

Introducing TRI-SIGNAL AI-enabled Predictive Equity Analytics with Dynamic State Space

Introducing a new portfolio predictive analytic strategy that avoids market downturns as well as identifies and captures gains for individual stocks, mutual funds, ETFs, managed portfolios, quantitative research and direct indexing.



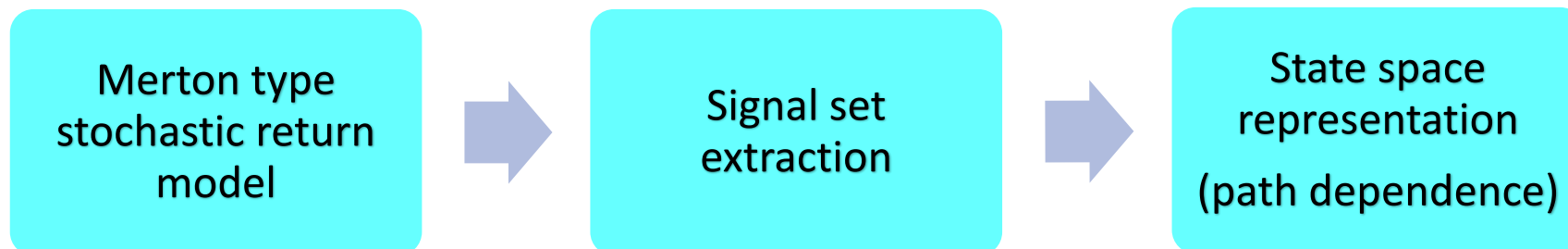
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Predictive Equity Analytics (PEA) defined

PEA is an analytic framework that predicts the price movement of individual stocks or portfolios of stocks with 90-95%+ accuracy for sufficiently strong price signals over the next 1- 5 trading days. It is based on extracting a set of price signals (i.e., signal_1 and signal_3) that facilitate dynamic state space representation of prices. PEA foundational path dependent aspects were first discussed in Bruno Dupire's 2019 paper Functional Ito Calculus.

PEA = Short range GPS for investment return



Predictive Equity Analytics with Dynamic State Space

Definitions:

Position,

Momentum

$$r_t = \mu_t + f(\sigma_t^2) + I_jump_process_t$$

Where return (r_t) is a function of drift (μ_t), volatility (σ_t) and jumps ($I_jump_process$)

- Predictive Equity Analytics with Dynamic State Space **position**
 - defined as the *level of* μ_t
- Predictive Equity Analytics with Dynamic State Space **momentum**
 - defined as the *rate of change of* μ_t

Cf. the **standard momentum** considered in the literature:

- Time series momentum
 - **A security's own past return predicts its future return**
- Cross-sectional momentum
 - **A security's outperformance relative to peers predicts future relative outperformance**

Moskowitz, Tobias J., Yao Hua Ooi, and Lasse Heje Pedersen. 2012. "Time Series Momentum." *Journal of Financial Economics* 104 (2): 228–250. doi:10.1016/j.jfineco.2011.11.003.

For the **first-time**, the time dependent drift term 'meu' including dynamics has been measured with sufficient accuracy and sensitivity to be distinct from variance components.

"The standard assumption of measuring "combined drift and variance produces no bias or error is not valid."

