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ÖZET

Bu tez çalışması enerji piyasalarında son yıllarda önem arz eden üç ayrı konuyu bir arada incelemektedir. Birinci bölümde Türkiye'de dikey yapılanma ve market gücünün elektrik fiyatlarına etkisi araştırılmıştır. Çalışmadaki modeller elektrik üretim miktarı, sistem marjinal fiyatı ve piyasa takas fiyatı verilerini saatlik frekansta kullandığı için ARx (otoregresif hareketli ortalamalar modeli) ekonometrik modelleri tercih edilmiştir. Sonuç olarak YAP-İŞLET-DEVRET santrallerin fiyatlar üzerindeki etkisi ekonometrik modellerindeki açıklayıcı değişkenlerin istatistiki anlamlılığının yüksekliği ile teyit edilmiştir.

İkinci bölümde ise Petrol Emtia Fiyatları ve Enerji Şirketleri'nin Hisse Getiri Davranışları araştırılmıştır. Asimetrik beklenti oluşum süreçlerine izin veren EGARCH tahmin yöntemi kullanılarak elde edilen tahmin sonuçları ve elde edilen Haber Etki Eğrileri (News Impact Curve)'nin gösterdiği üzere petrol emtia fiyatları ile enerji sektöründe faaliyet gösteren şirketlerin hisse getirilerinin farklı şoklara farklı tepkiler vermesidir. Dolayısıyla şirket hisseleri ve şirket değerlerini analiz ederken ele alına şirketlerin ürün portföylerinin, stratejik hedeflerinin, faaliyet gösterdikleri bölgelerin ve bilanço kompozisyonlarının değişmesi sonucu emtialardan ayrışan performanslar sergilediklerine dikkat çekilmiştir.

Son bölümde ise önemli enerji ETF'leri, petrol türev ürünleri ve spot petrol fiyatları arasındaki ilişkiyi inceleyerek petrol fiyatlarının yeni finansal enstrümanların da emtia piyasaları ile etkileşime geçtikten sonra petrol fiyatlarının ne şekilde etkilendiği araştırılmış ve emtia fiyatlarında asıl yönlendiricinin future piyasasının olduğu sonucuna varılmıştır.

ABSTRACT

This study is composed of three different but connected chapters considering the important developments and restructuring dynamics in both worldwide energy markets and local electricity market of Turkey. Based on the quantitate models it incorporates and the subjects it compiles this thesis is a comprehensive study offering a condensed academic approach supported with applicable market approaches.

In Chapter 1 the impact of vertical integration on electricity prices was analyzed based on time series models with a thick data. The first chapter is also unique compared to previous studies in the related academic area as it is one of the first article which utilizes newly established Energy Exchange Istanbul (EXIST)'s dataset in volatility models.

In Chapter 2 we used news impact curves which showed that the behavior of commodity prices and company stock prices react differently to bad and good news. Based on our findings in Chapter 2, since commodity returns and company stock returns react differently to both bad and good market news we wanted to go one step further and focused on the price discovery of commodity prices in the market.

Finally, in Chapter 3 we investigated the impact and integration of financial assets with oil prices. Price discovery of crude oil prices was our first focus area by operating causality tests. Our paper contributes to the energy economics literature focusing on the impact of energy related Exchange Related Funds (ETFs) on crude oil prices. In the previous studies we overviewed so far we concluded that this relationship is studied only between equity markets and crude oil markets.

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PREFACE

World energy consumption has increased consistently and rapidly over the past century. Annual global energy consumption in 2016 stood a little over 13,000 Mtoe[1] which equals to the energy content of approximately 85bn barrels of crude oil. Crude oil is still the dominant energy resource in the world however, natural gas and coal are performing higher growth rates.

Although Paris agreement is supported by many of the major developed countries, which produces most of the CO_2 released in the air, fossil fuels seem to be in the lead of energy supply to match the global energy demand. Due to the recent statistics on consumption and oil reserves it is expected that a most of the world's oil reserves has already been utilized. Based on the assumptions of the reputable institutions including International Energy Agency (IAE) peak oil[2] rates will be reached within 25 years.

The increase in coal consumption was significant in the last few years basically driven by Asian economic developments. Although there is an incredible fast development in hydro and renewables based on both technological developments and cost reduction in parallel, they still can satisfy a relatively small portion of global requirements.

According to the IAE estimates the expansion in world oil demand dropped to the lowest of the last 5-year in 2014. Moreover, record growth of oil supply from non-OPEC countries, primarily US with 1,9 million barrels per day made Brent crude oil futures contract to decline more than 48% in the second half of 2014 and is currently trading around $60/barrel.

As such, electricity (power) is the apex of energy commodities. All other energy commodities can be converted to power through one form of generation. For most societies electricity is

[1] BP Statistical Review of World Energy 2017

[2] Peak oil describes the amount at which global oil production will come to a maximum level and decline afterwards.

central to the viability of lifestyle and commercial process. Total world electricity generation in 2016 was approximately 24,816 tera watt hours with a 2,2% increase compared to 2015.

The common problem in energy industry is that mainly the energy generated area and the area that this energy is consumed are distant to each other which requires a separate value chain settlement for generation, transmission and reaching the energy to end users (retail). After 2001 electricity market in Turkey started to liberalize from the distribution part of the whole value chain. The electricity distribution network was allocated into 21 distribution regions. Capital owner Turkish conglomerates, mainly construction business originated, entered in to electricity business in every part of the value chain and as a result a vertically integrated private market was the natural outcome of the liberalization process. For example, still the electricity retail market did not liberalize yet one hundred percent.

In this context, this study is composed of three different but connected chapters considering the important developments and restructuring dynamics in both worldwide energy markets and local electricity market of Turkey. Based on the quantitate models it incorporates and the subjects it compiles this thesis is a comprehensive study offering a condensed academic approach supported with applicable market approaches.

A reduced form of Chapter 1 was published in International Journal of Energy Economics and Policy, VOL 7, NO 3 (2017). The impact of vertical integration on electricity prices was analyzed based on time series models with a thick data. The first chapter is also unique compared to previous studies in the related academic area as it is one of the first article which utilizes newly established Energy Exchange Istanbul (EXIST)'s dataset in volatility models. At the time this thesis is being written EXIST is preparing to open natural gas market for trading also which makes it more important to apply such quantitative models on real market data to be able to avoid and be prepared for possible market inefficiencies and price volatility impacts as well. In this context our expectation is to be able to reach more detailed data in the transparency platform of EXIST to analyze the market better.

Though major crude oil and energy entities are affected much by the recent oil price crisis stock returns of these companies react differently to market information based on their business strategies and diversified product portfolio and well optimized financing resources for their investments.

In Chapter 2 we used news impact curves which showed that the behavior of commodity prices and company stock prices react differently to bad and good news. We also examined the effect of oil price volatility on both selected companies and developing markets. Though time series models we operated in this chapter are no unique, the novelty of this chapter is that it includes the recent oil price crisis compared to previous articles in this field and considers in details the oil and gas company business acumen to explain the results of the econometric models which is not the case in previous studies. Furthermore, we also included the impact of oil price fluctuations on developing markets since oil prices have an importance as explanatory variable of exchange rate movements which makes our study a very comprehensive one.

Based on our findings in Chapter 2, since commodity returns and company stock returns react differently to both bad and good market news we wanted to go one step further and focused on the price discovery of commodity prices in the market.

Finally, in Chapter 3 we investigated the impact and integration of financial assets with oil prices. Price discovery of crude oil prices was our first focus area by operating causality tests. Our paper contributes to the energy economics literature focusing on the impact of energy related Exchange Related Funds (ETFs) on crude oil prices. In the previous studies we overviewed so far we concluded that this relationship is studied only between equity markets and crude oil markets

CHAPTER 1: IMPACT OF VERTICAL INTEGRATION ON ELECTRICITY PRICES IN TURKEY

ABSTRACT

Government's active participation in to the energy markets requires us to understand its vertical and horizontal integrated involvement. Coherently, in order to diversify their portfolios and reduce their business risks, vertical integration of the major private players in the market is another important topic. Under these market conditions market power becomes prominent. Our paper utilizes ARX models to analyze market power and portfolio diversification impact on electricity prices. In the aggregate models since we used high frequency time series data for all bidding hours of day ahead market, autoregressive structure within the system marginal prices vitiated the effect of power production type. Accordingly, we benefited various hours of the day as separate time series where a baseload (hour 24) and a peak hour (hour 11) were selected. The contribution of our paper to the policy debate is to highlight that such issues exist in the first place and that market power remains an important concern in Turkish electricity market.

Keywords: Electricity prices, renewable energy, time series, market power, vertical integration

1 INTRODUCTION

Turkish energy sector has been in a liberalization process since 1993. In this liberalization process big conglomerates invested and established vertically integrated business structures while government held its position as both a vertically and horizontally integrated market player who still has the market power both in electricity generation, wholesale and retail. In energy sector, strategic targets for Turkey are to maintain the security of energy supply as well as to increase competition for the benefit of the customers and reducing the costs within all steps of the value chain.

Coherent with global benchmarks renewable energy investments expanded rapidly which provided diversity in the energy production portfolio of Turkey. YEKDEM[3] mechanism is one of the most encouraging factors for both strategic and financial investors. Renewable projects generate sustainable cash due to hard currency feed-in tariff and greatly available funding resources. However, renewable producers who sell in the market help Market Clearing Price (MCP) to settle at a lower rate in the merit order, has an important impact on electricity prices.

Electricity prices have different stochastic properties to those of standard financial products and even other commodities mainly because of its non-storable nature. Electricity prices contain strong seasonality, very short-lived spikes and mean-reverting behavior. Models which tries to describe and estimate the dynamics structure of electricity quantity has been continued even before deregulations began in other countries. Electricity market models require energy prices for balancing, spot and short-term forward transactions. Estimating short term load is very crucial in operation and planning of power systems. The obtained electricity price forecast models facilitates the development of bidding strategies and negotiation process in order to increase profits in an extremely volatile market.

In this chapter we try to understand the dynamics between electricity prices and production type of electricity as an application study of merit order based on regression models. Our contribution to the growing literature on Turkish electricity market is applying models incorporating newly established EXIST high frequency data. To our knowledge, our paper is one of the first attempts which incorporates hourly EXIST data in applied models for electricity prices.

The study is organized as the following: In the sub-parts of Section 1, market fundamentals of Turkish electricity market is summarized. Section 2 includes the literature review on previous

[3] YEKDEM is a support mechanism for electricity manufacturers from renewable energy resources.

research on electricity price modeling and market power. Section 3 presents the data utilized and we discussed our empirical findings in Section 4. Finally, section 5 provides conclusion remarks and further study areas within this topic. Our analysis is based on basic ARx models so we included brief information about the methodology only in the appendix part.

1.1 Open Electricity Markets

Electricity markets cover a number of specialized products and services that are largely invisible to the public. An average consumer of electricity is naturally concerned with the price of kWh, but does not realize how complex is the machinery that delivers energy to their house with an exceptional level of reliability (Kaminski 2012).

Establishment of Electricity Markets do not change the physical properties of electricity energy. Electricity Market Design is different from other commodity market designs due to the following 3 main properties of electricity:

- Electricity Energy cannot be stored easily as other commodities
- Electricity Flow is subject to physics rules ("Kirchoff Laws") and do not follow the commercial contract flow.
- Transmission system constraints significantly limits the commercial operations.

The most important aspect of market design is the electricity price. Accordingly, in order to supply the price that would change depending on the maturity (risk) the market design is basically composed of;

- Short term price mechanisms,
- Long term price mechanisms and
- Constraint management

Schweppe et al. (1988) applied the spot pricing theory to electrical energy for the first time which is represented more detailly in Schweppe's book. It is often used to provide theoretical background for the discussions of competition in power systems (Kirchen and Strbac 2004).

Electricity we are consuming today is a result of planning and investment in 15 years ago.

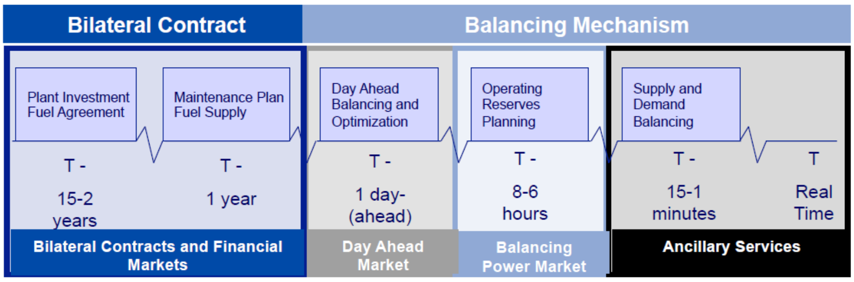


Figure 1: Life Cycle of Consumed Electricity

Based on natural investment and optimization flows of electricity market activities, electricity trading can be broadly classified as bilateral contracts complimented by balancing mechanism

Despite Tesla's all innovative actions as it is still not economically feasible to store significant amount of electricity, it has to be produced and consumed simultaneously as much as it can be which is why trade in electricity refers to a particular amount of megawatt-hours to be distributed over a specific time period. The duration of this hour is settled as an hour.

There are six basic specifications for a good electricity market design:

- **Economic efficiency:** Encourage customers to revise their own electric energy consumption to balance with utility marginal costs
- **Equity:** Decrease customer cross-subsidies
- **Liberalized markets:** Deliver customers options on the cost and stability of supply and how they prefer to consume electric energy
- **Customer recognition and understanding:** Customers should be able to realize the nature of the transactions and be convinced that they are fair
- **System control, operation and planning:** Full fill the engineering requirements for controlling, operating and planning a power system

- **Customer control, operation, and planning:** The customers' reaction to transactions should require simple steps

Electric energy should be distinguished from other commodities since it can be bought, sold, and traded based on its unique time- and space-varying values and costs. The hourly spot price is the fundamental unit of the energy market environment. It provides the necessary infrastructure for all transactions. An hourly spot price, which is presented in dollars per kilowatt hour, reflects the operating and financial costs of generating, transmitting and distributing electric energy. It fluctuates each hour and from market to market (Schweppe 1988).

1.1.1 Bilateral Trading

Bilateral trading composes of just two sides; a buyer and a seller. Parties thus agree on a contract without participation and/or facilitation by a third party.

In this context, buyers and sellers can agree on different forms of bilateral trading due to the duration and the quantities to be traded:

- **Customized long-term contracts**: Such kind of contracts have flexible terms and conditions since they are bargained privately to fulfill the objectives and needs of all sides. Usually they require large amounts of electricity sales for long time periods. These contracts become feasible only when the buyer plans to buy large amounts of electricity due to transaction costs which will be born in the transaction.

- **OTC Transactions:** These transactions compose of smaller amounts of standard profile energy to be delivered. It is a standard identification of how much electricity will be sold during various hours of the day or week. That kind of transaction will require lower transaction costs. They are mainly preferred by generators and costumers to adjust their portfolio as delivery time comes closer.

- **Electronic trading:** Parties may choose to trade electricity in a computerized marketplace directly. All related parties are able to explore the price and amount offered however they don't have an insight about the identity of the party that offered each bid or ask. When a market participant places a bid, the software that runs the exchange tries to match the offer for the period of the delivery of the bid. If the software can find an offer whose price is greater than or equal to the price of the bid, a match is automatically generating a deal and the price and the quantity are exhibited for all parties to see. If the software cannot find any proper match based on the restrictions mentioned above, the new bid is placed in the list of open bids and will keep placing there until an offer is matched with it. Otherwise the bid will be withdrawn or it expires when the market ends that period.

1.1.2 Electricity Pools

At the very beginning of introducing competition to the electricity trading, bilateral trading was seen as too much differentiation for the existing practice. It was a shared view that trading could be operated with a centralized approach and include all producers and consumers since electricity is pooled as it flows from producers to the loads. As a result, electricity pools were created to fuel the competition in the energy markets. Although pooling is not a common practice for commodity trading, they have established the basics which enabled operating large power systems. Actually, monopoly utility companies with neighbor service territories are the ones who developed the basis of collaborative pools and created competitive electricity pools which are currently operative (Kirschen, 2004).

Briefly, operational process of those pools are as mentioned below:

- Production companies (generators) submit bids to provide a specific load of electricity at a specific price in the agreed period. Afterwards, submitted bids are ranked in an increasing order of the offered prices. This ranking composes a curve which shows the bid price as an output of the cumulative bid quantity. As a result, this composed curve represents the total market supply curve.

- As expected, the market demand curve can be prepared as the opposite of demand curve preparation method by asking all the customers to send their offers designating load amount and purchasing price and sorting these offers in a decreasing order of price. The inelastic structure of the demand curve for consumers drives us to assume that it will be a vertical line at the value of the load estimation.

- We reach the market equilibrium by the intersection of the demand curve and the supply curve. After acceptance of all the bids offered at a price lower than or equal to market clearing price, the generators are informed to produce the amount of energy related to their accepted bids. Coherently, after acceptance of all the offers sent by consumers at a price greater than or equal to market clearing price, the consumers are informed about the energy amount that they are allowed to draw from the system. If they consume more than they are obliged to pay for balancing costs.

- System marginal price (SMP) is the market clearing price which refers to the marginal price for one megawatt-hour of electricity. Producers earn this SMP for every megawatt-hour that they produce while consumers pay the SMP for every megawatt-hour that they consume, is they do not tick to bids and offers that they have sent.

1.1.3 Pool vs bilateral trading

Centralized form of system management can be provided by pools. There are not much incentives settled for most of small and medium electricity consumers to take an enabler in an electricity market and play an active role. The retailer that represents them has no direct impact of revising consumption in response to changes in prices even in an aggregated level which suggest us the inelastic structure of demand.

Pools provided a mechanism to reduce the scheduling risk exposed by producers which enables them to decrease costs. A producer takes the risk that for some periods it may not have sold enough load to keep the plant on-line when it sells electricity on the basis of simple bids. In this context, the decision point is if to sell electricity without any profit or to keep the power plant operating or to close it down and pay the cost of another start-up for coming periods. In each case the cost of energy production will increase for this power plant and push producers to increase its average bid price. Hence pool implemented a scheduling algorithm which tries to prevent unnecessary shutdowns and optimize the process. Tough existence of an algorithm is a strong instrument in the market in real life it is not so precise if complex bids and pool-based scheduling actually decreases power prices or not.

1.2 The Settlement Process

After the buyer is delivered the proposed amount of electricity by the seller, the buyer pays seller the agreed price and the commercial transaction directly settles between the parties. In case the load delivered is less than the load agreed, the consumer has the right not to release some of the payment or if the consumer uses more than the entitled amount, the seller has the right to request an extra payment. This process is more complex for electricity markets from the producers to the consumers since the produced electricity is pooled during its transmission which is the main issue why the market needs a centralized settlement system.

1.2.1 Electricity Retailers

Consumers with a peak demand of at least a few hundred kilowatts can make high amount of money by recruiting personnel with good know-how to forecast their demand and establish a strategy to trade in the electricity markets for getting lower prices. Although such skilled consumers may directly participate and be active in the markets, establishing such a trading strategy is not beneficiary for smaller consumers. These smaller consumers usually choose to purchase at a constant price per kilowatt-hour that is updated mostly a few times per year. This constant price is called “tariff”. At that point existence of electricity retailers provides reducing the difference between the wholesale market and these smaller consumers.

The main issue for retailer is to manage and balance their trading portfolio since they have to buy electricity at a fluctuating price on the wholesale market and sell it at a fixed price at the retail market. A retailer loses money when the markets experience high prices as the it will have to supply energy with a higher price than the price at which it resells to the customer. However, when the prices are low it will make profit because its selling price will be higher than its procurement price. A non-monopoly retailer on the supply side of electricity in a given region can estimate the demand of its customers less consistent than what a monopoly utility can estimate. This problem induces customers to change their supplier to get a better price. A customer base with high churn rates makes it more difficult for the supplier (retailer) to have the reliable statistical data that it needs to adjust its demand estimation.

Competitive markets model represents a universe that all incumbent suppliers and new entrant’s suppliers have the same level of marginal cost of electricity supply driven by the spot price. The competition is expected result in putting pressure on both supply costs and operational costs. If some conditions are met like access to transparent information, consumers pay no switching costs, entrants in areas of local incumbents pay small entry and exit costs– then electricity retail competition can be on price in a setting of Bertrand-like oligopolistic competition (Boroumand 2015).

1.2.2 Vertical Integration in Electricity Markets

In his study Perez (2007) compares totally disrupted and partially vertically integrated markets utilizing a comparative statics method and analyses the bidding process of the parties. He concludes that partial vertical integration between producers and retailers obviously reduces wholesale prices. Based on which firms has more capacity and according to level of demand, prices may not change or even increase. Since electricity commodity is a very homogenous product the structure of the oligopoly looks like a Bertrand price competition unless the retailers do not face a capacity constraint.

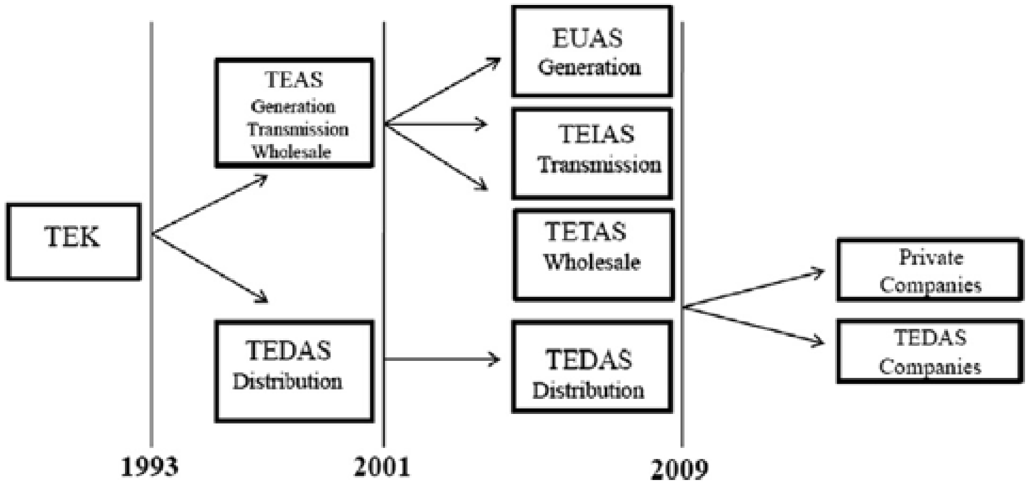
Another important point is multimarket competition theory which refers to potential entrants as existing companies on related markets. Usually these companies face same competitors in many markets that stabilize the competitive game (Gimeno and Woo, 1999).

1.3 Evolution of Power Markets in Turkey

Turkey experienced a complex privatization of utilities process in the last decades mainly in three separate stages. First is clearly a change in ownership from the public to private investors. Secondly, the restructuring of the firms and thirdly one is a change in the way the market operates, mostly involving an adoption of competitive procedures. The government-owned Turkiye Elektrik Kurumu ("TEK") which was vertically integrated company in all parts of the value chain was also the dominant monopoly until the beginning 1990s. Market liberalization started in 1993 with a privatization approach and as a result TEK was divided into TEAS which was operating in generation, transmission and wholesale while TEDAS became the main distribution body. Afterwards in 2001 Electricity Market Law was enacted and TEAS was separated into two. As a result of this separation EUAS became the main generation company while TETAS became responsible for wholesale and TEIAS became the transmission company. Consequently, this unbundling process created organizations as separate legal entities.

As exhibited in Figure 2, the privatization process in the electricity distribution sector was initiated in 2009 and completed in a total of 12 regions by early 2013. As of 2017 there are 21 regions in the market but accordingly, vertically integrated energy groups exist in the market as major players (Karahan et all 2013).

Figure 2: The Restructuring Process in Turkish Electricity Market



In the strategy paper covering the transition period 2006-2010 it was mentioned that distribution companies would buy 85% of the regional electricity demand consumed by non-eligible customers from TETAS. In this context the portfolio generation companies were carved out of EUAS.

TETAS was established to manage wholesale operations and take over the available agreements for electricity sale and purchase from TEAS and TEDAS. TETAS' responsibility area also included managing the problematic costs related with the Build Operate Transfer (BOT), Transfer of Operating Rights (TOR) and Build Operate (BO) production contracts.

If it is needed, EUAS had also rights to build, lease and operate new generation facilities coherent with the EMRA approved installment capacity estimations along with the planned production capacity investments by the private entities.

Based on the latest 2016 annual electricity market report of Republic of Turkey Energy Market Regulatory (EMRA) we can see the market competition of electricity generation (Table 1). The change in HHI Index by including or excluding BO-BOT power plants is quite self-explanatory. BO-BOT power plants still have a significant impact in the generation part of the value chain.

Table 1: HHI Index Based on Generation and Installed Capacity

	Generation			Installed Capacity		
	2014	**2015**	**2016**	**2014**	**2015**	**2016**
Excluding EUAS and TETAS	1416	1123	673	1132	996	820
Including EUAS and TETAS	2748	2153	1242	1918	1645	1289

Source: EMRA

However, HHI decreased significantly within the last three years with the retirement of some BO-BOT power plants in the ARx models exhibited in section 3 and 4 we will see the dominant effect of those government owned power plants in the market. The important point is after 2019 when most of the BO-BOT power plants retire how will the structure of merit order will change also with the inclusion of nuclear power plants in the following years.

As stated by the Privatization Administration of the Prime Ministry, the primary outcomes desired with the privatization in the sector can be summarized with the following properties:

- Lowering costs through effective and efficient operation of electricity distribution assets.
- Decreasing loss and theft ratios, by reducing technical losses in distribution and preventing illegal use, and hence
- Reducing consumer prices by reflecting all the gains obtained on to consumers.

Regulations are the main market shapers in Turkey like other energy regulators in other countries. Most of the companies are obliged to in Turkey, more than 67% of the electricity is generated from fossil fuels. Suppliers who utilize the grid network have to compensate the amount of electricity which their customers consume and pay penalty to the network operator if any imbalances occur. The network operator keeps some generating reserves to ensure that the network can operate in balance and does not face system shutdowns. In this context power generation companies face with limitations on their productivity and obligations to comply with grid operator requests reduces their profit levels significantly.

Securing the supply of a particular resource, such as natural gas, can become crucial. Supply from countries with large natural resources increases their supplier power. Such situations can also create political problems if the supplier is a government owned facility.

