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Stock Vulnerability and Resilience

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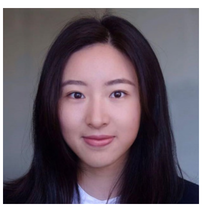

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KEY FINDINGS

- The authors present a novel data-driven approach to identify the vulnerability and resilience of stocks in advance of a market decline.
- The approach compares a stock's factor attributes to those of stocks known to have been vulnerable or resilient in prior drawdowns, including nonlinear conditional information that outperforms the best ex post linear combination of factor attributes.
- Investing in low-vulnerability and high-resilience stocks may offer effective protection during market drawdowns; the risk of high-vulnerability and low-resilience stocks has not been adequately compensated with excess returns in the historical sample.

ABSTRACT

The authors propose a parsimonious yet flexible statistical method for predicting the relative vulnerability or resilience of individual stocks to market drawdowns. The authors' approach compares a stock's unique circumstances—as reflected in popular factor attributes—to the circumstances of stocks that have proven vulnerable or resilient to previous market drawdowns. Unlike other approaches, the authors' method allows the influence of each factor attribute to vary across stocks in a nonlinear, conditional way. The authors test their explicit method for predicting stock vulnerability and resilience out of sample using the five largest market drawdowns since the global financial crisis. The nonlinear composite scores the authors derive are reliably better predictors of cross-sectional return than any of the individual factor attributes or an ex post linear combination of factor attributes.

It stands to reason that stock market crashes are not good for stock prices on average. There is, however, a large amount of cross-sectional variation in performance during market sell-offs. We might expect that stocks with less sensitivity to broad market moves, as determined by their capital asset pricing model (CAPM) beta, should fare better than their peers. Other factors such as size, valuation, and earnings quality also may matter, although the nature of those relationships is often less clear. In this article, our goal is to predict stock vulnerability or resilience to a market crash based on firm characteristics observed prior to the crash. A distinguishing feature of our approach is that we do not rely on fixed linear combinations of factor attributes to score stocks. Instead, the method we propose allows the influence of each factor to vary from one stock to the next according to its unique circumstances. Introducing this nonlinear conditionality in the influence of factors is simple and intuitive; it is achieved by statistically comparing a company's circumstances to those we observe from prior experience rather than seeking a universal rule for the impact of each factor.

We create vulnerability and resilience scores for stocks by statistically comparing their present circumstances, as defined by a collection of financial statement fundamentals, to those of similarly situated stocks that we know performed well or poorly during prior market sell-offs. We apply a multivariate statistical method that was originally introduced by Kinlaw, Kritzman, and Turkington (2021) to analyze the business cycle. Here, we apply this method to individual stocks. In short, we measure the similarity of each stock's attributes to the typical attributes of stocks that performed best or worst in prior crashes. A well-motivated statistic called the Mahalanobis distance determines similarity. It accounts for the typical variances and correlations of the attributes across companies in each sample. The key benefit of this technique is that, unlike linear regression, it is capable of picking up on patterns that appear differentially in one sample (stocks with the best returns) versus another (stocks with the worst returns).

In out-of-sample tests, we find that both the vulnerability and resilience scores offer reliable predictions of cross-sectional stock performance during market downturns. Even though these scores are derived from simple factor attributes, we find that the predictive capacity of the scores exceeds what is possible from even an ex post best linear fit of the factors themselves. The incremental information in vulnerability is particularly robust. These findings point to the importance of nonlinear conditionality in assessing stock vulnerability to market moves.

We proceed as follows. First, we describe the data and methodology we use to compute stock vulnerability and resilience scores. Second, we present out-of-sample regression tests for the efficacy of these measures, both in a pooled panel setting and for individual market drawdown events. Third, we evaluate the performance of portfolios formed from these measures, during both drawdowns and non-drawdowns and as both total returns and returns in excess of traditional factors, and we consider the asset pricing implications of these findings. Last, we conclude.