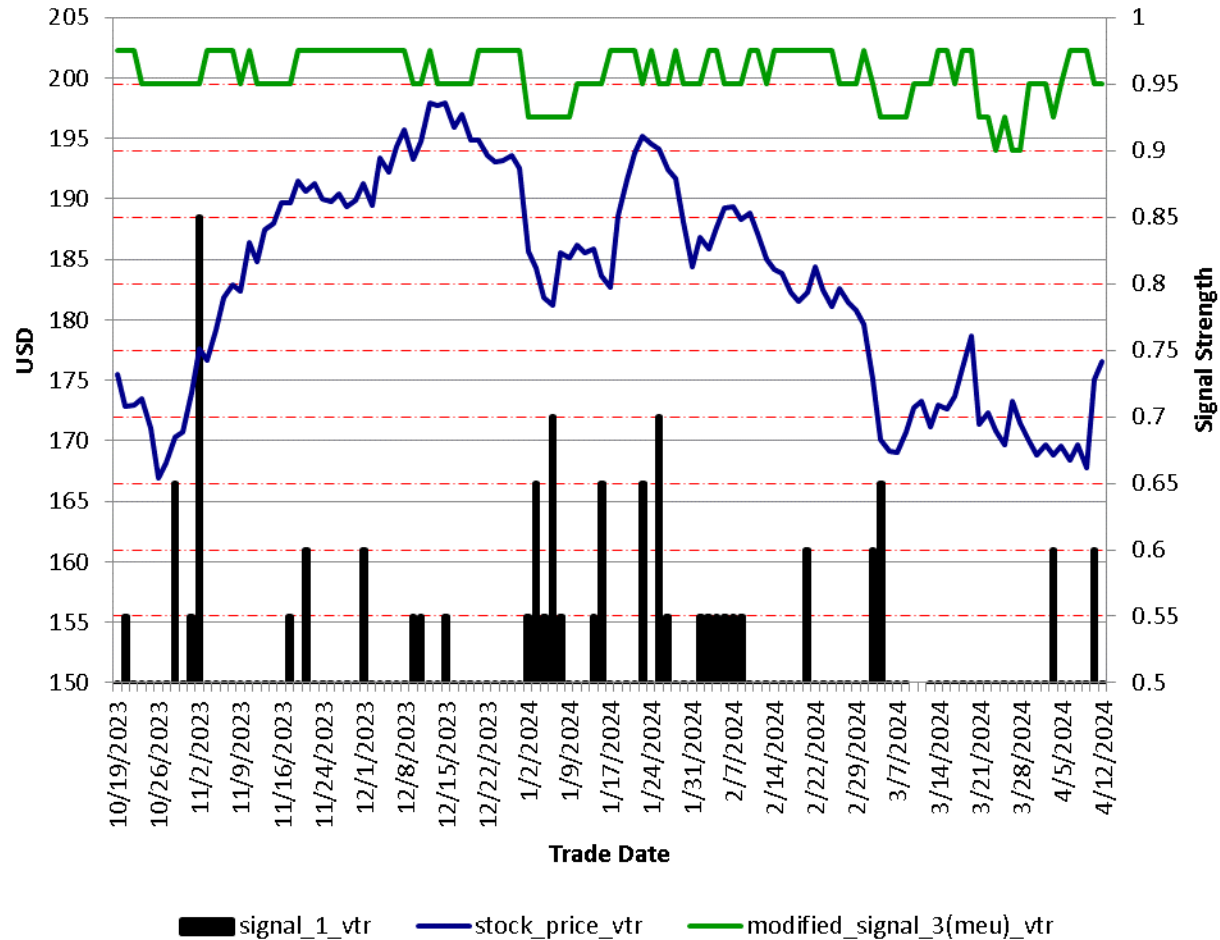
Important

TRI-SIGNAL AI-enabled Predictive Equity Analytics

Prospective and Retrospective Analytics

- **Prospectively** TRI-SIGNAL produces 3 signals for each equity symbol prior to market open. Signals {1,3} used together predict in advance of likely coming change point in next 1 to 3 trade-days. Signal 2 is somewhat predictive for changes in “overall variance” but the same information is available within heavy variance matrix “B” and Poisson point-mass matrix “A” below.
- **Retrospectively** TRI-SIGNAL maps the original time-series to a set of 3 x 3 matrices (‘similar in function to ‘Dolby type music filter’) consisting of Signal “C” matrix, Heavy Variance(tail) “B” matrix and Poisson point mass “A” matrix. The eigenvalues and eigenvectors are calculated for a series of 60 trade-day sliding window at time points {-60,...,-20,-10,-5,-1} which enables **earliest retrospective change-point verification signified by uniform change in sign of eigenvector coefficients**. This referred to as ‘AI-enabled’.

Apple Inc. Common Stock(AAPL) TRI-SIGNAL 121 Trade-day Report ending 2024-04-12 prior to market open.



Prospectively TRI-SIGNAL produces 3 signals for each equity symbol prior to market open. Signals {1,3} used together predict in advance of likely coming change point in next 1 to 3 trade-days.

Predictive signals available prior to market open:

- 1) when (Signal_3) meu (green line) drifts up or down, the time-series moves in “similar direction.”
- 2) The level of meu also is predictive by itself, the more time points at levels above 0.95, the move likely the series is NOT moving down. Below 0.95 the series is definitely moving down.
- 3) Signal_1 at level = 1.0 is associated with prospective change-point detection since it acts much like second derivative of a function in Calculus 1.

S.

Apple(AAPL) Sample Retrospective Matrices

- 1) Original series ABC (yellow),
- 2) Signal "C" matrices (light orange) and
- 3) Combined variance matrices "AB" (light green)

Return is partitioned into drift/meu and variance components over time.

