Impact of Ramadan on Global Raw Sugar Prices

A thesis presented
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Impact of Ramadan on Global Raw Sugar Prices

Abstract

The effect of annual religious event of Ramadan on raw sugar prices is the central theme of this research. This research investigates whether incremental demand for sugar due to sugar-based diet in Ramadan influences global raw sugar prices. The impact of Ramadan on global raw sugar price was estimated using a modified seasonal ARIMA model with four dummy and fractional indicator variables separately to represent Ramadan and its intensity. The study used monthly raw sugar price data (ICE contract no. 11) for thirty-four years from January, 1981 to January, 2015 to ensure that the sample size covered beginning of Ramadan on every Gregorian month.

The results revealed that there was a significant impact of Ramadan on global monthly raw sugar prices as raw sugar prices grew by approximately 6.06% on account of Ramadan. This was later also supported by an estimated Unobserved-Components Model on raw sugar price series. Growth in monthly raw sugar prices from this model was found to be approximately 6.82% which ensures robustness of results from ARIMA model. These results also revealed price increase to be anticipatory as raw sugar prices began to rise one month prior to Ramadan and continued till the end of Ramadan. However, the rise in monthly average price during Ramadan was dependent on the intensity of Ramadan in a Gregorian calendar month.

These results will help policy makers in countries with dense Muslim population to strategize on timing bulk raw sugar procurement for consumption during Ramadan. The results are also useful to sugar refiners and traders who require better visibility on price movements while assessing the needs for availing commodity price derivative products to mitigate commodity price risk. Furthermore, this methodology can act as a framework to assess impact of events such as Ramadan, whose recurrence is not based on Gregorian calendar, on other time series variables such as commodity prices, inflation, exchange rates etc.

[**Keywords:** Raw Sugar Price, Ramadan, Seasonal ARIMA, Unobserved-Components Model]

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1. Introduction

Every year, a large segment of global Muslim population of approximately 1.6 billion (PewResearchCenter 2015) observe fasting in Ramadan, the ninth month of Islamic (Hijri) lunar calendar. As deemed mandatory by Islam, healthy adult Muslims fast by abstaining from eating, drinking, smoking, and having sexual intercourse from dawn to dusk through 29 or 30 days of Ramadan. Hence, meal schedule and frequency of fasting Muslims change drastically during Ramadan (Aadil, et al. 2005). Every day before dawn, fasting Muslims observe a pre-fast meal called "Suhoor" to support their nutritional requirement to last through the day. After sunset, they break their fast by observing "Iftar" to recover from fatigue and restore nutritional balance. Some Muslims continue food and fluid consumption throughout the night at intervals until next day's Suhoor.

Meal composition in terms of nutrient intake also changes to cope with altered meal schedule and frequency. Typically, core nutritional item in Suhoor consists of slow-digesting foods such as grains and seeds (barley, wheat, oats, millet, semolina, beans, lentils etc.) accompanied by protein (Takruri 1989). On the other hand, due to both physiological and cultural factors, Iftar consists of a wide variety of specialty meals across the globe. While Muslims across the globe traditionally break their fasts with dates, it is followed by protein-based fried meals and cereal-based dishes. However, the highlight of Iftar meals across the globe are sugar based desserts and drinks, the origin of which can be attributed to the evolutionary requirement for immediate and easily available source of glucose in a glucose-depleted fasting body (Neslisah, et al. 2006). Social gatherings to observe the festive month of Ramadan are also responsible for increasing popularity of sugar-based traditional desserts. Egyptian Umm Ali, Turkish Kunafeh and Baklava, Emarati Luqaimat, Indonesian Kolak, Bangladeshi Jilapi are some examples of traditional desserts among numerous across the globe. Although there are regional and cultural variations in dietary practices, overall diet composition in Ramadan tends to be higher in sugar than typical diet outside of Ramadan which is further influenced by purchasing power (Leiper and Molla 2003) (Sakr 1975).

As per Oxford Dictionary of Chemistry, Sugar is defined as "any group of water-soluble carbohydrates of relatively low molecular weight and typically having a sweet taste" (Oxford University Press 2007). However, in everyday language, the word sugar is used to refer specifically to sucrose or table sugar. In 2013/14, approximately 50.3 million metric tons (29% of global production of 172.4 million metric tons) of sugar was traded globally, of which raw sugar accounted for roughly 70% as illustrated later in chapter 3. This made sugar the second most traded commodity across the globe.

A google search with key words of "price movements", "essential food commodities"/ "food inflation", and any country with dense Muslim population such as "Indonesia", "Pakistan", "India", "Bangladesh" etc. reveal that historically essential food (such as sugar, flour, peas, edible oil etc.) prices have usually soared suddenly before and during Ramadan. Most of these commodities, including sugar, are consumed in their processed forms. Hence, it may be possible that refiners, wholesalers, or retailers hike prices of final consumable commodities for higher profit due to increasing demand created by Ramadan. It may also be possible that the alleged price increase is passed through from increase in raw or refined commodity price in the international market, in which case the price increase in the international market should occur prior to Ramadan. As sugar fits the sample of food items whose consumption increases during Ramadan, the impact of Ramadan on sugar prices can be an exciting topic of study. Hence, the objective of this paper was to estimate the impact of Ramadan on raw sugar prices. Among the two types of sugar, raw and refined, raw sugar was selected as the subject of this study as raw sugar accounts for larger trade share than refined sugar as well as higher imports from countries with dense Muslim population as mentioned later in chapter 3.

The major challenges that needed to be addressed to assess and isolate the impact of Ramadan on raw sugar prices were: (a) Seasonality in raw sugar prices, (b) Underlying factors that influence raw sugar prices, and (c) Misalignment between Islamic lunar calendar and the traditional Gregorian solar calendar.

This research is divided into six chapters. Chapter one introduces the topic while chapter two discusses review of relevant literature on commodity price modeling, sugar price modeling, and econometric methods of measuring impact of Ramadan. Chapter three provides an overview on global sugar market. Chapter four introduces the methodology used to measure impact of Ramadan on raw sugar prices along with sources of data. The fifth chapter discusses results obtained from this research. It also evaluates coherence among results from different methods of estimation. The final chapter draws relevant conclusions.

2. Literature Review

2.1 Introduction to Commodity Price Modeling

Commodity price modeling and forecasting have raised the curiosity of numerous researchers for decades. Commodity price records have been kept since ancient civilization of India, Mesopotamia, Greece, Egypt and Rome (Fischer 1996). In the 18th century, Granger and Elliott analyzed the price mechanism of wheat. (Granger and Elliott 1967). Subsequently, a more formal approach at analyzing commodity price dynamics began in early 20th century. Throughout the history of financial econometrics, a large number of models have been developed to simulate commodity prices to be used for the purpose of risk minimization and forecasting (Gasana 2013).

Due to the possible randomness in commodity market prices and quantities, commodity market forecasting is inherently risky and uncertain. The type of price fluctuations changes as the causes are observed in short, medium, or long term. Underlying economic analysis of long term price movements has an extensive history (W. C. Labys 2005). Practically, long term price trend prediction has been important for evaluation of investments in commodity industries (Duncan 1984). Factors that influence commodity prices in medium term can be of political and cataclysmic nature, however, these factors tend to relate to national economic conditions or market forces more. Demand-Supply dynamics and underlying market equilibrium reveal these factors (W. C. Labys 2005). Furthermore, agricultural commodity prices are affected by variations in weather conditions as proven by research conducted by Adams and Behrman (1978), Ghosh, Gilbert and Hughes (1987), Marquez (1984) and Rausser and Hochman (1979). Finally, in the short term, financial factors related to speculation and hedging on commodity derivatives are responsible for market shocks. This topic has recently experienced high interest due to growing focus on futures markets and discovery of chaos and nonlinear dependence. Studies conducted by Working (1958), Samuelson (1965) showed that short term commodity price movements follow random walk behavior or a variant known as a martingale. However, subsequently, other works by Houthakker (1961), Labys and Granger (1970) have confirmed deviations from random walk in the form of occasional autocorrelations or linear dependence.

From the aforementioned studies, one common finding is that price fluctuations have made market and price forecasting an extremely difficult task. Structural models emphasize market interactions as a source of price shocks. Nonstructural models using time series methods have also been employed in commodity price analysis.

As per Labys (2005), structural models, based on econometric and economic theory, are the most comprehensive analytical tools for commodity markets. These models are also supported by other modeling theories such as programming, optimization, computable general equilibrium, input-output etc. He proposed that competitive market model is the most basic type of commodity model from which econometric and modeling methodologies have developed. Such a model initially neglects market imperfections and assumes that commodity demand and supply interact to produce an equilibrium price reflecting competitive market conditions. A number of combined regression equations, each explaining a single market or sector variable separately, can form this type of models. He also insisted that market models or equivalent industry models are applicable to all agricultural, mineral or energy production and use categories. Based on studies conducted by Labys (1999) or Lord (1991), the basic structure of a competitive market model typically explains market equilibrium as an adjustment process between demand, supply, inventory and price variables. Simply, it consists of the following equations:

$$D_t = d(D_{t-1}, P_t, PC_t, A_t, T_t) \ldots\ldots\ldots (2.1)$$

$$Q_t = q(Q_{t-1}, P_{t(.)}, N_t, Z_t) \ldots\ldots\ldots (2.2)$$

$$P_t = p(P_{t-1}, dI_t) \ldots\ldots\ldots (2.3)$$

$$I_t = I_{t-1} + Q_t - D_t \ldots\ldots\ldots (2.4)$$

Where:

D = Demand

Q = Supply

P = Prices

PC = Prices of substitutes

P (.) = Prices with lag distribution

I = Inventories

A = Income or activity level

T = Technological factors

N = Resource characteristics

Z = Policy variables influencing supply

In the above case, commodity demand is explained as being dependent on prices, economic activity, prices of substitutes and possible technological influences. Labys (1999) used a lagged price variable as supply is normally explained using some general class of lag distributed function. In order to utilize this model, further specification, estimation and simulation is required. Analysis of commodity prices independent of other market variables, which essentially relates to a single economic sector, works as reduced form or nonstructural equation methods. Any structural commodity model as above, can be reduced to a single equation with endogenous variables appearing on one side and exogenous variables on the other.

2.2 Sugar Price: Non-Structural and Structural Modeling

Sugar, being the second most traded commodity after oil (Abbott 2003), has been a case in point for meddling researchers in commodity markets. Most of these studies focused on non-structural time series modeling with and without seasonality. One particular study used GARCH-M model to establish significant impact of conditional variance on change in future prices using a simple price model while measuring impact of commodity futures on marginal process price of sugar (Nijman and Beetsma 1991). The estimates implied overvalued price of sugar in futures market. Another study used cointegrated vector autoregression /error correction (VAR/VEC) model to establish existence of cointegration in the vector of sugar based time series from sugar market and value-added downstream markets such as confectionary and soft drinks which use sugar as one of their raw materials. The study also established seasonality in raw sugar market. Furthermore, Gudoshnikov, Jolly, and Spen (2004) estimated the presence of additive seasonality using X-11 seasonal adjustment method. As proposed by Diebold (2007), seasonality based on additive model (Unobserved-Components Model) like that in equation 2.5 can also be estimated using dummy variables for each month as used in a study conducted by to model seasonality in soybeans futures prices (Hernandez 2005).

$$y_t = Sn_t + Tr_t + Cl_t + \varepsilon_t \ldots\ldots\ldots (2.5)$$

On the contrary, a number of studies focused on structural models to estimate and forecast sugar price based on observable exogenous variables. One such study conducted by Pereira, Ribeiro and Securato (2012) developed a pricing model for

Brazilian sugar market. The major factors affecting sugar prices identified in that model were: (a) Change in demand and price of ethanol, another principal sub-product of sugar cane, with prices of both Ethanol and sugar moving in same direction; (b) The price of oil which can influence the price of sugar either directly, being a factor of production, or indirectly, influencing the price of ethanol; (c) Spread between spot and future contract prices of sugar to account for arbitrage opportunities; (d) Convenience yield, as proposed in the theory of storage, which may increase due to supply disruptions of adverse climatic impacts of harvest; (e) Seasonality, which was addressed using a sine function; and (f) Volatility in financial markets which may result in increased fund flow to soft commodities. The model estimated a system of three equations using standard iterative techniques of Kalman Filter. Another study also suggested that oil prices are long run drivers of Brazilian sugar price (Balcombe and Rapsomanikis 2008).

