RMBS Through-the-Cycle Macroeconomic Scenarios

April 9, 2017

Structured Securities Group

Structured Securities Group (SSG)

National Association of Insurance Commissioners

BACKGROUND

National Association of Insurance Commissioners

Rationale

- Interested parties requested that the NAIC explore the use of economic scenarios for the year-end modeling process which are consistent year to year and can be modelled internally.
    - This is an issue that has been consistently raised since the NAIC adopted financial modeling methodology.
- The TF asked SSG to research and propose such set of scenarios.

National Association of Insurance Commissioners

Use of Economic Scenarios

- In the context of the Year-end project, the macro-economic scenarios are the initial step and are used by the mortgage credit model to calculate performance metrics.

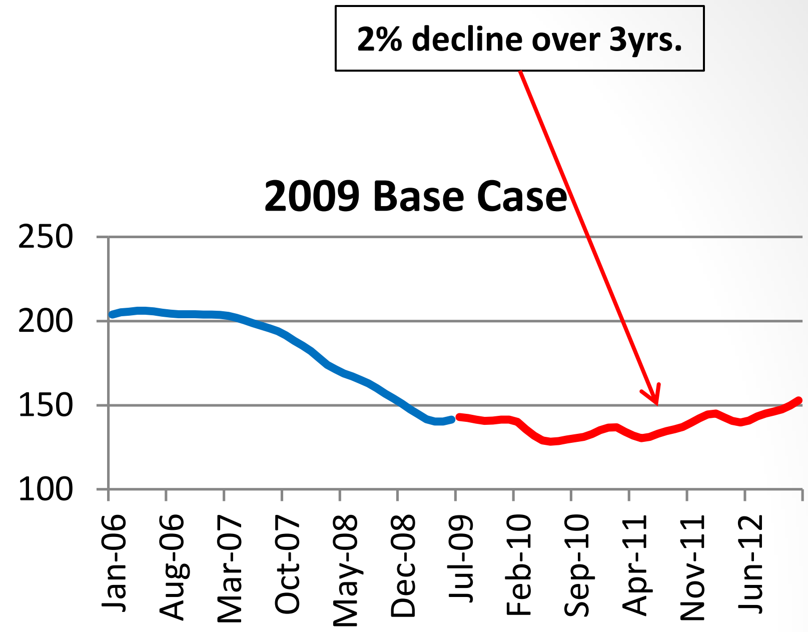
Macroecon. Model	Credit Model	Waterfall	Valuation
Projects macroeconomic variables	Projects the performance of each loan based on macroeconomic scenario and loan characteristics	Allocates cash-flows/ losses to each tranche in the deal	Calculates some aspect of risk (e.g. rating, price)

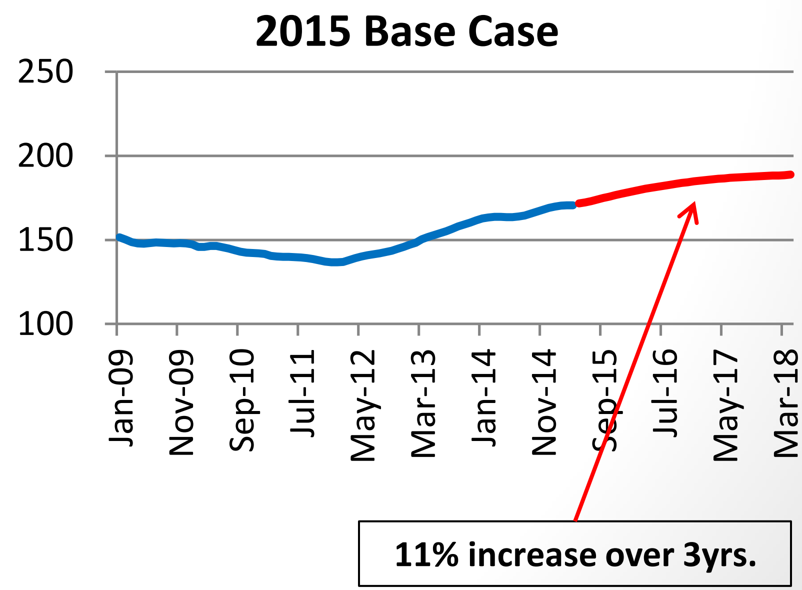
National Association of Insurance Commissioners

