Stable volatility outlook, but tail risk management critical in late cycle

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IN BRIEF

- Our broad volatility forecasts are little changed compared with last year, despite the spike in financial asset volatility at the beginning of 2018.
- With major markets becoming further entrenched in late-cycle dynamics, more frequent volatility spikes are likely – but we see little in the way of structural change to alter our long-term view.
- Late cycle highlights the need to pay attention to the left-tail risks of financial assets. We remind investors that return distributions for financial assets are non-normal, with a higher probability and magnitude of left-tail returns, notably in equities and especially in credit.

NO MAJOR CHANGE IN FORWARD-LOOKING RISK OUTLOOK, DESPITE CHOPPY, LATE-CYCLE MARKET DYNAMICS

Our broad volatility forecasts are little changed compared with last year. Despite the spike in financial asset volatility at the beginning of 2018, volatility has trended back to near historically low levels. Reviewing the underlying dynamics has generally revalidated our forward-looking risk view. Our Long-Term Capital Market Assumptions (LTCMA) risk forecast is cycle-neutral with full-cycle dynamics embedded. Even as markets have become further entrenched in late-cycle dynamics since last year's report, we see little in the way of structural change to alter our long-term view.

The volatility spike of early 2018 was technical in nature, in our view, likely driven by investors building excessive positions in short-volatility financial products as part of a reach for yield. Their unwinding led to a sudden and sharp rise in volatility. Without an underlying shift in fundamentals to sustain those sizable market moves, calmer markets returned promptly (Exhibit 1). As markets remain firmly in late cycle, especially in the U.S., more frequent volatility spikes and corrections are to be expected. However, we do not envision these likely short-lived events altering our long-term risk forecast.

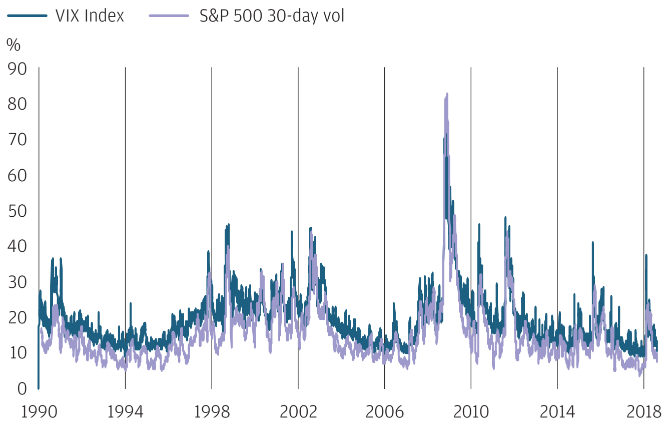
In terms of Sharpe ratio, we see very similar risk-return trade-offs for equities compared to prior years, which is broadly in line with long-run historical experience. What is changing this year is the improvement of risk-adjusted returns for fixed income assets. In prior years, the headwind of rate normalization dampened our rate return forecasts. With U.S. yields resetting to a higher level, returns are normalizing, along with their Sharpe ratios (SR). Fixed income assets in recent decades have delivered very high ex-post risk-adjusted returns (an ex-post SR over 1), given the backdrop of steadily declining yields.

Although we are not necessarily forecasting a return to historical highs, this year's LTCMA forecasts do suggest a reversion to more normal fixed income risk-adjusted return (with SR rising to 0.5 vs. 0.3 last year – the highest thus far in this expansion). Within fixed income, credit instruments are expected to deliver better risk-adjusted return over the cycle, compared with last year's forecast. However, we continue to caution against simply relying on SR, as credit tends to exhibit a higher likelihood of left-tail events.