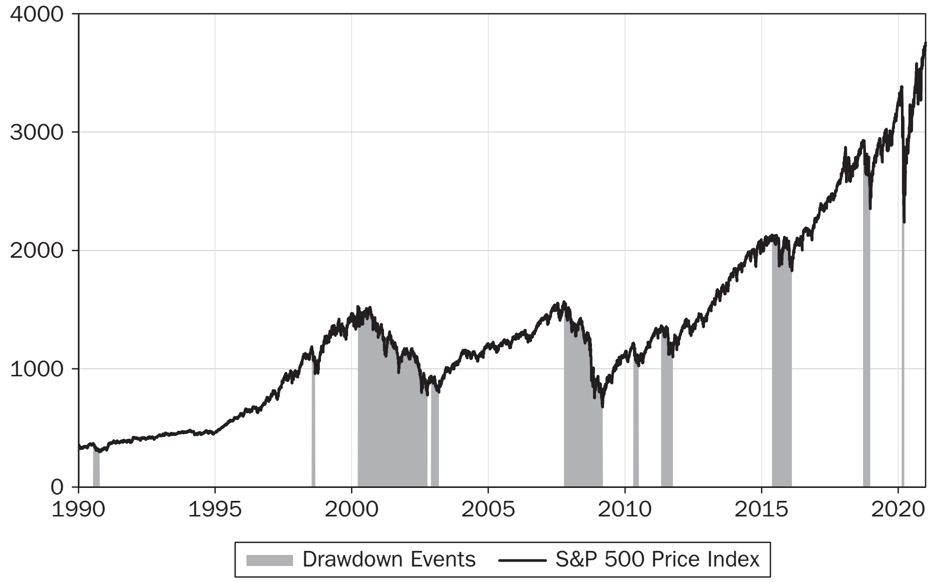
DATA AND METHODOLOGY

We study the relative vulnerability and resilience of stocks in the S&P 500 Index. Specifically, we compute a measure of relative vulnerability and one of relative resilience for each stock prior to the start of the five largest market drawdowns from 2010 to 2020. These peak-to-trough losses in the S&P 500 occurred in 2010, 2011, 2015, 2018, and 2020. In each case, we use only the information that would have been available at the start of the event to derive vulnerability and resilience scores. Our methodology relies on a sample of observed stocks prior to each period, so we also identify the five largest market drawdowns that occurred from 1990 to 2010. Exhibit 1 shows each market crash episode along with the performance of the index.

Starting with the 2010 market crash, we form a historical event sample from the five preceding drawdowns. We refer to a given stock's return in a particular historical drawdown as a stock experience. Each historical drawdown includes roughly 500 stock experiences, which we pool together across the five events to obtain a composite sample of approximately 2,500 total stock experiences that span multiple years and securities. We use point-in-time index constituents, so the stock experiences that occurred early in the sample may include companies that did not exist later in the sample, and vice versa.

EXHIBIT 1

Market Drawdown Events (peak to trough)



Next, with the benefit of hindsight for the events prior to 2010, we assign each stock experience to one of three groups based on its total return during the market drawdown:

- Vulnerable: If the cumulative return is in the bottom 10% of stocks for that drawdown
- Resilient: If the cumulative return is in the top 10% of stocks for that drawdown
- Other: Everything else

We include the "other" category so that stocks that bear no resemblance to the first two categories can comfortably reside in the third. They are not forced to decide between two highly unlikely classifications, which could otherwise introduce noise to the scores.

We obtain five fundamental attributes that are observed prior to the relevant historical crash for each historical stock experience. To avoid the undue influence of extreme outliers that might result from noise or other unwanted anomalies, we truncate extreme values to the 0.5th or 99.5th percentile of the pooled historical distribution. We use five attributes that are widely available, are relatively easy to measure, and have a potentially intuitive link to stock performance during periods of broad market distress.[1]

- Market beta (slope from regressing the prior five years[2] of monthly stock returns on the returns of the S&P 500)
- Size (market capitalization)
- Book-to-market value ratio
- Return-on-equity
- Dividend yield (dividend-to-price ratio per share)

[1] These attributes correspond to several seminal articles on asset pricing, including Sharpe (1964), Lintner (1965), Black (1972), and Fama and French (1992, 1993, 2015). We obtained attribute data from Datastream and Worldscope Fundamentals.

