Quantifying the impact of Ramadan on global raw sugar prices

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Abstract

Each year during the month of Ramadan (Muslim fasting month) consumption of sugar increased dramatically across the globe as Muslims traditionally break their fast with some sweet drinks or products. Since Muslims use lunar calendar, the months are not fully aligned with the Gregorian calendar or with the seasonal calendar for agricultural crops. In this paper, we quantify the impact of Ramadan on both the price and its growth of global raw sugar price. To set the stage for the empirical work that follows, we employ a dummy and a fractional variable to capture Ramadan in order to overcome the asynchronicity of time between Ramadan fasting (which is based on Islamic lunar calendar) and movement in prices (which follows the Gregorian solar calendar). In order to capture seasonality of production in sugar production, data on sugar price spans over thirty-four years so that the Islamic calendar makes a complete cycle of the Gregorian calendar. Using ARIMA and UCM models, we find strong evidence that monthly raw sugar prices in the global market increases by roughly 6.06% (or $17.78 per metric ton) every year ahead of Ramadan.

Keywords: Raw Sugar Price, Ramadan, ARIMA, Unobserved-components model.

JEL codes: C22, Q02; Z12.

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1. Introduction

In the 9th calendar month of every year Muslims around the world perform fasting (from dawn to dusk) as a part of their religious practice. Majority of the 1.6 billion Muslims in the world observe this ritual (Pew Research Center 2015). During this time, healthy adult Muslims fast and abstain from eating, drinking, and also smoking from dawn to dusk. Number of days for fasting depends on moon sighting and so it varies between 29 and 30 days in the month each year. As a result, meal schedule, frequency and also composition change drastically (Roky et al., 2005). As a part of the ritual Muslims break their fast with "iftar" which is made to recover from fatigue from fasting and to restore nutritional balance quickly. There is also a mid-night supper, called "Suhoor" in order to prepare for the fast during the day.

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 is 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 (Rakicioğlu et al., 2006). Social gatherings to observe the festive month of Ramadan are also responsible for increasing the 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 (Sakr 1975, Leiper et al., 2003).

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. During 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 Section 3). This made sugar the second most traded commodity (after oil) 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. reveals that historically essential food (such as sugar, flour, peas, edible oil etc.) prices have usually soared suddenly before and during the month of 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 during the 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 the Ramadan. As sugar fits the sample of food items whose consumption increases during Ramadan, the impact of Ramadan on sugar prices can be an interesting topic of research for economists. Hence, the objective of this paper is to estimate the impact of Ramadan on global raw sugar prices. Among the two types of sugar, raw and refined, raw sugar is selected as the subject of this study as it accounts for larger trade share than refined sugar. Moreover, raw sugar is mainly imported by countries with dense Muslim population.

Since Ramadan month follows the lunar calendar, which is of 354 or 355 days and sugar production follows the solar calendar, which is of 365 days, Ramadan roughly moves up by 10 days in every Gregorian calendar. As a result, there is a likely misalignment between sugar production season and the sugar consumption cycle. The major challenges that need to be addressed to assess and isolate the impact of Ramadan on raw sugar prices are: (a) seasonality in changes in raw sugar price, (b) other factors influencing sugar prices, and (c) the inherent misalignment between lunar and solar calendars as the latter dictates seasons of sugar production around the globe.

The rest of the paper is organized as follows. Section 2 reviews relevant literature on sugar price modeling and econometric method(s) of measuring the impact of Ramadan. Section 3 provides an overview of the global sugar market. Section 4 discusses the statistical procedure used in measuring the impact of Ramadan on raw sugar prices. It also contains a discussion on the sources of data. Section 5 presents the empirical results. Section 6 concludes the paper.

2. Literature review

Despite being the second most traded commodity after oil (Abbott 2011), there is scant empirical analysis on sugar prices in the literature. Devadoss and Kropf (1996) empirically quantify the effect of trade liberalization agreements negotiated under the Uruguay Round on sugar production, consumption, trade and prices among major sugar exporting and importing countries. On the demand side, consumers in countries with strong domestic and trade policy interventions tend to enjoy lower domestic prices. On the supply side, low-cost sugar producing countries benefit slightly from higher world prices than the high-cost sugar producing countries. Reitz and Westerhoff (2007) examine the cyclical commodity price formation of sugar (among other agricultural commodities) using a STAR-GARCH estimation procedure on monthly data over the period 1973 and 2003. In particular, their analysis seeks to understand to what extent the heterogeneous trading strategies between technical and fundamental traders contribute to price fluctuations in commodity markets. They find that the more the price deviates from its long-run equilibrium value, the more fundamental traders become active in the market to push prices back to more moderate values. Poonyth et al. (2000) analyze the effect of WTO restrictions on subsidized exports on the EU sugar sector and the world sugar market. Their results show that the world price of sugar has a major influence on EU sugar production even though EU market prices are above the world price. Nolte et al. (2012) model the effects of an abolition of the EU sugar quota on internal prices, production and imports using a spatial price equilibrium model. They find that the abolition of the quota raises production and reduces imports in the EU. The effect is more pronounced when world market price for sugar is higher.