The Long-Term Capital Market Assumptions' risk forecasts are focused on volatility – which is particularly useful for mean-variance analysis. However, investors should not lose sight of the broader concept of risk, including more extreme experiences – i.e., tail risks.[1] Financial assets tend to exhibit more extreme movements during market downturns and recessions, affecting not only short-term volatility but also the distribution of long-run returns, with a higher likelihood of severe losses (i.e., left tails) than of extreme gains (i.e., right tails). Financial asset returns have historically exhibited what we refer to technically as "fat left tails" – situations in which the probability of a negative return is more frequent and the probability of a decline more sizable than a simple normal distribution would suggest. Although we do not provide forecasts here for these alternative risk measures, we would like to highlight the importance of understanding these dynamics, which become particularly relevant in late cycle.

Despite a spike in early 2018, asset volatility returned to historical lows

EXHIBIT 1: EQUITY MARKET VOLATILITY



Source: Bloomberg, J.P. Morgan Asset Management; data as of July 31, 2018. For illustrative purposes only.

[1] We define tail risk as the risk of a generally unlikely but extreme outcome. See further discussion in the "Special topic" section.

Declining quality and lengthening maturity suggest higher risk vs. long-run history

EXHIBIT 2A: MARKET SHARE (%) BY CREDIT RATING FOR U.S. CORPORATE INVESTMENT GRADE BONDS

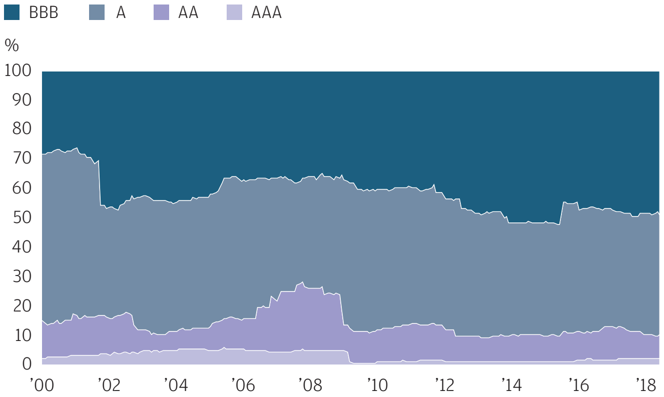
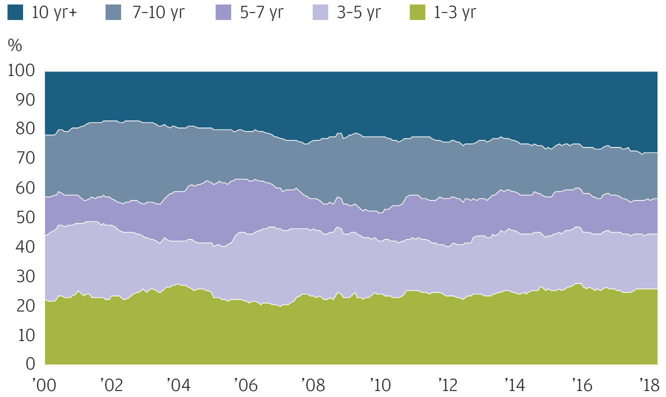


EXHIBIT 2B: MARKET SHARE (%) BY MATURITY FOR U.S. CORPORATE INVESTMENT GRADE BONDS



Source: J.P. Morgan Asset Management Multi-Asset Solutions; data as of June 30, 2018.

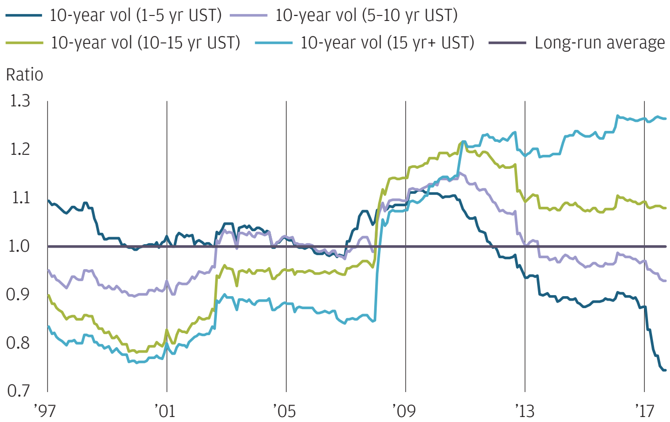
RISKS FOR SELECTED FIXED INCOME MARKETS HIGHER THAN WHAT HISTORY WOULD SUGGEST; EQUITY EXPECTATIONS LITTLE CHANGED

