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Viewpoint

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RISK SOLUTIONS | WHITE PAPER

Inflation Modeling Revisited

Part Two: Modeling a Complex Market

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Introduction

In part one of this series on inflation, we looked at what the longer-term historical context could tell us about the current situation. In this, part two, we will look at the important topic of how inflation and inflation markets should be modeled within the context of an economic scenario generator (ESG), such as the GEMS® Economic Scenario Generator from Conning ("GEMS®").

What Determines Model Performance?

Two of the most important aspects that determine the performance of a risk model are *target setting* and *model structure*.

Target setting is the process of determining which statistical properties are relevant to a particular modeled economic variable and then assigning a desired value to those statistics. Targets typically include values for the mean and standard deviation of the variable as well as higher moments such as percentiles (e.g., the 1-in-200-year event). Targets may also include correlations with other variables.

Closely related to target setting is parameterization, which can be defined as the setting of model parameters to generate distributions that match the assigned targets as closely as possible. The parameterization process will also determine the dynamics that the model produces. The aim of a good target setting and parameterization process should be to generate model dynamics that closely resemble the dynamics of the modeled variable. This implies that a good model does not just try to reproduce distributions, but also reproduce how the distribution is arrived at through time.

Model structure is the mathematical form of the model. The number of factors and parameters that a model has may determine in part the number and type of targets that are set. For instance, there is no point in defining a target for the skewness of the simulated distribution if the model can only produce normal distributions.

Put simply, model structure determines what a model *can do*, and target setting and parameterization determine what it *will do*.

Why Did Some Models Fail to Capture the 2021 Inflation Episode?

Given our recent experience with inflation and looking at the historical context detailed in part one of this whitepaper series, we might ask how it came to be that so many models failed to capture the prevailing levels of inflation. To answer this question, it is first pertinent to discuss the broader issue of paradigms and how they develop before directly considering inflation.

Paradigms develop in many areas, including sociology, industrial production, and politics, but also in finance and economics. When such a paradigm is adopted, the ideas underlying it are likely to become so entrenched and widely accepted that little weight is given to alternative hypotheses. In the case of risk management, where models are expected to reflect an uncertain future, behavioral science makes it clear that humans have difficulty imagining a world radically different from recent experience. This is relevant because it may help to explain why, by 2020, models of inflation and interest rates were parameterized with inadequate levels of volatility.

Indeed, we could view the thinking in the aftermath of the 2008 financial crisis as a classical paradigm. By the mid-2010s a great deal of groupthink had developed, dominated by ideas such as, "lower for longer," "history and the 1970s are not relevant," and "inflation has been stable since the 1990s and is likely to remain so." This thinking flowed through into the target-setting process for many models, resulting in volatility targets that were too low to capture the current inflation environment. As we have seen in part one, the period of 1993–2020 was a timespan in which inflation volatility and levels were generally low, but this period represents something of an outlier in history and should always have been treated as such in a prudent target-setting process. For instance, basing a volatility target on this period would have implied that the peak of the post-December 2020 inflation episode was between a 6 and 11 standard deviation event depending on economy.