Another study investigated price linkage between sugar, ethanol and oil using cointegration after accounting for structural breaks. The study estimated that oil prices change sugar prices indirectly through affecting ethanol prices (Chen and Saghaian 2015).

Some studies also indicate that climate driven change should be reflected in world price dynamics as considerable share of world sugar production is designed for export. However, Gudoshnikov et al. (2004) argued that regional impacts of cataclysmic weather are smoothened over due to wide geographical spread of sugar production. They also suggested that key factors resulting in high level of instability in the market are marginality in world market, long production cycle characteristics, immobility of resources once invested in sugar crop processing capacity, and government intervention.

2.3 Adjustments for Difference between Islamic and Gregorian Calendars

While the Gregorian solar calendar year lasts for 365 days (366 days in leap years), a typical Islamic lunar calendar lasts for 354 or 355 days. Hence, each Gregorian year the latter recedes back by 11 or 12 days. This observation should draw our attention to an important data property called asynchronization. Isolating any impact of Islamic calendar event (like Ramadan) would have been simpler had the data were also compiled and adjusted according to Islamic calendar. However, commodity prices and macroeconomic statistics are all available according to Gregorian calendar which poses the main challenge in modeling impact of any event based on Islamic calendar. Further complication arises as most Islamic societies follow observation based calendar announced at the beginning of the month by religious authorities after sighting of new moon. As a results, any attempt to convert Islamic dates to Gregorian dates has a margin of error up to two days. Furthermore, established models used to account for seasonality are based on Gregorian calendar. Hence, standard X-11 or X-12 ARIMA models may distort any impact arising from an event based on Islamic or any other lunar calendar.

Lin and Liu (2002) used holiday regressors to analyze impact of lunisolar Chinese calendar. However, the major difference between Chinese lunisolar calendar and Islamic lunar calendar lies in the fact that the Chinese calendar gets adjusted with solar Gregorian calendar every four years through Chinese leap years (a year with 13 months). Hence, the date differences revolve around a band of 15 to 50 days. On the contrary, no such adjustment is made in the Islamic lunar calendar, hence, date differences do not revolve around a band and perform one complete rotation in every 34 to 36 years. As a result, holiday regressors cannot be used to isolate impact of any Islamic calendar event on a time series variable.

In one study (Yucel 2005) conducted to measure the impact of Ramadan on food prices in Turkey, three different approaches were used. The first approach was to use a dummy variable for the Gregorian calendar month(s) which overlap with Ramadan. The second approach was to use a Ramadan intensity variable which was defined for each Gregorian month by taking the ratio of Ramadan days to number of days in that Gregorian month. To illustrate, Ramadan was spread over February and March in 1994. Out of 29 days of Ramadan, 17 were in February and rest 12 were in March. In the first approach, a dummy variable of 1 was assigned to February and March in 1994 and remaining months were assigned the dummy variable of 0. In the second approach, Ramadan Intensity variable of 0.607 (17/28) and 0.387 (12/31) was assigned to February and March of 1994 respectively. The third approach was to convert the entire data set from Gregorian calendar based to Islamic calendar based. The results indicated that food prices in Turkey tended to rise in Ramadan. The study concluded that the best results were found from the final approach, however, it may not be feasible as many of the historical monthly data are available for Gregorian calendar months only. The results were also supported by the second approach of using fractional dummy variables. However, this method can be criticized due to its lack of full representation and timing of data recording.

Another study used fractional indicator variables to measure Islamic calendar effect on currency circulation in Pakistan with an extended standard ARIMA model (Riazuddin and Khan 2005). To find the effect of Ramadan in any Gregorian calendar month, unit value of dummy was distributed in months with partial presence of Ramadan to the extent of length of Ramadan falling in respective Gregorian months. The study concluded presence of systematic variations of circulated currency in four selected Islamic months. Riazuddin and Khan also asserted that measuring impact of Islamic calendar effects would have been simpler had existing data were compiled according to Islamic calendar. A study conducted by Akmal and Abbasi (2010) to measure Ramadan effect on price movements in Pakistan also used an adjusted ARIMA based on Riazuddin, Khan, and Yucel's model. However, the study could not reveal any significant impact of Ramadan on consumer price levels in Pakistan.

Although all the above studies were conducted to measure impact of lunar calendar events on time series data only, the models still provide a basic framework for structural modeling of variables.

3. Overview of Global Sugar Market

History of table sugar dates back to 8th century BC, where one of the earliest historical mentions of sugar cane is included along with the fact that the knowledge of sugar cane was derived from India (Rolph 1917). Since then, sugar production and trade has journeyed through the course of history to establish sugar as one of the most prevalent commodities. Global sugar production in 2013/14 was approximately 172.4 million metric tons. Brazil, India, European Union, China, Thailand and United States, the top 6 sugar producing countries, contributed to 64% of global production as shown below Figure 3.1 and Table 3.1.

Table 3.1 Geographic Distribution of Cane and Beet Sugar Production (2013-14)[1]

Country	Raw Sugar (Total)	Raw Sugar (Cane)	Raw Sugar (Beet)
Brazil	35,800	35,800	-
India	27,250	27,250	-
EU-27	16,300	275	16,025
China	13,300	12,450	850
Thailand	10,200	10,200	-
US	7,677	3,259	4,418
Mexico	6,508	6,508	-
Pakistan	4,700	4,660	40
Australia	4,600	4,600	-
Russia	4,200	-	4,200
Guatemala	2,850	2,850	-
Indonesia	2,500	2,500	-
Philippines	2,500	2,500	-
Turkey	2,400	-	2,400
Colombia	2,300	2,300	-
Others	29,278	22,984	6,294
Total	172,363	138,136	34,227

[1] Source: United States Department of Agriculture (USDA) Fact Sheets

Although sugar is found in most plant tissues, efficient extraction for commercial production is possible mostly from sugarcane and sugar beet although there are other minor sources such as honey, palm, sorghum and sugar maple (SKIL 2015). Approximately 80% of global sugar production in 2013/14 was cane based while rest was produced from sugar beet as shown in Table 3.1 and Figure 3.2.

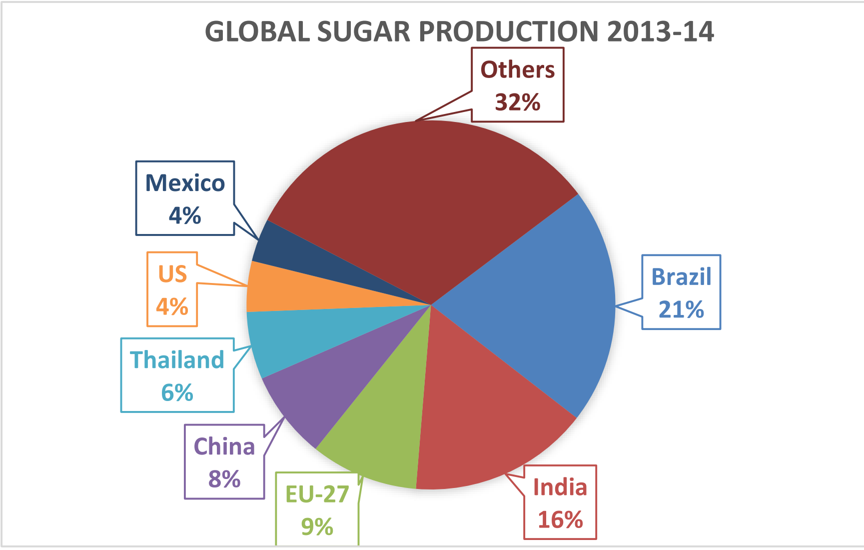


Figure 3.1 Geographic Distribution of Sugar Production (2013-14)[2]

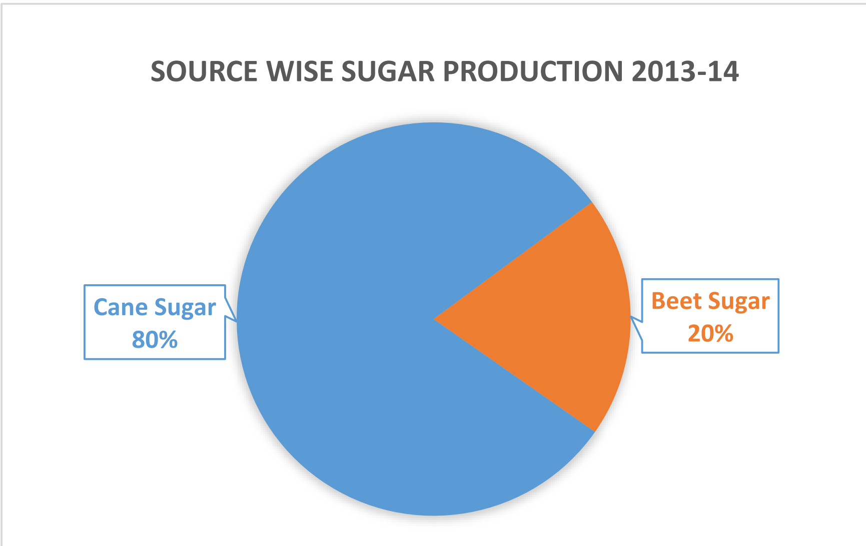


Figure 3.2 Source-wise Distribution of Sugar Production (2013-14)[3]

[2] Source: United States Department of Agriculture (USDA) Fact Sheets
[3] Source: United States Department of Agriculture (USDA) Fact Sheets

From these sources, raw sugar is separated in sugar mills through clarification, concentration, and crystallization. Crystallized raw sugars are then refined in sugar refineries to remove impurities and produce refined white table sugar. In 2013/14, approximately 50.3 million metric tons (29% of global production) of centrifugal sugar was traded, of which raw sugar accounted for roughly 70% as illustrated in Figure 3.3.

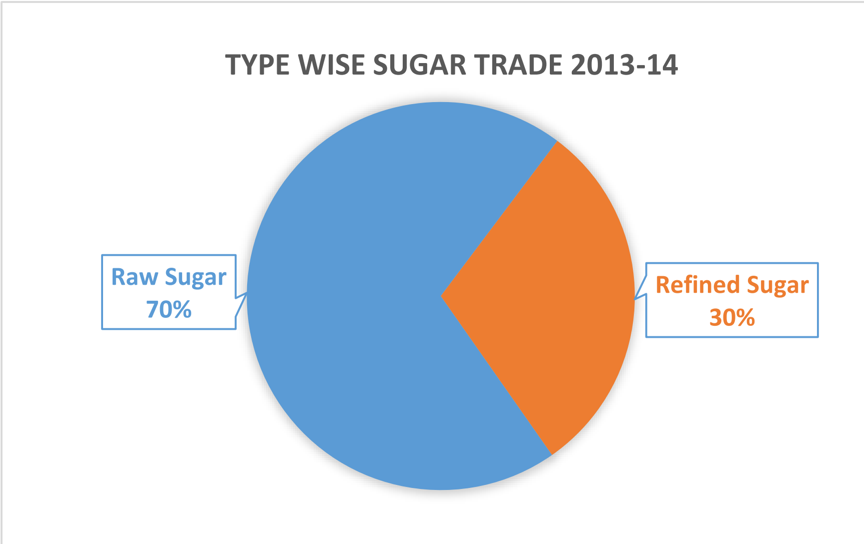


Figure 3.3 Type-wise Distribution of Global Sugar Trade (2013-14)[4]

Brazil, the leading exporter, and Thailand supported 60% of global export of both raw and refined sugar. On the other hand, raw and refined sugar imports were spread across a large number of countries such as, Indonesia, China, United States, European Union, United Arab Emirates, and even Bangladesh.

One interesting fact can be observed from geographical distribution of global sugar trade dynamics as per data provided in Tables 3.2 through 3.5. While none of the major sugar producing and exporting nations except for India has dense Muslim population, a large number of sugar importing nations such as Indonesia, Bangladesh, UAE, Malaysia and Iran are countries with dense Muslim population. Even India, having a large Muslim population of around 180 million, has a neutral trade balance for raw sugar. Hence, supply of global sugar trade dynamics is skewed towards countries with sparse Muslim population while demand is skewed towards countries with dense Muslim population.

