Practical Applications of

Identifying Economic Regimes: *Reducing Downside Risks for University Endowments and Foundations*

Practical Applications
Institutional Investor Journals

Overview

Institutions must protect their capital from erosion over long time horizons, with special attention paid to downside risks—especially contagion during severe economic conditions. Contagion negates the anticipated diversification built into a portfolio, and returns become correlated, causing securities to move downward together in a tight pack. Drawdown can be severe, causing setbacks to long-term investors who depend on capital to pay future liabilities.

Asset performance over long time periods can be separated into distinctive classes, called regimes, which display common characteristics. In order to identify distinct regimes, **John Mulvey** and **Han Liu** of **Princeton University** applied trend filtering, a type of machine learning, in which an algorithm categorizes regimes and thus helps to model downside risk. They present their research and findings in ***Identifying Economic Regimes: Reducing Downside Risks for University Endowments and Foundations*,** published in the Fall 2016 issue of ***The Journal of Portfolio Management***.

For investors who depend on endowment capital to provide a steady source of income, the authors use a two-regime approach. By studying phases of growth and contraction in relation to historical economic patterns, they are able to identify strategies that protect the long-term viability of invested assets. Mulvey and Liu also demonstrate the advantages of adjustable-spending rules during drawdown periods to improve the worst-case outcomes.

Practical Applications

- **Machine-learning techniques can help identify economic regimes.** A data-driven, trend-filtering algorithm can model downside risk more effectively by examining historical return data to pinpoint regimes.
- **A two-regime approach is more accurate in evaluating downside risk.** Accounting for both growth and contraction regimes provides better information than using a single static regime.
- **Flexible spending has a place.** Adjustable-spending rules can help to protect invested capital during drawdown periods.

Authors: John M. Mulvey and Han Liu
Source: *The Journal of Portfolio Management*, Fall 2016, Vol. 3, No. 1
Report written by: Howard Moore
Keywords: Contagion, Contraction, Correlation, Drawdown, Economic Regimes, Liability-Driven Investing, Machine Learning, Princeton University, Spending Rules, Systemic Risk Premia, Trend Filtering

Key Definitions

Contagion

The spread of market behavior from one asset class, sector, or other investment category to others.

Correlation

A measure of how two variables tend to move in the same direction.

Drawdown

The decline of investment value during a specific period.

> “When we have a crash period, we end up seeing much more contagion and very high correlations, which do not appear during normal economic periods.”
>
> **—John Mulvey**

Practical Applications Report

Over the past 30 years, Mulvey has worked closely with large institutional investors that require great precision in matching assets to liabilities. He believes there should be more effort to distinguish economic regimes—especially growth periods and contraction periods—in order to model downside risk and project the health of long-term investors. The traditional approach is to assume a single covariance matrix based on economic history, correlations, variances and expected returns. “But that’s not the way the world works,” explains Mulvey. “When we have a crash period, we end up seeing much more contagion and very high correlations, which do not appear during normal economic periods.”

Mulvey and Liu employed a trend-filtering algorithm to analyze S&P 500 Index historical total return data. The goal was to identify regimes in financial markets in a data-driven and model-free context. “Many other methods and predictive approaches have been used over time, but we wanted to use a nonparametric method, which does not apply strong probability assumptions on the structure of the information,” says Liu. The resulting function illustrates clear trends over a persistent period of time, which can help to pinpoint financial market regimes, and they were able to focus on transition dates, when the economy alternates between periods of growth and contraction.

Although their trend-filtering algorithm uses data only from the U.S. equity market, the authors also found consistent regime identification markers that are consistent in other asset classes as well. For example, international equity markets perform similarly to U.S. markets, and U.S. government bond returns perform much better during contraction regimes because of investors’ flight-to-quality behavior during crash periods.