[2] For stocks with less than five years of returns early in their sample, we start with a two-year window and grow it to five years as more data becomes available.

We compute the means and covariances of each attribute for each of our pooled subgroups: vulnerable, resilient, and other. We also obtain the same five attributes for the stock market constituents in March 2010, the last month prior to the start of the 2010 drawdown. With this information, we estimate the likelihood that a given stock's future experience will prove to be vulnerable or resilient during the 2010 drawdown event, based on its statistical similarity to previous stock experiences that are known to have been vulnerable, resilient, or other. Specifically, we apply the methodology originally introduced by Kinlaw, Kritzman, and Turkington (2021) as follows:

1. We measure the Mahalanobis distance of the current stock to each of the three subgroups (vulnerable, resilient, and other). The Mahalanobis distance is an essential quantity in statistics that can be motivated by information theory (Czasonis, Kritzman, and Turkington 2022) and is defined as

$$d = (x - \mu)\Sigma^{-1}(x - \mu)'$$

   Here, x is the row vector of attribute values for the current stock, μ is the row vector of average attribute values for one of the subgroups, Σ^{-1} is the inverse of the covariance matrix of attribute values for that subgroup, and $'$ denotes matrix transpose. The Mahalanobis distance between two vectors accounts for the variance of the attributes in the subgroup as well as the correlations between each pair of attributes in the subgroup.
2. We convert the distance d to each subgroup into a corresponding likelihood ξ using the multivariate normal probability density function:

$$\xi(d) = \frac{1}{\sqrt{\det(2\pi\Sigma)}} e^{-d/2}$$

3. We compute the relative likelihood that the current stock belongs to each subgroup. This relative likelihood falls between 0 and 1, and we may loosely interpret it as a probability.

$$p_{vulnerable} = \frac{\xi_{vulnerable}}{\xi_{vulnerable} + \xi_{resilient} + \xi_{other}}$$

$$p_{resilient} = \frac{\xi_{resilient}}{\xi_{vulnerable} + \xi_{resilient} + \xi_{other}}$$

We repeat this process for every stock in the universe for the month of March 2010. The result is a cross section of vulnerability and resilience scores that we will later compare to the subsequent performance of the relevant stocks during the drawdown that begins in April 2010.

We move to the next drawdown and repeat this process until we have generated stock-level vulnerability and resilience likelihoods for all five drawdown events between 2010 and 2020. For each event, we apply the same methodology using the stocks in the market index just prior to the start of the relevant drawdown and the attributes that are available at that time. Moreover, in each case, we use the five most recent drawdowns preceding the event as the pooled sample of historical stock experiences. For example, to predict the 2020 crash, we rely on the 2018, 2016, 2011, 2010, and 2009 drawdowns. This construction ensures that the predictions do not use any forward-looking information. We use a rolling window of the past five events so that the method of prediction remains the same throughout our testing sample.

The key advantage of this approach is that the relative importance of each attribute changes depending on the circumstances of each stock. For example, if a stock today looks similar to historically resilient stock experiences in every attribute except one, the nonconforming attribute will heavily influence the determination. There may be, however, another stock today that looks similar to historically vulnerable stock experiences, and for which the unusual attribute from the first stock is perfectly in line with expectations for this second stock. Therefore, it will not matter much in the determination for the second stock. The importance of attributes is determined collectively as a statistical function of current circumstances. This is not true of linear regression, which always places equal importance on each attribute regardless of current circumstances.

