RiskMetrics Group
Working Paper Number 01-01

Financial crises, implied volatility and stress testing

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October 2001

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Abstract

This paper surveys the behavior of forward-looking asset prices during market crises, with particular focus on historical and implied volatilities. We focus on two specific episodes, the European monetary crisis of 1992-1993 and the Asian crisis of 1997 to 1999. Implied volatilities are shown to contain useful information for predicting market stress in the immediate future.

JEL classifications: G13, G15
Keywords: Asset prices, currency crises, option pricing

1 What happens in crises?

Market risk measurement has come a long way since its Value-at-Risk (VaR) origins in the 1980's. The most important developments come under the rubric "stress testing" and address limitations of the classical joint-normal return model underpinning VaR. Stress testing does not generally propose an alternative model, but rather measures how a trading book or portfolio would fare under a set of stress scenarios. Scenarios can be drawn from historical episodes or can be based on traders' or risk managers' judgement regarding likely or particularly adverse events. Scenarios can be parameterized to reflect current or anticipated correlations of the risk factors of primary focus with the remaining risk factors in the portfolio.[1]

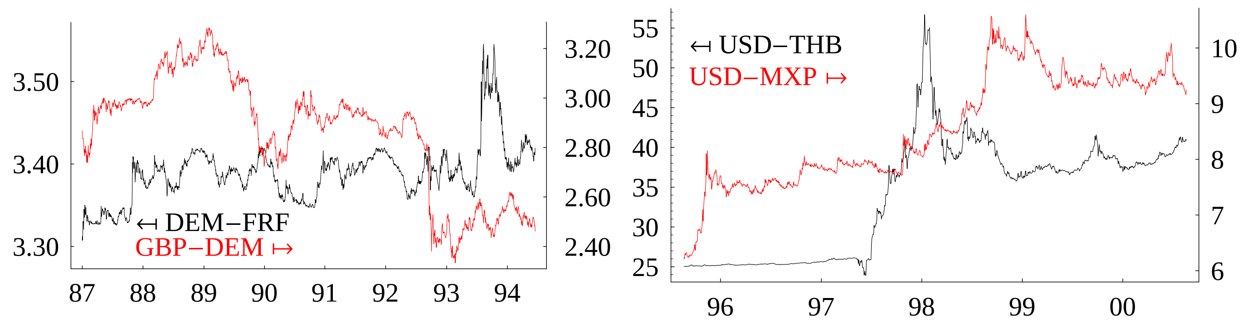
Stress testing is as much art as science. Since not all adverse scenarios can be tested all the time, choosing or designing stress scenarios involves judgement, as does the choice of how frequently to stress test. In order to develop sound judgement, risk managers need to understand how markets behave during crises and stress events. This essay provides an overview of how asset prices, volatilities and correlations evolve during crises, focusing on two particularly dramatic events of the last decade, the European monetary crisis of 1992-1993, in which the Exchange Rate Mechanism (ERM) of the European Monetary System was effectively destroyed, and the Asian-Russian-Long-Term Capital Management (LTCM) crisis of 1997 to early 1999. Currency crises have had a special role in postwar crises: foreign exchange is one of the few asset prices subjected to price controls since the breakdown of the Bretton Woods system. Figure 1 displays exchange rates during these episodes, while Table 1 provides an outline chronology.

A frequent criticism of stress testing is that scenarios do not in themselves contain information on the probability of their realization, and are thus difficult to evaluate and combine with other risk measures. We propose using market prices as signals of the likelihood of market stress, and hence as guidance on the design and timing of stress tests, and support this both on the anecdotal evidence

[1] See Kupiec (1995) for a discussion of scenario choice and Mina and Xiao (2001), pp. 31ff. for a summary of current best practice.

Figure 1: **Spot exchange rates in the ERM and Asian currency crises**

A. DEM-FRF and GBP-DEM spot rates ***B. USD-THB and USD-MXP spot rates***



End-of-day midpoints. DEM-FRF French francs per mark, GBP-DEM German marks per pound sterling, USD-THB and USD-MXP, baht or pesos per U.S. dollar. Source: DataMetrics.

and with time-series statistical tests that incorporate full blown crises as well as less dramatic stress events. Market signals can be used to complement macroeconomic warning signals of economic stress, which have a much longer lead time measured in months or years rather than days or weeks.[2]

Crises are marked not only by sharp asset price moves, but by a variety of additional phenomena, such as volatility spikes and correlation breakdown. Volatility spreads to markets unrelated to the source of the original disturbance via market sentiment, hedging, and the search for liquidity. Central bankers speak of systemic risk, in which the price discovery, credit allocation and payment processing functions of the financial system, particularly as carried out by commercial banks, are compromised. Currency crises, which have had have had a special role in postwar instability, are closely associated with systemic risk because they involve the banking system in an essential way through short-term capital inflows and outflows.

