Orange Juice and Weather

By RICHARD ROLL*

Frozen concentrated orange juice is an unusual commodity. It is concentrated not only hydrologically, but also geographically; more than 98 percent of U.S. production takes place in the central Florida region around Orlando.[1] Weather is a major influence on orange juice production and unlike commodities such as corn and oats, which are produced over wide geographical areas, orange juice output is influenced primarily by the weather at a single location. This suggests that frozen concentrated orange juice is a relatively good candidate for a study of the interaction between prices and a truly exogenous determinant of value, the weather.

The relevant weather for OJ production is easy to measure. It is reported accurately and consistently by a well-organized federal agency, the National Weather Service of the Department of Commerce. Forecasts of weather are provided by the same agency and this makes it possible to assess the predictive ability of OJ futures prices against a rather exacting standard.

Geographic concentration is the most important attribute of orange juice for our empirical purposes, but the commodity also possesses other convenient features. It seems unlikely to be sensitive to *non*weather influences on supply and demand. For example, although the commodity is frozen and not very perishable, only a small amount is carried over in inventory from one year to the next. During 1978, for example, inventory declined to about 20 percent of the year's "pack" of new juice.[2]

Data on short-term variability in demand are nonexistent, but there is little reason to suspect much. Orange juice demand might very well respond to price variation in substitutes such as, say, apple juice; but national income and tastes probably do not fluctuate enough to explain a significant part of the *daily* OJ juice movement[3] (which is substantial, as we shall see).

Short-term variations in supply induced by planting decision must also be quite low because of the nature of the product. Oranges grow on trees that require five to fifteen years

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[1] The proportion produced in Florida is now close to 100 percent. Indeed, the annual publication, *Agricultural Statistics*, by the U.S. Department of Agriculture, no longer gives a breakdown by area, reporting the production only for Florida (presumably because production elsewhere is so small). The last breakdown by area was for 1961 (see *Agricultural Statistics*, 1972, Table 324). In 1961, Florida produced 115,866,000 gallons while California and Arizona combined produced 2,369,000 gallons. It may surprise the reader to know that OJ production for frozen concentrate is mainly a Florida industry; many *table* oranges do come from California. This difference between Florida and California oranges is attributable to differences in their sugar and juice content and in their exteriors. Florida oranges are sweeter and make better-tasting juice. California oranges, being less sweet, have a longer shelf life and they also tend to have less juice but more appealing skins. Apparently, there is not as much substitutability as might have been imagined. Actually, Florida produces the bulk of all oranges for both table and juice. In 1972–73, for example, Florida orange production by weight was about 80 percent of the U.S. total. (See *Florida Agricultural Statistics*, Table 3, p. 4.)

[2] See Tables 380 and 382 of *Agricultural Statistics* (1979, pp. 252 and 254).

[3] A rough indication of exogenous shifts in demand due to income and tastes can be obtained from U.S. consumption of all citrus fruit which has hovered closely around 27 pounds per capita for a number of years (see Table 384, p. 255, *Agricultural Statistics*, 1979).

to mature.[4] Thus, any vagaries in farmers' planting decisions are felt much later and do not impact the current year's crop. There might, however, be short-term effects from farming decisions concerning fertilizer use or harvesting methods. These could be influenced by the prices of fertilizer and energy.

It should be emphasized that even unstable conditions of demand and supply would not eliminate the influence of weather, they would simply make that influence harder to measure empirically. The main argument in favor of studying orange juice instead of other commodities is the geographical concentration of OJ production. The fact that nonweather influences seem unlikely to generate much empirical noise is simply an added benefit.

I. Data

A. *Orange Juice Futures*

Futures contracts in frozen concentrated orange juice are traded by the Citrus Associates of the New York Cotton Exchange. There are usually nine contracts outstanding with deliveries (expirations) scheduled every second month, January, March, etc., the most distant delivery being 17 to 18 months from the present. A contract is for 15,000 pounds of orange solids standardized by concentration (termed "degrees Brix") and with minimum "scores" for color, flavor, and defects.[5]

Price data[6] are available for each day since the exchange began OJ trading in the early 1970's. However, the weather data are available only for October 1975 through December 1981, so this constitutes the sample period. There were 1,564 trading days during this period.