Select credit markets are likely to experience higher volatility over the forecast horizon. The composition of the investment grade corporate bond market has seen a gradual decline in quality over the past decade (**Exhibit 2A**). With cheap financing readily available for a wide spectrum of borrowers, including those with relatively lower quality balance sheets and a poorer ability to pay, companies have had little incentive to pursue elite rating status in recent years. A similar decline in credit quality can be observed in Europe. At the same time, corporates also lengthened the maturity of new debt issuance to lock in low rates (**Exhibit 2B**). Without a further decline in rates, both of these factors contribute to our view that forward-looking risks in investment grade corporate bonds are likely to be higher than long-run history would suggest in the U.S. and euro area.

Volatility will also likely be higher for short-duration instruments as quantitative easing (QE) unwinds over the next few years. The unconventional central bank policies of recent years created an artificial force that dampened fixed income volatility. The result was an unusually low-volatility environment in fixed income markets, especially at the short end of the Treasury yield curve. The results for one- to five-year maturity instruments (**Exhibit 3**) illustrate how this distortion helped volatility break out below its historical range. Our volatility assumptions incorporate the normalization of volatility levels for short-duration instruments to reflect the gradual removal of QE and other central bank stimulus over our forecast horizon.

Volatility is unusually low at the short end of the Treasury curve

EXHIBIT 3: ROLLING 10-YEAR HISTORICAL VOLATILITY, NORMALIZED BY LONG-RUN AVERAGE



Source: J.P. Morgan Asset Management; data as of September 30, 2018

The lines represent the rolling volatility divided by the full sample average of the rolling volatility, by maturity bucket.

Looking across credit markets, all roads don't lead to increased volatility. We expect European high yield (HY), for example, to be less volatile in the future, relative to historical standards, as the quality of the market has improved in recent years and fallen angels are likely to regain their investment grade status over time. We expect equity risks to stay in line with long-run historical levels.

In alternatives, our hedge fund and private equity volatility forecasts are little changed. Since we have revised our LTCMA return assumptions this year for select alternative assets — real estate, infrastructure and direct lending — to incorporate leverage, we are adjusting those volatility estimates accordingly. Our real estate volatility forecast rises from 10.75% to 12.25% for U.S. core to reflect leverage. However, even with this increase our forecast remains lower than the historical average of 14% — driven by an expectation that the peak level of leverage in this cycle will be lower than it was during the credit crisis. Similarly, we forecast lower U.S. REITs volatility over our forecast horizon, compared with recent history. We do not expect U.S. REITs to be as extended in this cycle; thus, in our opinion, recent history overstates likely future volatility.

SPECIAL TOPIC: DON'T FORGET ABOUT TAIL RISK, DESPITE LOW PROBABILITY

Investor interest in tail risk has seen a resurgence since the global financial crisis. We emphasize an important distinction in financial asset risks: Volatility (derived assuming a normal market condition) and tail risk (the behavior of risk at or beyond a typically high level quantile) are two different topics and should be studied separately. In the context of our Long-Term Capital Market Assumptions, volatility is the primary risk measure we forecast and our output has direct applicability in mean-variance frameworks. However, it is essential that investors be acutely aware of financial assets' total return distribution, which encompasses more than what a simple volatility measure can capture.

