Prof. Dr. Narges Salehnia is Assistant Professor of Economics at Economics Department of Ferdowsi University of Mashhad (FUM). She was born in 1980 in Ferdos and graduated from Ferdowsi University of Mashhad with a B.A (during 3 years) in Business Economic Administration in 2002. She passed all of her courses with A^+ and was elected as elite undergraduate student in Economics Department of FUM. So, she got full scholarship for M.Sc. of Pure Economics in FUM and graduated in 2006.

She also worked as economic advisor in the Governor's Office of the Khorasan State for Managed Drought Adaptation Integrated Plan, Water & Wastewater Corporation of Khorasan Razavi Province, Hydro-Tech Toos Consulting Engineers Corporation and the Governor's Agricultural Organization of Khorasan Razavi Province.

She received "A" grade for Ph.D Entrance Exam and got full scholarship for Ph.D of energy Economics in FUM and graduated in 2015. During her Ph.D course she acquired a scholarship as Ph.D visiting student from Mathematics and Statistics department of Calgary University under the supervision of Prof. Dr. Tony Ware and a Ph.D visiting scholar from Surrey University in England (Professor Dr. Newman).

She has been elected as Elite Graduated Student (Iran Ministry of Sciences, Researches and Technology) in 2015. Her Ph.D thesis title was "Pricing of Natural Gas Derivatives Using Stochastic Modelling of International Spot Prices in Henry Hub". She started her career as an Assistant Professor in FUM in 2016. Currently, she is working on stochastic modelling, water economics, energy pricing, dynamic programming and agent based modelling of natural resources.

Modelling Price Volatility in Energy Markets

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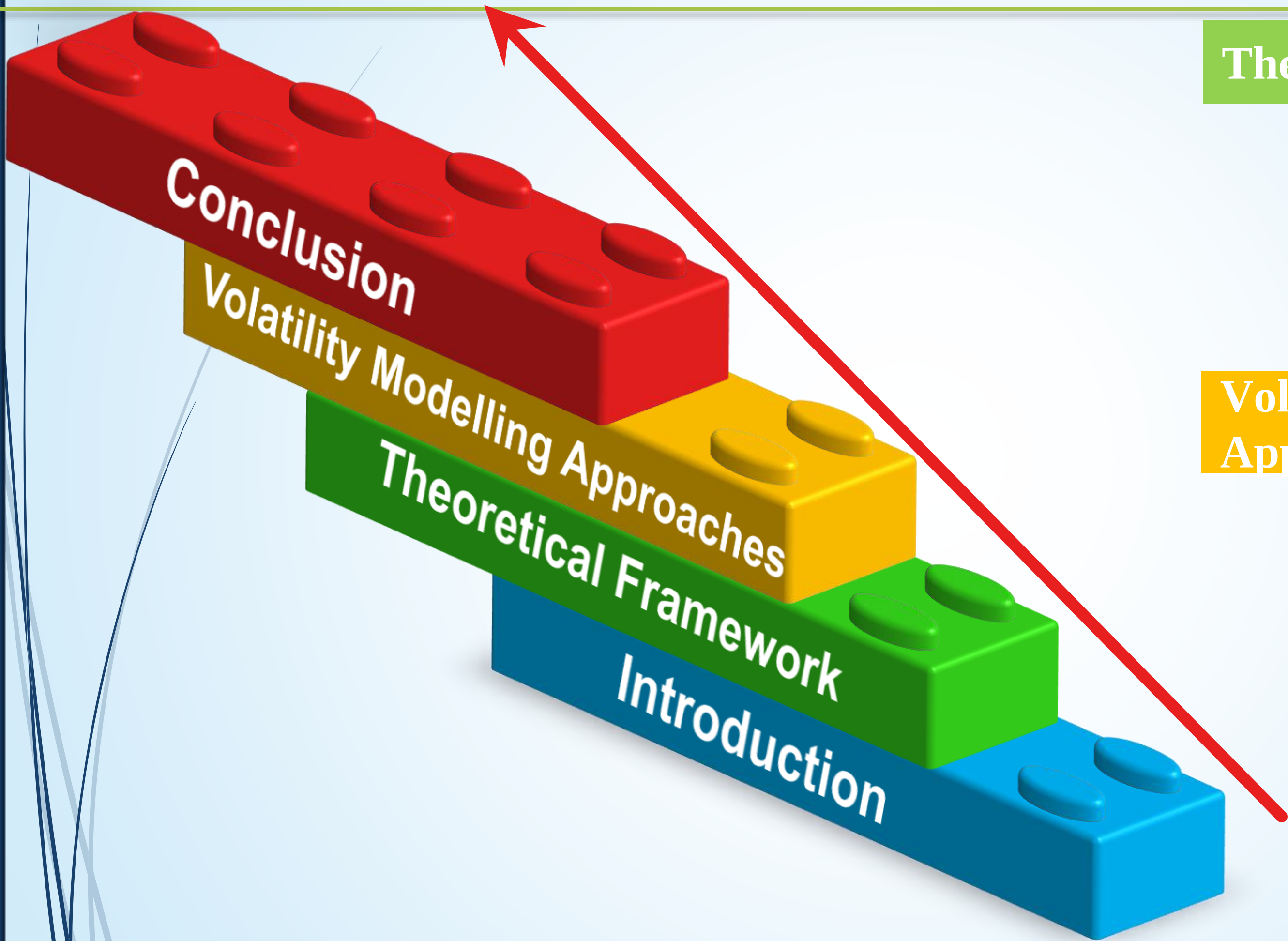
Ferdowsi University of Mashhad

Presentation Plan



Theoretical Framework

- Volatility Origins
- Effects of Energy Price Volatility
- Preventive Actions

Volatility Modelling Approaches

- Energy Price Behavior Models
- Price Characteristics for volatility evaluation
- Two points for measuring volatility
- Volatility Statistical Measurements
- Different Volatility Models

Introduction: Why Volatility?

