PIMCO

Equity Fragility

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- This paper develops a formal framework for assessing the likelihood of large equity market drawdowns.
- We estimate a parsimonious logistic regression model for both the U.S. and a cohort of four additional developed equity markets, and find that large market impairments have historically been associated with a set of factors centered around valuation, technical and macroeconomic indicators.
- We show that our framework is effective for both recessionary and nonrecessionary drawdowns; this differentiates our work from previous research focused on predicting economic downturns.
- Finally, we show that while the U.S. is indeed a fundamental driver of market fragility globally, country-specific factors are still relevant for predicting the likelihood of large equity market drawdowns.

INTRODUCTION

Markets are fragile. Equities, in particular, residing at the bottom of the capital structure, have been subject to booms and busts, at times giving even the most steadfast investors bouts of fear and euphoria. The late 1990s provide an excellent example of the latter: A years-long market rally resulted in valuations so extreme that, by some measures, U.S. equities were characterized by a *negative* risk premium by the beginning of the 21st century (Baz et al. 2019). Of course, extremes in the right tail of the return distribution can portend similar disruptions on the downside, resulting in scenarios in which equity markets experience significant performance downturns. The aftermath of the 1990s tech bubble resulted in a cumulative 39% decline in the S&P 500 between March 2000 and December 2002; most recently, the 2008 credit crisis produced the most severe equity market drawdown since the Great Depression.

Exhibit 1 shows the frequency of different drawdown sizes for five developed equity markets and indicates whether each drawdown was recessionary in nature.[1] Relatively small market drawdowns – less than 5% – are commonplace, occurring between 27% and 48% of the time. Substantial impairments in equity prices are significantly rarer and much more likely to coincide with a recession, particularly in the U.S. Large recessionary drawdowns can have significant consequences for the general economy. When markets are severely impaired, companies may need to inject additional capital into their pension plans, insurance companies may be required to write down the value of balance sheet assets, endowments may be forced to

1 To determine the size of a drawdown, we compare the price index for each equity market at the end of each month with the index's peak price over the prior 12 months. We compute the return from the peak to the current price. If this value is negative, we consider the observation to be in a drawdown and bucket it accordingly. If an observation is flagged as a drawdown and it overlaps with a recessionary period, we consider the drawdown to be recessionary in nature. For the U.S., we use National Bureau of Economic Research (NBER) recession definitions. For all other countries, we define a recession as two consecutive quarters of negative real GDP growth.

curtail spending plans, and individuals become more risk averse, reducing consumption, which potentially leads to a more severe decline in economic activity and further degradation of markets. Therefore, understanding the nature and drivers of large equity market drawdowns is of paramount importance. This paper explores these large market drawdowns and the extent to which investors can reasonably form probabilistic estimates of their occurrence.

To accomplish this, we estimate the probability of severe equity market drawdowns by calibrating a discrete choice regression model for both the U.S. and a cohort of four other developed equity markets. We find that while small drawdowns are essentially unpredictable, large market impairments have historically been associated with a set of factors centered around valuation, technical and macroeconomic indicators. We show that our framework is applicable to both recessionary and nonrecessionary drawdowns; this distinguishes our work from previous research focused on predicting recessions. Finally, we show that while the U.S. is indeed a fundamental driver of market fragility globally, country-specific factors are still relevant for predicting the likelihood of large equity market drawdowns.

Exhibit 1: Drawdowns, U.S., 12-month horizon

Country	Size	Frequency	% Recessionary
United States	(0%, 5%]	47.6%	3.2%
	(5%, 10%]	19.6%	7.7%
	(10%, 20%]	14.6%	35.3%
	>20%	8.7%	59.4%
Germany	(0%, 5%]	27.0%	8.0%
	(5%, 10%]	20.4%	7.5%
	(10%, 20%]	23.7%	19.8%
	>20%	18.1%	16.8%
Japan	(0%, 5%]	31.3%	6.5%
	(5%, 10%]	15.8%	4.0%
	(10%, 20%]	23.2%	18.0%
	>20%	17.7%	31.4%
Australia	(0%, 5%]	38.7%	2.6%
	(5%, 10%]	16.1%	3.9%
	(10%, 20%]	19.7%	7.7%
	>20%	10.3%	16.0%
United Kingdom	(0%, 5%]	40.0%	6.9%
	(5%, 10%]	19.3%	10.5%
	(10%, 20%]	18.9%	8.0%
	>20%	9.1%	37.5%
Panel	(0%, 5%]	36.9%	5.1%
	(5%, 10%]	18.2%	6.9%
	(10%, 20%]	20.0%	17.0%
	>20%	12.8%	29.5%

Source: PIMCO and Global Financial Data. Based on daily data from 31 March 1953 to 30 April 2019. "Frequency" refers to the percentage of months that the market was down by a given percentage from the peak observed in the previous 12 months. Refer to appendix for additional information concerning data sources.

LITERATURE REVIEW

Most academic and practitioner research has focused less on modeling drawdowns than on predicting changes in economic activity or, more directly, recessions. For example, Estrella and Mishkin (1998) use a probit model to estimate the likelihood of U.S. recessions and find yield curve slope and stock prices to be most predictive at a horizon of up to four quarters. More recently, Schularick and Taylor (2012) study 79 financial crises in 14 economies over the past 140 years. Using a logit panel regression, the authors show that credit growth is a relevant predictor of financial crises; furthermore, they find that a bull equity market, combined with strong credit growth, indicates a higher likelihood of a banking crisis. Research that has focused more on predicting equity drawdowns has been primarily based on technical considerations. For example, Xiong and Ibbotson (2015) find that an acceleration in price momentum leads to greater instability in future prices. This finding potentially reconciles the somewhat contradictory findings of Jegadeesh and Titman (1993), who find that 12-month momentum is predictive of positive future returns, with Lehmann's (1990) finding of the short-term "reversal" effect. The results of Xiong and Ibbotson are consistent with Sornette and Cauwels (2014), who find that market crashes are typically preceded by a bubble phase, characterized by a rapid acceleration in asset prices followed by periodic oscillations. Chen et al. (2001) find some evidence that high price momentum and above-average trading volume lead to a higher degree of negative equity market skewness. Finally, Campbell and Shiller (1998), while not focused on drawdowns per se, show that future equity market returns are negatively related to the cyclically adjusted price-to-earnings ratio, which provides a basis for equity market valuation as a predictor of future returns.