WHY TWO REGIMES ARE BETTER THAN ONE

The authors then implemented Monte Carlo simulations for the case of an institution that derives a substantial portion of its operating budget from endowment capital. With a clear need to generate income and protect capital, spending rules were built into the scenarios, and each scenario is a mixture of normal and contracting regimes. “The single-regime approach assumes having one covariance matrix, but we think a better approach is to look at normal economic periods and contracting economic periods,” says Mulvey. Depending on the number of normal versus contracting periods, one can determine the average time of contraction over a specific period. Each scenario contains a mixture of normal periods and contraction periods over a long horizon of 50 years, for example.

“We think of it in terms of two sets of data versus one set,” Mulvey says, one for each regime. “In the two-regime approach, you get fatter tails, and the worst-case distributions tend to be more historically accurate than using data from a single regime.” For example, the data show that historically, 10% to 15% of the quarters have been recession periods. “That’s a starting point that you would try to represent in the future, which would be somewhat consistent with the past,” he says. “The scenarios that we generate are closer to the way things ought to have looked.”

Institutions have several levers to improve their long-term viability: They can implement dynamic asset allocation strategies, adjust spending rules, and seek additional funds from outside sources. “We stick with the same asset allocation, and we rebalance to that mix each period,” says Mulvey. Taking a more dynamic approach requires estimating the chances of being in a regime. “We don’t want to make that assumption—we just want to be closer to what’s currently done,” he says, which is to regard a severe event as a major drawdown on an endowment, affecting the health of an institution over time.

> “We show that there’s a big impact on the tail by making modest adjustments to the spending rule.”
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MINIMIZING DOWNSIDE RISK

Ultimately, the question is, what can be done to reduce downside risks? One approach is to manage drawdown periods with adjustments to asset allocation under adverse circumstances. Another approach is to reduce spending in a dynamic fashion when large drawdown thresholds are breached. “Changing the spending rule tends to help quite a lot,” says Mulvey. If there is a contraction, it’s best not to spend too much during that period, because it might lead to severe difficulties later. “We show that there’s a big impact on the tail by making modest adjustments to the spending rule,” he says, at least for a university, and perhaps for other types of long-term investors as well.

“Our current work is not meant to be predictive,” says Liu. “We’re looking at historical patterns and trying to represent them going forward.” When the markets are in a growth regime, there’s a chance they can switch to a contraction, but the authors are not making strong judgments about how that might occur. It’s important to distinguish using regime modeling to help make more informed dynamic decisions versus taking the current approach and making it more accurate in terms of downside modeling. “However, machine learning can be helpful in financial modeling, and combining it with statistics could help to develop new methodologies and take us in an extremely interesting new direction,” he says. Regime detection could support factor investing, for example. “We find that the factors that drive returns in different asset categories have specific differences across regimes,” says Mulvey. “It’s a natural next step.”

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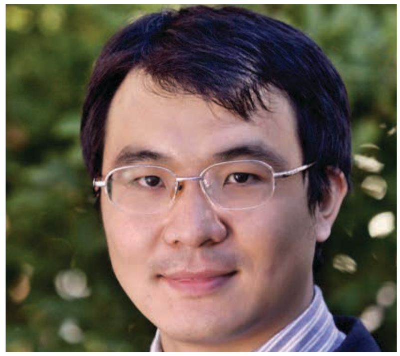
John was a 2005 fellow at the Institute for Operations Research and Management Science and winner of the **Franz Edelman Award** for Towers Perrin–Tillinghast in 1999. He is a prolific author, having published in ***The Journal of Portfolio Management***, the ***European Journal of Operational Research*** and the ***International Review of Financial Analysis***, among others.



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Han has received several research awards, including the **Tweedie New Researcher Award** from the **Institute of Mathematical Statistics**, the **Noether Young Scholar Award** from the **American Statistical Association**. His papers have been recognized at the **Fifth International Conference on Continuous Optimization**, the **26th International Conference on Machine Learning**, and the **16th International Conference on Artificial Intelligence and Statistics**.