[4] Source: United States Department of Agriculture (USDA) Fact Sheets

Table 3.2 Major Raw Sugar Importing Nations and Their Muslim Population[5]

Country	Raw Sugar Imports (1000 MT)	Muslim Population		
		Total (million)	% of Country Population	% of Global Muslim Population
Indonesia	3,700	204.85	88.1%	12.7%
China	3,500	23.31	1.8%	1.4%
United States	2,786	2.60	0.8%	0.2%
EU-27	2,700	19.00	3.8%	1.2%
Bangladesh	1,825	148.61	90.4%	9.2%
South Korea	1,775	0.04	0.2%	less than 0.1%
Malaysia	1,775	17.14	61.4%	1.1%
Algeria	1,650	34.78	98.2%	2.1%
Iran	1,600	74.82	99.7%	4.6%
Japan	1,400	0.19	0.1%	less than 0.1%
Nigeria	1,345	75.73	47.9%	4.7%
Egypt	1,190	80.02	94.7%	4.9%
UAE	1,100	3.58	76.0%	0.2%
Russia	1,100	16.38	11.7%	1.0%
India	1,000	177.29	14.6%	10.9%
Saudi Arabia	850	25.49	97.1%	1.6%
Morocco	850	32.38	99.9%	2.0%
Venezuela	750	0.10	0.3%	less than 0.1%
Others	4,321	-	-	-

Table 3.3 Major Raw Sugar Exporting Nations and Their Muslim Population[6]

Country	Raw Sugar Imports (1000 MT)	Muslim Population		
		Total (million)	% of Country Population	% of Global Muslim Population
Brazil	18,950	0.04	0.1%	less than 0.1%
Thailand	4,500	3.95	5.8%	0.2%
Australia	3,300	0.40	1.9%	less than 0.1%
Guatemala	1,050	0.00	less than 0.1%	less than 0.1%
India	1,000	177.29	14.6%	10.9%
Cuba	850	0.01	0.1%	less than 0.1%
UAE	600	3.58	76.0%	0.2%
South Africa	450	0.11	1.5%	less than 0.1%
El Salvador	390	0.00	less than 0.1%	less than 0.1%
Egypt	350	80.02	94.7%	4.9%
Others	3,124	-	-	-

[5] Source: United States Department of Agriculture Fact Sheets and Pew Research Center
[6] Source: United States Department of Agriculture Fact Sheets and Pew Research Center

Table 3.4 Major Refined Sugar Importing Nations and Their Muslim Population[7]

Country	Raw Sugar Imports (1000 MT)	Muslim Population		
		Total (million)	% of Country Population	% of Global Muslim Population
UAE	1,250	3.58	76.0%	0.2%
EU-27	800	19.00	3.8%	1.2%
Sri Lanka	575	1.73	8.5%	0.1%
Cambodia	550	0.24	1.6%	less than 0.1%
Yemen	550	24.02	99.0%	1.5%
Saudi Arabia	500	25.49	97.1%	1.6%
Sudan	500	30.86	71.4%	1.9%
Russia	400	16.38	11.7%	1.0%
Iraq	400	31.11	98.9%	1.9%
Singapore	399	0.72	14.9%	less than 0.1%
Others	9,182	-	-	-

Table 3.5 Major Refined Sugar Exporting Nations and Their Muslim Population[8]

Country	Raw Sugar Imports (1000 MT)	Muslim Population		
		Total (million)	% of Country Population	% of Global Muslim Population
Brazil	5,050	0.04	0.1%	less than 0.1%
Thailand	4,000	3.95	5.8%	0.2%
Mexico	1,779	0.11	0.1%	less than 0.1%
EU-27	1,495	19.00	3.8%	1.2%
Guatemala	900	0.00	less than 0.1%	less than 0.1%
Colombia	660	0.01	less than 0.1%	less than 0.1%
Algeria	500	34.78	98.2%	2.1%
India	500	177.29	14.6%	10.9%
Belarus	478	0.02	0.2%	less than 0.1%
Mauritius	350	0.22	16.6%	less than 0.1%
Others	3,383	-	-	-

A graphical representation of this observation is provided in Figure 3.4 using a world map and marking net exporters with different shades of red based on export volume and net importers with different shades of green based on import volume. Furthermore, countries with dense and scarce Muslim population are marked with blue and red markers respectively.

[7] Source: United States Department of Agriculture Fact Sheets and Pew Research Center Data Sheet
[8] Source: United States Department of Agriculture Fact Sheets and Pew Research Center Data Sheet

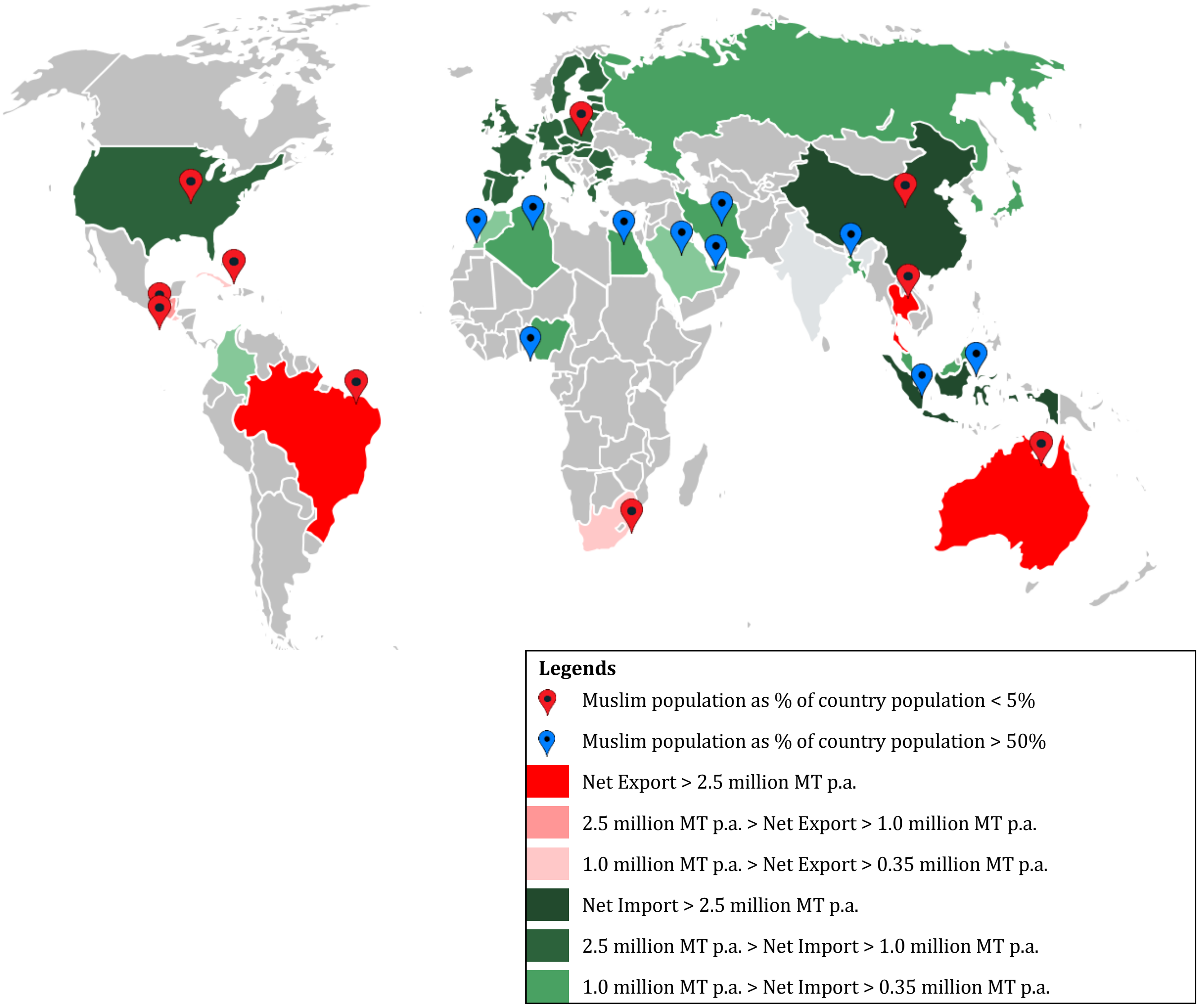


Figure 3.4 World Map of Sugar Trade Dynamics

4. Methodology

4.1 Source of Data

As a global benchmark for raw sugar trading prices, monthly price of ICE (Intercontinental Exchange Inc.) sugar contract no. 11 was obtained from World Bank's monthly GEM commodities database. Price data was obtained for the thirty-four year period from January of 1981 to January of 2015 in order to ensure that the sample size covers beginning of Ramadan on every Gregorian month as Ramadan revolves around the Gregorian calendar every thirty-five years (due to accumulation of 10-11 days difference each year). An online calendar converter[9] was used to find out historical comparative Gregorian calendar date which coincided with the beginning of Ramadan in each year over the sample period. EViews and Stata were used for statistical analysis while Microsoft Excel was used for data analysis.

4.2 Research Model

In order to measure impact of Ramadan on raw sugar prices, this study estimated raw sugar prices using two different methods. Firstly, raw sugar price series was estimated using seasonal ARIMA model with Ramadan variables. Subsequently, an Unobserved-Components Model (UCM) was estimated to verify results obtained from the first model. However, before both models were estimated, suitable variables had to be developed to represent Ramadan in these models. Hence, this chapter starts with discussion on development of dummy and fractional variables representing Ramadan. Then, Box-Jenkins methodology for seasonal ARIMA model and its use in this research is discussed. Finally, core concepts of UCM is introduced. This chapter also discusses how UCM was used to measure Ramadan effect and verify results from seasonal ARIMA model.

4.2.1 Developing Ramadan Dummies and Fractional Indicators

As monthly price series of raw sugar is published using Gregorian calendar, suitable variables need to be developed for Gregorian months signifying impact of Ramadan. While developing these variables, two separate dimensions were considered:

(i) identifying the Gregorian month in which Ramadan began to measure whether there is any anticipatory movement in raw sugar price prior to Ramadan

(ii) measuring intensity of Ramadan in said Gregorian month (in terms of percentage of Ramadan days in that month) as it might impact timing of price movements

[9] www.islamicfinder.org

With these considerations, four different dummy and fractional variables were developed to isolate impact of Ramadan, which are as follows:

(i) Ramadan Month (RAMDUM): a dummy variable which takes a value of 1 for each Gregorian month containing any Ramadan day and 0 (zero) otherwise.

(ii) Ramadan Start (RAMST): a dummy variable which takes a value of 1 for only that Gregorian month in which Ramadan starts and 0 (zero) otherwise.

(iii) Ramadan Month Intensity (RAMINT): a fractional indicator which is calculated by dividing the number of Ramadan days in a Gregorian month by the total number of days in that Gregorian month.

(iv) Ramadan Start Intensity (RAMSTINT): a fractional indicator which is calculated by dividing the number of Ramadan days in the Gregorian month in which Ramadan starts by the total number of days in that month. Technically, this can be generated by taking RAMINT variable for the month in which Ramadan begins but by taking 0 (zero) for all other months.

To illustrate, calculation of these variables are provided in Table 4.1 for the years 2012 and 1989. In 2012, Ramadan started on 20th July and continued till 19th August. As both July and August contained Ramadan days, RAMDUM was 1 for these two months and 0 for rest. As Ramadan started in July, RAMST was 1 for July and 0 for rest. Out of total 31 days in July, the last 12 days were Ramadan days. Hence, RAMINT for July was 12/31 or 0.39. Similarly, as August contained remaining 18 Ramadan days, RAMINT for August was 18/31 or 0.58. As RAMSTINT consider RAMINT for the month in which Ramadan begins only, RAMSTINT for July was 0.39, the same as RAMINT. However, RAMSTINT for August was 0, unlike RAMINT, as Ramadan did not begin in August. Another sample value set for 1989 is also provided in Table 4.1.