In this paper, we contribute to the literature in the following ways. First, we directly model equity market drawdowns rather than recessions. Although the two are related, they are not the same, because markets experience declines for both recessionary and nonrecessionary reasons. Second, we expand the list of explanatory variables beyond technical indicators by incorporating macroeconomic and valuation-based measures. Third, rather than focusing on return prediction, we center our attention on the likelihood, or probability, of a significant equity market drawdown through the use of a logistic regression model. Finally, we extend the analysis beyond the U.S. by looking at the drawdown experience of four other developed equity markets, thus bringing a global perspective to the concept of equity market fragility.

THE MODEL

U.S.-only fragility model

Our objective is to determine whether equity market drawdowns have historically coincided with innovations in an identifiable set of characteristics. In other words, looking back over a long history of equity market declines, could those turning points have been explained by changes in certain economic or financial variables? We use a logistic regression model to assess the probability of a large market decline in the future. Specifically, for a given drawdown threshold and time horizon, we define an indicator variable that takes the value of 1 if the equity market experiences a fall greater than the threshold over the horizon, and zero otherwise. Formally, for a given time horizon, $T - t$, and drawdown threshold, X, the indicator variable, $y_t \in \{0,1\}$, is defined as

$$y_t = \begin{cases} 1, & if \min\limits_{i \in [t,t+T]} \left[\dfrac{P_i}{\max\limits_{j \in [t,i]} (P_j)} - 1 \right] < -X \\ 0, & otherwise \end{cases} \qquad (1)$$

where P is a price index of the equity market total return (inclusive of dividends), less the short-term cash rate.[2] Given an exogenous set of explanatory variables, $\boldsymbol{x}$, we use maximum likelihood to estimate a set of coefficients, $\boldsymbol{\beta}$, for the following equation:

$$Prob(y = 1|\boldsymbol{x}) = \int_{-\infty}^{x'\beta} \delta(t)dt \qquad (2)$$

where $\int_{-\infty}^{x'\beta} \delta(t)dt = \Delta(\boldsymbol{x'\beta}) = \frac{\exp(\boldsymbol{x'\beta})}{1+\exp(\boldsymbol{x'\beta})}$ i is the logistic cumulative distribution function.[3]

Our explanatory variables fall into three categories: macroeconomic, valuation and technical. The macroeconomic variables we use are yield curve slope (10-year minus three-month), year-over-year inflation and three-year credit growth. Our valuation variable is the equity dividend yield, and our technical measure is the 12-month Sharpe ratio for equities. The details of the calculation and the source of each variable are contained in the appendix.

We initially estimate our model for only the U.S. equity market, and do so for various drawdown sizes and forecast horizons. Our objective is to determine if there is any differentiation in the explanatory power of our set of factors for various combinations of drawdown size and time horizon. Exhibit 2 shows heteroscedasticity- and serial correlation-corrected t-statistics (t-stats) from our estimation of Equation 2 for different drawdown sizes at a 12-month horizon. (We do not present the coefficients because coefficients from logistic models are difficult to interpret.) T-stats in excess of 2 are shown here and in the following exhibits in gray.

Exhibit 2: T-stats from logistic regression model for various drawdown sizes, 12-month horizon

	t-stats					Goodness of fit	
Drawdown size	Dividend yield	12-month Sharpe ratio	Yield curve slope	Credit growth	Inflation YoY	R-squared[4]	PRAUC[5]
5%	-1.47	1.91	0.77	0.15	3.04	11%	4%
10%	-1.92	-0.38	-2.28	0.48	2.50	10%	21%
15%	-3.15	-2.08	-1.68	0.48	2.90	15%	29%
20%	-2.82	-2.63	-2.05	1.41	1.84	23%	35%
25%	-3.07	-2.02	-0.38	1.49	2.31	27%	44%
30%	-3.09	-2.44	0.12	1.30	2.27	33%	37%

Hypothetical example for illustrative purposes only. Source: PIMCO, Global Financial Data and JST Macrohistory Database. Monthly data from March 1951 to December 2018. Refer to appendix for additional information concerning data sources.

2 We use the S&P 500 for equity and GFD data on three-month Treasury bills for the cash rate.

3 We have corrected our estimation for heteroscedastic and serially correlated errors using the methodology of Estrella and Rodrigues (1998).

4 R-squared corresponds to the McFadden's pseudo R-squared, which evaluates how much the full model improves upon a constant model, based on their likelihood functions.

5 We have corrected our estimation for heteroscedastic and serially correlated errors using the methodology of Estrella and Rodrigues (1998).

Exhibit 3: T-stats from logistic regression model for various forecast horizons, 20% drawdown

	t-stats					Goodness of fit	
Horizon (months)	Dividend yield	12-month Sharpe ratio	Yield curve slope	Credit growth	Inflation YoY	R-squared	PRAUC
12	-2.82	-2.63	-2.05	1.41	1.84	23%	35%
18	-2.42	-1.83	-2.37	2.02	1.66	22%	30%
24	-2.24	-1.08	-3.33	2.27	1.61	23%	31%
36	-1.89	0.26	-2.25	2.96	2.31	30%	30%

Hypothetical example for illustrative purposes only. Source: PIMCO, Global Financial Data and JST Macrohistory Database. Monthly data from March 1951 to December 2018. Refer to appendix for additional information concerning data sources.

As evidenced by the increasingly high t-stats lower in the table, Exhibit 2 indicates that large equity market drawdowns are generally more explainable than small drawdowns. The model calibrated to drawdowns of at least 5% contains no t-stats in excess of 2, and the pseudo R-squared is only 11%. However, as the drawdown size increases, the number of factors that meet the threshold of statistical significance increases, as does the R-squared. These results indicate that it is generally difficult to predict small equity market declines relative to their larger counterparts. Moreover, larger declines in equity prices have historically been more strongly associated with specific factors, particularly dividend yield, momentum and inflation.

Exhibit 3 shows the t-stats associated with drawdowns of at least 20% for different forecast horizons. While Exhibit 2 shows a clear difference in predictability by drawdown size, the results for time horizon are less glaring, with goodness-of-fit tests showing somewhat similar results across time horizons. Momentum appears to be more important at the 12-month horizon, whereas inflation is more significant beyond three years. Valuation, slope and credit growth appear to be important across most forecast horizons.

Given the significant consequences of large drawdowns for investors, and the one-year horizon most investors use to assess performance, for the remainder of this paper we will focus on the 20% drawdown threshold over a 12-month horizon.