Ribeiro and Oliveira (2011) consider a hybrid model for forecasting sugar prices in Brazil and India. For the Brazilian prices, they find that changes in oil price, sale of biofuel vehicles and exchange rate have significant impact on future sugar prices. Whereas for the Indian prices, exchange rate and oil price improved the forecasts. Pereira et al. (2012) conduct a theoretical and empirical analysis of commodity pricing model with a particular focus on Brazilian sugar market. They examine whether a pricing model used for biofuel—which incorporates storage, the convenience of yield and the seasonality of harvests—can help to predict sugar prices in Brazil. They find that their underlying commodity-price model with a deterministic trend yield superior forecasts of sugar prices than a standard two-factor model of Gibson and Schwartz (1990). Chen and Saghaian (2015) identify a major structural break in 2008 in the Brazilian sugar industry, when following the surge in sugar prices in the international market resources were diverted from ethanol production to sugar production. Sugar prices appear to drive ethanol prices before the break, while they reinforce each other after the break.

On the other hand, there are only a few studies looking at the impact of religious calendar or holidays on food prices in particular. In the case with Ramadan, the consumption cycle for sugar is influenced by lunar cycle, while the production season of sugar remains fixed over the year, leading to a mismatch between the timing of consumption and production of sugar. Further complication arises as most Muslim societies follow observation-based calendar announced at the beginning of the month by religious authorities after sighting of the new moon. As a result, any attempt to convert Islamic dates to Gregorian dates has a margin of error to around two days. Furthermore, standard methods of seasonal adjustment such as X-11 or X-12 ARIMA models are not equipped to account for the religious event impacts, particularly for moving holidays.

Lin and Liu (2002) apply the holiday regressor method proposed by Bell and Hillmer (1983) to analyze the impact of lunisolar Chinese calendar on ten important economic series in Taiwan. 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 in every fourth year through the Chinese leap year (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 thus it gets a complete rotation in every 34 to 36 years. As a result, holiday regressor is not suitable to isolate the impact of any Islamic calendar event on a time series variable.

Yucel (2005) examines the impact of Ramadan on food prices in Turkey using three different approaches. The first approach uses a dummy variable for the Gregorian calendar month(s) which overlap with Ramadan. The second approach uses 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, in 1994 Ramadan was spread over February and March. Out of 29 days of Ramadan, 17 were in February and the rest 12 were in March. Using the first approach, a dummy variable with a value of 1 was assigned to February and March in 1994 and the remaining months were assigned a value of 0. Alternatively, a Ramadan intensity variable using number of Ramadan days in a month i.e. 0.607 (17/28) and 0.387 (12/31) was used in February and in March of 1994, respectively. The third approach involves converting the entire data set from Gregorian calendar to Islamic calendar. His results show that food prices in Turkey tend to rise during Ramadan. The most satisfactory results are obtained using the third approach. However, this approach is not feasible in practice as most of the monthly data are available for Gregorian calendar months only. His results supported using the second approach i.e. to use a Ramadan intensity variable. However, his method was criticized due to its lack of full representation and timing of data recording. Without a long data series it is difficult to isolate impact of lunar cycle events in the market when production seasonality follows the solar cycle.

Riazuddin and Khan (2005) also adopt fractional indicator variables to analyze the effect of Islamic calendar on currency circulation in Pakistan. Based on a ARIMA model, they document stock presence of Islamic calendar effects in currency in circulation. This finding has important implication for liquidity management for central banks in Muslim dominated countries. Akmal and Abbasi (2010) analyze Ramadan's effect on price movements in Pakistan using measures similar to Yucel (2005) and Riazuddin and Khan (2005). However, their results show no significant impact of Ramadan on consumer price levels in Pakistan.

3. An overview of global sugar market

Global sugar production in 2013/14 was approximately 172.4 million metric tons. Brazil, India, European Union, China, Thailand and the United States—the top 6 sugar producing countries—contributed to 64% of global sugar production (Table 1 and Figure 1). Although sugar is found in most plant tissues, efficient extraction for commercial production is possible mostly from sugarcane and sugar beet. Approximately 80% of global sugar production in 2013-14 was cane based while the rest was produced from sugar beet. 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 1.

