

# **RIPPLES ON FINANCIAL NETWORKS**

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**NAMAN GUPTA**

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# RIPPLE EFFECT



SINGLE DROP <=> SINGLE ASSET



MULTIPLE DROPS <=> MULTIPLE ASSETS

# GOALS AND OBJECTIVES

“To find the exact path the ripple effect follows on the whole network of assets”

WHY DOES RIPPLE PROPOGATE?

“Because of the interlinkages across stocks, volatility shock to a particular asset propagates through the network creating a ripple effect.”

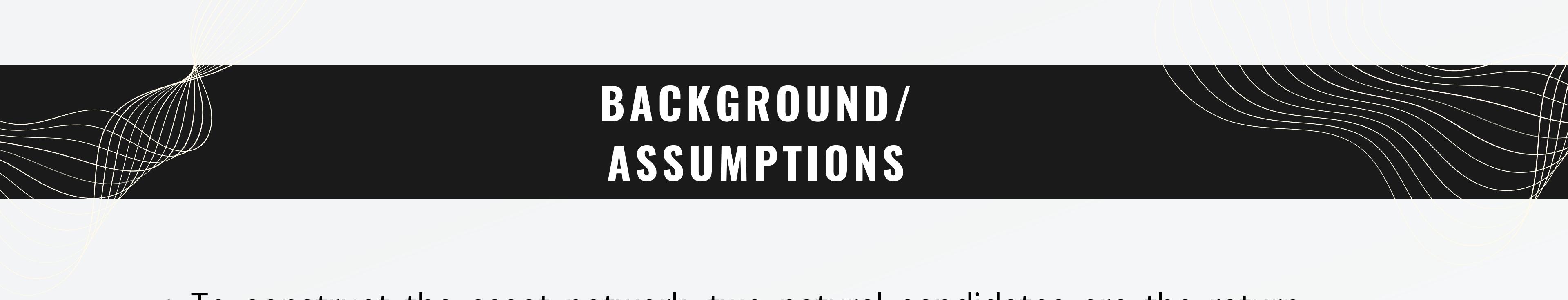
# INTRODUCTION

**'If any one of the domestic companies should fail, we believe there is a strong chance that the entire industry would face severe disruption'.**

A. MULLALY, CHIEF EXECUTIVE OF FORD MOTORS

**'Due to the complexity and interconnectivity of today's financial markets, the failure of a major counterparty has the potential to severely disrupt many other financial institutions, their customers, and other markets'**

PLOSSER (2009)



# BACKGROUND/ ASSUMPTIONS

- To construct the asset network, two natural candidates are the return series and the volatility series.
- Volatility is not observed and has to be estimated from the data.
- We'll study top 100 NYSE stocks (based on market cap) from 2002-2017 in 4 windows

## WHY THIS TIME FRAME?

Because it captures periods of all – boom, crisis, recovery and stability.

# MATHEMATICAL MANIPULATIONS

RETURNS

$$r_{it} = \log(p_{it}) - \log(p_{i,t-1})$$

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CONDITIONAL VOLATILITY

$$r_{it} = \mu_i + \sigma_{it}\epsilon_{it}$$

$$\sigma_{it}^2 = c_i + \sum_{l=1}^p \alpha_{il} r_{i,t-l}^2 + \sum_{j=1}^q \beta_{ij} \sigma_{i,t-j}^2.$$

(BASED ON  
GARCH MODEL)

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CORRELATION MATRIX

$$\gamma_{ij}^x = \frac{E((x_{it} - \bar{x}_i)(x_{jt} - \bar{x}_j))}{\sigma_i^x \cdot \sigma_j^x}$$

CORRELATION MATRIX  $\Omega_T X$  FROM BOTH THE RETURN SERIES  $\{R_{IT}\}$  AND THE VOLATILITY SERIES  $\{\Sigma_{IT}\}$  ARE CALCULATED