Exhibit 4: Logistic regression results for a 20% drawdown, one-year horizon, U.S. only

	Coefficient	Standard error	t-stat	p-value	Marginal effect[6]	Standard deviation
Constant	0.77	0.97	0.80	0.43	0.00%	0.00
Dividend yield	-0.78	0.28	-2.82	0.00	-11.46%	1.27
12-month Sharpe ratio	-0.64	0.24	-2.63	0.01	-9.83%	1.32
Yield curve slope	-0.50	0.24	-2.05	0.04	-6.58%	1.14
Credit growth	13.67	9.67	1.41	0.16	6.19%	3.90
Inflation YoY	18.98	10.29	1.84	0.07	6.28%	2.85
					R-squared	24%
					PRAUC	35%
					ROCAUC[7]	82%
					llf[8]	-298.61

Hypothetical example for illustrative purposes only. Source: PIMCO, Global Financial Data and JST Macrohistory Database. Monthly data from March 1951 to December 2018. Refer to appendix for additional information concerning data sources.

6 Marginal effects are the average impact on the drawdown probability of a 1 standard deviation increase in the variable.

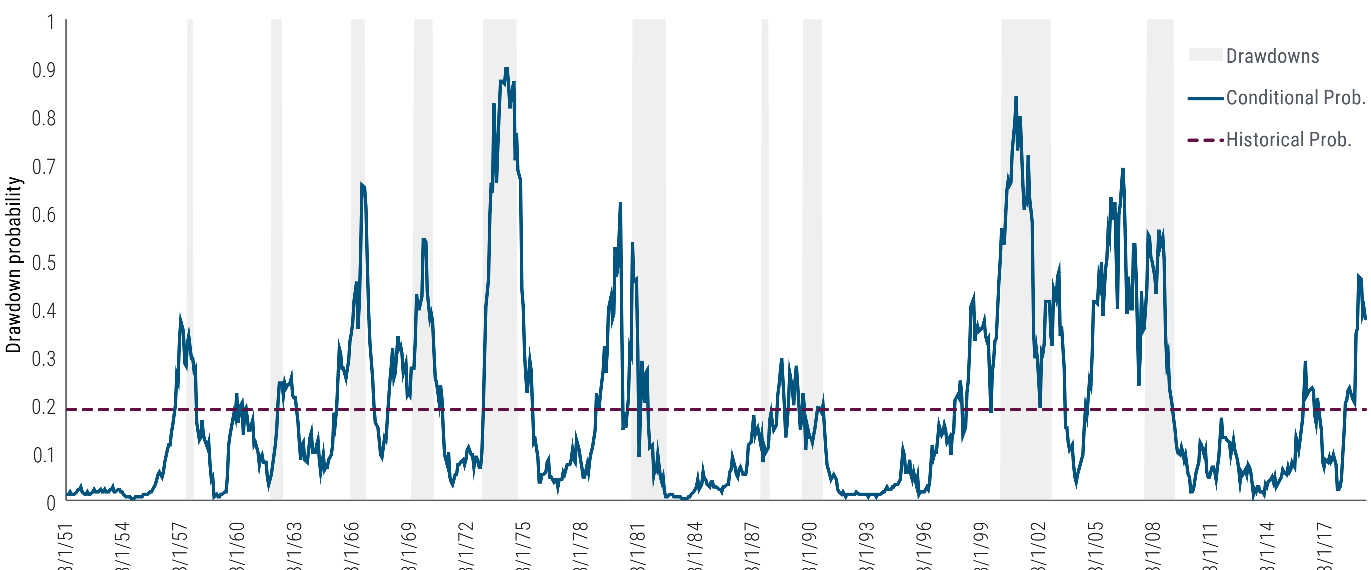
7 ROCAUC represents the area under the Receiver Operating Characteristics curve. This metric balances Recall (true positive rate, TPR) and the proportion of false alarms (false positive rate, FPR). On average, a higher ROCAUC implies a higher TPR for a given level of FPR.

8 llf is the value of the likelihood function.

The full regression results for a 20% drawdown/12-month horizon are shown in Exhibit 4 for the U.S. only. The dividend yield, Sharpe ratio and yield curve slope each have negative coefficients and are highly statistically significant. A negative coefficient implies that an increase (decrease) in the variable leads to a decline (rise) in the probability of a drawdown. The marginal effects can be useful in assessing the magnitude of the impact of each factor. For example, the -11.5% marginal effect for dividend yield implies that a 1 standard deviation increase in the equity dividend yield (a 1.3 percentage point increase) decreases the probability of a drawdown by 11.5%. Hence, more expensive equity markets, as measured by the dividend-to-price ratio, are associated with greater fragility, whereas more favorable equity valuations imply a lower likelihood of drawdown. Comparing the size of the marginal effects, we find that valuation is the most important variable, followed by the 12-month Sharpe ratio on equities. The negative coefficient on the Sharpe ratio means that major drawdowns tend to be preceded by degradation in risk-adjusted market performance. This is a convenient result because the dividend yield is relatively slow moving, while the Sharpe ratio may change rather quickly. As such, the model can be considered to be anchored by long-term valuation yet still responsive to intermediate-term evolutions in market performance. The credit growth and inflation variables both have positive coefficients, implying that increases in these variables correspond to increases in the likelihood of a market drawdown. Though neither of these variables is statistically significant (inflation is just barely insignificant using a 5% threshold), we retain both because they turn out to be statistically significant when estimated in a global model.

Exhibit 5 shows the historical drawdown probability based on the model parameters in Exhibit 4, with the 20%-plus drawdown periods shaded in gray. The average drawdown probability is 19%; the minimum and maximum are 0.4% and 90%, respectively, the latter occurring in March 1974 as a result of supply-side shocks stemming from the Arab oil embargo. Although by no means prescient, a visual inspection of Exhibit 5 generally shows the drawdown probability rising before large market corrections. Examples of periods in which the model worked particularly well are the 2000 tech bubble and the 2008 financial crisis: Both periods coincided with identifiable movements in the factors. However, the model failed to flag the 1987 stock market crash and the "flash crash" of 1962, both of which have no clear explanation for their occurrence. The lack of model foresight concerning these events provides further evidence that the crashes were not directly related to an easily identifiable set of factors. Exhibit 6 shows the contributions of each factor to the conditional drawdown probability.[9] The large increase in early