(Insert Table 1 and Figure 1 here)

Brazil (the leading exporter) and Thailand provide around 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, the United States, European Union, the United Arab Emirates and Bangladesh.

One interesting fact that emerges from Tables 2 and 3 is that, while none of the major sugar producing and exporting nations (barring India) have a dominant Muslim population, a large number of sugar importing nations such as Indonesia, Bangladesh, UAE, Malaysia and Iran are primarily Muslim dominated countries. Even India with 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. A graphical representation of this observation is shown in Figure 2.

(Insert Tables 2 and 3 here)

(Insert Figure 2 here)

4. Data, construction of Ramadan dummies and econometric methodology

4.1 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 over 34-year period from January 1981 to January 2015 in order to ensure that the sample size covers beginning of Ramadan in every Gregorian month as Ramadan revolves around the Gregorian calendar in every thirty-five years (due to accumulation of 10-11 days difference each year). An online calendar converter[6] was used to identify historical comparative Gregorian calendar dates that coincide with the beginning of Ramadan in each year over the sample period.

4.2 Construction of Ramadan dummies and fractional indicators

As monthly prices of raw sugar are available in Gregorian calendar, suitable adjustments are applied to capture the impact Ramadan on Gregorian months. While developing these indicators, two separate dimensions were considered:

- Identifying the Gregorian month in which Ramadan began to determine whether there is any anticipatory movement in raw sugar price prior to Ramadan.
- Measuring Ramadan intensity for that Gregorian month (in terms of percentage of Ramadan days in that month) as it might impact timing of price movements.

[6] www.islamicfinder.org

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

(i) Ramadan Dummy (**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 Dummy (**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 Intensity Dummy (**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 Dummy (**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.

(Insert Table 4 here)

To illustrate, calculation of these variables are provided in Table 4 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 the rest. As Ramadan started in July, RAMST was 1 for July and 0 for the 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 the remaining 18 Ramadan days, RAMINT for August was 18/31 or 0.58. As RAMSTINT considers 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. The bottom panel of Table 4 illustrates the same for the year 1989.

Each of these variables has its own 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 indicators capture the intensity of Ramadan month(s). However, the interpretation of results for the fractional indicators become difficult as opposed to dummy variables.

4.3 Econometric methodology

In order to empirically quantify the effect of Ramadan on world price of raw sugar, we employ the autoregressive integrated moving average (ARIMA) model and the unobserved components model (UCM). The ARIMA model is developed by Box and Jenkins (1979) and is a popular tool to model nonstationary variables as having both an autoregressive (AR) and a moving average (MA) components. However, during estimation the series needs to be transformed as stationary, usually through first differencing the data. Besides, to account for the possible seasonality in our monthly data, we also incorporate seasonal AR and MA components in the ARIMA models. We rely on the Akaike information criteria in selecting the best ARIMA model for raw sugar price from a set of candidate models. After an ARIMA model is properly specified, we include each Ramadan dummy variables separately as regressor in the regression equation and test for statistical significance of the coefficients on dummy variables. If the model is found to be statistically significant after the inclusion of a Ramadan variable, lead values of that dummy variable is then included in the model to evaluate the 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:

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

In Equation (1), β_1 captures the impact of Ramadan (more specifically, RAMST dummy) on dth difference series of sugar price on the month in which Ramadan starts. Similarly, coefficients β_2 and β_3 represent impact of Ramadan on sugar prices one month and two months prior to the beginning of Ramadan, respectively. Hence, with this model, this study could extract anticipatory impact of Ramadan on global raw sugar prices.

Next, as an alternative to the ARIMA model, we employ the unobserved components model (UCM), which allows to decompose a time series into trend, seasonal, cyclical and idiosyncratic components. Harvey (1989) shows that for i.i.d. disturbances, the reduced form of an UCM is an ARIMA with appropriate restrictions on the parameter space. Since ARIMA models include one aggregate error while UCMs incorporate component disturbances, Pellegrini et al. (2007) argue that given a correct structural formulation the UCMs may lead to the discovery of features of the series that are not apparent in the reduced form ARIMA models. Furthermore, Harvey (2006) stress that UCMs are more effective than conventional ARIMA models when the data is subject to unusual features like missing values, mixed frequencies, outlier, structural breaks, and nonlinear non-Gaussian errors. Yet, there are benefits with both approaches. ARIMA is much better at easily handling complicated short-term dynamics, while UCM is better at decomposing the series into interpretable components.

