Rare Disaster Risk and the Equity Premium Puzzle

Henk Berkman[a], Ben Jacobsen[b], John Lee[a]

[a] *University of Auckland, Auckland, New Zealand*
[b] *Massey University, Auckland, New Zealand*

Abstract

The probability of rare disasters helps to explain the longstanding equity premium puzzle. Global political instability, our proxy for rare disaster risk, is a significant determinant of the expected market risk premium based on analyst target prices. Consistent with long-run risk models, uncertainty about expected GDP growth and expected consumption growth are also significantly positively related to the expected market risk premium. We obtain similar results when we use the earning-price ratio and the dividend-price ratio as proxies for the expected market risk premium.

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Corresponding author: h.berkman@auckland.ac.nz (H. Berkman)

1. **Introduction**

This study provides novel evidence supporting the claim that the probability of rare disasters explains the longstanding equity premium puzzle raised in Mehra and Prescott (1985).[1] Figure 1 illustrates the main point of our paper. We plot the expected market risk premium based on estimates from analyst target prices against the expected level of global political instability based on the crisis severity index developed in Berkman, Jacobsen and Lee (2011).

[Figure 1 here]

The correlation between the two annual series in Figure 1 is 0.51 (p-value is 0.006; at a monthly frequency the correlation is 0.34 with a p-value of 0.0001). This highly significant correlation confirms the main prediction in time-varying disaster risk models: expected returns on stocks relative to bonds are high when the probability of disasters is high (see, e.g., Gabaix 2009, Wachter 2009, and Gourio, 2008).

Figure 2 plots the (annualized) *realized* market risk premium (CRSP value-weighted stock market return in excess of the 30-day Treasury bill rate) against the expected level of global political instability. The correlation is negative and insignificant at -0.25 (p-value = 0.20). The corresponding monthly figure is 0.06 with a p-value of 0.24.

[1] Barro (2006) resurrects the rare disaster model in Rietz (1988). In his calibrations, rare disasters explain the high observed equity premium, based on estimates of disaster probability and disaster size from contractions in gross domestic product (GDP) around World War I, the Great Depression, and World War II for different countries.

[Figure 2 here]

Arguably the much stronger result in Figure 1 is the result of market-wide expected returns being better proxied by returns estimated from target prices and dividend forecasts rather than realized returns. Note that use of expected returns is in line with calls from, for example, Elton (1999) and Fama and French (2002), who emphasize that realized market returns are a noisy proxy for expected market returns.

Our results are robust to alternative proxies for expected returns. Following Fama and French (2002), we also use the earnings-price ratio and dividend yield as proxies for the expected equity premium and find that the positive relation between the expected market risk premium and global political instability holds over a long period, from 1918 to 2007. Overall, our results are consistent with time-varying rare disaster risk models and strongly suggest that global political instability increases the expected market risk premium.

We show the expected market risk premium is also significantly positively related to fluctuations in uncertainty about expected GDP growth and expected consumption growth, consistent with long-run risk models (Bansal and Yaron, 2004 and Bansal and Sahliastovich, 2008). The model that includes our proxies for disaster risk and consumption risk explains about 30 percent of the time-variation in the expected market premium.

2. Crisis Variables and Expected Returns.

2.1 Crisis variables

In Berkman, Jacobsen and Lee (2011) argue that the small sample problem inherent in the use of *actual* rare disasters can be avoided by using a much larger sample of *potential* disasters in the form of international political crises. Even though the large majority of international crises do not escalate into full-scale wars or major conflicts, financial market prices are forward-looking, allowing us to use these events to gauge the impact of changes in the probability of rare disasters on stock market prices.

Our source of international political crisis events is the International Crisis Behavior database. This database contains detailed information on more than 400 international political crises over the period 1918-2007 (see http://www.cidcm.umd.edu/icb/). All crises are classified based on numerous characteristics, such as superpower involvement, duration, and gravity. In addition to the large number of observations and the consistent way in which crises are measured, this ICB database is also attractive due to its definition of *crisis*. A crisis does not necessarily start with an attack or military action; rather, it is the perceived change in the probability of a threat that results in the start or end of an international political crisis. We use these start and end dates to create a time-series of the perceived level of global instability.