Table 4.1 Sample Calculations for Different Ramadan Variables

Month		RAMDUM	RAMST	RAMINT	RAMSTINT
2012	June	0	0	0	0
	July	1	1	12/31 = **0.39**	12/31 = **0.39**
	Aug.	1	0	18/31 = **0.58**	0
	Sept.	0	0	0	0
In 2012 Ramadan started on 20th July and continued till 19th August					
Month		RAMDUM	RAMST	RAMINT	RAMSTINT
1989	March	0	0	0	0
	April	1	1	23/30 = **0.77**	23/30 = **0.77**
	May	1	0	6/31 = **0.19**	0
	June	0	0	0	0
In 1989 Ramadan started on 8th April and continued till 7th May					

Each of these variables has its own set of benefits and drawbacks. RAMDUM assumes the impact of Ramadan to be consistent over the month of Ramadan whereas the impact may be anticipatory and only evident for the month in which Ramadan begins. While RAMST overcomes this drawback, both RAMDUM and RAMST do not take into account the intensity of Ramadan into consideration. This may pose problem as putting the same weight on two Gregorian months in which Ramadan starts at the beginning and at the end respectively cannot reflect price movement at a particular time before Ramadan as the study uses monthly average prices. Hence, fractional indicators, such as RAMINT and RAMSTINT, can better capture any price movements that may happen due to Ramadan as these represent intensity of Ramadan. However, interpretation of results become difficult for fractional indicators as opposed to dummy variables.

4.2.2 Modeling Ramadan Effect using Seasonal ARIMA Model

In econometric analysis, before a time series variable is estimated using techniques such as ARMA, ARIMA or SARIMA model, it must fulfil the condition of stationarity.

The Concept of Stationarity:

Stationarity is one of the most common assumptions of many time-series techniques. In reality, many time series variables are non-stationary. According to Green (2003) estimation with such variables may result in "spurious regression", the erroneous estimation with significance due to presence of unit root. Hence, each time series variable must be tested for stationarity prior to estimation. Stationarity is defined as a stochastic process whose joint probability distribution does not change when shifted in time or space (Priestley 1988). Hence, mean (Equation 4.1), variance (Equation 4.2) and auto-covariance (Equation 4.3) of stationary time series do not change over time.

$$E(x_t) = \mu; \ for\ all\ t \ldots\ldots\ldots (4.1)$$

$$E(x_t^2) = \sigma^2; \ for\ all\ t \ldots\ldots\ldots (4.2)$$

$$Cov(x_t x_k) = Cov(x_{t+s} x_{k+s}); \ for\ all\ t, k, and\ s \ldots\ldots\ldots (4.3)$$

Most time series variables used in business and economics are non-stationary in their original form. Sometimes, even after seasonal adjustment, these series may still exhibit trends, cyclicality, and other non-stationary behavior. Sometimes, a series can be made stationary by de-trending, by taking logarithm, or by differencing. Such series are called trend-stationary, log-stationary and difference-stationary respectively (Green 2003).

There are a number of methods for testing stationarity in a time series variable, such as, Dickey Fuller Test, Augmented Dickey Fuller Test, Phillips-Perron Test etc. In this research, stationarity of raw sugar price series was tested using DF-GLS test, a modification of Augmented Dickey Fuller Test using Generalized Least Square rationale as proposed by Elliott, Rothenberg, and Stock (1996). If any unit root/non-stationarity was found in the series, the series was transformed using methods mentioned above until the transformed series became stationary for estimation using ARIMA model.

ARIMA Model:

As introduced first by Yule (1926), an autoregressive (AR) process of order ‘p’ can be modelled as:

$$\text{AR (p)}: y_t = c + \varphi_1 y_{t-1} + \varphi_2 y_{t-2} + \cdots + \varphi_p y_{t-p} + e_t \ \ldots\ldots\ldots (4.4)$$

Here e_t is white noise error with zero mean and constant variance. In AR process, the value of the time series variable depends on its past values.

On the other hand, a moving average (MA) process y_t of order ‘q’ can be written as:

$$\text{MA (q)}: y_t = c + e_t + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \cdots + \theta_q e_{t-q} \ldots\ldots\ldots (4.5)$$

In MA process, the value of the time series variable depends on its past random error terms (Slutsky 1937).

Subsequently, Wold (1938) combined these two processes to show that it is possible to model stationary time series variables using ARMA (Autoregressive Moving Average) processes if the order of AR and MA processes are properly specified. A simple ARMA (p,q) model can be written as:

$$\text{ARMA (p,q)}: y_t = c + \varphi_1 y_{t-1} + \cdots + \varphi_p y_{t-p} + \theta_1 e_{t-1} + \cdots + \theta_q e_{t-q} + e_t \quad \ldots\ldots\ldots (4.6)$$

In case of non-stationary series with unit root, stationarity can sometimes be achieved by taking first, second or higher order differences of the original series. Such models are known as ARIMA (Autoregressive Integrated Moving Average) processes where the number of differences required to make the series stationary is known as the order of integration and is usually denoted by 'd'. A simple ARIMA (p,d,q) model can be written as:

$$\text{ARIMA(p,d,q)}: \Delta_d y_t = c + \varphi_1 \Delta_d y_{t-1} + \cdots + \varphi_p \Delta_d y_{t-p} + \theta_1 e_{t-1} + \cdots + \theta_q e_{t-q} + e_t \quad (4.7)$$

This model can also be modified to include seasonal components for both AR and MA processes using seasonal differencing. For agro-commodities like sugar, seasonality in price is very common due to crop seasonality. Hence, price seasonality for agricultural commodities is usually found at the twelfth difference for monthly price series. Using backward shift operators, a multiplicative seasonal ARIMA (p,d,q)x(P,D,Q)$_s$ model can be written as:

$$(1-B)^d(1-B^s)^D y_t = \mu + \frac{\theta(B)\theta_s(B^s)}{\varphi(B)\varphi_s(B^s)}\alpha_t \ldots\ldots\ldots (4.8)$$

Where,

μ is the mean term

B is the backshift operator, i.e. $BX_t = X_{t-1}$

$\varphi(B) = 1 - \varphi_1 B - \ldots \ldots - \varphi_p B^p$ (The autoregressive operator)

$\theta(B) = 1 - \theta_1 B - \ldots \ldots - \theta_p B^q$ (The moving-average operator)

α_t is the independent disturbance term

P is the order of seasonal autoregressive process

D is the order of seasonal differencing

Q is the order of seasonal moving-average process

s is the length of seasonal cycle

$\varphi_s(B^s) = 1 - \varphi_{s,1}B^1 - \ldots \ldots - \varphi_{s,p}B^{sP}$ (The seasonal autoregressive operator)

$\theta_s(B^s) = 1 - \theta_{s,1}B^1 - \ldots \ldots - \theta_{s,p}B^{sP}$ (The seasonal moving-average operator)

To illustrate, the mathematical form of seasonal ARIMA (0,1,0)(1,1,2)$_{12}$ is:

$$(1 - B^{12})y_t = \mu + \frac{(1-\theta_1 B)(1-\theta_{s,1}B^{12} - \theta_{s,2}B^{24})}{(1-\varphi_1 B)(1-\varphi_{s,1}B^{12})}\alpha_t \ldots\ldots\ldots (4.9)$$

Box-Jenkins (1976) subsequently developed and popularized a methodology to estimate ARIMA models using the following steps:

(i) Stationarity Checking and Differencing: As explained in the previous section, the time series variable must first be tested for stationarity.

(ii) Model Identification: The order of MA and AR is then identified using Autocorrelation (AC) and Partial Autocorrelation (PAC) coefficients of the transformed stationary time series. By identifying the number of statistically significant spikes in AC and PAC functions, the order of MA and AR can be identified respectively. Seasonality in underlying series can also be identified by observing sudden significant spikes of AC and PAC functions at regular lagged intervals (such as twelfth for monthly data). Under this methodology, more than one model can be identified. Final selection is made at later steps.

(iii) Parameter Estimation: The parameters of the identified model are then estimated using maximum likelihood estimation.

(iv) Diagnostic Checking and Model Selection Criteria: The best model from a number of estimates is selected using t-tests, residual analysis, and model selection criteria such as AIC or SBC.

In this research, after obtaining stationarity in original or transformed raw sugar price series, ARIMA or Seasonal ARIMA model could be estimated using above methodology. However, due to evolution of superior statistical software, an add-in was used in EViews to identify the model. The add-in used a number of criteria such as highest order of AR, MA, seasonal difference, maximum lag, and order of integration to find out a set of model estimates. From that set, the model with lowest Akaike Information Criteria (AIC), a relative quality of statistical models, was selected. AIC is calculated as:

$$AIC = -\frac{2l}{T} + \frac{2k}{T} \dots\dots\dots (4.10)$$

Where,

t = Log-likelihood

T = Number of observations

k = Number of parameters

After ARIMA or Seasonal ARIMA model was specified and estimated using aforementioned selection criteria, all four Ramadan variables were introduced separately as independent variables in the specified model and the model was estimated again for statistical significance. If the model was found to be statistically significant after inclusion of any Ramadan variable, lead values of that Ramadan variable were included in the model as independent variables to measure and assess anticipatory impact of Ramadan on raw sugar prices. To illustrate, the mathematical form of an ARIMA (p,d,q) model with RAMST up to 2 lead periods is expressed as follows:

$$\begin{aligned} \Delta_d y_t \ &= c + \varphi_1 \Delta_d y_{t-1} + \cdots + \varphi_p \Delta_d y_{t-p} + \theta_1 e_{t-1} + \cdots + \theta_q e_{t-q} + \beta_1 RAMST_t \\ &\quad + \beta_2 RAMST_{t+1} + \beta_3 RAMST_{t+2} + e_t \quad \dots\dots\dots (4.11) \end{aligned}$$

In this equation, β_1 represents impact of Ramadan (more specifically, RAMST dummy) on d^{th} difference series of sugar price on the month in which Ramadan starts. Similarly, β_2 and β_3 represent impact of Ramadan on the same series of sugar prices one month and two months prior to beginning of Ramadan respectively. Hence, with this model, this study could extract anticipatory impact of Ramadan on global raw sugar prices.

4.2.3 Modeling Ramadan Effect using Unobserved-Components Model

In order to ensure robustness of the results, from ARIMA or seasonal ARIMA time series modeling of raw sugar prices with independent Ramadan variables, this research tested the same data series using Unobserved-Components model (UCM) to measure impact of Ramadan on raw sugar prices.

UCM is used to decompose a time series into trend, seasonal, cyclical, and idiosyncratic components while allowing for exogenous variables. Mathematically, UCM can be expressed as:

$$y_t \;= \tau_t + \gamma_t + \psi_t + \beta X_t + \epsilon_t \;\; \dots \dots \dots (4.12)$$

Where,

y_t = *Dependent variable*

τ_t = *Trend component*

γ_t = *Seasonal component*

ψ_t = *Cyclical component*

β= *Vector of fixed parameters*

X_t= *Vector of exogenous variables*

ϵ_t = *Idiosyncratic component*

By placing restrictions on τ_t and ϵ_t, Harvey (1989) derived a series of models for trend and idiosyncratic components. To these models, Harvey added models for seasonal and cyclical components, and he also allowed for the presence of exogenous variables.

In UCM, the trend component can be mathematically decomposed in the following manner:

$$\tau_t = \mu_t \dots \dots \dots (4.13)$$

$$\mu_t = \mu_{t-1} + \alpha_{t-1} + \eta_t \dots \dots \dots (4.14)$$

$$\alpha_t = \alpha_{t-1} + \xi_t \dots \dots \dots (4.15)$$

Where,

μ_t = *Local level*

α_t = *Local slope*

η_t = *i.i.d. normal error with mean 0 and variance* σ_η^2

ξ_t = *i.i.d. normal error with mean 0 and variance* σ_ξ^2

This research first used UCM to estimate stationary cyclical component using the stochastic-cycle model developed by Harvey. As per Stata Time-Series Reference Manual (2013), the stochastic-cycle model uses three parameters, viz. (i) λ, the frequency at which the random components are centered, (ii) ρ, the damping factor that parameterizes the dispersion of the random components around central frequency, and (iii) the variance of the stochastic-cycle process that acts as a scale factor. There can be more than one cyclical component in a time series of different (high and low) frequencies. The cyclical component can be mathematically expressed as:

$$\psi_t = \psi_{t-1}\rho\cos\lambda + \tilde{\psi}_{t-1}\rho\sin\lambda + \kappa_t \text{ ……… } (4.16)$$

$$\tilde{\psi}_t = -\psi_{t-1}\rho\sin\lambda + \tilde{\psi}_{t-1}\rho\cos\lambda + \tilde{\kappa}_t \text{ ……… } (4.17)$$

Where,

λ = Frequency (in radians)

ρ = Damping effect, a unit-less scaling variable between 0 and 1

κ_t = i.i.d. normal error with mean 0 and variance σ_κ^2

$\tilde{\kappa}_t$ = i.i.d. normal error with mean 0 and variance $\sigma_{\tilde{\kappa}}^2$

To further elaborate on these parameters, the smaller the central frequency (λ) of the cyclical component, the more centered the cyclical component is on low-frequency components and vice versa. Furthermore, the lower the damping factor (ρ), the further the cyclical component is from the estimated central frequency and vice versa. For further analysis, estimated central frequency was converted to an estimated central period ($\frac{2\pi}{\lambda}$) representing average periodicity of repetition of estimated cycle.