Using combined ABC series, the drop-off of variance contribution is masked as well as drop and then recovery of Signal_3 from t = -40 to t = 0.

		Combined & Collapsed Matrices: A			Combined & Collapsed Matrices: C			Combined & Collapsed Matrices: AB		
(FREQ. / TOTAL COUNT) * AVE.		Signal_3(meu)			Signal_3(meu)			Signal_3(meu)		
		meu < 0.95 meu in [0.9 meu > 0.97			meu < 0.95 meu in [0.9 meu > 0.97			meu < 0.95 meu in [0.9 meu > 0.97		
	Momentun	.0083	.0334	.1253	.0083	.0334	.1253	.	.	.
120 TD, t= 0	Momentun	.0833	.2499	.334	.0667	.2247	.309	.0166	.0252	.0251
	Momentun	.0492	.1166	.	.0328	.0831	.8833	.0164	.0335	.1167
	Momentun	.0166	.0501	.1665	.0166	.0501	.1665	.	.	.
60 TD, t= 0	Momentun	.0833	.1826	.2676	.0833	.1826	.2508	.	.	.0167
	Momentun	.0823	.1503	.	.9993	.0495	.0832	.8827	.0328	.0671
	Momentun	.	.0336	.1329	.	.0336	.1329	.	.	.
60 TD, t= -20	Momentun	.1334	.2655	.2839	.1002	.2491	.2671	.0332	.0165	.0167
	Momentun	.0323	.1161	.	.9977	.0161	.0664	.8655	.0162	.0497
	Momentun	.	.0168	.1335	.	.0168	.1335	.	.	.
60 TD, t= -40	Momentun	.0833	.2495	.3845	.0501	.233	.3511	.0332	.0165	.0334
	Momentun	.0161	.1162	.	.9998	.0161	.0827	.8834	.	.0334
	Momentun	.	.0168	.084	.	.0168	.084	.	.	.
60 TD, t= -60	Momentun	.0833	.3172	.4005	.0501	.2668	.3671	.0332	.0503	.0334
	Momentun	.0161	.083	.	1.0008	.0161	.083	.8839	.	.

Apple(AAPL) Sample Retrospective Matrices- Eigenvalues, Eigenvectors and Change-point detection

- 1) Original series ABC (yellow),
- 2) Signal "C" matrices (light orange) and

Notice the change in sign of coefficients of eigen vectors.

Notice difference in timing of change-point detection of original time series ABC and Signal C.

Apple Inc. Common Stock(AAPL) 120 Trade days ending 2024-04-12 prior to market open 2024-04-15 (L: 172.11, C: 176.55, H: 184.19)												
Message Area												
Time Index		t = -40	t = -30	t = -20	t = -15	t = -10	t = -5	t = -3	t = -2	t = -1	t = 0	
Date		02-14-2024	02-29-2024	03-14-2024	03-21-2024	03-28-2024	04-05-2024	04-09-2024	04-10-2024	04-11-2024	04-12-2024	
Stock Price		184.15	180.75	173.	171.37	171.48	169.58	169.67	167.78	175.04	176.55	
Combined Signal ABC		t = -60	t = -40	t = -30	t = -20	t = -15	t = -10	t = -5	t = -3	t = -2	t = -1	t = 0
EIGEN_	Momentum(+)	-0.08191	-0.144229	-0.150873	-0.186119	0.233846	0.2665292	0.2889321	0.3086047	0.3159887	0.3234333	-0.337098
	Momentum (0)	-0.97593	-0.944968	-0.933831	-0.935787	0.9046502	0.8788221	0.8777273	0.8696358	0.8642952	0.8588073	-0.83621
	Momentum(-)	-0.2021	-0.293656	-0.324341	-0.299435	0.3562642	0.3957703	0.3822472	0.3853526	0.3913372	0.3972921	-0.432572
	Eigenvalues:	0.407095	0.3816754	0.3902823	0.3828923	0.3585815	0.3501389	0.3673287	0.3657806	0.3599267	0.3542388	0.3546193
	Change-Point detected.					Chg_Pt						Chg_Pt
Combined Signal ABC	Average TRENDS	1.000785	0.9997947	0.9991215	0.9976648	0.9986268	0.998336	0.9984977	0.9984048	0.9985792	0.998364	0.9992904
Signal C		t = -60	t = -40	t = -30	t = -20	t = -15	t = -10	t = -5	t = -3	t = -2	t = -1	t = 0
EIGEN_	Momentum(+)	0.098836	0.1478821	0.1545314	0.1833217	0.2433206	-0.280361	-0.295333	0.3138355	0.3250977	0.3365796	0.3365796
	Momentum (0)	0.968513	0.9577948	0.9472883	0.9613511	0.9305483	-0.905799	-0.911625	0.9044623	0.8981205	0.891442	0.891442
	Momentum(-)	0.228504	0.2464954	0.2806509	0.2054199	0.2736334	-0.317689	-0.285863	0.2888856	0.2961265	0.3033895	0.3033895
	Eigenvalues:	0.358555	0.3311189	0.3448169	0.3252626	0.2972636	0.2951451	0.316534	0.3143318	0.3067474	0.299447	0.299447
	Change-Point detected.						Chg_Pt		Chg_Pt			
Signal C	Average TRENDS	1.000652	1.0000539	0.9992786	0.9986052	0.9997151	0.9993796	0.999461	0.9993559	0.9995534	0.9993097	0.9993097