1 Engle's Noble Prize

The importance of volatility forecasting was highlighted when in 2003 Professor Engle was awarded a Noble prize for his outstanding contribution in modelling volatility dynamics.

2 Significant Price Fluctuations of Fossil Fuels

Today, fossil fuels constitute almost 90 % of the global energy mix and they have all exhibited price volatility for some portion of the period.

Introduction: Why Volatility?

3 Generating Economic Uncertainty

Energy Providers/ Companies

- hurts their image
- creates doubt about the industry's integrity and competency to reliably provide energy.

Investors & Consumers

- delay decisions to purchase appliances and equipment or make investments.
- Result in lost market opportunities and inefficient long-run resource allocations.

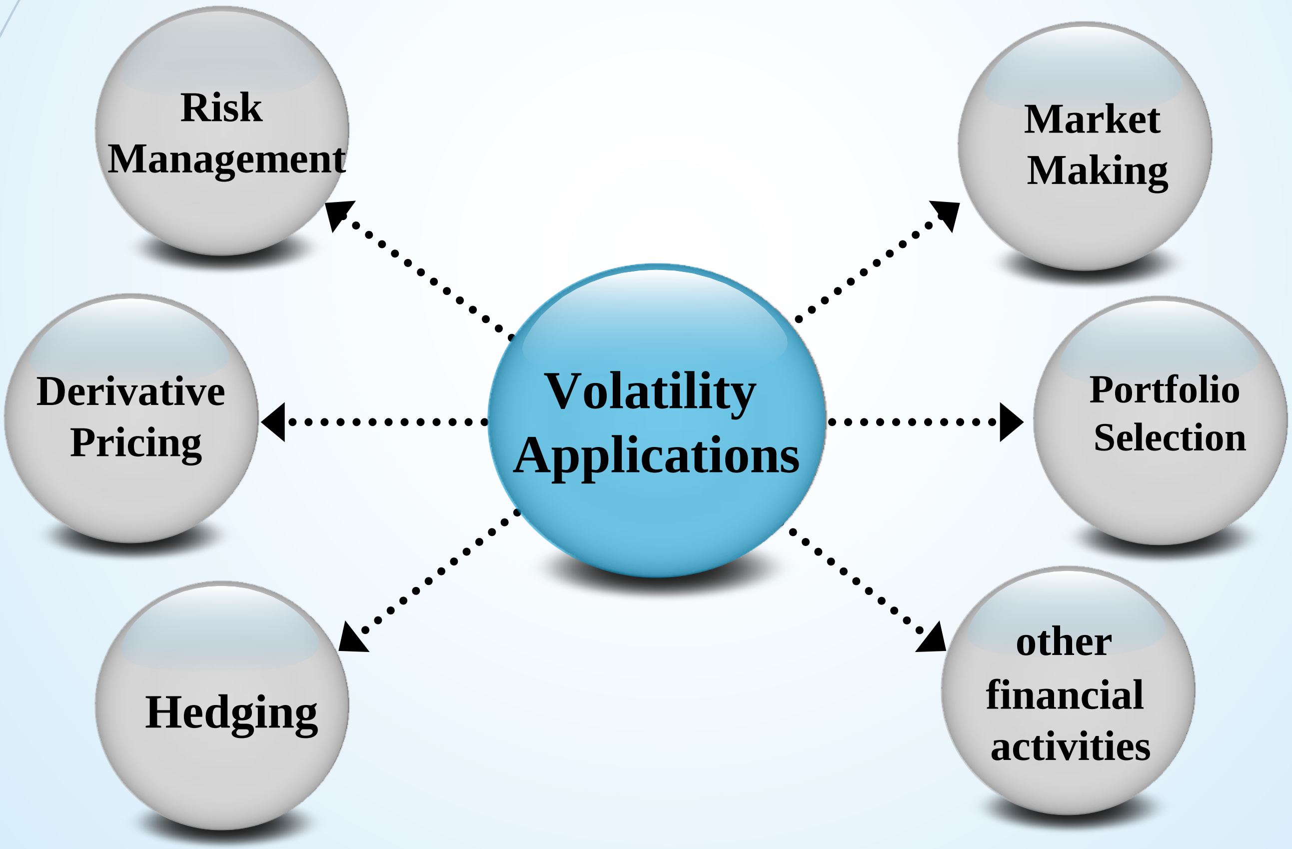
Regulators & Legislators

- pressures for regulatory intervention which biases the market and penalize market participants with unpredictable revenue swings.

Introduction: Why Volatility?