A tail event and its behavior can be observed from historical return distributions, and in this section we select a few representative asset classes for illustration: U.S. large cap equities, U.S. intermediate Treasuries, U.S. high yield debt and emerging market sovereign debt.[2] We use a sample of monthly data covering the period from February 1990 to June 2018.[3] We then standardize the monthly returns using sample mean and sample standard deviation for each individual asset (i.e., determine the z-score).[4]

First, for each asset we look at the histogram of standardized monthly return distribution vs. standard normal distribution to help visualize and compare the existence and magnitude of tail events (Exhibit 4). We calculate the ratio of left-tail events below negative three standard deviations (-3 STD) to the total number of observations in the sample period, and compare it to the cumulative distribution function (cdf) value at -3 STD of a standard normal distribution, which is 0.13%.

During the sample period, we can observe that equity and credit (i.e., high yield and emerging market debt [EMD]) have had both a greater number of and more severe left-tail events than the normal distribution would imply. For equities, the distribution of returns included 0.59% below -3 STD events, compared with the 0.13% that a normal distribution would suggest. It is more extreme for credit assets, where the historical probability was more than 10 times what normal distribution would imply (HY at 1.47%/EMD at 1.36% vs. 0.13%). Although a left-tail event remains unlikely, the historical frequencies clearly exceed the normal probability density curve. The return distribution of U.S. government bonds, on the other hand, is relatively close to normal, with a cdf value of 0.29% and no significant loss below -4 STD.

Interestingly, credit indices (high yield and EMD) experienced many more negative standard deviation events than the equity index, despite having lower volatilities at the total return level.[5] For example, in October 2008, monthly returns of U.S. large cap, high yield and EMD were -16.8%, -16.3% and -16.0%, respectively. Yet when we convert these returns into z-scores, they become -4.3, -7.4 and -5.0 standard deviation events, respectively. This could be driven by major default events in the credit market. EMD's worst drawdown event, a -26.0% monthly return, occurred in August 1998, when the Russian government defaulted on its debt. This is -7.9 standard deviations away from the mean. Statistically, the probability of a -7.9 standard deviation event, assuming normal distribution, would only occur in one in 700 trillion observations.

Given these observations about the probability of left-tail events, we then attempt to measure the magnitude of the risk. The most popular tail risk measures used in banking and insurance are value at risk (VaR) and conditional value at risk (CVaR), also known as expected shortfall. The VaR metric,

[2] Indices used: U.S. large cap: S&P 500 Total Return Index (SPTR Index); U.S. intermediate Treasuries: Bloomberg Barclays U.S. Intermediate Treasury Total Return Index (LT08TRUU Index); U.S. high yield: ICE BofAML U.S. Cash Pay High Yield Index (J0A0 Index); emerging market sovereign debt: J.P. Morgan EMBI Global Diversified Composite Index (JPGCCOMP Index). All these are total return indices.

