORS

Structured DPC Name	Rating[a] (S&P/ Moody's)	Parent/Sponsor Name	1995 Rating (S&P/ Moody's)
Merrill Lynch Derivative Products (MLDP)	AAA/Aaa	Merrill Lynch	A+/A1
Salomon Swapco	AAAt/Aaa	Salomon Brothers	BBB+/Baa1
Paribas Derives Garantis (PDG)	AAAt/Aaa	Banque Paribas	A/A1
Westpac Derivative Products (WDP)	AAAt/Aaa	Westpac Banking	A+/A1
Morgan Stanley Derivative Products (MSDP)	AAAt/Aaa	Morgan Stanley	A+/A1
Lehman Brothers Financial Products (LBFP)	AAA/Aaa	Lehman Brothers	A/Baa1
Credit Lyonnais Derivatives Program (CLDP)	AAAt/Aaa	Credit Lyonnais	A-/A3
Tokai Derivative Products (TDP)	AAA/Aaa	Tokai Bank	A-/A2
Sumitomo Bank Capital Markets Derivative Products (SBCM DP)	AAA/Aaa	Sumitomo Bank	A+/A1

Sources: Moody's and Standard and Poor's.

[a] The suffix "t" in five of the Standard and Poor's ratings denotes a termination structure and emphasizes that counterparties to a terminating DPC face the risk that their contracts will not run to maturity. Moody's does not distinguish between the two structures.

THE MAJOR INTERMEDIARIES IN THE DERIVATIVES MARKETS

Over the past few years, six U.S. money-center commercial banks and two U.S. securities firms have been the dominant intermediaries in the over-the-counter markets for derivatives, with each having a derivatives book exceeding $1 trillion in notional value at year-end 1994 (Table 2). Together, the six banks accounted for a total of $13 trillion, or about one-third of the global over-the-counter derivatives markets, which total perhaps $40 trillion in notional value.[3] Even the smallest derivatives book held by these banks was sizable, approaching a notional value of $1.3 trillion at the end of 1994.[4] The two securities firms are also major players, having the fifth and seventh largest derivatives books in the markets when ranked with the banks.

CREDIT RATINGS

In a derivatives transaction, the intermediary's credit rating would, in principle, be more critical than the customer's credit rating because a credit-sensitive customer would deal with credit risk not so much by "managing" it as by simply choosing a creditworthy intermediary. When intermediaries manage credit risk, they rely on a large number of counterparties to pool risks so that statistical calculations can

Table 2
DERIVATIVES AND CREDIT RATINGS OF MAJOR U.S. COMMERCIAL BANKS AND SECURITIES FIRMS

Institution	Notional Value (Billions of Dollars)	Rating (S&P/Moody's)
Commercial banks		
Chemical Bank	3,178	A+/Aa3
Citibank	2,665	A+/A1
Morgan Guaranty	2,473	AAA/Aa1
Bankers Trust New York	2,026	A+/A1
BankAmerica	1,401	A/A2
Chase Manhattan Bank	1,306	A/A2
Total	13,049	
Securities firms		
Salomon Brothers	1,509	A-/A3
Merrill Lynch	1,300	A+/A1
Total	2,809	

Source: Annual reports for 1994.

provide reasonable estimates of actual losses. Few customers have the luxury of being able to pool risks; the best they can often do is choose an intermediary. The creditworthiness of that intermediary, in turn, depends on how well it manages risk.

Surprisingly, the banking and the securities firm intermediaries that dominate the derivatives markets do not seem to require triple-A credit ratings. In 1994, only one bank had a triple-A rating from one of the two major rating agencies; the rest, along with the securities firms, were grouped in single-A territory.[5] In fact, a triple-A rating may not be as important to derivatives customers as one might think.

RISK MANAGEMENT BY THE MAJOR INTERMEDIARIES

The major derivatives intermediaries actively manage two basic types of risk: market risk and credit risk.[6] As contracts that derive their values from the market prices of underlying assets, derivatives are volatile instruments that can change in price very rapidly. Market risk is the exposure to changes in derivatives prices, and indeed derivatives tend to be contracts that concentrate such risk. Market risk, in turn, gives rise to credit risk, which is the risk that a counterparty on the losing side of a contract will default on its obligation (Box 1 uses swaps to illustrate market and credit risk).[7] An important distinction between these risks is that market risk can often be hedged, while credit risk cannot so readily be hedged.[8]

In general, derivatives intermediaries manage their risks to strike a balance between risk and return.[9] Their chosen trade-off typically results in some exposure to market risk as well as to credit risk. They routinely try to hedge a large part of their market risk but rarely can they run a perfectly hedged derivatives book in the normal course of business. The major intermediaries have recently developed quantitative models to measure unhedged market risk, summarizing it in a measure called value at risk. Intermediaries mitigate credit risk largely by taking advantage of netting agreements and by holding collateral.[10] Even these efforts, however, still leave intermediaries with a significant amount of credit risk to be measured and controlled.

Market Risk

To measure market risk, the banks with the largest derivatives books have invariably moved from traditional approaches based largely on "risk buckets" to proprietary quantitative models that track not only individual market movements but also comovements among markets. Traditional approaches separated investments by type into various buckets, such as residential mortgages, government securities, and commercial loans, each of which would be assigned a risk weight. By turning to a model-based approach, the banks can now consolidate their exposures into a value-at-risk summary measure, which specifies the potential loss from adverse market movements over a specified time horizon and for a given confidence interval.[11]

The banks' measures of value at risk reveal significant exposures to market risk in the normal course of operations. The precise concept of value at risk used by different banks varies with the chosen confidence interval and the way volatilities and correlations are estimated (Table 3). The confidence intervals range from 95 percent to 99 percent. Because the internal models differ, the value-at-risk numbers are not precisely comparable, even given the same confidence intervals. Nonetheless, the reported numbers show significant market risk exposure, with likely average daily losses of up to \$8 million (with a 5.0 percent probability of greater losses) for one bank and daily losses of up to \$65 million (with a 2.5 percent probability of greater losses) for another.

In general, derivatives intermediaries manage their risks to strike a balance between risk and return. Their chosen trade-off typically results in some exposure to market risk as well as to credit risk.

Credit Risk

Since credit risk is inherently difficult to hedge, much of the effort to manage it involves measuring it. To measure credit risk, intermediaries estimate both current and potential credit exposures. Current exposures are the market values or replacement costs of contracts with positive market value to the intermediary at the time. These are the contracts for which counterparties would currently have obligations to the intermediary and on which they could default. Credit exposures depend significantly on the extent of netting agreements and the amounts of collateral held. One major intermediary, for example, reported current gross exposures of $26.7 billion at the end of 1994.[12] Netting agreements reduced this exposure to $12.9 billion, and collateral held

BOX 1: THE MARKET RISK AND CREDIT RISK OF SWAPS

Swaps, which are among the most common over-the-counter derivatives contracts, provide a simple illustration of market risk and credit risk. Swaps are contracts that exchange one type of cash flow for another. For example, interest rate swaps exchange flows based on fixed interest rates for flows based on floating interest rates. The typical swap has zero value at origination, but market movements will in short order lead to gains for one of the counterparties and losses for the other. The counterparty with losses will have suffered from market risk, while the one with gains will have benefited. At the same time, however, the one with gains will be exposed to credit risk, the possibility that the other counterparty could default on its obligation. Because market values can change so quickly, this potential credit exposure may be quite large, and quantifying it is important.

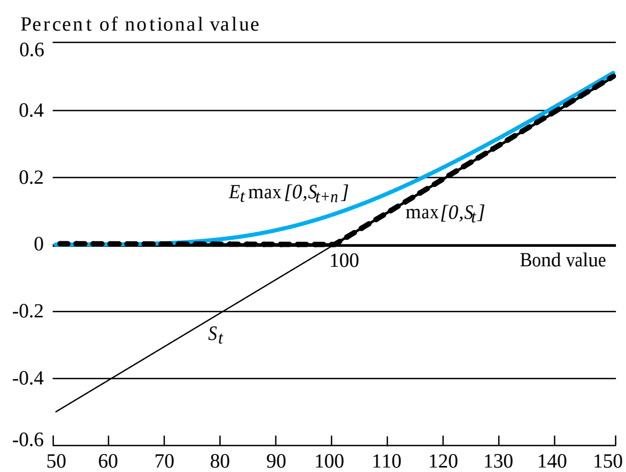
The size of the potential credit exposure of a derivatives contract will depend on the volatility of the underlying asset and on the time horizon being considered. The expected exposure of a swap at time t looking n periods ahead can be denoted by $c_t(n)$ and written as

$$c_t(n) = E_t \max [0, s_{t+n}],$$

where s_{t+n} is the uncertain value of the swap n periods in the future.[1] The value of the swap may turn negative in the future, but for credit exposure we care only about the positive outcomes, that is, about $\max [0, s_{t+n}]$.

The chart helps characterize the expected credit exposure for a plain vanilla interest rate swap from the point of view of the fixed-rate receiver. For market valuation purposes, the swap is equivalent to a long position in a fixed-rate bond and a short position in a floating-rate note that is assumed to trade at par at inception and reset dates (Litzenberger 1992). Hence, the swap value s_t is a linear function of the underlying asset, the fixed-rate bond, and is shown as the straight line crossing the horizontal axis at the bond's par value of 100. At initiation, the swap is typically priced to be consistent with the bond starting at its par value, so that $s_t = 0$. As time passes, interest rate movements will change the underlying bond's value, and the current swap exposure will be given by $\max [0, st]$, which is shown by the broken line that turns positive for bond values beyond 100. For n periods ahead, the expectation $E_t \max [0, s_{t+n}]$ behaves like the value of a call option and is depicted by the curve. The potential exposure is then $E_t \max [0, s_{t+n}]$ minus $\max [0, s_t]$, a difference that behaves like the time value of swaptions, which are call options on swaps.[2]

Swap Exposures



Source: Authors' calculations.

[1] See Smith, Smithson, and Wilford (1990) and Hull (1993) for related discussions.

[2] Simons (1993), Duffie (1994), and Hendricks (1994) explain how such exposure profiles may be estimated.

Table 3
U.S. COMMERCIAL BANKS' DAILY VALUES AT RISK

Bank	Value-at-Risk Concept	Confidence Interval (Percent)	Average Daily Value at Risk in 1994 (Millions of Dollars)
Chemical Bank	Value at risk	97.5	12
Citibank	Earnings at risk	97.5	65
Morgan Guaranty	Daily earnings at risk	95.0	15
Bankers Trust New York	Daily price volatility	99.0	35
BankAmerica	Earnings at risk	95.0	8
Chase Manhattan Bank	Earnings at risk	97.5	17

Source: Annual reports for 1994.

reduced it further, to $10.9 billion. Such current net exposure represented 0.5 percent of the total notional value of the intermediary's derivatives.

Potential exposures represent the values over time of contracts with possible future positive market values and thus are potentially subject to default. These potential exposures are especially important for derivatives because of the contracts' sensitivity to market movements (Box 2). To measure potential exposures, the major intermediaries often use their quantitative models to take account of market movements over time.[13] By combining current and potential exposures with measures of counterparty creditworthiness, the intermediaries can estimate credit risk.

Clearly, the creditworthiness of an intermediary depends on its risk management, specifically on how much market risk and credit risk it chooses to bear relative to the capital it allocates to absorb these risks. In balancing risk against return, major intermediaries have chosen a certain degree of risk exposure. As a result of such exposure, the assessment by credit rating agencies has typically not led to triple-A ratings.

THE EMERGENCE OF STRUCTURED DPCS

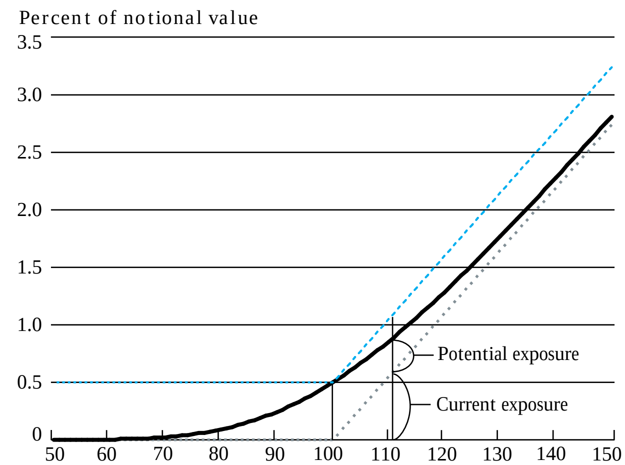
The perceived importance of an intermediary's creditworthiness led to the creation of the first structured DPCs. The bankruptcy in February 1990 of Drexel Burnham Lambert, a securities firm with a sizable derivatives book, made

BOX 2: POTENTIAL CREDIT EXPOSURE FOR AN INTEREST RATE SWAP

The advantage a quantitative model can bring in the case of an interest rate swap with more than a year to maturity is demonstrated in the chart. At origination, the swap would present a current exposure of zero and a potential exposure of 0.5 percent of the notional value, as indicated by the curve. The curve's position is such that for a newly initiated swap the potential exposure would correspond to the existing Basle capital standards for credit risk. The rest of the curve is drawn to represent the way a model would measure exposure.

If interest rates fall, the swap will go into-the-money for the fixed-rate receiver. The chart shows one such point, indicating the amounts of current and potential exposures. The amount of potential exposure at this point will be significantly less than it was when the current exposure was zero or when the swap was at-the-money. In general, potential exposure will decline as the swap moves away from its initial value of zero. By contrast, the traditional buckets approach will set potential exposure at a fixed fraction of notional value, regardless of the swap's current value.

Exposures on a Long-Maturity Interest Rate Swap



Source: Authors' calculations.

many derivatives customers suddenly aware of very real credit risk (Chesler-Marsh 1990).[14] Some observers predicted "credit gridlock," whereby most derivatives customers would refuse to deal with intermediaries other than those with the highest credit ratings (Chew 1994). Merrill Lynch responded to such perceived customer concerns by organizing the first structured DPC in 1991, followed by Salomon in 1993.

The structured DPCs set themselves apart from nonstructured DPCs by using a special operating structure to gain triple-A ratings. By the time Merrill Lynch and Salomon created their subsidiaries, a variety of highly rated, nonstructured DPCs had already been in operation, but they had received their credit ratings by conventional means. For example, the first group of DPCs in Table 4 obtained their credit ratings primarily by virtue of their parents' ratings. The second group of asset-backed DPCs received their triple-A ratings simply by maintaining enough capital to absorb nearly any risk they might take on.

Table 4
A VARIETY OF DPCS

Date	Name	DPC Rating[a] (S&P/Moody's)	Parent Rating (S&P/Moody's)
DPCS WITH HIGHLY RATED PARENTS			
5/85	Prudential Global Funding	AA-/	AA-/Aa3
1/87	AIG Financial Products	AAA/Aaa	AAA/Aaa
5/90	Mercadian Capital	A+/	A+/A3
	Mercadian Funding	NR/NR	NR/NR
7/90	Credit Suisse Financial Products	AAA/Aa2	AAA/Aa2
10/90	General Re Financial Products	AAA/Aaa	AAA/Aaa
12/93	Goldman Sachs Mitsui Marine Derivative Products	AAA/	AAA/Aaa[b]
ASSET-BACKED DPCS			
3/92	Goldman Sachs Financial Products International	AAA/Aaa	A+/A1
7/93	Goldman Sachs Financial Products U.S.	AAA/	A+/A1
STRUCTURED DPCS			
11/91	Merrill Lynch Derivative Products	AAA/Aaa	A+/A1
3/93	Salomon Swapco	AAAt/Aaa	BBB+/Baa1
11/93	Paribas Derives Garantis	AAAt/Aaa	A/A1
11/93	Westpac Derivative Products	AAAt/Aaa	A+/A1
1/94	Morgan Stanley Derivative Products	AAAt/Aaa	A+/A1
1/94	Lehman Brothers Financial Products	AAA/Aaa	A/Baa1
10/94	Credit Lyonnais Derivatives Program	AAAt/Aaa	A-/A3
2/95	Tokai Derivative Products	AAA/Aaa	A-/A2
4/95	Sumitomo Bank Capital Markets Derivative Products	AAA/Aaa	A+/A1

Sources: Moody's and Standard and Poor's.

[a] The suffix "t" in five of the Standard and Poor's ratings denotes a termination structure and emphasizes that counterparties to a terminating DPC face the risk that their contracts will not run to maturity. Moody's does not distinguish between the two structures.

[b] The Moody's Aaa rating applies to Mitsui.

The structured DPCs' unusual approach to risk management drew considerable notice in the derivatives markets and initially led observers to believe that they would take over much of the markets (Chew 1994; Locke 1995). However, such market success has not been evident. The first two structured DPCs, Merrill Lynch Derivative Products (MLDP) and Salomon Swapco, now boast the biggest derivatives books among the structured DPCs. However, they had derivatives books at the end of 1994 with notional values of only \$91 billion and \$67 billion, respectively, with each book representing less than 7 percent of their parents' derivatives books. To put this in greater perspective, the fifth largest derivatives book among the major bank intermediaries—with a notional value of \$1.4 trillion—was at least fourteen times bigger than either MLDP's or Swapco's books. We will attempt to explain why, despite their superior credit ratings, structured DPCs have so far remained relatively small players in the derivatives markets.

HOW STRUCTURED DPCS MANAGE RISK

The structured DPC approach to risk management can be characterized as an effort to minimize capital subject to the constraint of meeting credit rating agency standards for triple-A ratings. Such an approach has evolved to include the complete hedging of market risk in the normal course of operations, the precise measurement of credit exposures combined with a dynamic allocation of capital, and the creation of an automatic "workout" process to control risk in the event that the regular risk management process begins to fail. Hence, with each type of risk, the DPCs have found ways to reduce the need for capital. Credit rating agencies consider such risk management to be so viable that they assign structured DPCs their highest ratings, even while assigning the parents significantly lower ratings.[15]

Market Risk and Mirror Transactions

A common feature of structured DPCs is the elimination of market risk in the normal course of operations. Such a DPC would typically insulate itself from market risk by engaging in collateralized hedging transactions—known as mirror transactions—with its parent or an affiliated company. The DPC would undertake one such transaction each time it entered into a transaction with a customer. The parent is required to post collateral to cover the net market value of all the mirror transactions, enabling the DPC to avoid any credit risk from its parent.[16] Because the collateral is based on the net exposure to a single counterparty, the amount of collateral required would be much less than if the parent collateralized each transaction with customers.

We illustrate how a mirror transaction works in conjunction with a simple interest rate swap transaction, since the DPCs are primarily vehicles for such transactions (Exhibit 1). In this example, the DPC is the fixed-rate receiver and the customer is the floating-rate receiver. The DPC faces market risk through its exposure to a possible rise in interest rates and a resulting drop in the swap's market value. To hedge against this risk, the DPC simultaneously engages in a mirror transaction with its parent, in which it now becomes the floating-rate receiver and the parent becomes the fixed-rate receiver. In this way, the DPC is insulated from market risk.

The balance sheets of MLDP and Swapco also illustrate the role of mirror transactions (Table 5). The DPCs' main assets are their customer derivative receivables and affiliate derivative receivables, which are respectively the marked-to-market values of the customer transactions and mirror transactions that have positive values. The DPCs' main liabilities are their customer derivative payables and affiliate derivative payables, which are respectively the marked-to-market values of the customer and mirror transactions that have negative values. At the end of 1994, MLDP was "out-of-the-money" (that is, the derivatives had lost value) in its mirror transactions, which are thus reported as affiliate payables of $553 million. In this case, collateral was not required from the parent. MLDP's affiliate payables plus customer payables of $1,320 million exactly match its customer receivables of $1,873 million. In contrast, Swapco was "in-the-money" (the contracts had gained value) in its mirror transactions, which are reported as affiliate receivables of $154 million. In this case, the parent posted collateral amounting to $154 million. The amount of affiliate receivables added to the amount of customer receivables equals the amount of customer payables.