Current Approach

- Since 2009, the NAIC has followed the same approach for determining macro-economic scenarios.
  1. Use a base case scenario, from a third party, which constitutes their best estimate of future events given current conditions.
  2. Generate stress "paths" around the base.

- This approach generates inherent pro-cyclicality i.e. the base prediction is negative in bad times and positive in good times.





National Association of Insurance Commissioners

Study Criteria

- The scenarios produced by the SSG must be able to meet the following criteria:

    1. Be based on historical and publically available data: e.g Case-Shiller for RMBS.
    2. The model must be able to generate several forecast “paths” which can statistically represent various percentiles (e.g. 5th, 50th, 75th and 95th).
    3. Qualitatively, we would expect that the extreme scenarios approximately mimic historical extremes (e.g. the RMBS Most Conservative scenarios should approximate the recent financial crisis).
    4. Be “memoryless” (i.e. possess the Markov property). This is the key criteria that ensures consistency and a-cyclicality.

- The resulting paths / scenarios would be converted into periodic percentage changes to be applied annually to then current value (e.g. HPI).

National Association of Insurance Commissioners

MODEL DEVELOPMENT LOG

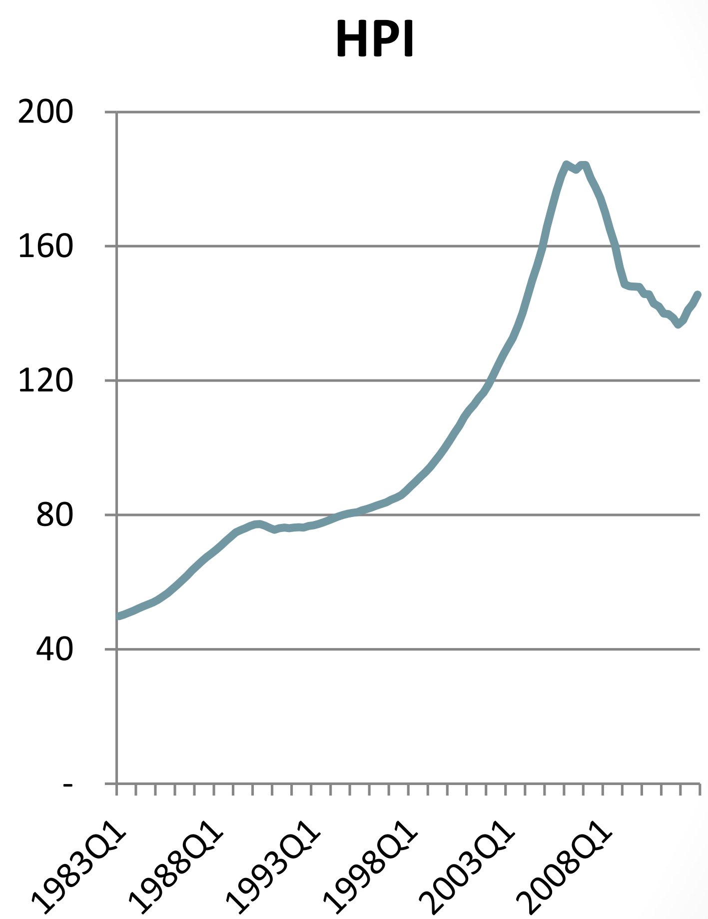
Introduction

- The process of developing the scenario flows through four stages:
- Data Analysis
  - Ensure data is stationary; apply transforms
- Model Fitting
  - Select and parametrize an ARIMA model
  - Analyze residuals
- Simulation Model
  - Simulate the selected model to produce a number paths.
- Scenario generation
  - Select appropriate percentiles for macro-economic scenarios