For example, with the announcement made by EPİAŞ on November 22, 2016, the restriction on the amount of natural gas provided by BOTAŞ to TETAŞ and EÜAŞ natural gas power plants was increased to around 50% as a result of further increase in consumption on 14 December 2016. According to sector sources, BOTAŞ increased the amount of cuts applied to natural gas plants to 75% on 21 December 2016 and to 90% on 22 December 2016. Continuation of the shortfall to natural gas power plants carried average electricity prices to record levels in the Day-ahead Market (DAM) between December 15 and December 21.

In this context:

- Power plants are ordered according to their short-term marginal costs to establish the merit order (Figure 3)
- Marginal plant determines the price and all power plants on the left side of demand are dispatched while the ones on right side of the demand are not dispatched.
- Pricing strategy is determined due to the competition between different types of plants and within the same group of plants.
- Above 90% of the time electricity prices are determined by plants whose fuel costs are in USD (CCGT and import coal).
- Since CCGTs are the marginal plants 85% of the time natural gas prices are the most important determinant of electricity prices.

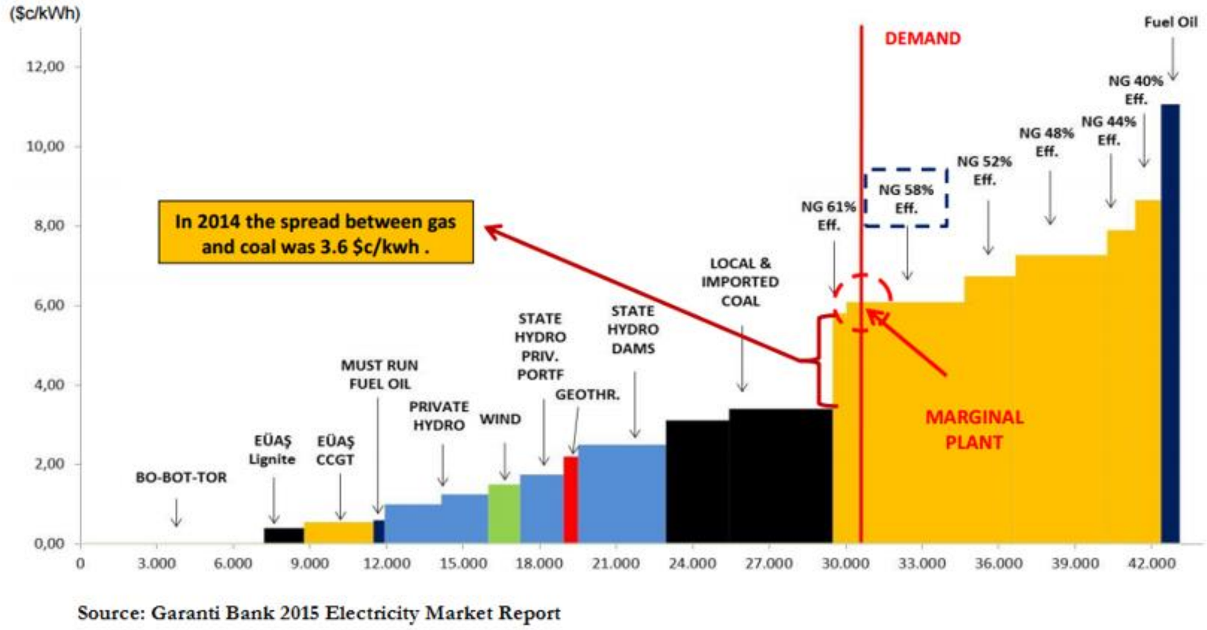


Figure 3: Merit Order Scheme

In Turkish energy market renewable energy has become a priority for the past few years as coherent with the developments in global energy markets, policymakers also realized the role that renewables will play in expanding electricity generation, diversifying the energy supply mix, providing a domestic energy supply resource and decrease supply risk and provide a sustainable energy supply market. Turkey's dependency on imported natural gas for electricity production has triggered the increasing concerns over both supply security and the increasing current account deficit from a more macroeconomics perspective. However further analysis and more developed forecast models should be studied in order to not to experience negative electricity prices in the market as it happened in Germany with the tremendous renewable energy production increase

Accordingly, government is the main driver of degree of competition in utility sector which determines the structure of the industry. Some countries have already experienced the liberalization by unbundling generation, transmission, distribution, and retail operations in electricity markets which empowered all end-users to switch suppliers. Those markets are evolved in to a buyers' market from being a sellers' market. Others markets still struggle with less liberalized structures such as suppliers are monopolies within specified geographical regions.

1.3.1 Day Ahead Market in Turkey

An organized wholesale spot electricity market established on 1st of December 2012 to purchase and sale of electricity to be delivered in the day ahead which is called Day ahead market (DAM). Market Operator manages the delivery of electricity on the basis of settlement period which is 1 Hour. This mechanism enables the market participants to balance their production, consumption and bilateral contract obligations.

An important aspect of DAM brought to electricity market is chance of demand side to adjust its consumption based on price levels. Coherently, demand side began to actively participate to market thus has the chance of hedging itself against price volatility. Participation to DAM is not mandatory. Moreover, DAM enabled financial settlement in daily basis and performance of daily clearing of payables/receivables due to commercial transactions at next day after commercial transactions date. This situation allowed market participants to receive revenues generated by sales of generated electricity on daily basis rather than monthly basis which provides them liquidity.

1.3.2 Balancing Power Market in Turkey

In order to maintain the physical supply and demand balance through a transparent market mechanism Balancing Power Market (BPM) is designed. Since market participants are not capable of complying with their accepted bids/offers in the day ahead market there was clear need for an essential market establishment.

Firstly, System Operator sorts offers and bids sent by the market participants on BPM according to their prices. Maximum accepted hourly offer price applied to up-regulated balancing entities in the system is accepted as the System Marginal Price (SMP) if any deficit occurs in the system. However, in case any surplus occurs in the system, the minimum accepted bid price applied to down-regulated balancing entities to compensate the imbalance in the system will be the System Marginal Price (SMP).

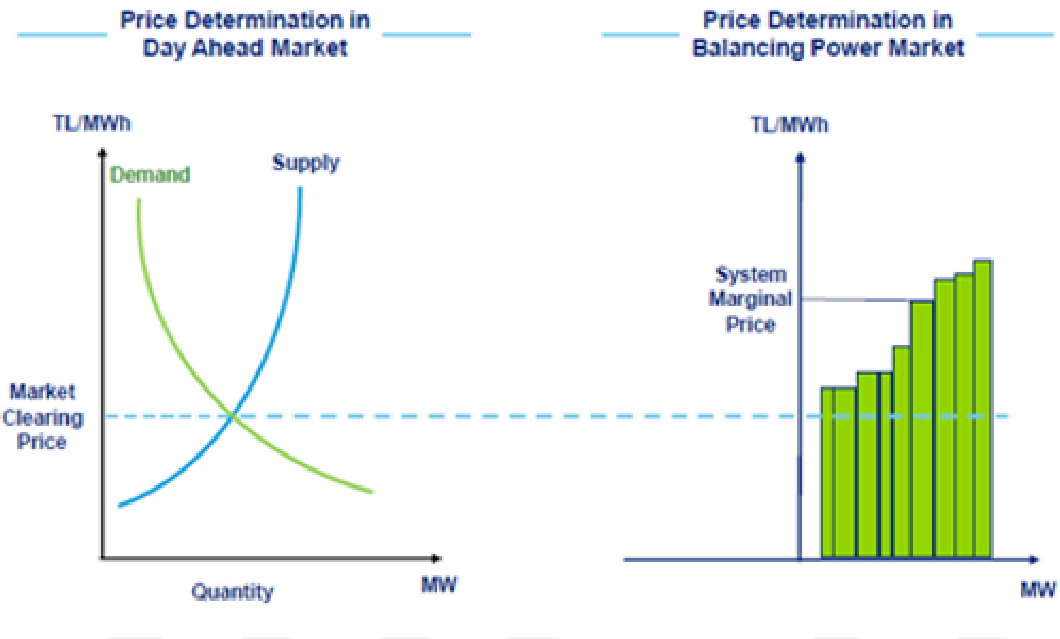


Figure 4: Price Relationship between DAM and BPM

Figure 4 exhibits the relation between day ahead market and balancing power market prices. By nature, the price calculated in balancing power market will be higher than price settled in day ahead market. BPM price is used to compensate imbalances and this relationship incentives system players for trading into a balance on the DAM to avoid imbalanced price.

1.3.3 General Offering Principles of DAM in Turkey

Participants can submit hourly and daily for a particular period of hour/hours and/or flexible offers to DAM.

- Offers are composed of quantity and price information that can change for different hours
  - ✓ Submitted offer prices have centesimal sensitivity.
  - ✓ Offers can be made in terms of Turkish Lira, US Dollar, and Euro currencies
  - ✓ Offer prices submitted other than Turkish Lira are assessed by converting these prices into Turkish Lira by using daily CBRT bid rate
  - ✓ Offer quantities are submitted in terms of Lot as an integer number. 1 Lot is equivalent to 0,1 MWh
- Offers can be submitted as both buying and selling offers. Depending on the sign in front of the quantity, the offer is either buying or selling offer. (For instance 100 Lot indicates a buying offer whereas -100 Lot indicates a selling offer)
- Minimum and maximum price limits are determined by the market operator between 0 TL and 2000 TL respectively. Depending on changing market circumstances, the market operator updates minimum and maximum price limits and announce them via Market Management System to market participants.
- Minimum and maximum offer quantities are determined by the market operator as 0 Lot and 100.000 Lot respectively.
- Offers submitted for same delivery date are recorded to the system as a new version in case they are updates.
  - ✓ Latest version of an offer is considered during matching,
  - ✓ Older version of offers can be viewed via Version Filter

2 LITERATURE REVIEW

Industry concentration and individual company market share are usually accepted as a proxy for market power however there are many other elements like the number and size of other competitors in a market which affects the degree of a competition. Price sensitivity of demand, incentivizing the producers and the potential for output expansion by competitors and potential new entrants can be referred as such elements. Although concentration measures represent the current distribution of sales or capacity, they cannot predict how market prices will change when one company decreases its output. Since electricity is a commodity which is not storable and there is no demand elasticity in the short-run this is a very important topic in electricity sector. In this context analyzing the strategic behaviors of the firms becomes important.

According to Stoft (2002) HHI has some deficiencies since it does not capture some key factors that are very important such as competition style, price sensitivity of demand, vertical integration of companies, forward contracting and geographical structure. In accordance, since electricity is non-storable, market power can cause big inter-temporal variations. as concluded commonly in Borenstein et al. (2002) and Fabra and Toro (2005)

Economics of vertical integration exist and have significant impacts in the electricity production sector as mentioned by Kaserman and Mayo, Lee and Goto and Nemote (1991). Borenstein et al (2000) highlights the integration of network-generator that may be profitably encourage bottlenecks and enable the producer to become a monopolist on residual demand. Moreover, lack incumbent producer incentives to go for brand-new competitive markets was highlighted by Proseperetti (2000).

Borenstein et all (1999) modeled only the large market players as Cournot competitors where significantly smaller players were assumed as price takers. In accordance with Cournot-Nash equilibrium, strategic players in the market apply quantity strategies. Each of these strategic players determines its quantity to produce taking as given the output being produced by all other strategic players. Smaller players simply take the market price as given and produce all output as long as its incremental cost is lower than the settled market price by major strategic players in the market. Furthermore, Andersson and Bergman (1995) and Oren (1997) utilized Cournot model to analyze electricity markets.

Modeling of equilibria is applied to electricity markets as a game-theoretic concept when bidders specify cost/quantity supply functions. Rather than the inflexible quantity bid given by the Cournot model, are actual price quantity bid functions. However, in some markets, trades do not exist specifically via a supply-function bid process. In most of the restructured markets in the world, it is common practice that specified quantities are traded by bilateral trading. In many of these markets players bid energy prices along with ramping rates, other supply characteristics and startup costs. If any competitive fringe exists in the market for the players due to capacity limitations based on either generation or transmission constraints, the supply function approach may not justify itself.

Nevertheless, the supply side is the main driver of a potential to execute market power. Deregulation process in many countries is triggered by issues such as initiatives to mitigate market power and pursue market efficiency. This is quite interesting since the exploitation of market power can transform the sellers' market in to a buyers' market by eroding the consumer benefits. This will change the market structure from a regulated business environment to a competitive market in electricity generation (Fezzi, 2015). In this context, Cournot model for a base case analysis is supported by the centralized price mechanism and suppliers with limited capacity during peak timed in electricity markets.

Moreover, government's active participation to the energy markets requires us to understand its vertical and horizontal integrated involvement. Private companies operating in the energy market are also vertically integrated in order to diversify their portfolios and reduce their business risks.

Bosco et. all (2016) focus on the degree of vertical integration effects of bidding strategy of monopolistic players in Italian energy markets. In this paper they addressed the question of how the supply conduct of a vertically integrated power generator can be coordinated in a wholesale market with the buying activity of a downstream retailer. Their model shows the relationship of a vertically integrated energy group composed of a holding company, production and retailer companies along with Principal-Agent (P-A) model. In the absence of an incentive, the generation branch would behave in an opportunistic manner raising equilibrium prices in the market to its own advantage which will reduce profits of the retailer branch which buys electricity in the wholesale market and sells it to customers to fixed prices. The crucial point here is that the holding that parents generator and retailer companies should be pivotal one who has the power to make the market.

Vertical integration issue which is being operated as the joint ownership of production and retail business in the value chain, empowers anti-competition more and more within electricity and gas market regulation (Bunn et al. 2001). In the previous studies which utilizes agent- based approach where producers may offer above or below marginal costs, producers offer their unutilized production capacity to the market as a discontinuous increasing supply function with much differing offer prices from marginal costs (Weidlich and Veit, 2008).

Aid et. all (2011) claim that reducing the gap between producers and retailers to demand risk can be achieved by vertical integration. A negative relationship between the development of forward markets and incentives for players to merge with vertically related segments was predicted in their findings. Ceteris paribus, in industries that are more exposed to uncertainty and risk management tools are not less utilized efficiently, their estimation is that vertical integration will be higher. In addition to that Aid et. all (2011) also state that according to their expectations in industries which have greater risk aversion profiles through more regulatory pressure and higher bankruptcy costs, regardless of whether forward markets are developed or not vertical integration will be observed more widespread.

3 ECONOMETRIC DATA DESCRIPTION

After establishment of Energy Exchange Istanbul (EXIST) the day a head electricity settlement data is not provided by Market Financial Settlement Center (PMUM[4]). Moreover, the publicly available data on EXIST transparency platform is not sufficient for such a vertical integration and degree of market power study since we cannot see the generator company and region information from these data series. Therefore, we worked on an aggregated model to analyze the SMP in electricity market with publicly available hourly data on EXIST.

We can emphasize the factors that affect spot prices based on two approaches such as production approach and consumption approach;

Production Approach:

- installed capacity
- power plant type (natural gas, fuel-oil, hydro etc.)
- power plant efficiency, maintenance and breakdown, management policy (private or public company)
- gas restrictions
- generation by renewables resources (wind, solar, hydro, geothermal etc.)
- generation by build operate transfer model and build operate models

Consumption Approach:

- macroeconomics growth
- weather conditions and seasonality
- consumption variance between peak-off and peak hours
- consumption variance between weekend and weekdays, public holidays

[4] Piyasa Mali Uzlastirma İş Merkezi

A new commercial instrument has been introduced to electricity markets after the Intra Day Market (IDM) was opened on 1st of July 2015 which reduced the imbalance and electricity trade volume in spot markets. Moreover, new feed in tariff (FIT) regulation for renewables became effective at the end of April 2016. In this context Model 2 is based on the dataset between 01.07.2016 and 01.09.2016 in order to analyze the regulation change and IDM opening effect on SMP. Most of the data set are stationary. (see Table 7 in the appendix part for ADF test results and Table 8 for LM test results). The dataset definitions which are used in our models are as exhibited below:

Table 2: Model Dataset Descriptions

#	Variable	Description	Frequency
1	log(brent usd)	Logarithm of daily brent oil prices	Daily
2	log(blocksales)	Logarithm of block matched sales amount	Hourly
3	log(wind)	Logarithm of injection quantity by wind	Hourly
4	log(lignite)	Logarithm of injection quantity by lignite	Hourly
5	log(geothermal)	Logarithm of injection quantity by geothermal	Hourly
6	log(natural gas)	Logarithm of injection quantity by natural gas	Hourly
7	log(dammed)	Logarithm of injection quantity by dammed hydro	Hourly
8	log(pibid)	Logarithm of hourly aggregate price independent bid quantity at 2000 TL/MWh	Hourly
9	log(fuel_oil)	Logarithm of injection quantity by fuel oil	Hourly
10	log(biomass)	Logarithm of injection quantity by biomasss	Hourly
11	log(LNG)	Logarithm of injection quantity by LNG	Hourly
12	log(mcp)	Logarithm of market Clearing Price is the hourly energy price that is determined with respect to oders that are cleared according to total supply and demand	Hourly
13	log(smp)	Logarithm of price that corresponds to the net regulation quantity of the Balancing Power Market	Hourly
14	log(usdtry)	Logarithm of Dolar against Turkish Lira FX closing rates	Daily
15	log(mcp)	Logarithm of market Clearing Price is the hourly energy price that is determined with respect to oders that are cleared according to total supply and demand	Hourly
16	log(tetas)	Logarithm of TETAS Final Daily Production Program	Hourly
17	log(consumption)	Logarithm of total hourly real-time consumption	Hourly
18	log(aksa)	Logarithm of Aksa Final Daily Production Program	Hourly
19	log(enerjisa)	Logarithm of Enerjisa Final Daily Production Program	Hourly
20	log(renewables)	Logarithm of wind, geothermal, biomass, river and dammed injection quantity sum	Hourly
21	systemproxy	Proxy variable which gets the value "1" for energy excess and "0" for energy deficit in the system	
22	daypeak	Proxy variable which gets the value "1" for hours between 07:00 and 21:00 and "0" for other hours	
23	@trend	Trend variable	

4 APPLICATION AND FINDINGS

In this study our main intention was to use electricity consumption, production and price hourly data provided by EXIST to drive models with high frequency data. For this reason, we applied simple ARX models since we faced high degree of autocorrelation in hourly time. Our first goal was not to find an innovative econometric model but to apply models via newly established EXIST database in order to check the energy policy effects on electricity prices.

Consequently, we analyzed the data in two aspects; first we tried to find the relationship between the SMP and electricity production type to see the impact of merit order mechanism on settlement prices. Secondly, we used hourly production data of Enerjisa and Aksa along with EUAS and TETAS who affect the price levels significantly by their level of production in the merit order. Enerjisa and Aksa are among the biggest private companies who operate in energy market with their well-diversified portfolios.

4.1 Aggregate Models

Briefly, two I(1) variables could exhibit significant correlation, without an underlying relationship however the regression must make economic “sense”. This is called spurious regression problem. To avoid this problem, we checked whether the variables are stationary or not in our dataset via Augmented Dickey-Fuller (ADF) tests. We also included a @trend variable in Model 1 and Model 2 (exhibited in Table 3) to eliminate spurious relationships between independent variables.

Model 1 and Model 2 are based on same independent variables with two different times zones, 18.12.2015-01.09.2016 and 01.07.2016-01.09.2016 respectively. In this context econometric model equation for Model 1 and Model 2 is as mentioned below:

$$\log(SMP) = \beta_1 \log(brentusd) + \beta_2 \log(blocksales) + \beta_3 \log(wind) + \beta_4 \log(lignite) + \beta_5 \log(geothermal) + \beta_6 \log(naturalgas) + \beta_7 \log(dammed) + \beta_8 \log(pibid) + \beta_9 \log(fuel\_oil) + \beta_{10} \log(LNG) + \beta_{11} \log(mcp) + \beta_{12} systemproxy + \beta_{13} trend)$$

Table 3: Model 1 and Model 2 for System Marginal Price Estimation

	MODEL 1			MODEL 2		
Variables	Est.	S.E.	T-Statistics	Est.	S.E.	T-Statistics
log(brent usd)	-0,80	0,24	-3,37	0,84	0,33	2,55
log(blocksales)	0,23	0,05	4,74	0,10	0,04	2,29
log(wind)	0,24	0,03	6,90	0,01	0,03	0,30
log(lignite)	-0,61	0,21	-2,90	-0,13	0,17	-0,77
log(geothermal)	0,71	0,25	2,90	0,13	0,19	0,66
log(natural gas)	2,13	0,16	1,34	0,00	0,16	-0,02
log(dammed)	0,86	0,11	7,95	0,23	0,09	2,66
log(pibid)	-2,18	0,24	-9,08	-0,30	0,20	-1,48
log(fuel_oil)	0,32	0,10	3,10	0,01	0,07	0,11
log(biomass)	-1,26	0,29	-4,31	-0,31	0,19	-1,59
log(LNG)	0,14	0,03	4,08	0,00	0,02	0,21
log(mcp)	0,72	0,02	3,07	0,75	0,02	3,77
systemproxy	-0,87	0,04	-2,12	-0,69	0,03	-2,42
@trend	0,00	0,00	-1,93	0,00	0,00	-0,05
R^2	0,62			0,74		
Durbin-Watson	0,99			1,21		
df	6187			1483		

When we compare Model 1 and Model 2 primarily we can clearly see that Model 2 has a greater power to explain SMP changes with a R^2 of .7413 which means that we can explain 74% of SMP changes with Model 2 while we can explain only 62% of SMP changes with Model 1. Since @trend variable is not statistically significant in Model 2 we can conclude that Model 2 does not include a significant trend impact as Model 1 do. Although comparing models based on R^2 values is a poor econometric approach, it is a good signal to conclude that after new tariff regulation and IDM establishment efficiency of the model increases. This is important to check the impact of energy policies.

Singularly wind, lignite, natural gas, fuel oil, LNG, geothermal generation amount variables lose their strength in order to explain SMP changes individually in Model 2 however F-statistics is quite significant which makes us suspicious for multicollinearity between variables. Since generation power plants are expected to behave and produce in the same way due to demand trend in the market, existence of multicollinearity is not an unexpected result.

In this case, multiple regression coefficients can change irregularly responding to small changes in the model or the data. However, this situation does not decrease the predictive power of the model totally. It has only impact on calculations related with individual predictors.

As a result of this, correlated predictors in a multiple regression model can indicate how well the entire collection of explanatory variables can estimate the outcome variable where it may not give valid results about any individual estimator. Actually even extreme multicollinearity does not violate OLS assumptions and they are somehow still unbiased.

In Model 2, although significant varices are observed between average SMP and MCP, MCP is more active to explain SMP changes between 01.07.2016 and 01.09.2016 which suggests that Intra Day Market works efficiently. After the energy generation by renewable resources increased in the system, balancing demand and supply became harder but new FIT regulation and establishment of IDM seem to reduce this instability based on the results in Model 2.

Due to Model 1 when generation by wind, geothermal and dammed hydro power plants increase 1%, SMP is expected to increase 0.23%, 0.71% and 0.85% respectively. Although hydro, wind and other renewable sources produce a significant amount of electricity, fossil fuels such as gas and coal are still primary production resources.

In Table 4 we tried to model SMP changes with a more compact model. Similarly, OLS estimations in Model 3 and Model 4 are based on same independent variables with two different times zones, 18.12.2015-01.09.2016 and 01.07.2016-01.09.2016 respectively. In this context econometric model equation, for Model 3 and Model 4 are as mentioned below:

$$\log(SMF) = \beta_1 \log(mcp) + \beta_2 systemproxy + \beta_3 daypeak + \beta_4 \log(consumption) + u$$

Daypeak proxy variable gets the value "1" for hours between 07:00 and 21:00 and "0" for other hours. Based on DW statistics and R^2 values we do not suspect for multicollinearity in Model 3 and Model 4.

Table 4: Model 3 and Model 4 for System Marginal Price Estimations

	MODEL 3			MODEL 4		
Variables	Est.	S.E.	T-Statistics	Est.	S.E.	T-Statistics
log(mcp)	0,82	0,01	5,79	0,62	0,02	3,18
systemproxy	-0,98	0,02	-4,13	-0,86	0,03	-2,56
daypeak	0,13	0,03	4,94	0,08	0,03	2,29
log(consumption)	0,11	0,01	1,59	0,20	0,01	2,09
R^2	0,55			0,60		
Durbin-Watson	0,85			0,89		
df	5910			1491		

If we compare Model 1 and Model 2 with Model 3 and Model 4 we can see that production based approach model is more efficient than consumption approach models due to higher R^2 values. However, since R-square is not a sufficient decision point to compare regression models the important take away from Models 1-4 are the relationship of variables and their consistency with energy policies.

Electricity markets can be characterized by dynamic interactions. For example, if the supply function shifts upwards and as a result of this shift the clearing price increases, the quantity can response to this impulse with some delay since demand will require more time to adjust to the shock. Conversely, only after many lags the impact of an impulse can be fully absorbed (Fezzi, 2015).

In case the supply function shifts upward and the clearing price increases resulting from that, cleared quantity on the market may decrease with some delay since the demand may need more time to absurd this shock. The quantity cleared on the market responds to past equilibrium in the supply function even if the demand is not sensitive to price changes in the market. This asymmetric effect is due to the fact that demand reacts if prices are higher than the equilibrium but does not show any significant feedback if price is lower. Zhang (2015) suggest that when there is a positive relationship between electricity price elasticity (in absolute terms) and households' income, a uniform increase in the price of electricity can be quite regressive.

It is not so rare to experience time series regression equations with significantly high degree of fit but with an extremely low value for the Durbin-Watson (DW) statistic. The impact of economic and other variables is not commonly instantaneous. For producers, consumers and other economic agents to adjust against macroeconomics developments takes time. Since the equilibrium impact is felt only after the passage of some time, econometric models utilizing time series data are usually structured with lags in behavior (dynamic model). Lags in behavior might also take the form of the lags in the dependent variable.

Weron and Misiorek (2005) used ARMA and ARMAX models which are tested on a time series of California electricity market system prices and loads for forecasting electricity prices. They obtained best results with pure ARX models which included AR(i) processes and exogenous variables.

