#### Monthly Presentation of Drawdown project

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#### Overview

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  - Serial Correlation and Risk Measurements
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#### Maximum drawdown distribution

As we move to longer period, the maximum drawdown distribution tends to:

- 1 have larger mean and variance
- 2 be multi-mode
- 3 lack variability of values
- 4 be centered around several specific values

Take RMZ as an example. (RMZ: The MSCI US REIT Index, a free float-adjusted market capitalization index that is comprised of equity REITs.)

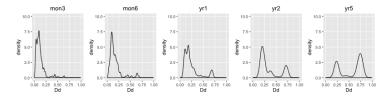


Figure: Maximum drawdown distribution of RMZ as rolling period increases

Later in our project, we mainly use 3 month period.

#### High Correlation between Risk Measures

Maximum drawdown, expected shortfall (ES), value at risk (VaR) and volatility are highly correlated. For our 10 assets of interest, the correlation between the later three are all above 90%. The correlation between maximum drawdown and the later three are weaker with an average around 80%.

The following figure shows the rolling risk measures of RMZ.

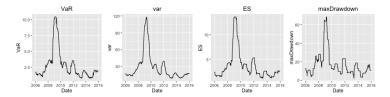
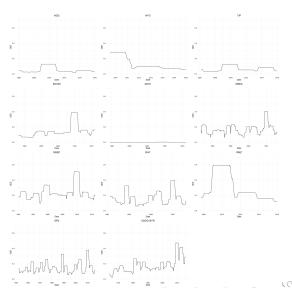


Figure: Comparison of different risk measures of RMZ

#### **CED**

The right column shows the rolling CED under 3-month-2-year Rolling Window (confidence level = 0.9). That means, the maximum drawdowns are calculated based on a 3-month rolling window and the tail means are calculated based on 2-year maximum drawdowns.



#### CED

Note that CED is also highly correlated with other risk measures. The following table is calculated based on 2 year and 3 month rolling windows.

Volatility	VaR	ES
0.94	0.89	0.95
0.98	0.97	0.97
0.77	0.85	0.85
0.84	0.89	0.89
0.84	0.83	0.86
0.91	0.91	0.93
0.92	0.85	0.92
0.96	0.96	0.97
0.84	0.81	0.84
0.91	0.93	0.95
	0.94 0.98 0.77 0.84 0.84 0.91 0.92 0.96 0.84	0.94     0.89       0.98     0.97       0.77     0.85       0.84     0.89       0.84     0.83       0.91     0.91       0.92     0.85       0.96     0.96       0.84     0.81

Table: Correlation between CED (confidence level = 0.9) and other risk measures

#### **Motivations**

- Find a correct model to characterize the returns of financial assets.
- 2 Check the relationship between serial correlations (here we use  $\kappa(1)$ ) and risk measurements.

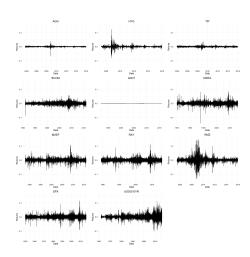


Figure: Daily Returns

#### $\kappa(1)$ and Risk Measurements

- 1 Time series models
  - AR(1)
  - MA(1)
  - ARMA(1,1)
- ② Risk measurements
  - VaR
  - ES
  - CED

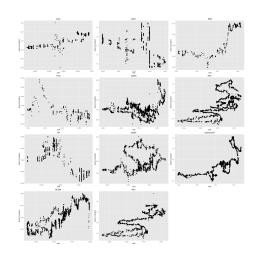


Figure: AR(1):  $\kappa(1)$  versus VaR



## ARMA is not enough...

- Inherently non-stationary
- 2 Clustered Variance
  - Regime Model
  - GARCH Model

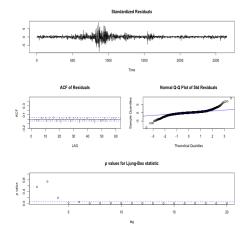


Figure: Fit RMZ Data using MA(1)

#### Regime switching models

Many economic time series data tend to behave differently in adjacent time period. We use the following two-regime switching model to fit the returns:

$$y_t - \mu_{s_t^*} = \phi_{s_t^*}(y_{t-1} - \mu_{s_{t-1}^*}) + \epsilon_t \tag{1}$$

where the number of autoregressive coefficient is set to 1.  $s_t^*$  is a two state Markov chain.  $s_t^*=1$  represent regime 1 and  $s_t^*=2$  represent regime 2.  $s_t^*$  depends on the past only through the most recent values:

$$P(s_t = j | s_{t-1}, s_{t-2}, \dots) = P(s_t = j | s_{t-1}) = p_{ij}$$
(2)

Asset	Regime 1 High volatility	Regime 2 Low volatility
AGG	-0.134	-0.114
HYG	-0.010	0.025
TIP	0.039	-0.026
BCOM	-0.046	0.050
MXEA	0.095	0.109
MXEF	0.221	0.254
RAY	-0.039	0.052
RMZ	-0.244	0.007
SPX	-0.018	0.113
USGG10YR	-0.031	0.082

#### Regime switching models

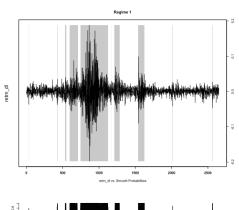
Returns of high volatility regime has larger standard deviation, skewness and kurtosis than that of the low volatility regime. The return distribution of high volatility regimes are more like to be sknewed (both positive and negative). They also tend to have fatter tailed than the return distribution of low volatility regimes.