NAIC
National Association of Insurance Commissioners

Data: Source

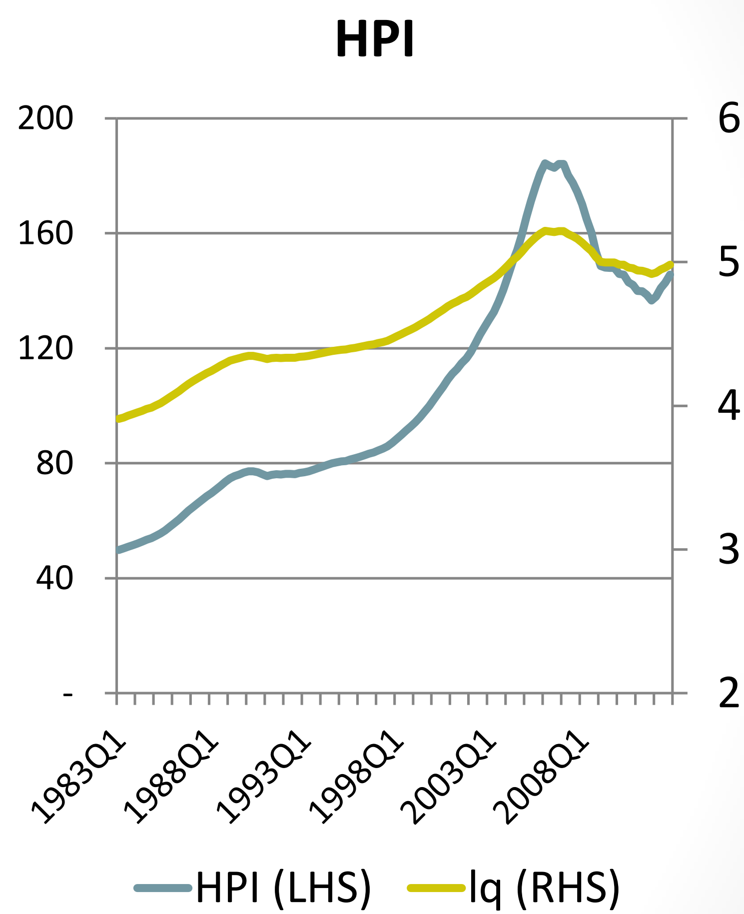
- Used the U.S. Case-Shiller Home Price Index: Single-Family Aggregate Index from Q1 1983 to Q4 2012. The index is already Seasonally Adjusted.
  - Time frame matches one used by the AAA for Bond Factor Research
  - Used Quarterly data to reduce noise
- Since the time series is proprietary, we would not be able to redistribute to interested parties.



National Association of Insurance Commissioners

Data: Log Transform

- Most financial time-series show increasing variance with time.
- However, time-series models require that the time series be at least “weakly stationary”.
- One popular way to stabilize variance is a log transform.
  - In our case, the new data set is called **`lq`**.



Data: Analysis of Stationarity

- To further test unit roots and to determine if the data is stationarity, we used the Augmented Dickey-Fuller test ("ADF") for **`lq`**.
- The test <u>rejects</u> the null hypothesis that **`lq`** has unit roots / is "explosive".

R Console:

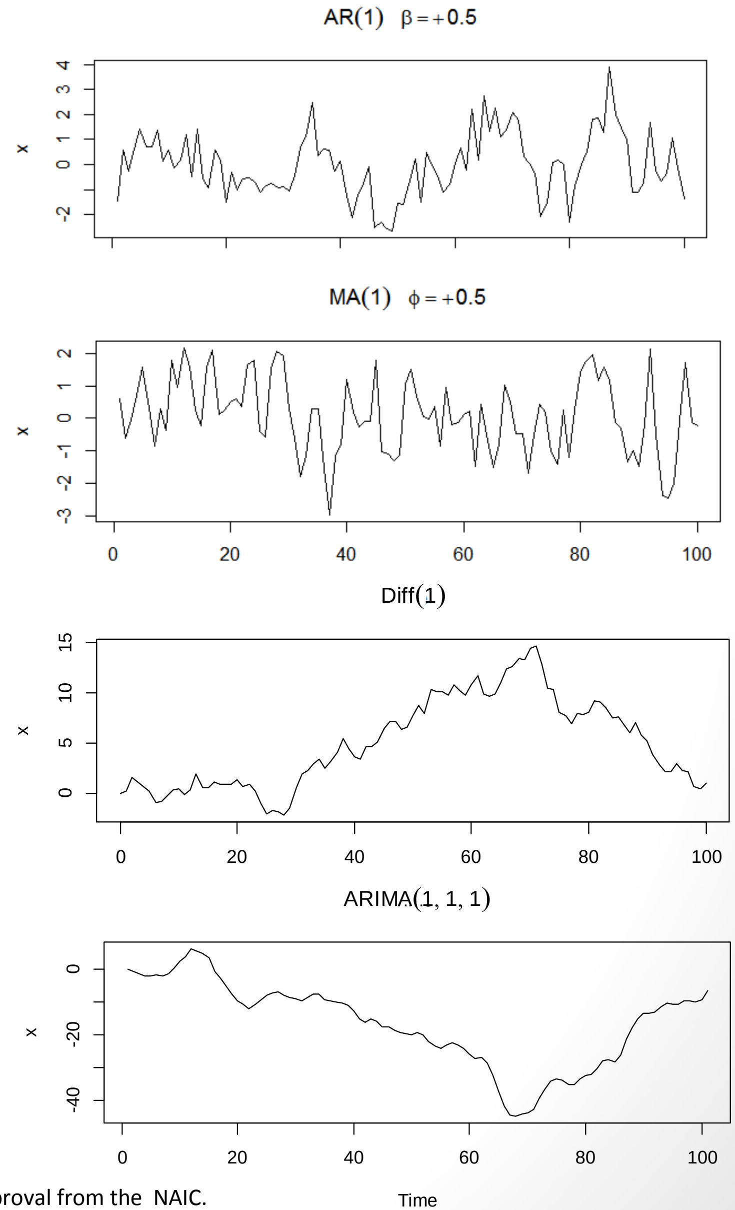
```
> adf.test(lq)

        Augmented Dickey-Fuller
        Test

data:  lq
Dickey-Fuller = -3.9467, Lag order
= 4, p-value = 0.01422
alternative hypothesis: stationary
```

Structured Securities Group (SSG)

NAIC
National Association of Insurance Commissioners

Model Fitting: ARIMA models

- ARIMA (**A**uto**R**egressive **I**ntegrated **M**oving **A**verage) are the workforce of time-series modeling.
  - They are capable of linearly combining several auto-regressive and moving average parameters.
- For analytics, Revolution **`R`** version 7.5 (running **`R`** 3.2.2) and Prof Hyndman **`forecast`** package version 7.3 were utilized.



National Association of Insurance Commissioners

Model Fitting: `auto.arima`

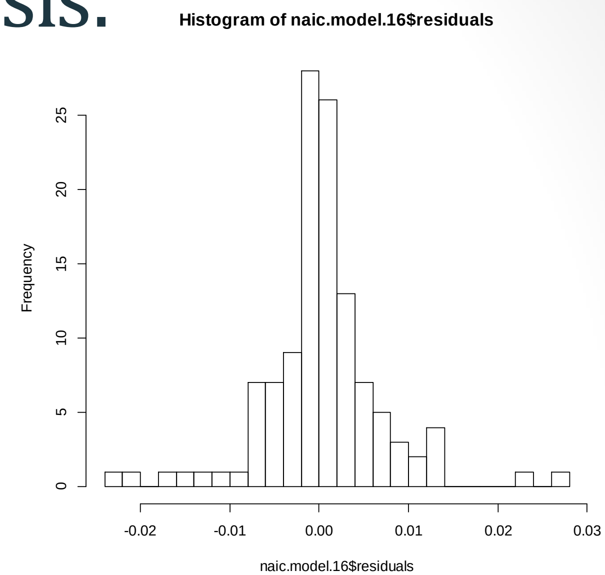
- We used the **`forecast`** package's **`auto.arima`** function to select an ARIMA (2,0,0) model.
- **`auto.arima`** selects the model by maximizing the log likelihood while minimizing complexity based measures (e.g. AIC, AICc, BIC).
  - Models which are highly complex tend to overfit the data and not be useful for prediction.