4

It’s Broad Usages



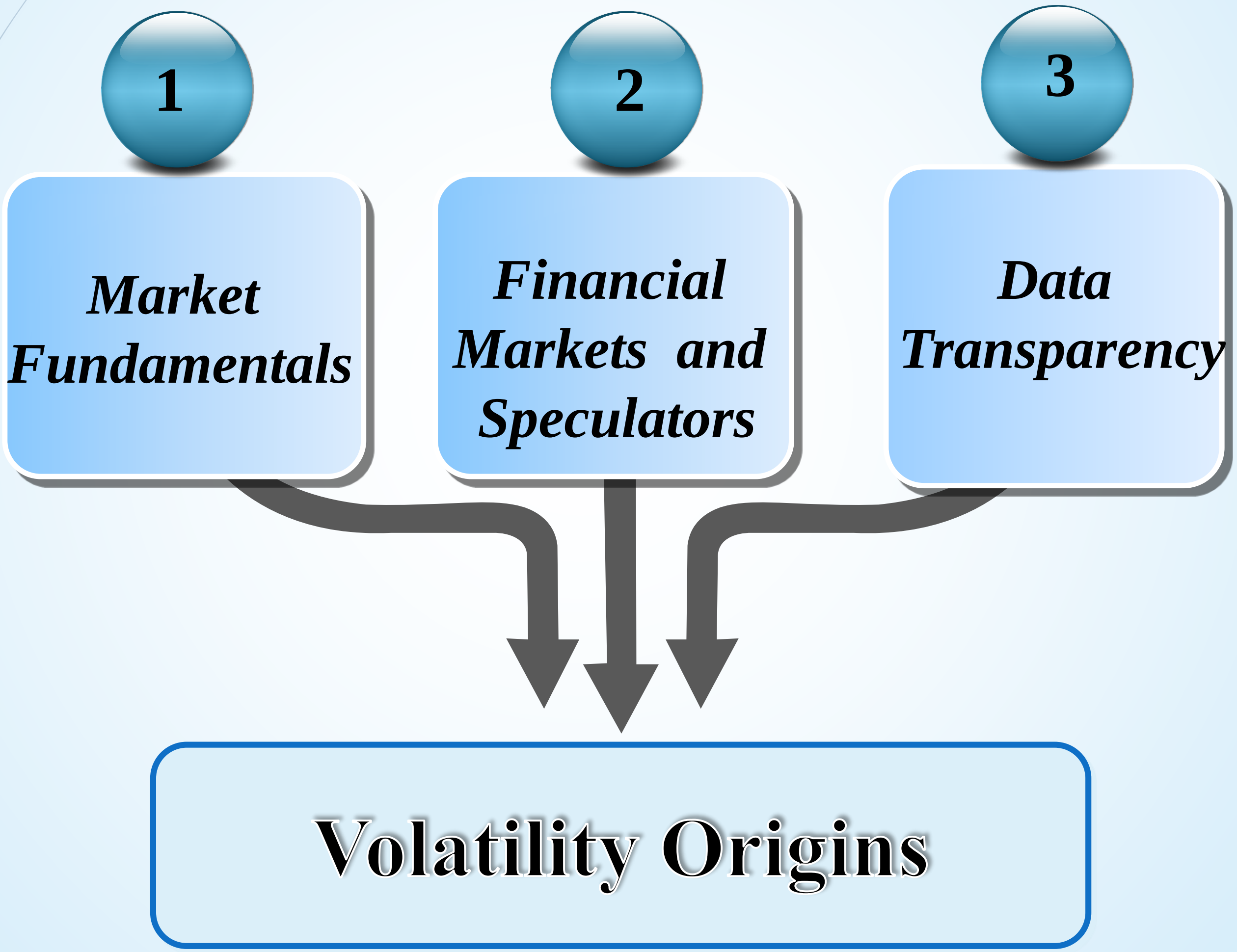
Introduction: Review Literature

Researcher	Commodity	Modelling Approach	Conclusion
Horan et al. (2004)	**OPEC Crude Oil**	**Implied Volatility**	When biannual OPEC conferences are held, volatility increases but after 5 days of the meeting it drops 5%.
Sadorsky (2006)	**Oil, Natural Gas, Gasoline**	**Conditional Volatility**	The TGARCH model fits well for natural gas and the GARCH model fits well for crude oil and gasoline volatility.
Mu (2007)	**Natural Gas**	**Implied Volatility**	He shows that weather surprises have a significant effect on the implied volatility of natural gas prices.
Lee & Zyren (2007)	**Oil, Gasoline**	**GARCH/TARCH**	They show that persistence of volatility is transitory and structural shift cause to higher volatility.

Introduction: Review Literature

Researcher	Commodity	Modelling Approach	Conclusion
Agnolucci (2009)	Crude Oil	Implied/Conditional Volatility	He shows that the predictive ability of conditional volatility is better than the implied one.
Benatzky (2009)	Power	ARMA/ GARCH	ARMA can forecast volatility better than GARCH.
Bakanova (2010)	Crude Oil	Implied/Historical Volatility	He finds that implied volatility outperforms historical volatility as a predictor of future realized volatility.
Ergen and Ridvanoglu (2014)	Natural Gas	GARCH	They point that volatility is much higher on the storage level in announcement days

Theoretical Framework : Volatility Origins



Theoretical Framework : Volatility Origins

1 Market Fundamentals

1859

- oil was produced in large commercial quantities in Pennsylvania

1946-1960

- The control of oil markets by international oil companies meant low and relatively steady oil prices.

1960

- A new era began with the foundation of OPEC in 1960.

1968-2000

The 1968 coup in Libya led to:

- new agreements with the independent oil companies
- lost control of Seven Sisters
- oil prices quadrupled
- a new era of high oil price volatility started.