Once the cyclical component was identified, this study tried to identify presence of seasonal component in the model. A seasonal component shows cyclical behavior at defined seasonal periodicities, for example, monthly, quarterly, or hourly seasonality. As seasonal components are estimated in time domain; the period of the season is specified as the number of time periods required for the season to complete.

There are two different types of seasonal effects, deterministic and stochastic. Deterministic seasonal effects with '*s*' parameters can be mathematically expressed as:

$$\gamma_t + \gamma_{t-1} + \cdots + \gamma_{t-(s-1)} = 0 \text{ ……… } (4.18)$$

On the contrary, the more flexible stochastic seasonal model allows seasonal effects to sum to ς_t, where $\varsigma_t \sim \text{i.i.d.}\, N(0, \sigma_\varsigma^2)$. This can mathematically be expressed as:

$$\gamma_t + \gamma_{t-1} + \cdots + \gamma_{t-(s-1)} = \varsigma_t \ldots \ldots \ldots (4.19)$$

In this research, stochastic-seasonal model was used to estimate seasonal effect in raw sugar prices.

Once each component of UCM was estimated, Ramadan variable(s) which was(were) found to be significant in ARIMA/Seasonal ARIMA model estimation was(were) included in UCM separately as exogenous variables and UCM was estimated again for statistical significance. If estimated UCM was found to be statistically significant after inclusion of any Ramadan variable, lead values of that Ramadan variable were included in the model as independent variables to measure and assess anticipatory impact of Ramadan on raw sugar prices. To illustrate, the mathematical form of a UCM with RAMDUM up to 2 lead period is expressed as follows:

$$y_t = \tau_t + \gamma_t + \psi_t + \beta_1 RAMDUM_t + \beta_2 RAMDUM_{t+1} + \beta_3 RAMDUM_{t+2} + \epsilon_t \ldots \ldots (4.20)$$

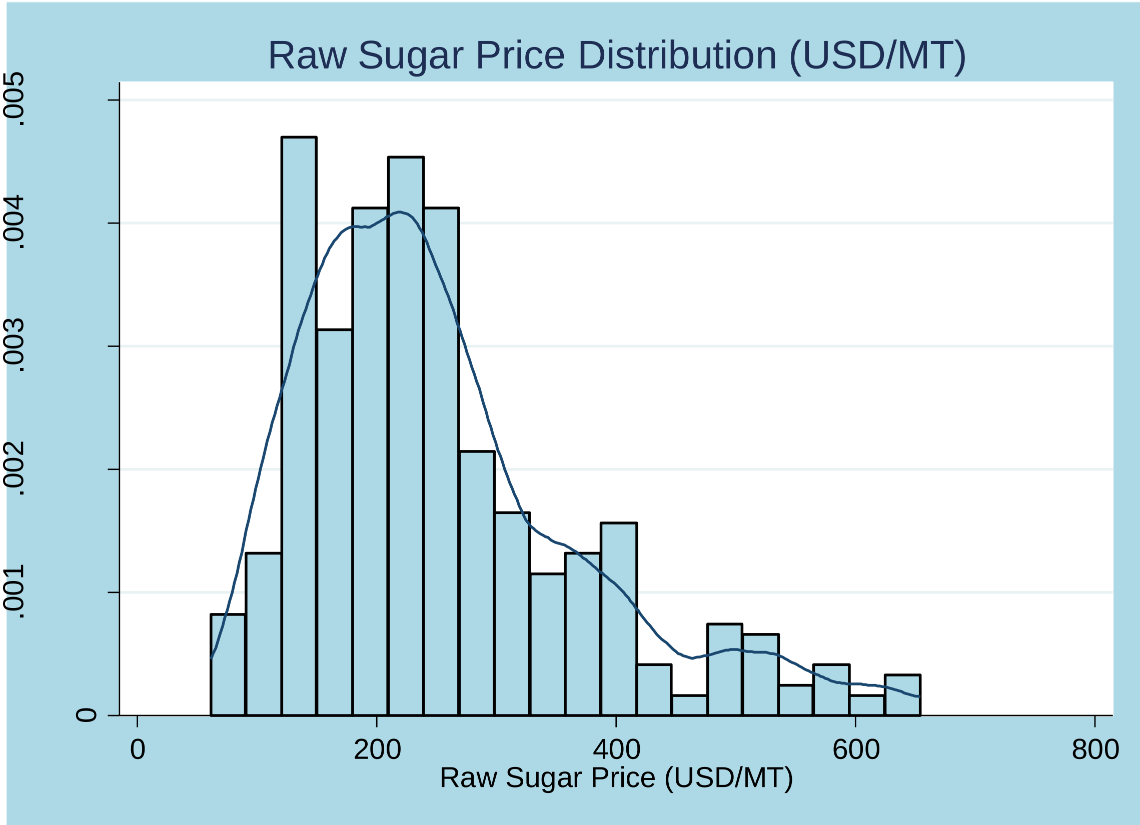
In this equation, β_1 represents impact of Ramadan (more specifically, RAMDUM dummy) on raw sugar price on the month in which Ramadan starts. Similarly, β_2 and β_3 represent impact of Ramadan on the same series of sugar prices one month and two months prior to beginning of Ramadan respectively. Hence, with this model, this research could verify results obtained from ARIMA and Seasonal ARIMA models.

5. Results

5.1 Descriptive Statistics and Testing for Stationarity

Firstly, in order to obtain better understanding of raw sugar price series, summary statistics were calculated along with frequency distribution as provided in Table 5.1.

Table 5.1 Summary Statistics and Frequency Distribution of Raw Sugar Prices[10]



Distribution		
Percentiles		**Smallest**
1%	78.3	61.3
5%	115.5	62.2
10%	128.3	70.8
25%	165.22	75.4
50%	228.14	
		Largest
75%	306.46	635.14
90%	**412.06**	644.82
95%	515.24	648.34
99%	616.88	654.28

Summary Statistics	
Observations	409
Mean	**252.3386**
Standard Deviation	**119.0616**
Variance	14175.66
Skewness	**1.147558**
Kurtosis	4.10064

[10] Source: World Bank Global Economic Monitor (GEM) Commodities World Data Bank

From sample statistics, it was found that mean value of monthly raw sugar price for the sample period was USD 252.3 per metric ton with high standard deviation of USD 119.1 per metric ton. Also, raw sugar price distribution was skewed to the right as seen from the distribution as well as skewness value of 1.15.

In order to test for stationarity of original raw sugar price series, a DF-GLS test was performed. From the DF-GLS test, it was found out that the original series was non-stationary. Even at 17th lag, the series could not be made stationary by differencing as can be observed from Table 8.1 in Appendix A. Also, upward trend was observed as can be seen from graphical representation of original raw sugar price series in Figure 5.1.

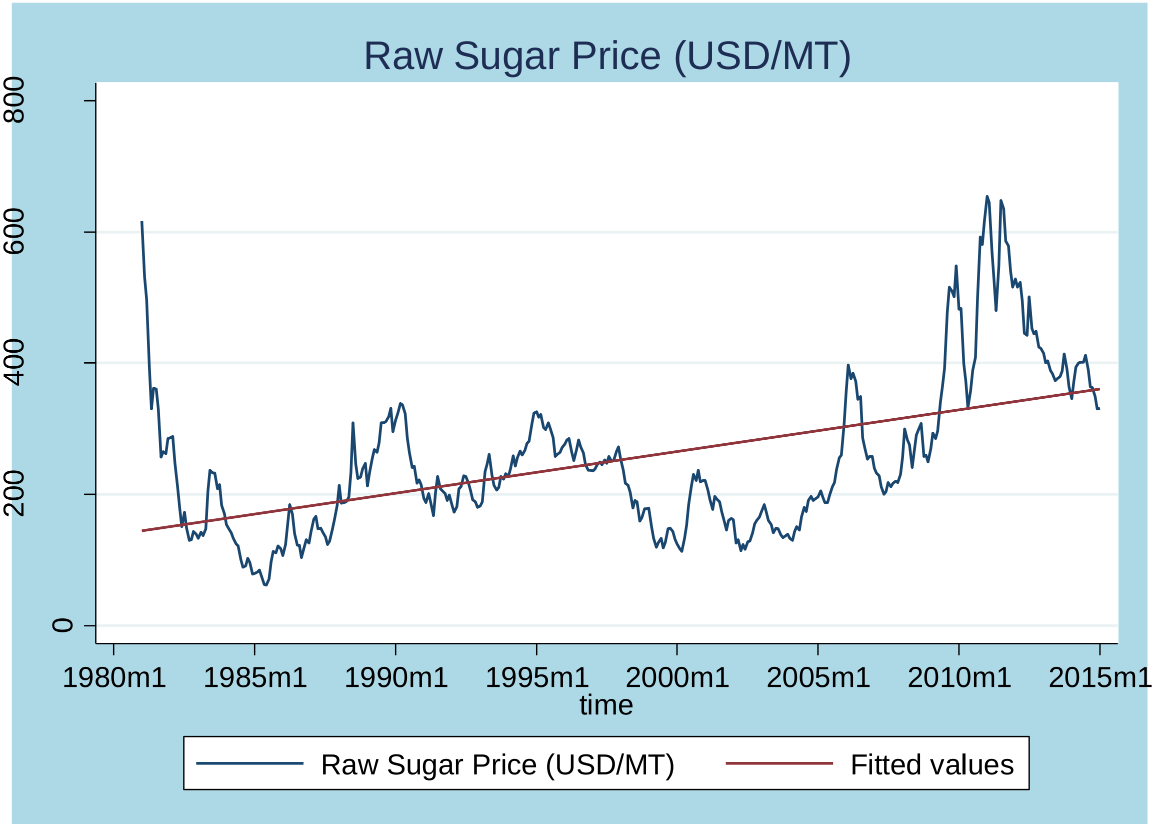


Figure 5.1 Global Raw Sugar Price Series (in USD per metric ton)[11]

In an attempt to transform original raw sugar price series into a stationary series, a new series was generated by taking natural logarithm of raw sugar prices. After performing a DF-GLS test on the transformed series, presence of unit root was found to be statistically significant at first lag (Table 8.1 in Appendix A). Hence, stationarity was obtained by taking the first difference of the natural logarithm of raw sugar price series

[11] Source: World Bank Global Economic Monitor (GEM) Commodities World Data Bank

or Δln(sugarprice) series. This first difference series was then used for ARIMA and seasonal ARIMA modeling. Also, as seen in graphical representation of Δln(sugarprice) series in Figure 5.2, characteristics of stationarity stationary could be observed.