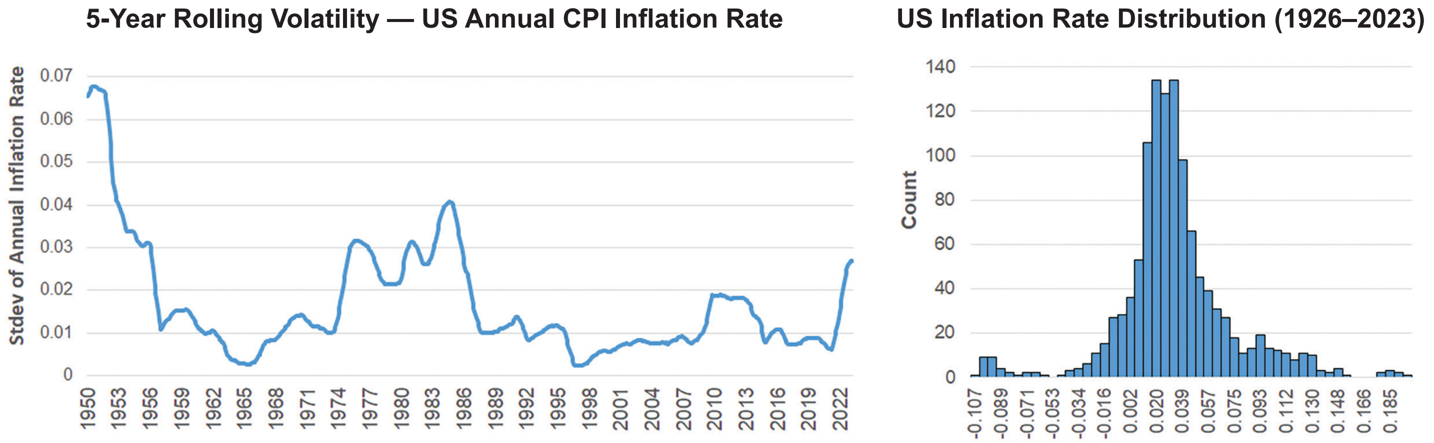


Figure 1: The volatility of the United States year-on-year inflation rates in a five-year rolling window (monthly observations) (left), and the distribution of US CPI inflation rates between 1926 and 2023 (right). Prepared by Conning, Inc. Source: ©2023 Bloomberg L.P.

Undoubtedly, setting an appropriate target for inflation volatility is difficult for several reasons. Two of the key challenges are illustrated in **Figure 1** above. Firstly, inflation volatility has been far from stable through time, as illustrated by the left-hand chart. The chart shows that the volatility in any 5-year window of history has fluctuated between a low of 0.24% and a high of 6.78% between 1950 and 2022. Secondly, the distribution of historical inflation rates is often not continuous; instead, as we see in the histogram on the right of Figure 1, there are discontinuities (i.e., gaps) in the distribution, as well as multiple modes. The consequence of this is that measured standard deviations tend to be too high when applied to a model with a continuous distribution.

When setting inflation volatility targets for the GEMS® Expert View Parameterization, we applied a methodology designed to minimize the impact of some of these issues. The end goal was to arrive at targets that were conservative enough to capture future events ex ante but not so conservative that high-inflation environments are simulated at unreasonably high probability levels. The starting point in achieving this was to intentionally use a longer history of data; we have for many years argued that long histories are generally the right thing to use for estimating risk distributions, and the GEMS® Expert View Parameterization uses a 50-year data window for this purpose. As well as allowing for more significant shocks to inflation to be included within the calibration targets, long histories also generate more stable targets and parameters through time. This makes the model output less sensitive to localized changes in the data.

Further to this, we correct for the instability and bimodality of the distributions by fitting a weighted continuous distribution to the data. An example of this can be seen in **Figure 2** below. The type of distribution chosen for the fit is based on a Cullen-Frey analysis comparing the kurtosis and skew of the market data to the known properties of different distributions (e.g., normal, exponential, beta, gamma, etc.). To arrive at a final target for the model, it is the standard deviation of this fitted distribution that is used rather than the raw historical value.

Finally, once targets have been set and parameters estimated, the model output and targets are subject to a process of continual review. This process is meant to balance the need to keep the model up-to-date and relevant with the desire for parameter stability.

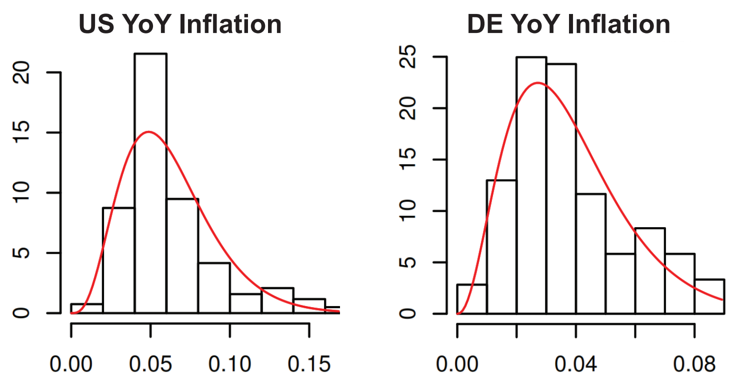


Figure 2: Examples of fitted distributions (red solid line) to historical US (left) and Eurozone (right) inflation rates (histogram) Prepared by Conning, Inc. Source: ©2023 Bloomberg L.P.

