Influence of weather variability on the orange juice prices

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Abstract

The aim of the paper is to emphasize the dependence between the return of the price of the frozen orange juice (FCOJ) and the variation of the temperature. Here, we considered only a demand approach meaning that we just look at variation in temperature in cities where orange juice has been consumed. Roll (1984) proved that the market of frozen concentrated juice is influence by weather variable like temperature and rainfall. In order to correlation between this two variables, a preliminary work is necessary to extract time series which could be (un)correlated as an economic meaning.

Keywords:

1. Introduction

The concern around climate change brought a lot of focus around the impact of climatic variables on various economic parameters.

The research literature around orange juice markets is very scarce compared to others financial market or even other commodities. Here we try to find a link between orange juice market price and the temperature from cities where there orange juice has been consume.

We can observe that a high volatility affects orange juice price, due to the fear of extreme climatic event which could have an impact on production (supply side). Except this extreme climatic event, we can consider that the impact of temperature variation on orange juice return is due to a demand effect. The price of FCOJ is also influenced by legal and political decisions ad by the biological risk. But,

Carter and Mohapatra (2006) studies the impact of monthly FCOJ imports from Brazil on U.S. prices and find the econometric evidence around
the policies. He argues that FCOJ is a weather market due to the fact that production is regionally concentrated, in the state of Sao Paulo in Brazil and the state of Florida in the United States, accounting for about 85% of global production and both regions are subject to weather shocks. This makes Brazil the world’s largest exporter of orange juice and the EU and the U.S. are the largest importers. M. (2010). Annually, imports from Brazil account for over two-thirds of total U.S. orange juice imports. Brasil export 99% of their global production, while 90% of Florida production is locally
consumed (in the USA). European Union is the one of the biggest importer accounting for around 80% of its consumption. The main players in Orange Juice trading are Citrosuco, Cutrale, Cargill and Louis Dreyfus which hold 90% of the world wide production. The retail market is shared by beverage production and distribution companies like Nielsen, Coca-Cola and PepsiCo. For the beverage retail companies the weather risk is fundamental as the consumption of soft drinks is heavily driven by weather conditions. The annual report of PepsiCo (2010) underlines that the beverage and food divisions are subject to seasonal variations. The beverage sales are higher during the warmer months and certain food sales are higher in the cooler. The influence of weather variable on the FCOJ price through the impact on consumption is one of the main issues explored in this paper.

In his seminal work Roll (1984) showed that weather explains only a small fraction of the observed variability in futures prices. The importance of weather is confirmed by the fact that it is the most frequent topic of stories concerning oranges in the financial press and by the ancillary fact that other topics are associated with even less price variability than is weather. Roll (1984)’s results are mainly based on the influence of the weather through its effects on US domestics supply, given the fact that in the 80’s FCOJ futures prices were linked primarily to the Florida orange production.

Boudoukh et al. (2007) shows that this literature has misinterpreted the data by ignoring the state dependence inherent in the structural relation between FCOJ returns and their fundamentals. In particular, the primary identified fundamental, i.e., the temperature surprise, should theoretically impact FCOJ futures returns only in one state of nature, when this surprise provides the market with new information about the probability and severity of a freeze. He shows that in most circumstances the $R^2$ between FCOJ futures returns and temperature changes is close to zero. However, around freezing temperatures, we estimate $R^2$ on the order of 50% using a relatively simple model. The magnitudes of these $R^2$ are economically important even though freezing temperatures are relatively uncommon.

Recently few papers assessed the weather role as a psychological factor influencing the decisions of traders and investment managers. Daniel et al. (2002) reviews evidence about how psychological biases affect investor behavior and prices. He argues that limited attention and overconfidence cause investor credulity about the strategic incentives of informed market participants. Hirshleifer and Shumway (2003) examines the relationship between weather in the city of a country’s leading stock exchange and daily market
index returns across 26 countries from 1982 to 1997. He underlines that substantial use of weather-based strategies was optimal for a trader with very low transactions costs.

Akhtari (2011) shows that the relationship between weather and market prices exhibits a distinct cyclical pattern over the last 50 years. He assumes that one possible explanation for the existence of such a pattern is the entry of non-rational investors into the market during certain periods which results in the identification of a significant weather effect.