Theoretical Framework : Volatility Origins

1 Market Fundamentals

The Oil Cycle (2000-2017)

2000-2007 — Boom and Bottleneck

- -China’s booming economy
- - Inability of supply
- -Leading to high prices

2005-2012 — Flight to the Frontiers

- -New areas like deep water being explored
- -new technologies being produced

2011-2014 — Resource Realization

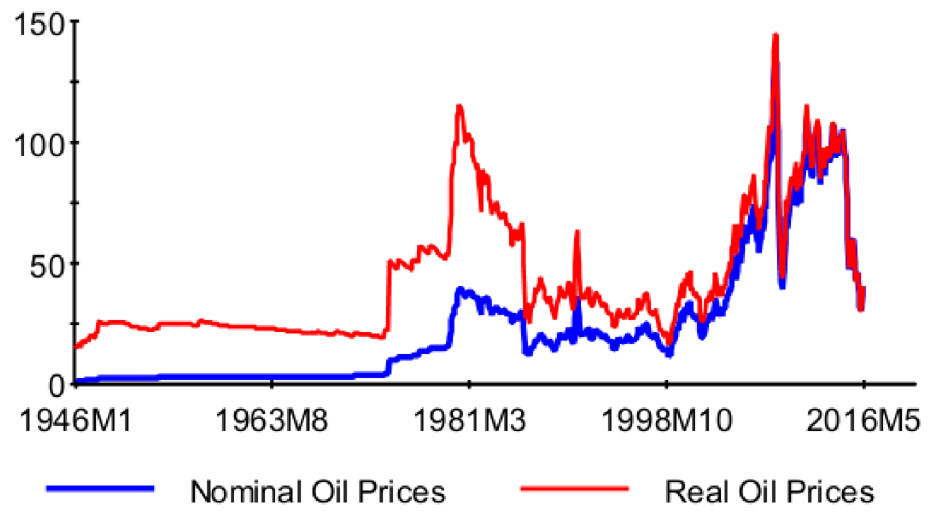
- -a larger amount of oil coming online
- -downward price pressure mounting

2014-… — Great Reset

- -Market imbalances,
- -Downturn in prices
- -Slowdown of oil production

Theoretical Framework : Volatility Origins

1 Market Fundamentals



Data sources: United States Energy Information Administration (EIA).

Oil markets have experienced frequent episodes of boom and bust. It has fluctuated between highs of $145 to lows of $15 per barrel over the period 1946M1 and 2016M6.

Theoretical Framework : Volatility Origins

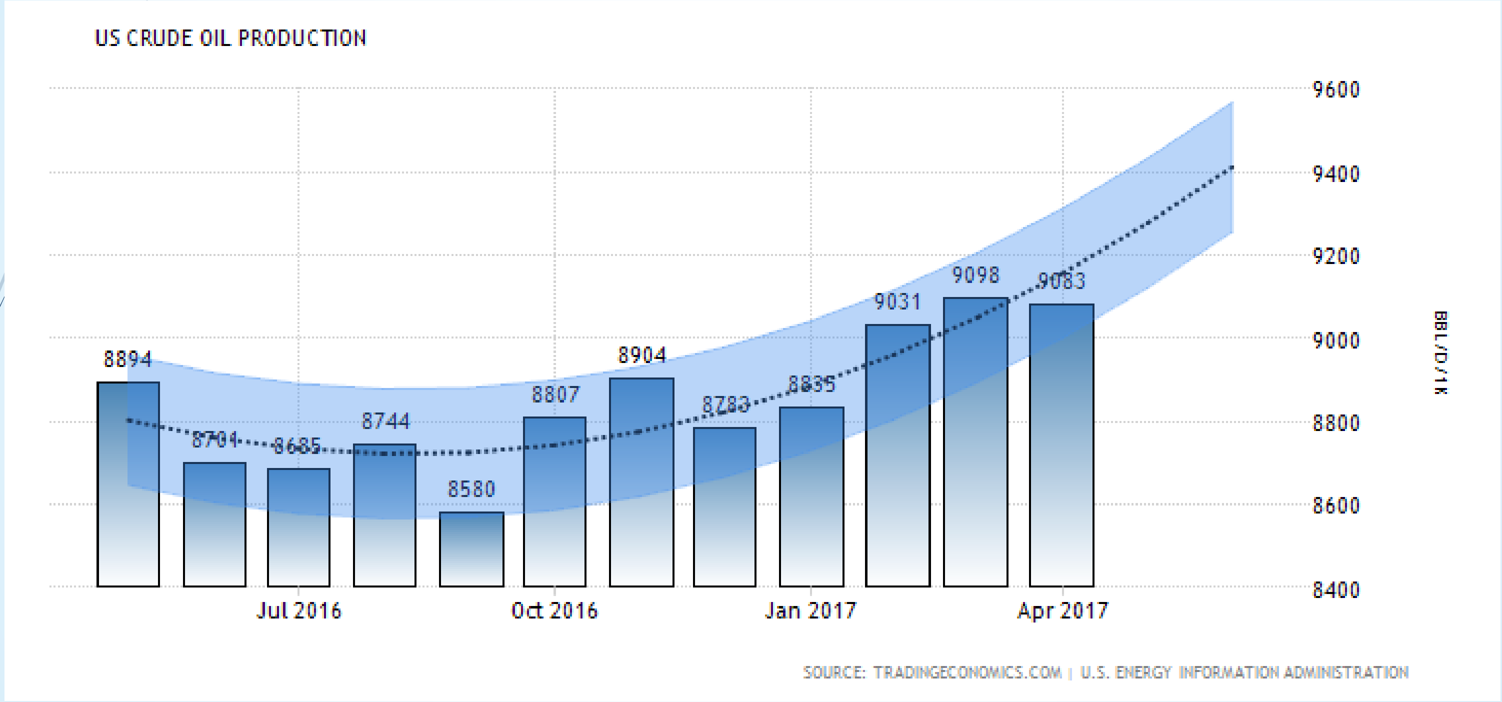
1 Market Fundamentals

Recent Oil Price Drops Reasons

- **- Supply outpacing demand by almost three times**
- 1. emerging new players like Canada, Brazil, and the US(shale)
- 2. Continuous OPEC production despite the disruptions in Libya and Iraq
- **- Simultaneous demand decreasing**
- 1. emerging economies growth slowdown (specifically China)
- 2. oil subsidy reform in many countries
- 3. new technological developments (fuel efficiency and renewables)
- **- US and Saudi Arabia collusion to put pressure on Iran or Russia**