Formally, an UCM can be written as:

$$y_t = \tau_t + \gamma_t + \psi_t + \epsilon_t, \tag{2}$$

where y_t is the dependent variable which is raw surge price in our data, τ_t is the trend (or permanent) component, γ_t is the seasonal component, ψ_t is the cyclical (or transitory) component, and ϵ_t is the idiosyncratic component. Equation (2) can be augmented by incorporating a vector of exogenous variables including lagged dependent variable. By placing restrictions on τ_t and ϵ_t, Harvey (1989) derived a series of models for trend and idiosyncratic components. For the sake of brevity, we do not elaborate on component models in any detail, a full explanation of the UCMs can be found in Harvey (1989, Chapter 2).

In what follows, we augment Equation (2) with Ramadan variables where we include each dummy variable separately in the UCM regression. As before, if the estimated coefficient on the dummy variable is found to be statistically significant, we then include the lead values of that variable in the regression to gauge the effects 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:

$$y_t \ = \tau_t + \gamma_t + \psi_t + \beta_1 RAMDUM_t + \beta_2 RAMDUM_{t+1} + \beta_3 RAMDUM_{t+2} + \epsilon_t \tag{3}$$

In Equation (3), 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 measure the effects of Ramadan on the same series of sugar prices one month and two months prior to beginning of Ramadan respectively.

5. Empirical results

5.1 Descriptive statistics and unit root tests

Figure 3 reports line plot and histogram (with a kernel density superimposed) of raw sugar price over the entire sample period (from January 1981 to January 2015). The line plot provides a visual evidence of possible unit root in the data. The histogram shows not much evidence of outlying observations in the data, with most of the observations being relatively close to the median. The average value of monthly raw sugar price is around \$252, with the minimum value of \$61 observed in June 1985 and the maximum value of \$654 observed in January 2011. The coefficient of variation is 0.47, indicating that the series is not very volatile. The values of skewness (1.14) and kurtosis (4.10) are not very far away from standard normal distribution. The Ljung-Box Q-test rejects the null hypothesis of zero autocorrelation (p-value 0.00). Additionally, we can also reject the null hypothesis of normality of raw sugar prices (p-value 0.00).

(Insert Figure 3 here)

Next, we apply the DF-GLS unit root test of Elliott et al. (1996) to monthly raw sugar price to determine whether the series contains a unit root. The DF-GLS test is implemented with a constant as a deterministic component in the test regression. Hence, the null hypothesis of the test is that the series contains a unit root (or the price data is nonstationary) against the alternative hypothesis that the series is stationary around a mean. Since the DF-GLS method applies the conventional ADF test to locally detrended data, it is unnecessary to include a time trend in the test regression. Following Ng and Perron (2001), we use the modified AIC to select the optimal lag length in the test regression. Ng and Perron (2001) show that the combination of modified AIC and GLS detrended data yield a desirable size and power properties of the unit root test.

The result of the DF-GLS tau statistic with lags p=1 is -1.895. At the 5% significance level, the critical value of the DF-GLS test is -2.886, suggesting that the null hypothesis of a unit root in raw sugar prices cannot be rejected. This means that shocks to sugar prices have permanent effects and have no tendency to revert to its mean.

As our data are sampled monthly, following convention in the literature we now examine the possibility of seasonal unit root in raw sugar prices. In fact, Ramadan constitutes a good example of moving holidays/seasonality since it is based on the lunar cycles. Hence, if the Ramadan were to have any effect on world raw sugar prices, that effect should change from year to year and thus may affect different months across years.[7] To this end, we apply the most widely used procedure for testing for seasonal unit root of Hylleberg et al. (1990), which is implemented in Eviews 9.0.[8]

The seasonal unit root test is implemented using constant, trend and seasonal dummies as deterministic components in the test regression. The lag length is chosen using the AIC. The critical values and p-values for the test are obtained using 1000 Monte Carlo simulations. According to the Hylleberg et al. (1990) test, there is no evidence of seasonal unit roots at any seasonal frequencies (2, 3, 4, 6, and 12 months per cycle) as we are able to strongly reject the null hypothesis of seasonal unit root. This implies that there is no presence of stochastic seasonality in the data such that the usual $(1 - L)Y_t$ or first differencing filter is adequeate to model raw sugar price. However, there might be deterministic seasonality in the data, which can be addressed by including seasonal dummy variables in a regression model. Next, we proceed to model the data using the ARIMA procedure on the first difference of raw sugar price.