Apple(AAPL) Predictive Report

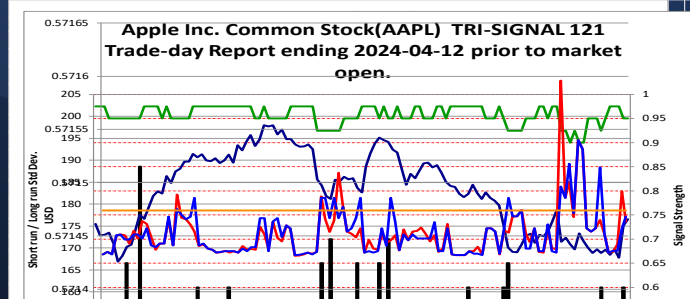
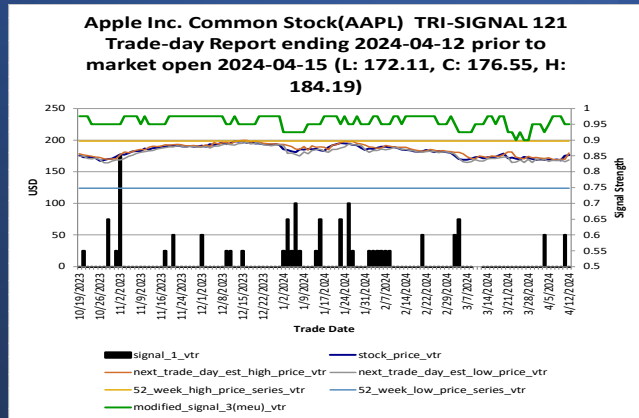
Column V is combined original time-series signal+noise.

Column W is Signal C contribution.

Columns X is combined variance "AB" matrices.

Change-points detected

Yellow highlighted rows indicate bi-weekly pay-date.