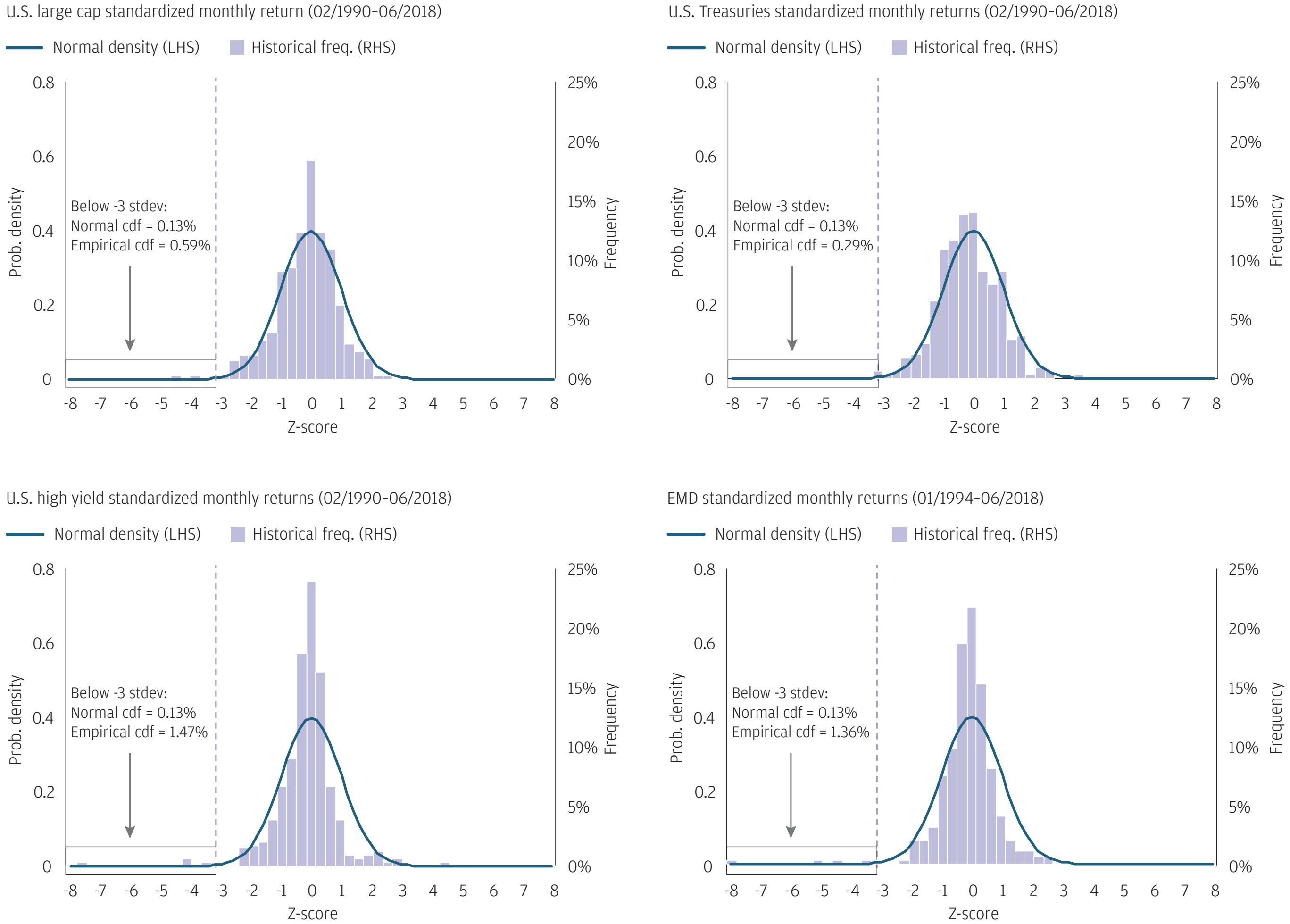
[3] In all, 341 observations. The exception is emerging market debt data, with a start date of January 1994 and 294 observations.

[4] Z-score is a measure of how many standard deviations a data point is above or below the mean.

[5] Sample period annual volatility: U.S. large cap 14.10%; U.S. high yield 7.96%; EMD 11.66%.

Probability of historical large left-tail events for risky financial assets is much higher than normal distribution would suggest

EXHIBIT 4: HISTOGRAM OF STANDARDIZED MONTHLY RETURN DISTRIBUTION VS. STANDARD NORMAL DISTRIBUTION



Source: Bloomberg, J.P. Morgan Asset Management. Monthly return data from February 1990 to June 2018; emerging market debt return data starts in January 1994.

introduced by J.P. Morgan in 1990, measures the maximum potential loss in value of an investment with a given probability, over a pre-set time horizon.[6] However, VaR was criticized as an inaccurate measure of downside exposure due to its inability to capture the true loss in the left tail during periods of significant financial market stress. Researchers therefore proposed CVaR as a more prudent and coherent measure of tail risk, which, by definition, is the average loss given that a loss below a certain probability has occurred.