We should note that two of the structured DPCs, Paribas Derives Garantis and the Credit Lyonnais Derivatives Program, do not use mirror transactions because they deal with customers not as derivatives counterparties but as providers of a credit enhancement in the form of a third-party guarantee, with the parent or sponsor still serving as the derivatives intermediary.[17] In this way, the DPCs avoid market risk even as their guarantees expose them to credit risk.

Exhibit 1
Payment Flows for a Structured DPC
A Simple Interest Rate Swap Example

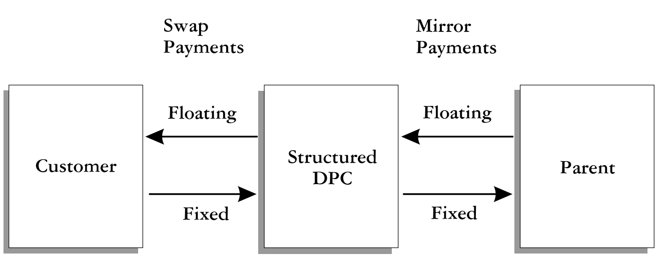


Table 5
Balance Sheets for MLDP and Swapco
Millions of Dollars at December 1994

Balance Sheet	MLDP	Swapco
Total notional book	90,691.0	66,844.0
Assets		
Cash and investments	362.1	432.0
Customer derivative receivables	1,873.3	874.6
Affiliate derivative receivables		154.4
Other assets	15.0	63.4
Total assets	2,250.4	1,524.3
Liabilities		
Customer derivative payables	1,320.3	1,029.0
Affiliate derivative payables	553.0	
Other liabilities	9.0	214.8
Total liabilities	1,882.3	1,243.8
Stockholder's equity	368.1	280.5

Source: Annual reports for 1994.

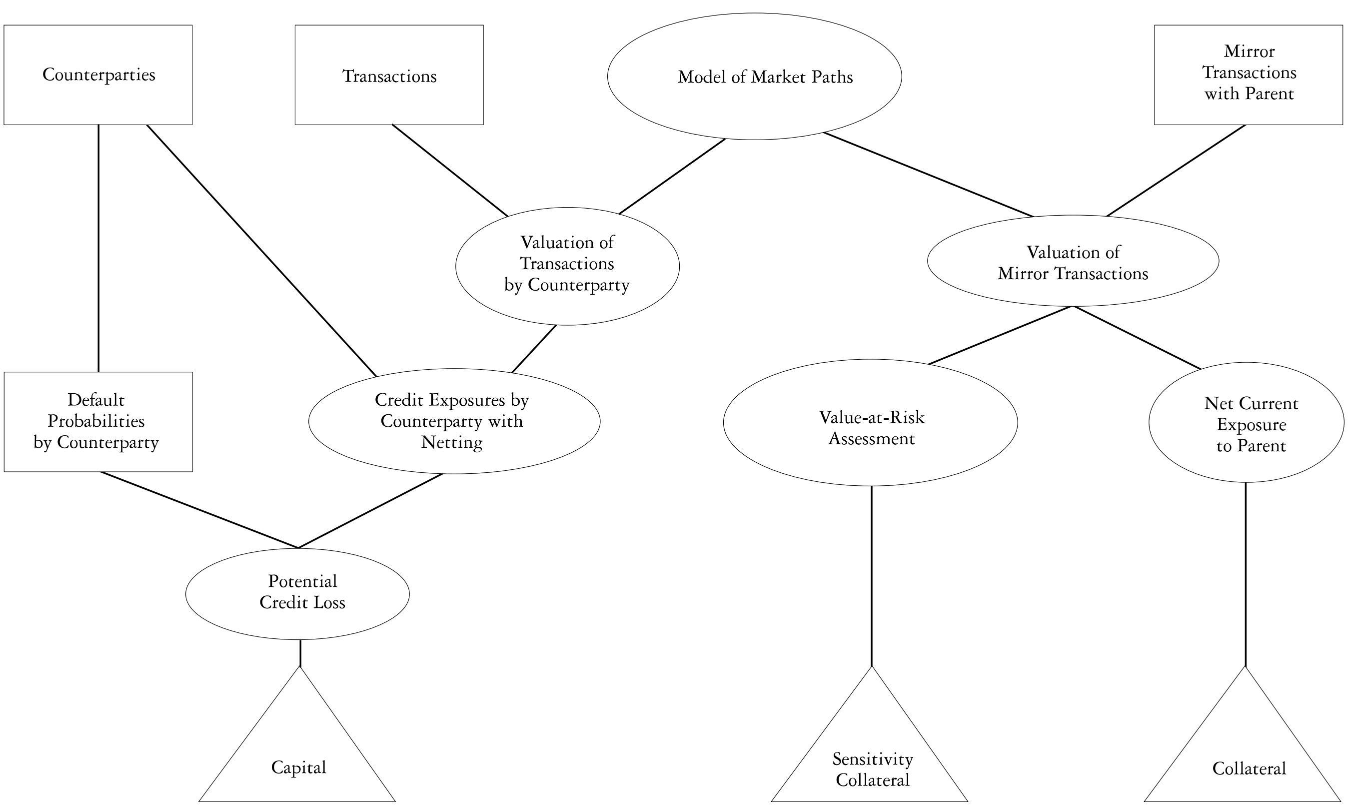
Credit Risk and Capital

With the mirror transactions providing insulation from market risk, structured DPCs are still exposed to the credit risk inherent in their transactions with customers. DPCs earmark capital to manage such credit risk. Again using Exhibit 1 as our example, we see that a decline in interest rates will present the DPC with a gain in the market value of its swap with the customer, but this customer may default on its obligation. The required amount of capital to manage this risk is the amount adequate for the DPC to absorb such a customer default and still meet its obligations to its other customers with a default probability or an expected loss rate consistent with what the rating agencies expect for triple-A borrowers. Since the DPCs rely on their internal models to determine the required capital, additional capital is set aside for model risk, or the risk that the models may not capture credit exposures adequately.[18]

Again, we should note that the two DPCs that rely on a guarantee structure, Paribas Derives Garantis and the Credit Lyonnais Derivatives Program, deal with credit risk in the same way the other structured DPCs do, using internal models to measure potential exposures and maintaining sufficient capital to absorb credit losses consistent with their triple-A ratings. One advantage of the guarantee structure is that insurance coverage for individual customers may be explicitly specified in terms of net exposures, even for jurisdictions where netting agreements would otherwise not be enforceable.

Various portfolio restrictions provide additional protection against credit risk. For example, structured DPCs bar themselves from dealing with counterparties below investment grade and place limits on gross and net exposures to the counterparties with whom they deal. In some cases, the limits may be exceeded if collateral is

Exhibit 2
Use of Model for Credit Risk Management



posted by third parties. The DPCs also deal only in the types of derivatives that do not pose valuation or hedging problems. The capital, collateral, and portfolio restrictions are designed to ensure that the structure remains viable even in the face of unusual strain. MLDP's capital and exposure limits, for example, are designed to allow it to withstand the simultaneous default of seven double-A-rated counterparties.

Using a Model to Measure Credit Risk

Structured DPCs rely on quantitative models that attempt to measure credit risk precisely (Exhibit 2). Such a model would run Monte Carlo simulations, which involve generating a large number of possible future paths for every relevant market variable—mainly interest rates and exchange rates—based on estimated volatilities and correlations among the variables. Using transaction data, the model would evaluate each transaction along each path and thus measure the DPC's exposure to each counterparty.

For mirror transactions, the net current exposure would determine the amount of collateral to be posted by the parent. The net potential exposure would represent a measure of value at risk for an event in which the parent is unable to sustain the mirror transactions, and sensitivity collateral would cover this market risk. For customer transactions, the model would provide potential credit exposure by counterparty, netting the exposures where appropriate. (Box 2 illustrates the advantage of having such a model in the calculation of potential exposures.) The model would then simulate counterparty defaults based on historical probabilities to calculate possible losses to the DPC. The default probabilities are typically assumed to be independent of market movements.[19] The potential credit losses would then set the required amount of capital.

Dynamic Allocation of Capital

The structured DPCs minimize their required capital by allocating an amount that is just enough to cover, with a high degree of confidence, credit risks measured over a short time horizon.[20] The choice of time horizon has resulted in two types of capital rules: a static rule and a dynamic rule. Of the nine structured DPCs in Table 6, MLDP is the only one that operates under the static rule, and is in the process of developing a dynamic model. The static rule imposes a time horizon of one quarter when calculating default probabilities and expected credit losses. Correspondingly, MLDP adjusts its capital requirements quarterly, although it monitors them much more frequently. The eight other DPCs operate under a dynamic capital rule, which shortens the time horizon for calculating default probabilities and expected credit losses to ten trading days. Under this rule, the eight DPCs adjust their capital requirements daily.

STRUCTURAL RISK AND WORKOUT PROCESSES

The various operating components of a structured DPC are so critical to one another that the failure of one component would reexpose the DPC to rising amounts of market risk. The DPC limits its exposure to such risk by triggering a workout process, in which the DPC would effectively self-

Table 6
CAPITAL OF TRIPLE-A DERIVATIVE PRODUCT COMPANIES

Name	Actual Capital	Minimum Required Capital at Inception	Capital Rule
Merrill Lynch Derivative Products	$368 million	$300 million	Static
Salomon Swapco	$285 million	$175 million	Dynamic
Westpac Derivative Products	$200 million	$100 million surety bond + $50 million	Dynamic
Morgan Stanley Derivative Products	$150 million	$150 million	Dynamic
Lehman Brothers Financial Products	$200 million	$150 million	Dynamic
Paribas Derives Garantis	FFr 800 million ($140 mil.)	FFr 800 million	Dynamic
Tokai Derivative Products	£100 million ($160 mil.)	£100 million	Dynamic
Credit Lyonnais Derivatives Program	$200 million surety bond+capital of Credit Lyonnais	$200 million surety bond+capital of Credit Lyonnais	Dynamic
Sumitomo Bank Capital Markets Derivative Products	$300 million	$300 million	Dynamic

Sources: Moody's and Standard and Poor's.

destruct, albeit in an orderly way. The DPC deals with the market risk during the workout process by holding additional collateral from its parent or sponsor. Each of the DPCs has adopted one of two workout structures: a contingent manager (continuation) structure or an early termination structure.

The various operating components of a structured DPC are so critical to one another that the failure of one component would reexpose the DPC to rising amounts of market risk. The DPC limits its exposure to such risk by triggering a workout process, in which the DPC would effectively self-destruct, albeit in an orderly way.

In the event of a structural failure, DPCs with a contingent manager structure would refrain from taking on new transactions and turn over operations to a predesignated contingent manager. The new manager would service the contracts and manage the risks of the whole derivatives book until the last contract matured. DPCs with an early termination structure would end all contracts within a few weeks, settling each contract for cash on the basis of valuations at mid-market prices.[21] The customers holding out-of-the-money contracts would make the first payments, and the DPC would use the proceeds to pay off the in-the-money contracts. Under either structure, the mirror transactions with the parent would be terminated early and settled for cash, an action that might involve liquidation of collateral. Standard and Poor's attaches the suffix "t" to its ratings of DPCs with the termination structure, while Moody's does not distinguish between workout structures in its ratings.[22]

Choosing the Workout Structure

Customers may have reasons to choose one DPC over another on the basis of workout structure. Structured DPCs let customers know from the outset which workout process will apply. This prespecification of the workout process is an important innovation.

Workouts similar to those specified under the contingent manager and early termination structures have been used before. The main methods by which derivatives were handled in the five largest defaults involving derivatives held by financial institutions are reported in Table 7. In three of the defaults, the derivatives books were transferred to another financial institution in much the same way a DPC would proceed under a contingent manager structure. In two of the defaults, the derivatives were terminated early, just as a DPC would treat its contracts under the termination structure. In no case, however, was the eventual workout process known by the customers at the origination of their contracts.

Customers with rules that bind them to dealing only with triple-A counterparties may prefer the early termination structure. Others, wishing to avoid replicating a

Table 7
DEFAULT EVENTS AND DISPOSITION OF MAJOR DERIVATIVES BOOKS

Defaulting Financial Institution	Event Date	Notional Amount of Derivatives	Number of Counterparties	Main Method of Disposition	Problem Counterparties
Development Finance Corp. of New Zealand	10/89	NZ$4 billion	60	Transfer to Barclays	1
Drexel Burnham Lambert	2/90	US$30 billion	200	Early termination	15
British and Commonwealth	4/90	£2-3 billion	50	Transfer to Barclays	1 or 2
Bank of New England	1/91	US$6.7 billion	387	Transfer to FDIC bridge bank	None
Confederation Life	8/94	C$23 billion	50-100	Early termination	N.A.

Sources: Asquith and Cunningham 1990; *Swaps Monitor*, March 5, 1990.

liquidated contract, may prefer the contingent manager structure. In the case of swaps and forwards, the standard contracts have zero value at inception, so replicating such a contract when it no longer has zero value would involve going to the "off market," where bid-ask spreads are wider. The more active a customer is in the derivatives markets, the more experience it would have with early termination clauses and with the off market; thus, it would be less likely to harbor qualms about an early termination structure.

Trigger Events

Several types of events would trigger a workout under the two different structures (Table 8). Under a contingent manager structure, a parent's failure to post collateral, a serious downgrading of the parent's credit rating on short-term debt, or a default or bankruptcy by the parent would lead to the DPC's self-destruction. Under an early termination structure, a parent's failure to meet capital or collateral obligations, a serious downgrading of the DPC's credit rating, or default or bankruptcy by the parent would result in the DPC's self-destruction. The parent's short-term debt rating tends to be more relevant than its long-term debt rating under the contingent manager structure because liquidity is a more important consideration.

By triggering a workout short of its default, a DPC may avoid problems that arise when out-of-the-money counterparties walk away from intermediaries that had defaulted on other contracts. In at least three cases, major defaulting financial institutions have been beset with problem customers who walked away from out-of-the-money contracts (Table 7). In the most serious case, 15 of Drexel's approximately 200 derivatives counterparties invoked limited two-way payments and refused to honor their out-of-the-money contracts. Appendix I provides a fuller description of problems associated with defaults by intermediaries.

Sensitivity Collateral

The absence of mirror transactions during the workout process would expose DPCs to market risk. To deal with such risk, DPCs hold additional collateral, called sensitivity collateral. The amount of such collateral is derived from a value-at-risk calculation, which depends on the composition of the DPC's derivatives book and the chosen workout structure.

An early termination structure implies a time horizon for market risk of only a few weeks, and exposure to market risk ends with liquidation of the portfolio. A contingent manager structure implies a longer horizon because of the time required for the contingent manager to reconstruct a hedge for the derivatives book in the absence of mirror transactions. Moreover, since the book must be managed until the last contract has expired, even for a book hedged against market risk, out-of-the-money counterparties will still pose a credit risk. Thus, for otherwise equivalent derivatives books, the early termination struc-

Table 8
TRIGGER EVENTS AT DPCS

Type of Structure	Failure of Parent to Meet Capital Obligations	Failure of Parent to Post Required Collateral	Downgrade of Parent (S&P/Moody's)	Downgrade of DPC (S&P/Moody's)	Bankruptcy or Default of Parent or Affiliate	Action by Regulatory Agency
Contingent manager (MLDP, LBFP, TDP, and SBCM DP)		Yes[a]	Below A-2 / P-2[b]		Yes	
Early termination (Swapco, WDP, PDG, MSDP, and CLDP)	Yes[a]	Yes[a]		Below A- / A3[c]	Yes	WDP and PDG

Sources: Moody's and Standard and Poor's.

[a] Swapco, MLDP, and MSDP have a two-day grace period to meet the deficiency.

[b] The trigger for TDP is the downgrade of Tokai Bank below Moody's rating of Baa2.

[c] WDP has three unique provisions: a downgrade of Westpac below BBB/Baa, a sale of WDP that results in a downgrade, or a downgrade of Australia's credit rating below the Standard and Poor's rating of A3.

ture requires less sensitivity collateral than the contingent manager structure does.

TRIPLE-A RATINGS AND COMPETITIVE ADVANTAGE

The emergence of structured DPCs in 1991 was viewed as a threat to bank dominance of the over-the-counter derivatives markets, particularly after the recent downgrades of a few banks' credit ratings (Locke 1995).[23] Market observers initially thought that a growing number of derivatives customers would insist on triple-A-rated intermediaries. However, four years after they first emerged, the DPCs had yet to make significant inroads into the derivatives markets, despite their triple-A ratings. The issue examined in this section is whether the DPCs' risk management techniques truly give them a competitive advantage. This advantage would depend on the real importance of a DPC's triple-A rating in the minds of customers and on the amount of capital required to maintain the rating.

THE IMPORTANCE OF TRIPLE-A RATINGS

Thus far, every structured DPC has been created to obtain a triple-A credit rating. Indeed, the DPCs are set up to cease operations as intermediaries once the rating can no longer be maintained. However, a closer look at the growth of derivatives on the books of the major U.S. intermediaries shows that a triple-A rating contributes to, but is by no means essential for, success in the derivatives business. For instance, if we examine the growth rate of swaps and options at the major intermediaries, we see no clear relationship between high credit ratings and high growth rates in a dealer's derivatives business (Table 9). Between 1991 and 1994, the intermediary with the highest growth rate in swaps was rated only BBB+/Baa3, and the one with the highest growth rate in options only A/A2.

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Regression Analysis

To analyze the effect of credit ratings more systematically, we ran several regressions to control for the initial size of

Table 9
GROWTH RATE OF SWAPS AND OPTIONS AT MAJOR DEALERS, 1991–94
Percent of Notional Amounts

Dealers	Rating in 1991 (S&P/Moody's)	Swaps Notional Amount Year-End 1990 (Billions of Dollars)	1991-94 Average Growth Rate (Percent)	Options Notional Amount Year-End 1990 (Billions of Dollars)	1991-94 Average Growth Rate (Percent)
Banks					
Morgan Guaranty	AAA/Aa1	260.5	39.1	146.1	41.1
Republic New York Bank	AA/Aa3	16.9	45.9	4.0	87.2
Bankers Trust New York	AA/A1	259.2	20.2	183.4	28.5
Citibank	A+/Baa2	280.1	9.4	220.1	11.9
BankAmerica	A/A2	68.3	14.9	35.7	17.0
Bank of New York	A-/A3	19.6	-13.1	9.1	14.8
Continental Bank[a]	/Baa1	56.9	-3.4	65.2	-5.9
Chase Manhattan Bank	BBB+/Baa3	226.6	9.0	65.8	35.8
Chemical Bank	BBB+/Baa3	224.3	80.0	166.2	25.0
Securities firms					
Salomon Brothers	A+/A2	131.0	38.8	72.0	34.7
Merrill Lynch	A/A2	126.1	55.1	19.4	90.4

Sources: Statements of condition and annual reports.

[a] Continental Bank was taken over by BankAmerica in 1994.

the derivatives books, the yearly growth rates of the overall markets, and whether or not the intermediary is a bank (Appendix II). We used annual growth rates in the notional value of derivatives at each dealer as the dependent variable. Caution should be exercised in interpreting the results because of the small sample size and the rapid growth of the overall derivatives markets during the period. Nonetheless, the regressions failed to show that triple-A ratings carry decisive importance in the derivatives markets. When we assigned numerical values to the ratings (an AAA rating received 9 and a BBB rating 0), the regressions showed that higher ratings do tend to be associated with higher derivatives growth rates. However, when we used dummy variables to find threshold effects in the ratings, the regressions showed that a double-A threshold explained derivatives growth rates better than a triple-A threshold. These results suggest that the expected widespread insistence on triple-A ratings by derivatives customers did not materialize.