For a pegged currency, the rise in volatility can be quite dramatic. As seen in Panel A of Figure 2, Thai baht volatilities were quite low as long as its peg held, and rose to extremely high levels in a short space of time. Some months later, volatility spread to non-Asian currencies such as the Mexican

[2]See Kaminsky, Lizondo and Reinhart (1998) and the papers collected in the August 1999 issue of the *Journal of International Money and Finance* for examples of this approach.

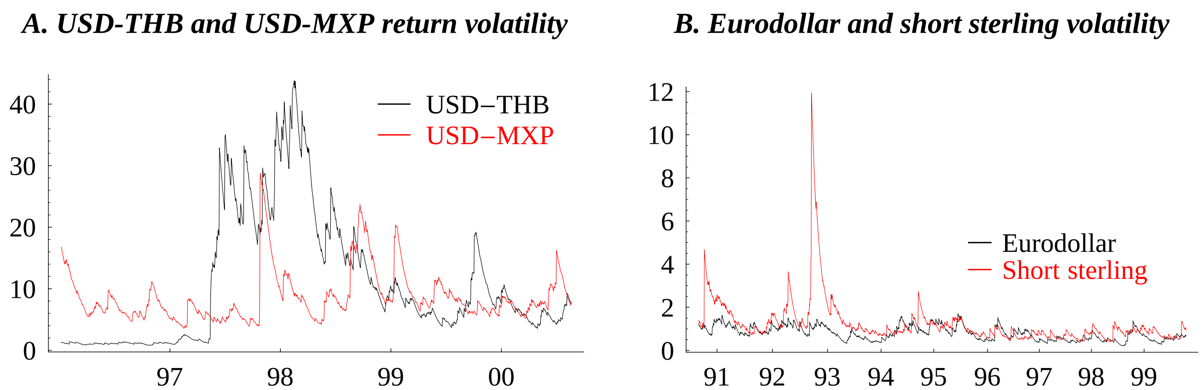
Table 1: **Brief chronology of the ERM and Asian crises**

ERM crisis	
June 2, 1992	Danish referendum rejects Maastricht.
July 16, 1992	Bundesbank raises key rates 75 basis points.
Sep. 3, 1992	Announcement of U.K. Treasury borrowing in defense of sterling.
Sep. 8, 1992	Finnish markka floats.
Sep. 16, 1992	Sterling leaves ERM. Swedish Riksbank raises key rate to 500 percent.
June 21, 1993	Banque de France cuts key rate below German level.
July 31, 1993	ERM bands widened to $\pm$15
Asian crisis	
May 14-15, 1997	First speculative attack on USD-THB.
Oct. 27, 1997	Drop in U.S. equity markets follows Taiwan devaluation.
June 18, 1998	Coordinated defense of yen by Fed and Bank of Japan.
Aug. 29, 1998	Russian devaluation and unilateral debt restructuring.
Sep. 23, 1998	LTCM bailout announcement.
Sep. 29, 1998	First FOMC crisis rate cut.
Oct. 7, 1998	Largest postwar one-day decline in USD-JPY.
Oct. 15, 1998	Second FOMC crisis rate cut.

peso. The volatilities of interest rates on pegged currencies can also experience unprecedented increases during a currency crisis. As seen in Panel B, short sterling volatility increased to over ten times its typical value during the ERM crisis, as the Bank of England attempted first to defend the ERM parities via penalty rates and then cut rates dramatically once the peg was broken and it was no longer obliged to follow Bundesbank tight-money policies.

Correlations may change dramatically during crises. Risk managers added “correlation breakdown” to their terminology in 1998, when yields on bonds with differing degrees of liquidity or different long-term maturities, which in normal times are close if not perfect substitutes, suddenly diverged (see Figure 3). This change in correlations is associated with a flight to quality and to liquidity.

Figure 2: **Historical volatility in the ERM and Asian currency crises**



Exponentially-weighted moving average volatilities of daily returns, with decay factor 0.94, at an annual rate. Price volatilities for 3-month constant maturity CME Eurodollar and LIFFE short sterling futures. Source: DataMetrics.