Theoretical Framework : Volatility Origins

1 Market Fundamentals



EIA forecasts U.S. crude oil production will reach a record annual average of 10 million barrels a day in 2018

Theoretical Framework : Volatility Origins

1 Market Fundamentals

- ✓ Lack of coordination between OPEC and countries with larger output
- ✓ OPEC’s inaction on a price floor or a production cap
- ✓ Negative correlation between price volatility and storage
- ✓ Production Capacity reduction because of exploration or investment drop
- ✓ Increasing in supply security risk: War
- ✓ Changing political regimes
- ✓ Political and economic crisis
- ✓ Structure of trade agreements
- ✓ Consumers' demand change
- ✓ Seasonal changes of demand and weather surprises
- ✓ High price policy in long-run supply and demand

Theoretical Framework : Volatility Origins

2 Financial Markets and Speculators

- **Hedging and effective risk management against price volatility.**
- **Exponential growth of financial markets: at least 14 times larger than physical market.**
- **Gradual expanded and increased in complexity and size with technological advancement.**
- **A suitable tool for speculating purposes.**

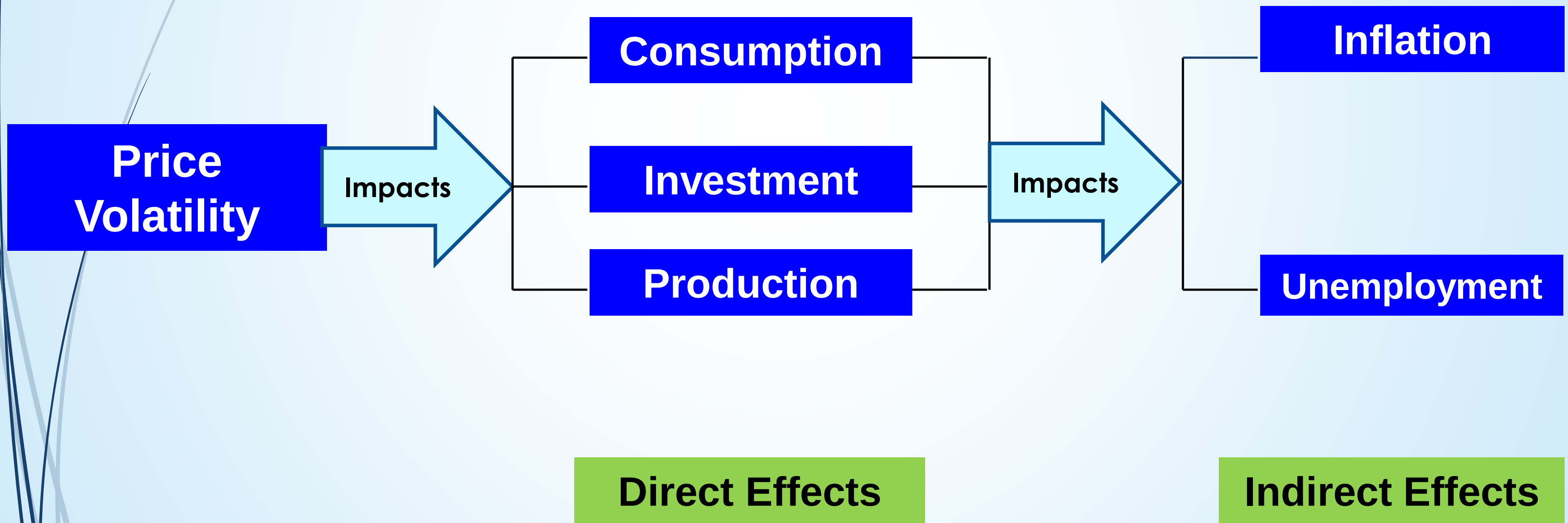
3 Data Transparency

- ✓ Inadequacies in the transparency, accuracy, and availability of critical energy market data, like:
- Inventories
- Demand
- Supply
- Production
- Stocks
- Reserves
- and ….

- ✓ Uncertainties regarding such variables

Theoretical Framework : Volatility Effects

Economic Impacts of Energy Price Volatility



Theoretical Framework : Volatility Effects

	⬆ OR ⬇	Reason
Consumption	**Decrease**	Price Volatility ⟶ Economic uncertainty ⟶ ↓ Consumer confidence ⟶ Precautionary savings behavior
Real Investment	**Decrease**	In SR to medium-term in response to: 1) uncertainties about investment profitability; 2) decreasing in consumer demand.
Financial Investment	**Both**	Depending on the degree of risk preference which dominates the financial market at any given time.

Theoretical Framework : Volatility Effects

	⬆ OR ⬇	Reason
Production	**Constant or Decrease**	- constant production levels by raising the final prices of goods; or - decline it in response to decreasing consumer demand.
Inflation	**Both**	whether the deflationary pressures created by decreasing consumer demand outweigh the inflationary pressures created by the increasing prices of goods.
Unemployment	**Both**	subject to two counterbalancing pressures: -decreased production levels increases unemployment -unemployment decreases as inflation increases (augmented PC).