Trade Date	Close Date	Behavior	Stock Price	State	Local Path Dependent Drift	Short run	Short run	Short run	Long run	Long run	Long run
12/2024	Horizontal		176.55	75	No Action	1.0010	Buy		.9993		.9991
11/2024	Up		175.04	50	Buy	.998	No Act chg. -5%	REFLECTION	.9993		.9991
10/2024	Down		167.78	77	Sell	.999	No Action		.9993		.9991
9/2024	Up		169.67	77	Buy	.999	No Action		.9993		.9991
8/2024	Down		168.45	71	Sell	.999	No Act chg. +5%	Strong Buy	.9993		.9991
5/2024	Up		169.58	69	Buy	0.9976	Sell chg. +2%	Buy	.9993		.9991
4/2024	Down		168.82	48	Sell	.993	No Act chg. -2	Sell	.9993		.9991
3/2024	Up		169.65	75	Buy	1.0010	Buy		.9993		.9991
2/2024	Down		168.84	75	Sell	1.0010	Buy		.9993		.9991
1/2024	Down		170.03	63	Sell	0.9930	Sell chg. +5%	Strong Buy	.9993		.9991
28/2024	Down		171.48	72	Sell	.996	No Action		.9993		.9991
27/2024	Up		173.31	78	Buy	0.9913	Sell chg. -5%	Strong Sell	.9993		.9991
26/2024	Down		169.71	67	Sell	1.0212	Buy chg. +5%	Strong Buy	.9993		.9991
25/2024	Down		170.85	78	Sell	0.9913	Sell chg. -5%	Strong Sell	.9993		.9991
22/2024	Up		172.28	72	Buy	.996	No Action		.9993		.9991
21/2024	Down		171.37	84	Sell	0.9989	Sell chg. -5%	Strong Sell	.9993		.9991
20/2024	Up		178.67	77	Buy	.999	No Action		.9993		.9991
19/2024	Up		176.08	71	Buy	.999	No Act chg. +5%	Strong Buy	.9993		.9991
18/2024	Up		173.72	81	Buy	.990	No Act chg. -5%	Strong Sell	.9993		.9991
15/2024	Down		172.62	77	Sell	.999	No Action		.9993		.9991
14/2024	Up		173.	71	Buy	.999	No Act chg. +5%	Strong Buy	.9993		.9991
3/13/2024	Down		171.13	75	Sell	0.9976	Sell		.9977		.9916
3/12/2024	Up		173.23	75	Buy	0.9976	Sell		.9977		.9916
3/11/2024	Up		172.75	69	Buy	.997	No Act chg. +2%	Buy	.9977		.9916
3/8/2024	Up		170.73	72	Buy	1.0050	Buy		.9977		.9916
3/7/2024	Horizontal		169.	73	No Action	1.0020	Buy		.9977		.9916
3/6/2024	Down		169.12	73	Sell	1.0020	Buy		.9977		.9916
3/5/2024	Down		170.12	48	Sell	0.9941	Sell chg. -2	Sell	.9977		.9916
3/4/2024	Down		175.1	51	Sell	0.9841	Sell chg. -5%	Sell	.9977		.9916
3/1/2024	Down		179.66	71	Sell	0.9973	Sell chg. +5%	Strong Buy	.9977		.9916
2/29/2024	Down		180.75	75	Sell	0.9976	Sell		.9977		.9916
2/28/2024	Down		181.42	75	Sell	0.9976	Sell		.9977		.9916
2/27/2024	Up		182.63	81	Buy	0.9924	Sell chg. -5%	Strong Sell	.9977		.9916
2/26/2024	Down		181.16	77	Sell	0.9983	Sell		.9977		.9916
2/23/2024	Down		182.52	77	Sell	0.9983	Sell		.9977		.9916
2/22/2024	Up		184.37	77	Buy	0.9983	Sell		.9977		.9916
2/21/2024	Up		182.32	47	Buy	1.0112	Buy	LOCAL INFLECTION	.9977		.9916
2/20/2024	Down		181.56	77	Sell	0.9983	Sell		.9977		.9916
2/16/2024	Down		182.31	77	Sell	0.9983	Sell		.9977		.9916

Predictive Equity Analytics with Dynamic State Space

Starting with base data and upon application of Predictive Equity Analytics with Dynamic State Space framework, the result is two mutually exclusive sets:

1. Equity symbols with predictable structure
2. Equity symbols that are “truly random.”

We analyze equity symbols with predictable structure.

10,000+ symbols over 5+ years: ETFs, mutual funds and stocks in U.S. markets.