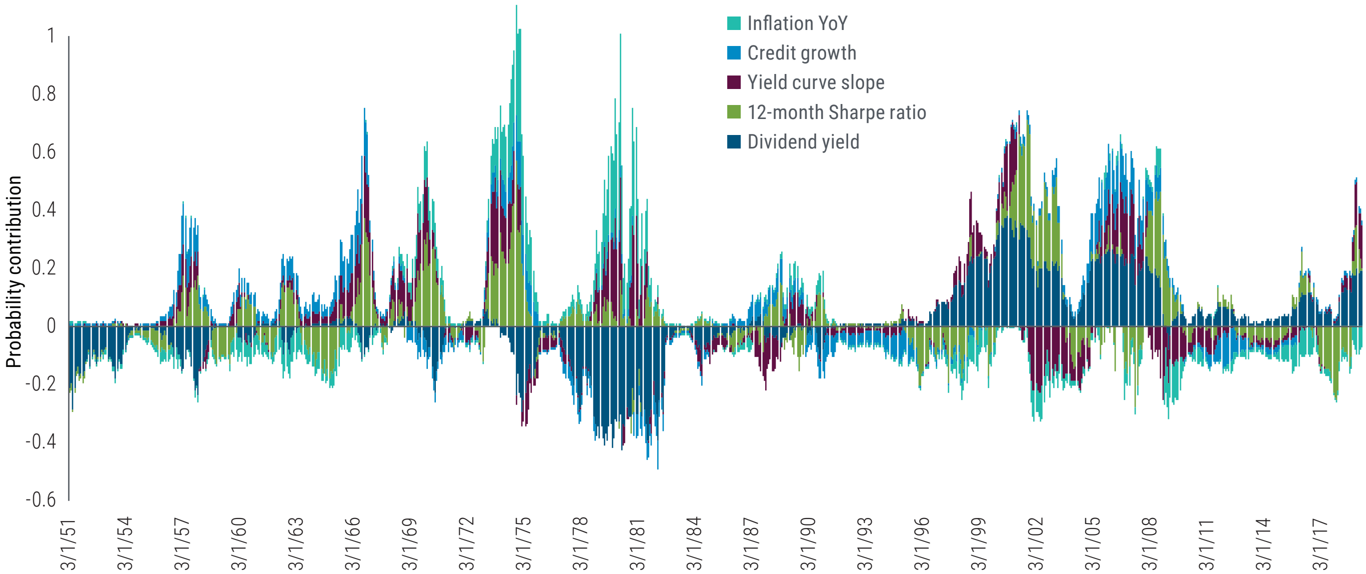
Exhibit 5: Drawdown probability versus drawdown occurrence



Hypothetical example for illustrative purposes only. Source: PIMCO, Global Financial Data and JST Macrohistory Database.
Monthly data from March 1951 to December 2018. Refer to appendix for additional information concerning data sources.

9 The probability contribution from a factor is defined as the difference between the estimated conditional probability and the probability if that factor was at its historical average. Any difference between the true conditional probability and the estimated conditional probability is allocated to each factor proportional to its contribution magnitude.

Exhibit 6: Factor contributions to drawdown probability



Hypothetical example for illustrative purposes only. Source: PIMCO, Global Financial Data and JST Macrohistory Database. Monthly data from March 1951 to December 2018. Refer to appendix for additional information concerning data sources.

2000 was primarily related to high valuation, poor momentum and a flattening yield curve. The 2008 credit crisis was similarly influenced by valuation and yield curve slope, as well as a high level of credit growth, largely a result of significant increases in leverage related to the boom in real estate lending. Drawdowns in the 1970s, on the other hand, were related less to valuation – in fact, dividend yield was largely a negative contributor to the drawdown probability – than to inflationary effects. These results highlight the importance of using a model estimated on a wide array of factors, spanning multiple drawdown periods and economic regimes – even if this comes at the expense of statistical significance – because different factors will be more or less influential at different points in time.

Global equity fragility

We now turn to addressing the fragility issue from a global perspective by investigating whether the same factors used in the U.S.-only version of the model are applicable to international markets. This exercise also allows for a convenient out-of-sample test of the U.S. version of the model. The equity markets we model in this section are the U.S., Germany, Japan, Australia and the U.K. We estimate two types of models for international markets: 1) country-specific models, in which each country model is estimated independently and 2) a panel regression with country fixed effects. In the panel version of the model, all countries are constrained to have the same coefficient for each variable. However, because equity markets have widely varying experiences in terms of their drawdown frequencies, country fixed effects are used to allow for variation in each country's unconditional drawdown probability. Exhibit 7 shows the t-stats for the panel regression in the last column, as well as for each country individually. For simplicity, we do not report the t-stats for the country fixed effects.

The U.S. version of the model in Exhibit 7 is the same as in Exhibit 4 and shows that the most important factors in the U.S. are valuation, momentum and yield curve slope. Looking at other markets independently, however, shows that the relevance of factors across markets differs rather notably. For example, inflation is significant in both Australia and the U.K., but not in Germany or Japan, and only marginally in the U.S.[10] Yield curve slope appears to matter only in the U.S., perhaps due to the Federal Reserve's long history of countercyclical monetary policy. In fact, valuation is the only factor that shows a high degree of statistical significance across all markets. The role of valuation in predicting equity market drawdowns appears to be ubiquitous, with high valuations more predictive of large drawdowns across major developed markets.

10 We determine significance at the standard 5% level. We regard a factor as marginally significant if it is significant at a 10% level but not at a 5% level.

Exhibit 7: T-stats from logistic regression for a 20% drawdown, one-year horizon, global markets

	U.S.	DEU	JPN	AUS	GBR	Panel (all countries)
Constant	0.80	3.14	0.49	-0.52	1.24	
Dividend yield	-2.82	-4.08	-2.03	-2.23	-2.75	-5.28
12-month Sharpe ratio	-2.63	-2.05	-0.72	1.09	-2.50	-2.47
Yield curve slope	-2.05	-0.95	-0.51	-1.36	-0.06	-2.28
Credit growth	1.41	0.65	1.32	0.08	2.40	2.14
Inflation YoY	1.84	1.65	0.30	3.19	3.69	4.62
R-squared	23%	15%	6%	13%	24%	12%
PRAUC	35%	23%	15%	24%	38%	22%
ROCAUC	82%	76%	68%	76%	83%	74%
llf	-298.61	-426.49	-435.92	-364.12	-340.61	-1,991.69

Hypothetical example for illustrative purposes only. Source: PIMCO, Global Financial Data and JST Macrohistory Database. Monthly data from March 1951 to December 2018. Refer to appendix for additional information concerning data sources.

Exhibit 7 shows that pooling data across markets materially improves the results over single-country models.[11] Because large drawdowns are relatively infrequent events, the improvement in statistical significance from pooling the data is material. In the pooled version, all factors are statistically significant, with valuation being the most important (t = -5.28), followed by inflation (t = 4.62). Interestingly, while credit growth is only significant in the U.K., its t-stat in the pooled regression is 2.14.