For this reason, Model 5 (exhibited in Table 5) specifies that the SMP depends linearly on its own previous values and on a stochastic term (an imperfectly predictable term); Model 5 is based on same independent variables between 18.12.2015 and 01.09.2016.

In this context equation for Model 5 is as mentioned below:

$$\log(SMP) = \beta_1 \log(brentusd) + \beta_2 \log(wind) + \beta_3 \log(geothermal) + \beta_4 \log(natura\lg as) +$$
$$\beta_5 \log(dammed) + \beta_6 \log(pibid) + \beta_7 \log(fuel\_oil) + \beta_8 \log(mcp) + \beta_9 systemproxy +$$
$$\sum_{i=1}^{5} \beta_{9+i} \log(SMP)_{t-i} + u$$

Table 5: Model 5 for System Marginal Price Estimations

	MODEL 5		
Variables	Est.	S.E.	T-Statistics
log(brent usd)	-0,52	0,18	-2,93
log(wind)	0,11	0,04	2,92
log(geothermal)	-0,44	0,14	-3,07
log(natural gas)	2,06	0,14	14,61
log(dammed)	1,31	0,08	16,69
log(pibid)	-2,79	0,19	-14,69
log(fuel_oil)	0,14	0,08	1,73
log(mcp)	0,76	0,01	54,43
systemproxy	-0,55	0,03	-20,77
AR (1)	0,56	0,02	35,66
AR (2)	0,04	0,02	2,14
AR (3)	0,07	0,02	3,87
AR (4)	0,05	0,02	2,68
AR (5)	-0,03	0,01	-2,06
R^2	0,71		
Durbin-Watson	1,77		
df	5442		

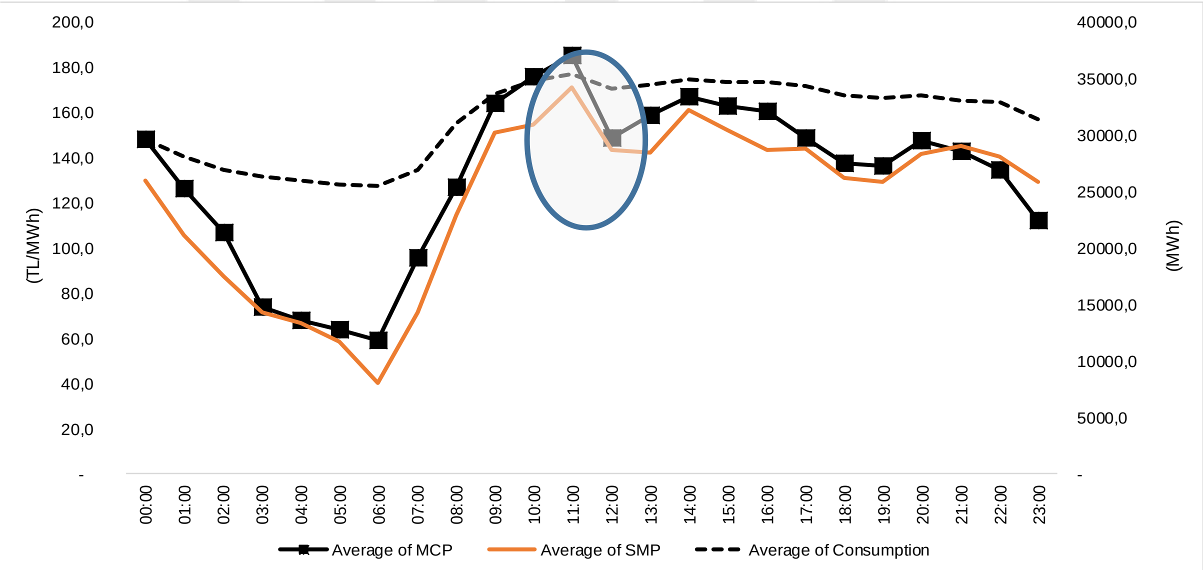
The serial correlation LM test results for this equation with 2 lags in the test equation strongly reject the null of no serial correlation for Model 1 while for Model 5 test equation cannot reject the null of no serial correlation. Another crucial topic to consider is the existence of excess capacity on the system such as the amount of electricity plants willing to generate and bid into the market for a specific hour or day. This is often indicated with the term "margin" and may highly fluctuate during the year due to the maintenance schedule of power plants as well as the strategic interaction of the suppliers (Borenstein et.al 1999 and Borenstein et al. 2002).

In Models 1-5 we can see that systemproxy variable is always significant and has a negative effect on SMP. Since the electricity prices are an outcome of the bids are submitted without knowledge of the future actual system load, this phenomenon might be explained by that situation.

As a result, in the aggregate models since we use high frequency data for all bidding hours of day ahead market, the effect electricity production type on SMP is vitiated. Following this consideration Model 6 and Model 7 were implemented considering market outcomes of different hours as separate time series where a baseload (hour 24) and a peak hour (hour 11) were selected.

Fezzi (2015) identified peak hour as hour 19 due to Pennsylvania, New Jersey and Maryland (PJM) market data however based on our analysis for EXIST which is exhibited in Figure 1, we decided to use hour 11 as our peak hour since both average electricity prices (MCP and SMP) and average consumption series intersect each other in this time period of the day hours at their highest levels.

Figure 5: Electricity Price and Consumption Trends



Source: EXIST

In this context econometric model equation for Model 6 and Model 7 are as mentioned below:

$$\log(SMP_{HR11/HR24}) = \beta_1 \log(blocksales) + \beta_2(d(brentusd)) + \beta_3 systemproxy + \beta_4 \log(impcoal) + \beta_5 \log(ng) + \beta_6 \log(ptf) + \beta_7 \log(renewable)$$

Differing from Models 1-5, in models 6 and 7[5] we summed up all renewable based production

[5] For model 6 and 7, we also tested alternatives with a weighted renewable production index (renweg) variable instead of totbal renewable production (renewable). Index was calculated as $\frac{production\ by\ wind}{total\ renewable\ production} \times wind\ production + \frac{production\ by\ dammed}{total\ renewable\ production} \times dammed\ production + \frac{production\ by\ river}{total\ renewable\ production} \times$

amounts in "renewable" variable. We also incorporated imported coal (impcoal) and natural gas (ng) based productions and first difference of brent oil prices (d(brentusd)) as well (Table 6). Furthermore, we included blocksales as explanatory variable in to the model considering the market power approach.

Table 6: Model 6 and Model 7 for HR11 and HR24

	MODEL 6			MODEL 7		
Variables	Est.	S.E.	T-Statistics	Est.	S.E.	T-Statistics
c	-2,20	1,97	-1,11	0,38	7,27	0,05
log(blocksales)	-0,12	0,05	-2,19	0,11	0,14	0,84
log(d(brentusd))	0,00	0,02	0,22	-0,01	0,07	-0,12
systemproxy	-0,51	0,04	-14,13	-0,69	0,14	-5,05
log(impcoal)	-0,06	0,15	-0,42	-0,63	0,53	-1,20
log(ng)	0,10	0,14	0,73	0,20	0,37	0,53
log(ptf)	0,76	0,12	6,17	0,78	0,11	7,04
log(renewable)	0,44	0,15	2,84	0,39	0,44	0,88
R^2	0,83			0,66		
Durbin-Watson	2,00			2,12		
df	246			246		

Block offers contain information regarding to price, quantity and time period encompassed and they are determined as consecutive and whole hours. If the block offers are under the average price of the encompassed time period, then the block offers are accepted or if block offers are higher than the average prices of the encompassed time period are accepted.

This market mechanism may have a pressure on the peak time electricity prices in favor of consumers. Block offers can be accepted only if they maximize total surplus in case supply and demand do not intersect and several offers are linked with each other. Coherently we observe

$river\ production + \frac{production\ by\ geothermal}{total\ renewable\ production} \times geothermal\ production + \frac{production\ by\ biomass}{total\ renewable\ production} \times biomass\ production +$. In section 7.6, Table 10 exhibits that alternative model results are not significantly different. Our expectation was to be able to find a better explanatory variable with Index terms compared to single production amount variables. However due to the test results we have concluded that Index terms do not contribute significantly better to the model efficiency. You can compare the results of Table 6 and Table 10 to compare both models more detailly.

that block sales have a significant negative effect on SMP at peak times while it is not a significant explanatory variable for base load.

These results bring additional support to the modeling philosophy that the estimation of separate models for each hour of the day can be a more efficient way to predict the exogenous variable effect on the electricity prices.

4.2 Company Models

Power generation companies may penetrate in to their buyer's operation area within the value chain such as retail for selling electricity to end-users depending on the regulatory regime. While it is not often possible for generation companies to sell their own electricity directly to end-users in the retail industry. This business portfolio diversification enables them to generate an additional revenue stream that can defend their margins. Some industries do have large energy supply companies with strong buyer power which enables them to protect themselves against volatile prices for wholesale power and their own inputs, such as coal or gas.

As a result of a decentralized market model most of the markets which have been liberalized are characterized by a more toward oligopolistic competition because of vertical integrated generators (Henney 2006). Electricity generators are encouraged to vertical integrate and leverage their portfolio by physical hedging to manage quantity and price risks inherited from electricity markets. Such kind of vertical integration prevents Bertrand-like competition to occur. If retail competition is a multimarket setting, then suppliers are induced to adopt oligopolistic behaviors (Boroumand 2015).

Rivality is mostly between the incumbent and new market players. Those new entrants are mostly incumbent in another local gas area or in the former national gas area in each geographic zone. It is reflected in the entries for the former gas national incumbent with dual fuel offers to compete against electricity incumbents in their historical former monopoly areas.

In many countries vertical integration of production, transmission and distribution operations has remained a dominant structure in the electricity sector which lowers the incentives for trading and for new entrants to the industry. However, moderate growth in recent years, coupled with a forecast for slightly faster growth through to 2018, makes the industry still attractive to new entrants.

For example, in addition to four main business lines being electricity generation, distribution, trading and sales, Enerjisa also manages a portfolio in natural gas. Although all these activities have different dynamics Enerjisa tries to leverage its business in an integrated way based on an efficient and flexible portfolio strategy focused on operational excellence. Accordingly, Kazancı Group, parent company of Aksa Energy, companies operate in all areas and carry out their operations in synergy with each and every link of the energy value chain, from production to distribution. The production portfolio of Aksa Energy includes 16 power plants which produce electricity using natural gas, lignite, wind, hydroelectricity, fuel-oil. Model 8 and Model 9 (exhibited in Table 7) are based on same independent variables with two different times zones, 18.12.2015-01.09.2016 and 01.07.2016-01.09.2016 respectively. Model equation for Model 8 is as mentioned below:

$$\log(enerjisa) = \beta_1 \log(usdtry) + \beta_2 \log(mcp) + \beta_3 \log(tetas) + \beta_4 \log(consumption) + \\ \beta_5 \log(aksa) + \beta_6 \log(renewable) + \beta_9 trend + \beta_9 \log(enerjisa)_{t-1}$$

and for Model 9 equation is as below:

$$\log(aksa) = \beta_1 \log(usdtry) + \beta_2 \log(mcp) + \beta_3 \log(tetas) + \beta_4 \log(consumption) + \\ \beta_5 \log(enerjisa) + \beta_6 \log(renewable) + \beta_9 trend + \beta_9 \log(aksa)_{t-1}$$

Table 7: Model 8 and Model 9 for ENERJISA and AKSA Final Daily Production Program

	MODEL 8			MODEL 9		
Variables	Est.	S.E.	T-Statistics	Est.	S.E.	T-Statistics
c	-15,89	2,87	-5,54	-58,20	3,77	-1,54
log(usdtry)	-7,42	2,41	-3,08	-7,46	3,22	-2,31
log(mcp)	-0,02	0,01	-3,60	-0,11	0,01	-1,32
log(tetas)	0,50	0,05	9,26	0,23	0,07	3,21
log(consumption)	2,11	0,15	14,02	6,93	0,18	3,76
log(aksa)	0,10	0,01	10,10	-	-	-
log(enerjisa)	-	-	-	0,18	0,02	10,10
log(renewables)	0,42	0,06	6,69	-0,42	0,08	-4,99
@trend	0,00	0,00	3,27	0,00	0,00	4,39
AR (1)	0,90	0,01	152,97	0,89	0,01	151,25
R^2	0,89			0,90		
Durbin-Watson	1,98			2,06		
df	5704			5704		

Electricity production in renewables has a positive effect on Enerjisa production planning while it has a negative effect on Aksa. The main reason of this fact is that Enerjisa production portfolio consists of approximately 30% renewables while most of the Aksa production is based on natural gas power plants. Moreover, production of TETAS have a positive impact on Enerjisa and Aksa production since they have a decreasing effect on MCP and reduces the equilibrium prices in the merit order.

TETAS and EUAS produce approximately 40% of the whole market which makes it in fact an oligopoly market. An oligopoly is a highly concentrated market structure in which only a few players dominate the whole market. However, it is not unlikely that many small firms may also operate in the market tough only a few firms dominate the market. In this case it is clear that TETAS and EUAS have the market power with their huge production capacity and they can force the market in to a Cournot equilibrium. A typical oligopoly market strategy is based on interdependency. Players in the market have to wait for the response of a rival to any given change in their price as they cannot exist in the market by acting independently. This is all to say, they need to plan and work on possible scenarios based on how the competitors in the market might react and repositions themselves. In this context oligopolists have to make critical strategic decisions, such as:

- Whether to compete with competitors, or cooperate with them.
- Whether to increase or decrease price, or keep price constant.
- Whether to be the first player to go for a new strategy or wait and see what competitors will do.

However, this is not the case in electricity markets. TETAS and EUAS make their production plans due to the collimation of government in line with Petroleum Pipeline Company's (BOTAŞ) current portfolio position. There are BO-BOT power plants with purchase guarantee from BOTAŞ until the end of 2018. There are no volume or price risk since the government has guaranteed the production of BO-BOT PPs. Approximately 1/3 of BOTAŞ' gas is consumed in BO-BOT plants. BOTAŞ has been trying to compensate its losses by selling expensive gas to these plants. As a result, regardless of the demand functions dynamics BO-BOT operators produce electricity which reduce the MCP in the merit order.

5 CONCLUSION

This study is mainly about the relationship between electricity prices and production type of electricity as an application study of merit order based on regression models. Our contribution to the growing literature on Turkish electricity market is applying models incorporating newly established EXIST high frequency data. To our knowledge, our paper is one of the first attempts which incorporates hourly EXIST data in applied models for electricity prices

The main difficulty we faced in the study is the limitations to high frequency in EXIST. We tried to show the impact of renewable energy generation increase in the market to both electricity prices and private company production strategies where we chose Enerjisa and Aksa companies as benchmark companies.

There is a need for detailed market power modelling for policy purposes due to the delicacy of the individual company effects. A more realistic baseload and peaking differentiation in strategies is possible with reinforcement learning on both capacity and pricing being specifiable compared to the existing conventional approaches of utilizing either price or capacity manipulation other across all technologies (Bunn 2010).

Another field for next research topics may be to dig deeper in bidding strategies of private companies if sales and consumption data by company and industry are provided publicly by EXIST in the transparency platform. Hortaçsu and Puller (2008) suggests that the behaviors of smaller players in newly restructured markets should be studies more detailly. Although the finding is not inconsistent with rational economic behavior, it is concluded that smaller players submit bids that differ substantially from the benchmarks we construct for optimal bidding. Such irrational or let say unexpected behaviors of the smaller players may have other edges for the conglomerates that they belong to which is the main logic for vertical integration in the whole value chain. The losses or irrational actions you see in one part of the value chain can be profit generator for another part of the value chain that the vertically integrated group or company operates.

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7 APPENDIX

In this part, before exhibiting additional test results which are not included in to the body of the text, a brief summary is presented covering the time series models and methods in the text. For further details and mathematical proofs, Hamilton 1994 and Enders 2004 can be revisited.

7.1 Linear Projection and Ordinary Least Squares Regression

In statistics, ordinary least squares (OLS) or linear least squares is a method for estimating the unknown parameters in a linear regression model, with the goal of minimizing the sum of the squares of the differences between the observed responses in the given dataset and those predicted by a linear function of a set of explanatory variables (visually this is seen as the sum of the vertical distances between each data point in the set and the corresponding point on the regression line - the smaller the differences, the better the model fits the data). The resulting estimator can be expressed by a simple formula, especially in the case of a single regressor on the right-hand side (Gujarati 2008 and Hamilton 1994).

A linear regression model relates an observation on y_{t41} to $\mathbf{x_t}$;

$$y_{t+1} = \boldsymbol{\beta}'\boldsymbol{X_t} + u_t. \qquad [7.1.1]$$

Given an sample of T observations on y and x, the sample sum of squared residuals is defined as

$$\sum_{t=1}^{T}(y_{t+1} - \boldsymbol{\beta}'\boldsymbol{X_t})^2 \qquad [7.1.2]$$

The value of $\boldsymbol{\beta}$ that minimizes [7.1.2] denoted by $\boldsymbol{b}$, is the OLS estimate of $\boldsymbol{\beta}$**.** The formula for b turns out to be

$$\boldsymbol{b} = [\sum_{t=1}^{T}\boldsymbol{X_t}\boldsymbol{X'_t}]^{-1}[\sum_{t=1}^{T}\boldsymbol{x_t}y_{t+1}] \qquad [7.1.3]$$

which equivalently can be written

$$b = \left[\left(\frac{1}{T}\right) \sum_{t=1}^{T} \boldsymbol{x_t x'_t}\right]^{-1} \left[\left(\frac{1}{T}\right) \sum_{t=1}^{T} \boldsymbol{x_t} y_{t+1}\right] \qquad [7.1.4]$$

In the OLS models natural logs for variables are used on both sides of the models. Such specification is called a log-log model. This model is handy when the relationship is nonlinear in parameters, because the log transformation generates the desired linearity in parameters (you may recall that linearity in parameters is one of the OLS assumptions).

In principle, any log transformation (natural or not) can be used to transform a model that's nonlinear in parameters into a linear one. All log transformations generate similar results, but the convention in applied econometric work is to use the natural log. The practical advantage of the natural log is that the interpretation of the regression coefficients is straightforward.

7.2 Autoregressive Process

Let's say we are studying a variable whose value at date *t* is denoted by $y_{t.}$. Suppose we are given a dynamic equation relating the value *y* takes on at date *t* to another variable w_t and to the value *y* took on in the previous period:

$$y_t = \boldsymbol{\varphi y_{t-1}} + w_t. \qquad [7.2.1]$$

Equation [7.2.1] is a linear first order difference equation. A difference equation is an expression relating a variable y_t to its previous values. Equation [7.2.1] can also be rewritten using a lag operator as:

$$y_t = \boldsymbol{\varphi L y_t} + w_t. \qquad [7.2.2]$$

This equation, in turn, can be rearranged using standard algebra;

$$(\mathbf{1}-\boldsymbol{\varphi}\boldsymbol{L})\boldsymbol{y_t} = w_t. \qquad [7.2.3]$$

The basic building block for all the processes considered in this part is a sequence

$\{\varepsilon_t\}_t^{\infty} = -\infty$ whose elements have mean zero and variance σ^2

$$\boldsymbol{E}(\boldsymbol{\varepsilon_t}) = 0 \qquad [7.2.4]$$

$$\boldsymbol{E}(\boldsymbol{\varepsilon_t^2}) = \sigma^2 \qquad [7.2.5]$$

and for which the ε's are uncorrelated across time.

$$\boldsymbol{E}(\boldsymbol{\varepsilon_t}\boldsymbol{\varepsilon_\tau}) = 0 \; for \; t \neq \tau \qquad [7.2.6]$$

A process satisfying [7.2.4] through [7.2.6] is described as white noise process.

In this context, a first order autoresgression, denoted AR(1), satisfies the following difference equation:

$$y_t = \boldsymbol{c} + \boldsymbol{\theta}\boldsymbol{y_{t-1}} + \epsilon_t. \qquad [7.2.7]$$

Again, $\{\varepsilon_t\}$ is a white noise sequence satisfying [7.2.4] through [7.2.6]. Notice that [7.2.7] takes the form of the first order difference equation [7.2.2] or [7.2.3] in which the input variable w_t is given by $w_{t=C+\varepsilon_t}$. We know from the analysis of first order difference equation that if

$|\theta| \geq 1$, the consequences of the ε's for $\boldsymbol{Y}$ accumulate rather than die out over time. It is thus perhaps not surprising that when$|\theta| \geq 1$, there does not exist a covariance stationary process for Y_t, with finite variance that satisfies [7.2.7]. In the case when$|\theta| < 1$, there is a covariance stationary process for Y_t satisfying [7.2.7]

7.2.1 White Noise

The basic building block for all the processes considered is a sequence $\{\varepsilon^{t}\}_{t=-\infty}^{\infty}$ whose elements have mean zero and variance σ^2,

$$\mathrm{E}(\varepsilon_t) = 0 \qquad [7.2.8]$$

$$\mathrm{E}(\varepsilon_t^2) = \sigma^2 \qquad [7.2.9]$$

and for which the $\varepsilon's$ are uncorrelated across time:

$$\mathrm{E}(\varepsilon_t, \varepsilon_\tau) = 0 \; for \; t \neq \tau \qquad [7.2.10]$$

A process satisfying [7.2.8] through [7.2.10] is described as a white noise process. We shall on occasion wish to replace [7.2.10] with the slightly stronger condition that the ε's are independent across time:

$$\varepsilon_t, \varepsilon_\tau \; independent \; for \; t \neq \tau \qquad [7.2.11]$$

Notice that [7.2.11] implies [7.2.10] but [7.2.10] does not imply [7.2.11]. A process satisfying [7.2.8] through [7.2.11] is called an independent white noise process.

Finally, if [7.2.8] through [7.2.11] holds along with

$$\varepsilon \sim N(0, \sigma^2), \qquad [7.2.12]$$

Then we have the Gaussian white noise process.

7.3 Stationarity

In neither the mean μ_t nor the autocovariances γ_{jt} depend on the date t, then the process for Y_t is said to be covariance-stationary or weakly stationary:

$$E(Y_t) = \mu \qquad for\ all\ t$$
$$E(Y_t - \mu)\big(Y_{t-j} - \mu\big) = \gamma_j \qquad for\ all\ t\ and\ any\ j.$$

For example the process in $Y_t = \mu + \varepsilon_t$ is covariance stationary:

$$E(Y_t) = \mu$$

$$E(Y_t - \mu)\left(Y_{t-j} - \mu\right) = \begin{Bmatrix} \delta^2 & for\ j = 0 \\ 0 & for\ j \neq 0 \end{Bmatrix}$$

By contrast if Y_t is a time trend plus Gaussian white noise the process of $Y_{t=\beta_t+}\varepsilon_t$ is not covariance stationary, because its mean, β_t, is a function of time.

Notice that if a process is covariance-stationary, the covariance between Y_t and Y_{t-j} depends only on *j*, the length of time separating the observations, and not on *t*, the date of the observation. It follows that a covariance stationary process γ_j and γ_{-j}would represent the same magnitude. To see this, recall the definition:

$$\gamma_j = E(Y_t - \mu)\left(Y_{t-j} - \mu\right) \qquad [7.3.1]$$

If the process is covariance-stationary, then this magnitude is the same for any value of t we might have chosen; for example, we can replace t with t+j:

$$\gamma_j = E\left(Y_{t+j} - \mu\right)\left(Y_{[t+j]-j} - \mu\right) = E\left(Y_{t+j} - \mu\right)(Y_t - \mu) = E(Y_t - \mu)\left(Y_{t+j} - \mu\right).$$

But referring again to the definition [7.3.1] this last expression is just the definition of γ_{-j}. Thus for any covariance-stationary process,

$$\gamma_j = \gamma_{-j} \qquad for\ all\ integers\ j \qquad [7.3.2]$$

A different concept is that of strict stationarity. A process is said to be strictly stationary if, for any values of $j_1, j_2, \dots, j_n$, joint distribution of $\left(Y_t, Y_{t+j}, Y_{t+j_2,\dots}, Y_{t+j_n}\right)$ depends only on intervals separating the dates $j_1, j_2, \dots, j_n$ and not on the date itself (t). Notice that if a process is strict stationarity with finite second moments, then it must be covariance stationary-if the densities over which are integrating in $E(Y_t) \equiv \int_{-\infty}^{\infty} y_t F_{Y_t}(y_t) d_{y_t}$ and the jth autocovariance of Y_t which is denoted as γ_{jt} below:

$$\gamma_{jt} = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} \dots \int_{-\infty}^{\infty} (y_t - \mu_t)\big(y_{t-j} - \mu_{t-j}\big)\, x\, f_{Y_{t,Y_{t-1}}, \dots\dots Y_{t-j}}\big(y_{t,}y_{t-1}, \dots, y_{t-j}\big) d_{y_t}\, d_{y_{t-1}} \dots d_{t-j}$$

$$= E(Y_t - \mu_t)\big(Y_{t-j} - \mu_{t-j}\big) \qquad [7.3.3]$$

do not depend on time, then the moments μ_t and γ_{jt}will not depend on time. However, it is possible to imagine a process that is covariance stationary but not strictly stationary; the mean and autocovariances could not be functions of time, but perhaps higher moments such as $E(Y_t^3)$ are.