We briefly discuss the ICB database and the crisis variables used in this study. Berkman, Jacobsen and Lee (2011) provide a more extensive description. The ICB database contains several measures of crisis severity, allowing us to identify more serious crises (i.e., crises with more severe threats or with a broader international impact) that arguably resulted in greater changes in disaster probability. We use six dummy variables to capture different aspects of the severity of a crisis: whether or not a crisis started with violence, violence used during the crisis, full-scale wars, gravity of value threat, whether the crisis is part of a protracted conflict, and great power or superpower involvement. We then construct a Crisis Severity Index, *CSI,* which summarizes different aspects of crisis severity into one measure by aggregating the six dummy variables above and adding one. For example, a war with great power involvement that is part of a protracted conflict, has a score of four on the crisis severity index (one for being a crisis, one for being a war, one for having great power involvement, and one for being part of a protracted conflict).

The level of global instability at the start of month t, $CSI_{start,\ t}$, is the sum of the crisis severity indices of all ongoing crises in month $t\text{-}1$ and all crises that started in month $t\text{-}1$ minus the sum of the crisis severity indices of all crises that ended in month $t\text{-}1$. To obtain a measure for the expected level of global instability at the start of month t, we assume investors predict disaster risk based on the following AR(1) process:

$$CSI_{start,\ t} = \alpha + \beta\, CSI_{start,\ t-1} + \varepsilon_t \qquad (1)$$

Based on the previous 10 years (that is from *t-121* through to *t-1*), we estimate model (1) and use the estimated parameters and the actual value of $CSI_{start,\ t-1}$ to estimate the level of expected disaster risk at the start of month t.[2]

For each year in our sample period, Figure 1 above plots the expected disaster risk averaged across the months in each year. A brief discussion of recent history helps to show how this measure correlates with global political instability during the period of our main tests, from 1975 to 2001. In 1975 the world was still in a period of relative calm (détente) after the very serious cold war crises in the second half of the '50s and early '60s. Conflicts flared up again in 1979 and the early 1980s with the Soviet intervention in Afghanistan (described by President Carter as the "most serious threat to peace since the Second World War"). Other major international crises in this period are the labor strikes in Poland led by Solidarity and the start of the Iran-Iraq War. The end of the Cold War began with the Gorbachev's ascension to power in 1985 and ended with the dissolution of the Soviet Union in December 1991. In the next decade, several conflicts emerged that can be traced back to the Cold War and the break-up of the Soviet Union (e.g., crises involving North Korea, crises in and around the Balkans, and crises in the Caucasus). However, in this new uni-polar world with the United States as the only remaining superpower, the number of international crises has declined noticeably. Nevertheless, several major crises have broken out in this period. Prominent examples are the Taiwan Strait conflicts, the Gulf War and post–Gulf War crises, conflicts between Israel and neighboring countries, and crises in response to terrorist attacks by the Al Qaeda network.

[2] Our results are not sensitive to the estimation of the expected level of CSI. We obtain similar results when the expected CSI is based on twenty-year rolling windows, the entire sample period, or the previous month's CSI.

[Table 1 Here]

Table 1 presents descriptive statistics of the crisis variables in our sample period. An average month has 2.2 crises. The maximum number of international crises that start in a particular month is four. The maximum number of crises that ended in a given month is also four. CSI ranges from 0 to 28. It reached its maximum in February 1979. The worst crises to start in our sample period had a crisis severity level of 6. These crises included 9/11, the Gulf War in 1990, several crises during the Iran/Iraq war (1980-88) and the crisis that started when on 12 May 1975, when a U.S.-registered cargo ship, the Mayaguez, was seized off Cambodian coastal waters by the Khmer Rouge.

The column in Table 1 with the heading "Sum," shows that out of a total of 215 crises that started in our sample period, 106 crises began with a violent break, 96 crises involved serious violence, and 36 crises were full-scale wars. There are 106 crises that involved threats of the most basic values at some time during the crisis. In 22 of the crises, at least one major power was involved on both sides of the conflict, and 126 crises were part of a protracted conflict. The correlation between the different crisis variables is high and always significant at the 1% level (not reported). For example, crises that begin with a violent act (*Violent start*) tend to result in crises exhibiting either serious clashes or full-scale wars (*Violent* and *War*).

2.2 Expected Return Measure

The expected return data used in our study have been compiled by Brav et al (2005) and are downloadable from Reuven Lehavy's Web page.[3] The database provides annualized expected returns for individual stocks and is available on a monthly basis for the period from January 1975 to December 2001. The expected returns are based on target prices and dividend forecasts from Value Line, an independent research provider with no affiliation to investment banking. Value Line covers approximately 3,800 stocks, comprising 92% of the NYSE, AMEX, and Nasdaq in terms of market value.