PREDICTIVE RESULTS

We now test the ability of our composite stock-level vulnerability and resilience scores to predict the cross-sectional performance of stocks during market drawdowns. Specifically, we run pooled panel regressions to determine how well each likelihood measure explains relative stock returns during the drawdowns of 2010 to 2020. The regressions include the likelihood measures, individual attributes, and realized returns across all five events, allowing for event fixed effects. For comparison, we also test how well the individual attributes in isolation explain relative performance.

To mitigate the effect of outliers and ensure a representative result, we normalize every variable in these regressions by taking its cross-sectional percent rank within the relevant event. This approach puts the attributes in the same units, thereby facilitating their comparison. It also focuses the comparisons cross-sectionally rather than over time.

We regress stock returns on each attribute in isolation and collectively. However, we do not include the vulnerability and resilience scores in the same regression model because their ranks are very strongly correlated (–0.84), which distorts statistical inference. We correct all the panel *t*-statistics to account for the presence of correlated errors across the five stock cross-sections (e.g., the patterns of stock prediction errors are similar across events), which would otherwise lead to biased estimates of standard errors. Each of these regressions spans 2,512 out-of-sample stock experiences.

Univariate regressions:

$$Rank(Return_i) = \alpha + \beta Rank(Attribute_i) + Event\ \ fixed\ \ effects + u_i$$

Multivariate regressions:

$$\begin{aligned} Rank(Return_i) = {} & \alpha + \beta_1 Rank(Attribute\ \ 1_i) + \beta_2 Rank(Attribute\ \ 2_i) \\ & + \cdots + \beta_n Rank(Attribute\ \ n_i) + Event\ \ fixed\ \ effects + u_i \end{aligned}$$

Exhibit 2 presents the *t*-statistics and R^2 statistics from these regressions.

On a stand-alone basis, every attribute has a statistically significant relationship with cross-sectional performance. However, the vulnerability, resilience, and beta factors far exceed the others in terms of statistical significance (*t*-statistic) as well as explanatory power (R^2). In most cases, the signs of these relationships are as expected: Stocks with low vulnerability, high resilience, large market capitalization, high return-on-equity, high dividend yield, and low market beta tend to outperform their peers during market downturns. In the case of book-to-market, we find that more-expensive stocks (low book-to-market) tend to outperform on a relative basis.

EXHIBIT 2

Predictive Panel Regressions across Five Drawdowns: *t*-Statistics

	Univariate							Multivariate	
Vulnerability	–30.64							–17.40	
Resilience		30.41							1.99
Size (market cap)			7.38					1.29	1.67
Book-to-Market				–16.50				–3.31	–2.74
Return-on-Equity					11.68			–0.18	0.12
Dividend Yield						8.55		0.92	0.92
Market Beta							–28.75	–7.81	–4.74
Adjusted R^2	0.27	0.27	0.02	0.10	0.05	0.03	0.25	0.35	0.34

This result is contrary to prior findings for the value factor's performance during market sell-offs as described by Gormsen and Greenwood (2017). One possible explanation for these divergent findings is that the time period is notably different, spanning 2010 to 2020 in our case and 1963 to 2015 in the case of Gormsen and Greenwood. Growth stocks performed well in the decade of the 2010s, even during adverse market regimes. In addition, the investment universe, definition of the value factor, and definition of adverse periods are slightly different in the prior article, although we suspect this would only lead to a more modest difference in results.

Although each score (or attribute) has a statistically significant relationship in isolation, some of their predictive information may be redundant when they are considered collectively. The results of the multivariate regression suggest this is the case for market capitalization, return-on-equity, and dividend yield, whose relationships are statistically insignificant after controlling for the other factors. Only the vulnerability scores, resilience scores, book-to-market, and market beta reveal statistically significant relationships in the multivariate regressions, with vulnerability's relationship the most significant by far. Given that vulnerability is highly (inversely) correlated with resilience and they are conceptual opposites, it seems surprising that the vulnerability scores have much more predictive efficacy. One possible explanation is that the patterns of vulnerability are more reliable and easier to identify, whereas resilience may be a more idiosyncratic feature that depends on the specific stock and market drawdown in question.