Data Science

Predictive Equity Analytics with Dynamic State Space

Time-varying Fokker Planck

State Space Stochastic Processes

Bayesian Analysis and Mixture of Distributions

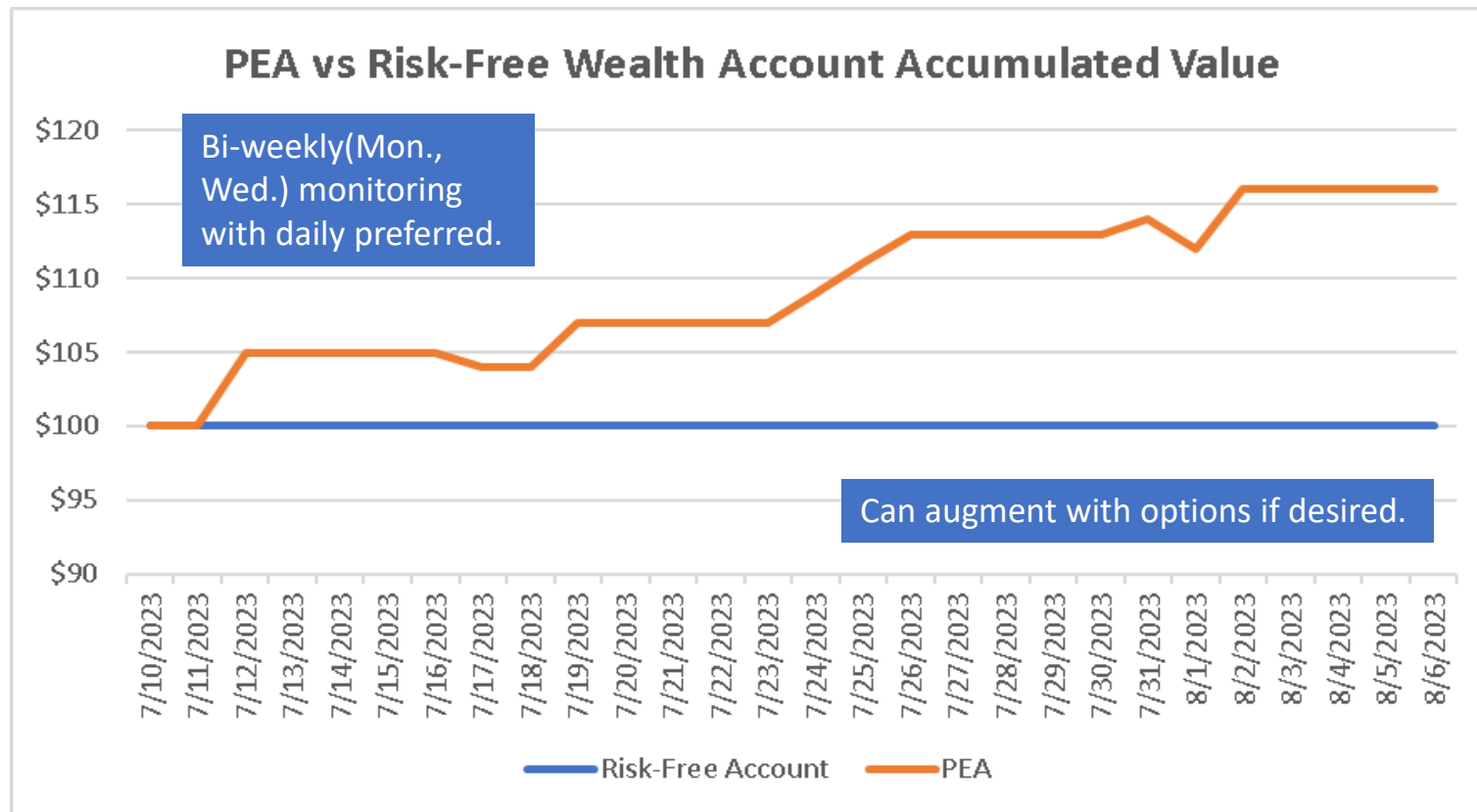
Classical Distributional Theory



Can we make a “GPS” type tool for equities? Answer: Yes

Strategic Goal is to Provide “Predictive Data Analytic Tool” that warns of downside and also informs of upside to increase financial wellness security – wealth accumulation rate and protection.

