Predictive Risk Analytics

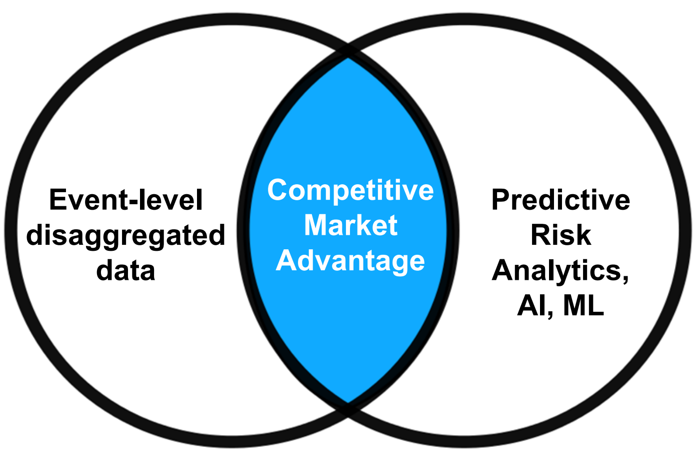
Data-Driven Risk Measurement & Mitigation for Competitive Market Advantage

Contents

"Measurement is the first step that leads to control and eventually to improvement. If you can't measure something, you can't understand it. If you can't understand it, you can't control it. If you can't control it, you can't improve it." - H.J. Harrington

I. Risk Types

- Operational Risk
- Enterprise Risk
- Model Risk
- Strategic Risk
- Credit Risk
- Market Risk
- Liquidity Risk



- Operational and Enterprise Risk have been especially underserved for both accurate measurement and effective mitigation due to i) underappreciated and misunderstood data and analytical challenges; ii) regulatory missteps and complete overhauls; and iii) regulatory requirements improperly driving business-decisioning.

- The proper marriage of the right data sources and sophisticated predictive analytics can achieve competitive market advantage across all risk silos, but especially in these.

II. Predictive Analytics, AI, ML Driving Capital Solutions

Underserved Risk Challenges in Need of (Better) Solutions: Opportunity for Market Advantage

1. **Statistically Significant Risk Driver Identification, Estimation, Monitoring/Verification, Dynamic Updating**
2. **More Accurate, Precise, and Robust Capital Estimation and Stress Testing**
3. **Capital Estimation, Aggregation, and Optimal Allocation Within and Across Risk Types and LoBs**
4. **Model Risk: Highly Efficient & Effective Model Development Frameworks that Exceed SR11-7 requirements but Avoid Regulatory Bloat**

II. Predictive Analytics, AI, ML Driving Capital Solutions

1. What drives operational and enterprise risk?

a. Unactionable heat maps based on the wrong type of data (i.e. aggregated ‘rolled-up’ data) cannot answer this question.

b. Green-Yellow-Red Traffic lights cannot answer this question.