Effect of Workout Risk

Even when derivatives customers value an intermediary's triple-A rating, they may not regard a structured DPC's rating as the equal of other triple-A ratings.[24] The DPC's rating may be differently regarded because the workout risk of such a DPC corresponds more closely to the parent's typically single-A rating. The pure risk of default or credit loss allows the credit rating agencies to assign the triple-A ratings. The integrity of the DPC's structure, however, depends on its parent's ability to sustain the mirror transactions and the capital and collateral requirements. Therefore, the risk of losing such parental support corresponds to the parent's rating. This loss of support triggers an automatic workout process that may cause difficulties for the DPC's customers, even in the absence of default or credit loss.

Under a contingent manager structure, the workout process at the very least would cost DPC customers a dealer relationship. The customers would be holding contracts with an intermediary that is no longer rated triple-A and with whom they can no longer engage in new transactions. Under a termination structure, the concerted liquidation of contracts would cause the DPC's customers who still need the derivatives to find ways to replicate terminated contracts and the out-of-the-money customers to make lump-sum cash payments on the spot.[25] Moreover, the workout process would proceed in markets that might still be reeling from the shock that led to the DPC's parent's financial distress or in markets coping with that distress. These market conditions could contribute to problems of liquidity for derivatives, making it difficult for a DPC's contingent manager to rehedge the book or for customers with terminated contracts to replicate their contracts.

Economies of Scope

Rather than focus on triple-A credit ratings, some derivatives customers may instead choose a lower rated bank because of economies of scope between derivatives and other bank products. The major bank intermediaries have affiliated securities firms, called Section 20 subsidiaries, which the Securities and Exchange Commission regulates as broker-dealers. Given the regulatory "firewalls" between banks and their Section 20 affiliates, it is significant that the banks, not the securities affiliates, are uniformly the ones that serve as derivatives intermediaries. The banks' decision to locate the derivatives business in the banking part of the organization is indirect evidence of the importance of economies of scope between derivatives and other bank products.

Given the regulatory "firewalls" between banks and their Section 20 affiliates, it is significant that the banks, not the securities affiliates, are uniformly the ones that serve as derivatives intermediaries.

In general, these economies of scope may arise from banks' informational advantages. Banks have traditionally specialized in the management of credit risk, and information about such risks can help with managing the credit risk of derivatives (Edwards and Mishkin 1995). Understanding a customer's credit needs may also help a bank understand the customer's hedging needs, allowing the bank to propose derivatives to help customers hedge the market risk of other bank products. Large banks, for example, dominate the international syndicated loan market, and interest rate and currency swaps may often be useful for hedging syndicated loans.

> *In principle, the DPCs' risk management techniques may allow them to operate with less capital than non-triple-A intermediaries for similar derivatives transactions. In practice, however, the DPCs seem to operate with considerably more capital than other intermediaries.*

THE CAPITAL REQUIRED FOR A DPC'S TRIPLE-A RATING

The cost of a structured DPC's triple-A rating is represented largely by the amount of capital required to maintain the rating. In competing with non-triple-A intermediaries for customers who do not insist on the higher rating, the DPCs would ordinarily face a cost disadvantage if they simply managed risks the way other intermediaries did.[26] In principle, the DPCs' risk management techniques may allow them to operate with less capital than non-triple-A intermediaries for similar derivatives transactions. In practice, however, the DPCs seem to operate with considerably more capital than other intermediaries.

DPC Capital and Bank Capital

Under current rating agency standards for triple-A ratings, the DPCs' actual capital requirements appear more stringent than those for banks. To meet the minimum requirements for banks under the 1988 Basle Accord, for example, in 1994 MLDP would have needed a minimum of $40 million in tier 1 capital, only about one-ninth the amount of capital it actually had (Table 10). Similarly, Swapco would have needed only one-seventh the amount it actually had.

In comparing DPC capital with bank capital, it should be noted that banks often hold capital well in excess of the Basle Accord's minimum. The well-capitalized double-A banks, for example, hold tier 1 capital amounting to as much as two-and-a-half times the minimum. The single-A banks hold capital amounting to about double the Basle requirement. Nonetheless, such capital still falls short of the capital held by DPCs, especially when measured relative to risk. The banks allocate capital to deal with both market risk and credit risk, while the DPCs allocate capital largely for credit risk because the mirror transactions already take care of market risk.

Capital for a Double-A Rating

If a triple-A rating requires so much capital and the rating is not so critical in the minds of customers, why don't the structured DPCs settle for a double-A rating? We may estimate what the DPC capital requirement would be for a double-A rating by relying on the expected loss approach used by Moody's (Box 3). Our calculations suggest that DPCs pursue triple-A ratings because these do not require much more capital than double-A ratings

Table 10
IMPLIED CAPITAL BY RATING AND REQUIRED CAPITAL
Millions of Dollars

Company Name	Actual Capital	Required BIS Tier 1 Capital	Implied Aa Capital	Implied A Capital
Merrill Lynch Derivative Products	368.1	40.0	317.4	192.3
Salomon Swapco	280.5	39.0	253.7	187.5
Morgan Guaranty	8,265	3,408	8,265	—
Bankers Trust New York	4,372	1,922	4,372	—
Citibank	16,919	8,676	—	16,919
Chase Manhattan Bank	7,759	3,739	—	7,759
Chemical Bank	10,003	4,880	—	10,003

Sources: Annual reports for 1994; FRBNY staff estimates based on Moody's expected loss rates of 0.002 percent, 0.02 percent, 0.04 percent, 0.14 percent, 0.24 percent, for Aaa, Aa1, Aa2, A1, and A2 ratings, respectively. Default rates are 0.7 percent, 0.9 percent, and 2.0 percent for Aaa, Aa, and A ratings, respectively.

(Table 10). For example, MLDP required $368 million for its Aaa rating. Had it settled for an Aa, it would still have needed $317 million, not a huge savings in capital. An A rating would have represented substantially more in savings, but its parent already had that rating. Similarly, Swapco would not have saved very much by settling for an Aa rating. Moreover, for MLDP and Swapco, the fixed costs of setting up the DPC, including the cost of lengthy discussions with the credit rating agencies, should be about the same for double-A and triple-A ratings.

Our analysis suggests that after all the effort to keep required capital to a minimum, the structured DPC approach to risk management still demands so much more capital than is required by non-triple-A intermediaries that the approach is unlikely to lend the DPCs a competitive edge in the derivatives markets as a whole. Moreover, DPCs would apparently not save much capital by simply settling for a lower rating. In attracting customers who must deal with a triple-A intermediary, the DPCs would enjoy a clear advantage, but beyond this niche of customers they would face a significant cost disadvantage.

Conclusion

The first structured DPCs created quite a stir in the derivatives markets in the early 1990s because it was thought that their unique approach to managing risks would allow them to become major intermediaries in the markets. The DPCs' brand of risk management allowed them to gain triple-A credit ratings with as little capital as possible, and market observers believed that increasingly credit-sensitive customers would flock to them. However, the DPCs have so far failed to live up to that promise. Banks without triple-A ratings are still among the dominant market players, and even the DPCs' parents, with at best single-A ratings, engage in considerably more derivatives transactions.

The structured DPCs manage risks in three ways: they hedge market risks as fully as possible by means of mirror transactions with their parents; they manage credit risks—which are inherently difficult to hedge—by using quantitative models to estimate exposures precisely and by allocating capital to just cover the risks as measured daily; and they prepare for the possibility that their structure may someday fail by providing an automatic workout pro-

Box 3: Calculating a DPC's Required Capital

Under the expected loss approach used by Moody's, the expected loss rate is the product qL, where q is the probability of the DPC defaulting and L is the loss rate given the default. The loss rate L is in turn calculated as

$$L = (D - K)/P,$$

where D is the loss from the defaulting receivables that would cause the DPC to default, K the amount of the DPC's capital, and P the amount of customer payables.

To satisfy the threshold for a triple-A rating, the expected loss rate faced by a DPC customer may not exceed 0.002 percent over a ten-year horizon (Gluck and Clarkson 1993). The DPC starts with a trial amount of capital for K and then uses its internal model to calculate the default probability q and the receivable losses D for its derivatives book. If the resulting expected loss exceeds 0.002 percent, the DPC continues to add more capital and to recalculate the expected loss until it reaches 0.002 percent. The resulting amount of capital at the threshold is then the requirement for the triple-A rating.

Knowing the triple-A DPC's expected loss rate, its capital, its default probability, and its potential amount of customer payables, we derive an estimate of D, or the implied loss from defaulting receivables, for the DPC's derivatives book. We then recalculate the required amount of capital for a DPC with the same book but one that would be rated only double-A or single-A by using the corresponding expected loss rates and default probabilities (Fons, Carty, and Kaufman 1994). Strictly speaking, this calculation would be incorrect, because the estimate for D, as well as the loss rate L and default probability q, would depend on the amount of capital. Nonetheless, if we assume that D, L, and q are relatively insensitive to the amount of capital, such a calculation would give us a rough order of magnitude for the capital requirements.

cess designed to limit the ensuing risk.

Considering the strength of their risk management, why haven't structured DPCs taken over a larger share of the derivatives markets? Our analysis suggests two basic reasons. First, credit gridlock did not materialize, and the DPCs' triple-A ratings, in particular, did not become a decisive factor in most customers' choice of intermediaries. In this regard, customers may not have been as comfortable with the DPCs' ratings as with other triple-A ratings because the DPCs are subject to a workout risk corresponding to their parents' typically single-A ratings. Second, despite their efforts to save on capital, under current rating agency standards, the DPCs still faced more demanding capital requirements than those faced by major intermediaries without triple-A ratings. Settling for lower ratings would not have saved the DPCs much capital. The DPCs did not just get off to a slow start; they seem to have been structurally inhibited from taking over a large share of the markets.

Nonetheless, the structured DPCs continue to receive capital support from their parents, and new ones will continue to be formed. In the near future, these DPCs are unlikely to dominate the markets as derivatives intermediaries. Instead, they will serve a market niche consisting of the relatively few, albeit important, customers who insist on triple-A ratings.

Appendix I: Recent Cases of Derivatives Defaults

The recent history of defaults or dispositions of derivatives portfolios points out many of the dangers that can arise when an intermediary defaults. Those dangers include the risk that the defaulting party will not be able to obtain full market value when it transfers its portfolio to an underinformed buyer. In addition, limited two-way payment options give rise to "walk-away" risk because counterparties can attempt to void their obligations to defaulting parties. Finally, some regulators have the authority to "cherry pick" from the portfolio and leave the in-the-money counterparties at the mercy of the bankruptcy courts. However, it appears that the structured DPCs have specific provisions and safeguards designed to mitigate these risks.

The contingent manager provisions of the DPCs would have helped Development Finance Corporation of New Zealand (DFC) and British and Commonwealth transfer their derivatives portfolios more easily. When DFC transferred its contracts to Barclays Bank, it had to make a payment to Barclays based on the mark-to-market value of the portfolio. In the case of British and Commonwealth, local client confidentiality laws prohibited disclosure of the names of its counterparties to potential purchasers of its portfolio.

In each case, the contracts signed by counterparties of Merrill Lynch Derivative Products and Lehman Brothers Financial Products would have specified that the transactions be transferred automatically to a previously agreed-upon contingent manager. Thus, there would be no need for the self-destructing DPC to "settle" the book with the contingent manager. Moreover, the contingent manager would have been familiar with the book and prepared to assume the day-to-day operations of the DPC.

The contingent manager structure also mitigates the risk from limited two-way payments that was experienced by DFC, British and Commonwealth, and Drexel Burnham Lambert. Under limited two-way payments, the nondefaulting counterparty is *not* obligated to make payments to the defaulting counterparty, regardless of the market value of the swap. Assignment to mutually agreed-upon contingent managers would probably prevent such clauses from being exercised.

More important, both terminating and continuation DPCs insist on full two-way payments clauses for the settlement of terminated contracts. This means that regardless of who defaults, the out-of-the-money counterparty must make the payments. The prespecified workout process may also help DPCs avoid walk-away risk by triggering a workout short of default. In addition, the counterparty must agree to settle the contracts based on the mid-market calculations of the DPC, thus eliminating some uncertainty surrounding the valuation of the termination payments.

In the failure of the Bank of New England (BNE), questions arose concerning the role of regulators in the disposal of the bank's derivatives portfolio. Immediately after BNE was declared insolvent, the Federal Deposit Insurance Corporation (FDIC) established a bridge bank to assume BNE's assets and liabilities and continue BNE's operations while a permanent solution was found. The FDIC had the authority, under the Financial Institutions Relief, Recovery, and Reform Act (FIRREA), to transfer to the bridge bank only those contracts with counterparties that were out-of-the money with respect to BNE.

However, the FDIC decided not to follow this course of action because of the existence of limited two-way payments clauses and the possibility of other detrimental actions by counterparties. Since BNE's portfolio was net in-the-money, the decision was made to transfer it to the bridge bank in its entirety. The DPCs are aware of the FIRREA clauses, but they feel confident that the International Swaps and Derivatives Association agreement and the additional protections that they seek from regulated counterparties would be sufficient to protect them from losses.

Appendix II: Explaining Derivatives Growth for Major Intermediaries

The relative importance of credit ratings can also be shown using regression analyses covering the 1991-94 period. The dependent variable is yearly derivatives growth by institution (DGROW). The independent variables are a credit rating variable (RATING), a dummy for whether an institution was a bank or nonbank dealer (BANK), the size of the book at the beginning of the year (BKSIZE), and a year dummy to control for changing marketwide conditions:

$$DGROW = a + b_1RATING + b_2BANK + b_3BKSIZE + b_4DUM91 + b_5DUM92 + b_6DUM93.$$

We ran several regressions based on different characterizations of the effect of credit ratings. In regression 1, we assumed that credit ratings would have a continuous effect on derivatives growth. Therefore, we defined a credit rating variable, which was assigned a value of 9 for AAA, 8 for AA+, 7 for AA, 6 for AA-, and so on, down to 0 for BBB-. The result shows that the dealer's credit rating was a significant positive factor in determining the growth of its derivatives book.

In regressions 2 to 6, we made the slightly different assumption that credit ratings had a threshold effect (that is, the effect was the same beyond a certain threshold rating). Regression 3, containing a dummy variable for companies rated double-A or higher, explained more of the variation in derivatives growth rates than any of the others. Regression 2 for the triple-A or higher threshold and regression 3 for the double-A or higher threshold yield similar coefficients, but the latter is estimated with a smaller standard error and a higher R-squared.

Regression Analysis of Yearly Derivatives Growth

Dependent variable: Yearly derivatives growth rates by institution, 1991-94

Independent variables: Credit rating variable, dummy for bank versus nonbank, size of book (lagged), dummy for year

Credit Rating Variables	Regression Number 1	2	3	4	5	6
Credit rating[a]	0.441[b] (3.36)	—	—	—	—	—
Dummy for AAA or higher	—	0.221[b] (2.46)	—	—	—	—
Dummy for AA or higher	—	—	0.225[b] (3.46)	—	—	—
Dummy for A+ or higher	—	—	—	0.141[b] (2.26)	—	—
Dummy for A or higher	—	—	—	—	0.103 (1.44)	—
Dummy for A- or higher	—	—	—	—	—	0.105 (1.07)
R^2	0.351	0.293	0.358	0.281	0.241	0.228

Source: Authors' calculations.

[a] We assigned a value of 9 for AAA, 8 for AA+, 7 for AA, 6 for AA-, and so on, down to 0 for BBB-.

[b] Denotes significance at 5 percent level of confidence or higher; R-statistics are in parentheses.

ENDNOTES

1. Remolona (1993) analyzes the economic forces driving the growth of derivatives markets. Figlewski (1994) describes some of the basic strategies that have resulted in losses.

2. Cantor and Packer (1994) provide a thoughtful discussion of the meaning and reliability of such ratings.

3. A survey of dealers conducted by the Bank for International Settlements in April 1995 suggests global markets of $40 trillion in notional value, a much larger estimate than those produced by the regular surveys of the International Swaps and Derivatives Association.

4. However, by merging with Chemical Bank in 1995, Chase Manhattan is now the world's largest derivatives intermediary.

5. In the last few years, only Morgan Guaranty had achieved an Aaa rating from Moody's, but it lost that rating in early 1995.

6. Intermediaries also manage other types of risk, such as legal risk (arising from uncertainty over the enforceability of contracts) and operational risk (arising from the possibility of a breakdown in internal controls or in systems for processing and settling transactions).

7. Credit risk is more of a concern in the over-the-counter markets than in organized derivatives exchanges, such as the Chicago Board of Trade (CBOT) or the London International Financial Futures and Options Exchange (LIFFE). There, the interposition of a clearinghouse as a counterparty and the use of frequent margin payments reduce credit risks drastically (Remolona 1993).

8. The development of the markets in credit derivatives may allow the hedging of some credit risk. Hedging products include credit swaps, credit-linked structured notes, and options on credit spreads, all of which allow investors to isolate and trade the credit risk of their portfolios in much the same way as interest rate and currency derivatives isolate market risk.

9. Santomero (1984), for example, shows how a bank would trade off risk and return in its whole portfolio.

10. There are other ways to mitigate credit risk, but netting and collateral are the most common ones. Netting agreements reduce credit exposures by bilaterally offsetting contracts with positive market values against contracts with negative market values between the intermediary and individual customers. Hendricks (1994) analyzes the effect of netting on credit exposures. The most common form of collateral is the use of interdealer margins in transactions among intermediaries. Chew (1994) and Comptroller of the Currency (1994) provide more general discussions.

11. The confidence interval is an estimate of the probability that losses will *not* exceed the value at risk.

12. Bankers Trust New York Corporation, *1994 Annual Report*, Table 4, p. 28.

13. See, for example, Iben and Ratcliffe (1994).

14. Drexel Burnham Lambert had derivatives amounting to $30 billion in notional value. Under bankruptcy, the contracts were terminated early without any apparent credit losses to counterparties.

15. The discussion in the rest of this section draws from Gluck and Clarkson (1993), Scheyd and Bahar (1994), and Bartmann, Milich, and Volstad (1994).

16. In a recent arrangement, MLDP will serve as the intermediary for swaps with customers of Dai-Ichi Kangyo Bank, but the bank will provide the collateralized mirror transactions.

17. Technically, Credit Lyonnais's ratings are assigned to its derivatives program, which relies on guarantees provided by CLFG Corporation, a special purpose, bankruptcy-remote corporation wholly owned by Financial Security Assurance Holdings, itself a triple-A-rated monoline U.S. insurer. The derivatives program will cover transactions with the New York branch of Credit Lyonnais (the sponsor).

18. The rating agencies rely on external auditors to monitor the DPCs' operations, including the verification of the models' results.

19. Duffie (1994) argues that the assumption of independence is a poor one, particularly in the case of interest rate contracts, because defaults tend to be more common when interest rates decline during a recession.

20. Structured DPCs typically choose a confidence interval of 99 percent, which would cover movements as large as 2.3 standard deviations from the mean and allow only a 1.0 percent probability that actual losses will exceed the threshold estimate.

21. Credit Lyonnais's derivatives program would settle the contracts on the basis of actual quotes from other intermediaries, and customers would have the choice of having their contracts taken over by another intermediary or of settling for cash.

22. Moody's uses an expected loss standard for its credit ratings. Under this standard, it is unnecessary to distinguish between continuation and termination structures.