It is worth noting that we may think of the vulnerability scores as comprising a linear combination of the other attributes, plus a nonlinear/conditional component that reflects the methodology's stock-specific consideration of each attribute. The vulnerability and resilience likelihood scores are formed ex ante, before the performance of stocks during events has been observed. In contrast, we may think of the multivariate regression in Exhibit 2 as identifying the best linear combination of individual attributes ex post, with the benefit of having observed stock returns during the drawdown event. The significant coefficients on vulnerability and resilience in the multivariate regression therefore reveal that there is a useful nonlinear component to the scoring that exceeds even the optimal ex post linear combination of pure factor attributes. In other words, the importance of each attribute to a stock is conditional on the more general circumstances of that stock.

To understand the consistency of these relationships across the drawdown events, we now repeat the multivariate regression analysis for each market drawdown event in isolation. We focus here on the multivariate regressions because they offer a more conservative test of the efficacy of our approach and they focus on its added value above the ex post best-fitting linear approximation (see the appendix for the univariate results for each event). Exhibit 3 shows the multivariate *t*-statistics for each event along with their R^2 statistics.

EXHIBIT 3

Cross-Sectional Regressions by Drawdown Event: *t*-Statistics

	2010		2011		2015		2018		2020	
Vulnerability	–2.63		–3.14		–4.42		–4.52		–2.82	
Resilience		4.79		2.69		0.08		1.09		1.59
Size (market cap)	–0.02	1.92	2.38	2.52	1.93	0.21	–1.81	0.76	2.15	3.39
Book-to-Market	–1.95	–1.60	–4.49	–5.23	–4.17	–4.92	–3.44	–4.16	–3.76	–3.19
Return-on-Equity	–0.54	–0.48	–1.58	–1.01	–2.11	–0.20	–3.97	–2.97	4.59	5.74
Dividend Yield	2.50	2.15	4.00	5.09	1.08	3.90	5.19	4.96	–1.68	–1.97
Beta	–5.69	–1.00	–4.42	–3.70	–2.55	–5.11	–3.46	–3.83	–4.00	–3.51
Adjusted R^2	0.35	0.37	0.42	0.42	0.36	0.34	0.36	0.33	0.40	0.39

These results reveal that the vulnerability scores, book-to-market value ratio, and market beta[3] are the only measures with directionally consistent and statistically significant relationships with cross-sectional performance in all five drawdown events. Resilience scores are statistically significant in the 2010 and 2011 events. It is important to remember that the vulnerability and resilience scores, by construction, do contain a linear blend of the other attributes in addition to the distinct nonlinear component that is highlighted in these multivariate regressions. Thus, these *t*-statistics do not convey the full efficacy of the scores, which contain pieces of the other linear effects.

PORTFOLIO PERFORMANCE AND ASSET PRICING IMPLICATIONS

So far we have shown that our methodology effectively predicts relative stock performance during market drawdowns. Now we consider the relationship with stock returns during non-drawdown periods as well by evaluating the performance of portfolios formed on vulnerability and resilience scores. Beginning in 2009, at the end of each year, we

1. Compute vulnerability and resilience scores for each stock in the S&P 500. We apply the methodology described earlier, using fundamental attributes that are available at the time and the five most recent drawdowns as the pooled sample of historical stock experiences.
2. Form capitalization-weighted portfolios of approximately 100 stocks each, corresponding to stocks with the following:
   a. 20% lowest vulnerability scores
   b. 20% highest resilience scores
   c. 20% highest vulnerability scores
   d. 20% lowest resilience scores

Exhibit 4 shows the annualized returns of the portfolios that we expect to perform better, followed by those we expect to perform worse, and the difference in performance between the two. We likewise construct portfolios corresponding to the five factor attributes (size, book-to-market, return-on-equity, dividend yield, and beta) using the same universe and portfolio construction method. We regress the full sample of monthly returns for the vulnerable and resilient portfolios on the returns of the relevant portfolios formed from these factors, and we retain only the intercept and residual that collectively represent the performance of vulnerable and resilient stocks in excess of the traditional factors.