7.4 Unit Root Test Results

Table 8: Augmented Dickey-Fuller Unit Root Test

#	Variable	t-statistics
1	log(brent usd)	-1,30
2	log(blocksales)	-6,15
3	log(wind)	-10,50
4	log(lignite)	-4,66
5	log(geothermal)	-5,86
6	log(natural gas)	-5,82
7	log(dammed)	-7,11
8	log(pibid)	-5,87
9	log(fuel_oil)	-5,23
10	log(biomass)	-6,66
11	log(LNG)	-9,24
12	log(mcp)	-6,52
13	log(smp)	-8,49
14	aksa	-19,14
15	enerjisa	-20,60
16	renewable	-12,98

7.5 LM Tests for Model 1 and Model 5

Table 9 Breusch-Godfrey Serial Correlation LM Tests

Model 1			
F-statistic	771,84	Prob. F(2,5889)	0.0000
Obs*R-squared	1225,99	Prob. Chi-Square(2)	0.0000

Model 5			
F-statistic	3,12	Prob. F(2,5440)	0,044
Obs*R-squared	6,25	Prob. Chi-Square(2)	0,044

7.6 Alternative Renewable Index Model for HR11 and HR24

Table 10: Model 6 and Model 7 for HR11 and HR24

	MODEL 6			MODEL 7		
Variables	Est.	S.E.	T-Statistics	Est.	S.E.	T-Statistics
c	0,79	1,32	0,59	1,79	6,37	0,28
log(blocksales)	- 0,08	0,05	- 1,55	0,08	0,13	0,59
log(d(brentusd))	0,00	0,02	0,20	- 0,01	0,07	- 0,11
systemproxy	- 0,50	0,04	- 13,81	- 0,66	0,15	- 4,46
log(impcoal)	- 0,07	0,14	- 0,52	- 0,61	0,53	- 1,15
log(ng)	- 0,05	0,14	- 0,35	0,21	0,38	0,54
log(ptf)	0,68	0,12	5,62	0,78	0,11	6,93
log(renweg)	0,32	0,09	3,50	0,26	0,32	0,81
R^2	0,84			0,66		
Durbin-Watson	2,13			2,09		
df	246			246		

CHAPTER 2: THE IMPACT OF OIL PRICE VOLATILITY TO OIL AND GAS COMPANY STOCK RETURNS AND EMERGING ECONOMIES

ABSTRACT

In this paper, we examine the impact of oil price shocks on both selected companies and emerging markets. The novelties of this study can be described as: i) it also includes the recent oil price crisis compared to previous articles in this field, ii) our study considers in details the oil and gas company business acumen to explain the results of the econometric models which is not the case in previous studies, iii) we also include the impact of oil price volatility on emerging markets since oil prices have an importance as explanatory variable of exchange rate movements which makes out study a very comprehensive one.

As mostly preferred in many previous studies in this literature, we employed the exponential GARCH (EGARCH) estimation methodology, we concluded that the volatility effect of a given shock to the oil prices and oil and gas company stock price returns are highly persistent. In addition, we also present The News Impact Curves (NIC) which indicate that the behavior of commodity prices and company stock prices react differently to bad and good news.

Keywords: Oil prices, time series, asymmetric volatility, stock returns, oil and gas companies, news impact curves

8 INTRODUCTION

Crude oil prices fluctuated heavily in the past thirty years and its volatility increased compared to the period from World War II to the beginning of 1970s. Since oil prices are traded in US dollars, their fluctuations in domestic currencies highly depend on the dollar exchange rates.

High volatility and specialness in energy markets result in more challenging trade execution, larger capital requirements and decreasing effectiveness of benchmark hedging compared to other asset classes. Major sources of energy are often discovered at considerable distances from the locations of ultimate consumption which created regional imbalances with consequences raging from international capital flows to geopolitical risks to the reliability of energy supply.

With an enthusiast for fossil fuels in the White House and former head of Exxon Mobil as US secretary of state the oil industry is expected to be a hot topic again while renewables continue to rise worldwide. Diminishing oil prices in the last years forced the energy giants such as BP, Exxon, Shell, Total, Chevron etc. BP had to contend with collapse of crude oil prices while at the same time paying out tens billions of dollars in compensation and clean-up costs caused of UK group's 2010 oil spill in the Gulf of Mexico.

A recovery in the industry is crucial for those companies in an environment where renewable energy grows substantially with the support of Paris Agreement. However Royal Dutch and Chevron better positioned themselves compared to BP and Exxon by investing aggressively amid the downturn. Shell acquired BG Group of the UK for 35bn £ during the depths of the oil crash. This strong portfolio acquired from BG including energy assets in Australia and deep water oil fields of Brazil recovered the Anglo-Dutch Company.

On the other hand, Exxon is interested in new asset acquisitions and it struck deals worth up to 6,6bn £ to buy shale oil companies with drilling right on a large area of the Permian basin in

New Mexico. BP is also rebuilding however the oil price needed to cover investment and its dividend-to 60$ per barrel this year from 55$ at the end of last year.

The stabilization of oil prices is more important than price itself since volatility makes it difficult to predict both for the major players and the countries as well. Oil price structure influenced economic operations, capital markets and the strategies of the energy companies. At that point modeling and forecasting the co-movements between oil priced and the dollar exchange rates becomes very important.

The paper is structured in such order: Section 9 includes the literature review on previous research on the interaction between oil prices and exchange rates along with macroeconomic implications of oil price shocks. In section 10 we describe the empirical methodology and in section 11 introduce the data operated in the models and in section 12 we discussed our empirical results. Finally, in section 13 we provide our results in a nut shell and further study areas within this topic.

Results show that the volatility of a given shock to the oil prices and oil and gas company stock prices are highly persistent the impact of such shocks disappear very slowly. The News Impact Curve indicates that the behavior of commodity prices and company stock prices react differently to bad and good news.

9 LITERATURE REVIEW

Before global financial crisis, there was a positive connection between oil price prices and dollar value. Chen and Chen (2007) studied the long run relationship of real oil prices and real exchange rates and concluded that exchange rate movements are mostly driven by world oil prices. Narayan et. al (2008) examined the relationship between oil prices and the Fiji-US exchange rate and concluded that a rise in oil prices triggers an increase in the Fijian-dollar. Krugman (1983) and Golub (1983) underlined the potential impact of oil prices as an explanatory variable of exchange rate fluctuations. Kang et. al (2015) examine the effects of global oil price shocks on the stock market return and volatility relation applying a structural VAR model which they conclude that the spillover index between the structural oil price shocks and covariance of stock return and volatility is big and highly statistically significant.

Coherently, Ratti and Vespignani (2016) state cointegration exists between global money, global industrial production and global oil prices. A rise in oil prices triggers global interest rates to rise significantly. According to the findings causality goes from global liquidity to oil prices and from oil prices to the global interest rate, global industrial production and global CPI which is more or less the structure of the whole economical transmission process. Moreover, if you give positive shocks to global M2, to global CPI and to global industrial production , global oil prices responses by increases in a statistically significant and persistent manner. Aloui et al (2013) tried to explain the negative relationship between the oil prices and the price of dollar can by the fact that oil is a hedging tool against rising inflation and serves as a low risk investment asset for risk aversive investors.

Furthermore, Lizardo and Mollick (2010) based on their cointegration tests and forecasts results claimed that real oil prices rise lead to a high level of depreciation in USD dollar against currencies of Canada, Mexico and Russia which are net oil exporting countries. On the other hand, when the real oil prices rise the value of dollar against to currencies of net oil importing countries, such as Japan, increases. Moreover, Federer (1996) and Lee et all (1995) concluded that oil price volatility changes affect macroeconomic variables significantly. It is stated that oil shocks may have an asymmetric impact on macroeconomic variables.

Although more than twenty years have passed for studying and establishing a comprehensive literature on volatility forecasting, there is still significant concerns on whether volatility can be modeled in a more successful way. One of the fundamentals of volatility forecasting is the observation that equity returns and volatility are correlated in a negative way. The abnormal behavior can be explained by a leverage effect, or a volatility feedback effect which is briefly if volatility has its market price, increase in volatility will increase in the return required by investors. For example, if a large amount of bad information on future dividends is heard in the market then the stock prices will go down. Takaishi (2017) propose a new ARCH-type model that uses a rational function to capture the asymmetric response of volatility to returns, which is leverage effect. Coherently, we also included analysis to find out the effect of shocks on stock returns of the major industry players in to this study.

In addition to macroeconomic impact, commodity prices such as oil have significant effects of company stock returns. Jorion (1990) models exchange rate exposure of US multinationals utilizing a dataset which covers the duration from January 1971 to December 1987. Similarly, Blose and Shieh (1995) test the effect of gold prices volatility on gold mining stock returns which is more or less the same concept which we will follow in this chapter. Due to their findings the gold price sensitivity of a mining stock was found to be greater than one. The volatility transmission mechanism in the financial markets based on the cointegration or causality impact with the introduction of brand new financial assets or investment indices is quite crucial in both modern finance literature and market practices. The hypothesis of unity gold price sensitivity was not rejected using monthly data over the period 1981–1990 for a sample of commonly traded companies. Those studies guide us to analyze the impact of oil price volatility on emerging market currencies to understand the macroeconomics aspect of energy price movements since for most of those countries it is the most important input of the whole economics activity.

Due to the results of the previous literature there is a clear asymmetric behavior between oil prices and other assets classes like company equities and currencies. Also since the effect of oil price shocks can be persistent for a long time period there are cyclical impacts on both microeconomics and macroeconomics indicators. In this respect one of the crucial points of this study is that it includes the recent oil price crisis period in the dataset. Narayan and Narayan (2007) paper appears to be the only notable paper that has attempted to model oil price volatility using different sub periods in order to judge the robustness of their results. This is the main reason why we will also use three sub periods in our analysis which will cover both 2008 global crisis and 2014 oil price crisis.

10 METHODOLOGY

Firstly, we used exponential GARCH (EGARCH) instruments to model the volatility behavior of oil prices. Major advantage of the model is that, instead of considering heteroskedasticity as a problem to be corrected, ARCH and GARCH models treat it as a variance to be modeled. Usually financial data suggests that some time periods are riskier than others; that is, the expected value of the magnitude of error terms at sometimes is greater than at others. The goal of such models is to provide a volatility measure, like a standard deviation, then can be used in financial decisions related with risk analysis, portfolio selection and derivative pricing (Engle 1982, 1993 and 2001).

ARCH model assumes that the variance of t u_t in period t, σ_t^2 depends on the square of the error term in t-1 period, u_{t-1}

In this context, ARCH(q) and GARCH(q) models are as follows;

α0 >0, αi >0

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}{}^2 + \alpha_2 \varepsilon_{t-2}{}^2 + ... + \alpha_q \varepsilon_{t-q}{}^2 + \nu_t \qquad [10.1]$$

GARCH models which express the generalized form of ARCH models were developed by Engle (1982) and Bollerslev (1986) to provide reliable estimations and predictions. GARCH models consist of conditional variance, in equation (2) in addition to conditional mean in equation [10.1].

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i r^2{}_{t-i} + \sum_{i=!}^{p} \beta_j h_{t-j} \qquad [10.2]$$

In this context, restrictions of variance model are as follows;

for αi ≥0 and βi ≥0, αi +βi <1

If αi +βi ≥1 it is termed as non-stationary in variance. For non-stationarity in variance, the conditional variance forecasts will not converge on their unconditional value as the horizon increases (Brooks 2008).

In this context ARCH and GARCH models have become very popular as they enable the econometrician to estimate the variance of a series at a particular point in time. Clearly asset pricing models indicate that the risk premium will depend on the expected return and the variance of that return (Enders 2004).

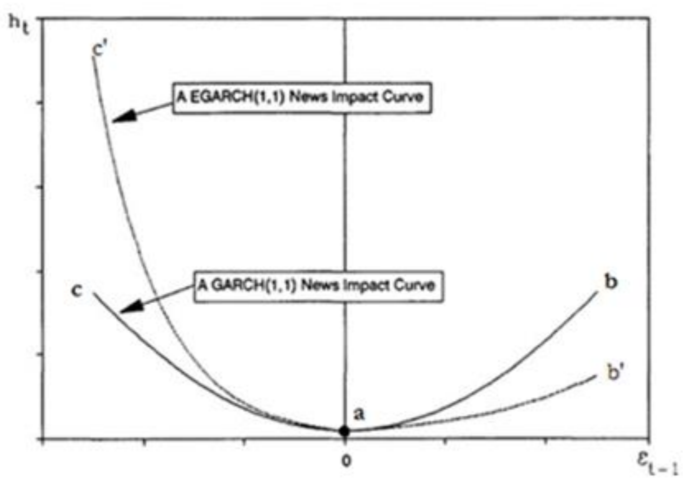
An important characteristic of asset prices is that "bad" news has more persistent impact on volatility than "good" news has. Most of the stocks has a strong negative correlation between the current return and the future volatility. In this context we can define leverage effect as such volatility tends to decrease when returns increase and to increase when returns decrease.

The idea of the leverage effect is exhibited in the figure below, where "new information" is defined and measured by the size of ε_{t-1}. If $\varepsilon_{t-1}=0$, expected volatility (h_t) is 0. Actually any news increases volatility but if the news is "good" (i.e., if ε_t is positive), volatility rises from point ***a*** to point ***b*** along ab curve (or abˈ for EGARCH model). However, if the news is "bad", volatility rises from point ***a*** to point ***c*** along ac curve (or acˈ for EGARCH model). Since ac and acˈ are steeper than ab and ab', a positive ε_t shock will have a lower impact on volatility than a negative shock of these same magnitude (Figure 6).

Asymmetric volatility models are the most interesting approaches in the literature since good news and bad news have different predictability for the future volatility. Overall, Chen and Ghysels (2010) found that partly good (intra-daily) news decreases volatility (the next day), while both very good news which is unusual high intra-daily positive returns, and bad news which is negative returns increase volatility. However, the latter has a more severe impact over longer horizons the asymmetries fade away.

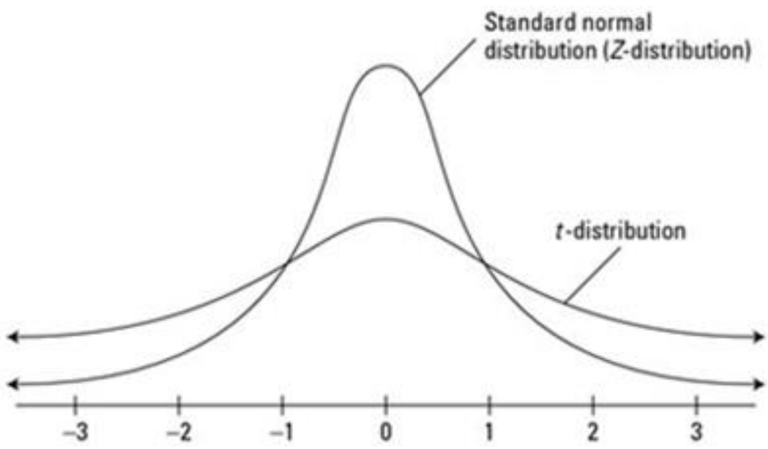
The news impact curve illustrates the impact of previous return shocks on the return volatility which is implicit in a volatility model. In the next sections we discuss several models of oil price and oil and company stock prices volatility and present the news impact curves.

Figure 6: News Impact Curves



Consequently, GARCH models enables us to analyze and distinguish the effect of news on oil prices in a quantitative way and guides us to understand if the markets recognize and react against such closely followed data by investors. T-distribution works better in GARCH models for most of the financial assets since the distribution function for the rate of return for assets is fat-tailed. This is actually quite consistent with the common sense market experience since most of the financial asset prices do not get any negative values. Compared to a normal distribution a fat-tailed distribution has more weight in the tails than a normal distribution. Let us assume that the rate of return on a single stock has a higher probability of a very large loss (or gain) than shown by the normal distribution. As such, you might not want to perform a maximum likelihood estimation using a normal distribution. Figure 7 below compares the standardized normal distribution to a t-distribution. You can see that the t-distributions achieves a greater likelihood on large realizations than does the normal distribution. As such, many computer packages allow you to estimate a GARCH model using a t-distribution.

Figure 7: Normal Distribution vs Student-t Distribution



Another model that allows for asymmetric effect of news is the EGARCH model. One problem with a standard GARCH model is that it is necessary to ensure that all of the estimate coefficients are positive. Nelson (1991) proposed a specification that does not require nonnegativity constrains.

Consider:

$$\ln(h_t) = \alpha_0 + \alpha_1 \left(\frac{\varepsilon_{t-1}}{h_{t-1}^{+0.5}}\right) + \lambda_1 \left| \frac{\varepsilon_{t-1}}{h_{t-1}^{0.5}} \right| + \beta_1 \ln(h_{t-1}) \qquad [10.3]$$

Equation (10.3) is called the exponential-GARCH or EGARCH model. There are three interesting features to notice about EGARCH model:

1. The equation for the conditional variance is in log-linear form. Regardless of the magnitude of $\ln(h_t)$, the implied value of h_t can never be negative. Hence, it is permissible for the coefficients to be negative.
2. Instead of using the value of ε_{t-1}^2, the EGARCH model uses the level of standardized value of ε_{t-1}^2 [i.e., ε_{t-1}^2 divided by $(h_{t-1})^{0.5}$]. Nelson argues that this standardization allows for a more natural interpretation of the size and persistence of shocks. After all, the standardized value of ε_{t-1}^2 is a unit-free measure.
3. The EGARCH model allows the leverage effects. If $\varepsilon_{t-1}^2/(h_{t-1})^{0.5}$ is positive, the effect of the shock on the log of conditional variance is $\alpha_1 + \lambda_1$. If $\varepsilon_{t-1}^2/(h_{t-1})^{0.5}$ is negative, the effect of the shock on the log of the conditional variance is $-\alpha_1 + \lambda_1$.

The trade-off between future risks and asset returns are the essence of most financial decisions. Risk mainly composes of two factors such as volatilities and correlations of financial assets. Since the economy changes frequently and new information is distributed in the markets second moments evolve over-time. Consequently, if methods are not carefully established to update estimates rapidly then volatilities and correlations measured using historical data may not be able to catch differentiation in risk (Cappiello et. all, 2006).

If we consider EGARCH models, the news impact curve has its minimum at $\varepsilon_{t-1}=0$ and is exponentially increasing in both directions but with different parameters. The news impact curves are made up by using the estimated conditional variances equation for the related model as such its given coefficient estimates and with the lagged conditional variance set to the unconditional variance.

Consider EGARCH (1,1)

$$\ln(h_t) = \alpha_0 + \beta \ln(h_{t-1}) + \alpha_1 z_{t-1} + \gamma(|z_{t-1}|) - E(|z_{t-1}|) \qquad [10.4]$$

where $z_t = {}^{\varepsilon_t}/_{\sigma_t}$. The news impact curve is

$$h_t = \begin{cases} Aexp\left[\frac{\alpha_1+\gamma}{\sqrt{h_t}}\right] & for\ \varepsilon_{t-1} > 0 \\ Aexp\left[\frac{\alpha_1-\gamma}{\sqrt{h_t}}\right] & for\ \varepsilon_{t-1} < 0 \end{cases} \qquad [10.5]$$

$$A \equiv h_t^{\beta} exp\left[\alpha_0 - \gamma\sqrt{2/\pi}\right] \qquad [10.6]$$

$$\alpha_1 < 0 \qquad \alpha_1 + \gamma > 0 \qquad [10.7]$$

Although in our analysis GARCH and EGARCH model results did not differ from each other significantly we proceeded with EGARCH models for News Impact curves. Further details can be found in Section 12.

11 ECONOMETRIC DATA DESCRIPTION

The NYMEX WTI futures contract is one of the world energy benchmarks. The notional quantity for one contract is 1000 barrels, which, as mentioned earlier, is one lot. As with all futures, trading for a given contract month ceases at a defined futures expiration date prior to the contract month.

In the case of the WTI contract, this is roughly two-thirds of the way through previous contract month. However, in the recent years the idiosyncrasies related to the delivery location of the WTI contract resulted in substantial and prolonged decoupling from global crude oil prices. As a result, despite complications of its own, the Brent futures contract which trades on ICE[6] is now viewed as the dominant crude oil benchmark. The settlement and delivery mechanism of Brent contracts are more complex than WTI futures. The Brent contract is described by the exchange physically settling with an option to settle financially on the ICE Brent Index. However, Salisu and Fasanya (2012) chose WTI as crude oil price benchmark due to the fact that WTI has become dominant in the world oil market. In this respect we also decided to use WTI in our models however we also incorporated Brent in the same models instead of WTI and experienced no significant result changes.

Our dataset contains daily crude oil, hard currencies such as Canadian dollar (CAD), Euro (EUR), Swiss Franc (CHF), UK Pound Sterling (GBP), Japanese Yen (JPY) as well as emerging currencies such as such as Turkish Lira (TRY), Mexican Peso (MXN), Russian Ruble (RUB) and dollar index (DXY) for the period between January 4, 2000 and February 9, 2017[7]. Furthermore, we have major industry players' daily stock prices which are Exxon Mobil, Chevron Corp, Conoco Phillips, Hess Corp, Marathon Oil Corp, BP, Shell and Total. We took the difference in logarithm of the two daily prices while computing the returns on crude oil price indices, exchange rates and stock prices.

At a glance all the currencies and oil prices fluctuate significantly on 2008 global financial crisis as we can see in Figure 8. In addition, we narrowed the period from September 15, 2008 to February 9, 2017 which we will emphasize as “Global Financial Crisis Period” in our GARCH models. In Figure 9 after global financial crisis we can clearly observe that after from 2014 to present there is an increase in oil price return volatility (RBRent and RWTI) as well as emerging market currencies go on to fluctuate after 2008 crisis.

[6] Intercontinental Exchange (traded as ICE) is an American business and finance company founded on May 11, 2000 by Jeffrey Sprecher, headquartered in Atlanta, Georgia. It owns exchanges and clearing houses for financial and commodity markets, and operates 23 regulated exchanges and marketplaces.
[7] Dataset is provided by Thomson Reuters Eikon

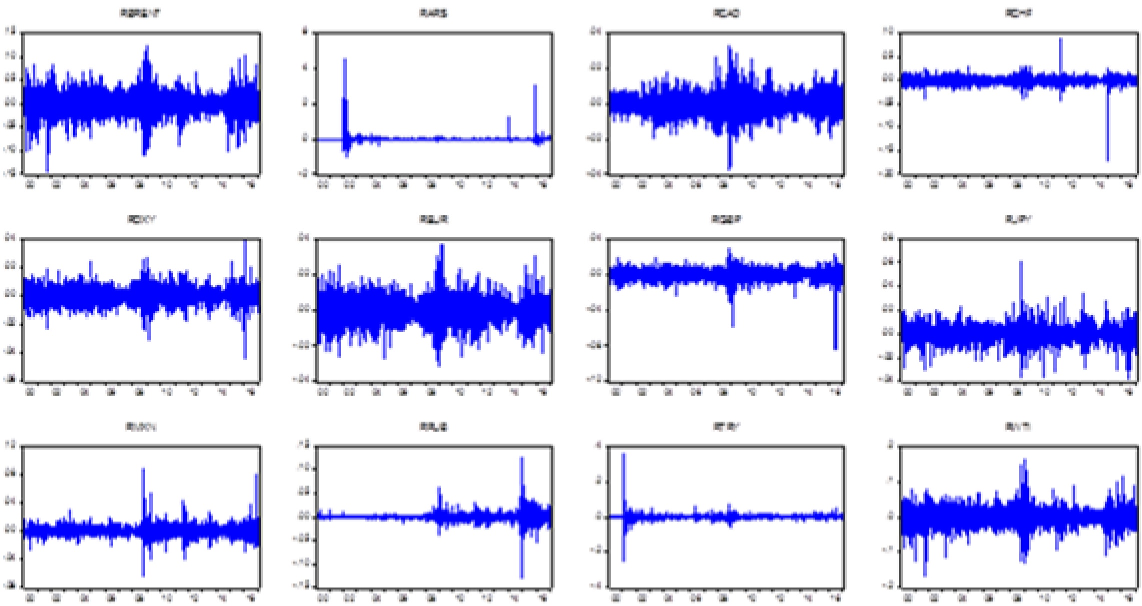
Table 11: Model Dataset Descriptions

#	Variable	Description	Frequency
1	RWTI	Returns** of NYMEX Light Sweet Crude Oil (WTI) Closing Prices	Daily
2	RWTI (-1)	One day lagged returns of NYMEX Light Sweet Crude Oil (WTI) Closing Prices	Daily
3	RCAD	Returns of USD Dollar/ Canadian Dollar (CAD) Closing Prices	Daily
4	REUR	Returns of USD Dollar/ Euro (EUR) Closing Prices	Daily
5	RCHF	Returns of USD Dollar/ Swiss Franc (CHF) Closing Prices	Daily
6	RGBP	Returns of USD Dollar/ UK Pound Sterling (GBP) Closing Prices	Daily
7	RJPY	Returns of USD Dollar/ Japanese Yen (JPY) Closing Prices	Daily
8	RDXY	Returns of USD Dollar Index*	Daily
9	RMXN	Returns of USD Dollar/ Mexican Peso (MXN) Closing Prices	Daily
10	RRUB	Returns of USD Dollar/ Russian Ruble (RUB) Closing Prices	Daily
11	RBrent	Returns of ICE Brent Crude Electronic Energy Futures Closing Prices	Daily
12	RBrent (-1)	One day lagged returns of ICE Brent Crude Electronic Energy Futures Closing Price	Daily
13	RTRY	Returns of USD Dollar/ Turkish Lira (TRY) Closing Prices	Daily
14	RXOM	Returns of Exxon Mobil Corp (XOM) Stock Closing Prices	Daily
15	RCVX.N	Returns of Chevron Corp (CVX.N) Stock Closing Prices	Daily
16	RCOP.N	Returns of Conoco Phillips (COP.N) Stock Closing Prices	Daily
17	RHES.N	Returns of Hess Corp (HES.N) Stock Closing Prices	Daily
18	RMRO.N	Returns of Marathon Oil Corp (MRO.N) Stock Closing Prices	Daily
19	RBP.L	Returns of BP PLC (RBP.L) Stock Closing Prices	Daily
20	RDSa.AS	Returns of Royal Dutch Shell PLC (RDSa.AS) Stock Closing Prices	Daily
21	RTOTF.PA	Returns of Total SA (TOTF.PA) Stock Closing Prices	Daily

* The US Dollar Index is an index of the value of the United States dollar relative to a basket (57,6% Euro, 13,6% Japanese Yen, 11,9% pound sterling, 9.1% Canadian dollar, 4.2% Swedish krona, 3.6% Swiss franc) of foreign currencies, often referred to as a basket of US trade partners' currencies

**returns are calculated as $\ln\left(\frac{x_t}{x_{t-1}}\right)$

Figure 8: Return Graph for Overall Period



Oil prices have fallen sharply since mid-2014 and reached a ten-year low in early 2016. From their peak in June 2014 to the trough in January 2016, Brent crude oil prices dropped by USD 82 per barrel (70%).