Another aspect of flight to quality is the sharp change in the correlation between stock and bond prices during the LTCM crisis, typically moderately positive, but rapidly becoming sharply negative as the crisis unfolded (see Panel A of Figure 4).

Correlations can change particularly rapidly when currency pegs are broken. When the durability of a currency peg is largely but not perfectly credible, interest rates for the anchor currency are lower than for the pegged currency. It is tempting for market participants with fixed-income obligations in the pegged currency to seek funding in the apparently near-perfectly positively correlated anchor currency. This variety of the "carry trade" comes to an abrupt halt when a peg is broken (see Panel B for the example of the ERM crisis).[3]

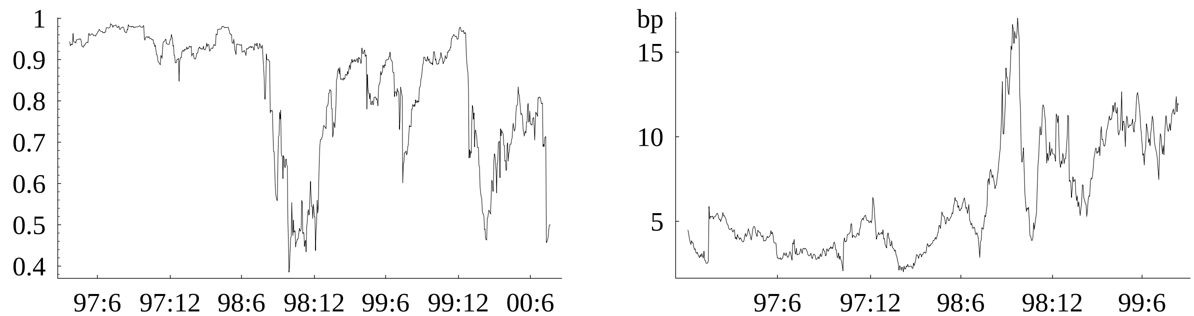
2 Expectations and market prices during crises

Expectations play a crucial role in crises, as market participants try to anticipate and position themselves for future events. A growing number of market participants, central banks, and international

[3]Kim and Finger (2000) discuss the construction of stress tests when correlations are changing drastically.

Figure 3: **Bond correlation breakdown during the LTCM crisis**

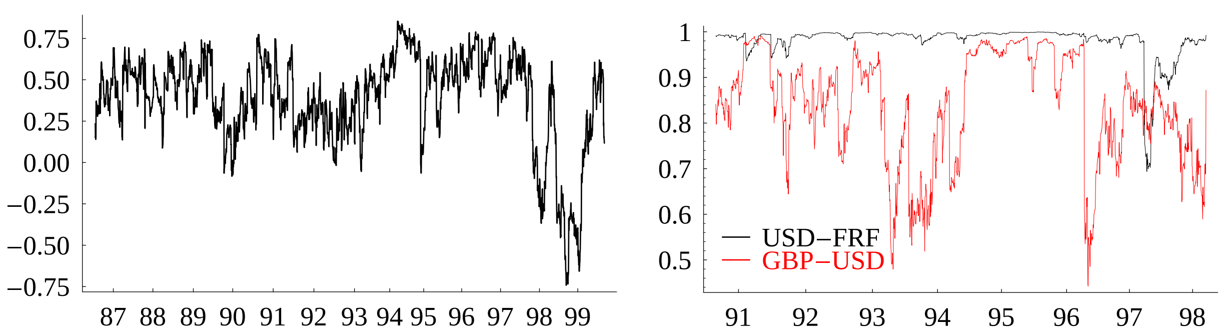
A. U.S. 10- and 30-year bond correlations ***B. U.S. on-the-run vs. off-the-run bond spread***



Panel A: Exponentially-weighted moving average correlation between daily 10- and 30-year U.S. Treasury benchmark zero-coupon discount factor returns, with decay factor 0.94. Panel B: Spread between yields of on-the-run and previously issued 30-year U.S. Treasury. Source: DataMetrics.