# GARCH?

**AR(1)**

Auto-Regression Model

$$R_t = (k) * R_{t-1} + E_t$$

**ARMA(1,1)**

Auto-Regression Moving Average Model

$$R_t = (\phi) * R_{t-1} + (\sigma) E_{t-1} + E_t$$

**ARCH(1)**

Autoregressive conditional Heteroskedasticity Model

$$R_t = E_t * (a + b * (R_{t-1})^2)^{0.5} = E_t * (\sigma)_t$$



**GARCH(1,1)**

Autoregressive conditional Heteroskedasticity Model

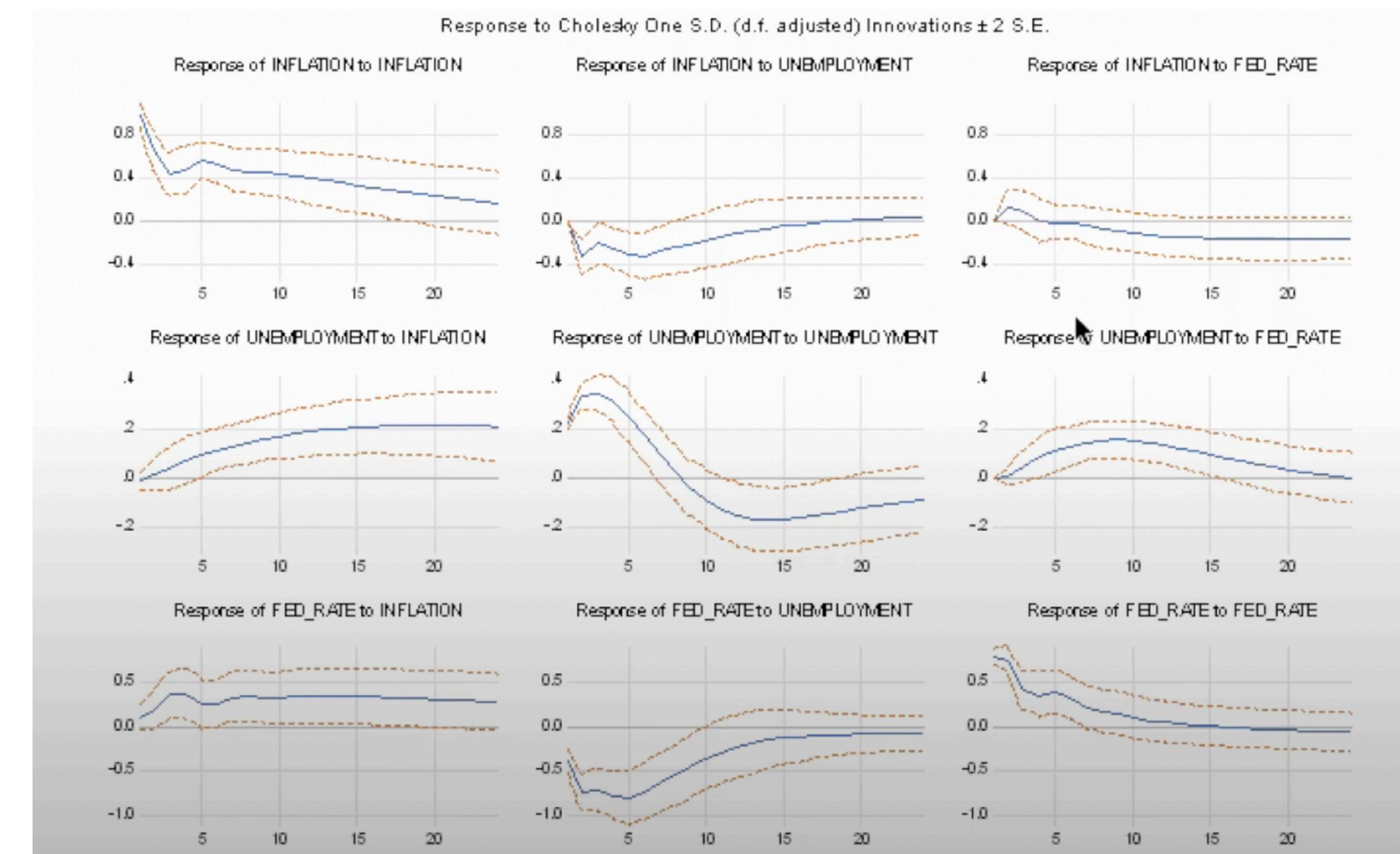
$$R_t = E_t * [a + b * (R_{t-1})^2 + c * (\sigma_{t-1})^2]^{0.5} = E_t * (\sigma)_t$$

# AN EXAMPLE HOW WE CALCULATE THE IMPULSE RESPONSE FUNCTION

Suppose given,  
inflation rate,  
unemployment rate  
and federal rate.

