Equity-Based Insurance Guarantees Conference

Nov. 11-12, 2019

Chicago, IL

Dynamic vs Static Replication

Jeff Greco, FRM Josh Dobiac, LLM, JD, MS, CAIA Hyunsu Kim, FSA

SOA Antitrust Compliance Guidelines SOA Presentation Disclaimer

Sponsored by





Dynamic vs Static Replication

JEFF GRECO, FRM JOSH DOBIAC, LLM, JD, MS, CAIA HYUNSU KIM, FSA Milliman Financial Risk Management LLC November 12, 2019 (1330 - 1430 hours) Senior Director, Head of Strategy Research Senior Director and Risk Consultant Actuary





Presentation Disclaimer

Presentations are intended for educational purposes only and do not replace independent professional judgment. Statements of fact and opinions expressed are those of the participants individually and, unless expressly stated to the contrary, are not the opinion or position of the Society of Actuaries, its cosponsors or its committees. The Society of Actuaries does not endorse or approve, and assumes no responsibility for, the content, accuracy or completeness of the information presented. Attendees should note that the sessions are audio-recorded and may be published in various media, including print, audio and video formats without further notice.



Overview of Options and Replicating Strategies





The World of Options

- Exposures can go far beyond vanilla calls/puts
 - Exercise types: European, American, Bermudan, Asian, ...
 - Underlying: single name, basket, chooser, rainbow, spread, variance/correlation, ...
 - Payoff profile: binary, power, range, ...

- Boundary conditions: barrier, knock-in/out,
 ...
- Exotic terms: cancelable, extendable, amortizing, ...
- Exotic strikes: lookback, cliquet, ...

• Frequently insurance liabilities (particularly life) are long dated and impacted by policyholder behavior



Dynamic vs Static Replication

- Delta hedge alone?
- Include market options to lower trade rebalancing?
- Not a yes/no choice, more of a continuum
- Even (relatively) model independent static replication of variance swaps requires continuous delta hedging



Hedge Effectiveness

- Accuracy is constrained
- Limited market instruments (e.g. long dated)
- Liquidity, transaction costs, slippage
- Model/data dependency
- Policyholder behavior



Costs of Trade Rebalancing

- Execution commission: roughly \$1.00/contract
- Exchange commission: CBOE charges up to \$0.80/contract (\$0.35-\$0.55/contract on SPX)
- Clearing commission: roughly \$1.00/contract
- Clearing fees: OCC charges up to \$0.055/contract
- Options Regulatory Fee: \$0.0388/contract
- Bid/ask spread: at least a few basis points



Hedge Ratio Model Dependency

Call Delta as of 2019-10-15 Expiration Date 2020-09-18 AM; Payoff Date 2020-09-21 Black Scholes Practioners' Black Scholes Heston 0.8 Heston (minimum variance) Call Delta 0,6 0,4 0,2 0-2000 2500 3000 3500 4000 Strike Price



Opportunities

- Dynamic replication can harvest implied volatility premium/term structure
- Can earn spread via cash management
- Optimized ALM, statistical hedge replication
- Maintain adaptability/flexibility/control



Example: "Static" 1-Year S&P 500 Volatility Management

Calendar Year 2018, Target Volatility = 15%							
S&P 500 Price Return 1/2/2018-12/31/2018	Static 15% VM Option Portfolio	Dynamic 15% VM Account (no leverage)					
< -14.73%	Outperform	?					
-14.73% - 0%	Underperform	?					
0%	-4.23%	?					
0% - +7.69%	Underperform	?					
> +7.69%	Outperform	?					
Realized: -7.01%	-10.21%	-5.87%					

- S&P 500 price return between -14.73% +7.69 (S&P 500 total return including dividends = -5.18%)
- Outcome: "static" 15% VM underperforms





"Static" VM Realized Volatility



Dynamic vs Static Hedging





Annualized Savings from CBOE Options Replication



- In this example, we replicated listed CBOE call options with futures contracts on the S&P 500.
- Savings are annualized and reflect the difference between the implied volatility of the call option versus the realized volatility of the replicated position.
- The assumed volatility used to calculate option delta for replication was based on the MGI value for the remaining time-to-maturity of the option.
- Longest option tenors were three years, but we modeled multiple tenors here.
- All savings figures were annualized for comparability.



Replicating 6Y Option – Stylized Example

- Used OTC Dealer Implied Data
- Only Data From 2009 Present is Available
- 5 Options Replicated (annually, starting at 1/9/2009, with 6-year maturity)
- Volatility Used for Delta Target for Replication Taken From MGI
- Bond Portfolio is ZCB with Maturity Matching Time to Expiry of Synthetic Option



Average Annualized Savings Via Replication: 1.62%



Milliman Dynamic Hedged Equity Strategy (MDHE)



For illustrative purposes only, does not represent the performance of any actual investment or portfolio, and should not be viewed as a recommendation to buy/sell.