Figure 4: **Correlation breakdowns in the ERM and Asian currency crises**

A. S&P 500 and bond return correlation ***B. ERM proxy hedging correlations***



Exponentially-weighted moving average correlations of daily returns, with decay factor 0.94. Panel A: Three-month constant maturity CME S&P 500 and CBOT U.S. Treasury bond futures. Panel B: DEM-FRF vis-à-vis USD-FRF and GBP-DEM vis-à-vis GBP-USD. Source: DataMetrics.

institutions have implemented asset price-based indicators of market sentiment alongside assessments based on macroeconomic data and forecasts, observation of transactions flows, and anecdotal evidence. Some of these indicators, such as the use of the slope of the term structure of interest rates or spreads between credit-risky and default-risk free interest rates to forecast inflation or turning points in the business cycle, are well established within traditional market analysis (see, for example Friedman and Kuttner (1993)). Others, such as forward, futures and option prices, are quite new.[4]

In efficient markets theory, expectations are embedded in cash, forward and option prices, but are entangled with premiums generated by perceptions of and the appetite for risk and liquidity. Forward and futures prices are closely related in theory to expected future spot prices, but are poor predictors in practice due to changing risk and liquidity premiums. Option implied volatility surfaces are also forward-looking asset prices, but react more strongly to changes in expectations.

To see why option implied volatility is potentially a more powerful stress predictor than forward rates, imagine a risk-neutral world, in which the forward price is equal to the mean future price and implied volatility is equal to the return standard deviation. Market participants agree on the set of possible outcomes:

- A ("random walk"): there are 2 outcomes, in which the future asset price is either \$0.90 or \$1.10, with a probability of 50% each). The forward price will be \$1.00 and the implied volatility 10%.

- B ("jump-diffusion"): there are 3 outcomes, in which the future asset price is \$0.90 or \$1.10, with a probability 45% each, or \$0.50, with a probability of 10%. The forward price will be \$0.95 and the implied volatility 17.75%.

If the set of outcomes contemplated by the market changes from scenario A to B, with the emergence

[4] The growing literature on this subject is summarized in Söderlind and Svensson (1997). A good example of the use of derivatives-based indicators are recent issues of the Bank of England's *Inflation Report* and *Financial Stability Review*. Market-based indicators are a potentially important response to the call for enhanced "early warning capabilities" as part of improved crisis prevention in the International Monetary Fund communique of April 29, 2001.

of a small probability of a large price decline, the forward price drops by only 5 percent, but implied volatility nearly doubles. Implied volatilities are therefore a more sensitive indicator of anticipated stress than forwards and futures. While they are commingled with risk and liquidity premiums, these premiums are less apt to overwhelm the indicator properties of implied volatility than those of forwards and futures, because the reactivity of implied volatility to changes in market expectations is so much greater.

To see how sensitive implied volatilities are to expectations or anxieties about large market moves, let us focus again on the ERM crisis and the devaluation of the Thai baht. Figure 5 displays spot exchange rate levels and historical and implied volatilities for sterling-mark and dollar-Thai baht during the crises. Both historical and implied volatility are typically mean-reverting, and generally not far apart.[5] Implied volatility anticipates the crises, in the case of sterling-mark by a few weeks, in that of dollar-Thai baht by a few days. Historical volatility reacts to crises, lagging implied slightly. Historical volatility spikes much higher than implied at first, but settles down rapidly after the massive asset level changes of the devaluation itself. Implied may continue to rise, and decays slowly, as the devaluations of recent decades have been more severe in the event than the market had anticipated. The markets expected a modest change in central parity for sterling, not an outright exit from the ERM followed by a 15 percent depreciation in a month. Nor did the markets expect an 85 percent depreciation of the baht within 6 months.[6]

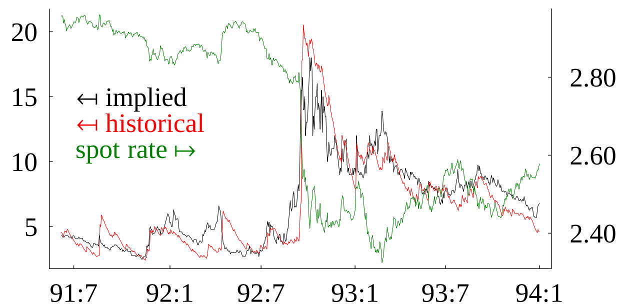
Anticipation of stress also influences the volatility smile, the relationship between equally out-of-the-money puts and calls on the same underlying asset and with the same maturity. The volatility smile is an indicator of perceived departures from the classical model. The degree of curvature of the volatility smile indicates a market perception of kurtosis in the return distribution of the

[5] See Malz (2000/2001) on the statistical properties of implied volatility.