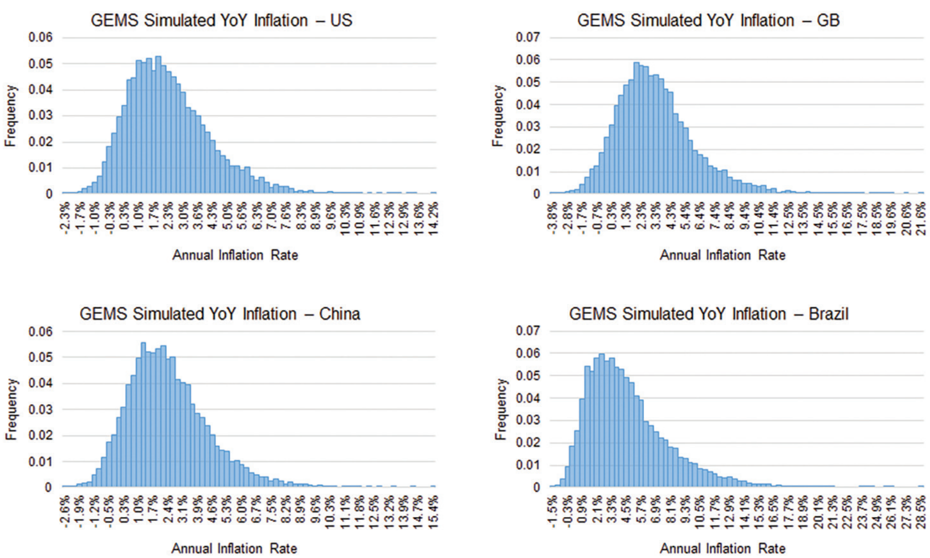
GEMS® Inflation Model Output

With a good process for setting targets and parameterizing the model in place, it is the model structure that determines the final evolution and distribution of financial variables such as inflation. There is a broad spectrum of outputs that the GEMS® inflation model generates, including inflation rates, real yields, returns on inflation-linked bonds, and prices for a range of inflation-linked derivatives. In this whitepaper, we will focus on two aspects of the model related to the inflation rate.

Figure 3 below shows the steady-state distributions of year-on-year inflation rates produced by the GEMS® Expert View Parameterization for four economies. A summary of the statistics for each economy is also shown in tabular form on the right of Figure 3. The simulation is based on the year-end 2019 calibration of the GEMS® models. In other words, the distributions can be interpreted as ex ante given what we now know ex post about inflation rates.

The simulated distributions exhibit several important and notable characteristics. Firstly and most importantly we note that the distributions had high inflation scenarios embedded within them from the start. The peak of realized inflation was also observed to be close to the 99.5th percentile of the model distribution, and the model was also able to produce inflation events well in excess of what we have observed so far. Based on this, it can be argued that the model reasonably balanced the features of the longer historical data with the more recent. Secondly, we observe that the distributions are positively skewed. This is consistent with what we see within the market data, where, depending on economy and data window, measured values of skew typically range between 1.5 and 4.[1] Third and finally, the models are capable of producing deflationary episodes at probability levels that appear reasonable relative to the economy under consideration.

1. Developing economies such as Brazil may have higher values for some historical windows.



	US	GB	CN	BR
avg	2.25%	3.20%	2.33%	4.50%
std	1.92%	2.79%	2.00%	3.43%
skew	0.95	1.07	0.95	1.37
kurt	1.61	2.38	1.78	2.90
0.10%	-1.80%	-3.02%	-2.08%	-1.09%
0.50%	-1.38%	-2.14%	-1.48%	-0.65%
1.00%	-1.08%	-1.74%	-1.21%	-0.42%
5.00%	-0.33%	-0.58%	-0.42%	0.41%
50.00%	1.98%	2.83%	2.07%	3.79%
95.00%	5.81%	8.38%	6.00%	11.10%
99.00%	7.86%	11.95%	8.42%	15.90%
99.50%	8.94%	13.54%	9.53%	17.69%
99.90%	10.92%	17.05%	11.67%	20.96%