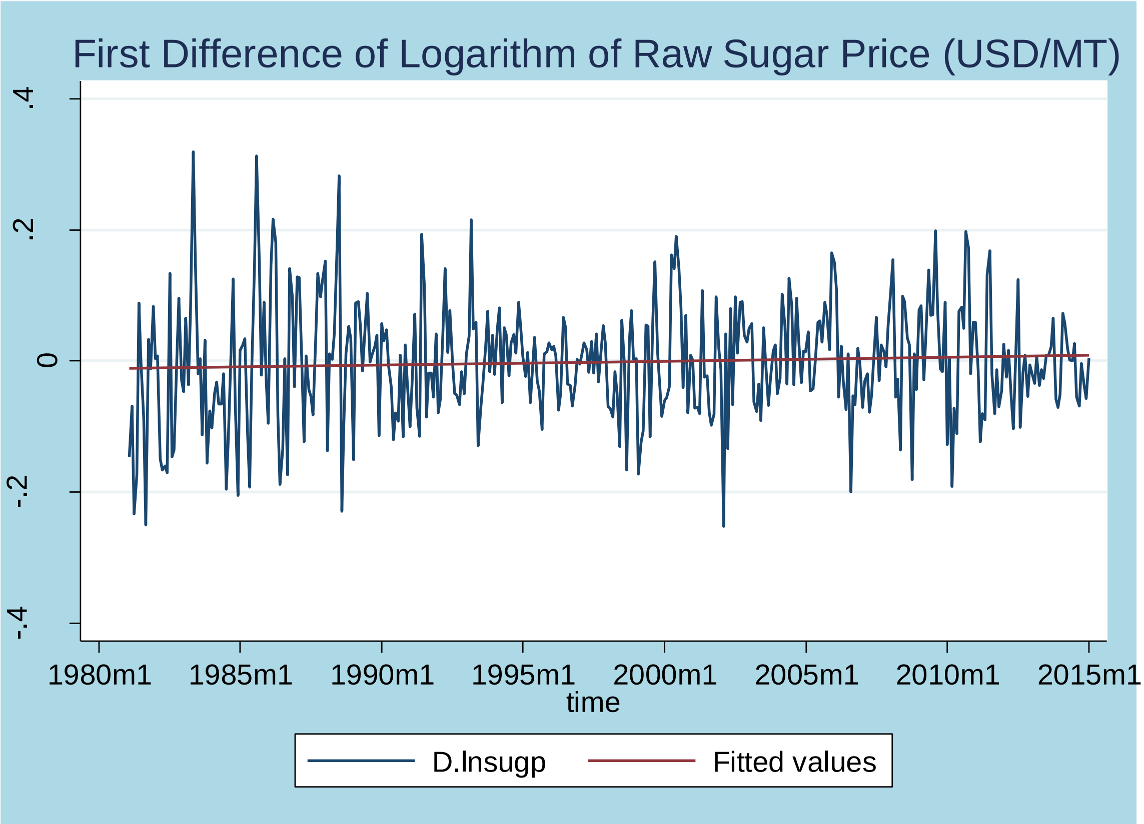


Figure 5.2 Δln(sugarprice) Series

5.2 ARIMA Model Estimation of Stationary Series

After stationarity was obtained, MA, seasonal MA (SMA), AR, and seasonal AR (SAR) orders of Δln(sugarprice) were identified using EViews add-in as stated in methodology. Based on AIC score, the best fit series was identified to have AR order of 2, SAR order of 1 (at 12 months' interval), MA order of 1, and SMA order of 1 (at 12 months' interval) or of the structure ARIMA (2,1,1)(1,0,1)$_{12}$. Coefficients of all these ARIMA components as well as the model were found to be significant as per Table 8.3 in Appendix A and are provided below in Table 5.2.

Table 5.2 Coefficients of ARIMA Model of Δln(sugarprice) Series

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	1.214597	0.055386	21.92981	0.0000
AR(2)	-0.285096	0.050747	-5.618046	0.0000
SAR(12)	0.890070	0.028733	30.97700	0.0000
MA(1)	-0.953465	0.025511	-37.37472	0.0000
SMA(12)	-0.935629	0.026984	-34.67317	0.0000

From the above table, it could be observed that both seasonal AR and MA components were statistically significant, reinforcing the idea that sugar prices follow an annual seasonal pattern. It was also found that current period value of the series was dependent on values of the past two periods and error term of the past period.

5.3 ARIMA Model Estimation of Stationary Series with Ramadan Variables

Once the structure of Δlog(sugarprice) series was determined to be ARIMA $(2,1,1)(1,0,1)_{12}$, Ramadan variables were included one by one separately as independent variables in this structure. When this ARIMA structure was modelled with RAMDUM variable, the coefficient of RAMDUM was not found to be statistically significant. Similar results were found when RAMST variable was included in the ARIMA structure as an exogenous variable.

However, the coefficient of RAMINT variable was found to be statistically significant when it was included in the original ARIMA structure. When the model was re-estimated using lead values of RAMINT, it was found that the coefficients were statistically significant (at 10% significance level) up to one lead as per Table 8.4 in Appendix A and are provided below in Table 5.3.

Table 5.3 Coefficients of ARIMA Model (with RAMINT) of Δln(sugarprice) Series

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.005179	0.002412	-2.147541	0.0324
RAMINT	**0.031323**	**0.014792**	**2.117590**	**0.0349**
RAMINT(1)	**0.029327**	**0.016671**	**1.759131**	**0.0793**
AR(1)	1.244075	0.047381	26.25691	0.0000
AR(2)	-0.277885	0.046023	-6.037958	0.0000
SAR(12)	0.928394	0.029531	31.43803	0.0000
MA(1)	-0.999109	0.008230	-121.3973	0.0000
SMA(12)	-0.966518	0.013089	-73.84306	0.0000

From the above table, it could be observed that coefficients of $RAMINT_t$ and $RAMINT_{t+1}$ were both positive and significant. Coefficient of $RAMINT_t$, which was found to be 0.0313, signified that global raw sugar price grew by roughly 3.13% due to Ramadan in a month as a factor of intensity of Ramadan (number of days in Ramadan divided by total number of days in a month) in that month. Similarly, coefficient of $RAMINT_{t+1}$, which was found to be 0.0293, signified that global raw sugar price grew by roughly 2.93% due to Ramadan in a month as a factor of intensity of Ramadan in the following month. To illustrate with an example, if Ramadan starts on the first day of June or $RAMINT_{June}$ = 1, raw sugar prices are expected to increase on account of Ramadan by 3.13% in June and 2.93% in the preceding month, May. This will result in total growth of 6.15% in raw sugar price on account of Ramadan. If Ramadan starts in the middle of any month, the calculations become a bit more complicated as the impact of next month's intensity gets captured in current month in addition to current month's impact. To illustrate, if Ramadan starts on the nineteenth of June, $RAMINT_{June}$ and $RAMINT_{July}$ will be 0.4 and 0.58 respectively. Hence, growth of sugar price due to Ramadan in May, June, and July are expected to be 1.17%, 2.96%, and 1.82% respectively (sum of RAMINT and Coefficient of RAMINT for the corresponding period) as shown in Table 5.4. This will result in total growth of 6.06% in raw sugar price on account of Ramadan. Overall average growth due to Ramadan from this model is estimated to be approximately 6.0%. There is a 0.2% absolute deviation in this growth rate caused by changing fractional indicator (RAMINT) values due to (i) number of days in Ramadan, (ii) number of days in Gregorian month in which Ramadan begins, and (iii) number of days in Gregorian month in which Ramadan ends.

Table 5.4 Example of Ramadan Impact on Price from ARIMA Model with RAMINT

Month	$RAMINT_t$	$RAMINT_{t+1}$	$\beta(RAMINT_t)$	$\beta(RAMINT_{t+1})$	Change
May	0.00	0.40	0.031323	0.29327	**1.17%**
June	0.40	0.58			**2.96%**
July	0.58	0.00			**1.82%**

Similar to RAMINT, the coefficient of RAMSTINT variable was also found to be statistically significant when it was included in the original ARIMA structure. When the model was re-estimated using lead values of RAMSTINT, it was found that the coefficients were statistically significant (at 10% significance level) up to two leads as per Table 8.5 in Appendix A and are provided below in Table 5.5.

Table 5.5 Coefficients of ARIMA Model (with RAMSTINT) of Δln(sugarprice) Series

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.004000	0.004228	-0.946086	0.3447
RAMSTINT	**0.035697**	**0.016403**	**2.176219**	**0.0301**
RAMSTINT(1)	**0.062597**	**0.027691**	**2.260517**	**0.0243**
RAMSTINT(2)	**0.046582**	**0.024491**	**1.901998**	**0.0579**
AR(1)	1.202921	0.059088	20.35828	0.0000
AR(2)	-0.269587	0.055211	-4.882867	0.0000
SAR(12)	0.886877	0.026397	33.59817	0.0000
MA(1)	-0.959545	0.022678	-42.31218	0.0000
SMA(12)	-0.943560	0.024390	-38.68560	0.0000

From the above table, it could be observed that coefficients of $RAMSTINT_t$, $RAMSTINT_{t+1}$, and $RAMSTINT_{t+2}$ were all positive and significant. Coefficient of $RAMSTINT_t$, which was found to be 0.0357, signified that global raw sugar price grew by roughly 3.57% due to Ramadan in the month in which Ramadan begins as a factor of intensity of Ramadan in that month. Similarly, coefficient of $RAMSTINT_{t+1}$, which was found to be 0.0626 signified that global raw sugar price grew by roughly 6.26% due to Ramadan on the month preceding the month in which Ramadan began as a factor of intensity of Ramadan in the month in which Ramadan began. Finally, coefficient of $RAMSTINT_{t+2}$, which was found to be 0.0466 signified that global raw sugar price grew by roughly 4.66% due to Ramadan on the month which is two months prior to the month in which Ramadan began as a factor of intensity of Ramadan in the month in which Ramadan began. To illustrate with an example, if Ramadan starts on nineteenth of June or $RAMSTINT_{June} = 0.4$, raw sugar prices are expected to increase on account of Ramadan by 1.43% in June, 2.50% in May, and 1.86% in April. These are in line with results found from the illustration provided for the model with RAMINT.

Results from ARIMA model with Ramadan variables have been summarized in Table 5.6

Table 5.6 Summary of Findings from ARIMA Models with Ramadan Variables

Ramadan Variable	Significance	Lead Structure
RAMDUM	Not Significant	None
RAMST	Not Significant	None
RAMINT	Statistically Significant	Up to one lead
RAMSTINT	Statistically Significant	Up to two leads

To summarize, no significant impact of Ramadan on raw sugar price was found while RAMDUM and RAMST were used as variables indicating Ramadan. One of the reasons why this might have happened is that these two are dummy variable which disregard starting date and duration of Ramadan in a particular month. Both variables treat the month in which Ramadan starts on the first day and the month in which Ramadan starts on the last day equally. Hence, these dummy variables cannot identify price movements due to Ramadan which is likely to occur on a daily gradual basis and is channeled into monthly average price (the data series for this research) by tipping monthly average price based on number of Ramadan days in a Gregorian month.

On the other hand, impact of Ramadan on global raw sugar price was found to be statistically significant for both fractional indicators, RAMINT and RAMSTINT, as these two variables could better capture the essence of starting date and duration of Ramadan in a Gregorian month. RAMINT was found to be significant up to one lead while RAMSTINT was found to be significant up to two leads which can be easily explained as RAMINT considers intensity of Ramadan in all the months in which Ramadan days are present while RAMSTINT considers intensity of Ramdan only on the month in which Ramdan begins. Among these two variables, RAMINT is more representative of Ramadan as it takes into consideration all months with Ramadan days by distributing a dummy variable into two separate fractional indicators. Hence, coefficients of RAMINT can be used to forecast growth in sugar prices due to Ramadan accurately. On the other hand, results from RAMSTINT are less representative as RAMSTINT considers only the month in which Ramadan begins. Hence, if coefficients of RAMSTINT are used to forecast growth, the results will be overstated for years in which Ramadan begins during the first half of a Gregorian month and understated for years in which Ramadan begins during the second half of a Gregorian month.

5.4 Unobserved-Components Model with Ramadan Variables

In order to verify the robustness of findings from ARIMA modeling, raw sugar data series was modelled using Unobserved-Components Model (UCM) with Ramadan variables. Before Ramadan variables were incorporated in the model, UCM was used to decompose raw sugar price series into different components as per methods prescribed in Methodology.

From UCM of raw sugar price series as can be observed from Table 8.6 in Appendix A, it was found out that global sugar price is primarily explained by the permanent (nonstationary) component, and less so by temporary (stationary) component. The series was found to be cyclical at low frequency (λ) of 0.41 as can be seen in Table 5.7. For the cyclical component, damping factor (ρ) was found to be 0.91. This damping factor close to 1 showed that the series had more persistent cycle. Alternatively, the cycle could be explained by a sine/cosine function. From the frequency value, estimated central period for the cycle ($\frac{2\pi}{\lambda}$) was found to be 15. As the research used monthly data, this result showed that the cycle in raw sugar prices repeated every 15 months.