ENDNOTES (*Continued*)

23. In early 1995, Standard and Poor's lowered its rating of Morgan Guaranty from AAA to AA+ and Bankers Trust from AA- to A+. The rating agency also downgraded the ratings of Credit Suisse, the Swiss Bank Corporation, Banque Indosuez, and the Long-Term Credit Bank of Japan.

24. Just as not all triple-A ratings may be created equal, a bank's credit rating may be "more equal" than others, particularly when such a bank is perceived to be too big to fail. The issue of what a bank's credit rating truly means is beyond the scope of this study.

25. Under the termination structure and depending on the type of customer, a workout may also constitute a tax event because of implied capital gains or losses.

26. This assumes that DPCs and other intermediaries face similar costs of capital.

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Evaluation of Value-at-Risk Models Using Historical Data

Darryll Hendricks

Researchers in the field of financial economics have long recognized the importance of measuring the risk of a portfolio of financial assets or securities. Indeed, concerns go back at least four decades, when Markowitz's pioneering work on portfolio selection (1959) explored the appropriate definition and measurement of risk. In recent years, the growth of trading activity and instances of financial market instability have prompted new studies underscoring the need for market participants to develop reliable risk measurement techniques.[1]

One technique advanced in the literature involves the use of "value-at-risk" models. These models measure the market, or price, risk of a portfolio of financial assets—that is, the risk that the market value of the portfolio will decline as a result of changes in interest rates, foreign exchange rates, equity prices, or commodity prices. Value-at-risk models aggregate the several components of price risk into a single quantitative measure of the potential for losses over a specified time horizon. These models are clearly appealing because they convey the market risk of the entire portfolio in one number. Moreover, value-at-risk measures focus directly, and in dollar terms, on a major reason for assessing risk in the first place—a loss of portfolio value.

Recognition of these models by the financial and regulatory communities is evidence of their growing use. For example, in its recent risk-based capital proposal (1996a), the Basle Committee on Banking Supervision endorsed the use of such models, contingent on important qualitative and quantitative standards. In addition, the Bank for International Settlements Fisher report (1994) urged financial intermediaries to disclose measures of value-at-risk publicly. The Derivatives Policy Group, affiliated with six large U.S. securities firms, has also advocated the use of value-at-risk models as an important way to measure market risk. The introduction of the RiskMetrics database compiled by J.P. Morgan for use with third-party value-at-risk software also highlights the growing use of these models by financial as well as nonfinancial firms.

Clearly, the use of value-at-risk models is increasing, but how well do they perform in practice? This article explores this question by applying value-at-risk models to 1,000 randomly chosen foreign exchange portfolios over the period 1983-94. We then use nine criteria to evaluate model performance. We consider, for example, how closely risk measures produced by the models correspond to actual portfolio outcomes.

We begin by explaining the three most common categories of value-at-risk models—equally weighted moving average approaches, exponentially weighted moving average approaches, and historical simulation approaches. Although within these three categories many different approaches exist, for the purposes of this article we select five approaches from the first category, three from the second, and four from the third.

By employing a simulation technique using these twelve value-at-risk approaches, we arrived at measures of price risk for the portfolios at both 95 percent and 99 percent confidence levels over one-day holding periods. The confidence levels specify the probability that losses of a portfolio will be smaller than estimated by the risk measure. Although this article considers value-at-risk models only in the context of market risk, the methodology is fairly general and could in theory address any source of risk that leads to a decline in market values. An important limitation of the analysis, however, is that it does *not* consider portfolios containing options or other positions with nonlinear price behavior.[2]

Clearly, the use of value-at-risk models is increasing, but how well do they perform in practice?

We choose several performance criteria to reflect the practices of risk managers who rely on value-at-risk measures for many purposes. Although important differences emerge across value-at-risk approaches with respect to each criterion, the results indicate that none of the twelve approaches we examine is superior on every count. In addition, as the results make clear, the choice of confidence level—95 percent or 99 percent—can have a substantial effect on the performance of value-at-risk approaches.

Introduction to Value-at-Risk Models

A value-at-risk model measures market risk by determining how much the value of a portfolio could decline over a given period of time with a given probability as a result of changes in market prices or rates. For example, if the given period of time is one day and the given probability is 1 percent, the value-at-risk measure would be an estimate of the decline in the portfolio value that could occur with a 1 percent probability over the next trading day. In other words, if the value-at-risk measure is accurate, losses greater than the value-at-risk measure should occur less than 1 percent of the time.

The two most important components of value-at-risk models are the length of time over which market risk is to be measured and the confidence level at which market risk is measured. The choice of these components by risk managers greatly affects the nature of the value-at-risk model.

The time period used in the definition of value-at-risk, often referred to as the "holding period," is discretionary. Value-at-risk models assume that the portfolio's composition does not change over the holding period. This assumption argues for the use of short holding periods because the composition of active trading portfolios is apt to change frequently. Thus, this article focuses on the widely used one-day holding period.[3]

Value-at-risk measures are most often expressed as percentiles corresponding to the desired confidence level. For example, an estimate of risk at the 99 percent confidence level is the amount of loss that a portfolio is expected to exceed only 1 percent of the time. It is also known as a 99th percentile value-at-risk measure because the amount is the 99th percentile of the distribution of potential losses on the portfolio.[4] In practice, value-at-risk estimates are calculated from the 90th to 99.9th percentiles, but the most commonly used range is the 95th to 99th percentile range. Accordingly, the text charts and the tables in the appendix report simulation results for each of these percentiles.

Three Categories of Value-at-Risk Approaches

Although risk managers apply many approaches when calculating portfolio value-at-risk models, almost all use past data to estimate potential changes in the value of the portfolio in the future. Such approaches assume that the future will be like the past, but they often define the past quite differently and make different assumptions about how markets will behave in the future.

The first two categories we examine, "variance-covariance" value-at-risk approaches,[5] assume normality and serial independence and an absence of nonlinear positions such as options.[6] The dual assumption of normality and serial independence creates ease of use for two reasons. First, normality simplifies value-at-risk calculations because all percentiles are assumed to be known multiples of the standard deviation. Thus, the value-at-risk calculation requires only an estimate of the standard deviation of the portfolio's change in value over the holding period. Second, serial independence means that the size of a price move on one day will not affect estimates of price moves on any other day. Consequently, longer horizon standard deviations can be obtained by multiplying daily horizon standard deviations by the square root of the number of days in the longer horizon. When the assumptions of normality and serial independence are made together, a risk manager can use a single calculation of the portfolio's daily horizon standard deviation to develop value-at-risk measures for any given holding period and any given percentile.

The advantages of these assumptions, however, must be weighed against a large body of evidence suggesting that the tails of the distributions of daily percentage changes in financial market prices, particularly foreign exchange rates, will be fatter than predicted by the normal distribution.[7] This evidence calls into question the appealing features of the normality assumption, especially for value-at-risk measurement, which focuses on the tails of the distribution. Questions raised by the commonly used normality assumption are highlighted throughout the article.

In the sections below, we describe the individual features of the two variance-covariance approaches to value-at-risk measurement.

Equally Weighted Moving Average Approaches

The equally weighted moving average approach, the more straightforward of the two, calculates a given portfolio's variance (and thus, standard deviation) using a fixed amount of historical data.[8] The major difference among equally weighted moving average approaches is the time frame of the fixed amount of data.[9] Some approaches employ just the most recent fifty days of historical data on the assumption that only very recent data are relevant to estimating potential movements in portfolio value. Other approaches assume that large amounts of data are necessary to estimate potential movements accurately and thus rely on a much longer time span—for example, five years.

The calculation of portfolio standard deviations using an equally weighted moving average approach is

$$(1) \qquad \sigma_t = \sqrt{\frac{1}{(k-1)} \sum_{s=t-k}^{t-1} (x_s - \mu)^2} ,$$

where σ_t denotes the estimated standard deviation of the portfolio at the beginning of day t. The parameter k specifies the number of days included in the moving average (the "observation period"), x_s, the change in portfolio value on day s, and μ, the mean change in portfolio value. Following the recommendation of Figlewski (1994), μ is always assumed to be zero.[10]

Consider five sets of value-at-risk measures with periods of 50, 125, 250, 500, and 1,250 days, or about two months, six months, one year, two years, and five years of historical data. Using three of these five periods of time, Chart 1 plots the time series of value-at-risk measures at biweekly intervals for a single fixed portfolio of spot foreign exchange positions from 1983 to 1994.[11] As shown, the fifty-day risk measures are prone to rapid swings. Conversely, the 1,250-day risk measures are more stable over long periods of time, and the behavior of the 250-day risk measures lies somewhere in the middle.

Exponentially Weighted Moving Average Approaches

Exponentially weighted moving average approaches emphasize recent observations by using exponentially weighted moving averages of squared deviations. In contrast to equally weighted approaches, these approaches attach different weights to the past observations contained in the observation period. Because the weights decline exponentially, the most recent observations receive much more weight than earlier observations. The formula for the portfolio standard deviation under an exponentially weighted moving average approach is

$$(2) \qquad \sigma_t = \sqrt{(1-\lambda)\sum_{s=t-k}^{t-1} \lambda^{t-s-1}(x_s-\mu)^2}\,.$$

The parameter λ, referred to as the "decay factor," determines the rate at which the weights on past observations decay as they become more distant. In theory, for the weights to sum to one, these approaches should use an infinitely large number of observations k. In practice, for the values of the decay factor λ considered here, the sum of the weights will converge to one, with many fewer observations than the 1,250 days used in the simulations. As with the equally weighted moving averages, the parameter μ is assumed to equal zero.

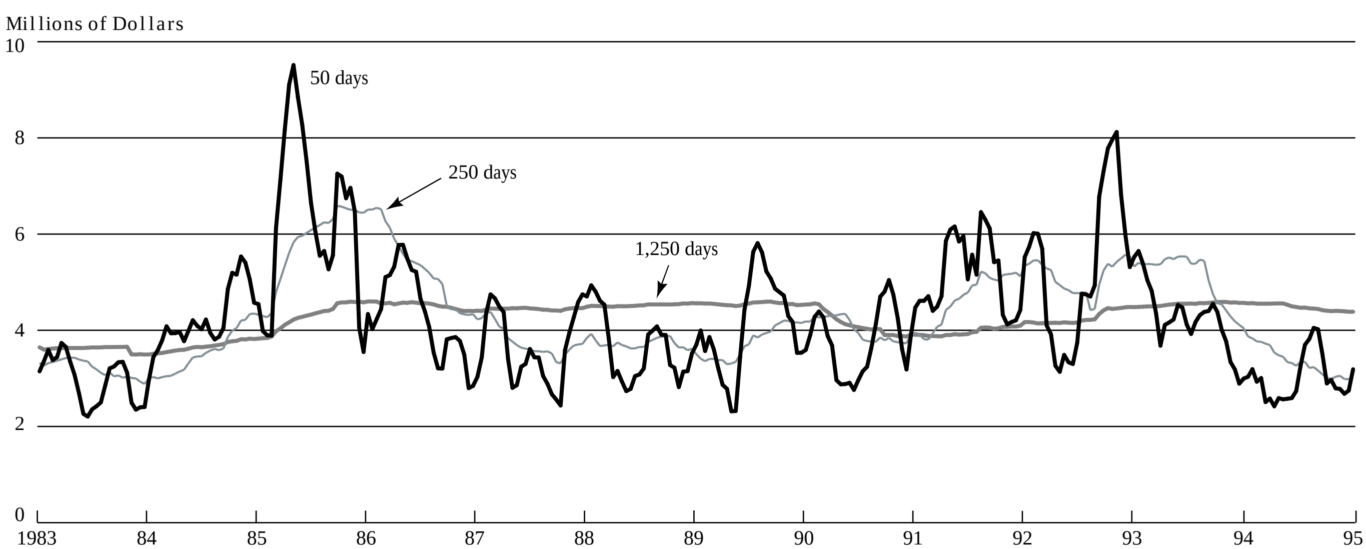
Exponentially weighted moving average approaches clearly aim to capture short-term movements in volatility, the same motivation that has generated the large body of literature on conditional volatility forecasting models.[12] In fact, exponentially weighted moving average approaches are equivalent to the IGARCH(1,1) family of popular conditional volatility models.[13] Equation 3 gives an equivalent formulation of the model and may also suggest a more intuitive understanding of the role of the decay factor:

$$(3) \qquad \sigma_t = \sqrt{\lambda\sigma_{t-1}^2 + (1-\lambda)(x_{t-1}-\mu)^2}\,.$$

As shown, an exponentially weighted average on any given day is a simple combination of two components: (1) the weighted average on the previous day, which receives a weight of λ, and (2) yesterday's squared deviation, which receives a weight of $(1 - \lambda)$. This interaction means that the *lower* the decay factor λ, the *faster* the decay in the influence of a given observation. This concept is illustrated in Chart 2, which plots time series of value-at-risk measures using exponentially weighted moving aver-

Chart 1

Value-at-Risk Measures for a Single Portfolio over Time
Equally Weighted Moving Average Approaches



Source: Author's calculations.

ages with decay factors of 0.94 and 0.99. A decay factor of 0.94 implies a value-at-risk measure that is derived almost entirely from very recent observations, resulting in the high level of variability apparent for that particular series.

On the one hand, relying heavily on the recent past seems crucial when trying to capture short-term movements in actual volatility, the focus of conditional volatility forecasting. On the other hand, the reliance on recent data effectively reduces the overall sample size, increasing the possibility of measurement error. In the limiting case, relying only on yesterday's observation would produce highly variable and error-prone risk measures.

HISTORICAL SIMULATION APPROACHES

The third category of value-at-risk approaches is similar to the equally weighted moving average category in that it relies on a specific quantity of past historical observations (the observation period). Rather than using these observations to calculate the portfolio's standard deviation, however, historical simulation approaches use the actual percentiles of the observation period as value-at-risk measures. For example, for an observation period of 500 days, the 99th percentile historical simulation value-at-risk measure is the sixth largest loss observed in the sample of 500 outcomes (because the 1 percent of the sample that should exceed the risk measure equates to five losses).

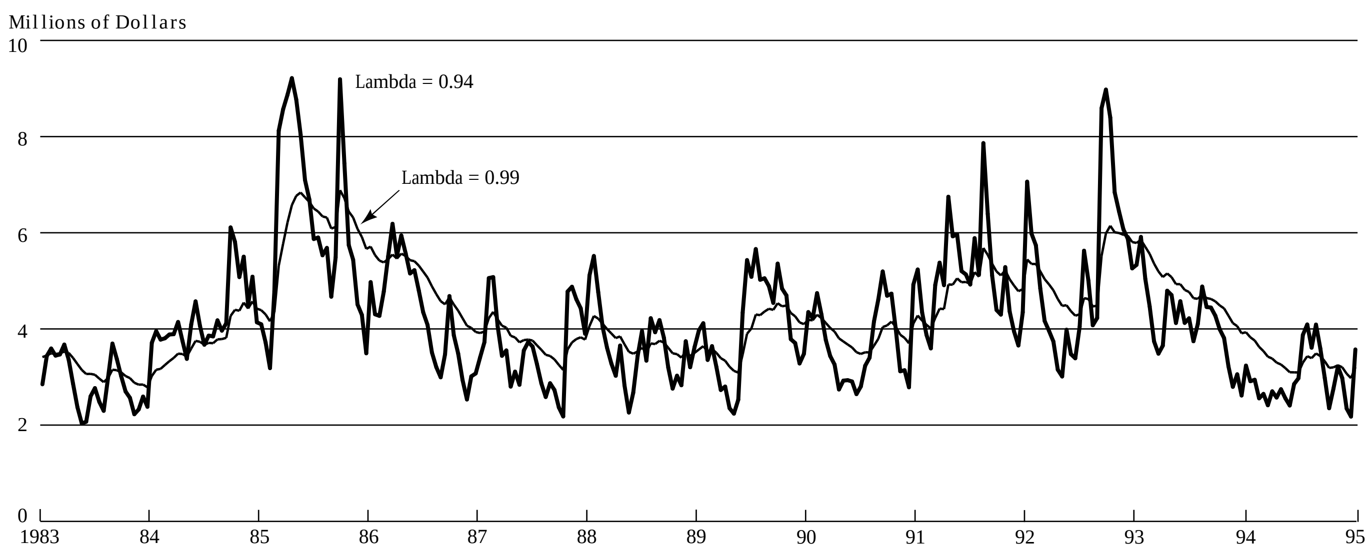
In other words, for these approaches, the 95th and 99th percentile value-at-risk measures will not be constant multiples of each other. Moreover, value-at-risk measures for holding periods other than one day will not be fixed multiples of the one-day value-at-risk measures. Historical simulation approaches do not make the assumptions of normality or serial independence. However, relaxing these assumptions also implies that historical simulation approaches do not easily accommodate translations between multiple percentiles and holding periods.

Chart 3 depicts the time series of one-day 99th percentile value-at-risk measures calculated through historical simulation. The observation periods shown are 125 days and 1,250 days.[14] Interestingly, the use of actual percentiles produces time series with a somewhat different appearance than is observed in either Chart 1 or Chart 2. In particular, very abrupt shifts occur in the 99th percentile measures for the 125-day historical simulation approach.

Trade-offs regarding the length of the observation period for historical simulation approaches are similar to

Chart 2

Value-at-Risk Measures for a Single Portfolio over Time
Exponentially Weighted Moving Average Approaches



Source: Author's calculations.

those for variance-covariance approaches. Clearly, the choice of 125 days is motivated by the desire to capture short-term movements in the underlying risk of the portfolio. In contrast, the choice of 1,250 days may be driven by the desire to estimate the historical percentiles as accurately as possible. Extreme percentiles such as the 95th and particularly the 99th are very difficult to estimate accurately with small samples. Thus, the fact that historical simulation approaches abandon the assumption of normality and attempt to estimate these percentiles directly is one rationale for using long observation periods.

SIMULATIONS OF VALUE-AT-RISK MODELS

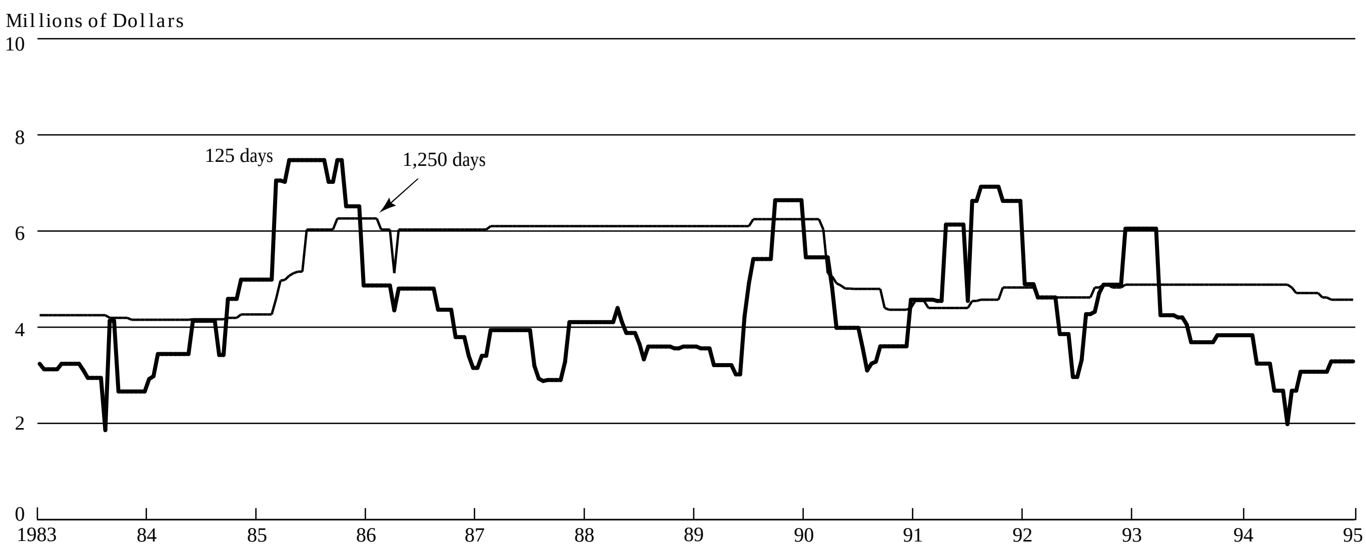
This section provides an introduction to the simulation results derived by applying twelve value-at-risk approaches to 1,000 randomly selected foreign exchange portfolios and assessing their behavior along nine performance criteria (see box). This simulation design has several advantages. First, by simulating the performance of each value-at-risk approach for a long period of time (approximately twelve years of daily data) and across a large number of portfolios, we arrive at a clear picture of how value-at-risk models would actually have performed for linear foreign exchange portfolios over this time span. Second, the results give insight into the extent to which portfolio composition or choice of sample period can affect results.