For our analysis, we use a historical approach, simply based on the monthly return history for the same period, February 1990 to June 2018. In **Exhibit 5**, we look at VaR and CVaR in monthly returns at 95% and 99% confidence levels for each asset, along with their theoretical values, assuming normal distribution (shown in parentheses). Taking U.S. large cap as an example, there is a 5% chance of a loss greater than -6.3% in a month (VaR 95); a normal distribution would suggest a 5% probability of a loss greater than -5.8%. If a 5% left-tail event was to occur, the average loss (CVaR 95) would be -9.2% (vs. -7.5% assuming a normal distribution). VaR and CVaR for risky assets – U.S. large cap, high yield and EMD – are mostly lower than their corresponding normal values at both confidence levels. This indicates that the magnitude of left-tail risk for these assets is higher than their theoretical values. In contrast to risky assets, historical VaR and CVaR numbers for bonds (U.S. intermediate Treasuries) are close to the theoretical value, assuming normal distribution.

[6] "RiskMetrics – Technical Document, Fourth Edition," J.P. Morgan/Reuters, 1996.

The magnitude of left-tail risk for risk assets is historically higher than their theoretical values, assuming normal distribution

EXHIBIT 5: HISTORICAL VALUE AT RISK (VaR) AND CONDITIONAL VALUE AT RISK (CVaR) VALUES IN MONTHLY RETURNS, WITH THEIR THEORETICAL VALUES, ASSUMING NORMAL DISTRIBUTION (IN PARENTHESES)

	U.S. large cap	U.S. high yield	EMD	U.S. Treasuries
VaR 95	-6.3% (-5.8%)	-2.9% (-3.1%)	-4.2% (-4.8%)	-1.0% (-1.0%)
CVaR 95	-9.2% (-7.5%)	-5.3% (-4.0%)	-8.7% (-6.2%)	-1.5% (-1.4%)
VaR 99	-10.8% (-8.6%)	-7.8% (-4.6%)	-13.5% (-7.1%)	-1.9% (-1.6%)
CVaR 99	-14.0% (-10.0%)	-11.0% (-5.4%)	-21.0% (-8.2%)	-2.2% (-1.9%)

Source: J.P. Morgan Asset Management; historical estimates with monthly return data from February 1990 to June 2018.

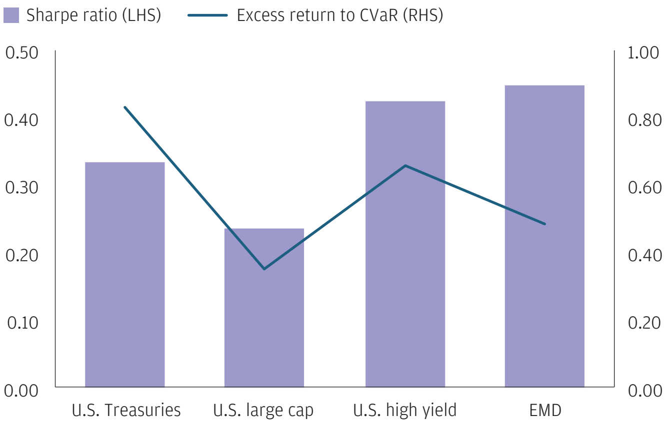
In short, historically both the probability and magnitude of left-tail risks for financial assets, especially risky assets such as equity and credit, are much higher than the normal distribution would suggest. Investors should be wary of the potential large losses associated with tail risks, something very difficult to capture in a single volatility metric in a traditional normal framework.

As **Exhibit 6** shows, the 2019 LTCMA Sharpe ratios of U.S. high yield and EMD are higher than the other two asset classes', suggesting an excellent return to risk. However, a more comprehensive picture using our CVaR analysis suggests otherwise: It finds U.S. Treasuries to be the best-compensated asset per unit of CVaR risk.