As is typical of many commodities, trading volume in OJ futures tends to be concentrated in the near-maturity contracts. The open interest of distant contracts, say 8 to 18 months maturity, is often only 10 percent or less of the open interest in nearer contracts, say from 2 to 6 months maturity. Because of well-known problems in price data from thin markets,[7] the fourth and longer maturities were discarded in the following empirical work.

The nearest-maturity contract was also discarded after a close examination of its price behavior around the maturity date. Volume of trading is quite high in the nearest contract until just a few days before expiration. But in the last several days of the contract's life, open interest declines and price volatility increases substantially. A good example of the ensuing econometric problem involved the contract which matured on November 16, 1977. During the last fifteen minutes before expiration, its price rose from $1.30 to $2.20 per pound, an annualized rate of return of about 1.8 *million* percent. Such events would seem to have little to do with the weather.

This leaves us with two contracts having, respectively, between 2 and 4 months and between 4 and 6 months to maturity; an equally weighted average of the daily returns on these two contracts was chosen as the basic OJ return for use in all subsequent analysis. (Using either contract separately gives virtually identical results. This is to be expected because the correlation between their returns is .97.)

On a contract expiration day, the shorter of these two contracts is dropped and a new contract, previously the fourth-from-the-shortest maturity, starts to be used in construction of the return series. The return on the new contract over the expiration date replaces the return on what has become the shortest maturity contract.[8]

[4]See John McPhee (1967) for a fascinating and entertaining description of orange tree propagation and of the citrus business in general.

[5]The contract quality is specified as follows: "U.S. Grade A with a Brix value of not less than 51° having a Brix value to acid ratio of not less than 13 to 1 nor more than 19.0 to 1 and a minimum score of 94, with the factor of color and flavor each scoring 37 points or higher, and defects at 19 or better..., provided that [OJ] with a Brix value of more than 66° shall be calculated as having 7.278 pounds of solids per gallon" (*Citrus Futures*, undated). "Degrees Brix" is a term used in honor of a nineteenth-century German scientist, Adolf F. W. Brix (McPhee, p. 129).

[6]The price used here is the "settlement" price. This price (which may or may not reflect an actual transaction) is determined by members of the exchange at the close of each day's trading. It is the price reported in the financial press.

[7]See Myron Scholes and Joseph Williams (1977), Elroy Dimson (1979), Marshall Blume and Robert Stambaugh (1983).

TABLE 1—OJ FUTURES DAILY RETURNS BY DAY OF WEEK AND BY SEASON OCTOBER 1975–DECEMBER 1981

Day of Week	Mean Returns[a] Winter[b]	Spring	Summer	Autumn	All Seasons
Monday[c]	−.256	−.321	−.107	.0309	−.158
	(2.58)	(1.84)	(1.52)	(1.84)	(1.96)
Tuesday	.224	.269	.199	−.107	.146
	(2.11)	(1.37)	(.147)	(1.48)	(1.62)
Wednesday	.301	.188	−.102	−.169	.0540
	(1.72)	(1.54)	(1.40)	(1.36)	(1.52)
Thursday	.167	−.219	.113	.153	.0518
	(2.14)	(1.16)	(1.21)	(1.35)'	(1.51)
Friday	.290	.0227	−.125	.242	.108
	(1.98)	(1.55)	(1.63)	(1.53)	(1.68)
Post-Holiday	−.0554	.311	.278	−.0817	.0102
	(1.78)	(1.72)	(1.25)	(1.37)	(1.52)
All Days	.141	−.00741	−.00079	.0253	.0392
	(2.09)	(1.51)	(1.51)	(1.52)	(1.66)

Notes: Levene's test (see Morton Brown and Alan Forsythe, 1974) for equal variances: $F = 3.59$; tail probability ≅ 0. Dummy variable regression:

$$R_t = \underset{(1.86)}{.0886} - \underset{(-2.30)}{.247}\, d_m - \underset{(.328)}{.0784}\, d_h \qquad R^2 = .00211$$

where d_m is 1 on Monday, 0 otherwise, and d_h is 1 on post-holiday day, zero otherwise.

[a]Average of the second- and third-nearest maturity contracts' returns. The mean returns (standard deviations) of the two contracts separately were .0388(1.70) and .0397(1.65), respectively; their correlation was .969. The returns are shown in percent; standard deviations are shown below in parentheses.