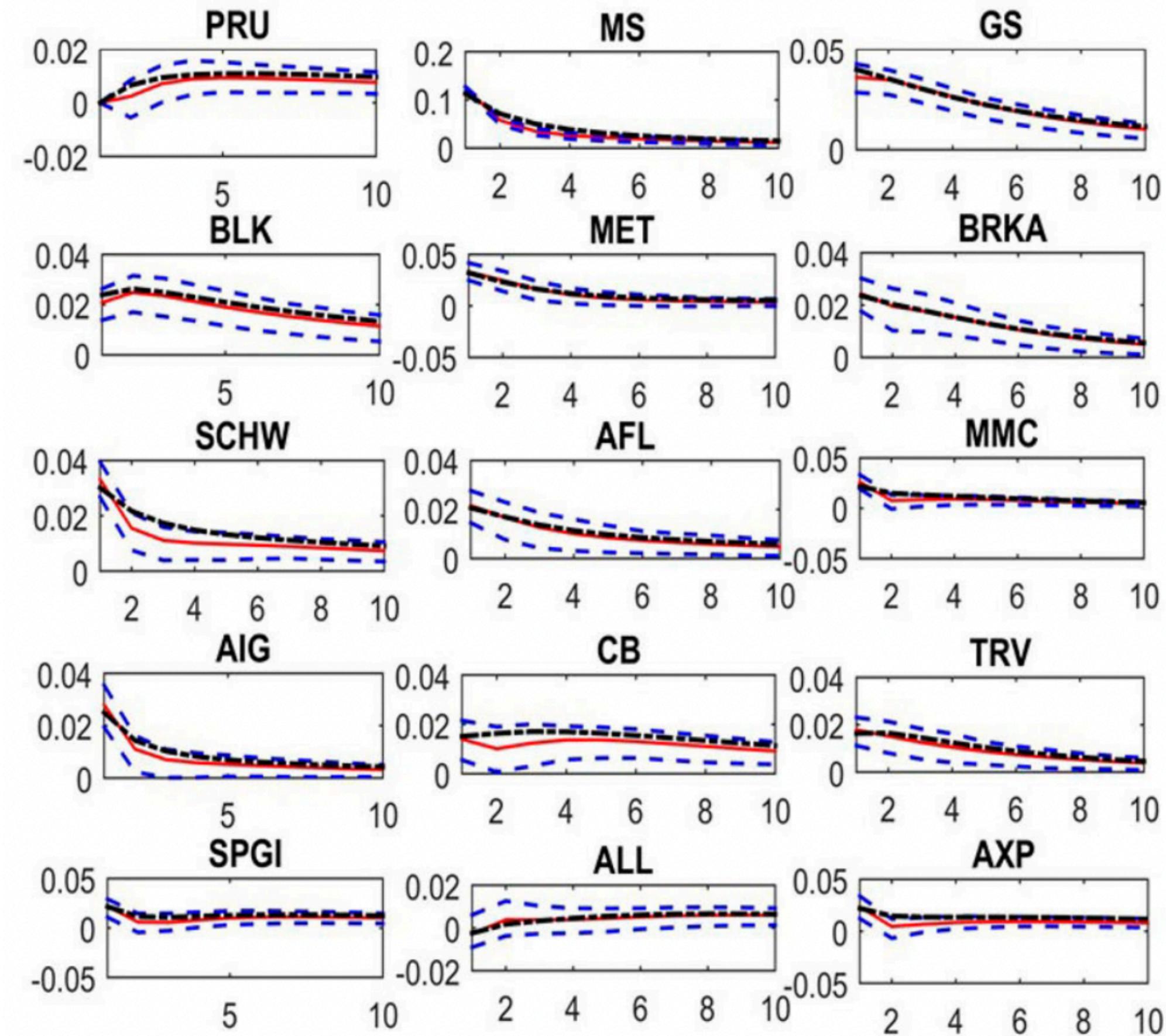
Then these graphs  
show the effect of 1  
SD shock given to  
one on others

$$A_{zt} = \begin{bmatrix} b_{11} & 0 & 0 \\ b_{21} & b_{22} & 0 \\ b_{31} & b_{32} & b_{33} \end{bmatrix} \begin{bmatrix} \pi_t \\ u_t^{une} \\ r_t^{Fed} \end{bmatrix} = BZ_{t-1} + \epsilon_t$$