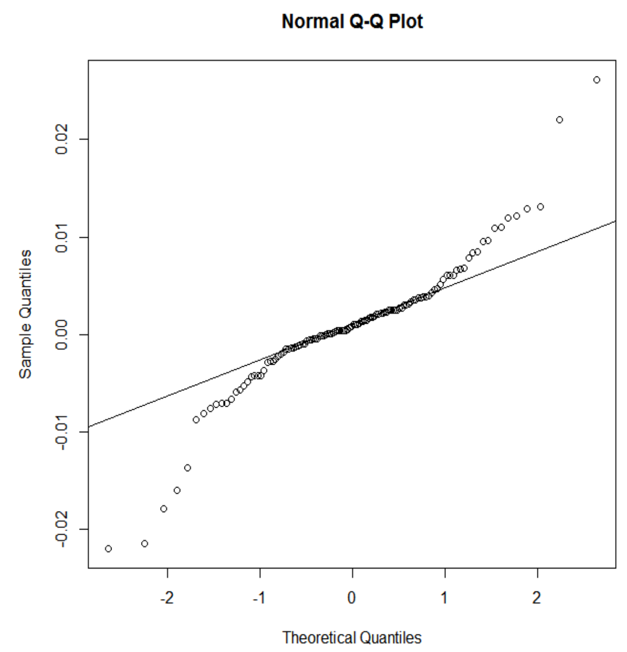
R Console:

```
>auto.arima(lq, test="adf")

Series: lq

ARIMA(2,0,0) with non-zero mean

Coefficients:

        ar1      ar2     intercept

        1.9316  -0.9323     4.9658
s.e.    0.0536   0.0542     2.5143

sigma^2 estimated as 4.625e-05:
log likelihood=429.86

AIC=-851.71   AICc=-851.36   BIC=-
840.56
```

Model Fitting: Residual Analysis:

- Lastly, we examine the residuals from the model.
  - Residuals are the difference between the x_{actual} and x_{fitted}
- In our case, the residuals appear to be heavy tailed – reflecting the increase in volatility during the crisis.
- Practically, this implies that for simulations we cannot use a normally distributed error term.   Instead we choose to bootstrap the residuals.





Structured Securities Group (SSG)

National Association of Insurance Commissioners

Simulation: Motivation

- We have a number of constraints in leveraging the model results for predictive value.
- Some are self-imposed:
  - Through-the-cycle i.e. independence of forecast from actual values before t_0.
  - Ability to select specific "paths" from the simulation.
- Others result from an analysis of model residuals – would like to maintain the non-normality of the error structure.
- We have chosen to implement a model-based moving block bootstrap, based on Lahiri [1999 and 2004].
  - "Model-based": we use the actual residuals from the fitted model
  - "Bootstrap": we resample the residuals with replacement
  - "Moving block": instead of sampling a single residual, we sample block which retain any dependence structure in the residuals.