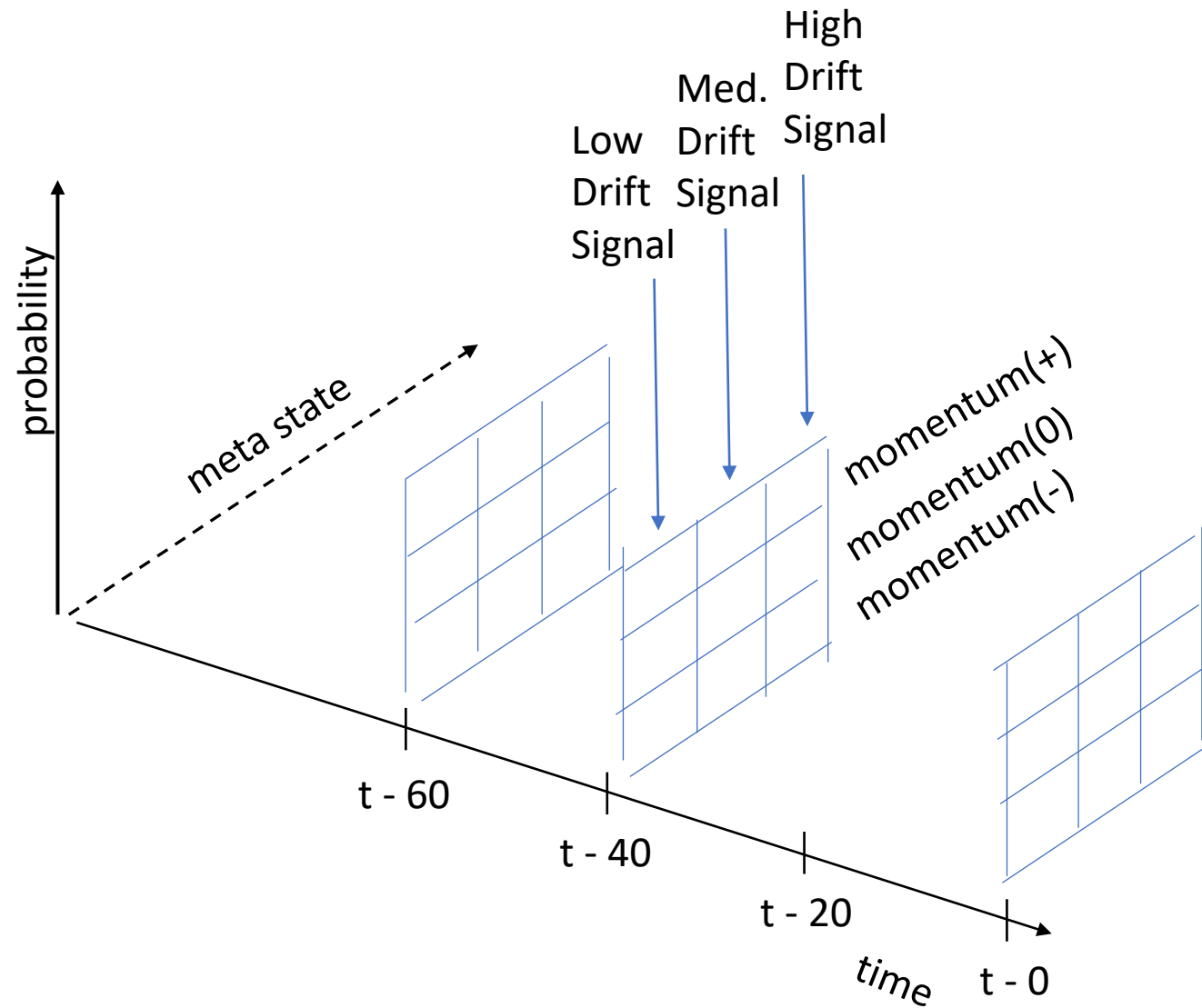
Today, there are no commercially available predictive equity analytic tools available to consumers or policyholders – in insurance or financial services. **What are the implications of first introduction?**



How?

Predictive Equity Analytics with Dynamic State Space can estimate current **eigenvalues** and **eigenvectors** for **discrete approximation to time-varying Fokker-Planck probability distribution transformation in two modes 1) (signal + noise) and 2.) core signal**. At points in time where dominant eigenvalue changes in excess of a threshold a “**change-point**” has occurred and with analysis future behavior of {up, horizontal, down} can be determined. PES w DSS can also **filter Poisson Outliers**.