Exhibit 8 shows the full econometric results for the pooled model, including the country fixed effects. Consistent with the U.S.-only version, valuation continues to be the most important variable in determining the likelihood of drawdowns. Unlike the U.S.-only version, however, inflation is a highly significant driver of drawdowns globally, likely a result of a longer history of inflationary shocks in countries such as Australia and the U.K. Exhibits 9 and 10 respectively show the time series of conditional drawdown probabilities and the probability decompositions. For the U.S., we show probabilities from both the U.S.-only and the global versions of the model. The graphs appear similar, with the U.S.-only version characterized by slightly larger peaks and troughs.

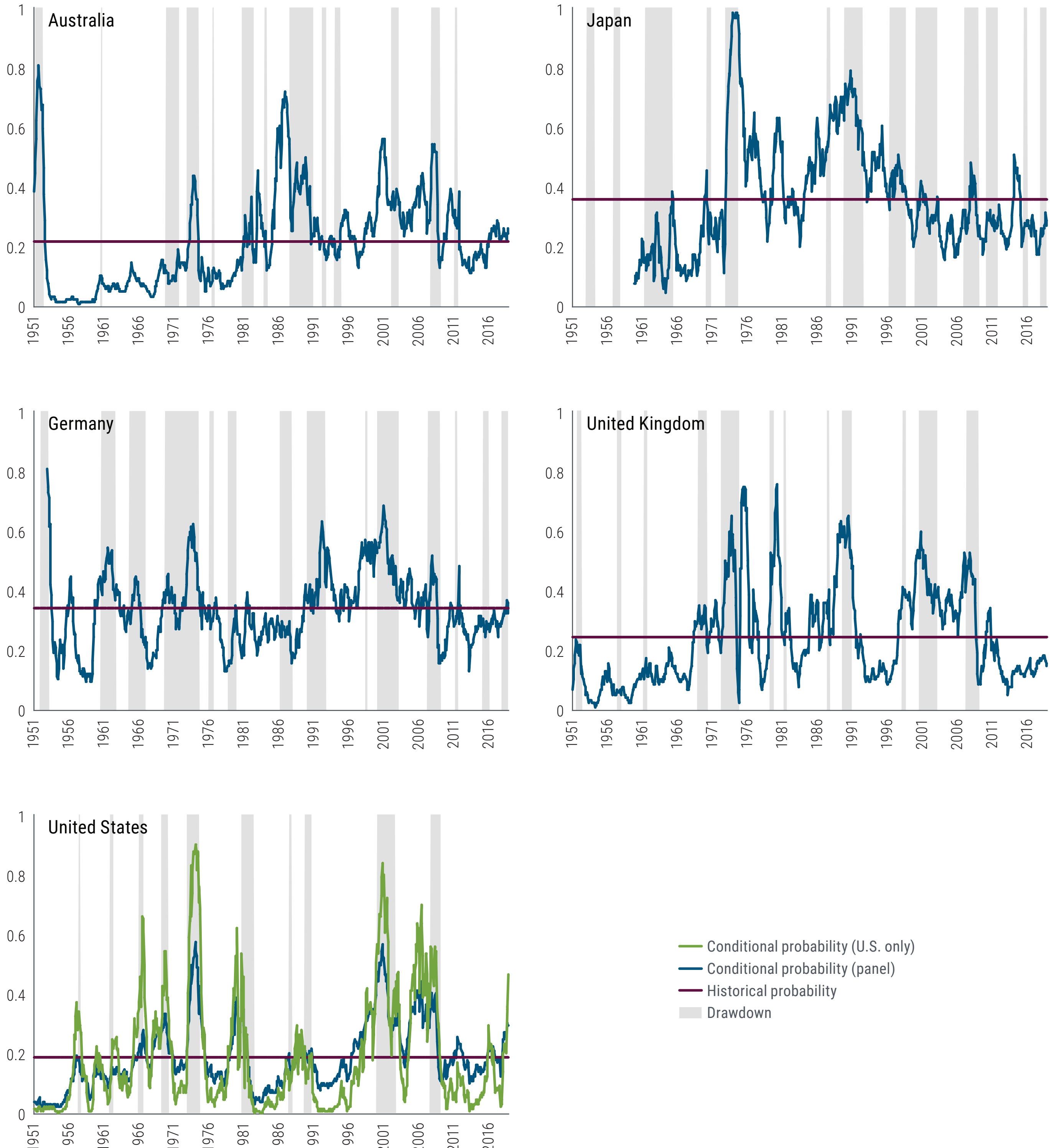
Exhibit 8: Panel logistic regression results for 20% drawdown, one-year horizon

	Coefficient	Standard error	t-stat	p-value	Marginal effect
Dividend yield	-0.62	0.12	-5.28	0.00	-13.07%
12-month Sharpe ratio	-0.21	0.08	-2.47	0.01	-4.96%
Yield curve slope	-0.17	0.07	-2.28	0.02	-3.99%
Credit growth	3.15	1.47	2.14	0.03	3.79%
Inflation YoY	17.68	3.83	4.62	0.00	11.39%
Fixed effects					
U.S.	0.06	0.44	0.14	0.89	–
DEU	1.24	0.47	2.62	0.01	–
JPN	0.34	0.35	0.97	0.33	–
AUS	0.90	0.59	1.53	0.13	–
GBR	0.69	0.53	1.31	0.19	–
				R-squared	12%
				PRAUC	22%
				ROCAUC	74%
				llf	-1,991.69

Hypothetical example for illustrative purposes only. Source: PIMCO, Global Financial Data and JST Macrohistory Database. Monthly data from March 1951 to December 2018. Refer to appendix for additional information concerning data sources.