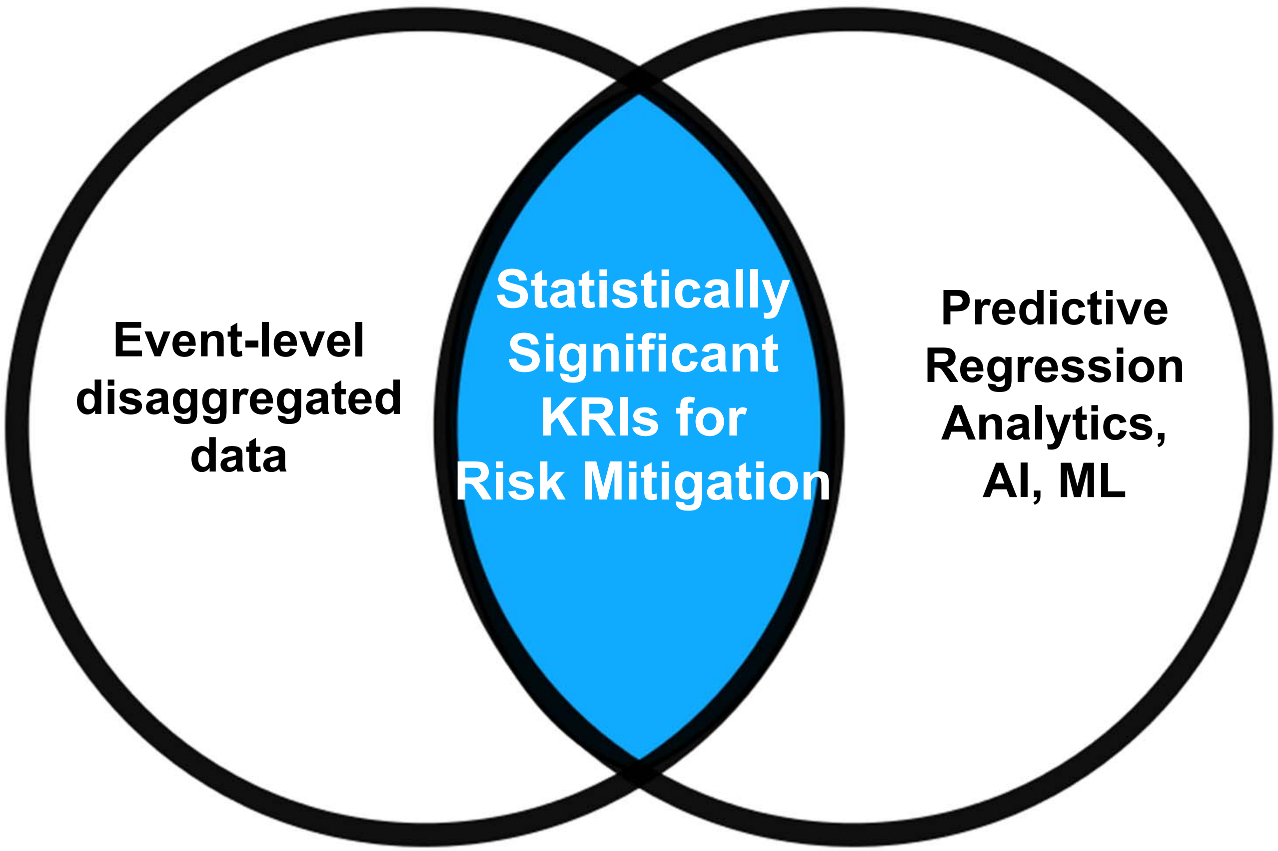
c. Even labor-intensive, exhaustive, and painfully detailed surveys cannot answer this question.

All 3 – the most common approaches used – often cause more harm than good as they create false senses of security but fail to accurately measure and quantify risk, let alone identify the statistically significant Key Risk Indicator (“KRI”) levers necessary to actually quantifiably and verifiably mitigate risk.

II. Predictive Analytics, AI, ML Driving Capital Solutions

1. What drives operational and enterprise risk?

- **Only the right kind of data combined with the right kinds of predictive regressions can answer this question.**



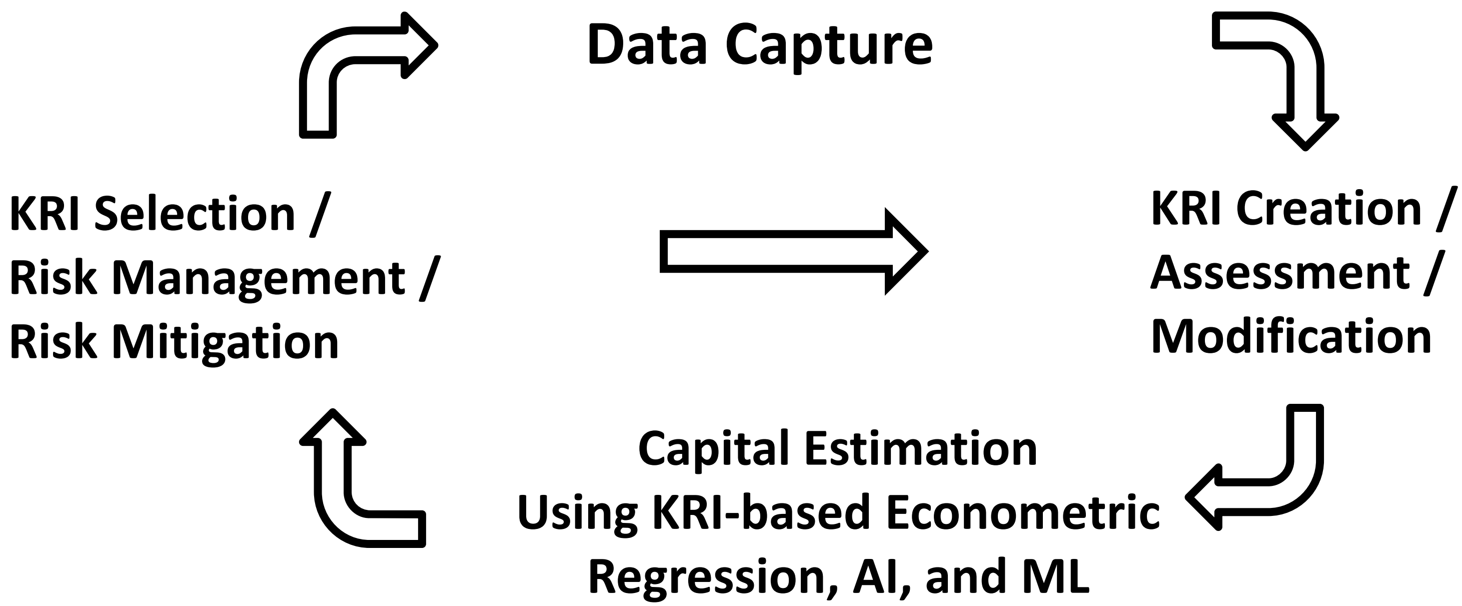
1. What drives operational and enterprise risk?