Theoretical Framework : Preventive Actions

- Foster Investment
- Diversify Energy Supply
- Increase Energy Efficiency
- Foster Innovation
- International Cooperation

Theoretical Framework : Preventive Actions

- **National Policies**
- **Financial derivatives**
- **Market segmentation**
- **Long-term contracts**

Volatility Modelling

Energy Price Behavior Approaches

- ***Economics of Exhaustible Resources***
- ***Supply – Demand Framework***
- ***Stochastic Processes***

Volatility Modelling

Energy price Characteristics for volatility evaluation

Geographic market

Time interval of the prices

Point in the energy supply chain

Spot /retail prices

Volatility Modelling

Two common points for measuring volatility

1 Using Absolute Energy Price Levels

- Volatile Market: is a market in which average prices are changing rapidly in unanticipated ways.
- Next month's prices, or next year's prices, are likely to be substantially different from current prices.
- Application: evaluating price volatility over a long run planning horizon.

Two common points for measuring volatility

2 Using Energy Price Returns

- ✓ Volatile Market: is a market in which day-to-day changes in prices are very large relative to the base price.
- ✓ Measuring volatility as a percentage change in prices.
- ✓ A measure of expected return on investment.
- ✓ Associated with financial markets, and a reference for traders and risk managers.

Volatility Modelling:

Statistical Measurements of Energy Price Volatility

1) Daily Price Range

Range: represents the spread in prices during a specific period.

In derivatives markets: It is the average spread between the bid-ask price during a specific time period.

It can be the difference between the daily high and low price.

An increase in the range indicates an increase in volatility.

Application: Parkinson Measure of Volatility.

Volatility Modelling:

Statistical Measurements of Energy Price Volatility

Standard deviation of prices

Measure of the actual price movement over a specific period

Expected deviation from the average market price

A higher standard deviation means a higher volatility

2) Standard Deviation

Volatility Modelling:

Statistical Measurements of Energy Price Volatility

A relative measure of price movement.

It is calculated as the standard deviation divided by the mean value.

A useful comparative measure of price volatility for different commodities with different price units.

3) Coefficient of Variation

Volatility Modelling:

Statistical Measurements of Energy Price Volatility

It Uses range to estimate price volatility.

Less useful for comparing volatility of different data series with different units.

Changing Parkinson measure over time is used as an indicator of changes in volatility between time periods.

$$Volatility = {(\ln(Hi) - \ln(Lo))^2}\big/{4\ln 2}$$

4) Parkinson's Measure of Volatility

Volatility Modelling:

Statistical Measurements of Energy Price Volatility

5) Returns

It is percentage change in prices.

It reflects the expected "return" on investment in a commodity.

It's log-normal form is used in order to create a more normal data distribution since prices are non-negative.

Volatility Modelling: Different Volatility Models

1) Implied Volatility

- Derived from the market price of the financial contracts.
- Used for mid-term future volatility in energy markets.
- Estimated with Black- Scholes equations.
- The key unknown is the expected SD of daily price returns.
- Other components: striking price, current commodity price, expiration date and interest rate.

Volatility Modelling: Different Volatility Models

2) Historical Volatility

Direct measure of the underlying price movement over recent history.

Application: for high-frequency data.

It doesn't include the current state of the market.

It is the SD of the price returns over a specified period of time.

$$\hat{\sigma} = \sqrt{T^{-1}\sum_{t=1}^{T}(r_t - \bar{r})^2}$$

Volatility Modelling: Different Volatility Models

3) Conditional Volatility

Homoscedasticity is rejected and volatility clustering is proven.

Volatility clustering: large (small) price changes tend to be followed by subsequent large (small) changes.

Price Returns are serially correlated; they are not independent. ($\neq$ iid in Fama Random Walk Model)

Ex.: ARCH, GARCH, GARCH-M, TGARCH, EGARCH, ….

Volatility Modelling: Different Volatility Models

3-1) ARCH

- **Autoregressive Conditional Heteroscedasticity**
- Engle (1982) introduced the ARCH (p) model in which the conditional variance is a function of lagged squared residuals in the past.
- Persistence implies that any shocks to volatility do not die quickly.

$$Y_t = \alpha + \beta X_t + u_t \qquad (1)$$

$$u_t \mid \Omega_t \sim \quad iid\ N(0, \sigma_t^2 = h_t) \qquad (2)$$

ARCH(1):

$$h_t = \gamma_0 + \gamma_1 u_{t-1}^2 \qquad (3)$$

ARCH(q):

$$h_t = \gamma_0 + \gamma_1 u_{t-1}^2 + \gamma_2 u_{t-2}^2 + \ldots + \gamma_q u_{t-q}^2 = \gamma_0 + \sum_{j=1}^{q} \gamma_j u_{t-j}^2 \qquad (4)$$

Volatility Modelling: Different Volatility Models

-Non-negativity variance condition:

$$\gamma_0 \succ 0 \qquad \gamma_j \geq 0 \quad , \quad \forall j \qquad (5)$$

-Stationarity condition:

$$\sum_{j=1}^{q} \gamma_j \prec 1 \qquad (6)$$

- **Estimation Method: ML**
- **ARCH Defects:**

- As q becomes bigger, the prementioned conditions contradict.

- ARCH specification form is similar to MA specifications not to Autoregressive ones.

Volatility Modelling: Different Volatility Models

3-2) GARCH

- ✓ Bollerslev (1986) introduced it in order to achieve a more parsimonious parameterization.
- ✓ GARCH (p,q): Shows that h_t is a function of lagged squared residuals in the past and its' lagged values.
- ✓ If p=0 then GARCH (p,q) changes into ARCH(q).
- ✓ GARCH estimation is preferred to a ARCH with high order because:

-GARCH estimation is much easier than ARCH;

-Loosing less degree of freedom.

- ✓ The addition of the lagged conditional variances, avoids the need for adding many lagged squared returns as in ARCH.