Simulation: Algorithm

Algorithm `naic.arima.3`

Given *model, npaths, sim length, and block len*gth

For each path:

Select random *starting point* in the historical data (this is the TTC element)

Create a path specific *innovation vector* by randomly (with replacement) stacking blocks (of *block length*) of residuals up to *sim length* (this is the moving block approach)

Simulate a path from the *starting point* using the *innovation vector* above

Normalize data by dividing the resulting values by the value at the *starting point*

Repeat *npaths* times

National Association of Insurance Commissioners

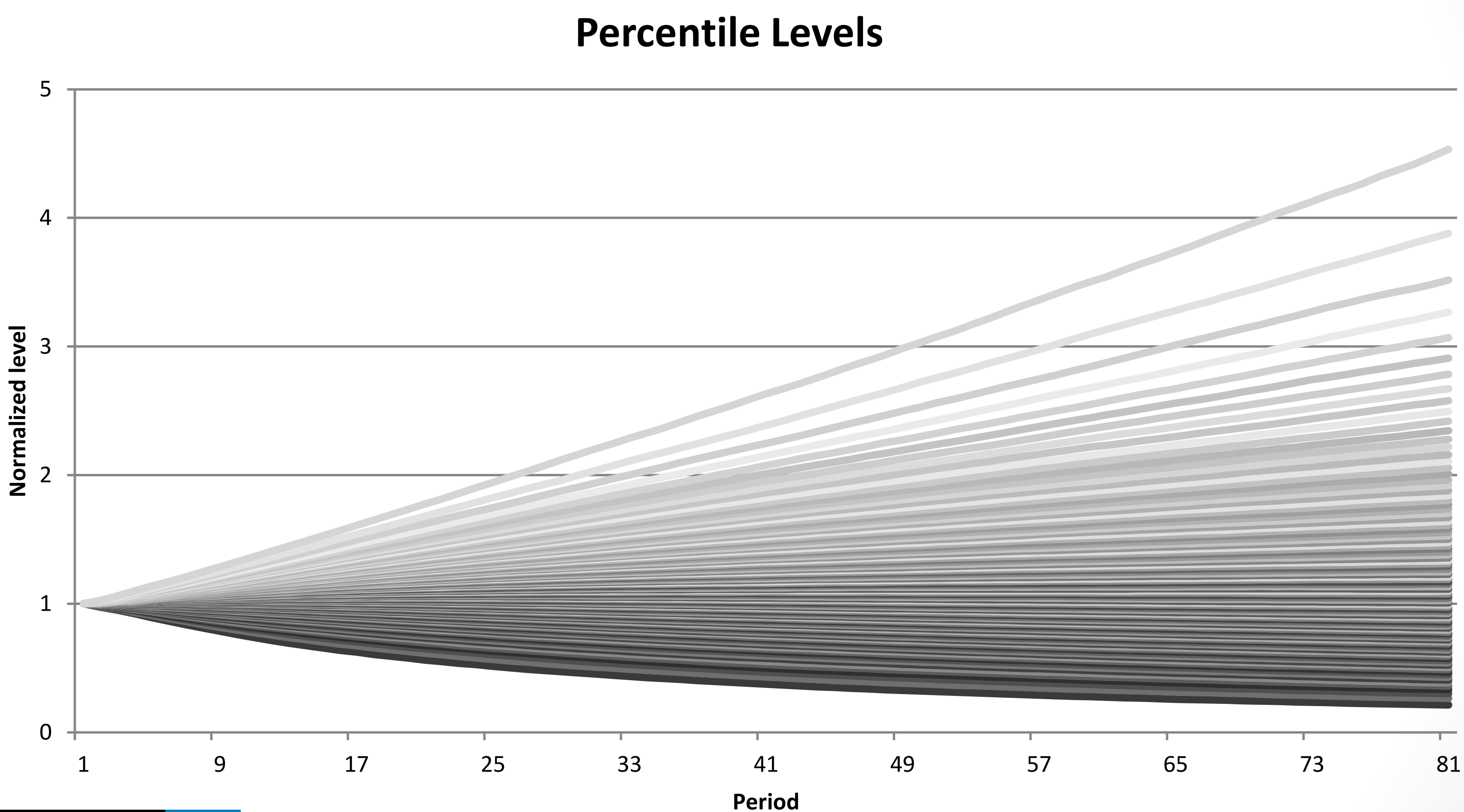
Scenario Generation

- The **R** code for the `naic.arima.3` function, along with the detailed model development log is available to interested parties.
- To create the required distribution we ran 100,000 paths, 80 quarters into future, using a block of 4 residuals.
- The data were then re-transformed into the original scale by the application exp() function and normalized by dividing the initial value.
- Percentiles were chosen by using by using the `quantile` function.
  - This selects the X percentile at each time period – independent of a particular path. We believe that this best fits the approach taken by the Academy.
  - However, we are also open to other (e.g. kernel based) methods of calculating the percentile.
- These scenarios would then be used for all future modeling.

NAIC
National Association of Insurance Commissioners