These are important considerations for portfolio construction. While a mean-variance framework is essential and useful, its assumptions inherently lead to an underestimation of the risks of holding fat-tail assets. The Sharpe ratio, one of the most referenced measures in the mean-variance framework, is therefore not a robust measure of risk-adjusted return for fat-tail assets or portfolios with large holdings of these assets. Investors can help protect their portfolios from the risk of left-tail events by using tail risk measures on a regular basis to monitor and forecast tail risks for their risky holdings. Investors may also consider expanding their portfolio construction objectives to include downside risk mitigation.

In determining which asset class offers the highest compensation per unit of risk, the winner changes depending on the risk measure used

EXHIBIT 6: 2019 LTCMA SHARPE RATIO VS. EXCESS RETURN TO CVaR RATIO



Source: J.P. Morgan Asset Management, September 30, 2018.

Sharpe ratio: (Total return-cash)/volatility. Excess return to CVaR ratio: (Total return -cash)/CVaR.

VOLATILITY AND CORRELATION ASSUMPTIONS METHODOLOGY

Long-term asset class volatilities and correlations tend to exhibit stability when measured over multiple cycles. As such, we use the following process in estimating long-term volatility and correlation assumptions for the main asset classes:

1. START WITH MONTHLY HISTORICAL RETURN DATA

- In prior estimates, we used 11 years of historical data as the anchor. This year, we increase the data window from 11 years to 12 years.

2. FILTER DATA OUTLIERS

- Extreme data outliers could bias volatility estimation and are filtered to improve robustness. This is done by winsorizing* historical raw data.
- For extreme data points above (or below) a 99.5% confidence level (or a 0.5% level of significance) for a normal distribution (or beyond 2.58 standard deviations from the mean), we adjust the return data by capping (or flooring) it at the 99.5% confidence level (or 0.5% level of significance).

3. CONSTRUCT ANCHOR MATRIX

- We leverage the historical experience to help anchor our forward-looking expectations, focusing on:
  - Simple historical return series (with each data point equally weighted)
  - Historical return series with each data point weighted by “relevance” (the expected frequency of stress vs. calm periods)**
- Variance-covariance matrix is calculated using the filtered data set.
  - Demean filtered data
    - After filtering the data, we demean each data point by the average of the full sample.
  - Calculate variance-covariance matrix
    - We multiply the weighted demeaned return time series matrix to calculate the covariance matrix.
    - Volatility and correlation are extracted from the covariance matrix. The monthly volatility is then annualized by the industry standard square root of 12 factor.

4. ADJUST FOR KEY THEMES AND STRUCTURAL CHANGES

- Key themes and structural changes that are expected over the forecast interval, such as those highlighted in this article, are reflected in the long-term risk forecast accordingly.

For alternative asset classes, serial correlations can be prevalent in illiquid and hard-to-price securities such as real estate. Because it is difficult to value the underlying assets at regular intervals, an investment manager must estimate fair prices, which are unobservable. This is typically done by updating lagged prices with changes in the economic environment. However, in our view, estimating using previous prices as an input artificially smooths returns, biasing risk estimates downward compared with the true economic risk. We correct for this bias by adjusting the returns from these hard-to-price assets for first-order serial correlation. We estimate the serial correlation coefficient using the same data window as we use for liquid assets, applying them to these illiquid assets’ returns before calculating their anchoring volatility and correlations.

There are a few additional things to keep in mind. First, the standard deviation calculation is not subject to sequence risk. Thus, our assigned aggregate weighting of stress periods matters, but not the order of the data points or the continuity of the stress periods. Second, the weights are consistently applied to all the various currency matrices we publish. The forward-looking periods and the treatment of historical data are identical across regions and assets. Third, the volatility estimates capture the likely movement of the return around our central return forecasts. However, it does not incorporate distribution elements, such as the tail risk of the assets and other upper moments. It is particularly important for investors that hold assets known to have fat tails — such as high yield bonds, emerging market debt, convertible bonds, etc. — to account for risk aspects in addition to volatility.