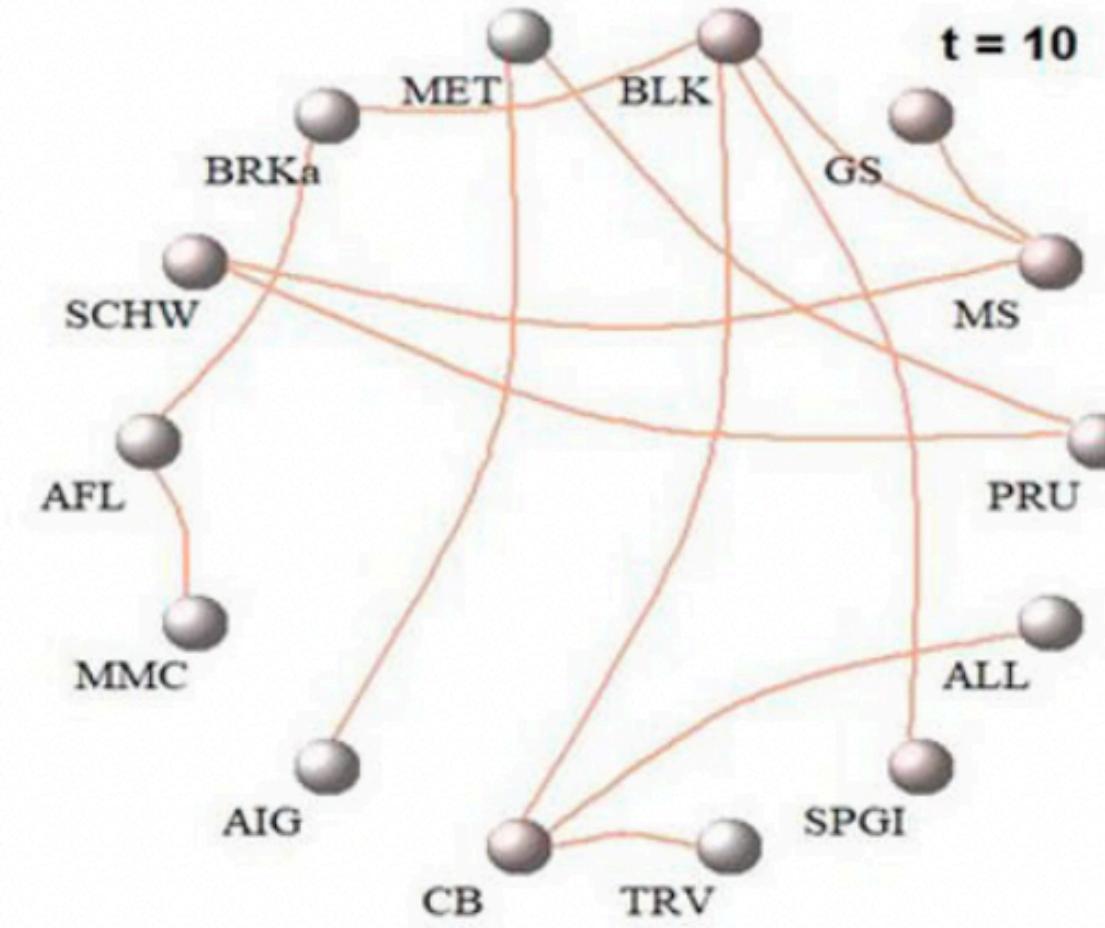
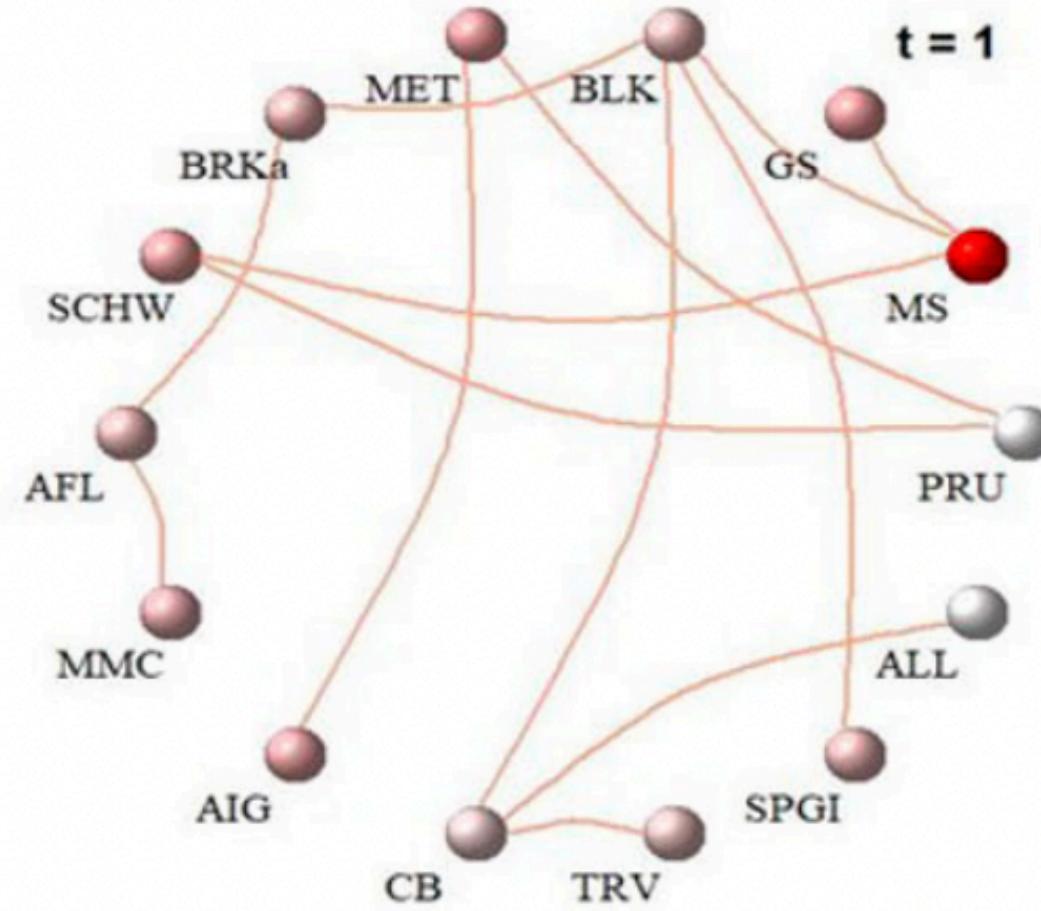