To obtain expected returns, Brav et al. (2005) use the price Value Line expects to prevail in four years time (the Target Price). To this price they add the expected dividends based on VL analysts' forecasts for both dividend growth rates and the next-year dividends. With these inputs, the expected return is defined as the rate of return that equates the current market price of a stock to the present value of the target price and the future dividends. VL analyzes each company on a quarterly cycle, but different stocks have different cycles so that expected return estimates are available for every month during the 27–year sample period.

In order to obtain expected annual excess returns, we subtract the one-year constant maturity Treasury rates (from the public Web site of the Federal Reserve Bank of St. Louise, FRED) from analysts' expected stock returns. Descriptive statistics for the VL expected return data are in Table 2 along with the yearly averages of monthly expected

[3] http://webuser.bus.umich.edu/rlehavy/VLdata.htm. We thank the authors for making the data available.

excess returns to the value-weighted portfolio used in Figure 1. For a more detailed description of the data, we refer to Brav et al. (2005).

[Table 2 here]

2.3 Control variables

We also examine the interaction between our expected crisis risk measure and well-known variables that have been shown to be related, theoretically or empirically, to the expected market risk premium. The intertemporal CAPM model of Merton (1973) posits a positive relation between market volatility and the market risk premium. To obtain a conditional market volatility measure, we follow French, Schwert, and Stambaugh (1987) and use the time-series of conditional forecasts of the realized return standard deviation.[4] We first estimate the month t variance of returns as the sum of the squared daily returns on the CRSP value-weighted portfolio plus twice the sum of the products of adjacent returns,

$$\sigma_{mt}^2 = \sum_{i=1}^{N_t} r_{it}^2 + 2\sum_{i=1}^{N_t-1} r_{it} r_{i+1,t}$$

Where N_t is the number of daily returns r_{it} in month t. We then estimate an ARIMA(0,1,3) model for the log of σ_{mt} using all available observations from CRSP. Our conditional volatility measure for each month is defined as the predicted value for the month from the ARIMA model.

[4] There is a substantial body of literature studying the risk-return relationship of ICAPM utilizing various conditional volatility measures. We present results with one of the most well-known volatility measures. In unreported analyses, we employ implied volatility (VXO) available from 1985 onwards as a conditional volatility measure and find similar results.

Bansal and Sahliastovich (2008) propose a long-run risk model where expected stock returns depend on investors' estimates of expected growth and their confidence about these estimates. Adopting the methodology of Bansal and Sahlisastovich (2008), we directly estimate investors' expected growth and confidence from the cross-section of forecasts from the Survey of Professional Forecasters (SPF) available from the Federal Reserve Bank of Philadelphia. Specifically, for each quarter, we proxy the expected growth rate in GDP with the average of next year's (four quarters ahead) forecasted growth rates. The uncertainty in the average forecast is estimated by dividing the cross-sectional variance of the forecasted annual growth rates at each point in time by the number of forecasts.[5]

An alternative measure of fundamental economic uncertainty is consumption volatility. To obtain a measure for consumption volatility, we first collect quarterly data on consumption of non-durables and services from NIPA accounts, Section 1. Next we estimate the following AR(1) specification for consumption growth,

$$g_{c,t} = \mu + a_1 g_{c,t-1} + \varepsilon_{c,t}.$$

Following Bansal, Khatchatrian, and Yaron (2004), the consumption volatility measure is computed as, $\sigma_{c,t} = log\left(\sum_{j=1}^{4}\left|\varepsilon_{c,t-j}\right|\right)$.

[5] While Bansal and Shaliastovich (2008) use the one-quarter-ahead forecasts, we use forecasts for yearly GDP growth rates to align the forecast period with our primary expected return measure, i.e. Value Line analysts' annual expected returns. Replacing annual GDP forecasts with one-quarter-ahead forecasts does not materially alter our results.

We also consider a set of predictor variables used in Lettau and Ludvigson (2001), Ang and Bekaert (2007), and Campbell (1987). We obtain monthly data for the stochastically detrended risk-free rate (the three-month secondary market T-bill rate minus its backward twelve-month moving average), the default spread between Moody's BAA and AAA corporate bond yields, and the term spread defined as the difference between the six-month T-bill rate and the three-month T-bill rate (from the Web site of the Federal Reserve Bank of St. Louise).