[b]Winter is defined as December, January, February, inclusive. Spring, Summer, and Autumn include, respectively, each subsequent three months.

[c]Monday returns are from settlement price Friday to settlement price Monday. Other days are from settlement on previous day. Post-Holiday returns are from settlement on day before holiday to close on day after holiday.

Table 1 gives information about OJ returns over the sample period. The grand mean return is .0392 percent per day, about 10.3 percent per annum. The rather large volatility of these returns is shown by the fact that the standard error of the mean daily return is $1.66/(1563)^{1/2} = .0420$. The standard error is larger than the mean despite the large sample size.

In the body of the table, means and standard deviations are broken down by season and by day of the week. The seasonal pattern shows a larger mean and larger variability during winter. This might have been anticipated on the grounds that colder temperatures and the risk of freezing make investments in orange juice more hazardous during the winter months. A finer breakdown indicates, however, that the larger winter mean OJ return is due to January alone, perhaps for the same reason that equities of small

[8]Specifically, let $R_{T,t}$ be the continuously compounded return on day t of a contract which matures on calendar date T. Say that contracts mature on days $T = 60, 120, 180, 240, 360$. The return series ($R_t^*$) used here is calculated as follows

$$R_t^* = (R_{120,t} + R_{180,t})/2 \qquad t \le 60$$

$$R_t^* = (R_{180,t} + R_{240,t})/2 \qquad 120 \ge t > 60$$

$$R_t^* = (R_{240,t} + R_{360,t})/2 \qquad 180 \ge t > 120,$$

and similarly as times goes on and contracts mature.

firms have larger January returns.[9] (Compare Donald Keim, 1983.)

The day-of-the-week results can be compared to recent work on equity returns (Kenneth French, 1980; Michael Gibbons and Patrick Hess, 1981) which found a significantly negative Monday effect. A similar pattern is observed here in the means.[10] Thus, insofar as mean returns are concerned, OJ futures seem to display annual and weekly seasonals similar to equities.

The intraweek pattern of standard deviations is interesting for what it does *not* display. Since Monday's return covers a three-day period, while other days of the week cover only 24 hours, one might have thought that Monday's variance of returns would be approximately three times as large as the other days. Yet the ratio of Monday's to the average of the other days' variances is only about $(1.96/1.58)^2 = 1.54$. Monday's return has too low a variance. (Note that post-holiday returns, which are always for at least two calendar days, also have too low a variance.) Because of this pattern of variances across days, it must be admitted that weather may not be the only relevant factor for OJ returns after all. If weather alone were moving OJ prices, Monday's return volatility should be larger because weather surprises must occur just as readily on a weekend as on any other day. Nevertheless, since no one has yet discovered just what factors *are* causing day-of-the-week patterns, I shall proceed with an examination of weather, which is at least a known factor.

The OJ futures exchange imposes limits on price movements. These limit rules (see Table 2) prevent the price from moving by more than a certain amount from the previous day's settlement price. When a significant event, such as a freeze in Florida, causes the price to move the limit, the settlement price on that day cannot fully reflect all available information. In other words, limit rules cause a type of market information inefficiency (but not a profit opportunity). This might be inconsequential if limit moves occurred rarely; unfortunately, they are rather common. During the October 1975–December 1981 period, one or both of the two contracts being used here moved the price limit on 160 different trading days, slightly over 10 percent of the trading days in the sample. This implies that about 10 percent of the recorded prices in the sample are known in advance not to reflect all relevant available information.

Limit rules might be suspected as the reason why Monday's variance is too low since these rules would be more frequently applied to limit the three-day weekend/Monday return. It turns out, however, that only 40 of the 160 limit moves in the sample occurred on Monday. This frequency is slightly higher than the frequency of 20 percent which would be expected if all five weekday returns covered the same number of hours. The ratio of Monday's return variance to the average variance on the other days is only 1.75 even when all limit move observations are excluded.

TABLE 2—LIMIT RULES OF THE CITRUS ASSOCIATES OF THE NEW YORK COTTON EXCHANGE AFTER (BEFORE) JANUARY 1, 1979

General Rule: Prices may move no more than 5 (3) cents per pound, \$750 (\$450) per contract, above or below the settlement price of the previous market session.