* Winsorization applies a cap and a floor to extreme data values to remove the impact of potentially spurious outlier data on statistical results.

** We define stress periods based on NBER recession periods and assign them a long-run average probability of 15%. We apply these weights on a global basis.

TAIL-RISK ANALYSIS METHODOLOGY

1. RETURN STANDARDIZATION:

In Exhibit 4, we use standardized monthly returns instead of raw monthly returns. This provides us a comparable scale for tail risk behaviors in all four assets by removing the impact of the sample mean and volatility. For return X at month *t* for asset *i*, standardization is done by following

$$Z_{t,i} = \frac{X_{t,i} - \mu_i}{\sigma_i}$$

where μ_i is the sample mean and σ_i is the sample standard deviation of asset *i returns*. Therefore, if we assume *X* follows a normal distribution $X \sim N(\mu,\sigma^2)$, then Z follows a standard normal distribution $Z \sim N(0,1)$.

2. VALUE AT RISK (VaR) AND CONDITIONAL VALUE AT RISK (CVaR):

In mathematical terms, VaR is a quantile. VaR at confidence level α is defined as the risk level at α quantile (or return level at $1-\alpha$ quantile). The level α here is close to 1 in practice (typically 0.95 or 0.99). CVaR is the average loss of investment given that a loss is occurring at or below the α quantile risk level (or $1-\alpha$ quantile return level).

Historical VaR at α confidence level is the value of $1 - \alpha$ percentile of monthly returns in the sample period, and historical CVaR at α confidence level is the average of all returns that are less than or equal to the α VaR–i.e., the average value of returns fall into the $(0, 1-\alpha]$ percentile range.

To calculate the theoretical VaR at α confidence level, one needs to first calculate the z-score (the number of standard deviations from the mean) of a standard normal distribution with a probability $1-\alpha$–i.e., to calculate the inverse cumulative standard normal distribution function value $\Phi^{-1}(1-\alpha)$. For example, a z-score of -1.64 corresponds to a cumulative probability of 5% in a standard normal distribution. One then translates the z-score back into the return form by multiplying the z-score by the standard deviation of the sample return series and adding the mean. Therefore, we have

$$\text{VaR}_\alpha(X)=\mu+\sigma \cdot \Phi^{-1}(1-\alpha)$$

where $\Phi^{-1}(\cdot)$ is the inverse cumulative standard normal distribution function (so $\Phi^{-1}(1-\alpha)$ is the z-score evaluated at $1-\alpha$ probability), σ is the sample standard deviation, and μ is the sample mean.

Theoretical value for CVaR at α confidence level is calculated based on its corresponding VaR value. By definition, CVaR is expressed as

$$\text{CVaR}_\alpha(X) = -E[X|X \leq \text{VaR}_\alpha(X)] = \frac{1}{1-\alpha}\int_\alpha^1 \text{VaR}_\chi(X)d\chi.$$

Applying the VaR formula, we could derive a closed-form CVaR for normal distribution

$$\begin{aligned}\text{CVaR}_\alpha(X) &= \frac{1}{1-\alpha}\int_\alpha^1 (\sigma\phi^{-1}(1-\chi) + \mu)d\chi \\ &= \frac{\sigma}{1-\alpha}\int_\alpha^1 \phi^{-1}(1-\chi)d\chi + \mu \\ &= \frac{\sigma}{1-\alpha}(-\phi^{1}(\Phi^{-1}(\alpha))) + \mu \\ &= \mu - \frac{\sigma}{1-\alpha}\phi(\Phi^{-1}(\alpha))\end{aligned}$$

where $\Phi(\cdot)$ is the standard normal density function. Given this, the theoretical value for CVaR at α confidence level could be easily calculated.*

* Jérémie Smaga, "Expected Shortfall Closed-Form for Normal Distribution," *Jérémie Smaga's Personal Blog*, November 6, 2016, http://blog.smaga.ch/expected-shortfall-closed-form-for-normal-distribution/.

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