- **The right framework of Predictive Regressions + Appropriate Data**
  - i. **identifies the STATISTICALLY SIGNIFICANT KRI's that cause financial losses based on operational and enterprise risk.**
  - ii. **estimates the SIZE of the effects of each KRI HOLDING ALL ELSE EQUAL.**
  - iii. **rank-orders these KRI's allowing for cost-benefit business decisions (e.g. whether to upgrade systems, how much to invest in new technologies, etc.).**
  - iv. **dynamically and automatically re-evaluates i.-iii. as market and firm conditions change, and as mitigation strategies based on i.-iii. actually work and mitigate risk by decreasing the severity and frequency of related financial losses. This regression-based mitigation is the only approach that is quantifiably verifiable.**

1. What drives operational and enterprise risk?

Framework for Proactively Selecting and Maintaining Statistically Significant KRIs:

Fully Automated, Dynamic Feedback Loop



2. More Accurate and Precise Capital Estimation

- **For business decision-making across multiple risk types, the Compound Distribution Approach remains the most widely used and understood model risk framework.***

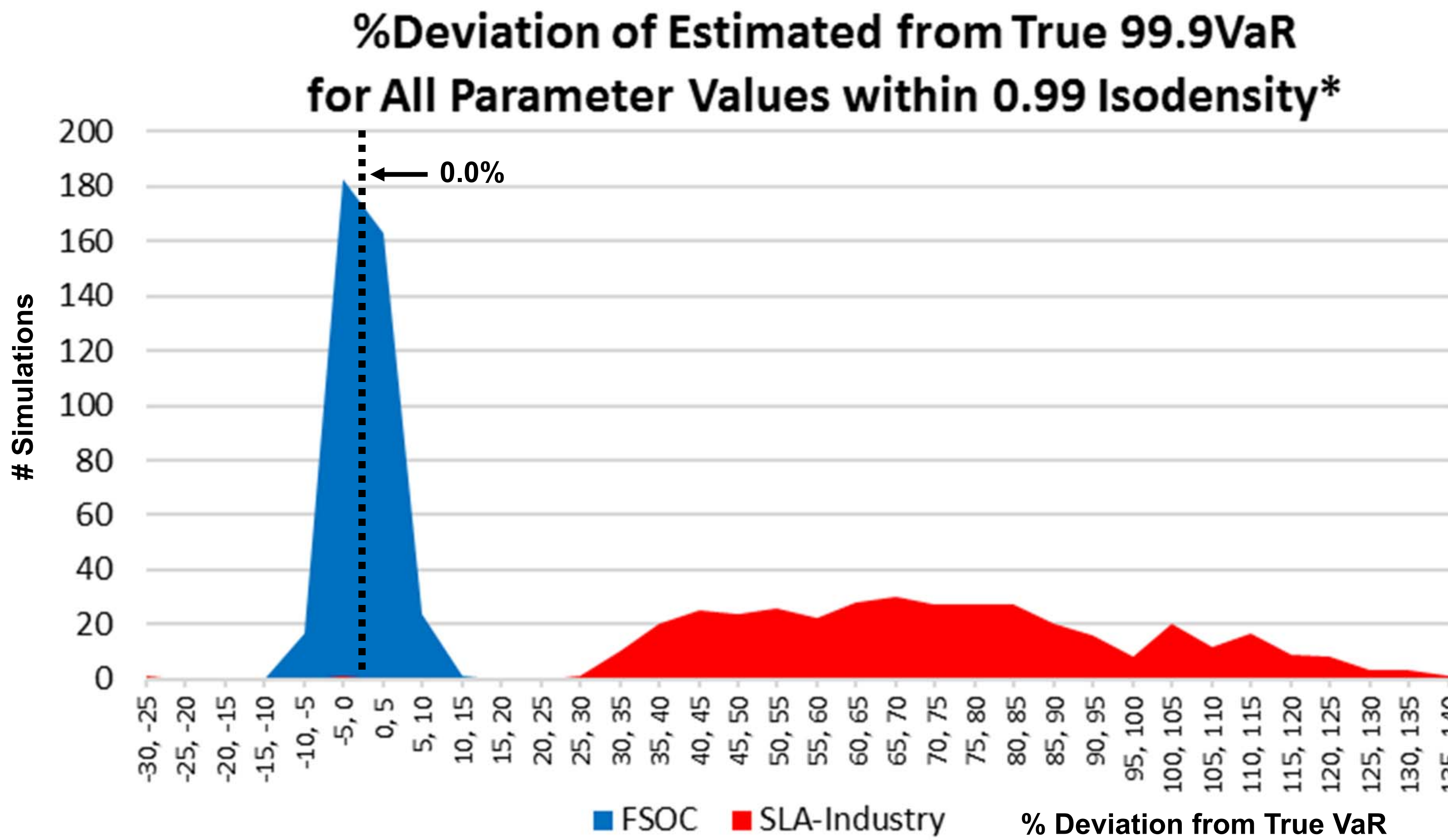
- **However, it is widely mis-implemented when, as is commonplace, loss or returns data is heavy-tailed and samples are modest in size. This results in upwardly biased and very imprecise estimates of, for example, operational and enterprise risk capital that are sometimes orders of magnitude too large (e.g. $100m+ USD).**