Volatility Modelling: Different Volatility Models

$$Y_t = \alpha + \beta X_t + u_t \qquad (1)$$

$$u_t \mid \Omega_t \sim \quad iid\ N(0, \sigma_t^2 = h_t) \qquad (2)$$

$$h_t = \gamma_0 + \sum_{i=1}^{p} \delta_i h_{t-i} + \sum_{j=1}^{q} \gamma_j u_{t-j}^2 \qquad (3)$$

-Non-negativity variance condition:

$$\gamma_0 \succ 0 \qquad \delta_i \geq 0 \quad , \quad \forall i \qquad \gamma_j \geq 0 \quad , \quad \forall j \qquad (4)$$

-Stationarity condition:

$$\sum_{i=1}^{p} \delta_i + \sum_{j=1}^{q} \gamma_j \prec 1 \qquad (5)$$

Volatility Modelling: Different Volatility Models

3-3) GARCH-M

- ✓ The return of a commodity may depend on its volatility (risk).
- ✓ To model such phenomena, the GARCH-in-Mean model adds a heteroscedasticity term into the mean equation.
- ✓ So it shows conditional mean dependency to conditional variance.

$$Y_t = \alpha + \beta X_t + \theta h_t + u_t \qquad (1)$$

$$u_t \mid \Omega_t \sim \quad iid\ N(0, \sigma_t^2 = h_t) \qquad (2)$$

$$h_t = \gamma_0 + \sum_{i=1}^{p} \delta_i h_{t-i} + \sum_{j=1}^{q} \gamma_j u_{t-j}^2 \qquad (3)$$

Volatility Modelling: Different Volatility Models

3-4) TGARCH

- ✓ In GARCH/ARCH models, the sign of lagged residuals does not play any role by squaring them in conditional variance equation.
- ✓ Energy returns volatility reacts more to positive shocks than to negative shocks.
- ✓ Glosten, Jagannathan and Runkle (1993) and Zakoian (1994) provided a dummy variable in variance equation which is an indicator for sign of error terms.
- ✓ The TGARCH model allows good news (positive return shocks) and bad news (negative return shocks) have different effect on volatility (capture asymmetries).

Volatility Modelling: Different Volatility Models

$$h_t = \gamma_0 + \gamma u_{t-1}^2 + \theta u_{t-1}^2 d_{t-1} + \delta h_{t-1} \quad \textbf{(1)}$$

Good News $\rightarrow u_t \succ 0 \rightarrow d_t = 1 \rightarrow$ News Effect: $\gamma + \theta$

Bad News $\rightarrow u_t \prec 0 \rightarrow d_t = 0 \rightarrow$ News Effect: γ

❖ **TGARCH high orders specification:**

$$h_t = \gamma_0 + \sum_{i=1}^{p} (\gamma_i + \theta_i d_{t-i}) u_{t-i}^2 + \sum_{j=1}^{q} \delta_j h_{t-j} \quad \textbf{(2)}$$

Volatility Modelling: Different Volatility Models

3-5) EGARCH

- **EGARCH model proposed by Nelson (1991) which overcomes two major drawbacks of symmetric GARCH model:**

-Capture the leverage effect (means the tendency for energy price changes to be negatively correlated with changes in volatility).

-Eliminate the non-negativity constraint (capture asymmetries).

$$\ln h_t = \gamma_0 + \sum_{i=1}^{p} \delta_i \left| \frac{u_{t-i}}{h_{t-i}} \right| + \sum_{j=1}^{q} \gamma_j \ln h_{t-j}$$

Volatility Modelling: Different Volatility Models

4) Stochastic Volatility

The idea behind a SV model is to incorporate the varying volatility and make the volatility itself a stochastic process.

In a SV model the volatility is changing randomly according to some SDE or some discrete random process.

It is suitable for energy price returns with special characteristics: fat tail returns, auto correlated returns, non-negative autocorrelation function for squared returns.

It includes an unobservable innovation term in the conditional variance of energy price returns.

Volatility Modelling: Different Volatility Models

4) Stochastic Volatility

Variance process is intrinsically hidden.

Technically: volatility process can not be measured just by all the available information, rather it contains a second innovation term for the future information.

Estimation Methods: quasi-maximum likelihood estimation approach (Harvey et al, 1994) and Markov Chain Monte Carlo methods (Jacquier et al, 1994, Pitt and Shephard, 1997, Durbin and Koopman, 2000).

SV models are more flexible than GARCH models.

Volatility Modelling: Different Volatility Models

4) Stochastic Volatility

In ARCH/GARCH, return distribution is defined explicitly but in SV it is explained by the model structure.

ARCH/GARCH models have one component error term but SV models have two components error term

Conditional variance is modelled with an additional factor ν_t which:

$$\boxed{\sigma_t = f(\nu_t, \nu_{t-1}, \nu_{t-2}, \ldots)}$$

Volatility Modelling: Different Volatility Models

4) Stochastic Volatility

Two components error term provides a better estimation and forecasting.

SV models are widely used in financial applications, modelling price and volatility separately with continuous diffusion paths in SDE framework.

It relaxes the assumption of fixed volatility in Black and Scholes model.

Volatility Modelling: Different Volatility Models

A Simple form of the Stochastic Volatility Model

- *mean eq.*: $r_t = \sigma_t \varepsilon_t, \ \varepsilon_t \sim N(0,1)$

$$\sigma_t = \sigma \exp(\frac{1}{2} h_t)$$

- *volatility eq.*: $h_t = \lambda + \alpha h_{t-1} + v_t, \ v_t \sim \mathrm{N}(0, \sigma_v^2)$

Stationarity Condition: $|\alpha| < 1$

Volatility Modelling: Different Volatility Models

Modelling Stochastic Volatility With SDE

$$dp(t) = r_t = \mu dt + \sigma(t)dW(t)$$

$$d\sigma^2(t) = \beta(\alpha - \sigma^2(t))dt + \nu\sigma^2(t)dW_\sigma(t)$$

- Two Wiener Processes are independent.