[7] For an empirical application on the effects of moving holidays on retail sales of the United States, see Findley and Soukup (2000).
[8] Nicolas Ronderos, HEGY – Seasonal Unit Root Test, Eviews Add-in, June 25, 2015. http://www.eviews.com/Addins/addins.shtml

5.2 ARIMA Estimation

The results of the ARIMA model are reported in Table 5. These results are chosen based on the minimum AIC value as a selection criteria among candidate models. Column (1) in Table 5 presents the results of baseline ARIMA model, without any Ramadan variable included in the regression equation. The results reveal that the changes in raw sugar price are significantly impacted by movement of prices in the previous two months as well as previous month's error innovations. All estimated coefficients are highly statistically significant at the 1% level. The coefficients on both seasonal AR and MA components confirm the notion that sugar prices follow an annual seasonal pattern.

(Insert Table 5 here)

We then augment the baseline ARIMA model by including each Ramadan indicator, in turn, to quantify its effect on changes in raw sugar price. Results are not statistically significant for the first two indicators: RAMDUM (which assigns a value of 1 for each Gregorian month containing any Ramadan day and zero otherwise) and RAMST (which assigns a value of 1 for only that Gregorian month in which Ramadan starts and zero otherwise).[9] One possible explanation of the finding is that both the dummy variables 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 (basic) dummy variables cannot identify price movements due to Ramadan which is likely to occur on a daily basis and is channeled into monthly average price by tipping monthly average price based on number of Ramadan days in a Gregorian month.

Column (2) in Table 5 presents the impact of Ramadan intensity (RAMINT) on changes in raw sugar price. Recall that RAMINT is calculated by dividing the number of Ramadan days in a Gregorian month by the total number of days in that Gregorian month. Additionally, since Ramadan usually falls across two Gregorian months, we also include one lead of RAMINT in the regression model. The coefficients on both Ramadan indicators are positive and both within a very narrow range of 0.029 to 0.031. This indicates that global raw sugar prices are very sensitive to the demand during the Ramadan. The estimated coefficients are statistically significant at the conventional levels. Although the R^2 is quite low, the F-value is highly significant.

Some simple illustrations will help to interpret the parameter estimates on Ramadan intensity. Suppose Ramadan starts on the first day of June or $RAMINT_{June} = 1$, then raw sugar prices are expected to increase on account of Ramadan by 3.13% in June and 2.93% in the preceding month. The combined impact of Ramadan on sugar prices would be 6.15%, which makes Ramadan an important factor in global sugar prices. However, 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, then $RAMINT_{June}$

[9] To save space, these results are not reported here.

and $RAMINT_{July}$ will be 0.4 and 0.6, respectively. Hence, changes in sugar price due to Ramadan in May, June, and July are expected to be 1.16%, 2.98%, and 1.86%, respectively.[10] This will result in a combines increase of 6% in raw sugar price on account of Ramadan. Overall, average growth due to Ramadan from this model is estimated to be approximately 6.15%. There is a 0.25% 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.

Column (3) in Table 5 reports the parameter estimates for model where RAMSTINT is used as a Ramadan indicator to quantify the effect of Ramadan on raw sugar prices. The main difference between RAMSTINT and RAMINT is that with the former only the intensity of starting month's Ramadan matters (see Table 4 for an illustration). The results show that the estimated coefficients of $RAMSTINT_t$, $RAMSTINT_{t+1}$, and $RAMSTINT_{t+2}$ are all positive and statistically significant. The coefficient of $RAMSTINT_t$, for example, suggests that global raw sugar price increases by roughly 3.5% in the month in which Ramadan begins as a factor of intensity. To illustrate with an example, suppose Ramadan starts on nineteenth of June or $RAMSTINT_{June} = 0.4$, raw sugar prices are expected to increase on account of Ramadan by 1.4% in June, 2.48% in May, and 1.84% in April.[11] These are in line with the results found from the illustration provided for the model with RAMINT.

To summarize, the impact of Ramadan on global raw sugar price is found to be statistically significant for both fractional indicators, RAMINT and RAMSTINT, as both the variables are able to better capture the essence of starting date and duration of Ramadan in a Gregorian month. RAMINT is found to be significant up to one lead while RAMSTINT is 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 Ramadan only on the month in which Ramadan begins. Among the two dummy variables, RAMINT is more representative of Ramadan as it takes into consideration all months with Ramadan days. Hence, coefficients of RAMINT can be used to forecast the growth in sugar prices due to Ramadan with higher precision. 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 to be used to forecast growth, the results are likely to 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.