This work enriches the literature on both orange juice and on the link between weather and financial markets. We explore the returns of the FCOJ future prices and the dependency with the temperature variation in the city where the exchanged is based (New York). Intuitively, we can think that when temperatures are higher (resp. lower) than the average seasonal temperature, the consumption of orange juice increase (resp. decrease). Obviously the New York temperature is not the most relevant index for the consumption impact that might affect the market prices. We do not search here an weather index that will account for the real consumption weighted by each regions temperature and number of potential consumers, but mostlikely the impact thorough a behavioral effect. In fact it is well known that the liquidity on futures market is mainly driven by speculators, that use anticipations in the underlying physical market in order to provides with exceeding risk adjusted return. Psychologically FCOJ is apprehended as a weather market and we prove that this apprehension implies a weather linked patter in FCOJ returns. Thus, working on both the demand effect and behavioral influence of weather, we explore dependence between the return of the orange juice price and the variation in temperature. More we show the positive dependency between temperature deviations and FCOJ daily returns as a long term effect.

The paper is structures as follows:

Section 2 In section 2, we will discuss on the econometric methodology which allow us to explain how temperature impact on orange juice return, using the spread of the temperature compare to the past mean for each day.

Section 3 deals with the integration of the Orange juice price in the global commodities markets. Thus we assess the structural link of Orange juice returns with the major commodity index Goldman Sachs Commodity Index GSCI over the last 20 years.
Section 3 Temperatures data set

Section 4

Section 5 presents an alpha providing investment strategy based on long/short positions on the front month Orange Juice future depending on the temperature anticipations.

Section 6 concludes.

2. Methodology

Following the work of Roll (1984) the paper investigates the dependency pattern between the temperature and the price of frozen orange juice. As we show in the previous section the temperature is one of the main driver for the soft drinks consumptions, thereby having a significant impact on the orange juice prices. The impact is either linked to the physical market or thorough the futures markets, used by companies for hedging. In addition the temperature has also a behavioral impact on the trading patterns of financial agents. The structure of the orange juice market is very particular with fundamentals very different from those of other commodities. Market integration and the increasing presence of institutional investors in commodities markets increased the dependency across priorly uncorrelated markets. Thus over the last decade the FCOJ futures returns (Figure 14) showed more dependency with the commodities markets, thereby exhibiting an increased correlation with the GSCI (Goldman Sachs Commodity Index).

In order to explore the structural impact of weather variables upon the FCOJ prices we assess in a first step the relationship between the FCOJ and the GSCI. In a second step the unexplained part of the FCOJ returns are tested against the temperature anomalies.

Let $p_{t,1}$ be the price of FCOJ and $p_{t,2}$ be the GSCI (Goldman Sachs Commodities Index) both rescaled in basis 100, for $t \in \{T_1, ..., T\}$. With the notation $i \in \{1, 2\}$ we compute the log-return as:

$$r_{t,i} = \ln \left( \frac{p_{t,i}}{p_{t-1,i}} \right)$$ (1)

The basic statistics for the two timeseries are showed in Table 1

In order to avoid spurious regression we have to test the stationarity of the time series. We can use augmented Dickey-Fuller test (1979) Results for Dickey Fuller test.
3. Orange juice and commodities markets

In order to capture the market effect, we first compute a simple linear regression, where we regress the GSCI Index return on the Orange Juice Price return:

\[ r_{t,1} = c + \beta_1 r_{t,2} + x_t \]  \hspace{1cm} (2)

Then, in order to cancel this market effect emphasized by the coefficient \( \beta \), we will work on the residuals \( x_t \):

\[ x_t = r_{t,1} - (c + \beta_1 r_{t,2}) \]  \hspace{1cm} (3)

We consider the daily front month futures price of orange juice (FCOJ) and the GSCI Index from \( T_1 = 01/02/1991 \) up to \( T = 01/01/2012 \). Thanks to Zivot-Andrews test (Zivot and Andrews (2002)), we identify structural breaks in the correlation between FCOJ and GSCI. We find four different type of period: between 1994 and 1997, we have a high correlation, for the second period (1997-2001) we observe a decrease in the correlation becoming strongly negative, then between 2001 and 2007, we go back to high correlation. Finally, since 2007, the correlation backs high (80%). Overall, GSCI and FCOJ prices have always a significant correlation. Then, to catch the dependence between orange juice and temperature, it seems reasonable to cancel the market effect on orange juice in order to avoid misspecification.