	Vola	tility	Skew	vness	Kur	tosis
Asset	Regime 1	Regime 2	Regime 1	Regime 2	Regime 1	Regime 2
AGG	0.141	0.036	-1.59	0.01	17.15	0.60
HYG	0.265	0.055	0.60	0.00	8.76	0.83
TIP	0.113	0.049	0.18	-0.06	2.50	0.16
BCOM	0.205	0.096	-0.25	-0.04	1.92	0.28
MXEA	0.253	0.101	-0.14	-0.02	4.26	0.25
MXEF	0.303	0.119	-0.08	-0.06	2.39	0.38
RAY	0.307	0.114	-0.39	-0.06	6.43	0.55
RMZ	0.661	0.159	0.29	-0.15	2.92	0.79
SPX	0.260	0.099	-0.43	-0.02	9.11	0.56
USGG10YR	0.314	0.098	0.09	-0.05	2.67	1.17

Table: Summary statistics of two regimes for various assets

## Regime switching models-Example: RMZ

The right panel shows the regime plot of RMZ returns and its smoothed probabilities. The regime switching model seperate the 2008 financial crisis as high volatilty regimes. The number of trading days of high and low volatility regime is 699 and 1954 seperately.





#### Regime switching models-Example: RMZ

In order to make a consistent comparison of risk diagnostics between two regimes, we ignore some short discontinuity and pick two longest single occurring episode for each regime. Both episode contain 530 trading days. The episode of regime 1 range from 10/30/2007 to 12/07/2009, and the episode of regime 2 range from 06/20/2013 to 07/29/2015. The right panel shows risk measures of two regimes.

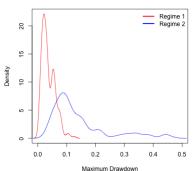
	Regime 1	Regime 2
	High volatility	Low volatility
VaR (empirical, $p = 0.95$ )	7.4%	1.5%
ES (empirical, $p = 0.95$ )	9.9%	2.1%
CED (one-month, $p = 0.9$ )	38.4%	8.4%
Serial correlation (order $= 1$ )	-0.257	-0.026
Serial correlation (order $= 2$ )	-0.023	0.008

Table: Risk diagnostics for RMZ of two equal-length episode of each regime

## Regime switching models-Example: RMZ

The right panel shows the maximum drawdown distributions of two regimes. The regime with high volatility has larger mean, variance, skewness and kurtosis.

#### Density of maximum drawdown distribution of two regim



## Summary of GARCH Model

Table: Best GARCH Model for the residuals after Fitting ARIMA

Asset	ARIMA (p,q) + GARCH(m,n)
AGG	ARMA(5,5) + GARCH(1,1)
HYG	ARMA(3,1)+GARCH(1,1)
TIP	GARCH(1,1)
ВСОМ	GARCH(1,1)
MXEA	ARMA(2,2)+GARCH(1,2)
MXEF	ARMA(4,2) + GARCH(1,1)
RAY	ARMA(2,2) + GARCH(1,1)
RMZ	MA(1) + GARCH(1,1)
SPX	ARMA(2,2) + GARCH(1,1)
USGG10YR	GARCH(1,3)

## RMZ example: Workflow and Diagnostics

- Fit Best ARIMA model, and extract residuals.
- Select proper GARCH model for the residuals, based on BIC.
- Check the diagnostic plots
  - Good in general.
  - Heavy Tail.

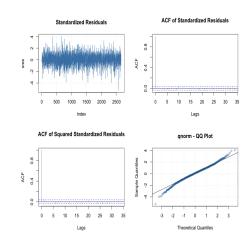


Figure: RMZ example: Diagnostics after Fitting Residual with GARCH(1,1)

#### RMZ example: Predictions

- Empirical results are similar to the estimation.
- The second plot give a confident interval for residuals
- 3 Several steps forward estimation.

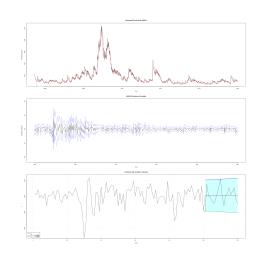


Figure: RMZ example: Some Prediction Results

## $\kappa(1)$ and CED Using the "Best" Model

- Almost no pattern there.
- Correlations are small, and almost negative.
- 3 Similar to other risk measurement, but less significant

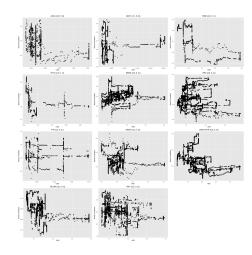
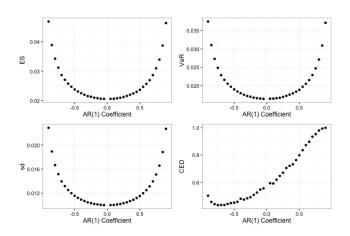


Figure:  $\kappa(1)$  versus CED



## Simulation of AR(1) model



# The End