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[10] The Ramadan effects (RAMINT) for representative months are calculated as follows: (i) May: $0.4 \times .029 = 1.16\%$; (ii) June: $0.4 \times .031 + 0.6 \times 0.029 = 2.98\%$; and (iii) July: $0.6 \times .031 = 1.86\%$.

[11] The Ramadan effects (RAMSTINT) for representative months are calculated as follows: (i) June: $0.4 \times .035 = 1.40\%$; (ii) May: $0.4 \times .062 = 2.48\%$; and (iii) April: $0.4 \times .046 = 1.84\%$.

5.3 Unobserved-Components Model

Table 6 reports the results of the UCM for three different regression specifications. First, we fit a pure UCM model for raw sugar price without any Ramadan indicators as explanatory variables. Unlike the ARIMA model where the dependent variable is transformed in log difference, the UCM model is robust to nonstationary variable. Therefore, we use the original raw data (without any transformation) during the estimation. Besides, to account for seasonality in the data, each UCM regression is augmented with deterministic seasonal dummy variables. As shown in column (1) in Table 6, the estimated central frequency for the cyclical component is 0.399 (λ), which corresponds to an estimated central period of 16,[12] implying that the cycle of global raw sugar price is repeated in every 16 months. The high damping factor (ρ) (with proximity to 1) indicates the degree of persistence in the temporary component of raw sugar price. Another way to interpret persistence is the notion of half-life: $HL = \ln(1/2)/\ln(\rho)$, which is estimated to be around 8, implying that it takes roughly 8 months for half of the shocks to raw sugar price to dissipate over time. The estimated variance of the level component is larger on order of four than that of the stochastic-cycle process, suggesting that movements in global raw sugar price are driven more by permanent (level) components that transitory (cyclical) factors. In addition, both components are statistically significant at the 5% significance level. Another way to interpret this result is that global raw sugar price is nonstationary over the sample period 1981-2014.

(Insert Table 6 here)

Next, we include RAMINT indicators to quantify the impact of Ramadan on global raw sugar price. The results are very similar to that of the baseline UCM model. Both the coefficient on RAMINT_t and RAMINT_{t-1} are positive and statistically significant (column (2) in Table 6). The coefficient on RAMINT_t suggests that global raw sugar price increased by \$9.66 per metric ton due to Ramadan in a month as a factor of intensity of Ramadan in that month. Similarly, the coefficient on RAMINT_{t-1} indicates that global raw sugar price increased by \$8.13 per metric ton due to Ramadan in a month as a factor of intensity of Ramadan in the following month. Like above, the practical implications of these results can be illustrated with simple examples. Suppose Ramadan starts on the first day of June or $RAMINT_{June} = 1$, raw sugar prices are expected to increase on account of Ramadan by \$9.67 per metric ton in June and \$8.12 per metric ton in the preceding month, May. However, if the Ramadan starts, say, on the nineteenth of June, $\text{RAMINT}_{\text{June}}$ and $\text{RAMINT}_{\text{July}}$ will be 0.4 and 0.60 respectively. Hence, global raw sugar price is expected to increase—thanks to Ramadan—by \$3.25, \$8.74, and \$5.79 per metric ton in May, June, and July, respectively (see footnote 6 for further details), resulting in total price increase of \$17.78 per metric ton on account of Ramadan.

The results are very similar if we consider RAMSTINT as an alternative indicator of Ramadan effect. But in this case, the magnitude of the estimated coefficients is relatively higher than those

[12] The conversion formula from central frequency to central period is: $\frac{2\pi}{\lambda} = \frac{2\times 3.1415926}{0.3997095} = 15.719 \cong 16.$

obtained for RAMINT indicators. As mentioned above, between the two Ramadan indicators, RAMINT is a better representative of Ramadan as it takes into consideration all months with Ramadan days.

To summarize, the results of both ARIMA and UCM models are broadly in line with each other in identifying and assessing the impact of Ramadan on global raw sugar prices. The main message that emerges from these models is that Ramadan fasting affects both the price (as well as growth) of global raw sugar, after controlling for trend, seasonal, cyclical, and idiosyncratic factors.

6. Conclusion

There is a general perception that prices of essential food items soar during Ramadan due to increased demand. The purpose of this study was to know whether increased demand for one such food item, sugar, is strong enough to affect global market price of that commodity that are traded in semi-processed form. However, the task proved to be challenging 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. To overcome this difficulty, this paper considers four alternative different Ramadan dummy and fractional indicator variables to detect the impact of Ramadan on price level as well as changes in price level of global raw sugar.