[3] With the slight exception of the 2010 regression that includes resilience.

EXHIBIT 4

Average Portfolio Returns (annualized, out of sample)

	Total Returns			Returns in Excess of Factor Blend		
	During Noncrash Periods	During Market Crashes	Full Sample	During Noncrash Periods	During Market Crashes	Full Sample
20% Least Vulnerable	25.5%	–9.4%	18.4%	5.5%	0.3%	4.5%
20% Most Resilient	17.4%	–3.0%	13.2%	1.5%	6.1%	2.5%
20% Most Vulnerable	18.9%	–33.6%	8.1%	–5.7%	–6.9%	–6.0%
20% Least Resilient	25.6%	–22.1%	15.9%	–1.3%	–6.4%	–2.4%
Least Minus Most Vulnerable	6.6%	24.2%	10.2%	11.3%	7.3%	10.4%
Most Minus Least Resilient	–8.2%	19.1%	–2.6%	2.9%	12.4%	4.8%

On average, the least vulnerable stocks outperformed the most vulnerable stocks by 24% per year during market crashes, and the most resilient stocks outperformed the least resilient stocks by 19% per year. Investing according to favorable resilience would have lost money during noncrash periods (–8%), whereas investing according to favorable vulnerability would have made money in the noncrash periods (+7%). Conceptually, given the strong relative performance of both strategies during market downturns, we might expect that both would underperform in the long run as a fair cost of downside protection. We investigate this pricing issue with more precision by looking at the performance in excess of the ex post factor blend that best explains the vulnerable and resilient portfolio returns. We see the opposite result. Specifically, both favorable strategies outperform during crash periods and during noncrash periods. In this sample, investors were not compensated for bearing the risk of high vulnerability or low resilience.

It is important to note that vulnerability and resilience are related, but distinct, concepts. In fact, 68% of stocks overlap between the two favorable portfolios (low vulnerability, high resilience) and 72% in the case of the two unfavorable portfolios (high vulnerability, low resilience). As expected, this degree of overlap is markedly higher than the 20% that would occur if vulnerability and resilience were entirely uncorrelated. However, it also is meaningfully less than 100%, indicating that the measures are not redundant.

Although the stocks that are identified as most or least vulnerable are not obvious, there are some intuitive patterns. In Exhibit 5, we show the 20 least (top panel) and most (bottom panel) vulnerable stocks identified prior to the 2020 market crash. Intuitively, we see that the least vulnerable firms had relatively low book-to-market ratios and high return-on-equity, and the opposite was true for the most vulnerable firms. Although this aligns with the earlier regression results, we again emphasize that these stocks were identified prior to the 2020 market crash, whereas the linear relationships were identified ex post. Patterns across other attributes are less consistent. In part, this reflects the fact that our methodology conditionally determines the relative importance of each attribute as a function of a stock's collective circumstances. Moreover, note that the vulnerability and resilience likelihoods are not redundant. Although they tend to align (the least vulnerable stocks tend to have high resilience scores and vice versa for the most vulnerable stocks), this is not always the case. For example, the 12 least vulnerable stocks also had near zero resilience scores. This underscores the point that vulnerability and resilience are overlapping but different concepts.