Table 5.7 UCM of Raw Sugar Price Series

Variable	Coefficient	Std. Error	Z	P > |z|
Frequency (λ)	.4111008	.0476951	8.62	0.000
Damping (ρ)	.9135842	.0325459	28.07	0.000
var(level)	366.217	54.56448	6.71	0.000
var(seasonal)	.0904475	.2182194	0.41	0.339
var(cycle)	99.13259	45.34334	2.19	0.014

Once raw sugar price series was broken down into its components, those Ramadan variables which were found to be statistically significant in ARIMA modeling, viz. RAMINT and RAMSTINT, were included one by one separately as exogenous variables in UCM. The coefficient of RAMINT variable was found to be statistically significant when it was included in UCM. When the model was re-estimated using lead values of RAMINT, it was found that the coefficients were statistically significant (at 5% significance level) up to one lead as per Table 8.7 in Appendix A and are provided below in Table 5.8.

Table 5.8 UCM of Raw Sugar Price Series with RAMINT

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Frequency (λ)	.4108377	.0465479	8.83	0.000
Damping (ρ)	.9170945	.0309663	29.62	0.000
RAMINT	**9.669772**	**3.914827**	**2.47**	**0.014**
RAMINT(1)	**8.123321**	**3.917779**	**2.07**	**0.038**
var(level)	360.6705	52.43702	6.88	0.000
var(seasonal)	.0914462	.2144619	0.43	0.335
var(cycle)	96.28442	43.15832	2.23	0.013

From the above table, it could be observed that coefficients of $RAMINT_t$ and $RAMINT_{t+1}$ were both positive and significant. Coefficient of $RAMINT_t$, which was found to be 9.67, signified that global raw sugar price increased by roughly USD 9.67 per metric ton due to Ramadan in a month as a factor of intensity of Ramadan in that month. Similarly, coefficient of $RAMINT_{t+1}$, which was found to be 8.12, signifies that global raw sugar price increased by roughly USD 8.12 per metric ton due to Ramadan in a month as a factor of intensity of Ramadan in the following month. To illustrate with an example, if Ramadan starts on the first day of June or $RAMINT_{June} = 1$, raw sugar prices are expected to increase on account of Ramadan by USD 9.67 per metric ton in June and USD 8.12 per metric ton in the preceding month, May. If Ramadan starts in the middle of any month, the calculations become a bit more complicated as the impact of next month's intensity gets captured in current month in addition to current month's impact. To illustrate, if Ramadan starts on the nineteenth of June, $RAMINT_{June}$ and $RAMINT_{July}$ will be 0.4 and 0.58 respectively. Hence, growth of sugar price due to Ramadan in May, June, and July are expected to be USD 3.25, USD 8.58, and USD 5.61 per metric ton respectively (sum of RAMINT and Coefficient of RAMINT for the corresponding period) resulting in total price increase of USD 17.45 per metric ton on account of Ramadan as seen in Table 5.9.

Table 5.9 Example of Ramadan Impact on Price from UCM with RAMINT

Month	$RAMINT_t$	$RAMINT_{t+1}$	$\beta(RAMINT_t)$	$\beta(RAMINT_{t+1})$	Change
May	0.00	0.40	9.67	8.12	**3.25**
June	0.40	0.58			**8.58**
July	0.58	0.00			**5.61**

Overall average increase in raw sugar price due to Ramadan from this model is estimated to be approximately USD 17.21 per metric ton for the sample period. In percentage terms, the growth is 6.82% of the mean monthly raw sugar price for the sample period. There is a 0.2% absolute deviation in price change caused by changing fractional indicator (RAMINT) values due to (i) number of days in Ramadan, (ii) number of days in Gregorian month in which Ramadan begins, and (iii) number of days in Gregorian month in which Ramadan ends.

Similar to RAMINT, the coefficient of RAMSTINT variable was also found to be statistically significant (at 5% significance level) up to one lead as per Table 8.8 in Appendix A and are provided below in Table 5.10.

Table 5.10 UCM of Raw Sugar Price Series with RAMINT

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Frequency (λ)	.4088512	.045493	8.99	0.000
Damping (ρ)	.9181769	.0303371	30.27	0.000
RAMSTINT	**11.77072**	**4.880317**	**2.41**	**0.016**
RAMSTINT(1)	**11.07775**	**4.881493**	**2.27**	**0.023**
var(level)	359.0036	52.17579	6.88	0.000
var(seasonal)	.0924393	.2186282	0.42	0.336
var(cycle)	97.91096	42.98837	2.28	0.011

From Table 5.10, it could be observed that coefficients of $RAMSTINT_t$, and $RAMSTINT_{t+1}$ were all positive and significant. Coefficient of $RAMSTINT_t$, which was found to be 11.77, signified that global raw sugar price increased by roughly USD 11.77 per metric ton due to Ramadan in the month in which Ramadan began as a factor of intensity of Ramadan in that month. Similarly, coefficient of $RAMSTINT_{t+1}$, which was found to be 11.08, signified that global raw sugar price increased by roughly USD 11.08 per metric ton due to Ramadan on the month preceding the month in which Ramadan began as a factor of intensity of Ramadan in the month in which Ramadan began. To illustrate with an example, if Ramadan starts on nineteenth of June or $RAMSTINT_{June} = 0.4$, raw sugar prices are expected to increase on account of Ramadan by USD 4.71 and USD 4.43 per metric ton in June, and May respectively. These are in line with results found from the illustration provided for the model with RAMINT.

5.5 Comparison of results from ARIMA and UCM

The results from UCM support findings from ARIMA modeling to identify and assess impact of Ramadan on global raw sugar prices. From both models, it was found out that Ramadan affected both level and growth in global raw sugar prices after controlling for factors such as trend, cycle and seasonality. Anticipatory price impact of Ramadan was also confirmed from both models as coefficients of lead values of Ramadan variables were also found to be significant in both models. Figures 5.3 and 5.4 provide visual cue to the lead structure and growth in raw sugar prices in anticipation of Ramadan found from both models.

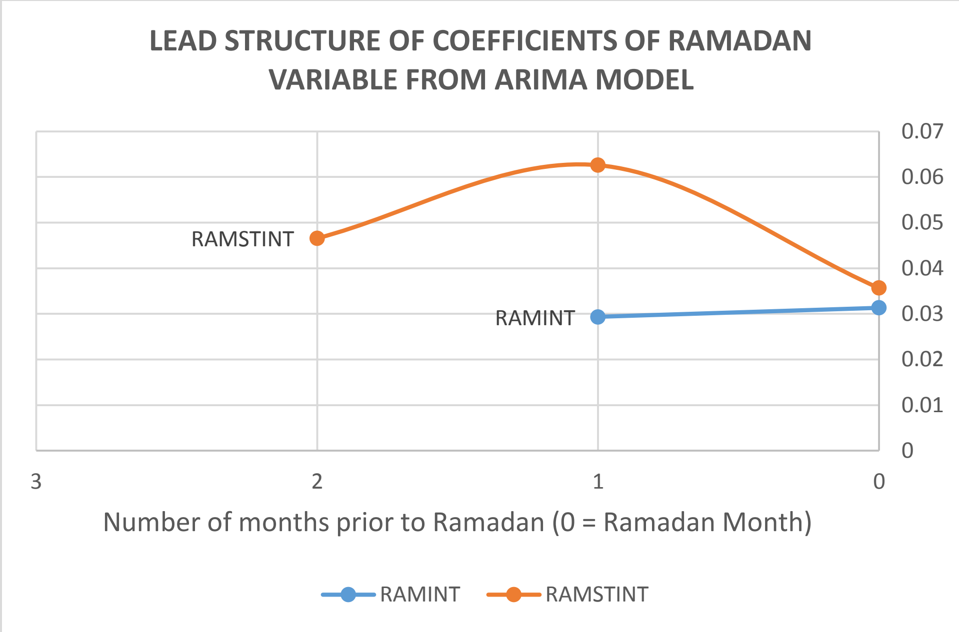


Figure 5.3 Lead Structure of Coefficients of Ramadan Variables from ARIMA Model

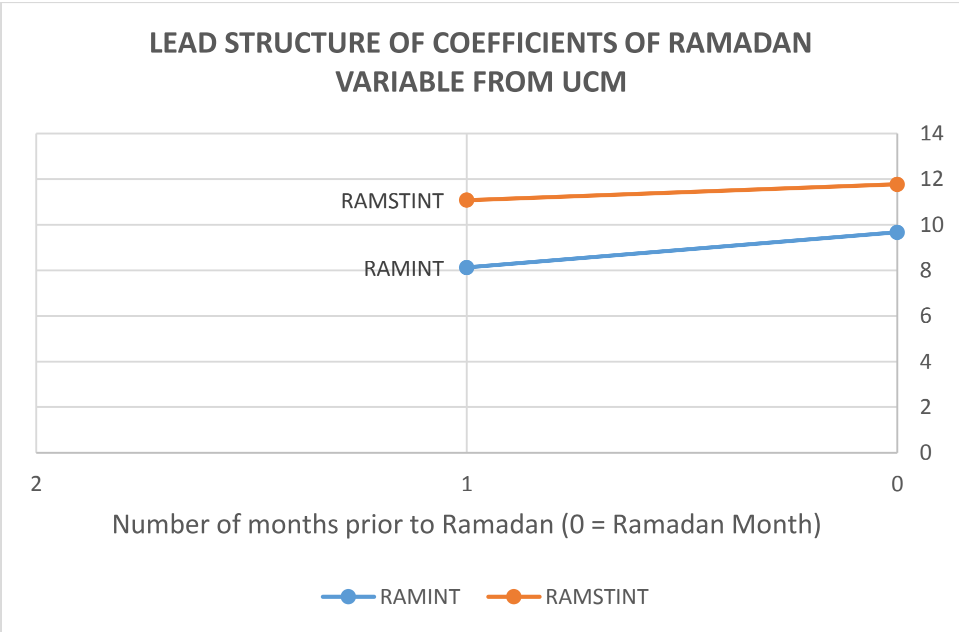


Figure 5.4 Lead Structure of Coefficients of Ramadan Variables from ARIMA Model

To summarize, findings from UCM reaffirmed robustness of findings from ARIMA modeling with Ramadan variables that there is an inflationary impact of Ramadan on global raw sugar prices which is anticipatory.

6. Conclusion

There is a general perception that essential food prices soar during Ramadan due to increased demand. The purpose of this study was to find out whether increased demand for one such food item, sugar, was strong enough to affect global trade prices of that commodity in semi-processed form. However, the task proved to be daunting as price data are available in Gregorian solar calendar format but Ramadan is based on Islamic lunar calendar. Hence, asynchronization of data made it difficult to detect impact of any Islamic calendar event such as Ramadan.

The study primarily used seasonal ARIMA model to measure impact of Ramadan on raw sugar prices. Raw sugar price series was first tested for stationarity using DF-GLS test and then was made stationary by taking the first difference of natural logarithm of original price series. Then, four different Ramadan dummy and fractional indicator variables were used separately to find the best indicator of Ramadan as well as to detect the impact of Ramadan in the estimated ARIMA model. The results indicated that two fractional indicator variables, namely RAMINT (Ramadan Intensity, calculated as number of Ramadan days in any Gregorian month divided by total number of days in that Gregorian month) and RAMSTINT (Ramadan Intensity for the month in which Ramadan begins) had statistically significant positive coefficients and thus proved growth impact of Ramadan on raw sugar prices.

Among these two variables, RAMINT was more representative of Ramadan as it took into consideration all months with Ramadan days by distributing a dummy variable into two separate fractional indicators as opposed to RAMSTINT which considered only the month in which Ramadan began. The results from ARIMA model with RAMINT showed that raw sugar prices grew by approximately 6.06% on average due to Ramadan with 0.2% absolute deviation caused by changing fractional indicator (RAMINT) values due to different combinations of Ramadan and Gregorian month days.

In order to further test the robustness of results from modified ARIMA modeling, raw sugar price series was then modeled using Unobserved-Components model (UCM). Statistically significant Ramadan variables from ARIMA modeling, RAMINT and RAMSTINT, were then incorporated separately as exogenous variables in UCM. The estimated model indicated that both these variables had statistically significant positive coefficients and thus proved level impact of Ramadan on raw sugar prices. The results from UCM with RAMINT showed that raw sugar price increased by approximately 6.82% on average due to Ramadan with 0.2% absolute deviation caused by changing fractional indicator (RAMINT) values due to different combinations of Ramadan and Gregorian month days.