Increased Limit Rule: When three or more contract months have closed at the limit in the same direction for three successive business days, the limit is raised to 8 (5) cents per pound for those contract months. The limit remains at 8 (5) cents until fewer than three contract months close at the limit in the same direction, then the limit reverts to 5 (3) cents on the next business day.

Current Rule for Near Contract: On the last three days before the near contract's expiration, its limit is 10 cents per pound. If that limit is reached during the market session, trading is suspended on *all* contracts for fifteen minutes. Then another 10 cents is added to or deducted from the near contract's limit and trading recommences. Limit moves and fifteen-minute suspensions can be repeated until the market's close. If this happens on the last day before expiration, trading hours are extended.

B. *Central Florida Weather*

The U.S. Weather Service reporting station in Orlando issues a variety of different weather bulletins. The most relevant information for oranges involve temperature and rainfall; the data[11] used here consist of daily information on these two variables.

Each 24-hour interval is divided into 12-hour daytime and evening periods. The daytime period begins at 7:00 A.M., eastern standard time, and ends at 7:00 P.M. on the same day. The evening period begins at 7:00 P.M. and ends at 7:00 A.M. the following day. For the daytime period, the weather service reports actual rainfall and the *maximum* temperature, while for the evening period, the rainfall and *minimum* temperature are reported.

Three different forecasts of both rainfall and temperature are also provided. They correspond to periods 36 hours, 24 hours, and 12 hours in advance of the 12-hour period to which the forecast applies. For example, say that the forecast is of the maximum temperature on January 5 (which could occur anytime from 7:00 A.M. until 7:00 P.M.). The first forecast is issued about 5:00 A.M. on January 4. (I call this the 36-hour-ahead forecast because it is developed and issued during the third 12-hour period prior to the 12-hour observation period of the actual maximum temperature.) A second forecast applying to the maximum January 5 temperature is issued at 5:00 P.M. on January 4; then, the third forecast is issued at 5:00 A.M. on January 5. This same cycle, but delayed by 12 hours, is used to issue forecasts of the minimum temperature on January 5 (from 7:00 P.M. January 5 until 7:00 A.M. January 6). Rainfall forecasts for the daytime and evening periods are issued along with the temperature forecasts.

Figure 1 gives a timing schematic of the actual weather, the forecasts of weather, and the trading times of orange juice futures. The symbol p_0 indicates the OJ settlement price on a particular calendar date. Note that p_0 is observed during the 12-hour daytime period, well before the evening period begins, and even before the last forecast of evening weather issued by the weather service. For this reason, we might anticipate that surprises in daytime weather would be

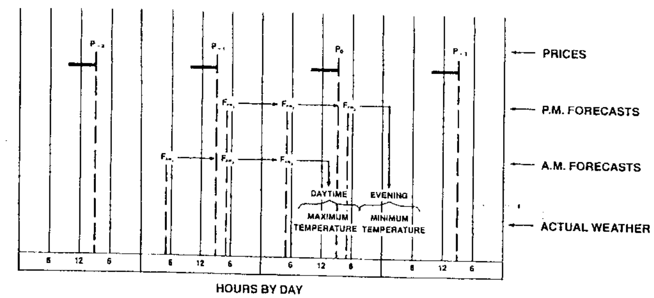

FIGURE 1. TIMING SCHEMATIC OF OJ FUTURES MARKET, WEATHER FORECASTS, AND ACTUAL PERIOD OF WEATHER AT ORLANDO

Note: ▬ indicates market trading hours

[9] January's average daily OJ return was .701 percent (standard error = .238) while all other months combined had an average daily return of −.0193 percent (standard error = .0402).

[10] When compared against other days of the week in an analysis of variance, Monday's return is found to be significantly lower (F-statistic of 5.20 and tail probability of .0228). Monday's mean return is, however, only marginally significantly negative; the standard error of the mean (of −.158) is .114 percent. The dummy variable regression reported at the bottom of the table shows that the Monday effect is significant but that the explained variance is low.

[11] The cooperation of Paul Polger of the National Oceanographic and Atmospheric Administration, who provided these data and provided a detailed explanation, is gratefully acknowledged.