It is important to emphasize, however, that neither the reported variability across portfolios nor variability over time can be used to calculate suitable standard errors. The appropriate standard errors for these simulation results raise difficult questions. The results aggregate information across multiple samples, that is, across the 1,000 portfolios. Because the results for one portfolio are not independent of the results for other portfolios, we cannot easily determine the total amount of information pro-

The simulation results provide a relatively complete picture of the performance of selected value-at-risk approaches in estimating the market risk of a large number of portfolios.

Chart 3

Value-at-Risk Measures for a Single Portfolio over Time
Historical Simulation Approaches



Source: Author's calculations.

Data and Simulation Methodology

This article analyzes twelve value-at-risk approaches. These include five equally weighted moving average approaches (50 days, 125 days, 250 days, 500 days, 1,250 days); three exponentially weighted moving average approaches (λ=0.94, λ=0.97, λ=0.99); and four historical simulation approaches (125 days, 250 days, 500 days, 1,250 days).

The data consist of daily exchange rates (bid prices collected at 4:00 p.m. New York time by the Federal Reserve Bank of New York) against the U.S. dollar for the following eight currencies: British pound, Canadian dollar, Dutch guilder, French franc, German mark, Italian lira, Japanese yen, and Swiss franc. The historical sample covers the period January 1, 1978, to January 18, 1995 (4,255 days).

Through a simulation methodology, we attempt to determine how each value-at-risk approach would have performed over a realistic range of portfolios containing the eight currencies over the sample period. The simulation methodology consists of five steps:

1. Select a random portfolio of positions in the eight currencies. This step is accomplished by drawing the position in each currency from a uniform distribution centered on zero. In other words, the portfolio space is a uniformly distributed eight dimensional cube centered on zero.[1]

2. Calculate the value-at-risk estimates for the random portfolio chosen in step one using the twelve value-at-risk approaches for each day in the sample—day 1,251 to day 4,255. In each case, we draw the historical data from the 1,250 days of historical data preceding the date for which the calculation is made. For example, the fifty-day equally weighted moving average estimate for a given date would be based on the fifty days of historical data preceding the given date.

3. Calculate the change in the portfolio's value for each day in the sample—again, day 1,251 to day 4,255. Within the article, these values are referred to as the ex post portfolio results or outcomes.

4. Assess the performance of each value-at-risk approach for the random portfolio selected in step one by comparing the value-at-risk estimates generated by step two with the actual outcomes calculated in step three.

5. Repeat steps one through four 1,000 times and tabulate the results.

[1] The upper and lower bounds on the positions in each currency are +100 million U.S. dollars and -100 million U.S. dollars, respectively. In fact, however, all of the results in the article are completely invariant to the scale of the random portfolios.

vided by the simulations. Furthermore, many of the performance criteria we consider do not have straightforward standard error formulas even for single samples.[15]

These stipulations imply that it is not possible to use the simulation results to accept or reject specific statistical hypotheses about these twelve value-at-risk approaches. Moreover, the results should not in any way be taken as indicative of the results that would be obtained for portfolios including other financial market assets, spanning other time periods, or looking forward. Finally, this article does not contribute substantially to the ongoing debate about the appropriate approach to or interpretation of "backtesting" in conjunction with value-at-risk modeling.[16] Despite these limitations, the simulation results do provide a relatively complete picture of the performance of selected value-at-risk approaches in estimating the market risk of a large number of linear foreign exchange portfolios over the period 1983-94.

For each of the nine performance criteria, Charts 4-12 provide a visual sense of the simulation results for 95th and 99th percentile risk measures. In each chart, the vertical axis depicts a relevant range of the performance criterion under consideration (value-at-risk approaches are arrayed horizontally across the chart). Filled circles depict the average results across the 1,000 portfolios, and the boxes drawn for each value-at-risk approach depict the 5th, 25th, 50th, 75th, and 95th percentiles of the distribution of the results across the 1,000 portfolios.[17] In some charts, a horizontal line is drawn to highlight how the results compare with an important point of reference. Simulation results are also presented in tabular form in the appendix.

MEAN RELATIVE BIAS

The first performance criterion we examine is whether the different value-at-risk approaches produce risk measures of similar average size. To ensure that the comparison is not influenced by the scale of each simulated portfolio, we use a four-step procedure to generate scale-free measures of the relative sizes for each simulated portfolio.

First, we calculate value-at-risk measures for each of the twelve approaches for the portfolio on each sample date. Second, we average the twelve risk measures for each date to obtain the average risk measure for that date for the portfolio. Third, we calculate the percentage difference between each approach's risk measure and the average risk measure for each date. We refer to these figures as daily relative bias figures because they are relative only to the average risk measure across the twelve approaches rather than to any external standard. Fourth, we average the daily relative biases for a given value-at-risk approach across all sample dates to obtain the approach's mean relative bias for the portfolio.

Intuitively, this procedure results in a measure of size for each value-at-risk approach that is relative to the average of all twelve approaches. The mean relative bias for a portfolio is independent of the scale of the simulated portfolio because each of the daily relative bias calculations on which it is based is also scale-independent. This independence is achieved because all of the value-at-risk approaches we examine here are proportional to the scale of the portfolio's positions. For example, a doubling of the scale of the portfolio would result in a doubling of the value-at-risk measures for each of the twelve approaches.

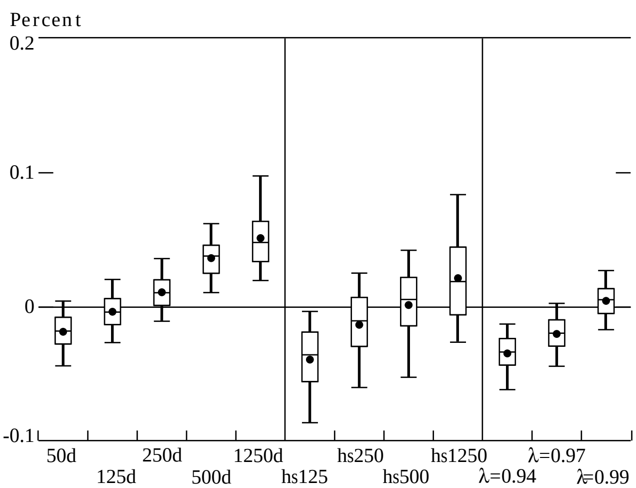
Actual 99th percentiles for the foreign exchange portfolios considered in this article tend to be larger than the normal distribution would predict.

Mean relative bias is measured in percentage terms, so that a value of 0.10 implies that a given value-at-risk approach is 10 percent larger, on average, than the average of all twelve approaches. The simulation results suggest that differences in the average size of 95th percen-

Chart 4a

Mean Relative Bias

95th Percentile Value-at-Risk Measures



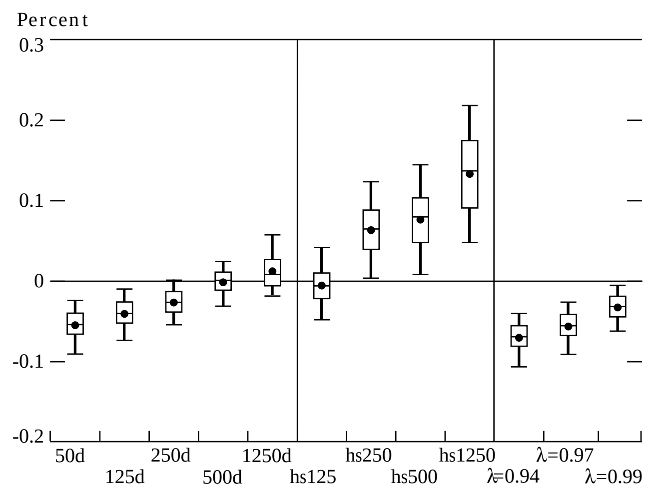
Source: Author's calculations.

Notes: d=days; hs=historical simulation; λ=exponentially weighted.

Chart 4b

Mean Relative Bias

99th Percentile Value-at-Risk Measures



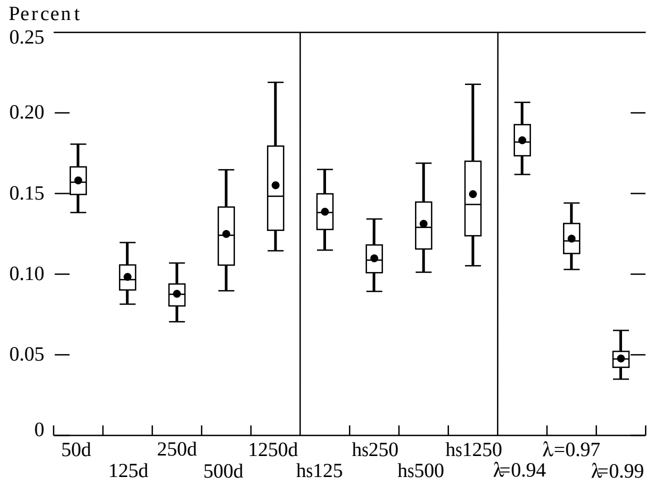
Source: Author's calculations.

Notes: d=days; hs=historical simulation; λ=exponentially weighted.

Chart 5a

Root Mean Squared Relative Bias

95th Percentile Value-at-Risk Measures



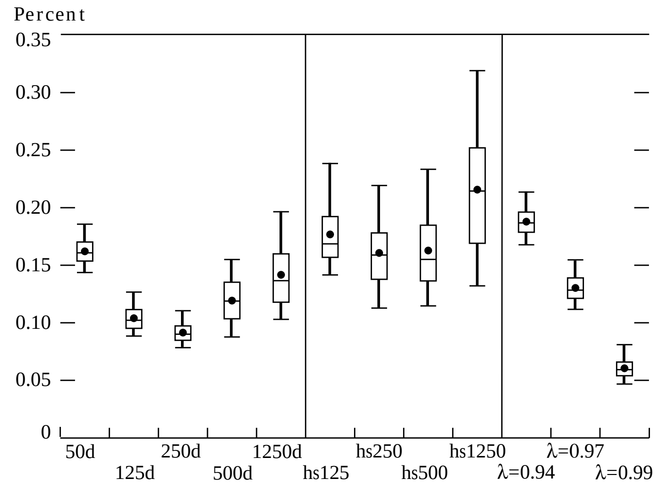
Source: Author's calculations.

Notes: d=days; hs=historical simulation; λ=exponentially weighted.

Chart 5b

Root Mean Squared Relative Bias

99th Percentile Value-at-Risk Measures



Source: Author's calculations.

Notes: d=days; hs=historical simulation; λ=exponentially weighted.

tile value-at-risk measures are small. For the vast majority of the 1,000 portfolios, the mean relative biases for the 95th percentile risk measures are between -0.10 and 0.10 (Chart 4a). The averages of the mean relative biases across the 1,000 portfolios are even smaller, indicating that across approaches little systematic difference in size exists for 95th percentile value-at-risk measures.

For the 99th percentile value-at-risk measures, however, the results suggest that historical simulation approaches tend to produce systematically larger risk measures. In particular, Chart 4b shows that the 1,250-day historical simulation approach is, on average, approximately 13 percent larger than the average of all twelve approaches; for almost all of the portfolios, this approach is more than 5 percent larger than the average risk measure.

Together, the results for the 95th and 99th percentiles suggest that the normality assumption made by all of the approaches, except the historical simulations, is more reasonable for the 95th percentile than for the 99th percentile. In other words, actual 99th percentiles for the foreign exchange portfolios considered in this article tend to be larger than the normal distribution would predict.

Interestingly, the results in Charts 4a and 4b also suggest that the use of longer time periods may produce larger value-at-risk measures. For historical simulation approaches, this result may occur because longer horizons provide better estimates of the tail of the distribution. The equally weighted approaches, however, may require a different explanation. Nevertheless, in our simulations the time period effect is small, suggesting that its economic significance is probably low.[18]

Root Mean Squared Relative Bias

The second performance criterion we examine is the degree to which the risk measures tend to vary around the average risk measure for a given date. This criterion can be compared to a standard deviation calculation; here the deviations are the risk measure's percentage of deviation from the average across all twelve approaches. The root mean squared relative bias for each value-at-risk approach is calculated by taking the square root of the mean (over all sample dates) of the squares of the daily relative biases.

The results indicate that for any given date, a dispersion in the risk measures produced by the different value-at-risk approaches is likely to occur. The average root mean squared relative biases, across portfolios, tend to fall largely in the 10 to 15 percent range, with the 99th percentile risk measures tending toward the higher end (Charts 5a and 5b). This level of variability suggests that, in spite of similar average sizes across the different value-at-risk approaches, differences in the range of 30 to 50 percent between the risk measures produced by specific approaches on a given day are not uncommon.

Surprisingly, the exponentially weighted average approach with a decay factor of 0.99 exhibits very low root mean squared bias, suggesting that this particular approach is very close to the average of all twelve approaches. Of course, this phenomenon is specific to the twelve approaches considered here and would not necessarily be true of exponentially weighted average approaches applied to other cases.

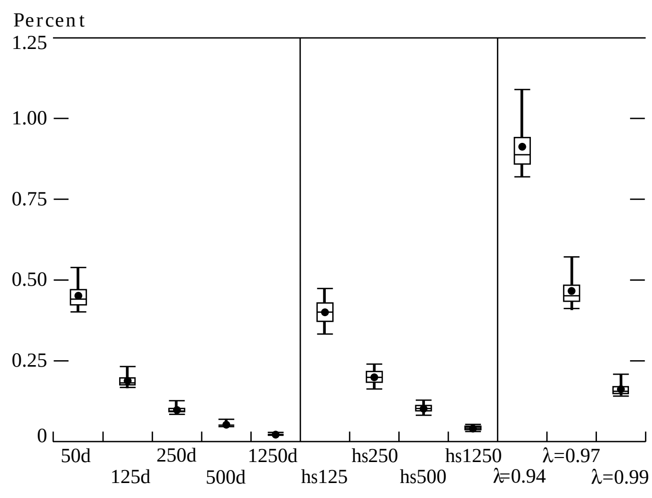
Annualized Percentage Volatility

The third performance criterion we review is the tendency of the risk measures to fluctuate over time for the same portfolio. For each portfolio and each value-at-risk approach, we calculate the annualized percentage volatility by first taking the standard deviation of the day-to-day percentage changes in the risk measures over the sample period. Second, we put the result on an annualized basis by multiplying this standard deviation by the square root of 250, the number of trading days in a typical calendar year. We complete the second step simply to make the results comparable with volatilities as they are often expressed in the marketplace. For example, individual foreign exchange rates tend to have annualized percentage volatilities in the range of 5 to 20 percent, although higher figures sometimes occur. This result implies that the value-at-risk approaches with annualized percentage volatilities in excess of 20 percent (Charts 6a and 6b) will fluctuate more over time (for the same portfolio) than will most exchange rates themselves.

Our major observation for this performance criterion is that the volatility of risk measures increases as reliance on recent data increases. As shown in Charts 6a and 6b, this increase is true for both the 95th and 99th percentile risk measures and for all three categories of value-at-risk approaches. This result is not surprising, and indeed it is clearly apparent in Charts 1-3, which depict time series of different value-at-risk approaches over the sample period. Also worth noting in Charts 6a and 6b is that for a fixed length of observation period, historical sim-

Chart 6a

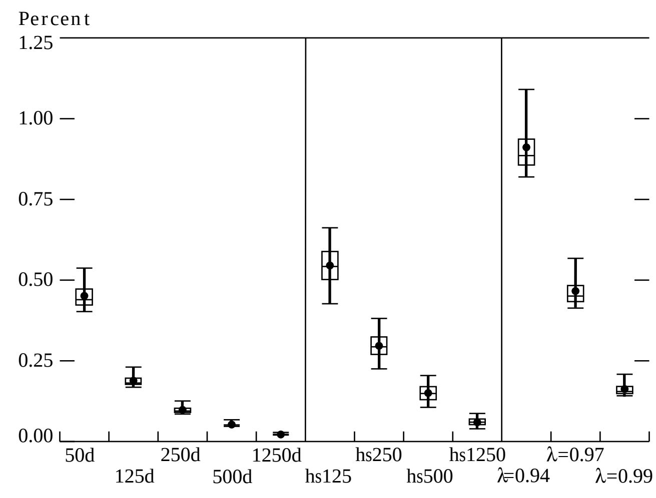
Annualized Percentage Volatility
95th Percentile Value-at-Risk Measures



Source: Author's calculations.
Notes: d=days; hs=historical simulation; λ=exponentially weighted.

Chart 6b

Annualized Percentage Volatility
99th Percentile Value-at-Risk Measures



Source: Author's calculations.
Notes: d=days; hs=historical simulation; λ=exponentially weighted.

ulation approaches appear to be more variable than the corresponding equally weighted moving average approaches.

Fraction of Outcomes Covered

Our fourth performance criterion addresses the fundamental goal of the value-at-risk measures—whether they cover the portfolio outcomes they are intended to capture. We calculate the fraction of outcomes covered as the percentage of results where the loss in portfolio value is less than the risk measure.

For the 95th percentile risk measures, the simulation results indicate that nearly all twelve value-at-risk approaches meet this performance criterion (Chart 7a). For many portfolios, coverage exceeds 95 percent, and only the 125-day historical simulation approach captures less than 94.5 percent of the outcomes on average across all 1,000 portfolios. In a very small fraction of the random portfolios, the risk measures cover less than 94 percent of the outcomes.

Interestingly, the 95th percentile results suggest that the equally weighted moving average approaches actually tend to produce excess coverage (greater than 95 percent) for all observation periods except fifty days. By contrast, the historical simulation approaches tend to provide either too little coverage or, in the case of the 1,250-day historical simulation approach, a little more than the desired amount. The exponentially weighted moving average approach with a decay factor of 0.97 produces exact 95 percent coverage, but for this approach the results

All twelve value-at-risk approaches either achieve the desired level of coverage or come very close to it on the basis of the percentage of outcomes misclassified.

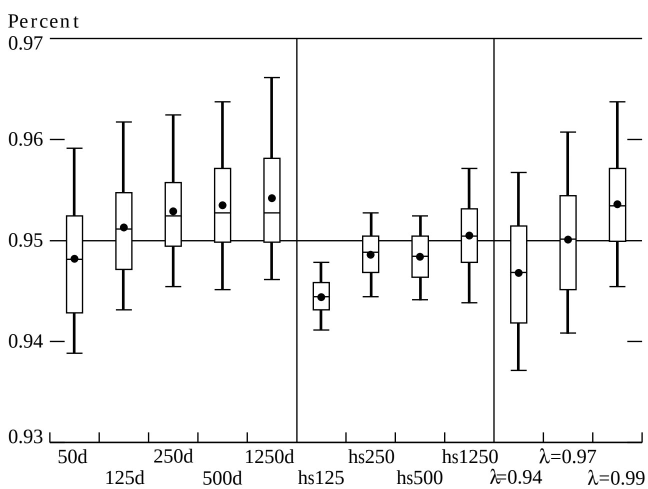
are more variable across portfolios than for the 1,250-day historical simulation approach.