Furthermore, as lead structure for Ramadan variables were used in both models, the results further indicated presence of anticipatory impact of Ramadan, i.e. the phenomenon of increase in raw sugar prices one month prior to Ramadan in anticipation of Ramadan whereby price growth or increase in a Gregorian month was a direct function of Ramadan intensity in that Gregorian month.

In order to put these results into perspective, during 2015, Bangladesh imported roughly 250,000 metric tons of raw sugar monthly prior to and during Ramadan. According to UCM results, estimated price increase due to Ramadan was approximately USD 17 per metric ton. Thus, monthly price premium was 250,000 × USD 17 = USD 4.25 million or BDT 331.5 million based on this study. Hence, policy makers in countries with dense Muslim population can take decisions by measuring impact of Ramadan on raw sugar prices and devise effective control mechanisms and procurement strategies to neutralize or minimize inflationary impact of Ramadan on raw sugar prices.

By understanding the impact calendar events may have on commodity prices, commodity traders may also use the findings of this study to better manage their trading positions. Sugar refiners can also benefit from this study by effectively managing cost, inventory position, and production planning to avoid mark-to-market losses for calendar event based price movements.

For future research prospects, this empirical model can be extended to test for potential structural breaks in the time series. This research can also be used as a framework to conduct further research to measure impact of Ramadan on other relevant commodities whose consumption increases during Ramadan, such as, edible oil, flour, chickpeas etc.

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8. Appendix

Appendix A: Output Tables of Statistical Tests

Table 8.1 DF-GLS Unit Root Test for Raw Sugar Price

DF-GLS for sugprice				Number of obs = 391
Maxlag = 17 chosen by Schwert criterion				
Lags	**DF-GLS tau Test Stat.**	**1% Critical Value**	**5% Critical Value**	**10% Critical Value**
17	**-1.558**	-3.480	-2.816	-2.534
16	-1.423	-3.480	-2.821	-2.539
15	-1.410	-3.480	-2.826	-2.544
14	-1.445	-3.480	-2.831	-2.548
13	-1.542	-3.480	-2.836	-2.553
12	-1.550	-3.480	-2.841	-2.557
11	-1.436	-3.480	-2.846	-2.561
10	-1.443	-3.480	-2.850	-2.566
9	-1.490	-3.480	-2.855	-2.570
8	-1.484	-3.480	-2.859	-2.573
7	-1.544	-3.480	-2.863	-2.577
6	-1.609	-3.480	-2.867	-2.581
5	-1.595	-3.480	-2.871	-2.585
4	-1.671	-3.480	-2.875	-2.588
3	-1.693	-3.480	-2.879	-2.591
2	-1.719	-3.480	-2.882	-2.595
1	-1.750	-3.480	-2.886	-2.598
Opt Lag (Ng-Perron seq t) = 17 with RMSE 20.72617				
Min SC = 6.154124 at lag 1 with RMSE 21.36591				
Min MAIC = 6.144557 at lag 1 with RMSE 21.36591				

Table 8.2 DF-GLS Unit Root Test for Natural Logarithm of Raw Sugar Price

DF-GLS for DSUGP				Number of obs = 390
Maxlag = 17 chosen by Schwert criterion				
Lags	**DF-GLS tau Test Stat.**	**1% Critical Value**	**5% Critical Value**	**10% Critical Value**
17	-1.689	-3.480	-2.816	-2.534
16	-1.709	-3.480	-2.821	-2.539
15	-2.017	-3.480	-2.826	-2.544
14	-2.216	-3.480	-2.831	-2.548
13	-2.324	-3.480	-2.836	-2.553
12	-2.326	-3.480	-2.841	-2.557
11	-2.434	-3.480	-2.846	-2.561
10	-2.645	-3.480	-2.850	-2.566
9	-2.900	-3.480	-2.855	-2.570
8	-3.239	-3.480	-2.859	-2.573
7	-3.556	-3.480	-2.863	-2.577
6	-3.746	-3.480	-2.867	-2.581
5	-4.198	-3.480	-2.871	-2.585
4	-5.004	-3.480	-2.875	-2.588
3	-5.599	-3.480	-2.879	-2.591
2	-6.933	-3.480	-2.882	-2.595
1	**-8.724**	-3.480	-2.886	-2.598
Opt Lag (Ng-Perron seq t) = 16 with RMSE 0.0842337				
Min SC = -4.788496 at lag 3 with RMSE 0.0884919				
Min MAIC = -4.825007 at lag 16 with RMSE 0.0842337				

Table 8.3 ARIMA(2,1,1)$(1,0,1)_{12}$ Model of Δln(sugarprice) Series

Dependent Variable: DLSUGP
Method: Least Squares
Sample (adjusted): 1982M04 2014M12
Included observations: 394 after adjustments
Convergence achieved after 17 iterations
HAC standard errors & covariance (Prewhitening with lags = 1 from AIC maxlags = 7, Bartlett kernel, Newey-West fixed bandwidth = 6.0000)
MA Backcast: 1981M03 1982M03

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.002718	0.003526	0.770970	0.4412
AR(1)	1.214597	0.055386	21.92981	0.0000
AR(2)	-0.285096	0.050747	-5.618046	0.0000
SAR(12)	0.890070	0.028733	30.97700	0.0000
MA(1)	-0.953465	0.025511	-37.37472	0.0000
SMA(12)	-0.935629	0.026984	-34.67317	0.0000

R-squared	0.124641	Mean dependent var	0.000731
Adjusted R-squared	0.113361	S.D. dependent var	0.087116
S.E. of regression	0.082030	Akaike info criterion	-2.148357
Sum squared resid	2.610808	Schwarz criterion	-2.087804
Log likelihood	429.2264	Hannan-Quinn criter.	-2.124363
F-statistic	11.04939	Durbin-Watson stat	1.991851
Prob(F-statistic)	0.000000		

Table 8.4 ARIMA(2,1,1)(1,0,1)$_{12}$ Model of Δln(sugarprice) Series with RAMINT

Dependent Variable: DLSUGP
Method: Least Squares
Sample (adjusted): 1982M04 2014M12
Included observations: 393 after adjustments
Convergence achieved after 11 iterations
HAC standard errors & covariance (Prewhitening with lags = 1 from AIC maxlags = 7, Bartlett kernel, Newey-West fixed bandwidth = 6.0000)
MA Backcast: 1981M03 1982M03

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.005179	0.002412	-2.147541	0.0324
RAMINT	**0.031323**	**0.014792**	**2.117590**	**0.0349**
RAMINT(1)	**0.029327**	**0.016671**	**1.759131**	**0.0793**
AR(1)	1.244075	0.047381	26.25691	0.0000
AR(2)	-0.277885	0.046023	-6.037958	0.0000
SAR(12)	0.928394	0.029531	31.43803	0.0000
MA(1)	-0.999109	0.008230	-121.3973	0.0000
SMA(12)	-0.966518	0.013089	-73.84306	0.0000

R-squared	0.142129	Mean dependent var	0.000721
Adjusted R-squared	0.126531	S.D. dependent var	0.087227
S.E. of regression	0.081522	Akaike info criterion	-2.155746
Sum squared resid	2.558636	Schwarz criterion	-2.074854
Log likelihood	431.6040	Hannan-Quinn criter.	-2.123689
F-statistic	9.112210	Durbin-Watson stat	1.982320
Prob(F-statistic)	0.000000	Wald F-statistic	3.847863
Prob (Wald F-statistics)	0.022150		

Table 8.5 ARIMA(2,1,1)(1,0,1)$_{12}$ Model of Δln(sugarprice) Series with RAMSTINT

Dependent Variable: DLSUGP
Method: Least Squares
Sample (adjusted): 1982M04 2014M11
Included observations: 392 after adjustments
Convergence achieved after 14 iterations
HAC standard errors & covariance (Prewhitening with lags = 1 from AIC maxlags = 7, Bartlett kernel, Newey-West fixed bandwidth = 6.0000)
MA Backcast: 1981M03 1982M03

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.004000	0.004228	-0.946086	0.3447
RAMSTINT	**0.035697**	**0.016403**	**2.176219**	**0.0301**
RAMSTINT(1)	**0.062597**	**0.027691**	**2.260517**	**0.0243**
RAMSTINT(2)	**0.046582**	**0.024491**	**1.901998**	**0.0579**
AR(1)	1.202921	0.059088	20.35828	0.0000
AR(2)	-0.269587	0.055211	-4.882867	0.0000
SAR(12)	0.886877	0.026397	33.59817	0.0000
MA(1)	-0.959545	0.022678	-42.31218	0.0000
SMA(12)	-0.943560	0.024390	-38.68560	0.0000

R-squared	0.143657	Mean dependent var	0.000870
Adjusted R-squared	0.125770	S.D. dependent var	0.087288
S.E. of regression	0.081615	Akaike info criterion	-2.150921
Sum squared resid	2.551153	Schwarz criterion	-2.059744
Log likelihood	430.5805	Hannan-Quinn criter.	-2.114785
F-statistic	8.031313	Durbin-Watson stat	1.979331
Prob(F-statistic)	0.000000	Wald F-statistic	2.512971
Prob (Wald F-statistics)	0.058194		

Table 8.6 Unobserved-Components Model of Raw Sugar Price

Unobserved-components model
Components: random walk, seasonal(12), order 1 cycle
Sample: 1981m1 - 2015m1

		Number of obs =	409
		Wald chi2(2) =	882.66
Log likelihood	= 1834.1488	Prob > chi2 =	0.0000

sugprice	Coef.	OIM Std. Err.	z	P > |z|	[95% Conf. Interval]	
Frequency	.4111008	.0476951	8.62	0.000	.3176201	.5045815
Damping	.9135842	.0325459	28.07	0.000	.8497954	.9773731
var(level)	366.217	54.56448	6.71	0.000	259.2725	473.1614
var(seasonal)	.0904475	.2182194	0.41	0.339	0	.5181497
var(cycle1)	99.13259	45.34334	2.19	0.014	10.26127	188.0039

Table 8.7 Unobserved-Components Model of Raw Sugar Price with RAMINT

Unobserved-components model
Components: random walk; seasonal(12) order 1 cycle
Sample: 1981m1 - 2014m9

		Number of obs =	408
		Wald chi2(4) =	974.17
Log likelihood	= -1826.359	Prob > chi2 =	0.0000

sugprice	Coef.	OIM Std. Err.	z	P > |z|	[95% Conf. Interval]	
frequency	.4108377	.0465479	8.83	0.000	.3196055	.5020699
damping	.9170945	.0309663	29.62	0.000	.8564017	.9777873
sugprice						
ramint						
--.	**9.669772**	**3.914827**	**2.47**	**0.014**	**1.996853**	**17.34269**
F1.	**8.123321**	**3.917779**	**2.07**	**0.038**	**.4446145**	**15.80203**
var(level)	360.6705	52.43702	6.88	0.000	257.8958	463.4454
var(seasonal)	.0914462	.2144619	0.43	0.335	0	.5117838
var(cycle1)	96.28442	43.15832	2.23	0.013	11.69566	180.8732

Table 8.8 Unobserved-Components Model of Raw Sugar Price with RAMSTINT

Unobserved-components model
Components: random walk; seasonal(12) order 1
cycle
Sample: 1981m1 - 2014m9

			Number of obs	=	408
		1019.62	Wald chi2(4)	=	974.17
Log likelihood	= -1826.532	0.0000	Prob > chi2	=	0.0000

sugprice	Coef.	OIM Std. Err.	z	P > |z|	[95% Conf.	Interval]
frequency	.4088512	.045493	8.99	0.000	.3196866	.4980157
damping	.9181769	.0303371	30.27	0.000	.8564017	.9776366
sugprice						
ramstint						
--.	**11.77072**	**4.880317**	**2.41**	**0.016**	**1.996853**	**21.33596**
F1.	**11.07775**	**4.881493**	**2.27**	**0.023**	**.4446145**	**20.64531**
var(level)	359.0036	52.17579	6.88	0.000	257.8958	461.2663
var(seasonal)	.0924393	.2186282	0.42	0.336	0	.5209427
var(cycle1)	97.91096	42.98837	2.28	0.011	11.69566	182.1666