For analyses using monthly estimates of the market risk premium, we match the most recent past with the monthly expected return. For example, the SPF data is released in the second month of each quarter and is matched with the three monthly return observations starting from the third month of the quarter. Other quarterly data are assumed to be available at the end of the quarter and are merged with the monthly observations in the following quarter. Summary statistics for the control variables for the sample period of 1975 – 2001 are given in Table 3.

[Table 3 here]

The correlation between analysts' expected returns and expected CSI at monthly frequency is 0.34. Consistent with long run risk models, expected GDP uncertainty and consumption risk are both positively related to our expected return measure.

3. Empirical Results

3.1 Main Results

To examine the relation between global instability and the expected market risk premium, we use simple linear regressions of expected returns on different sets of lagged explanatory variables. All reported t-statistics are based on Newey-West (1987) heteroskedasticity and serial correlation consistent standard errors.[6]

[Table 4 here]

Table 4 reports the results for monthly value-weighted VL expected returns in excess of 1-year constant maturity Treasury rates. The results in the first row show that expected market volatility has little impact on VL analysts' forecasted annual expected excess returns. The t-statistic is only 0.29 and the adjusted R^2 is negative. While these results do not support the Merton (1973) ICAPM, previous empirical studies using realized returns also document that the ICAPM risk and return trade-off is hard to find in the data (see, for example, Balillie and Degennaro, 1990, Campbell and Hentschel, 1992, and Harvey, 2001).[7]

Adding the predicted level of global political instability (row 2) greatly improves the fit of the model. The adjusted R^2 is now 0.11, and the coefficient on $E_{t-1}[CSI]$ is significantly positive (t-stat = 3.07). These results are consistent with the main prediction of time-varying rare disaster models and suggest that investors demand a higher risk

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[6] Since analysts can always update their expectations, expected returns are not overlapping even though forecasting periods are.

[7] The results in Table 4 are similar when expected market volatility is excluded from models 2 - 6.

premium when disaster probability is high. The point estimate of the regression coefficient is 0.0044, which indicates that a one-standard-deviation increase in predicted CSI (4.38) results in a 2% increase in the expected market risk premium.

In rows 3 – 6 of Table 4, we report estimates from regressions that include other predictor variables suggested in the literature. The inclusion of GDP forecast uncertainty and the GDP growth rate is motivated by Bansal and Sahliastovich (2008). The significantly positive coefficient on GDP uncertainty accords well with their long-run growth model. Row 4 shows that the relative T-bill rate, the term spread, and the default spread are all positively related to analyst-based expected stock market returns in excess of the 1-year Treasury rate. These results are broadly consistent with the predictive regressions in Bollerslev et al. (2009). Finally, consistent with Bansal, Khatchatrian, and Yaron (2004) consumption volatility positively impacts the VL expected return measure. Note that in all model specifications, the coefficient on expected CSI is positive and significant at the 10 percent level or better. We conclude that consistent with rare disaster models increased global political instability increases the expected market risk premium and that this result is robust to inclusion of other known predictor variables.

3.2 Robustness Test: Alternative expected return measures

This section considers the results of tests with the earnings-price and dividend-price ratios as alternative proxies for expected stock market returns. We use data from Robert Shiller's Web page.[8] E/P is defined as the trailing 10-year average of real earnings divided by the inflation adjusted S&P composite price (reciprocal of P/E10 or CAPE in

[8] http://www.econ.yale.edu/~shiller/data.htm. We thank Rober Shiller for making the data available.

the data). D/P is computed as the real dividends over the previous year divided by the real price. We are not the first to employ E/P and D/P as proxies for expected returns. For example, Fama and French (2002) argue that because dividend and earnings growth are largely unpredictable, E/P and D/P are effective proxies for expected stock returns. The results of the additional tests using E/P and D/P as proxies for expected stock returns are reported in Table 5.

[Table 5 here]

For each regression in Table 5, we report the start date and the end date of the relevant sample period in the last two columns. The results for the two valuation ratios in Table 5 are remarkably similar to the results in Table 4 based on VL analysts' expected returns. Most importantly, the regression coefficients on expected CSI, are always positive and significant. The coefficient for expected market volatility is significantly positive for the longest sample period, but becomes insignificant and even negative for sample periods that start after 1959 (Row 4). Consistent with the results in Table 4, GDP growth uncertainty, consumption volatility, and the three financial predictors are positively related to both E/P and D/P.