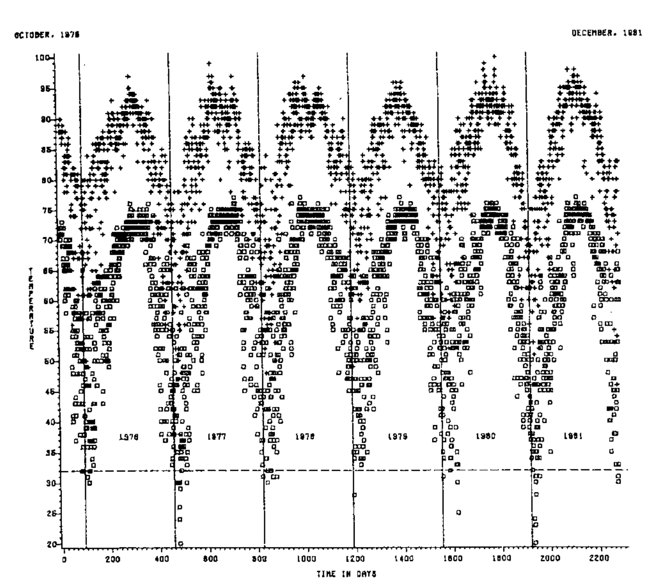

FIGURE 2. MAXIMUM AND MINIMUM DAILY TEMPERATURES AT ORLANDO

associated with price movements of p_{-1} to p_0 while evening weather surprises would influence price changes p_0 to p_{+1}.

The actual daily temperatures are plotted for the sample period in Figure 2 (+ indicates daily maximum and □ indicates minimum). The figure shows that temperatures in central Florida are not only lower during the winter season, they are also more variable. Damage to orange trees occurs if the temperature drops below freezing and stays there for a period of several hours. Thus, the minimum (P.M.) temperature during the winter months would seem to be an important factor influencing the size of the crop and the price of futures.

Table 3 shows that the Weather Service's short-term forecasts of temperature are quite accurate on average and that the forecast improves as its period approaches.[12] The OJ futures market has access to both the 36-hour-ahead and the 24-hour-ahead forecast of that day's P.M. minimum temperature (compare Figure 1). These two forecasts are issued prior to the market's opening. Thus, even aside from whatever private weather forecasts are made by OJ futures traders, two reasonably accurate forecasts of the day's crucial minimum temperature are publicly available during trading hours.

[12]However, there is a curiosity in these forecasts. Note that the A.M. level regressions tend to have slopes ($\hat{b}$) below 1.0. This could be due to errors in the data (rather than in the forecasts). The data were filtered and obvious transcription errors were corrected as detected. Of course, there may still be errors remaining. Errors-in-variables-induced attenuation bias cannot, however, explain why the P.M. forecast intercept is significantly negative. The Theil inequality proportions indicate significant bias in the P.M. forecasts. Note that the low Durbin-Watson statistics on the 36-hour-ahead forecasts are to be expected since there is an intervening actual between this forecast and the actual to which the forecast applies. (See Figure 1.) In other words, the 36-hour-ahead forecast on day t is issued before the forecast error is known for the 36-hour-ahead forecast from day $t-1$. This induces positive dependence in adjacent forecast errors.

TABLE 3—TEMPERATURE FORECAST ACCURACY FOR ORLANDO
OCTOBER 1975–DECEMBER 1981

Hours Forecast is Ahead[a]	Temperature Level $\hat{a}$ (1)	$\hat{b}$ (2)	R^2 (3)	U^m (4)	Temperature Change $\hat{a}$ (1)	$\hat{b}$ (2)	R^2 (3)	U^m (4)
Maximum (A.M.) Temperature Forecast								
36	4.23	.953	.872	1.15	.357	.832	.604	.777
(2,040)	(6.34)	(118.)	(1.53)	(1.60, 97.3)	(3.34)	(55.7)	(1.81)	(5.82, 93.4)
24	4.60	.951	.896	3.24	.667	.912	.663	2.57
(2,049)	(7.79)	(133.)	(1.81)	(2.16, 94.6)	(6.73)	(63.4)	(1.97)	(1.75, 95.7)
12	4.32	.952	.911	1.90	.511	.984	.708	1.55
(2,048)	(7.96)	(145.)	(1.91)	(2.46, 95.6)	(5.56)	(70.3)	(1.90)	(.061, 98.4)
Minimum (P.M.) Temperature Forecast								
36	−1.48	1.01	.884	6.14	−1.62	.771	.495	6.28
(2,048)	(−2.93)	(125.)	(1.42)	(.035, 93.8)	(−9.24)	(44.8)	(1.64)	(7.49, 86.2)
24	−2.71	1.03	.907	8.88	−1.89	.823	.575	8.86
(2,038)	(−5.92)	(141.)	(1.58)	(.532, 90.6)	(−11.7)	(52.5)	(1.64)	(5.35, 85.8)
12	−.852	1.00	.922	6.23	−1.49	.902	.648	5.92
(2,048)	(−2.11)	(155.)	(1.76)	(0.0, 93.8)	(−10.2)	(61.3)	(1.82)	(2.01, 92.1)