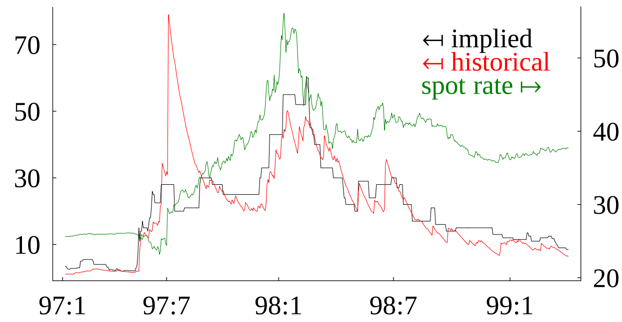
[6] At-the-money forward Black-Scholes implied volatilities with maturities of one or three months are displayed in the graphics and used in the statistical work described in this paper. A detailed description of the cash market and option data is provided in Malz (2000). Black-Scholes implied volatilities are identical to anticipated volatility only if the Black-Scholes hypothesis that the underlying asset return follows a geometric Brownian process holds exactly. If the asset price instead follows an alternative process such as stochastic volatility, the Black-Scholes implied volatility will be closely related to, but no longer identical with anticipated volatility.

Figure 5: **Implied and historical volatility in the ERM and Asian currency crises**

B. GBP-DEM volatility in ERM crisis



B. USD-THB volatility in Asian crisis



Historical: Exponentially-weighted moving average volatilities of daily returns, with decay factor 0.94, at an annual rate. Implied: one-month at-the-money forward implied volatilities. Source: DataMetrics.

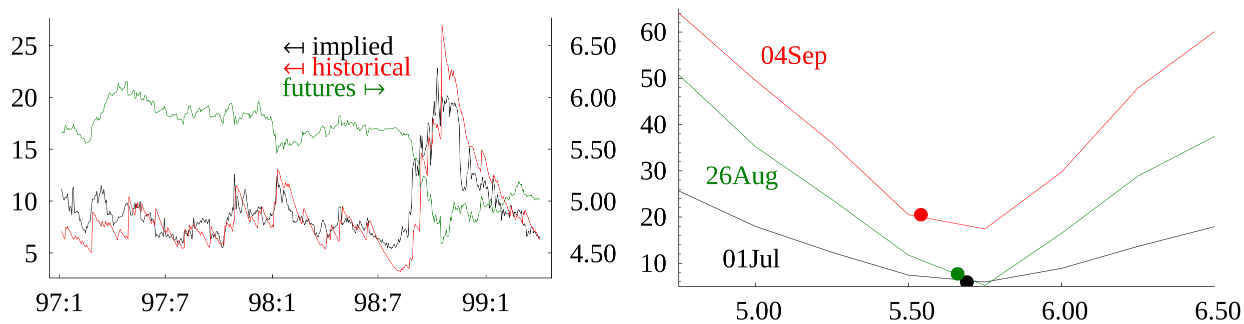
underlying asset, while the skewness indicates a perception of skewness in the return distribution.

Tracing these changes over time for CME Eurodollar futures shows how perceptions of the size and timing of rate cuts by the Fed evolved during the Russia-LTCM crisis. The prior change in key rates (a tightening) had been in March 1997, 16 months earlier, and the target Fed funds rate had been between 5.25 and 5.75 percent for about three years. Just before the onset of the crisis, therefore, implied and historical volatilities had been subdued (Panel A of Figure 6), while the smile had a modest degree of curvature and no visible skewness (Panel B). As the crisis developed, the market anticipated a cut in the Fed funds rate as part of the classic central bank monetary easing response to financial crisis. Eurodollar implied volatility began to rise, well ahead of historical volatility, the curvature of the smile became more pronounced, and the smile became skewed. By early September, options with positive payoffs in the event of a 25 basis point rise in the three-month forward rate had far lower implied volatilities than options with positive payoffs in the event of a 25 basis point decline in the forward rate.

A compact way to capture the information contained in forwards and implied volatilities is via estimates of risk-neutral probability distribution functions.[7] Figure 7 compares estimates of the

Figure 6: **CME Eurodollar volatilities during the LTCM crisis**

A. Historical and implied Eurodollar volatility ***B. Eurodollar volatility smile***



Panel A. Historical: Exponentially-weighted moving average volatilities of daily returns, with decay factor 0.94, at an annual rate. Implied: Three-month constant maturity at-the-money implied volatilities for CME Eurodollar options on futures. *Panel B*. Implied volatilities of options on CME Eurodollar front contract. Heavy dot indicates futures settlement price. Source: DataMetrics.

probability of a 10 percent depreciation of the dollar-Mexican peso exchange rate over the subsequent month, estimated in three different ways:

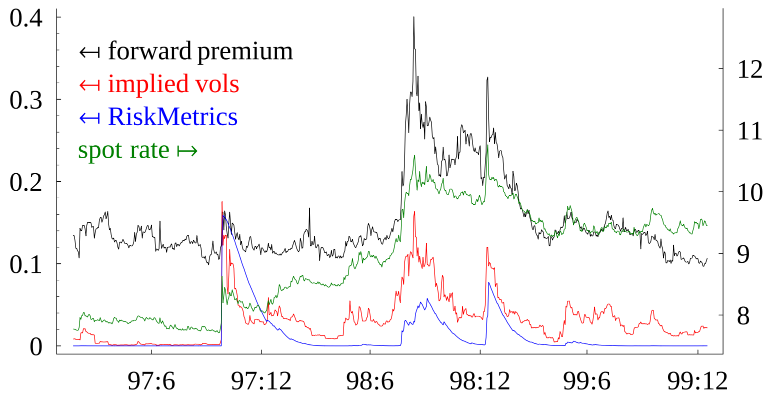
- From the forward premium, using a simple "peso problem" approach in which the market expects a 10 percent depreciation with a probability π and no change in the exchange rate with a probability $1 - \pi$.
- Using RiskMetrics historical volatilities with a decay factor of 0.97 and a drift rate of zero.[8]
- From the option-implied probability distribution, using a set of at- and out-of-the-money option prices.

The forward-based estimates, always well over 10 percent even in the peso's quietest trading periods, are much higher than using the other two techniques. The RiskMetrics and the option-based

[7] See Malz (1997) for an example, and Jackwerth (1999) and Bliss and Panigirtzoglou (2000) for recent surveys of these techniques. An extension of this approach is the extraction of implied correlations between dollar-based exchange rates from implied volatilities of cross-currency options; see for example Campa and Chang (1998) and Lopez and Walter (2000).

[8] See Mina and Xiao (2001) for details on RiskMetrics volatilities.

Figure 7: **Alternative measures of the probability of a 10% USD-MXP depreciation**



See text for explanation. Source: DataMetrics.

estimates are not generally far from one another, but there are important differences that point to greater accuracy of the latter for tracking market expectations of extreme moves. The implied volatility-based forecasts always show a small positive probability, typically lead the RiskMetrics forecasts, and generally display a more plausible variability, while the RiskMetrics forecasts fall to zero during quiet trading periods. These results underpin the importance of stress testing as a supplement to risk measures based on historical volatility such as VaR (as in Mina and Xiao (2001)).

3 Implied volatility warning signals: statistical tests

In a full-blown crisis, the early-warning properties of implied volatility are so clear they can be seen graphically, as in Figures 5 and 6. We can also detect these predictive properties statistically in less extreme situations. We carried out statistical tests of the predictive ability of implied volatility for stress events for a range of assets, including major and emerging-market currency pairs, money markets, bonds, equity indexes, and commodities.[9] We used squared returns as a metric for market stress, focusing on the kurtosis of the return distribution. If squared returns are plotted, a handful of large realizations is visible.

One test of predictive ability is Granger causality tests. A time series y is said to cause another time series x if past values of y help to predict the current value of x, that is, the conditional forecast variance of x can be reduced by including information on past y in the conditioning set along with past values of x (see for example Hamilton (1994), p. 302ff.). A standard test for causality is to set a lag length k, carry out the ordinary least squares regression

$$x_t = \sum_{i=1}^{k} \alpha_i x_{t-i} + \sum_{i=1}^{k} \beta_i y_{t-i} + u_t, \qquad t = 1, \ldots, T, \tag{1}$$

and test the exclusion restrictions $\beta_1 = \beta_2 = \cdots = \beta_k = 0$, that is y fails to Granger cause x. In our application, squared returns are the dependent x variable, while implied volatilities and historical volatilities are the potentially causative y variables.

We find that for all assets, the null hypothesis that implied volatility Granger-causes—that is, systematically precedes—large-magnitude returns cannot be rejected, even at high confidence levels (columns (1) and (2) of Table 2). Interestingly, we also find confirmation of the predictive ability of RiskMetrics exponentially weighted moving average volatilities for large-magnitude returns (columns (3) and (4)), while in contrast, the predictive ability of conventionally computed equally-weighted historical volatilities was readily rejected (columns (5) and (6)).