MDHE has been a component of the Milliman Managed Risk Strategy since MMRS was incepted.

- MDHE is a long-dated constant maturity put replication that uses a delta adjustment to the equity exposure
 - Similar to a protective put, or synthetic long call
 - Implemented with futures contracts
- Seeks to reduce the downside exposure of the portfolio during significant and sustained market declines by:
 - Capturing gains after favorable returns on the portfolio's underlying holdings
 - Harvesting gains from the portfolio's offsetting positions after severe market downturns
- Can augment the strategy with options which may reduce capital in shock scenarios and increase downside protection



Milliman Dynamic Hedged Equity Strategy (MDHE)

- The addition of the options is designed to further enhance the tail risk protection provided by the capital protection strategy
- Long S&P 500 put options are incorporated into Milliman Dynamic Hedged Equity (MDHE) strategy in a delta-neutral manner by utilizing long equity futures to maintain consistent net equity exposure with the core MDHE strategy
- The amount of equity options to be held by the fund is established by evaluating a 5% equity shock scenario on a daily basis and the resulting projected trading requirements that are generated by the shock in order to restore the fund to its volatility and target equity range.
- The options strategy is designed to hold options that will provide 80% of these projected equity trading requirements
- The put options purchased are ~6 month (180-day) to expiration and are sold when there is ~35 days to expiration



Growth of \$100mm **Dynamic Hedged Equity**: All Equity Portfolio



SEE SLIDE 23 FOR ADDITIONAL INFORMATION

Growth of \$100mm **Dynamic Hedged Equity**: All Equity Portfolio



SEE SLIDE 23 FOR ADDITIONAL INFORMATION



Growth of \$100mm **Dynamic Hedged Equity + Options:** All Equity Portfolio



SEE SLIDE 23 FOR ADDITIONAL INFORMATION



Growth of \$100mm **Dynamic Hedged Equity + Options:** All Equity Portfolio



SEE SLIDE 23 FOR ADDITIONAL INFORMATION



Backtested Performance Analysis: All Equity Portfolio Analytics and Standardized Performance (2000-2018)

Analytics and Standardized Performance (2000-2018)								
Full Period	Non-Mgd	MDHE	MDHE + Options 6.90% 11.36% -33.10%					
Return	4.03%	7.77%						
Volatility	15.96%	11.79%						
Drawdown	-58.00%	-34.53%						
Max Volatility	73.40%	30.17%	24.68%					
Return/Risk	0.25	0.66	0.61					

AVG SII CHARGE	37.95%	35.22%	14.70%
RETURN/CAPITAL	0.11	0.22	0.47

		Ann. Returns		Volatility			
Time Period	Non-Mgd	MDHE	MDHE + Options	Non-Mgd	MDHE	MDHE + Options	
1 YR	-8.95%	-7.88%	-7.91%	12.52%	11.58%	10.97%	
3 YR	7.20%	7.63%	6.83%	10.96%	9.72%	9.32%	
5 YR	4.85%	5.19%	4.44%	11.04%	9.77%	9.40%	

	Max Drawdown			Net Equity (Avg.)		
Time Period	Non-Mgd MDHE		MDHE + Options	Non-Mgd	MDHE	MDHE + Options
1 YR	-18.56%	-16.99%	-17.09%	-	96.26%	96.26%
3 YR	-18.56%	-16.99%	-17.09%	-	97.09%	97.09%
5 YR	-18.88%	-16.99%	-17.09%	-	97.08%	97.08%