Scenario Generation: Results

➢ The Chart below shows the probability cone for the simulation.



Potential Scenarios

- Based on the slightly conservative skew employed for YE process since 2011, we recommend using the scenarios below.
- We believe these scenarios meet our qualitative criteria of capturing the effect of housing bubble of the 2000s.

Scenario	Percentile Chosen	3 yr.	5 yr.
Optimistic	75th	16%	26%
Base	50th	7%	10%
Conservative	25th	-3%	-7%
Most Cons	5th	-19%	-29%

5 year scenario comparison

- A comparison of the generated scenarios versus those used for the past two years.

Scenario	5 yr.	2016 5 yr.	2015 5 yr.
Optimistic	26%	37%	43%
Base	10%	13%	18%
Conservative	-7%	-11%	-8%
Most Cons	-29%	-26%	-23%

NAIC
National Association of Insurance Commissioners

NEXT STEPS

Next Steps

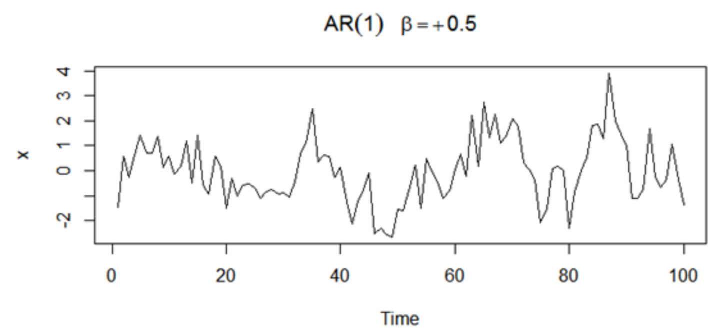
- We ask that the Task Force expose the proposed model for comments.
- The comments should be technical – we have taken extra steps to be transparent and expect detailed, technical comments in return.
- Once the comments are received, the TF can decide to proceed with the CMBS portion of the project.

APPENDIX 1: ARIMA MODELS

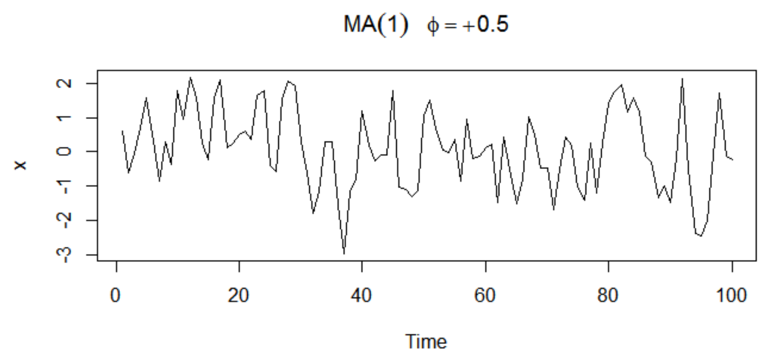
Side Bar: ARIMA models 1

- ARIMA stands for **A**uto**R**egressive **I**ntegrated **M**oving **A**verage.

  - **A**uto**R**egressive: Next observation is a "regression on itself", so ARIMA (1,0,0) is: $Y_t = \beta Y_{t-1} + \varepsilon_t$ where $\boldsymbol{\varepsilon}$ is a random factor.