There are five key moments in oil price decline which are:

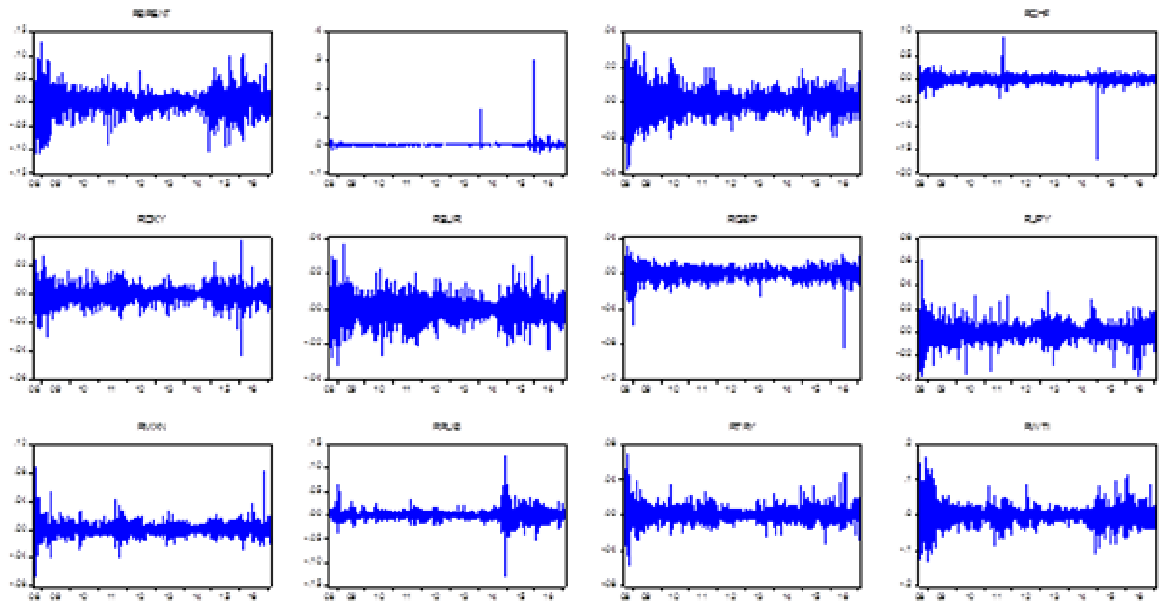
i. **November 2014:** OPEC decides not to cut output
ii. **April 2015:** Shell and Total delay west African projects
iii. **January 2016:** Brent hits 12 year low
iv. **November 2016:** OPEC agrees to reduce output
v. **December 2016:** BP approves expansion of Mad Dog field.

Descriptive statistics and distributional characteristics of returns are reported in Table 14 and Table 15. The normal distribution has a skewness of zero however financial data can be rarely perfectly symmetric. In such cases to understand the skewness of the data series shows either mean deviates from the mean positively or negatively. The hard currency returns like GBP and CAD are negatively skewed which means that the mass of the distribution is concentrated on the right side of the figure. Emerging market currency returns like TRY and ARS are positive skewed which means that the right tail is longer and the mass of the distribution is concentrated on the left side of the figure.

The kurtosis of any univariate normal distribution is 3 and distributions with kurtosis less than 3 are said to be platykurtic which has thinner tails. It means the distribution produces fewer and less extreme outliers than does the normal distribution. Distributions with kurtosis greater than 3 are said to be leptokurtic. All the series in our dataset is highly leptokurtic which has fatter tails which is expected for financial assets.

Thus we will also analyze the oil prices in a third sub-sample namely ‘oil price crisis’ which includes the data between November 1, 2014 and February 7, 2017. We will also analyze industry company stock prices in the same sub-period in order to find out the effect of oil price volatility on company stock returns and their business strategies.

Figure 9: Return graph for Global Financial Crisis Period



12 APPLICATION AND FINDINGS

We applied all our models by using Brent instead of WTI and any significant difference was not detected. The analysis for countries and company stock returns are exhibited in two separate sub-sections in order to make the reader focus easier on the fundamental differences of results and news impact curve behaviors of the assets.

12.1 Country Implication

We present our results in Table 12 and Table 13 by fitting GARCH and EGARCH models with both normal and student-t distributions. The series were modeled by GARCH (1,1) and EGARCH (1,1) satisfactory. Note that for all models the parameter β is close to 0,9 (even 1,0 in EGARCH model with student-t distribution) highly significant which thus indicates that conditional volatility is past dependent and very persistent over time.

While Table 12 and 13 exhibit models for overall period Table16 and 17 exhibit models for global financial crisis period in which we see that the parameter β is still close to 0,9 and highly significant but slightly less than overall period models. The effect of ε_t and past values of ε_t on y_t is the effect of shocks which include news effect or extra ordinary days.

In Table 20 and 21 models exhibit results for oil crisis period which shows that the effect of news and extra ordinary days increase compared to overall period and global financial crisis period. It appears that there is a high level of persistence in the oil price volatility that may be associates with crisis such as 2008 and 2014.

In all EGARCH (1,1) models exhibited in Tables 13, 17 and 21, λ_1 is negative for all periods. This validates the argument which claims that negative shocks tend to reduce volatility more than positive shocks referring to asymmetric impacts on crude oil price volatility.

Moreover, we included first lags of WTI, CAD, EUR, CHF, GBP, JPY, DXY, MXN and RUB returns in the mean equation for the all models. Russia and Canada are among top world oil producers while Switzerland is a net oil importer who does not have any domestic oil resources. Although Japan is one of the biggest oil importers following China, US, India and South Korea, its current account balance and having nuclear power plants as alternative generation resources help it to reduce the dependence of the Yen value on fluctuations in the price oil. Mail EU countries such as Germany, Italy, Netherland and France are also in the list of biggest oil importers.

Table 12: RWTI GARCH Model for Overall Period

Distribution	Normal Distribution				student t-Distribution			
	Mean Equation		Variance Equation		Mean Equation		Variance Equation	
	coefficient	z-stats	coefficient	z-stats	coefficient	z-stats	coefficient	z-stats
RWTI (-1)	-0,04	-2,69			-0,04	-3,17		
RCAD	-0,88	-14,29			-0,89	-14,67		
REUR	-0,52	-5,22			-0,40	-3,44		
RCHF	0,00	0,00			0,08	1,27		
RGBP	0,04	0,65			0,08	1,20		
RJPY	0,29	6,66			0,25	5,32		
RDXY	-0,87	-6,95			-0,74	-4,84		
RMXN	-0,09	-2,02			-0,12	-2,73		
RRUB	-0,66	-21,75			-0,66	-18,28		
α_0			0,00	4,61				
α_1			0,07	14,00			0,06	8,31
β_1			0,92	155,23			0,94	132,1
Observations				4266				4266
R^2				0,177				0,178
DW				2,029				2,087

In this context, EUR, CAD, RUB returns have a negative effect on WTI returns while JPY returns are expected to have a positive effect. Since Canada[8] and Russia[9] are oil producers and exporters while Japan is an importer country, the signs of the coefficients are quite coherent with macroeconomics theory. Oil prices are traded as US dollar denominated. Therefore, when Russia and Canada export oil, RUB and CAD will come down since there will be US dollar inflow in to these markets while JPY will rise as there will be US dollar outflow from Japanese market.

[8] 215.5 million tonnes in 2015 (4.9% of total production), BP Statistical Review of World Energy June 2016
[9] 540.7 million tonnes in 2015 (12.4% of total production), BP Statistical Review of World Energy June 2016

Table 13: RWTI EGARCH Model for Overall Period

Distribution	Normal Distribution				student t-Distribution			
	Mean Equation		Variance Equation		Mean Equation		Variance Equation	
	coefficient	z-stats	coefficient	z-stats	coefficient	z-stats	coefficient	z-stats
RWTI (-1)	-0,03	-2,61			-0,04	-3,16		
RCAD	-0,89	-14,37			-0,90	-14,79		
REUR	-0,48	-4,78			-0,37	-3,26		
RCHF	-0,02	-0,40			0,06	1,02		
RGBP	0,08	1,33			0,09	1,48		
RJPY	0,26	6,01			0,24	5,19		
RDXY	-0,76	-5,74			-0,69	-4,50		
RMXN	-0,10	-2,35			-0,13	-2,84		
RRUB	-0,64	-20,03			-0,63	-17,22		
α_0			-0,21	-9,20			-0,16	-6,38
α_1			0,15	15,17			0,12	8,70
λ_1			-0,04	-6,68			-0,04	-4,58
β_1			0,99	423,1			1,0	416,6

Observations	4266	4266
R^2	0,180	0,178
DW	2,030	2,080

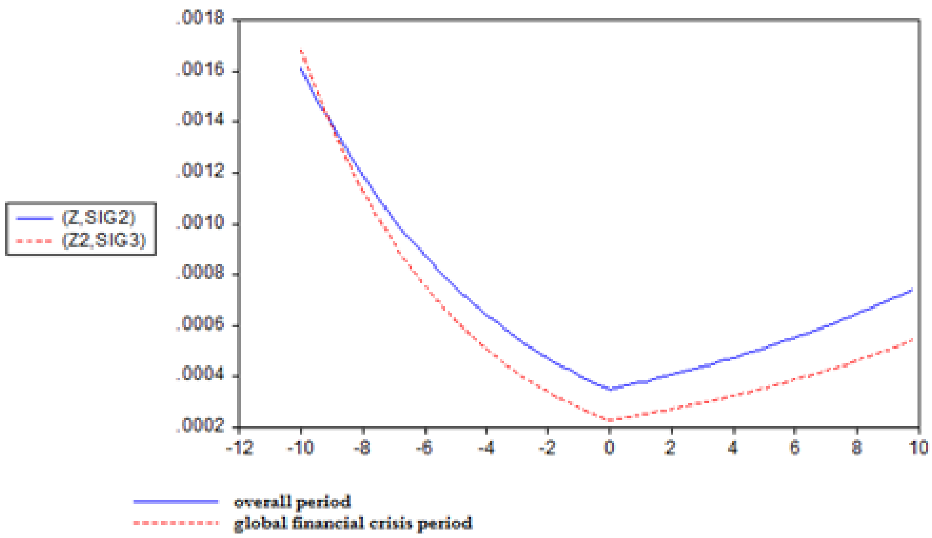
Wang et all. (2013) found that response of stock market in terms of the magnitude and duration of a country against oil price shocks is highly related with whether the country is a net oil importer or oil exporter and whether volatilities in oil price are driven by supply or aggregate demand. In Table 18, we performed Granger Causality tests in order to understand the signs of coefficients better in the mean equation. Based on our findings the causality between CAD and oil prices is one way from CAD to oil prices however it is just in the opposite way for RUB. Flexible exchange rates can provide a measure of protection to countries like Russia which mitigated some of the impact of low oil prices with fallen ruble: in dollar terms. Lower oil revenues are offset by cheaper domestic expenditures. Consequently since Mexico[10] is an oil producer two way causality between crude oil prices (Brent and WTI) and MXN is also relevant.

[10] 127.6 million tonnes in 2015 (2.9% of total production), BP Statistical Review of World Energy June 2016

In Table 19 results show that there is one-way causality from crude oil prices (Brent and WTI) to TRY given by the fact that Turkey is an oil importing country. Oil prices increase pressure over TRY since oil is traded as US dollar denominated. As Berk and Aydoğan (2012) state that fluctuations in Turkish stock market returns highly depend on the global liquidity conditions. Although there is some evidence that pure oil price shocks have an impact on stock market returns, this effect is less significant and weaker than the liquidity constraints in the global financial markets.

Hamilton (1985) stated that a given rise in oil prices have weaker impact on macroeconomic conditions after 1973 than an increase of same magnitude would have had before 1973. The article concluded with the statement: “The political history of the Middle East makes it almost inevitable that sometime within the next decade economists will be granted some more data with which to assess the economic effects of oil supply disruptions.” This is exactly the situation which occured in 1990 when Iraq got in to war with Kuwait, and consequently the oil shock was a key indicator in the recession that happened afterwards (Hamilton 1996). Considering the latest oil price crisis and macroeconomic developments in the world we can conclude that Hamilton’s statement is still valid.

Figure 10: News Impact Curves



In Figure 10, the news impact curve of the EGARCH (1,1) is compared for overall and global financial crisis sub-periods. In this context, news impact curves are asymmetric since negative shocks affecting more on future volatility than positive shocks of the same magnitude. However, after 2008 global financial crisis we can see that news impact on volatility decreases.

12.2 Company Analysis

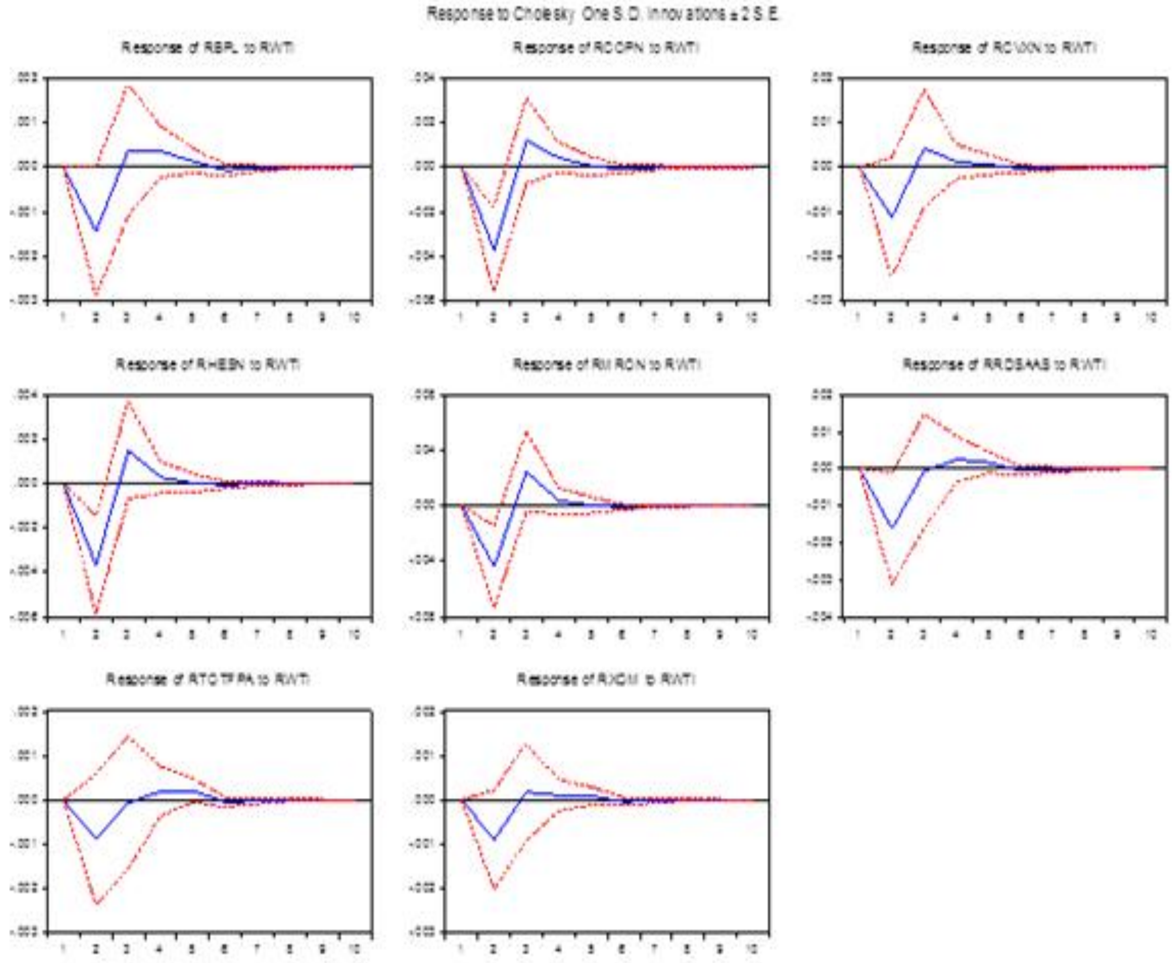
Table 22 exhibits models for oil crisis period in which we see that the parameter β is below 0,9 and highly significant. The effect of ε_t and past values of ε_t on y_t is the effect of shocks which include news effect or extra ordinary days. Table shows that the effect of news and extra ordinary days in company stocks volatility forecast models has more effect compared to oil price volatility forecast models.

In most of the EGARCH (1,1) models exhibited in Tables 22 λ_1 is positive which validates that negative shocks generate less volatility than positive shocks in company stock returns. Diaz et all (2016) study the effect of real oil price shocks on real stock returns of four oil and gas corporations[11] where they conclude that both linear and non-linear specifications oil price changes have a positive significant impact on real stock returns of these companies in the short-run.

First of all, the impulse response functions using the oil price changes of WTI are exhibited in Figure 11. Shortly we find out a negative effect of the linear specification of oil price on stock returns within two days after the shock and then a positive impact which is absorbed within nearly one week. In all cases, the impulse responses revert to zero usually within 6 to 8 days. The impulse response analysis was also tested with overall period data and any significant behavior change was not detected.

[11] Exxon, BP, Chevron, Shell.

Figure 11: Impulse Response Analysis for Oil and Gas Company Stock Returns



News impact (NI) curves of the major industry players’ differentiate from oil price NI curves in a way that most of them are either close to symmetric or good news increase volatility more than bad news (Figure 12). NI curves of Exxon, Conoco Phillips and Shell are almost symmetric which shows that both good and bad news increase volatility in the same way. For Chevron, BP and Total good news increase volatility more while for Hess Corp and Marathon Oil bad news have more impact to increase volatility of stock returns.

NI curves of asymmetric ARCH-type models exhibit for BP stock returns that the higher volatility response to negative stocks in the oil prices period while it is the opposite for the oil prices period. The tragic accident and oil spill in the Gulf of Mexico may be one of the key factors in this behavior change however further analysis can be provided by using proxy variables in the EGARCH variance equations to drill down more. Exxon[12] and Chevron[13] react to the shocks equally based on their NI curves which suggest that bad or good, any kind of news increases the volatility of the stock returns significantly more in the oil prices period compared to overall period. As of January, 31 2017 Exxon and Chevron have stronger financial positions compared to Shell, Total, BP and others. Both companies focused on investing in higher return investments with shorter-cycles and optimizing their costs via flexible capex programs which enabled them to improve their cash flows in the oil crisis period.

For Hess and Marathon, negative shocks have greater impact on volatility both in overall and oil prices period. Considering Shell NI curves, we can conclude that while in overall period good news increase the volatility more in the oil crises period both bad and good news have a balanced impact on the volatility of stock returns.

Finally, for Total we see that news effect changes for overall and oil crises period significantly where good news has a significant impact on volatility in the oil prices period. Total has a diversified portfolio of gas developments both in downstream and upstream and implements its strategy through portfolio management. However, countries do not have such flexibilities to optimize their spending or changing the dynamics of macroeconomics and production schemes against oil shocks in order to adjust themselves like oil and gas companies can do.

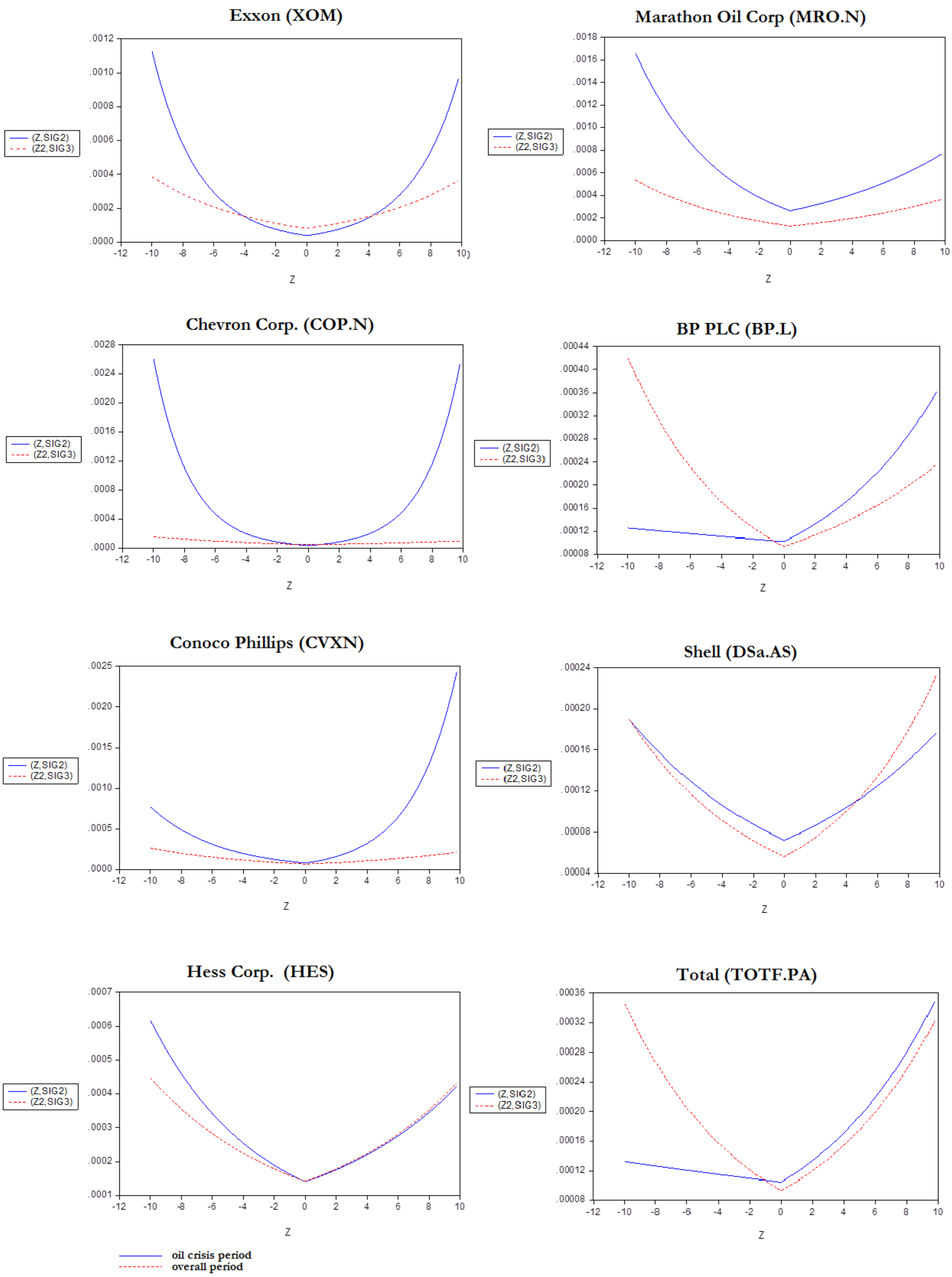
We should also keep in mind that Shell and Total stocks are quoted in Amsterdam stock exchange and Euronext respectfully. Since the exchange markets of the other companies are

[12] Exxon Mobil Corporation (XOM) is the largest of the vertically integrated oil majors as well as the largest publicly-traded corporation in the world by revenue. The firm generates the majority of its income from liquid natural gas sales, with earnings of 7.8$ bln in 2016.The geographical diversity of Exxon Mobil’s exploration and production (E&P) activities make it less vulnerable to the regional production uncertainties that disturb the industry. The company is also an international leader in downstream refining industry. (Trefis, Thompson Reuters)

[13] Chevron is Corporation the second largest energy company in the US after Exxon Mobil. Chevron has operations in 180 countries along with a strong network of retail gas stations under Chevron, Texaco, and Caltex brands. The company is also involved in pursuing alternative energy solutions. (Trefis, Thompson Reuters

US, there will be different systemic and un-systemic risks for the stocks that can affect the returns and volatiles rather than oil price fluctuations.

Figure 12: News Impact Curves for Major Industry Players' EGARCH Models



13 CONCLUSION

In this paper we analyzed the oil price and oil and gas company stocks volatility forecast and the impact of oil price shocks to both selected companies and emerging markets. The innovation part in this paper are: i) we analyze the oil price across three sub-periods which also includes the recent oil price crisis, ii) we use alternative models to model volatility forecast, iii) we make the analysis both in macroeconomics and microeconomics level considering both production and consumption areas of oil as a commodity. First we analyzed the country specific models and both EGARCH models and causality tests showed that based on if the country is an oil exporter or importer, the magnitude and sign of the currency of the related country as an explanatory variable in oil price change compatible with macroeconomics theory.

We also showed that bad news increase volatility more than bad news for oil prices which is coherent with the theory. It is quite coherent with the theory since a slowdown in global economy is likely to result in a further decline in crude oil prices. The view mentioned in Hamilton (1998a, b) is that oil shocks affect the macroeconomics preliminary by depressing demand for key consumption and investment goods. If that is in practice how oil shocks affect the economy, then a reduction in oil price would not create a positive impact on the economy. However, on the supply side, significant investment and technological innovations (especially in shale oil extraction) caused oil production to fluctuate in a slowing world growth putting downward pressure on oil prices.

NI curves of the company stock returns clearly exhibits that news impact on volatility changed significantly during oil price crisis compared to overall period.

All those companies we have chosen for the analysis operate both in upstream and downstream businesses along with alternative energy segments. Leveraging their business portfolio and dividend payments provided them room for maneuvers in oil price crisis period. This is one of the major reasons why bad and good news impact differentiates for commodity prices and industry company stock prices[14].

[14] Strong (1991) analyses whether oil equities portfolios are sufficient tools to hedge oil price risk. They utilize monthly data between 1975 and 1987. Due to their findings firm returns are not significantly sensitive to oil prices, and on average the percentage of oil price fluctuations offset by the returns of the hedge portfolio is only about one-third. In this context, further improvements and additional studies can be achieved by examining the relation between the commodity hedge market and the underlying commodity itself along with its permanent effects on the real industry and macroeconomics activities.