The results based on ARIMA model show that Ramadan contributes to 6% increase in global raw sugar price. As a check of robustness, the model is also estimated using the unobserved components model. According to the UCM, Ramadan contributes to an increase of $17.78 per metric ton in global raw sugar price. To put these results into perspective, in 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 $17.78 per metric ton. Thus, monthly price premium was 250,000 × $17.78 = $4.44 million, according to the findings of 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 that 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. Future research can use our framework to conduct further work to study the impact of Ramadan on other relevant commodities (e.g., edible oil, flour, chickpeas) whose consumption also increases during Ramadan

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Table 1. Geographic distribution of cane and beet sugar production (2013-14, MMT)

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

Source: United States Department of Agriculture Fact Sheets. Figures are in million metric tones.

Table 2. Major raw sugar importing nations and their Muslim populations (2013-14)

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	-	-	-

Source: United States Department of Agriculture Fact Sheets and Pew Research Center.

Table 3. Major raw sugar exporting nations and their Muslim populations (2013-14)

Country	Raw sugar exports (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	-	-	-

Source: United States Department of Agriculture Fact Sheets and Pew Research Center.

Table 4. 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

Table 5. ARIMA estimation

	(1)	(2)	(3)
Constant	0.002	-0.005**	-0.004
	(0.003)	(0.002)	(0.004)
AR(1)	1.214***	1.244***	1.202***
	(0.055)	(0.047)	(0.059)
AR(2)	-0.285***	-0.277***	-0.269***
	(0.050)	(0.046)	(0.055)
MA(1)	-0.953***	-0.999***	-0.959***
	(0.025)	(0.008)	(0.022)
SAR(12)	0.890***	0.928***	0.886***
	(0.028)	(0.029)	(0.026)
SMA(12)	-0.935***	-0.966***	-0.943***
	(0.026)	(0.013)	(0.024)
$RAMINT_t$		0.031**	
		(0.014)	
$RAMINT_{t-1}$		0.029*	
		(0.016)	
$RAMSINT_t$			0.035**
			(0.016)
$RAMSINT_{t-1}$			0.062**
			(0.027)
$RAMSINT_{t-2}$			0.046**
			(0.024)
R-squared	0.124	0.142	0.143
Prob (F-statistic)	0.00	0.00	0.00
Observations	394	393	392

Note: RAMINT and RAMSINT refer to Ramadan Intensity Dummy and Ramadan Start Intensity Dummy, respectively. *, **, and *** refer to statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6. UCM estimation of global raw sugar price (MT)

	(1)	(2)	(3)
Frequency	0.399***	0.399***	0.398***
	(0.044)	(0.043)	(0.042)
Damping	0.916***	0.919***	0.921***
	(0.032)	(0.031)	(0.030)
Var(level)	362.76***	357.09***	355.56***
	(53.01)	(50.85)	(50.57)
Var(cycle)	94.62**	92.07**	93.54**
	(44.52)	(42.31)	(42.11)
$RAMINT_t$		9.66**	
		(3.86)	
$RAMINT_{t-1}$		8.13**	
		(3.86)	
$RAMSINT_t$			11.79**
			(4.82)
$RAMSINT_{t-1}$			11.13**
			(4.82)
Log-likelihood	-1846.35	-1838.48	-1838.65
Observations	409	408	408

Note: All regressions include deterministic seasonal dummy variables. RAMINT and RAMSINT refer to Ramadan Intensity Dummy and Ramadan Start Intensity Dummy, respectively. *, **, and *** refer to statistical significance at the 10%, 5%, and 1% levels, respectively.

Figure 1. (a) Left – geographic distribution of sugar production (2013-14), (b) Right – Type wise sugar trade