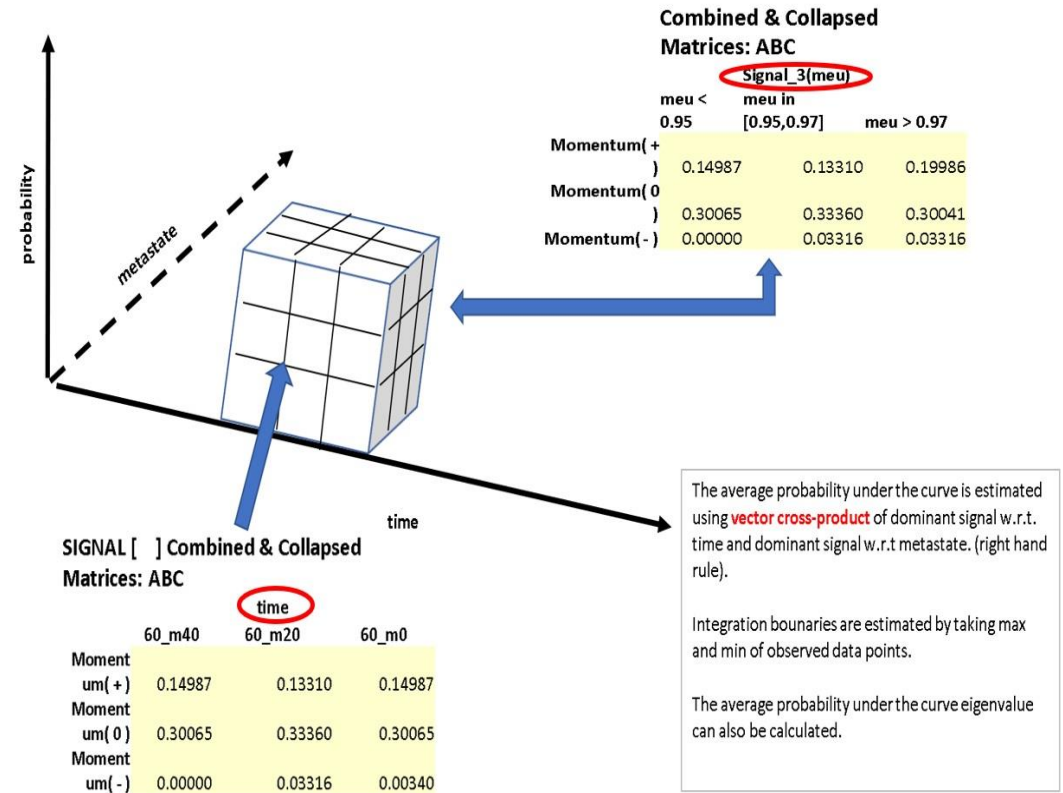
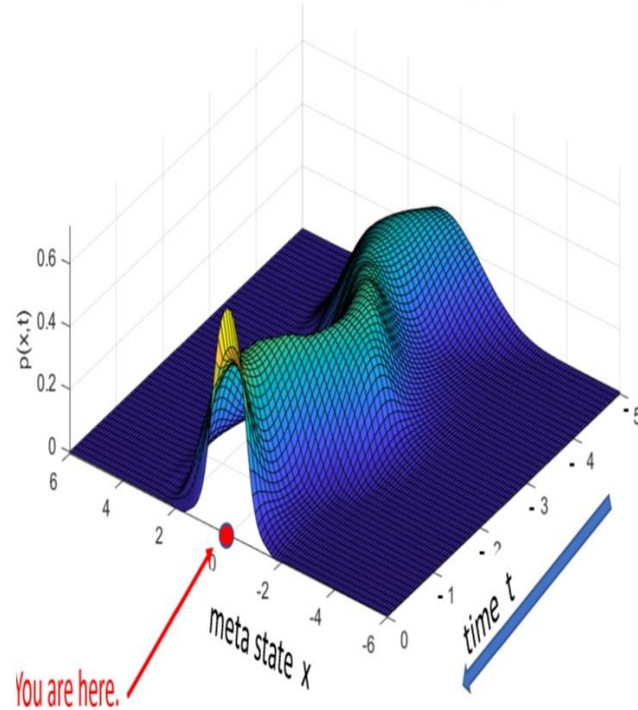
Matrix Theory
Representation as
Alternative
Measurement
Framework: Earliest
possible Change-point
Detection in meta
state dimension as
well as time
dimension.



PREVIEW:

Predictive Equity Analytics with Dynamic State Encapsulates enables Approximation of Time-varying Fokker-Planck Equation using Eigenvalues and Eigenvectors in Meta-state(spatial) and Time dimensions for NEXT Trade-day including Change-point.

Fokker-Planck Eqn. for Stochastic Process with Time-varying Drift and Volatility





APPENDIX

Theoretical Foundations: TRI-SIGNAL Predictive Equity Analytics with Dynamic State Space

What is at the heart of Predictive Equity Analytics with Dynamic State Space that “makes it work?”

Answer: “The core solution is a sufficiently accurate discrete approximation to the time-varying Fokker-Planck probability distribution transformation using eigenvalues and eigenvectors (i.e., linear algebra).”

Viewers are more familiar with Black-Scholes equation which is non-time varying Fokker-Planck equation.

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Drift as predictor

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Poisson outlier process and option pricing

- Merton, Robert (1976) “Option Pricing When Underlying Stock Returns are Discontinuous.”, Journal of Financial Economics. Available at <https://pages.stern.nyu.edu/~dbackus/Disasters/Merton%20jumps%20JFE%2076.pdf>

Change-point Brodsky, Boris, Change-Point Analysis in Non-Stationary Stochastic Models, CRC Press 2017.

Existence and uniqueness of discrete spectral solution (eigenvalue and eigenfunction) to time-varying Fokker-Planck probability transformation equation (Chapters 4 – 9 with chapters 1 -3 as foundation). [Spectral solution is theoretically valid (existence and uniqueness). Estimation of eigenvalues and eigenfunctions remained “a problem for applied research.” From calculus, we approximate eigenfunctions with eigenvectors/lines for small domain neighborhoods.]

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Chapters 1 – 4 of original manuscript available at: <https://www.ma.imperial.ac.uk/~pavl/PavliotisBook.pdf>

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