Compared with the 95th percentile results, the 99th percentile risk measures exhibit a more widespread tendency to fall short of the desired level of risk coverage. Only the 1,250-day historical simulation approach attains 99 percent coverage across all 1,000 portfolios, as shown in Chart 7b. The other approaches cover between 98.2 and

Chart 7a

Fraction of Outcomes Covered

95th Percentile Value-at-Risk Measures



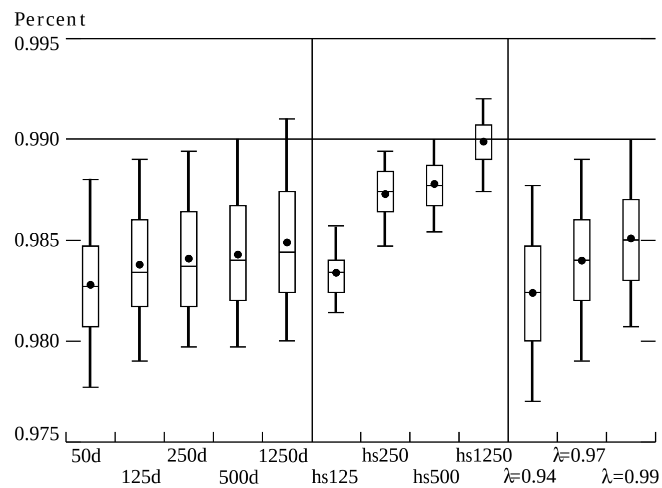
Source: Author's calculations.

Notes: d=days; hs=historical simulation; λ=exponentially weighted.

Chart 7b

Fraction of Outcomes Covered

99th Percentile Value-at-Risk Measures



Source: Author's calculations.

Notes: d=days; hs=historical simulation; λ=exponentially weighted.

98.8 percent of the outcomes on average across portfolios. Of course, the consequences of such a shortfall in performance depend on the particular circumstances in which the value-at-risk model is being used. A coverage level of 98.2 percent when a risk manager desires 99 percent implies that the value-at-risk model misclassifies approximately two outcomes every year (assuming that there are 250 trading days per calendar year).

Overall, the results in Charts 7a and 7b support the conclusion that all twelve value-at-risk approaches either achieve the desired level of coverage or come very close to it on the basis of the percentage of outcomes misclassified. Clearly, the best performer is the 1,250-day historical simulation approach, which attains almost exact coverage for both the 95th and 99th percentiles, while the worst performer is the 125-day historical simulation approach, partly because of its short-term construction.[19] One explanation for the superior performance of the 1,250-day historical simulation is that the unconditional distribution of changes in portfolio value is relatively stable and that accurate estimates of extreme percentiles require the use of long periods. These results underscore the problems associated with the assumption of normality for 99th percentiles and are consistent with findings in other recent studies of value-at-risk models.[20]

Multiple Needed to Attain Desired Coverage

The fifth performance criterion we examine focuses on the size of the adjustments in the risk measures that would be needed to achieve perfect coverage. We therefore calculate on an ex post basis the multiple that would have been required for each value-at-risk measure to attain the desired level of coverage (either 95 percent or 99 percent). This performance criterion complements the fraction of outcomes covered because it focuses on the size of the potential errors in risk measurement rather than on the percentage of results captured.

For 95th percentile risk measures, the simulation results indicate that multiples very close to one are sufficient (Chart 8a). Even the 125-day historical simulation approach, which on average across portfolios is furthest from the desired outcome, requires a multiple of only 1.04. On the whole, none of the approaches considered here appears to understate 95th percentile risk measures on a systematic basis by more than 4 percent, and several appear to overstate them by small amounts.

For the 99th percentile risk measures, most value-at-risk approaches require multiples between 1.10 and 1.15 to attain 99 percent coverage (Chart 8b). The 1,250-day historical simulation approach, however, is markedly superior to all other approaches. On average across all portfolios, no multiple other than one is needed for this approach to achieve 99 percent coverage. Moreover, compared with the other approaches, the historical simulations in general exhibit less variability across portfolios with respect to this criterion.

Shortcomings in value-at-risk measures that seem small in probability terms may be much more significant when considered in terms of the changes required to remedy them.

The fact that most multiples are larger than one is not surprising. More significant is the fact that the size of the multiples needed to achieve 99 percent coverage exceeds the levels indicated by the normal distribution. For example, when normality is assumed, the 99th percentile would be about 1.08 times as large as the 98.4th percentile, a level of coverage comparable to that attained by many of the approaches (Chart 7b). The multiples for these approaches, shown in Chart 8b, are larger than 1.08, providing further evidence that the normal distribution does not accurately approximate actual distributions at points near the 99th percentile. More generally, the results also suggest that substantial increases in value-at-risk measures may be needed to capture outcomes in the tail of the distribution. Hence, shortcomings in value-at-risk measures that seem small in probability terms may be much more significant when considered in terms of the changes required to remedy them.

These results lead to an important question: what distributional assumptions other than normality can be used when constructing value-at-risk measures using a variance-covariance approach? The t-distribution is often cited as a good candidate, because extreme outcomes occur more often under t-distributions than under the normal distribution.[21] A brief analysis shows that the use of a t-distribution for the 99th percentile has some merit.

To calculate a value-at-risk measure for a single percentile assuming the t-distribution, the value-at-risk measure calculated with the assumption of normality is multiplied by a fixed multiple. As the results in Chart 8b suggest, fixed multiples between 1.10 and 1.15 are appropriate for the variance-covariance approaches. It follows that t-distributions with between four and six degrees of freedom are appropriate for the 99th percentile risk measures.[22] The use of these particular t-distributions, however, would lead to substantial overestimation of 95th percentile risk measures because the actual distributions near the 95th percentile are much closer to normality. Since the use of t-distributions for risk measurement involves a scaling up of the risk measures that are calculated assuming normality, the distributions are likely to be useful, although they may be more helpful for some percentiles than for others.

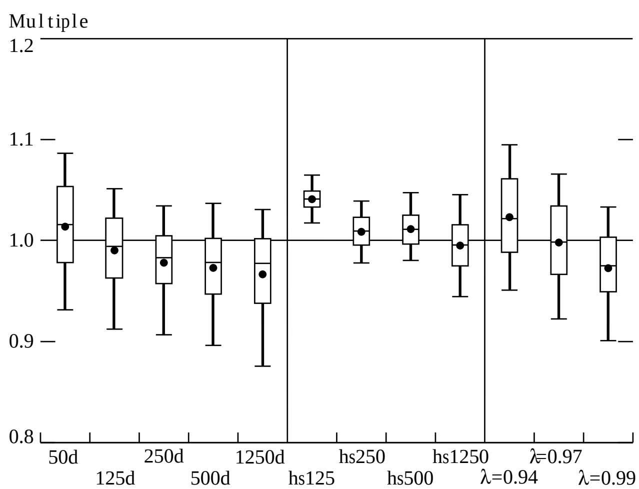
Average Multiple of Tail Event to Risk Measure

The sixth performance criterion that we review relates to the size of outcomes not covered by the risk measures.[23] To address these outcomes, we measure the degree to which events in the tail of the distribution typically exceed the value-at-risk measure by calculating the average multiple of these outcomes ("tail events") to their corresponding value-at-risk measures.

Tail events are defined as the largest percentage of losses measured relative to the respective value-at-risk estimate—the largest 5 percent in the case of 95th percentile risk measures and the largest 1 percent in the case of 99th percentile risk measures. For example, if the value-at-risk measure is $1.5 million and the actual portfolio outcome is a loss of $3 million, the size of the loss relative to the risk measure would be two. Note that this definition implies that the tail events for one value-at-risk approach may not be the same as those for another approach, even for the same portfolio, because the risk

Chart 8a

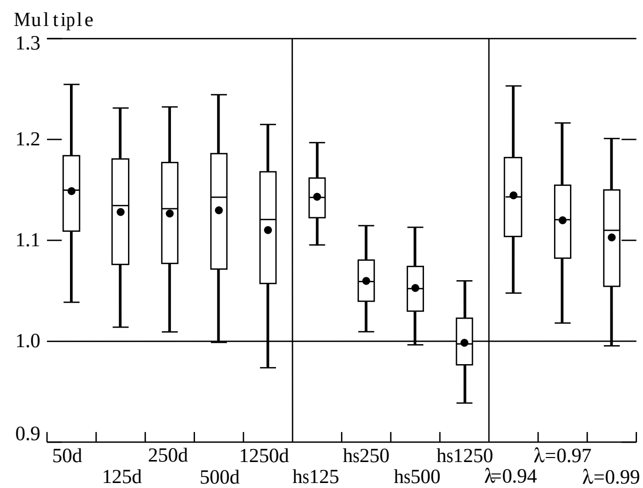
Multiple Needed to Attain 95 Percent Coverage
95th Percentile Value-at-Risk Measures



Source: Author's calculations.
Notes: d=days; hs=historical simulation; λ=exponentially weighted.

Chart 8b

Multiple Needed to Attain 99 Percent Coverage
99th Percentile Value-at-Risk Measures



Source: Author's calculations.
Notes: d=days; hs=historical simulation; λ=exponentially weighted.

measures for the two approaches are not the same. Horizontal reference lines in Charts 9a and 9b show where the average multiples of the tail event outcomes to the risk measures would fall if outcomes were normally distributed and the value-at-risk approach produced a true 99th percentile level of coverage.

In fact, however, the average tail event is almost always a larger multiple of the risk measure than is predicted by the normal distribution. For most of the value-at-risk approaches, the average tail event is 30 to 40 percent larger than the respective risk measures for both the 95th percentile risk measures and the 99th percentile risk measures. This result means that approximately 1 percent of outcomes (the largest two or three losses per year) will exceed the size of the 99th percentile risk measure by an average of 30 to 40 percent. In addition, note that the 99th percentile results in Chart 9b are more variable across portfolios than the 95th percentile results in Chart 9a; the average multiple is also above 1.50 for a greater percentage of the portfolios for the 99th percentile risk measures.

The performance of the different approaches according to this criterion largely mirrors their performance in capturing portfolio outcomes. For example, the 1,250-day historical simulation approach is clearly superior for the 99th percentile risk measures. The equally weighted moving average approaches also do very well for the 95th percentile risk measures (Chart 7a).

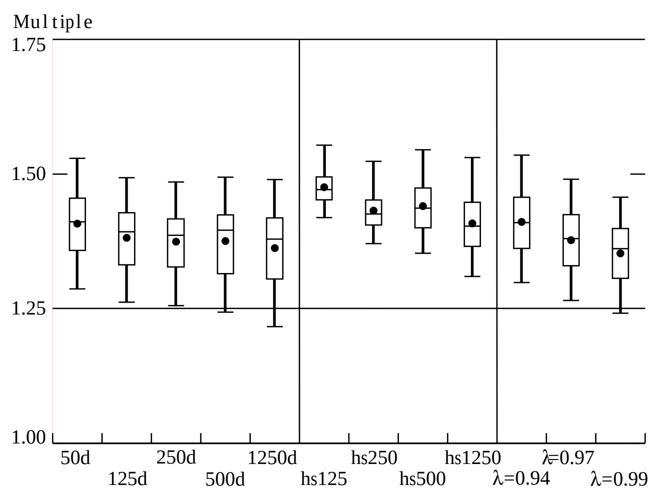
Maximum Multiple of Tail Event to Risk Measure

Our seventh performance criterion concerns the size of the maximum portfolio loss. We use the following two-step procedure to arrive at these measures. First, we calculate the multiples of all portfolio outcomes to their respective risk measures for each value-at-risk approach for a particular portfolio. Recall that the tail events defined above are those outcomes with the largest such multiples. Rather than average these multiples, however, we simply select the single largest multiple for each approach. This procedure implies that the maximum multiple will be highly dependent on the length of the sample period—in this case, approximately twelve years. For shorter periods, the maximum multiple would likely be lower.

Not surprisingly, the typical maximum tail event is substantially larger than the corresponding risk measure (Charts 10a and 10b). For 95th percentile risk measures, the maximum multiple is three to four times as large as the risk measure, and for the 99th percentile risk measure, it is

Chart 9a

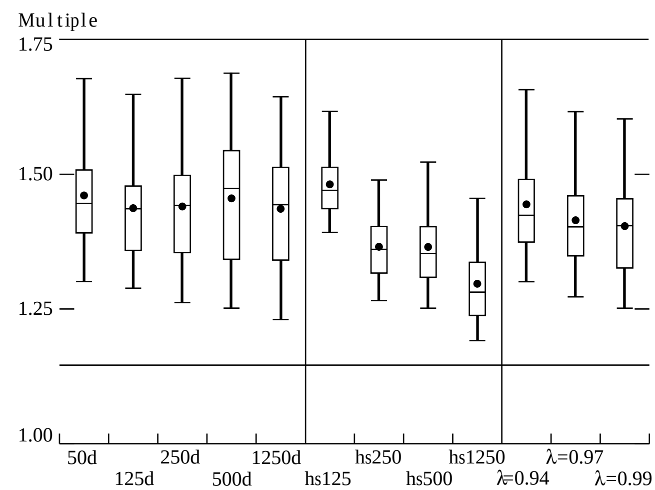
Average Multiple of Tail Event to Risk Measure
95th Percentile Value-at-Risk Measures



Source: Author's calculations.
Notes: d=days; hs=historical simulation; λ=exponentially weighted.

Chart 9b

Average Multiple of Tail Event to Risk Measure
99th Percentile Value-at-Risk Measures



Source: Author's calculations.
Notes: d=days; hs=historical simulation; λ=exponentially weighted.

approximately 2.5 times as large. In addition, the results are variable across portfolios—for some portfolios, the maximum multiples are more than five times the 95th percentile risk measure. The differences among results for this performance criterion, however, are less pronounced than for some other criteria. For example, the 1,250-day historical simulation approach is not clearly superior for the 99th percentile risk measure—as it had been for many of the other performance criteria—although it does exhibit lower average multiples (Chart 9b).

It is important not to view value-at-risk measures as a strict upper bound on the portfolio losses that can occur.

These results suggest that it is important not to view value-at-risk measures as a strict upper bound on the portfolio losses that can occur. Although a 99th percentile risk measure may sound as if it is capturing essentially all of the relevant events, our results make it clear that the other 1 percent of events can in extreme cases entail losses substantially in excess of the risk measures generated on a daily basis.

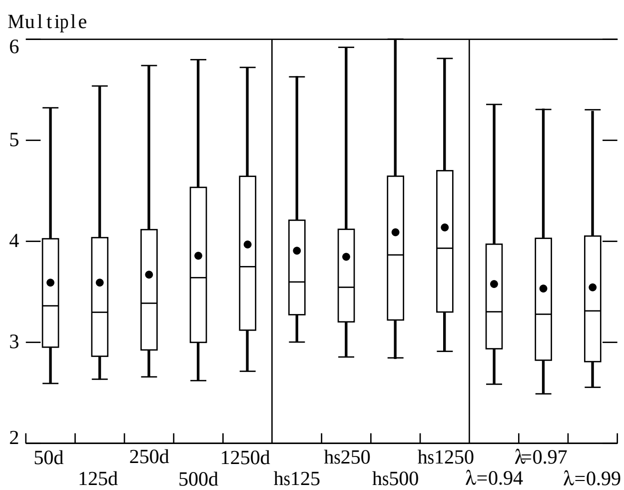
CORRELATION BETWEEN RISK MEASURE AND ABSOLUTE VALUE OF OUTCOME

The eighth performance criterion assesses how well the risk measures adjust over time to underlying changes in risk. In other words, how closely do changes in the value-at-risk measures correspond to actual changes in the risk of the portfolio? We answer this question by determining the correlation between the value-at-risk measures for each approach and the absolute values of the outcomes. This correlation statistic has two advantages. First, it is not affected by the scale of the portfolio. Second, the correlations are relatively easy to interpret, although even a perfect value-at-risk measure cannot guarantee a correlation of one between the risk measure and the absolute value of the outcome.

For this criterion, the results for the 95th percentile risk measures and 99th percentile risk measures are almost identical (Charts 11a and 11b). Most striking is the superior performance of the exponentially weighted moving average measures. This finding implies that these approaches tend to track changes in risk over time more accurately than the other approaches.

Chart 10a

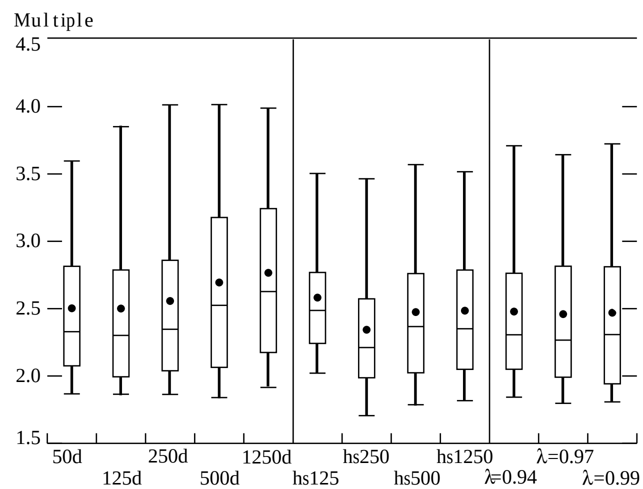
Maximum Multiple of Tail Event to Risk Measure
95th Percentile Value-at-Risk Measures



Source: Author's calculations.
Notes: d=days; hs=historical simulation; λ=exponentially weighted.

Chart 10b

Maximum Multiple of Tail Event to Risk Measure
99th Percentile Value-at-Risk Measures

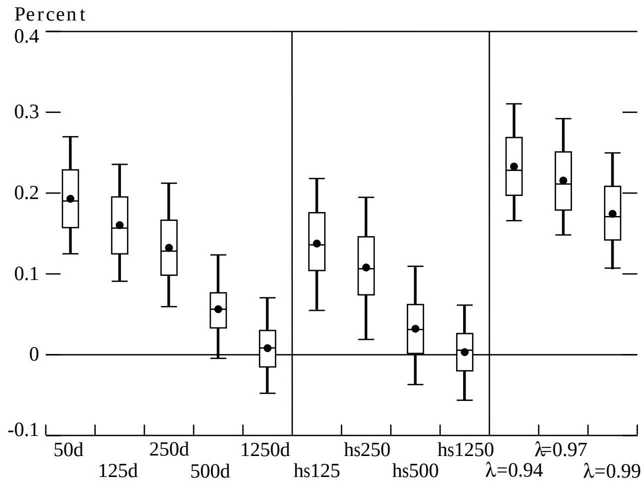


Source: Author's calculations.
Notes: d=days; hs=historical simulation; λ=exponentially weighted.

Chart 11a

Correlation between Risk Measure and Absolute Value of Outcome

95th Percentile Value-at-Risk Measures



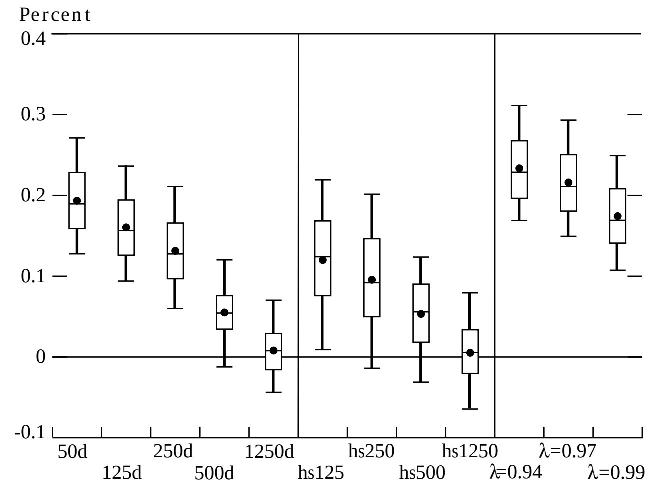
Source: Author's calculations.