EXHIBIT 5

20 Least Vulnerable and 20 Most Vulnerable Stocks: 2020 Drawdown

				Cross-Sectional Percentile Rank				
		Vulnerability Likelihood	Resilience Likelihood	Size (market cap)	Book-to-Market	Return-on-Equity	Dividend Yield	Beta
1	NRG ENERGY INC.	0%	0%	13%	0%	100%	19%	27%
2	HILTON WORLDWIDE	0%	0%	59%	4%	100%	23%	72%
3	BOEING CO	0%	0%	95%	5%	99%	61%	66%
4	KIMBERLY-CLARK CORP	0%	0%	73%	5%	99%	78%	17%
5	IDEXX LABORATORIES	0%	0%	49%	5%	99%	8%	39%
6	PHILIP MORRIS INTER	0%	0%	92%	1%	99%	97%	48%
7	MSCI INC.	0%	0%	44%	4%	99%	30%	60%
8	S&P GLOBAL INC	0%	0%	81%	5%	98%	27%	52%
9	O REILLY AUTOMOTIVE	0%	0%	62%	6%	98%	8%	25%
10	HOME DEPOT, INC.	0%	0%	96%	3%	98%	61%	45%
11	LOCKHEED MARTIN CORP	0%	0%	88%	7%	98%	63%	41%
12	MOODY'S CORP	0%	1%	68%	6%	98%	28%	70%
13	MCDONALD'S CORP	0%	21%	94%	2%	97%	61%	14%
14	AUTOZONE INC	0%	25%	53%	2%	97%	8%	22%
15	WESTERN UNION COMP	0%	70%	12%	4%	96%	84%	31%
16	LOWES COMPANIES	0%	37%	87%	7%	97%	50%	72%
17	QUALCOMM INC	0%	22%	86%	9%	97%	86%	90%
18	LILLY (ELI) AND CO.	0%	71%	90%	7%	97%	56%	7%
19	UNITED PARCEL SVCS	0%	55%	88%	8%	96%	83%	67%
20	STARBUCKS CORP	0%	72%	87%	2%	96%	51%	16%
486	WESTROCK CO	90%	0%	12%	98%	18%	95%	95%
487	SVB FINANCIAL GROUP	90%	3%	20%	74%	58%	8%	99%
488	CAPITAL ONE FINL	90%	0%	70%	98%	27%	47%	73%
489	IPG PHOTONICS CORP	90%	5%	6%	54%	20%	8%	99%
490	KRAFT HEINZ CO	91%	0%	67%	100%	10%	99%	50%
491	AMERICAN INTL GROUP	92%	0%	71%	99%	14%	66%	65%
492	UNITED RENTALS INC	92%	1%	16%	58%	79%	8%	100%
493	LOEWS CORPORATION	92%	0%	33%	98%	12%	21%	24%
494	DEVON ENERGY CORP	92%	1%	17%	82%	4%	35%	99%
495	ZIONS BANCORP	92%	1%	7%	96%	22%	67%	88%
496	CITIZENS FINANCIAL	94%	0%	35%	99%	22%	84%	83%
497	LINCOLN NATL CORP	94%	0%	20%	98%	15%	63%	97%
498	VIATRIS INC	94%	0%	17%	96%	6%	8%	95%
499	MARATHON OIL CORP.	94%	0%	18%	97%	10%	40%	99%
500	BAKER HUGHES CO	94%	0%	56%	99%	7%	74%	44%
501	MOSAIC CO	95%	0%	9%	97%	3%	23%	92%
502	UNUM GROUP	95%	0%	2%	100%	35%	84%	88%
503	NEWS CORP B	96%	0%	5%	99%	7%	42%	81%
504	NEWS CORP A	96%	0%	5%	99%	7%	42%	84%
505	L3HARRIS TECHN	100%	0%	9%	100%	28%	18%	34%

CONCLUSION

Some stocks suffer more than others during down market regimes. In this article, we presented a way to identify the vulnerability and resilience of stocks in advance of a market decline. Our approach builds on the methodology of Kinlaw, Kritzman, and Turkington (2021) to classify stocks based on their similarity to stocks that proved to be vulnerable, resilient, or neither during prior market drawdowns. This methodology uses the Mahalanobis distance to measure the multivariate similarity of each stock to the average of the vulnerable, resilient, or other subgroups, taking into account the variation and covariation of each attribute in each subgroup. As a result, the relative importance of each attribute depends on a stock's unique circumstances. Vulnerability and resilience scores thereby include nonlinear conditional information above and beyond the information that is contained in even the best ex post linear combination of factors. Although the choice of factors may be subject to debate, the main point we wish to emphasize is that the derived composite scores are not only effective but also contain significantly more information than a linear sum of the parts.