Overall, these tests show that i) the results in the previous section are not specific to the use of VL analysts' expectations as proxy for market-wide expectations, and ii) the results in the previous section are not limited to the period 1975 to 2001, but extend to the period 1926-2008.

3.3 Robustness Test: Quarterly data

In the Value Line database firms receive coverage only once per quarter and are therefore included in our value-weighted portfolio only once per quarter. A possible concern with our use of monthly data is that the firms that are covered in a particular month of each quarter are systematically different. We therefore repeat the analysis in Table 4 using quarterly value-weighted returns as dependent variables and all values for the explanatory variables are measured at the beginning of each quarter. Table 6 presents the quarterly regression results.

[Table 6 here]

The results are very similar to the results in Table 4, but with slightly lower t-statistics. Most importantly, predicted CSI and the measures of macro-economic uncertainty are significantly positively related to expected returns.

4. Conclusion

One of the fundamental predictions of rare disaster models is a positive intertemporal relation between disaster probability and the market risk premium. We empirically test this link using a unique measure of global instability and Value Line analysts' expected rates of return. Consistent with the predictions of rare disaster models, expected political instability is significantly correlated with expected excess stock market returns. The results are robust across different proxies for expected stock market returns (in addition to

Value Line target prices, we use the earning-price ratio and dividend-price ratio). Consistent with long-run risk models, we find also that uncertainty about expected GDP growth or expected consumption growth is significantly positively related to the expected market risk premium.

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Table 1. Descriptive statistics of crisis variables

The table reports the mean, standard deviation, minimum, maximum, and sum for all crisis variables used in our analysis for the sample period 1975 – 2001. Crisis denotes the number of crises that take place in any month consisting of starting (Start), on-going, and ending (End) crises. Violent Start gives the number of crises that start with a violent act. GP involvement is the count of crises that involve great powers. Protracted is the number of crises that are part of a protracted conflict. Grave denotes the number of crises that involve a threat to existence, a threat of great damage or a territorial threat. Violent crises are crises with either serious clashes or full-scale wars and crises in the subgroup War include all full-scale wars. The Crisis Severity Index is constructed by adding one (for being a crisis) to the sum of one each for the six aspects (Violent Start, GP Involvement, Protracted, Grave, War, and Violent).

	Mean	Std Dev	Min	Max	Sum
Crises	2.24	1.50	0	8	996
Start	0.48	0.72	0	4	215
End	0.48	0.72	0	4	213
CSI	7.75	5.44	0	28	3448
Start CSI	1.59	2.57	0	13	707
End CSI	1.59	2.58	0	19	707
Violent Start	0.24	0.52	0	3	106
GP involvement	0.05	0.23	0	2	22
Protracted	0.28	0.54	0	3	126
Grave	0.24	0.49	0	3	106
War	0.08	0.28	0	2	36
Violent	0.22	0.48	0	3	96

Table 2. Descriptive statistics of annual expected returns based on Value Line Target prices

This table provides summary statistics on the distribution of Value Line's expected annual return by year constructed from Value Line target prices. The data, also used in Brav et al. (2005), are obtained from Reuven Lehavy's Web page. The last column reports the value-weighted average expected returns in excess of one-year constant maturity Treasury rates where the weights are determined by the market capitalizations at the end of the preceding month.

Year	N	Mean Raw	Std Dev	Q1	Median	Q3	Mean VW Excess
1975	5571	0.3400	0.1260	0.2477	0.3262	0.4205	0.1858
1976	5050	0.2986	0.1027	0.2243	0.2875	0.3627	0.1839
1977	5851	0.2857	0.0930	0.2212	0.2806	0.3457	0.1983
1978	5860	0.2828	0.0879	0.2210	0.2783	0.3379	0.2001
1979	5958	0.3105	0.0993	0.2419	0.3100	0.3767	0.1967
1980	5799	0.3132	0.1211	0.2287	0.3159	0.3971	0.1828
1981	5974	0.2895	0.0927	0.2252	0.2881	0.3494	0.1420
1982	6010	0.3121	0.0984	0.2442	0.3073	0.3762	0.1846
1983	5056	0.1964	0.0731	0.1527	0.2019	0.2437	0.1063
1984	5610	0.2332	0.0728	0.1863	0.2292	0.2769	0.1197
1985	4989	0.1972	0.0783	0.1497	0.1908	0.2385	0.1033
1986	5191	0.1530	0.0710	0.1077	0.1478	0.1919	0.0769
1987	5292	0.1472	0.0785	0.0988	0.1380	0.1890	0.0588
1988	5395	0.1875	0.0730	0.1407	0.1801	0.2267	0.1016
1989	5245	0.1684	0.0701	0.1245	0.1628	0.2055	0.0716
1990	5196	0.2105	0.0918	0.1437	0.1968	0.2623	0.0951
1991	5202	0.1909	0.0848	0.1300	0.1786	0.2390	0.1000
1992	5184	0.1749	0.0803	0.1172	0.1670	0.2210	0.1098
1993	5292	0.1482	0.0722	0.0966	0.1443	0.1916	0.0975
1994	5184	0.1569	0.0657	0.1114	0.1539	0.1958	0.0904
1995	5174	0.1491	0.0611	0.1066	0.1444	0.1845	0.0747
1996	5067	0.1358	0.0653	0.0907	0.1289	0.1726	0.0582
1997	5101	0.1207	0.0622	0.0787	0.1137	0.1559	0.0423
1998	5100	0.1277	0.0813	0.0704	0.1153	0.1722	0.0321