Notes: Regression: Actual = $\hat{a} + \hat{b}$ (forecast). The "actual" is the minimum or maximum temperature observed during a 12-hour period. In the "changes" regression, the dependent variable is the actual percentage change from the previous day's corresponding 12-hour period and the explanatory variable is the predicted percentage change.
Cols. (1),(2): t-statistics are shown in parentheses.
Cols. (3): Durbin-Watson statistics are shown in parentheses.
Cols. (4): U^r, U^d are shown in parentheses. The inequality proportions are shown in percent. See Henri Theil (1966, pp. 32–34). U^m = bias, U^r = regression, U^d = disturbance, proportions of mean squared prediction error due to, respectively, bias, deviation of regression slope from 1.0, and residuals.
[a]Sample size is shown in parentheses. There were 2,284 calendar days in the sample. However, the data contain numerous missing observations.

Rainfall is also predicted by the Weather Service, but the form of the forecast is less useful for our purposes than in the case of temperature. The forecast "probability" of rain is always an even decile such as 30 percent and it rarely exceeds 60 percent. Weather service officials have told me that this forecast is intended to convey the chance of *any* measurable precipitation.

Table 4 reports the complete sample distribution of rainfall forecasts and actuals (the latter are provided in categories only). As shown, high forecast probabilities of rain are unusual even though there is measurable rainfall during about 28 percent of the reporting periods. The last column shows that the actual frequency of the rain is not far from the forecast probability. There is not a strong connection between the forecast probability and the *amount* of rain, but the Weather Service forecast is not intended to predict the amount, simply the chance of rain in *any* amount.

As shall be shown in the next section, there is an obvious relation between temperature and the price of OJ futures. The relation between rainfall and price is much more difficult to detect, if it is there at all. Perhaps this is due to temperature being a more important variable for the crop. Perhaps it is due to less useful weather data regarding rainfall.

TABLE 4—FORECAST PROBABILITY OF RAIN VS. ACTUAL RAINFALL BY CATEGORY IN ORLANDO OCTOBER 1975–DECEMBER 1981

Forecast Probability of Rain[a]	Actual Rainfall (inches) 0	.001–.009	.01–.120	.121–.25	.251–.50	.501–1.0	1.01–2.0	2.01–3.0	3.01–4.0	Total	Frequency of Measurable Precipitation[a]
	Frequency (All Forecasts)										
0	3157	79	28	12	3	1	1	0	0	3281	3.78
10	2439	216	100	39	29	14	9	1	0	2847	16.7
20	1401	266	153	51	34	17	11	2	0	1935	27.6
30	904	260	180	83	39	34	17	2	0	1519	40.5
40	420	178	156	68	58	56	35	7	1	979	57.1
50	279	133	177	80	72	59	40	6	5	851	67.2
60	116	70	120	63	48	37	30	0	3	487	76.2
70	18	22	29	22	16	23	7	1	0	138	87.0
80	8	4	6	2	5	12	3	1	0	41	80.5
90	1	1	7	3	0	5	1	0	0	18	94.4
100	0	0	1	0	0	1	1	0	0	3	100.
Total	8743	1229	957	423	304	259	155	20	9	12099	

Note: χ^2 Test of Dependence:

	χ^2	Tail Probability	Forecasts	χ^2	Tail Probability
All Forecasts	4151	$p = 0.0$	36-Hours-Ahead	1185	$p = 0.0$
All A.M. Forecasts	2277	$p = 0.0$	24-Hours-Ahead	1421	$p = 0.0$
All P.M. Forecasts	1559	$p = 0.0$	12-Hours-Ahead	1744	$p = 0.0$

[a]Shown in percent.