Now, we work on the logreturn \( r_{t,i} \), and apply the procedure above to find \( x_t \), recalling that regression are made on rolling windows. Figure .15 and .16 shows us the return of Orange Juice price and GSCI Index. Using Dickey-Fuller methodology, we find stationarity for the time series, then we can make regression in a good way.
Figure 2: Orange Juice Price (red), Index GSCI (blue) and Correlation (black), basis 100

<table>
<thead>
<tr>
<th>Period</th>
<th>Volatility FCOJ</th>
<th>Volatility GSCI</th>
<th>Correlation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Month 1991-1994</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Month 1994-1997</td>
<td></td>
<td></td>
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<tr>
<td>Month 1997-2001</td>
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<td></td>
<td></td>
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<tr>
<td>Month 2001-2007</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Month 2007-</td>
<td></td>
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</tbody>
</table>

Table 3: Structural breaks

The beta (market effect) rolling (Figure 3) partially confirms the preceding results concerning the correlation. We can notice that all the turning point are coherent. Figure 4 shows the R squared of the market effect regression and also here we confirms partially the preceding results. Figure 3.6 represents the residuals of the regression, and using Dickey-Fuller, we find stationarity of the time series, then we will work on it.
4. Temperature Analysis

We consider \( d_t \) as the empirical temperature without trend at \( t = \{1, ..., T\} \). In this section, the idea is to propose a methodology to compute the deviation between temperature \( d_t \) and the past daily mean temperature without trend. Indeed, because we look at the demand effect, we assume that the standard evolution of the temperature \((d_t - d_{t-1})\) does not affect the relation ask/demand unlike the deviation.

We consider the New York City temperature, \( d_t \), from \( 1 = 01/01/1973 \) up to \( T = 01/01/2012 \). We state \( n = 9 \) meaning that we consider that 9 days temperature forecasting are reliable as an information available knowing by the market. In all the regression, we consider a rolling windows of 250 days (a business year), meaning that coefficients are suppose to have a sensibility with respect to time.

Figure 6 shows the temperature in New York City, we can saw seasonality in the time series.
4.1. Cleaning the Global Warming effect

In order to clean the trend due to global warming, we make a simple linear regression on $d_t$ based on the least square error such that:

$$\hat{d}_t = \hat{a} + \hat{b} \times t$$  \hspace{1cm} (4)  

and let :

$$y_t = d_t - \hat{d}_t$$  \hspace{1cm} (5)  

Then we get a new temperature sample $\{y_t\}_{t=1,...,T}$ without trend and intercept (Table 4).

Then, using the methodology below, we find the regression emphasizes global warming:

$$d(t) = 16.41 + \underbrace{2.10^{-5}}_{\text{Global warming}} t$$  \hspace{1cm} (6)
Figure 5: Residuals of the regression $x_t$

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>Standard error</th>
<th>Student Test</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\hat{a}$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\hat{b}$</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 4: Long term temperature trend

Then:

$$y_t = d_t - 16.41 + 2.10^{-5}t$$ (7)

Figure .17 shows the temperature in New York City adding the global warming effect.
4.2. Cleaning seasonality

The idea is to find a daily mean temperature. We split the whole sample in two subsamples: \( \{y_1_t\}_{t=1}^{T_1-1} \) and \( \{y_2_t\}_{t=T_1}^{T} \). The first subsample \( \{y_1_t\}_{t=1}^{T_1-1} \) allows to compute the mean of daily temperature without trend for the past \( m \) years. Let \( \bar{y}_j \) be the mean degree of day \( j \in \{T_1, \ldots, T\} \) where:

\[
\bar{y}_j = \frac{1}{m} \sum_{i=1}^{m} y_{j-365i}
\]  

(8)

We define the variation of temperature as deviation between the real temperature for a day \( j \) and \( \bar{y}_j \), thus we let:

\[
\delta_j = y_j - \bar{y}_j
\]

(9)

Using again the procedure we want to extract seasonality effects to deal
with variations with respect to the seasonal mean. The results are the following (on the graph).

Figure 9 represents the daily mean temperature of the first subsample, and we compare to the empirical temperature, then we saw that there exist some large deviations (Figure 3.11). Thus, we can assume that there exist an impact between the spread of daily temperature compare to the past mean temperature of each day. Then, we plot this variation in Figure 3.11, and using Dickey-Fuller, we observe that the time series is stationary. Add a histogram of this residuals, Jarque ber test and Box Ljung at 95 %

<table>
<thead>
<tr>
<th>Statistics</th>
<th>Mean</th>
<th>Variance</th>
<th>Skewness</th>
<th>Kurtosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Temperature</td>
<td></td>
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</table>

Table 5: Statistics Temperature residuals
5. Dependence between Orange Juice without market effect and Temperature variation

In order to see if temperature as an impact on orange juice demand, we consider the linear regression below, for \( n \) fixed, where for \( i \in \{1, \ldots, n\} \), \( j + i \) is the day where we take into account \( \delta_{j+i} \) to explain \( x_j \), the return of orange juice price without market effect.

\[
x_t = c + \sum_{i=1}^{n} \beta_{t,i} \delta_{t-1+i} + \epsilon_t
\]  

(10)

We consider, for \( i \in \{1, 2\} \), that \( p_{t,i} \) is \( \mathcal{F}_t \)-measurable, \( \mathcal{F}_t = \sigma(p_{t,i}, i \in \{1, 2\}, i \leq t) \), where \( \mathcal{F}_t \)-measurable is the the information available on the market at time \( t \).