SEE SLIDE 23 FOR ADDITIONAL INFORMATION



Backtested Performance Analysis: All Equity Portfolio

	Annual Returns			Annual Volatility		Annual Max Drawdowns		Net Equity (Avg.)			
Year	Non-Mgd	MDHE	MDHE + Options	Non-Mgd	MDHE	MDHE + Options	Non-Mgd	MDHE	MDHE + Options	MDHE	MDHE + Options
2000	-14.0%	-10.8%	-11.8%	15.6%	12.8%	12.6%	-18.8%	-14.9%	-15.7%	83.7%	83.7%
2001	-15.8%	-1.7%	-2.9%	17.3%	9.5%	9.4%	-30.7%	-12.4%	-12.8%	60.9%	60.9%
2002	-18.9%	-4.1%	-3.5%	20.3%	9.8%	9.6%	-30.2%	-11.3%	-10.9%	64.0%	64.0%
2003	34.7%	33.3%	31.3%	13.6%	10.1%	10.0%	-14.0%	-6.7%	-7.1%	88.1%	88.1%
2004	15.8%	16.1%	14.5%	9.8%	10.0%	9.9%	-8.0%	-9.1%	-9.4%	101.4%	101.4%
2005	11.4%	10.2%	9.3%	7.9%	7.9%	7.9%	-6.3%	-6.2%	-6.3%	101.3%	101.3%
2006	21.6%	21.4%	21.0%	10.3%	10.3%	10.1%	-12.2%	-12.3%	-11.8%	103.0%	103.0%
2007	12.3%	11.8%	11.4%	13.3%	13.2%	12.6%	-11.3%	-10.9%	-10.1%	103.3%	103.3%
2008	-41.8%	-19.0%	-14.4%	33.2%	15.8%	14.7%	-51.5%	-27.5%	-22.3%	65.8%	65.8%
2009	35.5%	36.1%	29.4%	23.6%	18.5%	18.0%	-26.4%	-16.5%	-18.5%	93.0%	93.0%
2010	13.3%	15.4%	11.9%	16.4%	15.1%	14.1%	-15.5%	-14.5%	-13.9%	100.0%	100.0%
2011	-6.8%	-7.7%	-7.3%	21.1%	15.4%	14.3%	-22.9%	-19.3%	-18.0%	87.0%	87.0%
2012	16.8%	14.6%	11.5%	12.7%	10.4%	10.2%	-12.8%	-10.1%	-10.2%	88.7%	88.7%
2013	23.5%	22.7%	21.9%	9.9%	10.2%	10.0%	-8.5%	-9.6%	-9.4%	104.0%	104.0%
2014	4.8%	5.1%	4.8%	8.9%	8.6%	8.4%	-9.2%	-8.2%	-8.0%	101.2%	101.2%
2015	-1.8%	-1.7%	-2.7%	13.0%	11.0%	10.5%	-14.7%	-12.7%	-12.4%	93.0%	93.0%
2016	8.5%	8.0%	6.6%	13.0%	10.7%	10.3%	-11.3%	-6.4%	-6.3%	91.2%	91.2%
2017	24.7%	25.3%	24.2%	5.7%	5. 9 %	5.7%	-1.9%	-1.9%	-1.9%	103.9%	103.9%
2018	-9.0%	-7.9%	-7.9%	12.5%	11.6%	11.0%	-18.6%	-17.0%	-17.1%	96.3%	96.3%

SEE SLIDE 23 FOR ADDITIONAL INFORMATION



Additional information

- Net Equity: represents the net effective equity exposure of the Managed Risk Portfolio, including the baseline exposure from the underlying holdings, and the effect of the hedging strategy, which dials up or down the equity exposure in response to risk signals
- Dynamic Hedged Equity: All Equity Portfolio (slides 17, 18, 21, 22)
 - Non-Managed Risk: represents the hypothetical historical performance of a 100% MSCI ACWI Index portfolio, assuming that they did not employ an active risk management strategy
 - Managed Risk: represents the hypothetical historical performance of the non-managed risk investment portfolio, assuming they employed the Milliman Dynamic Hedge Equity (MDHE) Strategy over the entire time period
- Dynamic Hedged Equity + Options: All Equity Portfolio (slides 19-20)
 - Non-Managed Risk: represents the hypothetical historical performance of a 100% MSCI ACWI Index portfolio, assuming that they did not employ an active risk management strategy
 - Managed Risk: represents the hypothetical historical performance of the non-managed risk investment portfolio, assuming they employed the Milliman Dynamic Hedge Equity + Options (MDHE + Options) Strategy over the entire time period



Deep Reinforcement Learning Application





Overview of Deep Reinforcement Learning

What is Reinforcement Learning?

• Training an intelligent agent by allowing it to interact with a given environment and learning from trial and error within that environment

Why in Portfolio Management?

- Rather less mathematical constraints / assumptions for modeling model-free
- Proven to work well to capture complex / non-linear patterns
- Neural net based deep learning can alleviate curse of dimensionality enabling large scale portfolio management

Examples of Different Reinforcement Agents

- Deep Q-Network (DQN): Generic Q-network with deep learning overlay
- Policy Search Based
 - ✓ Policy Gradient (PG)
 - ✓ Generic Actor-Critic
 - ✓ Proximal Policy Optimization (PPO): Surrogate objective function



Deep Reinforcement Learning – Deep Hedging (1)

Objective of Deep Hedging

- Given market signal information up to time t, liabilities, and a number of hedging instruments in a pre-defined asset universe, it is trying to determine the most optimized holdings across different hedging instruments while meeting some of the key constraints (i.e. liquidity limit, trading costs, etc) within their risk appetite (i.e. convex risk measure such as CTE)
- And, this is done through the Deep Reinforcement Learning (DRL) by providing "proper" rewards within the environment for certain actions (how to allocate holdings across different assets to hedge liabilities) that the agent takes





Deep Reinforcement Learning – Deep Hedging (2)