$dw = \varepsilon\sqrt{dt} \rightarrow \varepsilon \sim N(0,1)$ $\qquad$ $dw \sim N\left(0, \sqrt{dt}\right)$

- In above equation, MR characteristic has been considered, but in a multi-factor model, JD can be mentioned, too

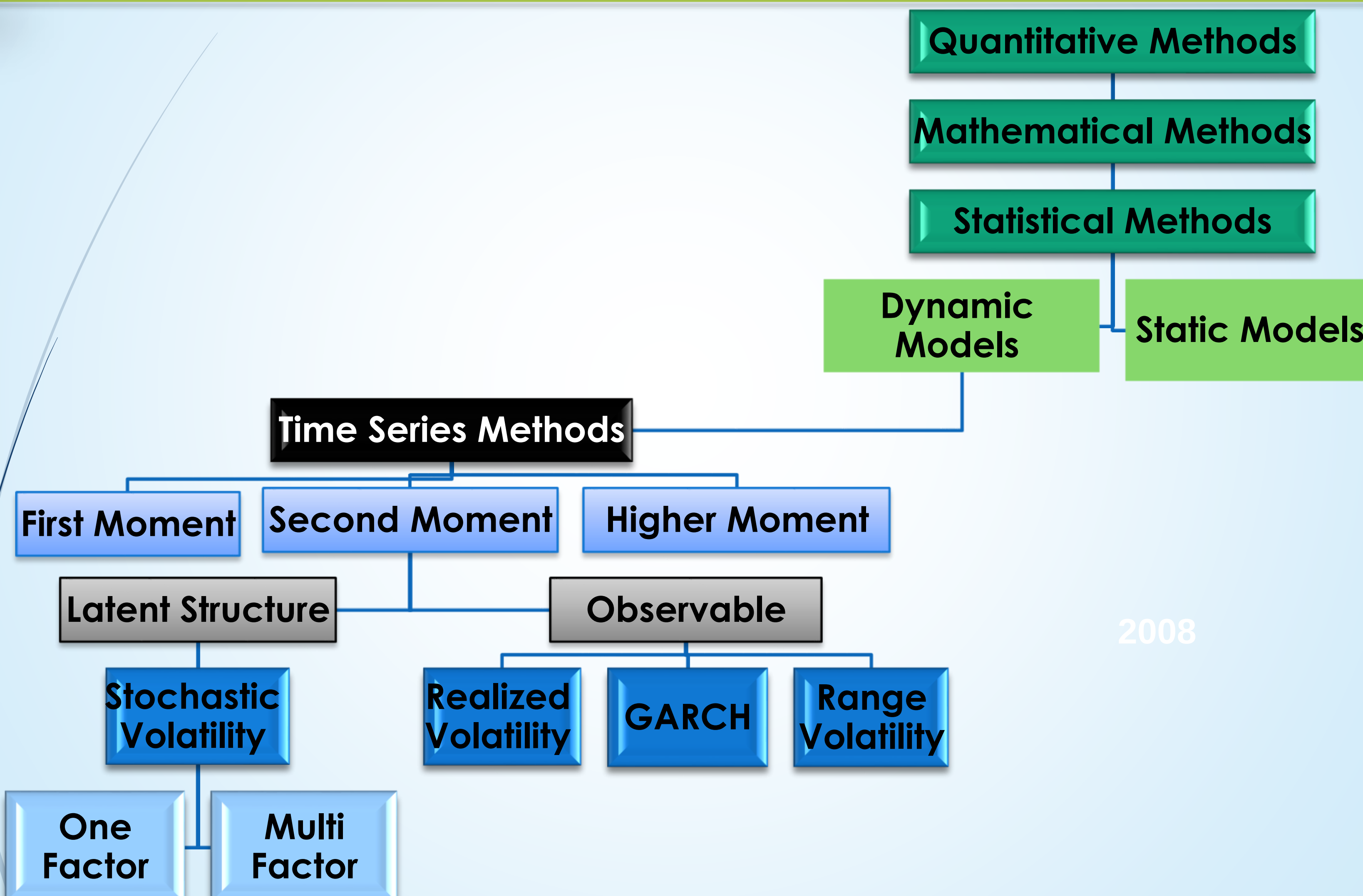
$$dp(t) = \mu(t)dt + \sigma(t)dW(t) + j(t)dq(t)$$

$$P_{t+1} - P_t = \alpha(\mu - P_t)\Delta t + P_t\sigma\varepsilon_{1t}\sqrt{\Delta t} + u\left[P_t(\kappa + \gamma\varepsilon_{2t})\right]$$

Conclusion

- A broad range of literature exists dealing with the analysis of fossil fuel price volatility.
- From a methodological point of view, the term "volatility" in the literature is not used in the same way and different measures and indicators are applied.
- The differences among these models are the manner under which σ_t^2 evolves overtime.
- So, price volatility is poorly defined, and there is not a consistent frame of reference for talking about and evaluating price volatility.

Conclusion



Quantitative Methods
Mathematical Methods
Statistical Methods
Dynamic Models
Static Models
Time Series Methods
First Moment
Second Moment
Higher Moment
Latent Structure
Observable
2008
Stochastic Volatility
Realized Volatility
GARCH
Range Volatility
One Factor
Multi Factor

Thank You

Ferdowsi University of Mashhad

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