Thus, \( r_{t,i} \) and \( x_t \) is \( \mathcal{F}_t \)-measurable. And we consider also that, \( \delta_{t+n} \), for \( n \)
fixed is $\mathcal{F}_t$-predictable. Indeed, temperature are forecasted in a finite horizon $n$, thus assuming that forecasting are trustworthy, we can impose that $\delta_{t+n}$ is $\mathcal{F}_t$-predictable.

As we said previously, we consider that the market knows temperature in a 9 days horizon. Thus, we consider:

$$x_t = c + \sum_{i=1}^{9} \beta_{t,i} \delta_{t-1+i} + \epsilon_t$$  \hfill (11)

Could you make a causality test Granger between the two set of innovations? Could you present a table with the coefficients of the equation, standard errors, Student test? And we find the following results:

Concerning the coefficients of the variables (Figure 3.12-13), we can remark that we have a high sensibility in time. And we can emphasize a confusing result: for some given period we can find some negative coefficients meaning that we have a negative relationship between return and variation.
Figure 10: Rolling coefficients for the variables of temperature which could be intuitively spurious.
Figure 11: Rolling coefficients for the variables

Figure 12 shows us the frequencies of the most correlated variation temperature day in rolling window \( t + i \) for \( i \in \{1, ..., 9\} \) with the residuals of the regression of the GSCI return on Orange Juice. An interesting thing is that the higher frequency lies between 7 and 9, meaning that the market considers more "far" future variation than "short". Figure 13 shows the correlation of the most correlated day with residuals \( x_t \). We can notice that correlation is nearly always positive, in mean the correlation is close to 0.10.

6. Investment Strategy

Because we found only positive correlation for the highest correlated variation temperature day, we can try to build a trading strategy using temperature which consists only to buy or short sell frozen concentrated orange juice (no hedging). Our trading strategy follows the work above. The idea is to work with the highest correlated variable. Could you propose few strategies using the same
day forecast, one day ahead, two days ahead. 9 days ahead. and one with the best of the days with highest beta

1. We consider a portfolio which is equal to 1 at $t=1$
2. We observe at $t-1$, the highest correlated variation temperature day $(t-1) + i^*, i^* = \{1, \ldots, 9\}$, and $\beta_{(t-1)i^*}$
3. We build our strategy like that:

$$S = \begin{cases} 
  \text{sign}(\beta_{t-1,i^*}) \text{ if } \delta_{t+i}^* > 0 \\
  (-1) \times \text{sign}(\beta_{t-1,i^*}) \text{ if } \delta_{t+i}^* < 0 
\end{cases}$$  \tag{12}

4. We iterate this strategy until $t = T$, reinvesting all the value of the portfolio $\forall t$.

Could you provide with a Table with a Sharp ratio for each strategy. Could you provide with distribution of the daily P&L.
This trading strategy seems to be interesting even if the return between 2004-2009 are roughly equal to 0 in mean, indeed, this strategy is not affected by bubbles and seems to do not crash. We can notice that the portfolio outperforms orange juice return since 2009.

7. Conclusion

Firstly, the application emphasize the fact that orange juice price return is not always positively correlated with GSCI index, which shows that Orange juice is not a common soft commodities because it does not following the trend generated by the soft commodity market. Secondly, we can extract global warming effect on our temperature data otherwise their is a bias on our estimation process. Then, it is not obvious to have a good explanation for each coefficient of each days of the 9 days horizon due to the high sensitivity of the rolling coefficient. But using the most correlated day we found that the highest frequency came from the 7,8 and 9th day ahead, meaning that
market anticipates future temperature in order to trade today. And we use this approach to compute a trading strategy which could be viewed as a hedge against the orange juice price.

References


Carter, C., Mohapatra, S., 2006. The sunshine state versus brazil: Economics of the orange juice trade.


Figure 1.5: Orange Juice price return
Figure 16: GSCI return

Figure 17: Temperature without trend and intercept