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15 APPENDICES

Table 14: Descriptive Statistics (1/2)

	RARS	RBRENT	RCAD	RCHF	RDXY	REUR	RGBP	RJPY	RMXN	RRUB	RTRY	RWTI
Mean	0,0006	0,0002	0,0000	-0,0001	0,0000	0,0000	-0,0001	0,0000	0,0002	0,0002	0,0005	0,0002
Median	0,0000	0,0006	-0,0001	-0,0001	0,0000	0,0001	0,0001	0,0000	-0,0001	0,0000	0,0000	0,0006
Maximum	0,4616	0,1271	0,0330	0,0893	0,0390	0,0372	0,0304	0,0622	0,0877	0,1240	0,3567	0,1641
Minimum	-0,1036	-0,1444	-0,0377	-0,1714	-0,0437	-0,0318	-0,0841	-0,0378	-0,0654	-0,1288	-0,2513	-0,1654
Std. Dev.	0,01	0,02	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,02
Skewness	21,88	-0,16	0,14	-2,52	-0,05	-0,01	-1,10	-0,07	1,09	0,56	5,56	-0,10
Kurtosis	775,07	5,90	5,83	74,39	6,20	4,62	15,44	7,47	18,64	45,51	228,35	6,93
Observations	4.267	4.267	4.267	4.267	4.267	4.267	4.267	4.267	4.267	4.267	4.267	4.267

Table 15: Descriptive Statistics (2/2)

	RBP_L	RCVX_N	RHES_N	RTOTF_PA	RXOM	RCOP_N	RRDSA_AS	RMRO_N
Mean	-0,0001	0,0003	0,0003	0,0001	0,0002	0,0002	24,9696	0,0002
Median	0,0000	0,0007	0,0006	0,0006	0,0003	0,0006	25,2050	0,0006
Maximum	0,1058	0,1894	0,1544	0,1279	0,1586	0,1536	37,5000	0,2099
Minimum	-0,1404	-0,1334	-0,2127	-0,0964	-0,1503	-0,1487	15,3800	-0,2177
Std. Dev.	0,02	0,02	0,03	0,02	0,02	0,02	4,08	0,02
Skewness	-0,14	0,09	-0,66	0,00	0,04	-0,30	0,34	-0,17
Kurtosis	7,51	13,43	11,05	7,46	13,06	8,53	2,81	10,68
Observations	4.189	4.189	4.189	4.189	4.189	4.189	4.189	4.189

Table 16: RWTI GARCH Model for Global Financial Crisis Period

Distribution	Normal Distribution				student t-Distribution			
	Mean Equation		Variance Equation		Mean Equation		Variance Equation	
	coefficient	z-stats	coefficient	z-stats	coefficient	z-stats	coefficient	z-stats
RWTI (-1)	-0,05	-2,95			-0,05	-2,92		
RCAD	-1,12	-14,49			-1,12	-14,72		
REUR	-0,64	-4,99			-0,51	-3,89		
RCHF	0,10	1,55			0,15	2,03		
RGBP	0,06	0,77			0,10	1,45		
RJPY	0,42	8,00			0,37	6,71		
RDXY	-1,14	-6,52			-0,96	-5,36		
RMXN	0,00	-0,01			-0,04	-0,84		
RRUB	-0,61	-20,87			-0,59	-16,53		
α_0			0,00	4,71			0,00	3,26
α_1			0,09	9,64			0,08	6,50
β_1			0,89	88,79			0,90	66,3
Observations				2118				2118
R^2				0,321				0,322
DW				2,078				2,079

Table 17: RWTI EGARCH Model for Global Financial Crisis Period

Distribution	Normal Distribution				student t-Distribution			
	Mean Equation		Variance Equation		Mean Equation		Variance Equation	
	coefficient	z-stats	coefficient	z-stats	coefficient	z-stats	coefficient	z-stats
RWTI (-1)	-0,05	-2,79			-0,05	-2,88		
RCAD	-1,09	-13,95			-1,12	-14,84		
REUR	-0,56	-4,35			-0,47	-3,53		
RCHF	0,06	0,98			0,12	1,80		
RGBP	0,06	0,85			0,09	1,34		
RJPY	0,38	7,48			0,35	6,63		
RDXY	-1,00	-5,55			-0,89	-4,96		
RMXN	-0,03	-0,62			-0,05	-1,04		
RRUB	-0,57	-18,34			-0,56	-15,32		
α_0			-0,25	-7,90			-0,21	-5,70
α_1			0,15	10,20			0,14	7,15
λ_1			-0,06	-6,39			-0,06	-4,55
β_1			0,98	314,74			0,99	282,4
Observations				2118				2118
R^2				0,320				0,322
DW				2,081				2,078

Table 18: Granger Causality Tests for Major Oil Exporter Countries

Null Hypothesis:	Overall Period		Global Financial Crisis Period	
	F-Statistic	Prob.	F-Statistic	Prob.
WTI does not Granger Cause CAD	1,26	0,17	1,31	0,14
CAD does not Granger Cause WTI	**1,62**	**0,03**	**1,34**	**0,12**
WTI does not Granger Cause RUB	**2,21**	**0,00**	**1,79**	**0,01**
RUB does not Granger Cause WTI	0,92	0,58	1,08	0,36
MXN does not Granger Cause WTI	**2,70**	**0,00**	**1,82**	**0,01**
WTI does not Granger Cause MXN	**2,67**	**0,00**	**1,90**	**0,01**
BRENT does not Granger Cause CAD	1,05	0,40	1,20	0,23
CAD does not Granger Cause BRENT	**2,25**	**0,00**	**2,03**	**0,00**
BRENT does not Granger Cause RUB	**2,05**	**0,00**	**1,49**	**0,06**
RUB does not Granger Cause BRENT	0,91	0,58	0,85	0,67
MXN does not Granger Cause BRENT	**3,29**	**0,00**	**1,51**	**0,05**
BRENT does not Granger Cause MXN	**2,27**	**0,00**	**2,29**	**0,00**
Observations		4243		2095
Lags		24		24

Table 19: Granger Causality Tests for Turkey

Null Hypothesis:	Overall Period		Global Financial Crisis Period	
	F-Statistic	Prob.	F-Statistic	Prob.
WTI does not Granger Cause TRY	**1,72**	**0,02**	**1,58**	**0,04**
TRY does not Granger Cause WTI	1,13	0,30	0,98	0,49
TRY does not Granger Cause BRENT	1,09	0,35	1,07	0,37
BRENT does not Granger Cause TRY	**1,21**	**0,22**	**1,67**	**0,02**
TRY does not Granger Cause EUR	0,89	0,61	1,29	0,16
EUR does not Granger Cause TRY	1,18	0,24	1,13	0,30
TRY does not Granger Cause MXN	**1,40**	**0,09**	**1,39**	**0,10**
MXN does not Granger Cause TRY	**5,79**	**0,00**	**2,92**	**0,00**
TRY does not Granger Cause RUB	**2,19**	**0,00**	**2,31**	**0,00**
RUB does not Granger Cause TRY	**1,81**	**0,01**	**2,08**	**0,00**
Observations		4243		2095
Lags		24		24

Table 20: RWTI GARCH Model for Oil Crisis Period

Distribution	Normal Distribution				student t-Distribution			
	Mean Equation		Variance Equation		Mean Equation		Variance Equation	
	coefficient	z-stats	coefficient	z-stats	coefficient	z-stats	coefficient	z-stats
RWTI (-1)	-0,05	-1,54			-0,05	-1,61		
RCAD	-2,09	-11,19			-2,12	-11,01		
REUR	-0,19	-0,54			-0,09	-0,26		
RCHF	0,16	0,77			0,19	0,79		
RGBP	0,08	0,50			0,07	0,49		
RJPY	0,45	3,00			0,42	2,76		
RDXY	-0,03	-0,06			0,10	0,22		
RMXN	0,03	0,31			0,01	0,14		
RRUB	-0,54	-13,44			-0,54	-11,47		
α_0			0,00	2,75			0,00	2,01
α_1			0,11	4,02			0,10	2,99
β_1			0,83	20,85			0,84	16,2

	Normal Distribution	student t-Distribution
Observations	594	594
R^2	0,440	0,441
DW	2,110	2,115

Table 21: RWTI EGARCH Model for Oil Crisis Period

Distribution	Normal Distribution				student t-Distribution			
	Mean Equation		Variance Equation		Mean Equation		Variance Equation	
	coefficient	z-stats	coefficient	z-stats	coefficient	z-stats	coefficient	z-stats
RWTI (-1)	-0,05	-1,50			-0,07	-2,24		
RCAD	-2,02	-10,64			-2,10	-10,82		
REUR	-0,20	-0,65			-0,08	-0,25		
RCHF	0,08	0,72			0,14	0,90		
RGBP	0,08	0,54			0,04	0,28		
RJPY	0,40	2,76			0,36	2,39		
RDXY	0,06	0,13			0,15	0,37		
RMXN	-0,01	-0,06			-0,04	-0,42		
RRUB	-0,53	-13,47			-0,51	-11,41		
α_0			-0,47	-2,92			-0,22	-1,82
α_1			0,18	4,42			0,09	2,14
λ_1			-0,06	-2,40			-0,08	-3,39
β_1			0,96	51,43			0,98	72,3

	Normal Distribution	student t-Distribution
Observations	594	594
R^2	0,439	0,442
DW	2,130	2,088

Table 22: Major Industry Players' EGARCH Model for Oil Price Crisis Period with student-t distribution

RXOM	Mean Equation		Variance Equation	
	coefficient	z-stats	coefficient	z-stats
RCVXN	0,63	25,81		
RHESN	0,04	2,56		
RWTI	0,01	0,80		
REUR	-0,06	-1,55		
RMXN	-0,08	-2,63		
α_0			-1,41	-2,68
α_1			0,33	3,62
λ_1			0,00	-0,08
β_1			0,88	17,76
Observations				564
R^2				0,682
DW				2,0353

RCVX.N	Mean Equation		Variance Equation	
	coefficient	z-stats	coefficient	z-stats
RXOM	0,66	23,76		
RWTI	0,02	1,68		
RBPL	0,10	5,50		
RCOPN	0,20	11,24		
α_0			-2,27	-3,26
α_1			0,43	4,62
λ_1			0,00	0,05
β_1			0,80	11,9
Observations				564
R^2				0,757
DW				2,045

RCOP.N	Mean Equation		Variance Equation	
	coefficient	z-stats	coefficient	z-stats
RCVXN	0,28	5,60		
RXOM	0,17	3,47		
RWTI	0,03	1,76		
RBPL	0,04	1,70		
RHESN	0,27	9,59		
RMRON	0,21	11,47		
α_0			-1,58	-2,37
α_1			0,29	3,50
λ_1			0,06	1,17
β_1			0,85	12,30
Observations				564
R^2				0,785
DW				1,788

RHES.N	Mean Equation		Variance Equation	
	coefficient	z-stats	coefficient	z-stats
RCOPN	0,39	10,33		
RXOM	0,26	5,40		
RWTI	0,12	5,27		
RMRON	0,27	11,92		
α_0			-0,37	-2,09
α_1			0,13	2,95
λ_1			-0,02	-0,59
β_1			0,97	52,3
Observations				564
R^2				0,747
DW				1,832

RMRO.N	Mean Equation		Variance Equation	
	coefficient	z-stats	coefficient	z-stats
RHESN	0,48	12,04		
RCOPN	0,59	12,67		
RBPL	0,10	2,65		
RWTI	0,08	3,22		
α_0			-0,20	-2,27
α_1			0,15	3,16
λ_1			-0,04	-1,42
β_1			0,99	112,43
Observations				564
R^2				0,752
DW				1,916

RBP.L	Mean Equation		Variance Equation	
	coefficient	z-stats	coefficient	z-stats
RCOPN	0,09	3,98		
RWTI	0,07	4,10		
RTOTFPA	0,68	28,26		
α_0			-1,03	-1,27
α_1			0,07	1,16
λ_1			0,05	1,28
β_1			0,89	10,2
Observations				564
R^2				0,649
DW				1,940

RDSa.AS	Mean Equation		Variance Equation	
	coefficient	z-stats	coefficient	z-stats
RWTI	0,04	2,22		
RTOTFPA	0,45	13,67		
RGBP	0,24	3,34		
REUR	-0,28	-3,91		
RXOM	0,09	2,71		
RBPL	0,42	14,72		
α_0			-15,13	-9,84
α_1			0,22	3,23
λ_1			0,08	1,75
β_1			-0,58	-3,5
Observations				564
R^2				0,78
DW				1,945

RTOTF.PA	Mean Equation		Variance Equation	
	coefficient	z-stats	coefficient	z-stats
RMRON	0,03	1,94		
RBPL	0,73	29,94		
RXOM	0,15	3,99		
α_0			-12,50	-1,42
α_1			0,07	0,64
λ_1			0,05	0,70
β_1			-0,37	-0,4
Observations				564
R^2				0,648
DW				2,037

CHAPTER 3: PRICE DISCOVERY IN CRUDE OIL MARKETS: INTRADAY VOLATILITY INTERACTIONS BETWEEN CRUDE OIL FUTURES AND ENERGY ETFS

ABSTRACT

In this paper we investigate the effect and integration of financial assets with crude oil prices. First we examine price discovery of crude oil prices by operating causality tests. Our paper differs from the existing literature focusing on the impact of energy related Exchange Related Funds (ETFs) on crude oil prices. In the previous studies we overviewed so far we concluded that this relationship is studied only between equity markets and crude oil markets however, ETFs are now a crucial tool of information dispersion.

We find that price discovery does not flow consistently from the futures to spot markets or vice versa. The causality is mostly bi-directional from futures market to spot markets for crude oil. Coherently, futures market drives energy based ETFs market however cross market information increases the explanation power of volatility. In this context, secondly we tested whether there is any interaction between price volatility, the crude oil prices and energy based ETF markets by employing EGARCH models using 5-min data. We used three different volatility measures which are square return, Garman and Klass (1980), Rogers and Satchell (1991) and Rogers et al. (1994).

Keywords: Oil prices, time series, volatility, ETFs, EGARCH, Granger Causality, News Impact Curves

16 INTRODUCTION

Exchange Traded Funds (ETFs) exist in United States since 1993 and in Europe since 1999. They typically track an index and so are an alternative to an index mutual fund for investors who are risk averse. ETFs are created by institutional investors. Since they can be bought or sold at any time of the day ETFs have advantage over open ended mutual funds[15]. They can be shorted in the same way that share in any stock are shorted. This ensures that the shares in the ETF trade at a price very close to the fund's net asset valued. In the past three years 90% of the

[15] An open-end fund is a type of mutual fund that does not have restrictions on the amount of shares the fund can issue. The majority of mutual funds are open-end, providing investors with a useful and convenient investing vehicle (www.investopedia.com).

net fund flows in the US have been in to passive funds[16]. According to the forecasts, growing investment market will overtake the active fund industry in the US by 2024[17]. ETFs have achieved a greater penetration in the US compared to Europe. 185 of mutual fund assets are invested in ETFs[18] in the US while it is below 4% in Europe.

Hedging demand in energy sector increases due to the high volatility in energy prices. Moreover, energy commodity's inflation-hedged nature and its low correlation with stocks and bonds makes it a strong investment alternative for fund managers. ETFs that track energy commodities or energy related companies enabled investors to invest in or hedge in energy sector as well as providing diversified portfolio strategies. ETFs are highly liquid and enables investors to expose quickly to the underlying index. Not necessarily you have to buy a "basket" of securities to replicate and track the index when you invest in ETFs. Also non-synchronous trading[19] problems associated with stock index price data are not a problem in case you make your investment via ETFs.

Energy companies use derivatives very intensely and create a significant volume and flow in the markets. Many energy products are traded in both the OTC market and on exchanges.

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[16] Source: ETFGI LLP, an equity research firm which provides proprietary research on the global exchange traded fund and exchange traded products industry. The firm publishes industry data and statistics and identifies trends within the industry on a global, regional and country basis. It offers specialist reports, bespoke data analysis and governance services on all aspects of this industry. The firm provides monthly report on global and regional industry trends. It offers monthly newsletter outlining the global asset movements within the industry.

[17] The shift towards cheap index-trading funds which account for nearly a third of assets under management in the US has already become a big challenge for active asset manager. The trend towards passive funds will mean less money invested in the active managers.

[18] The survey known as ETFGI's treasure map, shows that about 256$ bn of ETF assets are also held by Wells Fargo, Morgan Stanley, Goldman Sachs, UBS, JP Morgan, BMO and Citigroup, which control massive positions due to their dual roles as market makers and investment advisers. ETFG's report identifies ETF holdings of at least 1$ bn at four hedge funds: Passport Capital, Citadel, Two Sigma and Parallax Volatility Advisers. Citadel is a well-known- ETF market maker. (FTfm, September, 2017)

[19] Different stocks have different trading frequencies. Although even for a single stock the trading frequency varies from hour to hour and from day to day, we often analyze a return series in a fixed time interval such as daily.

16.1 Crude Oil Derivatives

A number of oil futures option contracts are traded on The New York Mercantile Exchange (NYMEX) and the International Petroleum Exchange (IPE). Crude oil contracts, which are underlined by one of the most important commodities in the world, are settled sometimes in cash and sometimes they require settlement by physical delivery. For example, the Brent crude oil futures traded oil futures traded on NYMEX requires physical delivery. In both cases the amount of oil underlying one contract is 1,000 barrels. NYMEX also trades popular contracts on two refined products: heating oil and gasoline. In both cases one contract is for the delivery of 42,000 gallons. In the last decade exchange-traded contracts became also popular in the markets.

Energy producers are exposed to risks which have mainly two components such as; price risk and volume risk. When there is a fluctuation in crude oil production prices adapt themselves to the new market equilibrium however, there is a not perfect relationship between the two.

16.1.1 Modeling Energy Prices

A realistic model for an energy and other commodity prices should incorporate both mean reversion and volatility. One possible model is:

$$\partial ln\, S = [\theta(t) - \alpha lnS]\partial_t + \sigma \partial z \qquad \textbf{[16.1.1]}$$

where S is the energy price, and α and σ are constant parameters and can be estimated from historical data. The parameters α and σ are different for different sources of energy. For crude oil, the reversion rate parameter α in equation [16.1.1] is about 0.5 and the volatility parameter σ is about 20%. The $\theta(t)$ term captures seasonality and trends (Hull, 2005).

Define:

Y: Profit for a month

P: Average energy prices for the month

T: Relevant temperature variable (HDD or CDD) for month

An energy producer can use historical data to obtain a best-fit linear regression relationship of the form:

$$Y = \alpha + \beta P + \gamma T + \epsilon \qquad \textbf{[16.1.2]}$$

Where ϵ is the error term. The energy producer can then hedge risks for the month by taking a position pf –β in energy forwards or futures and a position of –γ in weather forwards or futures (Hull, 2005).

16.2 Other Commodity Investment Vehicles

Commodity exposure can be achieved through other means than direct investment in commodities or commodity derivatives. One of the recent popular investment tools for commodities is ETFs.

ETFs may be suitable for investors who can buy only equity shares or seek simplicity of trading them. ETFs may invest in commodities or futures of commodities (often specializing in a particular sector) seeking to track the performance of the commodities. There are also index-linked ETFs.

Managers of portfolios invest in either passively or actively in the financial markets. Passive managers assume that markets are efficient and focus on beta drivers of return. Beta, a measure of sensitivity relative to a particular market index is a measure of systemic risk. Beta driven portfolios are positioned to efficiently take on market risk.

Holding highly diversified portfolios without spending too much efforts or other resources like using investment bank reports or individual asset valuation is the main essence of Passive Management. Obviously it is beneficial and more efficient to follow passive strategies if markets are perfect and prices reflect all available information to all investor universe without any discrimination. Portfolios of real estate investment trusts (REITs) and commodity ETFs may provide beta exposure to a category of alternative investments.

17 LITERATURE REVIEW

Tang and Xu (2016) examine nine leveraged ETFs tied to oil. 5 are based on oil stocks and the other four use commodity futures to track the price of oil itself. Their main findings are; stock based ETFs are much more correlated with the stock market than with oil prices, whereas the reverse is time for crude oil ETFs.

Ivanov (2011) found that the introduction of ETFs to the markets has shifted price discovery for gold and silver to the ETF market however the oil market does not verge to this development yet and has price discovery still occurs dominantly in the futures market for crude oil commodities. Chang and Ke (2014) examined the relationship between flows and return for 5 ETFs in the US energy sector in which they concluded that energy returns and subsequent energy ETF flows have a negative relationship.

Bernstein (2009) claims that high fluctuations in the underlying assets and futures markets of commodities happen due to the demand for ETFs. Garbade and Silber (1993) found that the futures commodity market drives the cash commodities market in price discovery. According to their findings 75% of the information for wheat, corn and orange juice is determined by the futures market.

Choi et all. (2014) applied a Granger-causality test for the OPEC crude oil spot market and the crack spread[20] futures market by splitting their dataset in to three sub-sample periods: the pre-crisis, crisis, and post-crisis periods. Due to their findings, a change in the lead-lag relationship between the oil spot and crack spread futures markets is observed over the sub-sample periods.

[20] Crack spread refers to the overall pricing difference between a barrel of crude oil and the petroleum products refined from it. The "crack" being referred to is an industry term for breaking apart crude oil into the component products, including gases like propane, heating fuel, gasoline, light distillates like jet fuel, intermediate distillates like diesel fuel and heavy distillates like grease.

In particular, a unidirectional relationship from the crude oil spot market to crack spread futures was detected for the pre-crisis and crisis periods. One interesting point is that this relationship between the two markets was reversed in the post-crisis period. This is also a good example why the essence of all the recent commodity prices and commodity derivative prices should be applied in different subsets for a huge dataset. In the last decade financial markets experienced various crisis and many different investment or hedging vehicles were introduced to the markets. Especially for major commodities which is both physically and financially traded so heavily in the market the direction and the level of interaction may change frequently based on mentioned developments. Also since we have experienced a recent oil price crisis in the last 4 years it is quite crucial to explore specific information for this period. At that point rather than introducing a new econometrical model or quantitative approach, updating the existing literature empowered by new dataset supported by new assets and their datasets will propose interesting results.

However, Quant (1992) states that the spot market for crude oil always leads the futures market and the crude oil futures market does not play an important role in price discovery. Schwarz and Szakmary (1994) start their study by criticizing Quant and concludes that light sweet crude oil futures dominate in price discovery relative to its deliverable spot instruments.

Consequently, cross-market volatility transmission become an important topic introducing a significant result between the crude oil price and the US stock market to the existing literature. The content of the literature works are quite rich which focuse on the volatility interaction between the crude oil and equity markets in the Gulf Cooperation Council (GCC countries). Arouri et al., 2011 point out that if there is a risk for oil prices, international portfolio management highly depends on the level of return and volatility spillovers between world oil prices and GCC stock markets. Malik and Hammoudeh (2007) used daily data between 14 February 1994 and 25 December 2001 and concluded that there is a significant interaction between second moments of the US equity and global oil markets. The study focused on the transmission of volatility and shocks among the markets of oil, US equity and each of the three oil-rich Gulf countries. Awartani and Maghyereh (2013) exploit a new spillover directional measure proposed by Diebold and Yilmaz (2009, 2012) to analyze the dynamic spillover of return and volatility between oil and equities and find that the information flow from oil returns and volatilities to the GCC stock exchanges is important, while the flow in the opposite direction is marginal. Jouini and Harrathi (2014) revisited the empirical issue related to the shock and volatility transmissions among Gulf stock and oil markets based on the asymmetric BEKK-GARCH process developed by Kroner and Ng (1998).

In our study we will merge these two literature scopes and investigate the interaction and price discovery direction of crude oil and energy based ETFs.

18 METHODOLOGY

Since commodity forward prices are based upon expected spot prices and expected spot prices are dependent upon expected supply and demand forces, forward prices for commodities need to be constant from period to period. In this context future contracts are essentially forward contracts that are arranged by an organized exchange. Since they usually require a margin deposit and this position is marked to market daily. ETFs appeared as a more flexible investment tools for asset managers.

However, there is one important topic which is how closely can the ETFs track their underlying assets. Briefly, Tracking Error (TE) is the varinace between the return on the underlying asset and the return of the EFT (Frino and Gallagher, 2001). Another important measure is the price deviation (PD) of the ETF which is the variance between the log price of the underlying asset and the log price of the ETF.

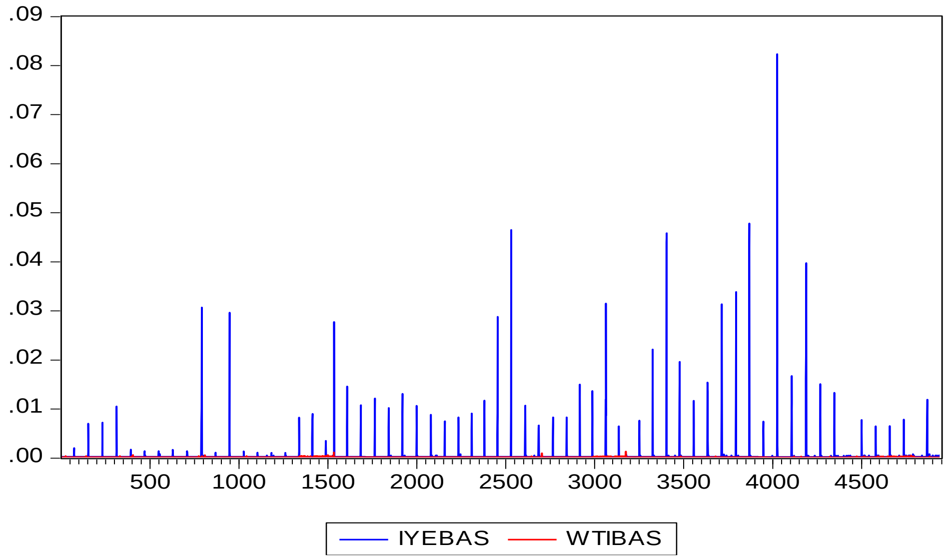
ETFs are designed to have a price which is based on a proportion of the underlying asset like index mutual funds. Since spot, ETF and future prices have unit roots and pricing deviations are stationary we will go for a cointegration test following Engle-Granger cointegration methodology as discussed in Enders (2004).

In this context, first we will employ Johansen Cointegration Test and the results are presented in Tables 30 and 31. Secondly, based on causality model results we will include additional information from bid-ask spread and trading volume and tests whether adding it will improve the quality of price volatility predictability.

Bid-ask spreads corresponds to the difference between prices at which one can buy (ask) and sell (bids). The bid-ask spread represents part of the profit of a market maker who posts bid-ask prices at which they are willing to buy and sell. Bid-ask prices differentiate from location to location, market to market and generally increase based on the contract size.

As a matter of fact, a liquid market is often defined as a market in which one can make transactions in significant volumes without affecting the prices or widening the bid-ask spreads. In this context the bid-ask spreads range differentiation between WTI and IYE exhibited in Figure 13 is quite coherent with the market principles. Bid-ask spread range is quite tighter compared to ETF spread range which is a much more liquid market than ETF market.