1999	5328	0.1556	0.0868	0.0954	0.1486	0.2086	0.0439
2000	5645	0.1869	0.1033	0.1155	0.1830	0.2508	0.0584
2001	5771	0.1742	0.0926	0.1104	0.1601	0.2221	0.1085

Table 3. Descriptive statistics of other variables

Panel A of this Table reports summary statistics for the variables used in this study, and Panel B presents the correlation matrix. The sample period is 1975 to 2001. $E_{t-1}[ln\sigma_m]$ is the expected stock market volatility for month t from an ARIMA(0,1,3) model calculated with information available at the end of month t-1. $E_{t-1}[CSI]$ is the expected level of the crisis severity index. UNC_{t-1} and $RGDP_{t-1}$ denote the cross-sectional mean and standard deviation of most recent GDP growth rate forecasts, respectively. $E_{t-1}[ln\sigma_c]$ is the log of the sum of the absolute value of the four preceding quarters' consumption growth AR(1) residuals. $RREL_{t-1}$ is defined as the three-month T-bill rate minus its trailing twelve month average. $TERM_{t-1}$ denotes the difference between the six-month and three-month T-bill rates. DEF_{t}*-1* is defined as the difference between Moody's BAA and AAA bond yields. Quarterly observations are converted to monthly observations by taking the most recently available quarterly observations. Correlation coefficients in bold denote significance at the 5% level.

Panel A: Summary Statistics

	Mean	Std Dev	Q1	Median	Q3
$E_{t-1}[ln\sigma_m]$	0.0401	0.0122	0.0306	0.0376	0.0475
$E_{t-1}[CSI]$	8.60	4.38	5.38	8.80	10.80
UNC_{t-1}	0.0646	0.0871	0.0144	0.0359	0.0748
$RGDP_{t-1}$	0.0251	0.0135	0.0215	0.0252	0.0311
$RREL_{t-1}$	-0.0004	0.0080	-0.0052	-0.0010	0.0045
$TERM_{t-1}$	0.0013	0.0024	0.0001	0.0012	0.0024
$E_t[ln\sigma_c]$	-4.27	0.50	-4.64	-4.21	-3.92
DEF_{t-1}	0.0111	0.0047	0.0076	0.0096	0.0139

Panel B: Correlations									
	$E_t[R_m]$	$E_{t-1}[ln\sigma_m]$	$E_{t-1}[CSI]$	UNC_{t-1}	$RGDP_{t-1}$	$RREL_{t-1}$	$TERM_{t-1}$	DEF_{t-1}	$E_{t-1}[ln\sigma_c]$
$E_t[R_m]$	1								
$E_{t-1}[ln\sigma_m]$	0.04	1							
$E_{t-1}[CSI]$	**0.34**	0.09	1						
UNC_{t-1}	**0.46**	0.07	0.09	1					
$RGDP_{t-1}$	-0.06	**-0.15**	-0.03	**-0.24**	1				
$RREL_{t-1}$	**0.26**	**0.21**	**0.33**	**0.21**	**-0.45**	1			
$TERM_{t-1}$	**0.23**	0.00	0.02	0.06	**0.27**	-0.08	1		
DEF_{t-1}	**0.47**	**0.28**	**0.14**	**0.31**	-0.11	0.09	0.06	1	
$E_t[ln\sigma_c]$	**0.42**	**-0.14**	**0.26**	**0.29**	-0.05	0.10	**-0.16**	**0.29**	1

Table 4. Monthly expected return regressions

The table reports estimates from OLS regressions of VL analysts' expected returns in excess of one-year constant maturity Treasury rates on lagged variables named at the head of a column. The returns are value-weighted using the preceding month's market capitalization. Newey-West corrected t-statistics with 12 lags appear in square brackets below the coefficient estimate. The sample period is 1975 – 2001. All variable definitions are identical to Table 3.