- **Unnecessarily tying up this much capital is VERY expensive!**

- **The estimation methodologies we have developed effectively address these financially material shortcomings, providing estimates of extreme losses (capital) that are dramatically more accurate and precise, allowing for superior risk measurement and the freeing up of large amounts of capital.**

* Regulatory missteps away from this approach, and the complete overhaul towards the 'SMA' framework have already, as predicted by experienced quants, notably increased the operational risk capital requirements of major banks (e.g. BNP Paribas, increase of €6b, or 8.8%, see Risk.net, "Switch to standard model boosts BNP Paribas' op risk," 8/1/18).

2. More Accurate and Precise Capital Estimation



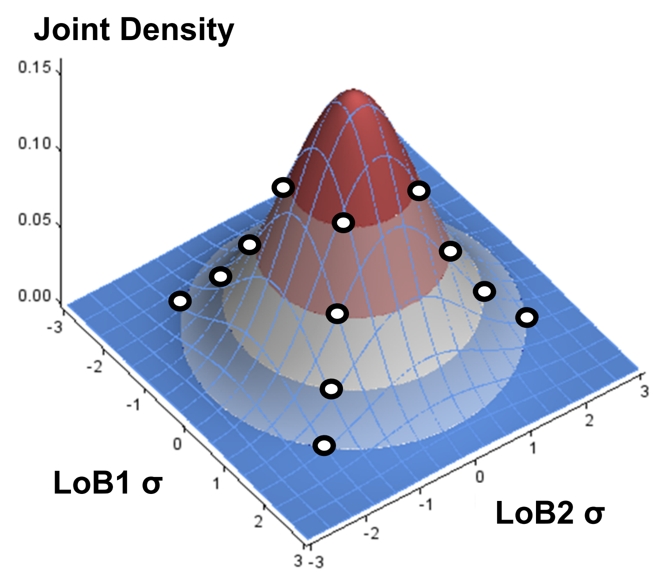
* Poisson Frequency λ=25 annually, ten years, GPD Severity (ξ = 0.95, θ = 5,000).