Figure 13: WTI and IYE Bid-Ask Spread Graph



We propose three specifications of EGARCH (1,1) models, as Narayan et all. (2016) did, which use different levels of trading information in estimating volatility of crude oil and ETF markets.

These three models are as follows:

$$Model\ 1\text{:} \begin{bmatrix} V_t^{WTI} = \beta_0^{WTI} + \beta_1^{WTI} V_{t-1}^{WTI} + \varepsilon_t \\ V_t^{IYE} = \beta_0^{IYE} + \beta_1^{IYE} V_{t-1}^{IYE} + \varepsilon_t \end{bmatrix} \quad [18.1]$$

$$\varepsilon \rightarrow N(0, \sigma^{2)}$$

$$\ln(0, \sigma^2) = \omega + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \alpha \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| + \beta \ln(\sigma_{t-1}^2)$$

$$Model\ 2\text{:} \begin{bmatrix} V_t^{WTI} = \beta_0^{WTI} + \beta_1^{WTI} V_{t-1}^{WTI} + \beta_2^{WTI} BAS_{t-1}^{WTI} + \beta_3^{WTI} ASKSIZE_{t-1}^{WTI} + \varepsilon_t \\ V_t^{IYE} = \beta_0^{IYE} + \beta_1^{IYE} V_{t-1}^{IYE} + \beta_2^{IYE} BAS_{t-1}^{IYE} + \beta_3^{IYE} ASKSIZE_{t-1}^{IYE} + \varepsilon_t \end{bmatrix}$$

$$\varepsilon \rightarrow N(0, \sigma^{2)}$$

$$\ln(0, \sigma^2) = \omega + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \alpha \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| + \beta \ln(\sigma_{t-1}^2) \quad [18.2]$$

$$Model\ 3\text{:} \begin{bmatrix} V_t{}^{WTI} = \beta_0^{WTI} + \beta_1^{WTI} V_{t-1}^{WTI} + \beta_2^{WTI} BAS_{t-1}^{WTI} + \beta_3^{WTI} ASKSIZE_{t-1}^{WTI} + \\ \beta_4^{IYE} V_{t-1}^{IYE} + \beta_5^{IYE} BAS_{t-1}^{IYE} + \beta_6^{IYE} ASKSIZE_{t-1}^{IYE} + \varepsilon_t \\ V_t{}^{IYE} = \beta_0^{IYE} + \beta_1^{IYE} V_{t-1}^{IYE} + \beta_2^{IYE} BAS_{t-1}^{IYE} + \beta_3^{IYE} ASKSIZE_{t-1}^{IYE} + \\ \beta_4^{IYE} V_{t-1}^{WTI} + \beta_5^{WTI} BAS_{t-1}^{WTI} + \beta_6^{WTI} ASKSIZE_{t-1}^{WTI} + \varepsilon_t \end{bmatrix}$$

$$\varepsilon \rightarrow N(0, \sigma^{2)}$$

$$\ln(0, \sigma^2) = \omega + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \alpha \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| + \beta \ln(\sigma_{t-1}^2) \quad [18.3]$$

where BAS_{IYE}, $ASKSIZE_{IYE}$, $BIDSIZE_{IYE}$ and V_{IYE} are the bid–ask spread, trading volume, and the price volatility of the ETF market, respectively, while BAS_{WTI}, $ASKSIZE_{WTI}$ and V_{WTI} are the corresponding variables for the crude oil market ε_t is the residual from mean equation, and σ_t^2 is the conditional variance generated from the model.

19 ECONOMETRIC DATA AND DESCRIPTION

Our dataset contains daily Brent crude oil spot prices (BRT), Brent crude oil futures prices (LCOc1), WTI crude oil spot prices (WTC), WTI crude oil futures prices (CLc1) and ETF funds such as Power Shares DB Commodity Index Tracking Fund (DBC), Barclays Bank iPath

Commodity ETF (BCM), First Trust Global Tactical Commodity Strategy (FTGC.O), iShares US Energy ETF (IYE[21]), Vanguard Energy Index Fund (VDE) and Energy Select Sector SPDR Fund (XLE) over the period from September 15, 2008 to October 2, 2017. All the data is provided from Thompson Reuters Eikon. In the first part, for causality tests we will analyze the data in two sub-periods. First, we will use whole data period from September 15, 2008 to October 2, 2017 which we will emphasize as "Global Financial Crisis Period" in our models. We will also analyze the oil prices in a second sub-sample namely 'oil price crisis' which includes the data between November 1, 2014 and October 2, 2017.

Table 23: Model Dataset Descriptions

#	Variable	Description	Frequency
1	RBRT	Returns of Brent crude oil spot prices	Daily
2	RLCOc1	Returns of Brent crude oil futures prices	Daily
3	RWTC	Returns of WTI crude oil spot prices	Daily
4	RCLc1	Returns of WTI crude oil futures prices	Daily
5	RDBC	Returns of PowerShares DB Commodity Index Tracking Fund	Daily
6	RBCM	Returns of Barclays Bank iPath Commodity ETF	Daily
7	RFTGC.O	Returns of First Trust Global Tactical Commodity Strategy	Daily
8	RIYE	Returns of iShares US Energy ETF	Daily
9	RVDE	Returns of Vanguard Energy Index Fund	Daily
10	RXLE	Returns of Energy Select Sector SPDR Fund	Daily
11	TEDBC	Tracking Error for PowerShares DB Commodity Index Tracking Fund	Daily
12	TEBCM	Tracking Error for Barclays Bank iPath Commodity ETF	Daily
13	TEFTGC.O	Tracking Error for First Trust Global Tactical Commodity Strategy	Daily
14	TEIYE	Tracking Error for iShares US Energy ETF	Daily
15	TEVDE	Tracking Error for Vanguard Energy Index Fund	Daily
16	TEXLE	Tracking Error for Energy Select Sector SPDR Fund	Daily
17	PDDBC	Pricing Differences for PowerShares DB Commodity Index Tracking Fund	Daily
18	PDBCM	Pricing Differences for Barclays Bank iPath Commodity ETF	Daily
19	PDFTGC.O	Pricing Differences for First Trust Global Tactical Commodity Strategy	Daily
20	PDIYE	Pricing Differences for iShares US Energy ETF	Daily
21	PDVDE	Pricing Differences for Vanguard Energy Index Fund	Daily
22	PDXLE	Pricing Differences for Energy Select Sector SPDR Fund	Daily

In the second part we will employ a 5-minute interval intraday time series data for daily Brent crude oil spot prices (BRT), Brent crude oil futures prices (LCOc1) which are used as a proxies

[21] The First stock-based regular energy ETF (ticker: IYE, tracking the DJUSEN Energy Stocks Index) was introduced to the market in June 2000, and the first futures-based energy ETF (ticker: USO, tracking the USCRWTIC Crude Oil Index) was launched in April of 2006. These two earliest energy ETFs both have over US$1 billion in AUM, representing the two largest and most popular energy ETFs.

for crude oil markets and ETF funds such as Power Shares DB Commodity Index Tracking Fund (DBC), Barclays Bank iPath Commodity ETF (BCM), First Trust Global Tactical Commodity Strategy (FTGC.O), iShares US Energy ETF (IYE), and Energy Select Sector SPDR Fund (XLE) which are used as proxies for the energy derivatives market.

The data was collected for the period from August 23, 2017 to November 23, 2017. For both the data samples, the intraday tick data is used to form a 5-minute interval time series, consisting of bid-ask spread (BAS), high price, low price, open price, close price and total number of shares traded in the 5-minute interval.

Table 24: Descriptive Statistics-1

Brent Oil	**Mean**	**SD**	**JB**	**ADF**	**ARCH (1)**	**ARCH (12)**	**LB (1)**	**LB (12)**
BAS_{Brent}	0,000229	0,000129	0,00	0,00	0,00	0,00	0,00	0,00
$ASKSIZE_{Brent*}$	9,452084	2,207209	0,00	0,00	0,00	0,00	0,00	0,00
$BIDSIZE_{Brent*}$	9,441165	2,200334	0,00	0,00	0,00	0,00	0,00	0,00
VSQ_{Brent}	0,000023	0,001689	0,00	0,00	0,00	0,00	0,00	0,00
VRS_{Brent}	0,000001	0,000001	0,00	0,00	0,02	0,26	0,00	0,00
$VSGK_{Brent}$	0,000001	0,000001	0,00	0,00	0,00	0,00	0,00	0,00
WTI	**Mean**	**SD**	**JB**	**ADF**	**ARCH (1)**	**ARCH (12)**	**LB (1)**	**LB (12)**
BAS_{WTI}	0,000204	0,00005	0,00	0,00	0,99	1,00	0,442	1,00
$ASKSIZE_{WTI}$	11,65384	1,97314	0,00	0,00	0,00	0,00	0,00	0,00
$BIDSIZE_{WTI}$	11,65932	1,97573	0,00	0,00	0,00	0,00	0,00	0,00
VSQ_{WTI}	0,00002	0,00161	0,00	0,00	0,00	0,00	0,721	0,037
VRS_{WTI}	0,00000	0,00000	0,00	0,00	0,00	0,00	0,00	0,00
$VSGK_{WTI}$	0,00000	0,00000	0,00	0,00	0,00	0,00	0,00	0,00
iShares	**Mean**	**SD**	**JB**	**ADF**	**ARCH (1)**	**ARCH (12)**	**LB (1)**	**LB (12)**
BAS_{IYE}	0,000576	0,002642	0,00	0,00	0,00	0,00	0,00	0,00
$ASKSIZE_{IYE}$	15,51631	1,119692	0,00	0,00	0,00	0,00	0,00	0,00
$BIDSIZE_{IYE}$	15,58425	1,106352	0,00	0,00	0,00	0,00	0,00	0,00
VSQ_{IYE}	0,000030	0,001450	0,00	0,00	0,00	0,00	0,00	0,00
VRS_{IYE}	0,000000	0,000001	0,00	0,00	0,83	0,00	0,00	0,00
$VSGK_{IYE}$	0,000000	0,000001	0,00	0,00	0,76	0,00	0,00	0,00

Notes: This table reports the correlations between bid–ask spread, trading volume, the price volatility of the ETF market/crude oil market and each of three measures of price volatility including square return, Garman and Klass (1980) volatility, and the volatility proposed by Rogers and Satchell (1991)and Rogers et al. (1994). BAS_{IYE}, $ASKSIZE_{IYE}$, $BIDSIZE_{IYE}$ and V_{IYE} are the bid–ask spread, trading volume, and the price volatility of the ETF market, respectively, while BAS_{BRENT}, BAS_{WTI}, $ASKIZE_{BRENT}$, $ASKSIZE_{BRENT}$, $BIDSIZE_{BRENT}$, $BIDSIZE_{WTI}$, V_{BRENT} and V_{WTI} are the corresponding variables for the crude oil market. In the fourth column of each panel, the table reports the p-value from the Jarque–Bera (JB) test, for which the null hypothesis is a joint hypothesis of the skewness and the excess kurtosis being zero. The p-values of the ADF test, which examines the null hypothesis of a unit root, are in the fifth column. The last four columns contain the p-values for the test of autoregressive conditional heteroskedasticity (ARCH) and the Ljung–Box (LB)test for the autocorrelation at lag 1 and lag 12. In addition Bid and Ask sizes are calculated as natural logrithm of trading volumes.

In this context our paper employs the EGARCH models to remedy the presence of heteroskedasticity of variables as noted in Table 24. The bid–ask spread (BAS) is calculated as

$BAS = \frac{\text{ASK}-\text{BID}}{(\text{ASK}+\text{BID})/2}$ while the trading volume (ASKSIZE) is measured as the natural log of trading volume in each 5-min interval. In our study, the intraday volatility (V) is calculated using three approaches, as below:

$$V_t^{SQ} = ln\left(\frac{CP_t}{CP_{t-1}}\right)^2 \quad [19.1]$$

$$V_t^{GK} = 0.5[\ln(HP_t) - \ln(LP_t)]^{\,2} - [2\ln(2) - 1][ln(CP_t) - ln(OP_t)]^{\,2} \quad [19.2]$$

$$V_t^{RS} = [\ln(HP_t) - \ln(OP_t)][\ln(HP_t) - \ln(CP_t)] + [ln(LP_t) - ln(OP_t)][ln(LP_t) - ln(CP_t)] \quad [19.3]$$

where VO_t^{SQ}, VO_t^{GK}, and VO_t^{RS} are the square return, volatility proposed by Garman and Klass (1980) which derives an estimator that has a minimum-variance among the class of unbiased estimators which are quadratic in *HP(t)*, *CP(t)* and *LP(t)*, and volatility proposed by Rogers and Satchell (1991) and Rogers et al. (1994), respectively. HP, LP, CP, and OP represent the high price, low price, closing price, and opening price, respectively.

20 APPLICANTIONS AND FINDINGS

With TE and PD we capture the fact that ETFs track both return and price level of the underlying for all three sub-periods. Table 25 provides the results for tracking errors and pricing deviations of the commodities ETFs. The calculations are based on the global financial crisis period.

The tracking errors of funds are economically small and statistically not different from zero as suggested by the high p-values (close to one for DBCM, FTGCO and DBC). However, the pricing deviations are statistically different from zero with p-values close to zero. The pricing deviation of DBC is approximately 20 cents showing on average the price of the ETF is lower than the price of spot crude prices. The pricing deviation is a 10 cents negative for VDE suggesting that it is trading on average above the spot price of oil.

Table 25: Descriptive Statistics-2

	PDBCM	PDFTGCO	PDDBC	PDXLE	PDVDE	PDIYE
Mean	0,206	0,164	0,518	0,041	-0,109	0,275
Median	0,247	0,000	0,537	0,097	-0,050	0,338
Maximum	0,462	0,589	0,650	0,279	0,110	0,518
Minimum	0,000	0,000	0,000	-0,303	-0,441	-0,052
Std. Dev.	0,178	0,204	0,128	0,144	0,137	0,149
Skewness	-0,065	0,584	-2,580	-0,463	-0,548	-0,429
Kurtosis	1,335	1,625	10,744	1,818	1,859	1,761
T-test (mean=0)	0,000	0,000	0,000	0,000	0,000	0,000
Observations	2.336	2.336	2.336	2.336	2.336	2.336

	TEBCM	TEFTGCO	TEDBC	TEXLE	TEVDE	TEIYE
Mean	0,000	0,000	0,000	0,000	0,000	0,000
Median	0,000	0,000	0,000	0,000	0,000	0,000
Maximum	0,180	0,180	0,145	0,166	0,124	0,132
Minimum	-0,167	-0,167	-0,142	-0,188	-0,186	-0,221
Std. Dev.	0,020	0,021	0,018	0,022	0,022	0,022
Skewness	0,129	0,167	0,143	-0,471	-0,574	-0,797
Kurtosis	10,686	9,660	9,766	11,903	10,931	13,481
T-test (mean=0)	0,972	0,821	0,997	0,504	0,525	0,518
Observations	2.336	2.336	2.336	2.336	2.336	2.336

It is not an unexpected result that there is an insignificant tracking error but a significant pricing deviation since ETFs are designed to have a price which is based on a proportion of the underlying asset. In this context pricing deviation can be a measure of the success of the ETF manager. Investors in the futures based or stock based ETFs should be aware that the underlying stock index may not well represent the energy commodity.

Coherently, we applied Granger Causality tests to crude oil spot prices, futures and selected energy ETFs to figure out the direction of the price discovery in crude oil commodity markets. We tested separately both for Brent and WTI[22] prices and concluded that for Brent spot prices

[22] Backmeier and Griffin (2006) examine daily prices for five different crude oils-WTI, Brent, Alaska, North Slope, Dubai Fateh and Indonesian Arun and conclude that the world oil markets are tightly linked to each other. Hammoudeh et all. 2008 also found cointegration in four oil benchmark prices-WTI, Brent, Dubai and Maya.

still drive futures prices and ETFs, however, the direction of causality is bi-directional for WTI[23] as exhibited in Table 31.

Overall results represented in Table 26 confirm negative relationship between bid-ask spread and price volatility and a positive relationship between trading volumes and price volatility. It is also interesting that trading volumes of WTI has positive relationship with ETF price volatility which is also consistent with our Granger Causality test results in Table 31. In the oil prices period we found out that there is a two-way direction causality between WTI[24] Futures and IYE ETF[25] prices.

Initially we display the impulse response functions using the oil price changes of WTI (Appendix-Figure 17). Crude oil spot price returns (WTC) has a positive and persistent impact of the linear specification of oil future price returns with PowerShares DB Commodity Index Tracking Fund (DBC) returns which has a temporary positive impact on WTI. Responses of WTI to other ETF impulses are quite weak which guides us to the conclusion that price discovery is still in crude oil futures market and energy ETFs in our dataset do not drive the oil prices.

Volatility in both crude oil and ETF market react irregularly to their bid-ask spread, trade volumes and three different volatility measures namely; square return, German and Klass, Roger and Satchel[26]. Also not all the correlation coefficients between variables are all statistically significant across all volatility measures.

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[23] The study results of Elder et all (2014) strongly support the leading role of WTI incorporating new information in to oil prices. Our causality test results in Table 7 also supports this. Global Financial Crisis period and Oil Crisis Period results differ from each other which makes us to make the comment that WTI can catch the current dynamics of the cross-markets.

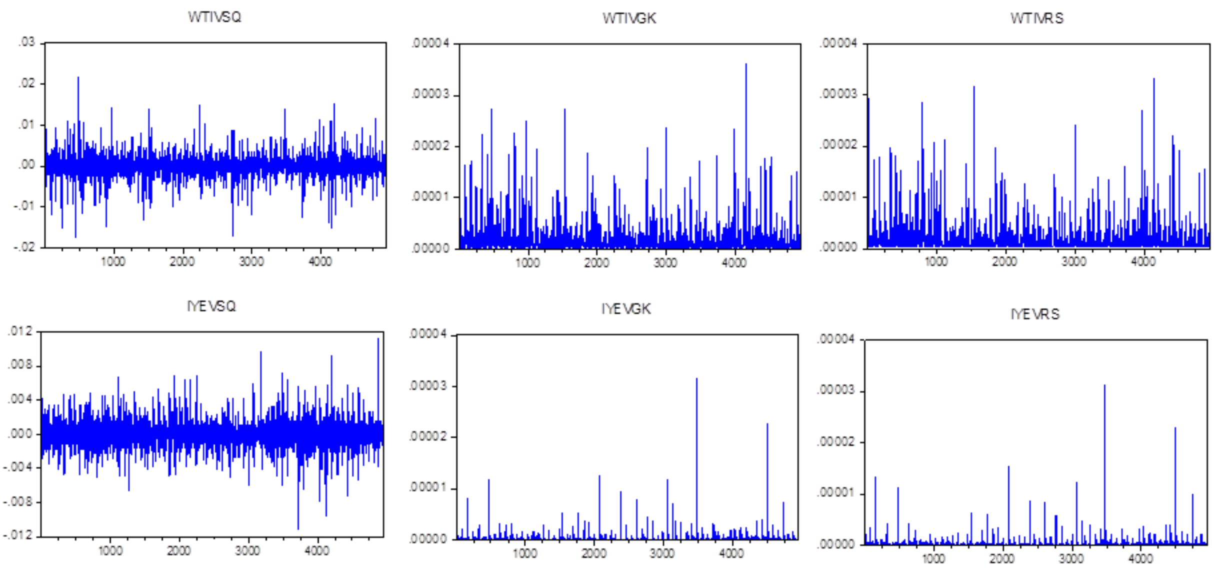
[24] Elder et all (2014) found that WTI maintains a dominant role in price discovery relative to Brent with an estimated information share in excess of 80%.

[25] Blackrock's iShares ETF arm registered record inflows of 140$ bn, beating the 130$ bn gathered in 2015. The ETF is composed of Exxon Mobil, Chevron Corp, Schlumberger, Conoco Phillips and others 24,0%, 15,3%, 5,9% and 4,2% as of 27.11.2017 respectively.

[26] In this context our results differ from our reference paper Narayan et all (2016). In their paper they concluded that volatility, bid-ask spread and trading volumes are positively correlated both with their own markets and cross markets.

Price volatility of Brent futures is negatively correlated with ETF bid-ask spread and correlation coefficients statistically significant for GK and RS volatility measures. When we test the same relationship replacing Brent futures with WTI we find out that the price volatility for GK and RS volatility measures are statistically significant for both WTI's own bid-ask spread and ETF bid-ask spread. Furthermore, price volatility is positively correlated with its own bid-ask spread while it is negatively ETF bid-ask spread. This result is consistent with Ivanov (2011) since oil markets have price discovery. All the volatility for WTI and IYE are exhibited in Figure 14. Above row represents square returns, GK and RS volatilities for WTI respectively while in the row below square returns, GK and RS volatilities for IYE.

Figure 14: 5 Minute Volatilities Using SQ, GK and RS for WTI and IYE



In 1973, Clark suggested with the mixture of distributions hypothesis a positive relationship between trading volume and price volatility. The price volatility with GK and RS measures are statistically significant and positively correlated with their own trading volumes for both WTI and Brent. However, correlation coefficients of ETF price volatility is not statistically significant for its own trading volume while it is positively correlated and statistically significant for Brent and WTI trading volumes. The correlation coefficients vary and in the range of 0,083 and 0,367 in the case of Brent while the range is 0,127 and 0,487 when using WTI.

Table 26: Correlations and Probability-Panel A

	Square Return		Garman and Klass Volatility		Roger and Satchel Volatility	
Panel A	Brent	iShares	Brent	iShares	Brent	iShares
BAS_{Brent}	-0,015	-0,009	-0,014	-0,021	-0,015	-0,017
	0,30	0,54	0,32	0,14	0,30	0,24
BAS_{IYE}	-0,008	0,000	-0,053	-0,007	-0,056	-0,015
	0,59	0,99	0,00	0,61	0,00	0,30
$ASKSIZE_{Brent*}$	0,015	0,008	0,356	0,099	0,354	0,083
	0,28	0,56	0,00	0,00	0,00	0,00
$BIDSIZE_{Brent*}$	0,000	-0,001	0,367	0,103	0,364	0,086
	0,99	0,97	0,00	0,00	0,00	0,00
$ASKSIZE_{IYE*}$	0,015	-0,003	0,179	0,012	0,179	-0,005
	0,29	0,83	0,00	0,41	0,00	0,70
$BIDSIZE_{IYE*}$	0,000	-0,001	0,193	0,012	0,194	0,012
	0,99	0,97	0,00	0,41	0,00	0,40
V_{Brent}	1,000	0,418	1,000	0,158	1,000	0,131
	0,00	0,00	0,00	0,00	0,00	0,00
V_{IYE}	0,418	1,000	0,158	1,000	0,131	1,000
	0,00	0,00	0,00	0,00	0,00	0,00

Notes: This table reports the correlations between bid–ask spread, trading volume, the price volatility of the ETF market/crude oil market and each of three measures of price volatility including square return, Garman and Klass (1980) volatility, and the volatility proposed by Rogers and Satchell (1991)and Rogers et al. (1994). BASIYE, ASKSIZEIYE, BIDSIZEIYE and VIYE are the bid–ask spread, trading volume, and the price volatility of the ETF market, respectively, while BASBRENT, BASWTI, ASKIZEBRENT,ASKSIZEBRENT, BIDSIZEBRENT, BIDSIZEWTI, VBRENT and VWTI are the corresponding variables for the crude oil market. Panel A reports the results when the crude oil market is proxied by the Brent Futures while the results when using the WTI are in Panel B. In addition Bid and Ask sizes are calculated as natural logrithm of trading volumes

The most obvious difference of energy commodities is that they cannot be treated as purely financial assets. The underlying assets of energy commodity derivatives re inputs to production process (especially crude oil), and/or consumption goods and this explains why many models developed to analyze financial markets may break down in the case of energy related assets are studied.