#	*Intercept*	$E_{t-1}[ln\sigma_m]$	$E_{t-1}[CSI]$	UNC_{t-1}	$RGDP_{t-1}$	$RREL_{t-1}$	$TERM_{t-1}$	DEF_{t-1}	$E_{t-1}[ln\sigma_c]$	*Adj.* R^2
1	0.1048	0.1797								-0.0016
	[4.00]	[0.29]								
2	0.0729	0.0345	0.0044							0.1105
	[2.78]	[0.06]	[3.07]							
3	0.0562	-0.0539	0.0039	0.2903	0.2272					0.2976
	[2.29]	[-0.12]	[3.05]	[3.22]	[0.34]					
4	0.0492	-0.7021	0.0028			1.4387	5.2516	5.4026		0.3732
	[2.35]	[-1.35]	[1.95]			[2.24]	[2.41]	[4.63]		
5	0.2486	0.3091	0.0031						0.0411	0.2310
	[3.27]	[0.71]	[2.07]						[2.61]	

Table 5. Monthly E/P and D/P regressions

The table reports estimates from OLS regressions of E/P and D/P on lagged variables named at the head of a column. E/P is the 10-year trailing average of real earnings divided by real price. D/P is the real dividends in the previous year divided by real price. Newey-West corrected t-statistics with 12 lags appear in square brackets below the coefficient estimate. The sample periods vary with data availability and are shown in the last two columns. All variable definitions are identical to Table 3.

#	*Intercept*	$E_{t-1}[ln\sigma_m]$	$E_{t-1}[CSI]$	UNC_{t-1}	$RGDP_{t-1}$	$RREL_{t-1}$	$TERM_{t-1}$	DEF_{t-1}	$E_{t-1}[ln\sigma_c]$	*Adj.* R^2	Begin	End
						Panel A: E/P						
1	0.0549	0.2976								0.0525	1926.02	2008.12
	[10.90]	[2.70]										
2	0.0382	0.3215	0.0021							0.1674	1928.02	2008.12
	[6.75]	[2.84]	[4.81]									
3	0.0426	-0.0336	0.0019	0.1870	-0.0240					0.3293	1968.12	2008.12
	[3.58]	[-0.14]	[3.10]	[3.04]	[-0.11]							
4	0.0199	-0.5322	0.0017			0.6316	1.2324	4.8161		0.5673	1959.01	2008.12
	[3.47]	[-2.42]	[2.69]			[2.15]	[1.86]	[8.79]				
5	0.1218	0.2493	0.0018						0.0193	0.2641	1948.07	2008.12
	[5.19]	[1.19]	[3.88]						[3.95]			

Panel B: D/P

1	0.0261	0.3269								0.1388	1926.02	2008.12
	[5.72]	[2.84]										
2	0.0196	0.3417	0.0008							0.1768	1928.02	2008.12
	[4.16]	[2.91]	[2.62]									
3	0.0261	-0.0927	0.0009	0.0770	-0.0837					0.3662	1968.12	2008.12
	[5.27]	[-0.85]	[3.66]	[3.14]	[-1.08]							
4	0.0194	-0.3007	0.0007			0.4144	0.6781	1.6545		0.4644	1959.01	2008.12
	[6.29]	[-2.95]	[2.86]			[3.22]	[2.39]	[6.99]				
5	0.0866	-0.0591	0.0008						0.0134	0.3605	1948.07	2008.12
	[7.30]	[-0.63]	[3.35]						[5.40]			

Table 6. Quarterly expected return regressions

The table reports estimates from OLS regressions of VL analysts' expected returns on lagged variables named at the head of a column. The dependent variable is value-weighted average of all VL stocks within each quarter. Newey-West corrected t-statistics with 4 lags appear in square brackets below the coefficient estimate. The sample period is 1975 – 2001. All variable definitions are identical to Table 3. Monthly series are converted to quarterly series by taking the most recent observation.