In an out-of-sample multivariate panel regression test using the five major stock market drawdowns from 2010 to 2020, vulnerability scores were robustly significant with a *t*-statistic of 17, and resilience scores had a *t*-statistic of 2. Nonetheless, both scores had the correct sign of their expected effect in each of the five events viewed in isolation. Vulnerability was highly significant in all five, and resilience was significant in two (2010 and 2011). We also find that both effects are economically meaningful, with the least vulnerable quintile of stocks outperforming the most vulnerable quintile by 24% annualized during market crashes and 10% overall in the full sample. This 10% outperformance persists even after we control for the linear effects of all other factors. A portfolio of most minus least resilient stocks outperforms by 5% after controlling for other factors. Vulnerability and resilience are overlapping concepts, but they are not completely redundant. Our findings suggest that low-vulnerability and high-resilience stocks may offer a viable hedge during market drawdowns. Moreover, they offer a viable protection strategy even in the absence of timing skill because their performance is still positive, on average, even in non-crash periods. The risk of high-vulnerability and low-resilience stocks, on the other hand, does not appear to be adequately compensated by long-run returns.

APPENDIX

Exhibit A1 shows the univariate predictive regression results for the five events from 2010 to 2020.

EXHIBIT A1

Univariate Cross-Sectional Regressions by Drawdown Event: *t*-Statistics

	2010	2011	2015	2018	2020
Vulnerability	–14.26	–15.81	–13.53	–11.72	–13.55
Adjusted R^2	0.29	0.33	0.27	0.21	0.27
Resilience	16.39	14.30	12.47	13.60	11.73
Adjusted R^2	0.35	0.29	0.24	0.27	0.21
Size (market cap)	1.83	3.08	2.89	1.78	7.11
Adjusted R^2	0.00	0.02	0.01	0.00	0.09
Book-to-Market	–4.12	–9.29	–7.78	–6.12	–10.07
Adjusted R^2	0.03	0.15	0.11	0.07	0.17
Return-on-Equity	4.75	5.75	4.78	–0.07	12.06
Adjusted R^2	0.04	0.06	0.04	0.00	0.23
Dividend Yield	7.43	7.81	4.82	4.62	–4.84
Adjusted R^2	0.10	0.11	0.04	0.04	0.04
Beta	–14.49	–14.25	–12.73	–13.44	–9.86
Adjusted R^2	0.29	0.29	0.24	0.26	0.16

REFERENCES

Black, F. 1972. "Capital Market Equilibrium with Restricted Borrowing." *The Journal of Business* 45: 444–455.

Czasonis, M., M. Kritzman, and D. Turkington. 2022. *Prediction Revisited*. Hoboken, NJ: John Wiley & Sons, Inc.

Fama, E. F., and K. R. French. 1992. "The Cross-Section of Expected Stock Returns." *The Journal of Finance* 47: 427–465.

——. 1993. "Common Risk Factors in the Returns on Stocks and Bonds." *Journal of Financial Economics* 33: 3–56.

——. 2015. "A Five-Factor Asset Pricing Model." *Journal of Financial Economics* 116 (1): 1–22.

Gormsen, N., and R. Greenwood. 2017. "Rainy Day Stocks." Working paper, Harvard Business School.

Kinlaw, W., M. Kritzman, and D. Turkington. 2021. "A New Index of the Business Cycle." *Journal of Investment Management* 19 (3): 4–19.

Lintner, J. 1965. "The Valuation of Risk Assets and the Selection of Risk Investments in Stock Portfolios and Capital Budgets." *Review of Economics and Statistics* 47: 13–37.

Sharpe, W. F. 1964. "Capital Asset Prices: A Theory of Market Equilibrium Under Conditions of Risk." *The Journal of Finance* 19 (3): 425–442.