These results suggest that much of the information about future squared returns in RiskMetrics and implied volatilities is common to both, raising the question, what incremental information content implied volatility contains over and above that also contained in RiskMetrics volatilities. Columns (7) and (8) of Table 2 displays results of a causality test of exclusion restrictions on implied volatility in a regression also including lags of squared returns and RiskMetrics volatility. In almost all cases, implied volatility is shown to contain information regarding future squared returns, even after the information also in RiskMetrics volatility is accounted for.[10]

[9]This section summarizes results presented in more detail in Malz (2000).

Table 2: Granger causality tests for squared returns, implied, historical and RiskMetrics volatility

	Implied		Historical		RiskMetrics		Implied given RiskMetrics	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Asset	p-value	$\bar{R}_2$	p-value	$\bar{R}_2$	p-value	$\bar{R}_2$	p-value	$\bar{R}_2$
CME S&P 500	0.000	0.081	0.669	0.076	0.000	0.091	0.023	0.093
CME Eurodollar	0.000	0.042	0.004	0.022	0.000	0.029	0.000	0.043
Liffe short sterling	0.000	0.055	0.310	0.005	0.000	0.048	0.000	0.081
CBOT 30-year bond	0.000	0.059	0.000	0.035	0.000	0.041	0.000	0.066
Nymex Crude light oil	0.000	0.054	0.015	0.034	0.008	0.035	0.000	0.057
Gold	0.080	0.162	0.044	0.163	0.000	0.238	0.152	0.241
USD-JPY	0.000	0.079	0.213	0.061	0.000	0.083	0.009	0.088
USD-EUR	0.000	0.055	0.209	0.032	0.000	0.046	0.000	0.056
GBP-EUR	0.000	0.110	0.012	0.078	0.000	0.091	0.000	0.112
USD-MXP	0.000	0.255	0.863	0.133	0.000	0.205	0.000	0.299
USD-THB	0.000	0.023	0.280	−0.000	0.000	0.020	0.241	0.022

p-values for test of exclusion restrictions. $\bar{R}_2$ is that of the unrestricted regression.

Another test of the predictive ability of implied volatility for stress events is to formulate a warning signal summarizing whether implied volatility is high relative to recent levels and rising fast, and examine whether that signal helps to predict the event that cash asset returns are unusually high or low. As a measure of how high implied volatility is currently, we calculate for each date the mean and standard deviation of implied volatility over the past year (250 trading days) and define as high any implied volatility higher than one standard deviation above its one-year mean. As a measure of how fast implied volatility is rising, we make use of the mean root square or volatility of daily logarithmic changes in implied volatility, the "vol of vol." High returns are defined as those exceeding 2.33 standard deviations (99th percentile) or 3.09 standard deviations (99.9th percentile) in magnitude.

[10]The exceptions are gold and USD-THB. In the case of gold, the results are dominated by the 15 percent price rise following the surprise announcement on September 26, 1999 of limits on gold sales by European central banks. For the Thai baht, although Figure 5 makes clear that implied did in fact anticipate historical volatility, the observation period is comparatively short and contains only one long run-up and one long wind-down of implied and historical volatilities.

Let $T = \{t_1, t_2, \ldots, t_N\}$ be the set of dates in the sample for an asset, using weekly data. On each observation date $t_\tau \in T$, if implied volatility is high and has risen more than 0.675 vols of vol (75th percentile) over the past week, the implied volatility is deemed to have sent a warning signal that high returns are likelier to occur over the next week. The signal is thus an event $A = \{t_\tau \in T : \text{IV high and rising}\}$ in T, as is the event $B = \{t_\tau \in T : \text{high returns}\}$. The intersection of the events $A \cap B$ is the set of dates on which the signal has been accurate.

Consider the S&P 500 index, for which we have 810 weekly observations. On 63 occasions, implied volatility was high (more than one standard deviation above its recent mean) and rising (by 0.675 vols of vol over the previous week). The signal lights up frequently enough to be useful, and not so frequently as to be meaningless. On 22 occasions, returns over the subsequent week were more than 2.33 standard deviations in magnitude, of which 3 coincided with high and rising implied volatility. On 7 occasions, returns were over 3.09 standard deviations, of which 2 coincided with high and rising implied volatility. For 99.9th percentile returns, we can summarize these results in a two-way contingency table:

	$N(B_{\text{S\&P500}})$	$N(\sim B_{\text{S\&P500}})$	total
$N(A_{\text{S\&P500}})$	2	61	63
$N(\sim A_{\text{S\&P500}})$	5	742	747
total	7	803	810

.