#	*Intercept*	$E_{t-1}[ln\sigma_m]$	$E_{t-1}[CSI]$	UNC_{t-1}	$RGDP_{t-1}$	$RREL_{t-1}$	$TERM_{t-1}$	DEF_{t-1}	$E_{t-1}[ln\sigma_c]$	*Adj.* R^2
1	0.0993	0.3044								-0.0050
	[3.45]	[0.43]								
2	0.0636	0.1039	0.0050							0.1320
	[2.21]	[0.15]	[2.79]							
3	0.0460	0.0063	0.0041	0.2862	0.4246					0.3129
	[1.81]	[0.01]	[2.56]	[3.02]	[0.62]					
4	0.0471	-0.5694	0.0033			1.4512	3.4352	4.7816		0.3378
	[1.95]	[-0.91]	[1.74]			[2.39]	[1.55]	[3.54]		
5	0.2370	0.3533	0.0037						0.0401	0.2520
	[2.87]	[0.68]	[2.02]						[2.38]	

Figure 1. Value-Weighted Annual Expected Return and CSI

This figure illustrates the time-series of the value-weighted analysts' expected returns of individual firms in excess of one-year constant maturity Treasury rates and the predicted level of crisis severity index. The predicted CSI in each month is estimated from an AR(1) model with the trailing 10-year data. Each point in the figure represents an annual average of the monthly figures within the same calendar year.

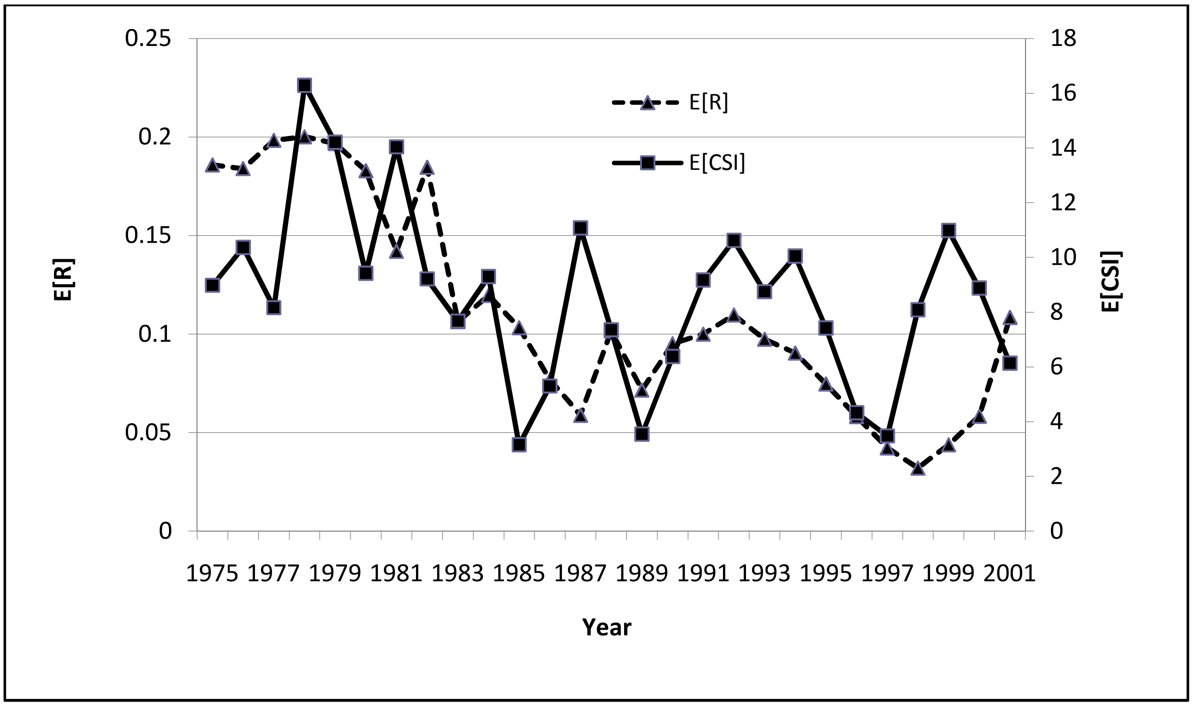

Figure 2. Value-weighted realized stock returns and predicted CSI

This figure illustrates the time-series of the annualized CRSP value-weighted stock market returns in excess of 30-day Treasury bill rates and the predicted level of crisis severity index. The predicted CSI in each month is estimated from an AR(1) model with the trailing 10-year data. Each point in the figure represents an annual average of the monthly figures within the same calendar year.