Notes: d=days; hs=historical simulation; λ=exponentially weighted.

Chart 11b

Correlation between Risk Measure and Absolute Value of Outcome

99th Percentile Value-at-Risk Measures



Source: Author's calculations.

Notes: d=days; hs=historical simulation; λ=exponentially weighted.

In contrast to the results for mean relative bias (Charts 4a and 4b) and the fraction of outcomes covered (Charts 7a and 7b), the results for this performance criterion show that the length of the observation period is inversely related to performance. Thus, shorter observation periods tend to lead to higher measures of correlation between the absolute values of the outcomes and the value-at-risk measures. This inverse relationship supports the view that, because market behavior changes over time, emphasis on recent information can be helpful in tracking changes in risk.

At the other extreme, the risk measures for the 1,250-day historical simulation approach are essentially uncorrelated with the absolute values of the outcomes. Although superior according to other performance criteria, the 1,250-day results here indicate that this approach reveals little about actual changes in portfolio risk over time.

Mean Relative Bias for Risk Measures Scaled to Desired Level of Coverage

The last performance criterion we examine is the mean relative bias that results when risk measures are scaled to either 95 percent or 99 percent coverage. Such scaling is accomplished on an ex post basis by multiplying the risk measures for each approach by the multiples needed to attain either exactly 95 percent or exactly 99 percent coverage (Charts 8a and 8b). These scaled risk measures provide the precise amount of coverage desired for each portfolio. Of course, the scaling for each value-at-risk approach would not be the same for different portfolios.

Because market behavior changes over time, emphasis on recent information can be helpful in tracking changes in risk.

Once we have arrived at the scaled value-at-risk measures, we compare their relative average sizes by using the mean relative bias calculation, which compares the average size of the risk measures for each approach to the average size across all twelve approaches (Charts 4a and 4b). In this case, however, the value-at-risk measures have been scaled to the desired levels of coverage. The purpose of this criterion is to determine which approach, once suitably scaled, could provide the desired level of coverage with the smallest average risk measures. This performance criterion also addresses the issue of tracking changes in portfolio risk—the most efficient approach will be the one that tracks changes in risk best. In contrast to the correlation statistic discussed in the previous section, however, this criterion focuses specifically on the 95th and 99th percentiles.

Once again, the exponentially weighted moving average approaches appear superior (Charts 12a and 12b). In particular, the exponentially weighted average approach with a decay factor of 0.97 appears to perform extremely well for both 95th and 99th percentile risk measures. Indeed, for the 99th percentile, it achieves exact 99 percent coverage with an average size that is 4 percent smaller than the average of all twelve scaled value-at-risk approaches.

The performance of the other approaches is similar to that observed for the correlation statistic (Charts 11a and 11b), but in this case the relationship between efficiency and the length of the observation period is not as pronounced. In particular, the 50-day equally weighted approach is somewhat inferior to the 250-day equally weighted approach—a finding contrary to what is observed in Charts 11a and 11b—and may reflect the greater influence of measurement error on short observation periods along this performance criterion.

At least two caveats apply to these results. First, they would be difficult to duplicate in practice because the scaling must be done in advance of the outcomes rather than ex post. Second, the differences in the average sizes of the scaled risk measures are simply not very large. Nevertheless, the results suggest that exponentially weighted average approaches might be capable of providing desired levels of coverage in an efficient fashion, although they would need to be scaled up.

CONCLUSIONS

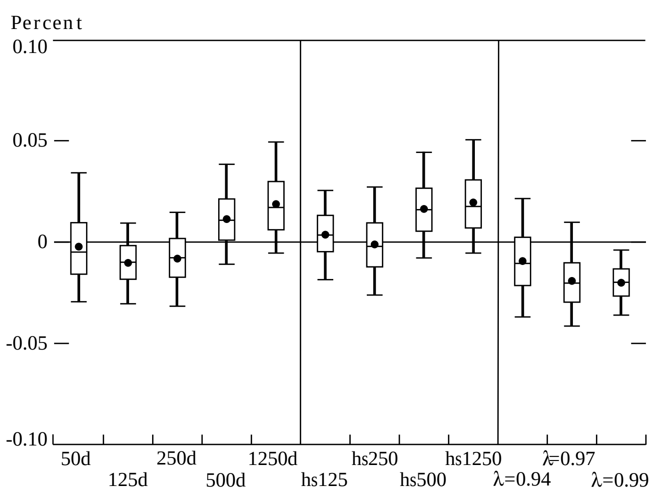
A historical examination of twelve approaches to value-at-risk modeling shows that in almost all cases the approaches cover the risk that they are intended to cover. In addition, the twelve approaches tend to produce risk estimates that do not differ greatly in average size, although historical simulation approaches yield somewhat larger 99th percentile risk measures than the variance-covariance approaches.

Despite the similarity in the average size of the risk estimates, our investigation reveals differences, some-

Chart 12a

Mean Relative Bias for Risk Measures Scaled to Cover Exactly 95 Percent

95th Percentile Value-at-Risk Measures



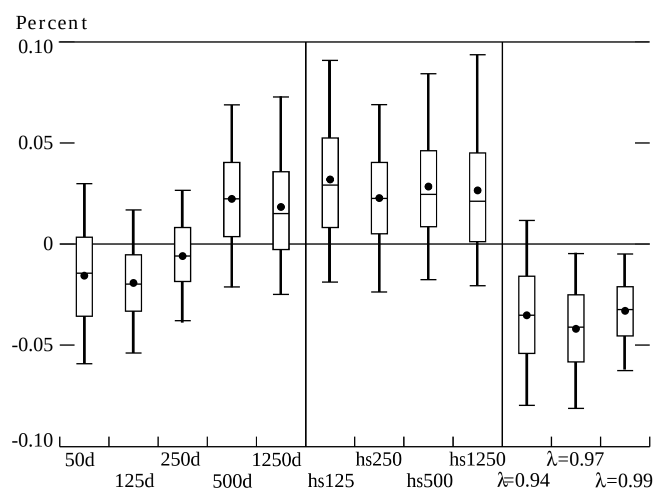
Source: Author's calculations.

Notes: d=days; hs=historical simulation; λ=exponentially weighted.

Chart 12b

Mean Relative Bias for Risk Measures Scaled to Cover Exactly 99 Percent

99th Percentile Value-at-Risk Measures



Source: Author's calculations.

Notes: d=days; hs=historical simulation; λ=exponentially weighted.

times substantial, among the various value-at-risk approaches for the same portfolio on the same date. In terms of variability over time, the value-at-risk approaches using longer observation periods tend to produce less variable results than those using short observation periods or weighting recent observations more heavily.

Virtually all of the approaches produce accurate 95th percentile risk measures. The 99th percentile risk measures, however, are somewhat less reliable and generally cover only between 98.2 percent and 98.5 percent of the outcomes. On the one hand, these deficiencies are small when considered on the basis of the percentage of outcomes misclassified. On the other hand, the risk measures would generally need to be increased across the board by 10 percent or more to cover precisely 99 percent of the outcomes. Interestingly, one exception is the 1,250-day historical simulation approach, which provides very accurate coverage for both 95th and 99th percentile risk measures.

The outcomes that are *not* covered are typically 30 to 40 percent larger than the risk measures and are also larger than predicted by the normal distribution. In some cases, daily losses over the twelve-year sample period are several times larger than the corresponding value-at-risk measures. These examples make it clear that value-at-risk measures—even at the 99th percentile—do not "bound" possible losses.

Also clear is the difficulty of anticipating or tracking changes in risk over time. For this performance criterion, the exponentially weighted moving average approaches appear to be superior. If it were possible to scale all approaches ex post to achieve the desired level of coverage over the sample period, these approaches would produce the smallest scaled risk measures.

What more general conclusions can be drawn from these results? In many respects, the simulation estimates clearly reflect two well-known characteristics of daily financial market data. First, extreme outcomes occur more often and are larger than predicted by the normal distribution (fat tails). Second, the size of market movements is not constant over time (conditional volatility). Clearly, constructing value-at-risk models that perform well by every measure is a difficult task. Thus, although we cannot recommend any single value-at-risk approach, our results suggest that further research aimed at combining the best features of the approaches examined here may be worthwhile.

Appendix: Value-at-Risk Simulation Results for Each Performance Criterion

The nine tables below summarize for each performance criterion the simulation results for the 95th and 99th percentile risk measures. The value-at-risk approaches appear at the extreme left of each table. The first column reports the average simulation result of each approach across the 1,000 portfolios for the particular performance criterion. The next column reports the standard deviation of the results across the 1,000 portfolios, a calculation that provides information on the variability of the results across portfolios. To indicate the variability of results over time, the remaining four columns report results averaged over the 1,000 portfolios for four subsets of the sample period.

Table A1
MEAN RELATIVE BIAS

	Entire Sample Period		1983-85	1986-88	1989-91	1992-94
	Mean across Portfolios	Standard Deviation across Portfolios	Mean across Portfolios	Mean across Portfolios	Mean across Portfolios	Mean across Portfolios
PANEL A: 95TH PERCENTILE VALUE-AT-RISK MEASURES						
50-day equally weighted	-0.02	0.01	-0.00	-0.05	0.01	-0.03
125-day equally weighted	-0.00	0.01	-0.00	-0.02	0.01	-0.00
250-day equally weighted	0.01	0.01	-0.01	0.03	0.00	0.03
500-day equally weighted	0.04	0.02	0.01	0.08	-0.01	0.07
1,250-day equally weighted	0.05	0.03	0.08	0.06	0.05	0.01
125-day historical simulation	-0.04	0.03	-0.04	-0.06	-0.03	-0.04
250-day historical simulation	-0.01	0.03	-0.03	0.00	-0.02	0.00
500-day historical simulation	0.00	0.03	-0.02	0.05	-0.05	0.03
1,250-day historical simulation	0.02	0.03	0.05	0.03	0.02	-0.02
Exponentially weighted (λ=0.94)	-0.03	0.01	-0.02	-0.07	-0.01	-0.04
Exponentially weighted (λ=0.97)	-0.02	0.01	-0.01	-0.05	0.00	-0.02
Exponentially weighted (λ=0.99)	0.00	0.01	-0.00	0.00	0.01	0.01
PANEL B: 99TH PERCENTILE VALUE-AT-RISK MEASURES						
50-day equally weighted	-0.05	0.02	-0.03	-0.09	-0.03	-0.06
125-day equally weighted	-0.04	0.02	-0.03	-0.06	-0.03	-0.04
250-day equally weighted	-0.03	0.02	-0.04	-0.01	-0.04	-0.01
500-day equally weighted	-0.00	0.02	-0.02	0.04	-0.05	0.03
1,250-day equally weighted	0.01	0.03	0.04	0.02	0.01	-0.02
125-day historical simulation	-0.01	0.03	-0.03	-0.00	0.01	-0.00
250-day historical simulation	0.06	0.04	0.02	0.08	0.07	0.08
500-day historical simulation	0.08	0.04	0.04	0.11	0.05	0.11
1,250-day historical simulation	0.13	0.05	0.18	0.13	0.13	0.09
Exponentially weighted (λ=0.94)	-0.07	0.02	-0.05	-0.10	-0.05	-0.08
Exponentially weighted (λ=0.97)	-0.06	0.02	-0.04	-0.08	-0.04	-0.06
Exponentially weighted (λ=0.99)	-0.03	0.02	-0.03	-0.04	-0.04	-0.03

Table A2
ROOT MEAN SQUARED RELATIVE BIAS

	Entire Sample Period		1983-85	1986-88	1989-91	1992-94
	Mean across Portfolios	Standard Deviation across Portfolios	Mean across Portfolios	Mean across Portfolios	Mean across Portfolios	Mean across Portfolios
PANEL A: 95TH PERCENTILE VALUE-AT-RISK MEASURES						
50-day equally weighted	0.16	0.01	0.17	0.15	0.14	0.16
125-day equally weighted	0.10	0.01	0.10	0.10	0.08	0.11
250-day equally weighted	0.09	0.01	0.08	0.09	0.08	0.09
500-day equally weighted	0.13	0.02	0.13	0.13	0.08	0.13
1,250-day equally weighted	0.16	0.04	0.18	0.14	0.14	0.14
125-day historical simulation	0.14	0.02	0.15	0.13	0.13	0.14
250-day historical simulation	0.11	0.01	0.12	0.11	0.10	0.11
500-day historical simulation	0.13	0.02	0.14	0.13	0.10	0.14
1,250-day historical simulation	0.15	0.03	0.17	0.13	0.13	0.15
Exponentially weighted (λ=0.94)	0.18	0.01	0.20	0.17	0.17	0.19
Exponentially weighted (λ=0.97)	0.12	0.01	0.13	0.11	0.10	0.13
Exponentially weighted (λ=0.99)	0.05	0.01	0.05	0.04	0.04	0.05
PANEL B: 99TH PERCENTILE VALUE-AT-RISK MEASURES						
50-day equally weighted	0.16	0.01	0.17	0.16	0.14	0.16
125-day equally weighted	0.10	0.01	0.11	0.11	0.08	0.11
250-day equally weighted	0.09	0.01	0.09	0.09	0.09	0.09
500-day equally weighted	0.12	0.02	0.13	0.12	0.10	0.12
1,250-day equally weighted	0.14	0.03	0.16	0.13	0.13	0.14
125-day historical simulation	0.18	0.03	0.15	0.19	0.17	0.17
250-day historical simulation	0.16	0.03	0.14	0.15	0.16	0.16
500-day historical simulation	0.16	0.04	0.15	0.18	0.12	0.17
1,250-day historical simulation	0.22	0.06	0.24	0.20	0.19	0.19
Exponentially weighted (λ=0.94)	0.19	0.01	0.20	0.19	0.17	0.19
Exponentially weighted (λ=0.97)	0.13	0.01	0.14	0.13	0.11	0.13
Exponentially weighted (λ=0.99)	0.06	0.01	0.06	0.06	0.05	0.06

APPENDIX: VALUE-AT-RISK SIMULATION RESULTS FOR EACH PERFORMANCE CRITERION (*Continued)*

Table A3
ANNUALIZED PERCENTAGE VOLATILITY

	Entire Sample Period		1983-85	1986-88	1989-91	1992-94
	Mean across Portfolios	Standard Deviation across Portfolios	Mean across Portfolios	Mean across Portfolios	Mean across Portfolios	Mean across Portfolios
PANEL A: 95TH PERCENTILE VALUE-AT-RISK MEASURES						
50-day equally weighted	0.45	0.05	0.49	0.42	0.44	0.45
125-day equally weighted	0.19	0.03	0.18	0.19	0.17	0.20
250-day equally weighted	0.10	0.02	0.10	0.09	0.09	0.11
500-day equally weighted	0.05	0.01	0.06	0.05	0.05	0.05
1,250-day equally weighted	0.02	0.00	0.03	0.02	0.02	0.02
125-day historical simulation	0.40	0.04	0.38	0.39	0.40	0.41
250-day historical simulation	0.20	0.02	0.20	0.19	0.19	0.21
500-day historical simulation	0.10	0.01	0.11	0.09	0.10	0.10
1,250-day historical simulation	0.04	0.01	0.04	0.04	0.04	0.04
Exponentially weighted (λ=0.94)	0.91	0.09	0.94	0.88	0.89	0.94
Exponentially weighted (λ=0.97)	0.47	0.06	0.49	0.43	0.44	0.49
Exponentially weighted (λ=0.99)	0.16	0.03	0.18	0.14	0.15	0.17
PANEL B: 99TH PERCENTILE VALUE-AT-RISK MEASURES						
50-day equally weighted	0.45	0.05	0.49	0.42	0.44	0.45
125-day equally weighted	0.19	0.03	0.18	0.19	0.17	0.20
250-day equally weighted	0.10	0.02	0.10	0.09	0.09	0.11
500-day equally weighted	0.05	0.01	0.06	0.05	0.05	0.05
1,250-day equally weighted	0.02	0.01	0.03	0.02	0.02	0.02
125-day historical simulation	0.55	0.07	0.49	0.55	0.51	0.57
250-day historical simulation	0.30	0.05	0.27	0.28	0.27	0.31
500-day historical simulation	0.15	0.03	0.16	0.13	0.14	0.15
1,250-day historical simulation	0.06	0.02	0.06	0.05	0.06	0.06
Exponentially weighted (λ=0.94)	0.91	0.10	0.94	0.88	0.88	0.94
Exponentially weighted (λ=0.97)	0.47	0.06	0.49	0.43	0.44	0.49
Exponentially weighted (λ=0.99)	0.16	0.03	0.18	0.14	0.15	0.17

Appendix: Value-at-Risk Simulation Results for Each Performance Criterion (*Continued*)

Table A4
FRACTION OF OUTCOMES COVERED

	Entire Sample Period		1983-85	1986-88	1989-91	1992-94
	Mean across Portfolios	Standard Deviation across Portfolios	Mean across Portfolios	Mean across Portfolios	Mean across Portfolios	Mean across Portfolios
PANEL A: 95TH PERCENTILE VALUE-AT-RISK MEASURES						
50-day equally weighted	0.948	0.006	0.948	0.947	0.949	0.948
125-day equally weighted	0.951	0.006	0.950	0.953	0.951	0.953
250-day equally weighted	0.953	0.005	0.946	0.960	0.950	0.956
500-day equally weighted	0.954	0.006	0.946	0.963	0.947	0.958
1,250-day equally weighted	0.954	0.006	0.954	0.959	0.954	0.950
125-day historical simulation	0.944	0.002	0.943	0.946	0.943	0.946
250-day historical simulation	0.949	0.003	0.943	0.955	0.945	0.952
500-day historical simulation	0.948	0.003	0.942	0.959	0.941	0.952
1,250-day historical simulation	0.951	0.004	0.951	0.956	0.951	0.945
Exponentially weighted (λ=0.94)	0.947	0.006	0.948	0.946	0.947	0.946
Exponentially weighted (λ=0.97)	0.950	0.006	0.950	0.950	0.950	0.950
Exponentially weighted (λ=0.99)	0.954	0.006	0.950	0.957	0.951	0.956
PANEL B: 99TH PERCENTILE VALUE-AT-RISK MEASURES						
50-day equally weighted	0.983	0.003	0.985	0.982	0.982	0.983
125-day equally weighted	0.984	0.003	0.984	0.984	0.982	0.984
250-day equally weighted	0.984	0.003	0.982	0.987	0.982	0.986
500-day equally weighted	0.984	0.003	0.981	0.989	0.981	0.987
1,250-day equally weighted	0.985	0.003	0.984	0.988	0.984	0.983
125-day historical simulation	0.983	0.001	0.983	0.985	0.982	0.984
250-day historical simulation	0.987	0.001	0.984	0.991	0.986	0.989
500-day historical simulation	0.988	0.001	0.985	0.991	0.986	0.990
1,250-day historical simulation	0.990	0.001	0.990	0.992	0.989	0.989
Exponentially weighted (λ=0.94)	0.982	0.003	0.984	0.981	0.982	0.983
Exponentially weighted (λ=0.97)	0.984	0.003	0.986	0.983	0.983	0.984
Exponentially weighted (λ=0.99)	0.985	0.003	0.985	0.986	0.983	0.986