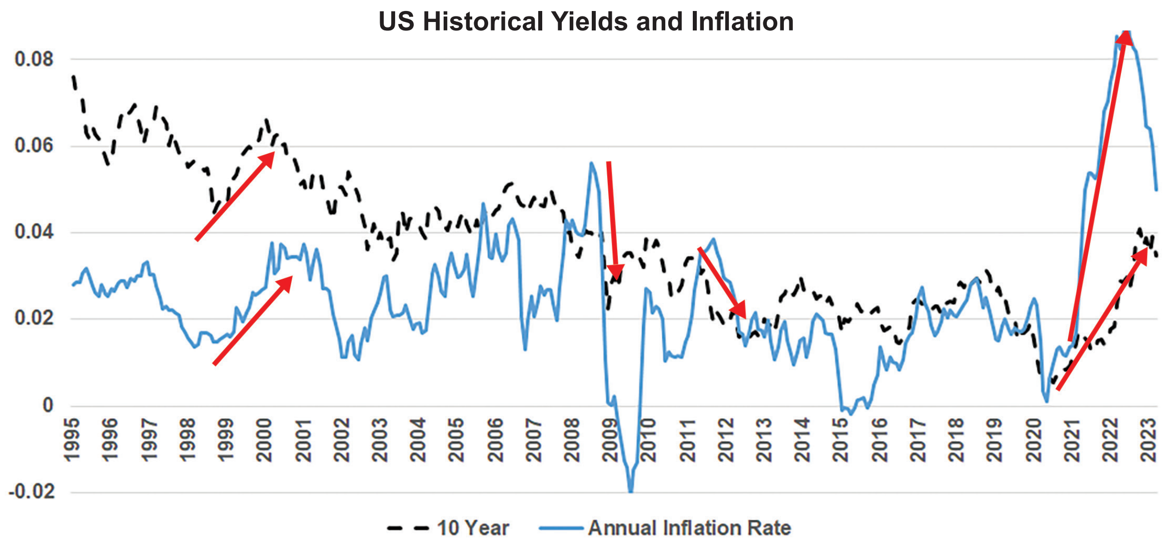
Figure 3: GEMS® simulated inflation rate distributions and steady-state statistics. Prepared by Conning, Inc. Source: GEMS® Economic Scenario Generator.

The second aspect of model output that we will look at here is the important topic of codependence between inflation and interest rates. In the GEMS® inflation model, there is a direct and inbuilt link between the stochastic processes governing the evolution of interest rates and those that govern inflation rates and real yields. However, there are enough degrees of freedom within the inflation model to enable significant decorrelation between inflation rates and nominal yields, as well as between nominal yields and real yields. This is important because the market data points towards a codependence that is neither stable nor perfect (i.e., the measured correlation coefficients are not always close to 1 or -1).

When considering the co-movement of these variables it is important to consider not just the measured correlation coefficient but the characteristics of the data. This is illustrated by the chart at the top of **Figure 4** (following page), showing the historical US Treasury 10-year yield (black hatched) and US annual inflation rate (blue solid) between 1995 and the end of 2022. From inspection we can clearly see that a relationship exists between these two variables; however, it is neither static nor rigidly defined, with the variables becoming more closely coupled during periods of inflation stress as indicated by the red arrows. Indeed, this is consistent with what can be measured within the data, where there have been 5-year periods where inflation and short-term interest rates have been negatively correlated (e.g., November 2008–2013, correlation = -0.63), and periods where they have been significantly positively correlated (e.g., November 2014–2019, correlation = 0.76).

The lower chart of Figure 4 shows the equivalent variables generated from the GEMS® inflation and interest rate models. Shown is a single simulated path from which we can discern many of the same characteristics that we see within the market data. In particular, larger movements in inflation tend to be accompanied by larger movements in interest rates, and during periods of lower volatility the co-dependence appears less rigidly defined.

However, as with all models, limitations do exist. Looking at the upper chart of Figure 4, an obvious limitation is that the kind of