Overall Set-up

- Discrete time and market with friction
- $\{I_0, ..., I_k\}$ is a set of market signals up to time k (t_k) that forms the filtration up to t_k
- Z is a F_T measurable random variable indicating liabilities (or, contingent claims)
- δ_k^i is ith asset holdings at time t_k
- H_k is a set of constraints that δ_k is subject to at t_k
- $(\delta * S)_T$ is defined as $\sum \delta_k * (S_{k+1} S_k)$
- $C_T(\delta)$ is defined as $\sum C_k(\delta_{k+1} \delta_k)$, where C_k can take fixed, proportional, and rather complicated cross-asset cost functional forms
- P₀ is defined as cash injection or extraction
- ρ is a convex risk measure meeting the following three properties:
 - Monotone decreasing: if $x_1 \ge x_2$, then $\rho(x_1) \le \rho(x_2)$; in words, this means more favorable positions require less cash injection
 - Convex: $\rho(\alpha x_1 + (1 \alpha)x_2) \le \alpha \rho(x_1) + (1 \alpha)\rho(x_2)$; in words, diversification works
 - Cash-invariant: $\rho(x + c) = \rho(x) c$, where $c \in \mathbb{R}$; in words, adding cash to a position reduces the need for more by that amount



Deep Reinforcement Learning – Deep Hedging (3)

Overall Set-up Cont.

- The problem we are trying to solve here becomes solving the following convex objective function:
- $\pi(-Z) := \inf_{\delta \in H} \rho(-Z + P_0 + (\delta * S)_T C_T(\delta))$
- , where **inf** indicates the greatest lower bound
- In the neural net sense, what we are after using that objective function here is getting the most optimized holdings across different hedging instruments while meeting some of the key constraints (i.e. liquidity limit, trading costs, etc.) within certain risk appetite (i.e. convex risk measure such as CTE)
- $\bullet \quad \delta_k^\theta \mathrel{\mathop:}= f^\theta(I_k, \delta_{k-1}^\theta)$
- , where $\boldsymbol{\theta}$ indicats a set of parameters for the trained neural net
- , where f is a composite functional form of neural nets $\left(i.e.f(g(k(h(x))))\right)$
- , where δ^{θ}_{k-1} indicates the recurrent nature of the neural nets
- (a. k. a. past information from the previous time steps cascade forward to form time dependencies)
- And, we do this rebalancing exercise on a daily basis
 - \checkmark The key structure of training an artificial agent is achieved through the DRL environment



Deep Reinforcement Learning – Equity Allocation Example (1)

Overall Environment Set-up and Assumptions

- Portfolio: M risk assets (in my case, plain equities) + 1 risk-free asset (cash); in this exercise, M == 5
- State: state space indicates the "market condition" at a specific point in time, such as closing prices, mid prices, volume, PE ratio, PB ratio, etc. can stem from one of those "signal processed" data by Natural Language Processing (NLP)
- In this study, somehow we use closing and high prices and we claimed that the combination of these two produced rather "better" results
- Fixed window for a time-series training == 10
- Action: action space is defined here as the "proper" or "desirable" allocating weights. Obviously $\sum_{i=1}^{M+1} a_{i,t} = 1$
- Reallocation is assumed to be done once a day in this exercise
- Reward: fluctuation of wealth minus transaction cost. Just for the experiment purpose, the transaction cost was assumed to be 0.25%
- Train the agent in a way that it maximizes the reward (i.e. Profit or Sharpe ratio in this example)



Deep Reinforcement Learning – Equity Allocation Example (2)

Sample Example Testing Results

- Agent 0: Deep Reinforced Agent
- Agent 1, 2, and 3: Other Sub-optimal Allocation Strategies





Additional Disclaimers

- The materials in this document represent the opinion of the author and are not representative of the viewpoints of Milliman Financial Risk Management LLC.
- For investment professionals use only. Not for public use or distribution.
- Past performance is not indicative of future results. Recipients must make their own independent decisions regarding any strategies or securities or financial instruments mentioned herein.
- Milliman Financial Risk Management LLC does not make any representations that products or services described or referenced herein are suitable or appropriate for the recipient. Many of the products and services described or referenced herein involve significant risks, and the recipient should not make any decision or enter into any transaction unless the recipient has fully understood all such risks and has independently determined that such decisions or transactions are appropriate for the recipient.
- Any discussion of risks contained herein with respect to any product or service should not be considered to be a disclosure of all risks or a complete discussion of the risks involved.
- The recipient should not construe any of the material contained herein as investment, hedging, trading, legal, regulatory, tax, accounting or other advice. The recipient should not act on any information in this document without consulting its investment, hedging, trading, legal, regulatory, tax, accounting and other advisors.
- Milliman Financial Risk Management LLC does not ensure a profit or guarantee against loss.