The null hypothesis of independence between events A and B

$$\mathcal{H}_0 : P\{t_\tau \in B | t_\tau \in A\} = P\{t_\tau \in B\},$$

that is, the hypothesis that implied volatility has no signalling value for large-magnitude returns, can be tested two ways. One is a chi-square test using Pearson's Q (see Stuart, Ord and Arnold (1999), pp. 27ff.). Under $\mathcal{H}_0$, the maximum likelihood estimate of the probability of $A \cap B$ is $\frac{63}{810}\frac{7}{810}$. Under the alternative hypothesis

$$\mathcal{H}_1 : P\{t_\tau \in B | t_\tau \in A\} \neq P\{t_\tau \in B\},$$

the estimate of the probability of $A \cap B$ is $\frac{2}{810}$. Pearson's Q is the sum, over the 4 cells in the contingency table, of the differences between these estimates.

Another test of the null is based on the hypergeometric distribution (see among others Mood, Graybill and Boes (1974), pp. 91ff.). Under $\mathcal{H}_0$, the probability of the event $A \cap B$ follows the hypergeometric distribution. Returning to the example of the S&P 500 index, the probability of drawing 3 or more high-return observations in a sample of 63 from a population of 810 containing 22 high-return observations is 8.4 percent, if high-return dates are as frequent in the entire population as in the high-and-rising-implied volatility sub-population.

Table 3 displays Pearson's Q and it's p-value, as well as one minus the cumulative distribution function of the hypergeometric distribution evaluated at $N(A \cap B)$, which can be treated as the p-value of a test of $\mathcal{H}_0$. Apart from USD-EUR, the null hypothesis is rejected at high confidence levels for all assets for either returns at the 99th percentile or at the 99.9th percentile, or both. If the null is rejected for returns at the 99.9th percentile but not the 99th percentile (as is the case, for example, for the s&P 500), implied volatility is likely to rise in anticipation of extremely large price moves, but less likely to move in anticipation of more routine large moves. The null is rejected for returns at the 99th percentile but not the 99.9th percentile (for example, dollar-yen) for assets that display more modest return kurtosis and for which extremely large moves are more infrequent even in our long samples. Both the chi-squared test and the test based on the hypergeometric distribution indicate that the implied volatilities provide a useful warning signal for large-magnitude returns.[11]

4 Conclusion

One of the most fundamental changes in risk measurement in recent years has been the emergence of stress testing as a crucial supplement to classical loss measures such as VaR. Stress testing has

[11] Changing the signal (for example, changing the vol-of-vol threshold for rising implied volatility to the 90th rather than 75th percentile) can change the results by increasing the number of false positives or reducing the number of successfully anticipated large returns. The thresholds used in this paper provided good performance across all asset classes, but could in further work be tailored to individual assets.

Table 3: **Test of independence of an implied volatility signal and large returns**

	returns 99th pctile			returns 99.9th pctile		
	χ^2 test			χ^2 test		
Asset	Q	p-value	HGD	Q	p-value	HGD
CME S&P 500	0.92	0.339	0.096	4.26	0.039	0.013
CME Eurodollar	4.78	0.029	0.012	0.71	0.401	0.071
Liffe short sterling	34.21	0.000	0.000	27.82	0.000	0.000
CBOT 30-year bond	11.37	0.001	0.001	11.03	0.001	0.002
Nymex Crude light oil	6.24	0.012	0.006	10.92	0.001	0.000
Gold	3.45	0.063	0.017	10.16	0.001	0.001
USD-JPY	6.27	0.012	0.006	0.13	0.717	0.152
USD-EUR	0.38	0.536	0.309	0.13	0.707	0.128
GBP-EUR	2.08	0.149	0.037	8.26	0.004	0.003
USD-MXP	3.21	0.073	0.013	0.11	0.735	0.104
USD-THB	9.87	0.002	0.001	18.90	0.000	0.000

HGD is 1 minus the CDF of the hypergeometric distribution.

retained something of an ad hoc character, as the design and timing of stress scenarios, as well as how stress test results should be combined with one another and with classical measures, remains a matter of judgement. The use of implied volatility as a stress indicator can increase the role of measurement over judgement in this process. In particular, it permits a market-based assessment of the likelihood of market stress. Implied volatility-based indicators and warning signals should be part of a wider toolkit of asset price-based stress indicators derived from forwards and futures, interest-rate term structures and spreads, and option prices.

Future work should focus on refining the implied volatility signal and attaching probabilities to the events signaled. The accuracy of implied volatility-based warning signals will also be improved as research on the relationship between risk and liquidity premiums and asset prices progresses.

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