  - **M**oving **A**verage: Next observation is a function of the previous random factors, so ARIMA (0,0,1) is: $Y_t = \phi\varepsilon_{t-1} + \varepsilon_t$ where $\boldsymbol{\varepsilon}$ is a random factor.



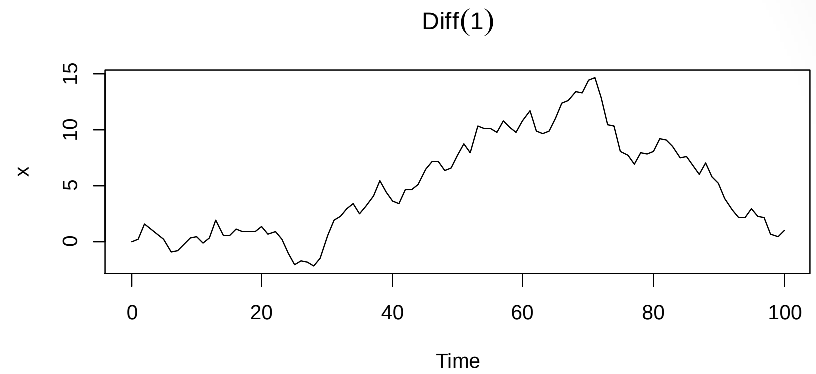
Structured Securities Group (SSG)

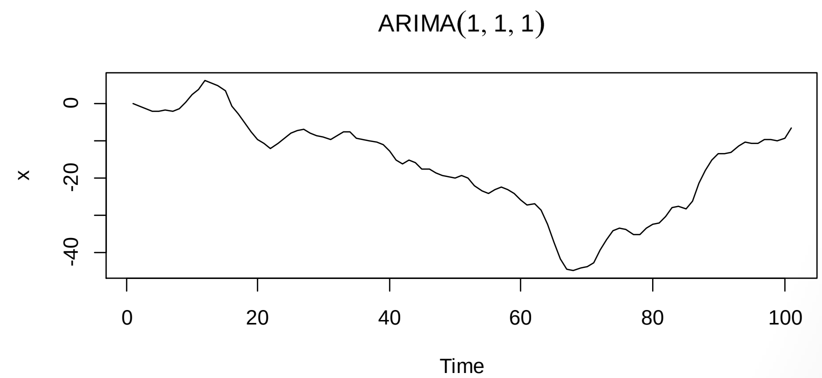
National Association of Insurance Commissioners

Side Bar: ARIMA models 2

- Lastly, "**I**ntegrated" relates to the differences between Y_t and Y_{t-1}. For example, a random walk can be written as an ARIMA (0,1,0): $Y_t - Y_{t-1} = \varepsilon_t$ where $\boldsymbol{\varepsilon}$ is a random factor.

- ARIMA combines all three elements in one set of modeling tools.





National Association of Insurance Commissioners

REFERENCES

References

- Box, G. E., Jenkins, G. M., Reinsel, G. C., & Ljung, G. M. (2015). *Time series analysis: forecasting and control*. John Wiley & Sons.
- Hyndman, R. J., & Khandakar, Y. (2007). *Automatic time series for forecasting: the forecast package for R* (No. 6/07). Monash University, Department of Econometrics and Business Statistics.
- Lahiri, S. N. (1999). Theoretical comparisons of block bootstrap methods. *Annals of Statistics*, 386-404.
- Lahiri, S. N. (2013). *Resampling methods for dependent data*. Springer Science & Business Media
- Pascual, L., Romo, J., & Ruiz, E. (2004). Bootstrap predictive inference for ARIMA processes. *Journal of Time Series Analysis*, *25*(4), 449-465.
- Ruiz, E., & Pascual, L. (2002). Bootstrapping financial time series. *Journal of Economic Surveys*, *16*(3), 271-300.

National Association *of* Insurance Commissioners