II. Predictive Analytics, AI, ML Driving Capital Solutions

3. Capital Estimation, Aggregation, Optimal Allocation

For business decision-making, and sometimes regulatory purposes, capital must be jointly estimated and aggregated across risk types/ LoBs, and then allocated back to each of these entities. Our framework uses

- **mathematically and economically optimal allocation methodologies.**
- **the most robust risk metrics, given the marginal loss distributions and estimated dependence structure(s) of the portfolio.**
- **the most efficient computational methods possible given our reliance on the most accurate and least restrictive distributional assumptions regarding the marginals of the portfolio.**
- **All of the above ensure that capital is not overestimated due to highly variable, non-robust methods/measures, and apply seamlessly to portfolios of returns as well as portfolios (distributions) of losses.**



4. Most Efficient & Effective Model Development

- **We use, and provide, <u>the most efficient and effective model development</u> framework and process possible based on**

- **i) <u>decades of sophisticated model development experience</u> across a wide range of verticals, on very large and complex projects, sometimes requiring nearly half a million lines of code.**

- **ii) years of experience with, and <u>deep knowledge of, all regulations</u> related to model development, verification, validation, and model risk management generally (e.g. SR11-7).**

- **Our framework enables us to <u>increase the scope and reliability</u> of model verification and validation, <u>while simultaneously decreasing the time, effort, and money required</u> to do so, achieving the proverbial 'win-win' for our clients.**

- **Model complexity for complexity's sake only serves to increase model risk. However, <u>we are experts in the use and implementation of sophisticated Artificial Intelligence and Machine Learning methods in this setting</u>, and when appropriate do not refrain from their application to achieve competitive market advantage for our clients. In short, we follow Einstein's tenet in our scientific model development efforts: "A scientific theory should be as simple as possible, but no simpler."**

III. Efficiently Satisfy Both Regulatory & Business Goals

- **All our predictive risk models are built for effective and efficient business decision-making for material financial benefit and competitive market advantage.**

- **Financially regulated institutions should not have to, and do not need to, reinvent the wheel adapting their business models to satisfy regulatory requirements. Nor should they have to develop models that serve little or no business purpose.**

- **Our in-depth knowledge of all relevant regulations allows us, in most cases, to intentionally design these models to simultaneously satisfy all relevant regulatory requirements for the risk type in question WITHOUT sacrificing their efficacy vis-à-vis achieving their business objectives. This saves considerable amounts of time and resources.**

- **When it is impossible or not efficient to use the same model to meet both business and regulatory objectives, we dovetail as much as possible to ensure a lean, and internally consistent, model development process: there is no "Use Test" we do not pass, unconditionally, with a "fit for purpose" grade.**

IV. Sample Project Plan/Timeline*

Efficient, Transparent and Modular Resource Planning + Lean Redundancy = Maximum Client Benefit and Competitive Market Advantage

PROJECT X: HIGH LEVEL RESOURCES AND TIMELINE

Phase	Task Description	Resource	Resource DSR Equiv.	Full Days	Timeline - Week #														
					1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
DATA	Define/Refine project scope	1 SME	3	7															
	Define Data Specs/request parameters	1 SME	3	18															
	Receive and Read Data	1 SME, 1 DSR	4	7															
	Data Cleansing / Internal (ext.) Validation	1 SME, 1 DSR	4	21															
	Data Re-request	1 SME, 1 DSR	4	12															
ANALYSIS	Lit Review	1 SME, 1 DSR	4	10															
	Methods Testing	1 SME, 2 DSR	5	35															
	OOS Testing/Verification	1 SME, 2 DSR	5	21															
	Backtesing (alternate data sources)	1 SME, 2 DSR	5	21															
	Front-test / Walk Forward Test	1 SME, 2 DSR	5	21															
RESULTS	Code Documentation	1 SME, 2 DSR	5	14															
	Technical Documentation	1 SME, 1 DSR	4	21															
	Executive Presentation(s)	1 SME, 1 DSR	4	14															
MRM Review	Turn over materials; performance tests	1 SME, 2 DSR	5	21															
PRODUCTION	Full Automation / Parameterization	1 SME, 2 DSR	5	28															
	Results review by LOBs	1 SME, 1 DSR	4	14															
TOTAL				285															

SME = Subject Matter Expert; DSR = Data Scientist/Replicator

*** Strictly for illustrative purposes only.**

V. Expertise and Experience: J.D. Opdyke

- 25+ years Data Scientist
- Risk Analytics expertise and experience spans operational, credit, market, and model risk
- Long-time established industry thought leader
- 14 peer reviewed methodological journal publications and book chapters
- Numerous Fortune and Global 50 financial clients
- Multiple Awards for Risk Methodology papers, Voted 'Paper of the Year' 2012 and 2015, and 'Best Statistics Paper' at National Statistical Computation Conference
- Degrees from Yale and Harvard Universities, post-graduate work in Mathematical Statistics at MIT
- Academic Honors and multiple paid, competitive scholarships