## GRAPHS FOR THE STOCKS WE SELECTED

IMPULSE RESPONSE  
FUNCTIONS ALONG WITH  
90% CONFIDENCE  
INTERVALS ACROSS  
DIFFERENT STOCKS, IN  
REACTION TO A POSITIVE  
VOLATILITY SHOCK GIVEN  
TO MORGAN STANLEY(MS)



# BETTER VISUALISATION?



DISTANCE & CORRELATION ->  $d_{ij} = \sqrt{2(1 - \gamma_{ij})}$ .

01

02

03

04

05

## SELECTION

We choose N stocks/assets and a timeframe with discrete periods

## CENTRALITY

Estimate a vector autoregression model on the log of latent volatility series across all stocks in the sample.

## VISUALISATION

We construct a network based on the correlation structure of the stocks and extract the minimum spanning tree .

## ESTIMATION

We estimate latent volatility series from each of the return series by using GARCH model

## IMPULSES

Characterise the shock propagation over the stocks by using estimated impulse response functions obtained the identified VAR model.

## WHY RETURN CENTRALITY?

- From a financial perspective, eigenvector centrality represents the relative weights of different stocks in a market portfolio. It measures the contributions of different stocks to market-wide movements and the impact of exogenous shocks on these stocks.

## WHICH CENTRALITY MEASURE?

Here, we analyze the stability of the rank-ordering obtained from two types of identification criteria. In principle, both of the dominant eigenvectors of the return correlation matrix and the volatility correlation matrix could have been candidates for identification criteria in terms of relative exogeneity. However, return is an observed variable and hence, free of measurement noise and/or model specification errors. Volatility, on the other hand, is latent and hence needs to be estimated. Such estimation results will be model specific. Thus return centrality is a more robust choice.

# CONCLUSION?



**THANK YOU !**