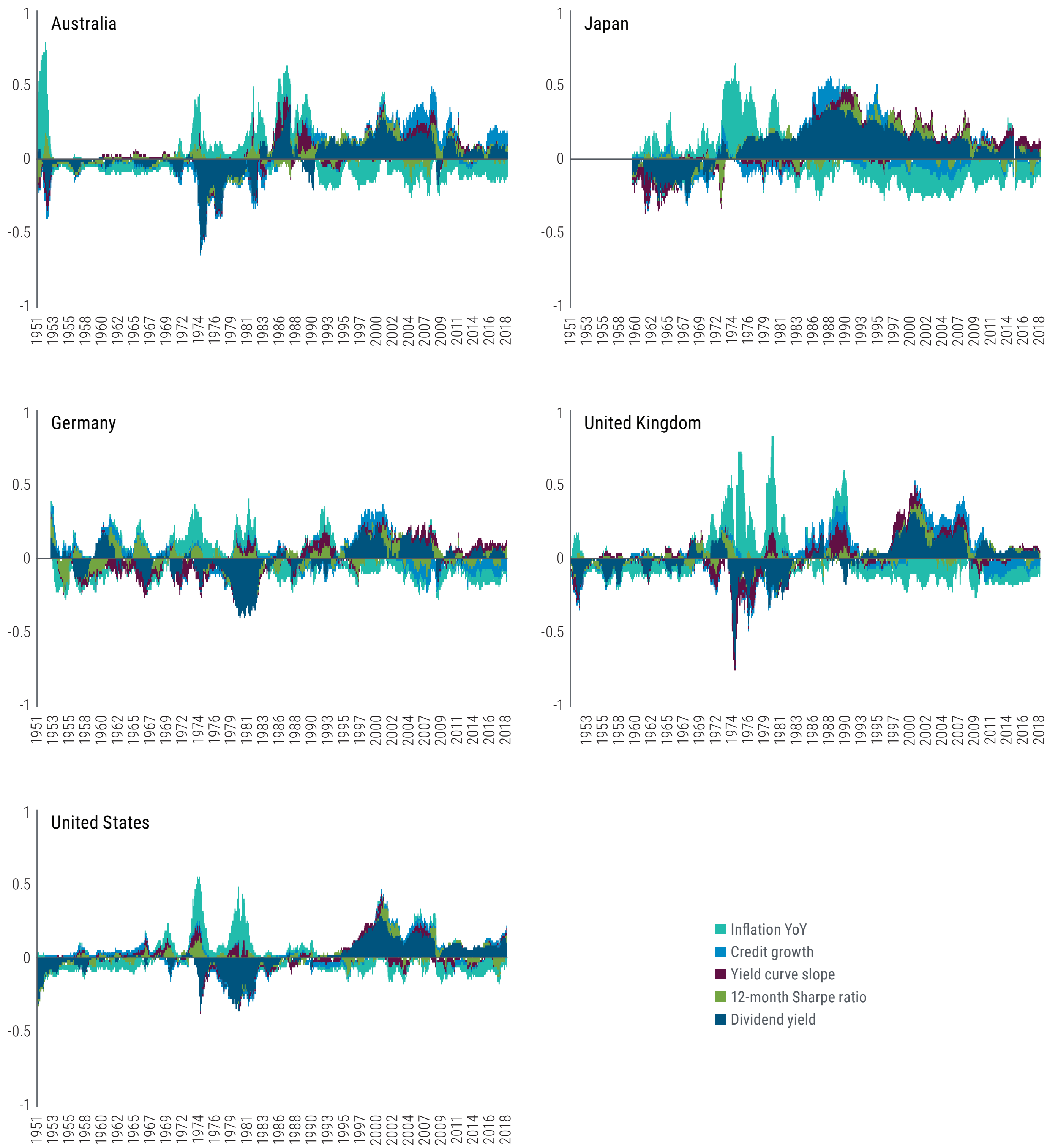
11 The goodness-of-fit metrics are not comparable between single-country and pooled regression because the sample sizes and the frequency of the drawdowns are not the same.

Exhibit 9: Drawdown probability versus drawdown occurrence by country (panel regressions)



Hypothetical example for illustrative purposes only. Source: PIMCO, Global Financial Data and JST Macrohistory Database.
Monthly data from March 1951 to December 2018. Refer to appendix for additional information concerning data sources.

Exhibit 10: Drawdown probability decomposition by country (panel regression)



Hypothetical example for illustrative purposes only. Source: PIMCO, Global Financial Data and JST Macrohistory Database. Monthly data from March 1951 to December 2018. Refer to appendix for additional information concerning data sources.

Exhibit 11: Drawdown probability and decomposition as of 31 July 2019 (panel regression)

	U.S.	DEU	JPN	AUS	GBR
Dividend yield	13.0%	-0.2%	2.2%	12.3%	3.3%
12-month Sharpe ratio	1.9%	4.0%	4.4%	-0.8%	1.9%
Yield curve slope	5.2%	3.9%	5.8%	3.5%	3.2%
Credit growth	0.6%	-7.6%	-1.4%	11.3%	-5.2%
Inflation YoY	-6.9%	-3.3%	-8.5%	-13.4%	-6.4%
Sum contrib.	13.9%	-3.1%	2.4%	13.0%	-3.2%
Unconditional prob.	16.4%	33.9%	25.5%	16.7%	20.6%
Conditional prob.	30.3%	30.8%	27.9%	29.6%	17.4%

Hypothetical example for illustrative purposes only. Source: PIMCO, Global Financial Data and JST Macrohistory Database. Monthly data from March 1951 to December 2018. Refer to appendix for additional information concerning data sources.

Current conditional probability decompositions

Exhibit 11 shows the current factor decomposition of each country's drawdown probability as of 31 July 2019. The conditional probability is equal to the sum of the contributions and the unconditional probability. Under our model, the U.S. is currently the furthest away from its unconditional probability, with a conditional probability of 30.3%. Germany, on the other hand, has the highest conditional drawdown probability at 30.8%, but this value is not materially different from the unconditional probability, reflecting the higher frequency of drawdowns in Germany compared with other countries. Across all markets except for Germany, valuation contributes positively to the probability of a large drawdown, with the U.S. being the most elevated. Given low year-over-year inflation today, inflation is a negative contributor across all markets.

Historical effectiveness of default probability

Beyond identifying statistically significant factors, it is important to understand how the estimated probability of drawdown relates to future performance of the market. Exhibit 12 shows the excess return and drawdown[12] over 12 months conditional on the probability implied by the fragility model. Whenever the estimated default probability has been above a 30% threshold, we determine the equity market to be fragile. Above such levels, on average, global markets have performed poorly during the following year with a flat excess return and an average 20.5% drawdown. To put this in perspective, since 1951, global markets have returned 7.7% over cash and experienced drawdowns as large as 15.8% over a one-year horizon. Moreover, for probabilities below 30% the market return has been 10.7%, roughly 10% higher than the return of a fragile market, according to our definition.