Table 27: Correlations and Probability-Panel B

	Square Return		Garman and Klass Volatility		Roger and Satchel Volatility	
Panel B	WTI	iShares	WTI	iShares	WTI	iShares
BAS_{WTI*}	0,015	0,015	0,046	-0,006	0,043	-0,003
	0,30	0,28	0,00	0,66	0,00	0,82
BAS_{IYE}	-0,010	-0,001	-0,049	-0,009	-0,052	-0,016
	0,49	0,95	0,00	0,52	0,00	0,26
$ASKSIZE_{WTI*}$	0,010	0,011	0,486	0,162	0,481	0,140
	0,49	0,42	0,00	0,00	0,00	0,00
$BIDSIZE_{WTI*}$	0,000	0,009	0,487	0,159	0,483	0,137
	0,99	0,52	0,00	0,00	0,00	0,00
$ASKSIZE_{IYE*}$	0,014	-0,002	0,166	-0,002	0,166	-0,004
	0,32	0,90	0,00	0,88	0,00	0,77
$BIDSIZE_{IYE*}$	-0,002	-0,003	0,176	0,013	0,177	0,013
	0,90	0,85	0,00	0,35	0,00	0,35
V_{WTI}	1,000	0,456	1,000	0,177	1,000	0,151
	0,00	0,00	0,00	0,00	0,00	0,00
V_{IYE}	0,456	1,000	0,177	1,000	0,151	1,000
	0,00	0,00	0,00	0,00	0,00	0,00

Notes: This table reports the correlations between bid–ask spread, trading volume, the price volatility of the ETF market/crude oil market and each of three measures of price volatility including square return, Garman and Klass (1980) volatility, and the volatility proposed by Rogers and Satchell (1991)and Rogers et al. (1994). BAS_{IYE}, $ASKSIZE_{IYE}$, $BIDSIZE_{IYE}$ and V_{IYE} are the bid–ask spread, trading volume, and the price volatility of the ETF market, respectively, while BAS_{BRENT}, BAS_{WTI}, $ASKIZE_{BRENT}$,$ASKSIZE_{BRENT}$, $BIDSIZE_{BRENT}$, $BIDSIZE_{WTI,}$ V_{BRENT} and V_{WTI} are the corresponding variables for the crude oil market. Panel A reports the results when the crude oil market is proxied by the Brent Futures while the results when using the WTI are in Panel B. In addition Bid and Ask sizes are calculated as natural logrithm of trading volumes

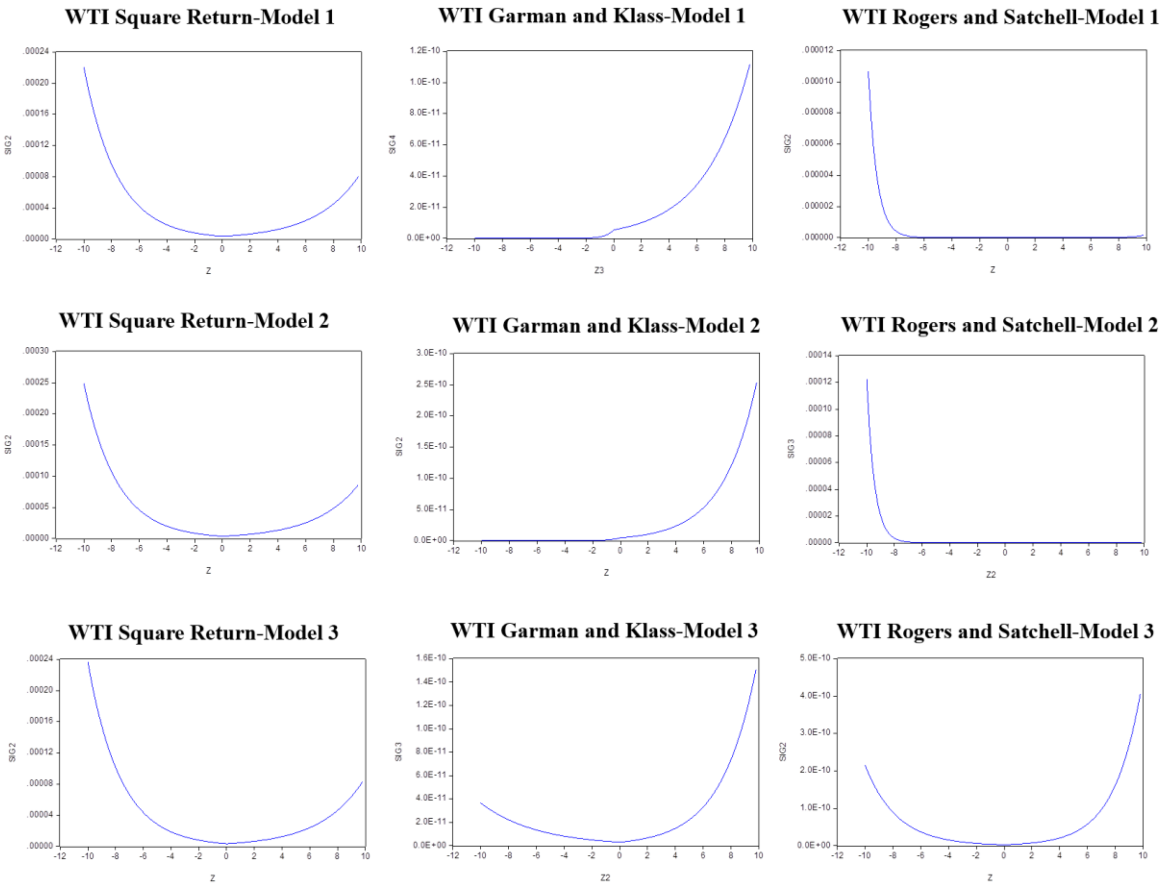
Table 28: Information Criterion

		Square Return			Garman and Klass volatility			Roger and Satchel volatility		
		Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
WTI										
	AIC	-9,4400	-9,4125	-9,4119	-23,4134	-23,294	-23,430	-23,404	-23,435	-23,424
	SIC	-9,4322	-9,4033	-9,3988	-23,4055	-23,283	-23,416	-23,396	-23,425	-23,409
	ADJ R-squared	-0,001%	-0,093%	-0,13%	6,53%	13,61%	12,72%	9,68%	11,61%	13,83%
IYE										
	AIC	-10,319	-10,356	-10,382	-25,3844	-25,47	-25,396	-25,515	-25,295	-25,274
	SIC	-10,316	10,3465	-10,367	-25,3765	-25,459	-25,382	-25,507	-25,285	-25,260
	ADJ R-squared	0,000%	-2,70%	-2,32%	2,42%	11,67%	12,82%	-5,11%	9,59%	10,41%

Notes: This table reports the Akaike Information Criterion, Schwarz Information Criterion, and the adjusted R-square of three EGARCH(1,1) models predictingvolatility in the crude oil and equity markets. The predictive regression models are presented as Eqs. (1)–(3) in the main text. Three price volatility measuresare used, namely, square return, Garman and Klass (1980) volatility, and the volatility proposed by Rogers and Satchell (1991) and Rogers et al. (1994)

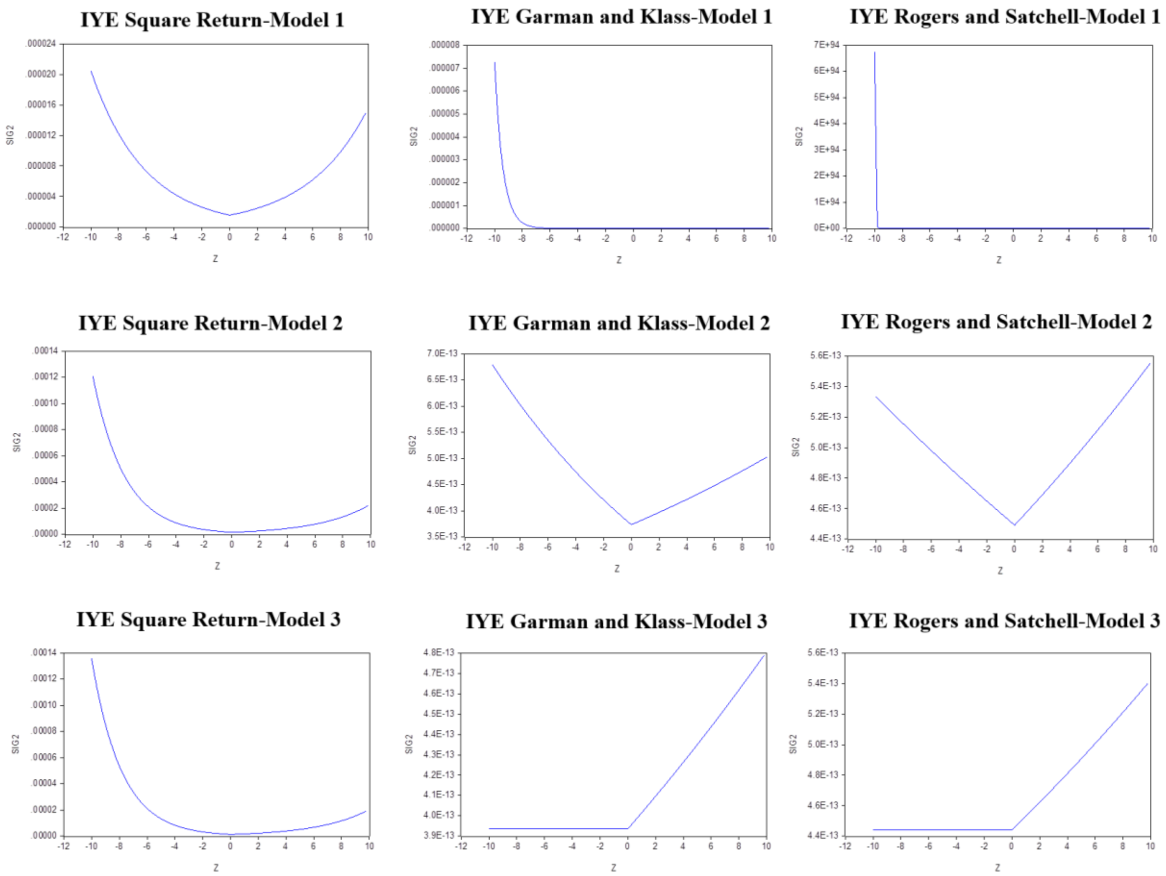
In Table 28, Model 1 estimates the price volatility of the crude oil or ETF market based on its own lagged volatility, while Model 2 is based on its own past trading information including volatility, bid–ask spread and trading volume. On the other hand, Model 3 estimates price volatility using lagged volatility, lagged bid–ask spread, and the lagged trading volume of crude oil futures market and also from the ETF market.

Figure 15: News Impact Curves for WTI Volatility Models



News impact (NI) curves of all volatility types and EGARCH(1,1) for crude oil are exhibited in Figure 15. All the WTI volatility models have asymmetric NICs however they distinguish among themselves. In square return models, negative shocks have more impact on future volatility than positive shocks of the same magnitude. For GS and RS models the outcome is just the opposite, positive shocks have more impact on future volatility than negative shocks of the same magnitude.

Figure 16: News Impact Curves for IYE Volatility Models



News impact (NI) curves[27] of all volatility types and EGARCH(1,1) ETF are exhibited in Figure 16. Most the IYE volatility models have asymmetric NICs however they distinguish among themselves. In square return models, negative shocks have more impact on future volatility than positive shocks of the same magnitude. GS and RS volatility NICs show irregularities for models 1-2 and 3. For Model 1 both GK and RS curves show that negative shocks have more impact on future volatility than positive shocks of the same magnitude. For Model 2 the results are much closer to a symmetric response structure for the shocks. Finally, for Model 3 both GK and RS curves show that positive shocks have more impact on future volatility than negative shocks of the same magnitude.

[27] The news impact curve plots the next period volatility (σ_t^2) that would arise from various positive and negative values of u_{t-1}, given an estimated model. The curves are drawn by using the estimated conditional variance equation for the model under consideration, with its given coefficient estimates, and with the lagged conditional variance set to the unconditional variance.

Table 29: Lagged Effect

	Square Return		Garman and Klass volatility		Roger and Satchel volatility	
	WTI	IYE	WTI	IYE	WTI	IYE
C	-0,0009	0,0027	0,0000	0,0000	0,0000	0,0000
	-0,018	0,000	0,000	0,000	0,000	0,000
$BAS_{WTI, t-1}$	-0,1518	1,6441	0,0024	0,0000	0,0029	0,0001
	0,735	0,000	0,000	0,930	0,000	0,404
$BAS_{IYE, t-1}$	0,0102	0,0198	0,0000	0,0000	0,0000	0,0000
	0,235	0,000	0,001	0,000	0,000	0,000
$ASKSIZE_{WTI, t-1}$	0,0001	0,0000	0,0000	0,0000	0,0000	0,0000
	0,678	0,285	0,000	0,000	0,000	0,000
$ASKSIZE_{IYE, t-1}$	0,0000	-0,0002	0,0000	0,0000	0,0000	0,0000
	0,333	0,000	0,000	0,000	0,000	0,000
$V_{WTI, t-1}$	-0,0009	0,0455	0,1291	0,0135	0,2241	0,0129
	0,018	0,000	0,000	0,011	0,000	0,017
$V_{IYE, t-1}$	0,0052	-0,0576	0,2247	0,1261	0,1707	0,0859
	0,735	0,002	0,000	0,000	0,000	0,000

Notes: BAS_{IYE}, $ASKSIZE_{IYE}$ and V_{IYE} are the bid–ask spread, trading volume, and the price volatility of the ETF market, respectively, while BAS_{WTI},$ASKSIZE_{WTI}$, V_{WTI} are the corresponding variables for the crude oil market. Three price volatility measures are used, namely, square return, Garman and Klass (1980) volatility, andthe volatility proposed by Rogers and Satchell (1991) and Rogers et al. (1994). The specification of the model underlying the results is presented by Eq. (3)in the main text. The p-value of the coefficient for each variable is under the coefficient numbers.

Model 2 outperformed Model 1 in predicting price volatility especially with GK and RS measures as Model 2 utilizes extra information, such as bid–ask spread and trading volume. Similarly, Model 3 is expected to be and is superior to Model 1 and Model 2 because of the additional information contained in the cross-market.

21 CONCLUSION

This paper contributes to the existing literature focusing on the impact of energy related ETFs on crude oil prices. First we examine the price discovery and causality relationship between spot, futures and ETF prices. In the previous studies we overviewed so far we concluded that this relationship is studied only between equity markets and crude oil markets however, ETFs are now an important source of information dissemination. We find that price discovery does not flow consistently from the futures to spot markets or vice versa. The causality is mostly bi-directional from futures market to spot markets for crude oil.

Secondly, we addressed the relative importance of information on trading volume and bid–ask spread using intraday data in predicting cross-market volatility in the crude oil and ETF markets. We tested price volatility interaction between the crude oil and energy based ETF markets by employing EGARCH models using 5-min data and three different volatility measures which are square return, volatility proposed by Garman and Klass (1980), and volatility proposed by Rogers and Satchell (1991) and Rogers et al. (1994).

Finally, we concluded that futures market drives energy based ETFs market however cross market information increases the explanation power of volatility.

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23 APPENDICES

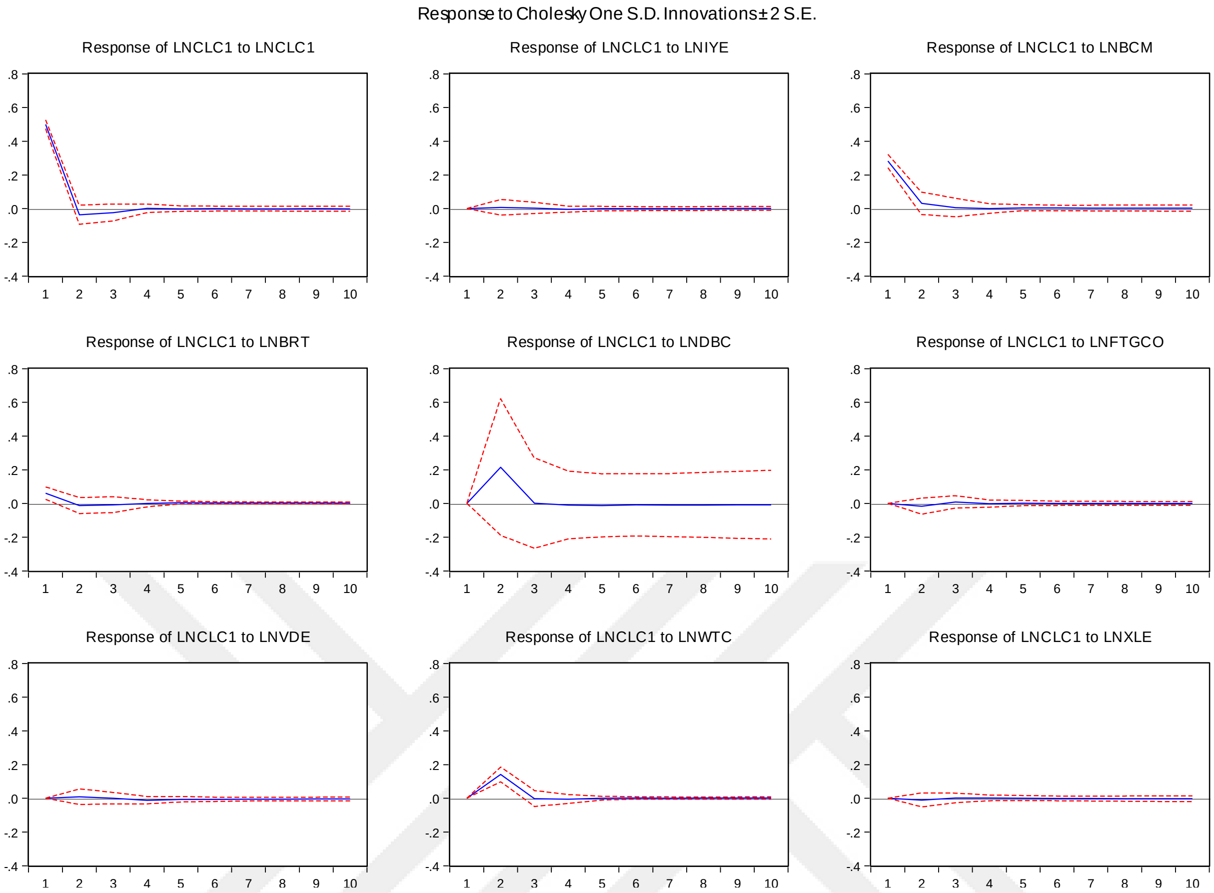
Table 30: Granger Causality Tests for Brent Spot Prices, Brent Futures and Selected ETFs

Null Hypothesis:	Global Financial Crisis Period		Oil Crisis Period	
	F-Statistic	Prob.	F-Statistic	Prob.
LNBRT does not Granger Cause LNBCM	**1,52**	**0,05**	1,04	0,41
LNBCM does not Granger Cause LNBRT	1,15	0,28	0,83	0,70
LNLCOC1 does not Granger Cause LNBRT	**4,58**	**0,00**	**2,42**	**0,00**
LNBRT does not Granger Cause LNLCOC1	0,91	0,59	1,32	0,14
LNDBC does not Granger Cause LNBRT	1,32	0,13	0,48	0,98
LNBRT does not Granger Cause LNDBC	**5,63**	**0,00**	**2,01**	**0,00**
LNIYE does not Granger Cause LNBRT	1,02	0,43	0,51	0,98
LNBRT does not Granger Cause LNIYE	**4,46**	**0,00**	**1,79**	**0,01**
LNVDE does not Granger Cause LNBRT	1,06	0,39	0,52	0,97
LNBRT does not Granger Cause LNVDE	**4,59**	**0,00**	**1,81**	**0,01**
LNFTGCO does not Granger Cause LNBRT	0,80	0,74	0,58	0,95
LNBRT does not Granger Cause LNFTGCO	1,26	0,18	**1,66**	**0,03**
LNXLE does not Granger Cause LNBRT	1,04	0,40	0,52	0,97
LNBRT does not Granger Cause LNXLE	**4,38**	**0,00**	**1,84**	**0,01**
Observations	2312			728
Lags	24			24

Table 31: Granger Causality Tests for WTI Spot Prices, WTI Futures and Selected ETFs

Null Hypothesis:	Global Financial Crisis Period		Oil Crisis Period	
	F-Statistic	Prob.	F-Statistic	Prob.
LNWTC does not Granger Cause LNBCM	1,12	0,31	**1,55**	**0,05**
LNBCM does not Granger Cause LNWTC	1,07	0,38	0,66	0,89
LNWTC does not Granger Cause LNCLC1	0,75	0,80	**1,83**	**0,01**
LNCLC1 does not Granger Cause LNWTC	**0,62**	**0,92**	**1,62**	**0,03**
LNWTC does not Granger Cause LNDBC	0,84	0,69	**1,74**	**0,02**
LNDBC does not Granger Cause LNWTC	1,35	0,12	**1,85**	**0,01**
LNWTC does not Granger Cause LNIYE	0,67	0,88	**1,53**	**0,05**
LNIYE does not Granger Cause LNWTC	**2,10**	**0,00**	**1,91**	**0,01**
LNWTC does not Granger Cause LNVDE	0,69	0,86	**1,65**	**0,03**
LNVDE does not Granger Cause LNWTC	**2,49**	**0,00**	**2,16**	**0,00**
LNWTC does not Granger Cause LNFTGCO	**2,15**	**0,00**	**1,47**	**0,07**
LNFTGCO does not Granger Cause LNWTC	0,94	0,55	**1,97**	**0,00**
LNXLE does not Granger Cause LNWTC	**2,31**	**0,00**	**2,20**	**0,00**
LNWTC does not Granger Cause LNXLE	0,67	0,89	**1,70**	**0,02**
Observations	2312			728
Lags	24			24

Figure 17: Impulse Response Function Graphs for WTI



23.1 Econometric Tests for Granger Causality[28]

Econometric tests of whether a particular observed series *y* Granger-causes *x* can be based on any of the three implications [23.1.1], [23.1.2] and [23.1.3] below:

In a bivariate VAR describing *x* and *y*, *y* does not Granger-cause *x* if the coefficient matrices φ_j are lower triangular for all *j*:

$$\begin{bmatrix} x_t \\ y_t \end{bmatrix} = \begin{bmatrix} c_1 \\ c_2 \end{bmatrix} + \begin{bmatrix} \varphi_{11}^{(1)} & 0 \\ \varphi_{21}^{(1)} & \varphi_{22}^{(1)} \end{bmatrix} \begin{bmatrix} x_{t-1} \\ y_{t-1} \end{bmatrix} + \begin{bmatrix} \varphi_{11}^{(2)} & 0 \\ \varphi_{21}^{(2)} & \varphi_{22}^{(2)} \end{bmatrix} \begin{bmatrix} x_{t-2} \\ y_{t-2} \end{bmatrix} + \cdots$$

$$+ \begin{bmatrix} \varphi_{11}^{(p)} & 0 \\ \varphi_{21}^{(p)} & \varphi_{22}^{(p)} \end{bmatrix} \begin{bmatrix} x_{t-p} \\ y_{t-p} \end{bmatrix} + \begin{bmatrix} \varphi_{11}^{(2)} & 0 \\ \varphi_{21}^{(2)} & \varphi_{22}^{(2)} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} \qquad [23.1.1]$$

[28] This part is a summary part for Granger-causality mechanism which utilizes Hamilton, 1994.

From the first row of this system, the optimal one-period-ahead forecast of x depends only on its own lagged values and not on lagged *y*:

$E = (x_{t+1} | \, x_t, x_{t-1}, \ldots., y_t, y_{t-1}, \ldots)$

$$= c_1 + \varphi_{11}^{(1)} x_t + \varphi_{11}^{(2)} x_{t-1} + \ldots . \varphi_{11}^{(p)} x_{t-p+1} \qquad [23.1.2]$$

Furthermore, the value of x_{t+2} from [8.1.2] is given by

$$x_{t+2} = c_1 + \varphi_{11}^{(1)} x_{t+1} + \varphi_{11}^{(2)} x_t + \ldots . + \varphi_{11}^{(p)} x_{t-p+2} + \varepsilon_{1,t+2}$$

Recalling [8.1.2], and the law of iterated projections, it is clear that the date *t* forecasts of this magnitude on the basis of $(x_t, x_{t-1}, \ldots., y_t, y_{t-1}, \ldots)$ also depends only on $(x_t, x_{t-1}, \ldots., x_{t-p+1})$. By induction, the same is true of an s-period-ahead forecast. Thus, for the bivariate VAR, *y* does not Granger-cause *x* if $\boldsymbol{\varphi_j}$ is lower triangular for all *j*, as claimed.

Based on the equation below:

$\boldsymbol{\omega}_s = \boldsymbol{\varphi}_1 \boldsymbol{\omega}_{s-1} + \boldsymbol{\varphi}_2 \boldsymbol{\omega}_{s-2} + \cdots + \boldsymbol{\varphi}_p \boldsymbol{\omega}_{s-p}$ for s= 1,2, …, with $\boldsymbol{\varphi}_0$ the identity matrix and $\boldsymbol{\omega}_s = \mathbf{0}$ for s<0. This expression implies that if $\boldsymbol{\varphi_j}$, is lower triangular for all *j*, then the moving average matrices $\boldsymbol{\omega}_s$ for the fundamental representation will be lower triangular for all s. Thus, if *y* fails to Granger-cause *x*, then the MA (∞) representation can be written

$$\begin{bmatrix} \boldsymbol{x_i} \\ \boldsymbol{y_i} \end{bmatrix} = \begin{bmatrix} \boldsymbol{\mu_1} \\ \boldsymbol{\mu_2} \end{bmatrix} + \begin{bmatrix} \boldsymbol{\omega_{11}(L)} & \mathbf{0} \\ \boldsymbol{\omega_{21}(L)} & \boldsymbol{\varphi_{22}(L)} \end{bmatrix} \begin{bmatrix} \boldsymbol{\varepsilon_{1t}} \\ \boldsymbol{\varepsilon_{2t}} \end{bmatrix} \qquad [23.1.3]$$

where

$$\omega_{ij}(L) = \omega_{ij}^{(0)} + \omega_{ij}^{(1)} L^1 + \omega_{ij}^{(2)} L^2 + \omega_{ij}^{(3)} L^3 + \cdots$$

with $\omega_{11}^{(0)} = \omega_{22}^{(0)} = 1$ and $\omega_{21}^{(0)} = 0$.

Another implication of Granger causality was stressed by Sims (1972). Consider a linear projection of y_t on past, present and future x's.

$$y_t = c + \sum_{j=0}^{\infty} b_j x_{t-j} + \sum_{j=1}^{\infty} d_j x_{t+j} + \eta_t, \qquad [23.1.4]$$

where b_j and d_j are defined as population projection coefficients, that is, the values for which

$E(\eta_t, x_\tau) = 0$ for all t and τ.

Then y fails to Granger-cause x if and only if $d_j = 0$ for all j=1, 2, …

The simplest probably best approach uses the autoregressive specification [23.1.1]. To implement this test, we assume a particular autoregressive lag length p and estimate

$$x_t = c_t + \alpha_1 x_{t-1} + \alpha_2 x_{t-2} + \cdots + \alpha_p x_{t-p} + \beta_1 y_{t-1}$$

$$+\beta_2 y_{t-2} + \cdots + \beta_p y_{t-p} + u_t \qquad [23.1.5]$$

By OLS. We then conduct an F test of the null hypothesis

$$H_0 = \beta_1 = \beta_2 = \ldots = \beta_p = 0 \qquad [23.1.6]$$

One way to implement this test is to calculate sum of squared residuals from [23.1.5][29],

$$RSS_t = \sum_{t=1}^{T} \hat{u}_t^2$$

and compare this with the sum of squared residuals of a univariate autoregression for x_t,

$$RSS_0 = \sum_{t=1}^{T} \hat{e}_t^2$$

where $x_t = c_0 + \gamma_1 x_{t-1} + \gamma_2 x_{t-2} + \cdots + \gamma_p x_{t-p} + e_t \qquad [23.1.7]$

[29] Note that in order for t to run from 1 to T as indicated, we actually neet T+p observations on x and yi namely, $x_{-p+1}, x_{-p+2}, \ldots, x_T \text{ and } y_{-p+1}, y_{-p+2}, \ldots, y_T$

is also estimated by OLS. If

$$S_t = \frac{(RSS_0 - RSS_1)/p}{RSS_t/(T - 2p - 1)}$$

is greater than the 5% critical value for an *F (p, T-2p-1)* distribution, then we reject the null hypothesis that y does not Granger-cause; that is, if S_1 is sufficiently large, we conclude that *y* does Granger-cause *x*.