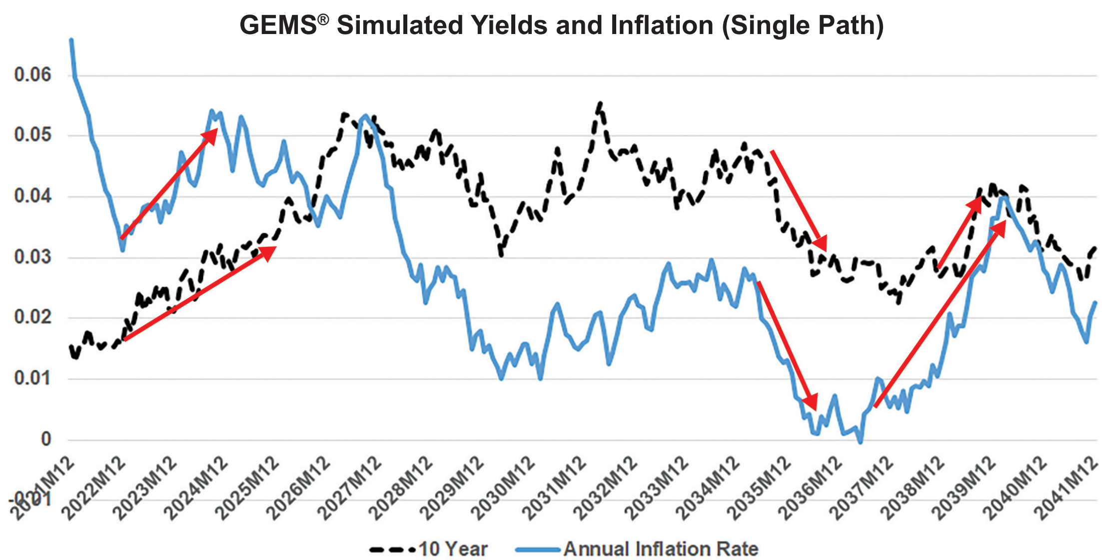


Figure 4: Historical (top) and GEMS® simulated (bottom) annual US CPI inflation rates (blue solid) and 10-year Treasury yields (black hatched). Prepared by Conning, Inc. Sources: ©2023 Bloomberg L.P. and GEMS® Economic Scenario Generator.

rapid drop to deflation that was observed during the 2008 crisis and Great Recession requires a jump mechanism to be adequately modeled. A key element of the GEMS® ESG is the continued improvement and development of the models, and in the next section, we finish with a short overview of a recent modeling development that addresses the issue of crisis modeling and tail dependence between multiple financial variables and across different modeled geographies.

The issue of tail dependency in inflation models is an important one to consider, especially in light of the data from the Great Recession as well as the most recent events. In both cases inflation rates were observed to jump nearly simultaneously across multiple economies with interest rates following suit, albeit with a lag to the initial inflation shock. Indeed, these kinds of joint shocks to market variables are often among the most critical factors in determining the aggregate tail risk of a globally diversified portfolio or asset allocation. However, it is often difficult to build this type of joint behavior into a stochastic model without accepting high correlation across all scenarios.

To address this issue, the GEMS® ESG now incorporates a shared crisis event called the Global Jump Process, which allows for the explicit modeling of joint shocks across multiple asset classes and economies. The details and features of this Global Jump Process were discussed in the 2020 whitepaper, *New Methods in*