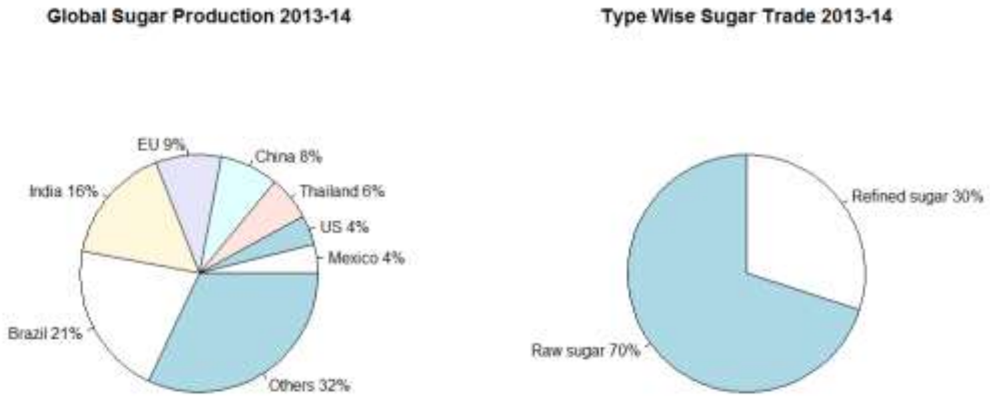

Figure 2. World map of sugar trade dynamics

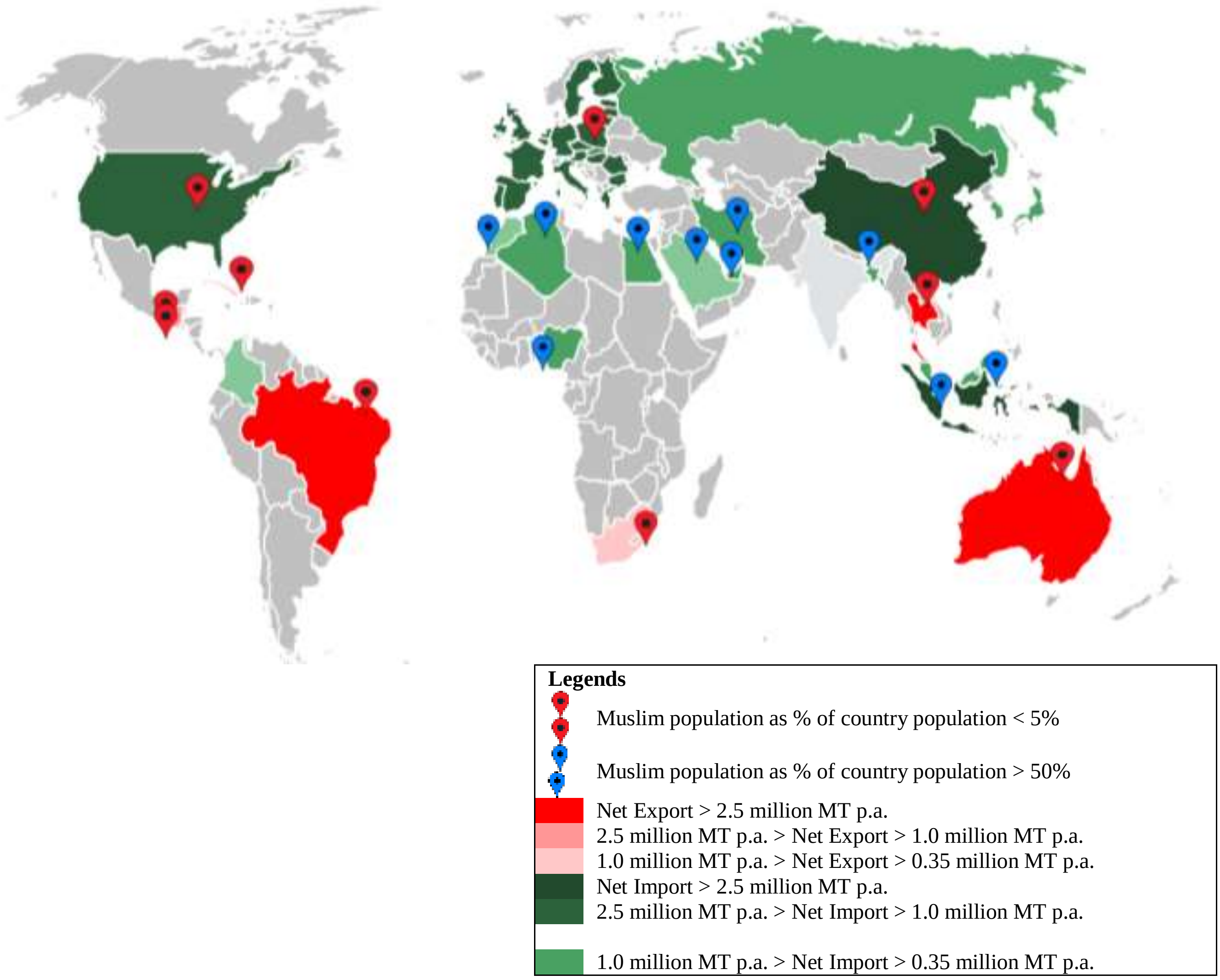

Figure 3. (a) Left – World raw sugar price (USD / MT), (b) Right – Histogram of raw sugar price with Kernel density plot