Exhibit 12: Average performance over next 12 months conditional on probability of default (panel regression)

	Excess return			Drawdown		
Country	**Mean**	**P(DD)<30%**	**P(DD)>30%**	**Mean**	**P(DD)<30%**	**P(DD)>30%**
U.S.	7.5%	9.7%	-3.8%	13.8%	12.2%	22.1%
DEU	8.0%	16.3%	2.3%	17.9%	13.9%	20.8%
JPN	8.8%	8.7%	3.6%	17.5%	17.0%	18.8%
AUS	6.9%	9.9%	-2.1%	14.6%	12.3%	21.1%
GBR	7.1%	11.5%	-1.5%	15.1%	11.9%	21.5%
Global	7.7%	10.9%	0.8%	15.8%	13.0%	20.5%

Hypothetical example for illustrative purposes only. Source: PIMCO, Global Financial Data and JST Macrohistory Database. Monthly data from March 1951 to December 2018. Refer to appendix for additional information concerning data sources.

12 Drawdown is defined as in equation (1).

DISCUSSION

In the previous section, we showed that equity drawdowns globally have generally been associated with a common set of characteristics centered around valuation, macroeconomic and technical variables. A key insight from these results is that factors explaining drawdowns in the U.S. are applicable to other major developed markets, implying a commonality in the predictive drivers of market turbulence. An obvious question, however, is to what extent the U.S. is fundamentally the driver of equity market corrections in other countries. Although we have shown that drawdowns in non-U.S. markets are driven by country-specific factors, it may be the case that drawdowns in the U.S. are ultimately the primary factor explaining drawdowns in the rest of the developed world. Given the increasing dominance of the U.S. economy since World War II, it is worth understanding whether the U.S. alone can explain large equity drawdowns globally.

To test this, we repeat the estimation of the global model in Exhibit 8 via a panel regression on Australia, Japan, the U.K. and Germany, excluding the U.S. Exhibit 13 shows these results in the "Baseline" column. As expected, without the U.S. in the model, only valuation and inflation are statistically significant, with momentum, yield curve and credit growth only marginally significant. To test whether U.S. drawdowns can help explain non-U.S. drawdowns, we add a dummy variable that takes the value of 1 if the U.S. is in a drawdown, and zero otherwise. This variable is contemporaneous, meaning that its value is realized at the time of the U.S. drawdown. This means that the U.S. dummy variable is not predictive; we use the variable in this manner because our objective is merely to determine whether the U.S. acts as a common factor.

Exhibit 13: T-stats from panel regression, excluding U.S., for a 20% drawdown, one-year horizon

	Non-U.S. models	
	Baseline	*U.S. DD*
Non-U.S. factors		
Dividend yield	-4.78	-4.34
12-month Sharpe ratio	-1.6	0.35
Yield curve slope	-1.65	-0.92
Credit growth	1.85	1.48
Inflation YoY	4.25	4.15
U.S. factors		
Drawdown	–	6.37
Goodness of fit		
R-squared	11%	19%
PRAUC	20%	32%
ROCAUC	73%	79%
llf	-1,662.85	-1,515.14

Hypothetical example for illustrative purposes only. Source: PIMCO, Global Financial Data and JST Macrohistory Database. Monthly data from March 1951 to December 2018. Refer to appendix for additional information concerning data sources.

The column labeled "U.S. DD" in Exhibit 13 shows the results of the pooled regression when the U.S. drawdown dummy is added. The t-stat on this variable is 6.37, and goodness-of-fit tests are materially higher, indicating that the U.S. being in a drawdown is highly indicative of a non-U.S. market also being in a drawdown. The incremental effect of a U.S. drawdown is 0.31, implying a 31% increase in each country's conditional drawdown probability if the U.S. equity market is impaired. This result lends strong credibility to the thesis that the U.S. acts as a fundamental driver of global equity market fragility. Still, even after the U.S. dummy variable is included, both valuation and inflation at the country level remain statistically significant, meaning that country-specific factors contain information beyond just the impact of the U.S. Although the U.S. matters – a lot, in fact – it isn't everything.

Given the well-documented relationship between the slope of the yield curve and the onset of U.S. recessions, the astute reader might surmise that our results are essentially a recession model. After all, every economic contraction in our data sample has been accompanied by a decline in equity prices of at least 12%, with an average drawdown of 31%.[13] Moreover, drawdowns of more than 20% have occurred in 100%, 50%, 75%, 86% and 70% of the recessions in Australia, Germany, the U.K., Japan and the U.S., respectively. So it may be that we are actually capturing the variables associated with recessionary periods rather than with drawdowns per se.

To test this, we estimated the global version of the model over both recessionary and nonrecessionary drawdowns to see whether one type of drawdown is more explainable than another. We define a drawdown as recessionary if any point between the peak and the trough of the drawdown corresponds to a recessionary period.[14] Exhibit 14 shows that for the five markets in our study, there have been 62 large equity drawdowns since 1951, 28 (45%) of which coincided with a recession. Hence, markets draw down for a wide array of reasons, and recessions are just one. It is interesting to note that although the U.S. had the fewest number of drawdowns over the sample period (10), a much higher percentage of U.S. drawdowns were recessionary in nature (70%).

Exhibit 14: Recessionary versus nonrecessionary 20% drawdowns

	Drawdown count	% Recessionary	% Nonrecessionary
AUS	13	31%	69%
DEU	14	43%	57%
GBR	12	42%	58%
JPN	13	46%	54%
U.S.	10	70%	30%
Total	62	45%	55%

Hypothetical example for illustrative purposes only. Source: PIMCO, Global Financial Data and JST Macrohistory Database. Monthly data from March 1951 to December 2018. Refer to appendix for additional information concerning data sources.

Exhibit 15 shows the t-stats for the original pooled model in the column labeled "panel" alongside the results for each drawdown type. As expected, the pooled results are stronger than those for the recessionary and nonrecessionary models independently. However, both recessionary and nonrecessionary versions exhibit meaningful explanatory power, although the t-stats for the recessionary model are generally higher. Perhaps unsurprisingly, yield curve slope works for recessionary drawdowns but not nonrecessionary ones. Credit growth, on the other hand, shows the opposite effect, and valuation and inflation appear to coincide with both drawdown types. In some sense, these results solidify valuation's prominent role in predicting market drawdowns; valuation is the sole statistically significant variable across all equity markets, and it is effective in explaining both recessionary and nonrecessionary drawdowns. Expensive markets are predictive not only of lower future returns but of increased fragility, regardless of the catalyst.