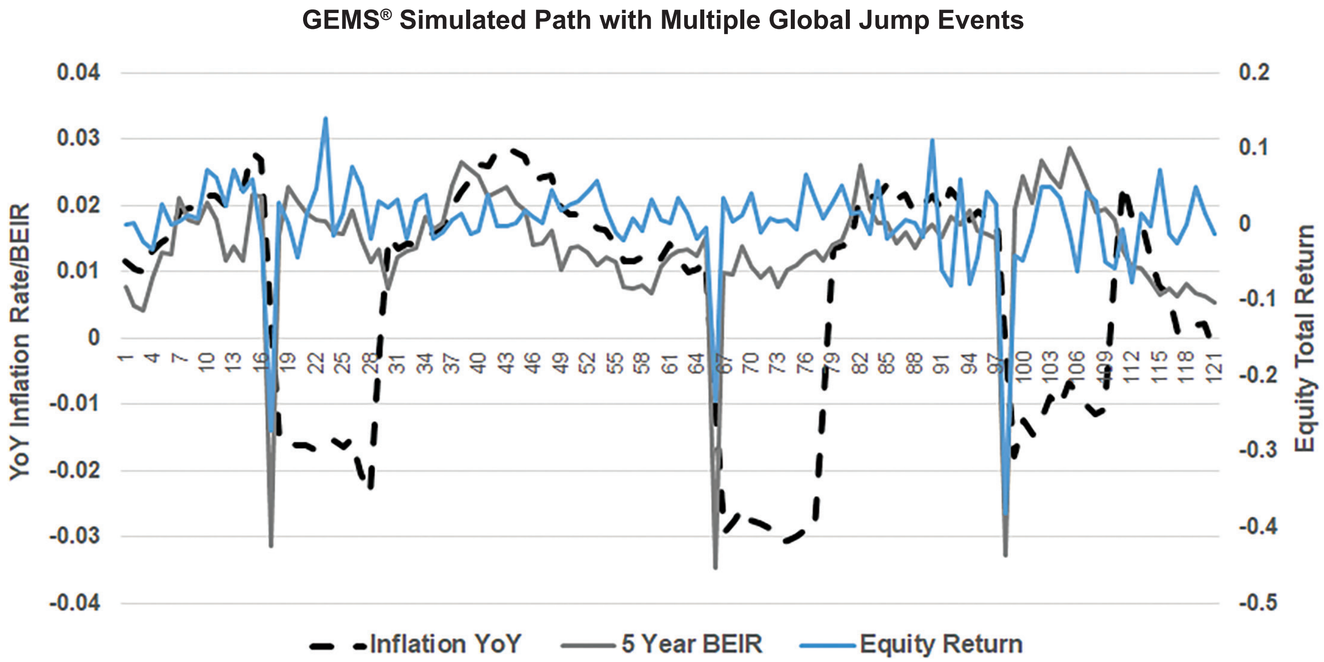


Figure 5: Example path from GEMS® with the inclusion of the Global Jump Process. Prepared by Conning, Inc. Source: GEMS® Economic Scenario Generator.

Modeling Global Economic Crises.[2] **Figure 5** above shows some GEMS® output that incorporates this mechanism for inflation; in the scenario shown, three global crises occur within a 10-year period.[3] In each, equity total returns fall sharply, along with the annual inflation rate and inflation expectations proxied here by the 5-year break-even inflation rate (BEIR). For inflation, the Global Jump Process is formulated such that the shock is persistent over a user-defined number of months, while equity returns and inflation expectations tend to recover more quickly.

When used as part of the existing GEMS® modeling framework, it is expected that this new feature will lead to greater model performance in stressed market conditions, as well as more control for users over the precise nature of tail dependence in GEMS®.

Summary

This document, the second in a two-part series, discusses the important topic of how inflation and inflation markets should be modeled within the context of an economic scenario generator. We have seen how two key factors, target setting and model structure, combine to determine the performance of models. It has been argued that the failure of many models to capture prevailing levels of inflation can be attributed to the adoption of entrenched paradigms, which flowed through into inadequate levels of volatility in the final model parameterization. Further, we showed how the GEMS® Expert View Parameterization adopted a methodology that avoided this pitfall by incorporating long histories into the target-setting process and by correcting for the instability and bi-modality of inflation distributions.

As we have seen, the targets that emerge from the GEMS® Expert View methodology are conservative yet realistic. The GEMS® inflation model can also generate steady-state distributions with high inflation scenarios embedded within them, closely resembling historical data and capturing events well beyond observed levels. As well as inflation, the model can produce deflationary episodes at reasonable probability levels, making it robust in terms of capturing different observed market conditions. Moreover, the incorporation of the Global Jump Process has, to a great extent, addressed the issue of tail dependence in inflation models, allowing for explicit modeling of joint shocks across multiple asset classes and economies, further enhancing model performance in stressed market conditions.

With a commitment to continued improvement and development, the GEMS® Economic Scenario Generator aims to provide users with ever-greater performance as well as improved control over model behavior such as tail dependence. The benefit of this to users is enhanced choice and flexibility in model setup as well as improved model robustness in terms of capturing complex future economic scenarios.

2. Available upon request or in the Conning Software Documentation Library.

3. For this document, a particularly high probability of global jump events was used for illustrative purposes.

Inflation Modeling Revisited Part One

In part one of this two-part whitepaper series, we look at inflation in a historical context. While the initiations of inflation shocks have similar root causes—wars, energy crises, and recessions—how they evolve depends more on the specific nature of supply and demand factors within the wider economy than the inflation shock itself. Part one of the whitepaper discusses what historical context can tell us about the current situation and why analysis of the long-term historical record is back in vogue. Click here or scan the QR code below to read part one now.

About GEMS® Economic Scenario Generator

Conning's GEMS® Economic Scenario Generator is a state-of-the-art stochastic economic scenario generator with leading-edge economic and financial models, including alternative assets and a wide range of derivatives. GEMS® provides a comprehensive analysis of the risks that firms face, the relationship between those risks, and the potential rewards in retaining them. GEMS® offers both real-world and risk-neutral functionality and supports integrated economies and capital markets in North and South America, Europe, Asia, and Australia. GEMS® comes with a comprehensive set of parameterized asset classes, and further asset classes can easily be added through built-in system functionality.

GEMS® is distinguished by its ability to simulate realistic tail risk events due to the structure of the stochastic models and the methodology used to calibrate the models. Additionally, the modeled correlation between variables within GEMS® means that its simulations are robust and consistent within economies, across economies, and over multiple time horizons. GEMS® supports strategic asset allocation, economic capital modeling, market-consistent valuation, business planning, and many more risk management applcations.

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