APPENDIX: VALUE-AT-RISK SIMULATION RESULTS FOR EACH PERFORMANCE CRITERION (*Continued)*

Table A5
MULTIPLE NEEDED TO ATTAIN DESIRED COVERAGE LEVEL

	Entire Sample Period		1983-85	1986-88	1989-91	1992-94
	Mean across Portfolios	Standard Deviation across Portfolios	Mean across Portfolios	Mean across Portfolios	Mean across Portfolios	Mean across Portfolios
PANEL A: 95TH PERCENTILE VALUE-AT-RISK MEASURES						
50-day equally weighted	1.01	0.05	1.01	1.02	1.01	1.02
125-day equally weighted	0.99	0.04	1.00	0.98	0.99	0.98
250-day equally weighted	0.98	0.04	1.02	0.93	1.00	0.95
500-day equally weighted	0.97	0.04	1.02	0.90	1.02	0.93
1,250-day equally weighted	0.97	0.05	0.95	0.93	0.97	1.00
125-day historical simulation	1.04	0.01	1.05	1.03	1.05	1.03
250-day historical simulation	1.01	0.02	1.05	0.96	1.03	0.98
500-day historical simulation	1.01	0.02	1.06	0.94	1.06	0.99
1,250-day historical simulation	1.00	0.03	0.98	0.95	0.99	1.04
Exponentially weighted (λ=0.94)	1.02	0.05	1.01	1.03	1.02	1.03
Exponentially weighted (λ=0.97)	1.00	0.04	0.99	1.00	1.00	1.00
Exponentially weighted (λ=0.99)	0.97	0.04	0.99	0.95	0.99	0.96
PANEL B: 99TH PERCENTILE VALUE-AT-RISK MEASURES						
50-day equally weighted	1.15	0.06	1.11	1.19	1.19	1.14
125-day equally weighted	1.13	0.07	1.12	1.11	1.17	1.13
250-day equally weighted	1.13	0.07	1.17	1.06	1.20	1.11
500-day equally weighted	1.13	0.08	1.22	1.03	1.20	1.10
1,250-day equally weighted	1.11	0.08	1.12	1.04	1.13	1.17
125-day historical simulation	1.14	0.03	1.15	1.13	1.18	1.16
250-day historical simulation	1.06	0.03	1.11	0.99	1.12	1.04
500-day historical simulation	1.05	0.03	1.13	0.98	1.10	1.02
1,250-day historical simulation	1.00	0.04	1.00	0.94	1.01	1.04
Exponentially weighted (λ=0.94)	1.14	0.06	1.12	1.19	1.14	1.16
Exponentially weighted (λ=0.97)	1.12	0.06	1.09	1.15	1.15	1.12
Exponentially weighted (λ=0.99)	1.10	0.06	1.11	1.08	1.17	1.09

Table A6
AVERAGE MULTIPLE OF TAIL EVENT TO RISK MEASURE

	Entire Sample Period		1983-85	1986-88	1989-91	1992-94
	Mean across Portfolios	Standard Deviation across Portfolios	Mean across Portfolios	Mean across Portfolios	Mean across Portfolios	Mean across Portfolios
PANEL A: 95TH PERCENTILE VALUE-AT-RISK MEASURES						
50-day equally weighted	1.41	0.07	1.40	1.41	1.41	1.41
125-day equally weighted	1.38	0.07	1.39	1.35	1.39	1.39
250-day equally weighted	1.37	0.07	1.43	1.28	1.41	1.36
500-day equally weighted	1.38	0.08	1.46	1.24	1.43	1.34
1,250-day equally weighted	1.36	0.08	1.35	1.27	1.35	1.43
125-day historical simulation	1.48	0.04	1.47	1.45	1.49	1.50
250-day historical simulation	1.43	0.05	1.49	1.34	1.46	1.44
500-day historical simulation	1.44	0.06	1.53	1.29	1.48	1.43
1,250-day historical simulation	1.41	0.07	1.39	1.31	1.39	1.50
Exponentially weighted (λ=0.94)	1.41	0.07	1.39	1.42	1.41	1.42
Exponentially weighted (λ=0.97)	1.38	0.07	1.37	1.38	1.38	1.38
Exponentially weighted (λ=0.99)	1.35	0.07	1.38	1.30	1.38	1.34
PANEL B: 99TH PERCENTILE VALUE-AT-RISK MEASURES						
50-day equally weighted	1.46	0.12	1.48	1.45	1.48	1.47
125-day equally weighted	1.44	0.11	1.45	1.41	1.42	1.50
250-day equally weighted	1.44	0.13	1.49	1.34	1.44	1.50
500-day equally weighted	1.46	0.14	1.56	1.29	1.46	1.47
1,250-day equally weighted	1.44	0.14	1.43	1.31	1.39	1.55
125-day historical simulation	1.48	0.07	1.51	1.47	1.46	1.55
250-day historical simulation	1.37	0.07	1.44	1.28	1.37	1.41
500-day historical simulation	1.37	0.09	1.46	1.25	1.34	1.40
1,250-day historical simulation	1.30	0.10	1.28	1.20	1.25	1.40
Exponentially weighted (λ=0.94)	1.44	0.11	1.45	1.44	1.44	1.48
Exponentially weighted (λ=0.97)	1.42	0.11	1.43	1.40	1.41	1.45
Exponentially weighted (λ=0.99)	1.40	0.11	1.44	1.35	1.42	1.44

Table A7
MAXIMUM MULTIPLE OF TAIL EVENT TO RISK MEASURE

	Entire Sample Period		1983-85	1986-88	1989-91	1992-94
	Mean across Portfolios	Standard Deviation across Portfolios	Mean across Portfolios	Mean across Portfolios	Mean across Portfolios	Mean across Portfolios
PANEL A: 95TH PERCENTILE VALUE-AT-RISK MEASURES						
50-day equally weighted	3.59	0.93	3.25	2.56	2.73	2.98
125-day equally weighted	3.59	0.98	3.01	2.54	2.56	3.09
250-day equally weighted	3.67	1.01	3.03	2.45	2.59	3.07
500-day equally weighted	3.86	1.08	3.25	2.33	2.66	3.04
1,250-day equally weighted	3.97	1.10	3.05	2.35	2.60	3.21
125-day historical simulation	3.91	1.02	3.13	2.84	2.78	3.49
250-day historical simulation	3.85	1.10	3.03	2.61	2.62	3.31
500-day historical simulation	4.09	1.16	3.35	2.44	2.73	3.30
1,250-day historical simulation	4.14	1.12	3.12	2.44	2.67	3.37
Exponentially weighted (λ=0.94)	3.58	0.99	3.16	2.55	2.75	3.03
Exponentially weighted (λ=0.97)	3.53	0.99	3.13	2.46	2.57	2.99
Exponentially weighted (λ=0.99)	3.55	0.96	3.03	2.40	2.55	2.96
PANEL B: 99TH PERCENTILE VALUE-AT-RISK MEASURES						
50-day equally weighted	2.50	0.61	2.26	1.83	1.91	2.08
125-day equally weighted	2.50	0.70	2.09	1.82	1.79	2.15
250-day equally weighted	2.56	0.73	2.11	1.75	1.81	2.14
500-day equally weighted	2.70	0.78	2.27	1.66	1.85	2.13
1,250-day equally weighted	2.77	0.77	2.14	1.67	1.81	2.24
125-day historical simulation	2.58	0.52	2.18	1.97	1.86	2.25
250-day historical simulation	2.34	0.57	2.00	1.66	1.72	2.02
500-day historical simulation	2.48	0.63	2.08	1.60	1.70	2.05
1,250-day historical simulation	2.49	0.65	1.89	1.54	1.63	2.02
Exponentially weighted (λ=0.94)	2.48	0.64	2.20	1.83	1.92	2.10
Exponentially weighted (λ=0.97)	2.46	0.66	2.18	1.76	1.79	2.08
Exponentially weighted (λ=0.99)	2.47	0.68	2.11	1.72	1.78	2.06

Table A8
CORRELATION BETWEEN RISK MEASURES AND ABSOLUTE VALUE OF OUTCOME

	Entire Sample Period		1983-85	1986-88	1989-91	1992-94
	Mean across Portfolios	Standard Deviation across Portfolios	Mean across Portfolios	Mean across Portfolios	Mean across Portfolios	Mean across Portfolios
PANEL A: 95TH PERCENTILE VALUE-AT-RISK MEASURES						
50-day equally weighted	0.19	0.05	0.21	0.15	0.12	0.19
125-day equally weighted	0.16	0.05	0.17	0.13	0.07	0.14
250-day equally weighted	0.13	0.05	0.12	0.15	0.02	0.13
500-day equally weighted	0.06	0.04	0.01	0.07	0.05	0.05
1,250-day equally weighted	0.01	0.03	0.05	0.05	-0.04	-0.02
125-day historical simulation	0.14	0.05	0.16	0.11	0.04	0.12
250-day historical simulation	0.11	0.05	0.10	0.12	0.02	0.10
500-day historical simulation	0.03	0.04	-0.00	0.06	0.03	0.01
1,250-day historical simulation	0.00	0.04	0.06	0.05	-0.03	-0.05
Exponentially weighted (λ=0.94)	0.23	0.05	0.26	0.18	0.15	0.24
Exponentially weighted (λ=0.97)	0.22	0.05	0.23	0.17	0.14	0.21
Exponentially weighted (λ=0.99)	0.17	0.04	0.17	0.15	0.09	0.17
PANEL B: 99TH PERCENTILE VALUE-AT-RISK MEASURES						
50-day equally weighted	0.19	0.04	0.21	0.15	0.12	0.19
125-day equally weighted	0.16	0.05	0.17	0.12	0.07	0.15
250-day equally weighted	0.13	0.05	0.12	0.15	0.02	0.13
500-day equally weighted	0.06	0.04	0.02	0.07	0.05	0.06
1,250-day equally weighted	0.01	0.04	0.06	0.04	-0.04	-0.02
125-day historical simulation	0.12	0.06	0.16	0.07	0.06	0.13
250-day historical simulation	0.10	0.07	0.10	0.09	0.01	0.12
500-day historical simulation	0.05	0.05	0.03	0.04	0.06	0.06
1,250-day historical simulation	0.01	0.04	0.05	0.04	-0.02	0.00
Exponentially weighted (λ=0.94)	0.23	0.05	0.26	0.18	0.15	0.24
Exponentially weighted (λ=0.97)	0.22	0.05	0.23	0.17	0.14	0.22
Exponentially weighted (λ=0.99)	0.17	0.04	0.17	0.15	0.09	0.17

Table A9

MEAN RELATIVE BIAS FOR RISK MEASURES SCALED TO DESIRED COVERAGE LEVELS

	Entire Sample Period		1983-85	1986-88	1989-91	1992-94
	Mean across Portfolios	Standard Deviation across Portfolios	Mean across Portfolios	Mean across Portfolios	Mean across Portfolios	Mean across Portfolios
PANEL A: 95TH PERCENTILE VALUE-AT-RISK MEASURES						
50-day equally weighted	-0.00	0.02	-0.00	-0.00	0.00	-0.00
125-day equally weighted	-0.01	0.01	-0.01	-0.00	-0.00	-0.01
250-day equally weighted	-0.01	0.01	-0.00	-0.01	-0.00	-0.01
500-day equally weighted	0.01	0.02	0.02	0.01	-0.01	0.01
1,250-day equally weighted	0.02	0.02	0.01	0.01	0.01	0.02
125-day historical simulation	0.00	0.01	0.00	0.01	0.01	0.01
250-day historical simulation	-0.00	0.02	0.01	-0.00	0.00	-0.01
500-day historical simulation	0.02	0.02	0.03	0.01	-0.00	0.02
1,250-day historical simulation	0.02	0.02	0.01	0.01	0.01	0.03
Exponentially weighted (λ=0.94)	-0.01	0.02	-0.02	-0.01	0.01	-0.01
Exponentially weighted (λ=0.97)	-0.02	0.01	-0.02	-0.02	-0.01	-0.02
Exponentially weighted (λ=0.99)	-0.02	0.01	-0.02	-0.02	-0.02	-0.02
PANEL B: 99TH PERCENTILE VALUE-AT-RISK MEASURES						
50-day equally weighted	-0.02	0.03	-0.03	0.02	0.00	-0.03
125-day equally weighted	-0.02	0.02	-0.03	-0.02	-0.00	-0.02
250-day equally weighted	-0.01	0.02	0.00	-0.02	0.01	-0.01
500-day equally weighted	0.02	0.03	0.06	0.00	-0.00	0.02
1,250-day equally weighted	0.02	0.03	0.04	-0.01	-0.01	0.03
125-day historical simulation	0.03	0.03	-0.00	0.06	0.05	0.05
250-day historical simulation	0.02	0.03	0.02	-0.00	0.05	0.02
500-day historical simulation	0.03	0.03	0.05	0.01	0.00	0.03
1,250-day historical simulation	0.03	0.04	0.04	-0.01	0.00	0.03
Exponentially weighted (λ=0.94)	-0.04	0.03	-0.05	0.01	-0.05	-0.04
Exponentially weighted (λ=0.97)	-0.04	0.02	-0.06	-0.01	-0.03	-0.05
Exponentially weighted (λ=0.99)	-0.03	0.02	-0.04	-0.03	-0.01	-0.04

ENDNOTES

1. See, for example, the so-called G-30 report (1993), the U.S. General Accounting Office study (1994), and papers outlining sound risk management practices published by the Board of Governors of the Federal Reserve System (1993), the Basle Committee on Banking Supervision (1994), and the International Organization of Securities Commissions Technical Committee (1994).

2. Work along these lines is contained in Jordan and Mackay (1995) and Pritsker (1995).

3. Results for ten-day holding periods are contained in Hendricks (1995). This paper is available from the author on request.

4. The 99th percentile *loss* is the same as the 1st percentile *gain* on the portfolio. Convention suggests using the former terminology.

5. Variance-covariance approaches are so named because they can be derived from the variance-covariance matrix of the relevant underlying market prices or rates. The variance-covariance matrix contains information on the volatility and correlation of all market prices or rates relevant to the portfolio. Knowledge of the variance-covariance matrix of these variables for a given period of time implies knowledge of the variance or standard deviation of the portfolio over this same period.

6. The assumption of linear positions is made throughout the paper. Nonlinear positions require simulation methods, often referred to as Monte Carlo methods, when used in conjunction with variance-covariance matrices of the underlying market prices or rates.

7. See Fama (1965), a seminal paper on this topic. A more recent summary of the evidence regarding foreign exchange data and “fat tails” is provided by Hsieh (1988). See also Taylor (1986) and Mills (1993) for general discussions of the issues involved in modeling financial time series.

8. The portfolio variance is an equally weighted moving average of squared deviations from the mean.

9. In addition, equally weighted moving average approaches may differ in the frequency with which estimates are updated. This article assumes that all value-at-risk measures are updated on a daily basis. For a comparison of different updating frequencies (daily, monthly, or quarterly), see Hendricks (1995). This paper is available from the author on request.

10. The intuition behind this assumption is that for most financial time series, the true mean is both close to zero and prone to estimation error. Thus, estimates of volatility are often made worse (relative to assuming a zero mean) by including noisy estimates of the mean.

11. Charts 1-3 depict 99th percentile risk measures and are derived from the same data used elsewhere in the article (see box). For Charts 1 and 2, the assumption of normality is made, so that these risk measures are calculated by multiplying the portfolio standard deviation estimate by 2.33. The units on the y-axes are millions of dollars, but they could be any amount depending on the definition of the units of the portfolio’s positions.

12. Engle’s (1982) paper introduced the autoregressive conditional heteroskedastic (ARCH) family of models. Recent surveys of the literature on conditional volatility modeling include Bollerslev, Chou, and Kroner (1992), Bollerslev, Engle, and Nelson (1994), and Diebold and Lopez (1995). Recent papers comparing specific conditional volatility forecasting models include West and Cho (1994) and Heynen and Kat (1993).

13. See Engle and Bollerslev (1986).

14. For obvious reasons, a fifty-day observation period is not well suited to historical simulations requiring a 99th percentile estimate.

15. Bootstrapping techniques offer perhaps the best hope for standard error calculations in this context, a focus of the author’s ongoing research.

16. For a discussion of the statistical issues involved, see Kupiec (1995). The Basle Committee’s recent paper on backtesting (1996b) outlines a proposed supervisory backtesting framework designed to ensure that banks using value-at-risk models for regulatory capital purposes face appropriate incentives.

17. The upper and lower edges of the boxes proper represent the 75th and 25th percentiles, respectively. The horizontal line running across the interior of each box represents the 50th percentile, and the upper and lower “antennae” represent the 95th and 5th percentiles, respectively.

18. One plausible explanation relies solely on Jensen’s inequality. If the true conditional variance is changing frequently, then the average of a concave function (that is, the value-at-risk measure) of this variance will tend to be less than the same concave function of the average variance. This gap would imply that short horizon value-at-risk measures should on average be slightly smaller than long horizon value-at-risk measures. This logic may also explain the generally smaller average size of the exponentially weighted approaches.

19. With as few as 125 observations, the use of actual observations inevitably produces either upward- or downward-biased estimates of most specific percentiles. For example, the 95th percentile estimate is taken to be the seventh largest loss out of 125, slightly lower than the 95th percentile. However, taking the sixth largest loss would yield a bias upward. This point should be considered when using historical simulation approaches together with short observation periods, although biases can be addressed through kernel estimation, a method that is considered in Reiss (1989).

20. In particular, see Mahoney (1995) and Jackson, Maude, and Perraudin (1995).

21. See, for example, Bollerslev (1987) and Baillie and Bollerslev (1989).

22. The degrees of freedom, d, are chosen to solve the following equation, $a{*}z(0.99)=t(0.99,d)\ /\sqrt{\frac{d}{d-2}}$, where a is the ratio of the observed 99th percentile to the 99th percentile calculated assuming normality, $z(0.99)$ is the normal 99th percentile value, and $t(0.99,d)$ is the t-distribution 99th percentile value for d degrees of freedom. The term under the square root is the variance of the t-distribution with d degrees of freedom.

23. This section and the next were inspired by Boudoukh, Richardson, and Whitelaw (1995).

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by Adam Posen. May 1995.

Granting central banks independence from short-term political control is widely assumed to decrease inflation by increasing the credibility of commitments to price stability. The author finds no evidence that the costs of disinflation are lower in countries with independent central banks or that central bank independence inhibits government collection of seignorage revenues or manipulation of economic policy for electoral gain.

THE COSTS AND BENEFITS OF DUAL TRADING, *by Hun Y. Park, Asani Sarkar, and Lifan Wu*. June 1995.

The authors find that marketmaking practices of dual traders are pit-specific. They compare the prices that dual traders obtain on their own trades, versus those of their customers, in the S&P 500 futures pit and the Japanese yen futures pit. Differences in dual traders' behavior in the two contracts appear to be related to whether the traders can profit from private information on their customers' order flow.

SHORT-TERM SPECULATORS AND THE ORIGINS OF NEAR-RANDOM-WALK EXCHANGE RATE BEHAVIOR,

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Normal speculative activity could be a source of random-walk exchange rate behavior. Using a noise trader model to analyze very short-term exchange rate behavior, the author shows that rational, risk-averse speculators will smooth the impact of shocks to exchange rate fundamentals. With sufficient speculative activity, an exchange rate could become statistically indistinguishable from a random walk, regardless of the generating processes of its fundamental determinants.

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The authors study the effects of inflation on wage changes made by firms in a unique thirty-seven-year panel of occupations and employers drawn from the Federal Reserve Bank of Cleveland Community Salary Survey. The authors' analysis identifies two relative prices embedded in wage changes and then draws inferences about the costs and benefits of inflation from the adjustments in these relative prices.

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