Exhibit 15: T-stat comparison between recessionary and nonrecessionary drawdowns in global markets (t-stats from panel regression for a 20% drawdown, one-year horizon)

	Panel	Recessionary	Nonrecessionary
Dividend yield	-5.28	-3.38	-3.21
12-month Sharpe ratio	-2.47	-2.90	0.37
Yield curve slope	-2.28	-3.14	0.92
Credit growth	2.14	0.31	2.08
Inflation YoY	4.62	3.93	2.42
R-squared	12%	17%	7%
PRAUC	22%	23%	13%
ROCAUC	74%	81%	70%
llf	-1,991.69	-1,222.19	-1,482.40

Hypothetical example for illustrative purposes only. Source: PIMCO, Global Financial Data and JST Macrohistory Database. Monthly data from March 1951 to December 2018. Refer to appendix for additional information concerning data sources.

Despite the evidence in Exhibit 15 indicating that both recessionary and nonrecessionary drawdowns are explainable, given the strong historical relationship between recessions and equity market drawdowns, we wanted to formally test whether our factors are associated with economic contractions. To do this, we simply replace the dependent variable with a recession dummy, which takes the value of 1 if a recession occurs in the next 12 months, and zero otherwise. We also include a "nowcasting" version of the model, in which the dependent variable takes the value of 1 if the economy is currently in a recession. Thus, the 12-month version measures the predictability of recessions, whereas the nowcasting version determines whether the economy is in a recession at the time.

13 We compute the drawdowns for every recession for all the countries in our sample from six months before the recession through the recession's end. The minimum and average across all drawdowns is 12% and 31%, respectively. The periods run from March 1951 to April 2019.

14 Drawdowns are considered recessionary if a recession occurs during the drawdown window or up to six months after the trough.

Exhibit 16 shows that the drawdown factors are generally, although not perfectly, associated with the predictability of recessionary periods. Focusing on the "12 months before" column, both a flattening of the yield curve and a low equity Sharpe ratio are associated with a higher likelihood of a future recession, with t-stats nearly double the size of the drawdown model. This is intuitive. The yield curve effect is well documented, with a flattening or outright inversion a strong predictor of U.S. recessions (Estrella and Mishkin, 1998). Importantly, the results in Exhibit 16, estimated across five developed economies, confirm this effect at the global level as well. The strong result for 12-month price momentum indicates that markets indeed begin to correct before the onset of a recession, as investors anticipate a decline in economic activity. In contrast to drawdowns, however, neither valuation nor credit growth is a strong predictor of U.S. recessions. In fact, the dividend yield is the opposite sign of the drawdown model (although not statistically significant), meaning that a high dividend yield is associated with a higher likelihood of recession. This is primarily due to the fact that the equity market turns prior to a recession (hence, the negative t-stat on the Sharpe ratio), increasing the dividend yield.

The effects are somewhat different in the nowcasting version of the model. The t-stat on the 12-month Sharpe ratio is twice as large in the nowcasting version, indicating that equities sell off dramatically in an actual recession. Yield curve slope, on the other hand, is not significant for nowcasting. This is likely a result of the central bank, aware that the economy is in a contraction, cutting short-term interest rates and producing a steepening of the yield curve. Finally, the t-stat on dividend yield is positive and in excess of 2, indicating that the equity market is indeed cheaper in a recession.

Exhibit 16: T-stats from panel regression for recessions, global markets

	Recession	
	12 months before	Nowcasting
Dividend yield	0.78	2.27
12-month Sharpe ratio	-3.11	-6.08
Yield curve slope	-6.45	-1.08
Credit growth	0.47	0.62
Inflation YoY	1.36	1.33
R-squared	26%	18%
PRAUC	42%	26%
ROCAUC	83%	80%
llf	-1,501.27	-1,105.06

Hypothetical example for illustrative purposes only. Source: PIMCO, Global Financial Data and JST Macrohistory Database. Monthly data from March 1951 to December 2018. Refer to appendix for additional information concerning data sources.

CONCLUSION

We have shown that large equity market drawdowns are related to a set of common factors centered around valuation, technical and macroeconomic variables. These factors are indicative of the degree of market fragility, not only in the U.S. but across four other major developed equity markets. The role of valuation appears to be ubiquitous, as it is a strong predictor of market downturns across all developed markets and works well for both recessionary and nonrecessionary drawdowns. Finally, we showed that although the U.S. is a key driver of fragility internationally, country-specific factors – particularly valuation – are still relevant, even after accounting for the impact of the U.S. Our findings make a strong case for a parsimonious factor model for measuring equity market fragility.

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APPENDIX

A. Variable definitions

Dividend yield: Based on trailing 12-month dividends of the equity index.

12-month Sharpe ratio: Based on equity index total return and cash rate. Excess return is the difference between the average monthly return of equity and the cash rate over the past year. The volatility is based on monthly returns over the past year.

$$Sh_t = \sqrt{12}\frac{\bar{r}_{E,t} - \bar{r}_{cash,t}}{\sigma_{E,t}} \tag{A1}$$

$$\sigma_{E,t} = \frac{\sum_{n=t-11}^{t}\left(r_{E,n} - \bar{r}_{E,n}\right)^2}{11} \tag{A2}$$

$$\bar{r}_{E,t} = \frac{1}{12}\sum_{n=t-11}^{t} r_{E,n} \tag{A3}$$

where $r_{E,n}$ is the monthly return of the equity index and $r_{Eash,t}$ is the monthly cash rate.

Credit growth: The credit-level data is in annual frequency; we forward-fill the data to make sure we are using real-time variables. We normalize the credit level by GDP and define credit growth as the change over three years:

$$c_t = \frac{d_t}{GDP_t} \tag{A4}$$

$$g_t = c_t - c_{t-3} \tag{A5}$$

where d_t is the credit level, c_t is the credit level by unit of GDP and g_t is the three-year credit growth.

Yield curve slope: The difference between the 10-year government bond yield and the three-month government bill yield.

Inflation: We use annual inflation based on the consumer price index (CPI) for all urban consumers (all items).

$$f_t = \frac{CPI_t}{CPI_{t-12}} - 1 \tag{A6}$$

B. Data sources

Global Financial Data: We use the GFD database for dividend yields, equity total return indices, cash rates, government bond/bill yields and inflation. The equity indices used for the U.S., Germany, Australia, Japan and the U.K. are, respectively, the S&P 500, CDAX,[14] All Ordinaries, TOPIX[15] and FTSE All-Share Index.[16]

Jordà-Schularick-Taylor Macrohistory Database: We use the JST database for credit levels and GDP. The credit level is defined as total loans to the nonfinancial private sector.

14 The Commerzbank Index is used before 1970.
15 The Nikkei weighting method (price) is used before 1968.
16 The Actuaries General Share Index is used before 1962.

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