II. Empirical Results

A. *Temperature*

Cold weather is bad for orange production. Orange trees cannot withstand freezing temperatures that last for more than a few hours. Florida occasionally has freezing weather and the history of citrus production in the state has been marked by famous freezes. In 1895, almost every orange tree in Florida was killed to the ground on February 8, production declined by 97 percent, and 16 years passed before it recovered to its previous level.[13] Farmers have since learned how to counter freezes with hardier trees, smudge pots, water spraying,[14] and air circulation by large fans; but although the trees are now more likely to survive a freeze, the crop can be severely damaged. Even a mild freeze will prompt the trees to drop significant amounts of fruit.

Figure 3 illustrates the impact of freezing weather on OJ futures prices during the sample period. The actual minimum temperature at Orlando is plotted along with the OJ price level.[15] Freezing level is indicated by the horizontal dashed line.

During this $6\frac{1}{4}$-year period, there were 27 recorded freezing temperatures (below 32°) at Orlando out of 2284 calendar days. However, only four periods registered temperatures below 30°. These occurred on January 17–21, 1977, January 2, 1979, March 2, 1980, January 11–13 and 18, 1981. (See Figure 2 also.) Figure 3 shows that these episodes were accompanied by significant price increases. The January freezes in 1977 and 1981 were particularly harsh in that six successive days and three successive nights,

[13]McPhee (p. 101).

[14]Spraying trees with water during a freeze can protect them under certain conditions. The water, freezing on the trees' leaves and buds, gives off heat in the process of changing from a liquid to a solid.

[15]Thirty cents has been added to the OJ price in order to keep the plots apart. The price is an average of the second and third shortest-maturity contracts. (See Section I.)

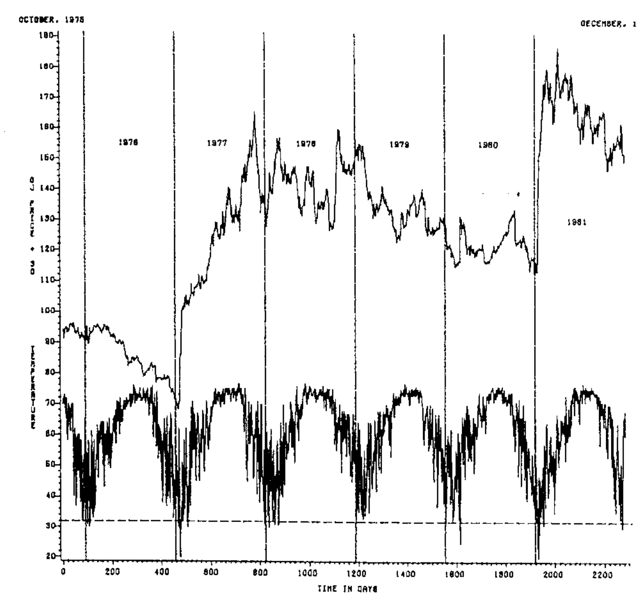

FIGURE 3. OJ FUTURES PRICES AND MINIMUM TEMPERATURES AT ORLANDO

respectively, had freezing temperatures. The most severe freeze during this sample, and the largest accompanying price increase, occurred during the latter period, on January 11, 12, and 13, 1981, when successive daily minimum temperatures were 24°, 23°, and 20°. During the week of January 12–16, OJ futures prices were up the limit on all five trading days.

Market participants realize, of course, that severe freezes are more likely during winter, so the price of OJ futures in the autumn should be high enough to reflect the probability of a freeze during the coming season. Each day thereafter that passes without a freeze should be accompanied by a slight price decline, a relief that winter is one day closer to being over. Also, harvesting of oranges begins in the fall and lasts until early summer, and inventories typically increase over the winter months.

For both of these reasons: freezes that do not occur and inventory build-up; there is a downtrend in futures prices during a typical nonfreeze winter. This pattern can be seen in every year of the sample (Figure 3), except 1977. A general downward movement with small fluctuations is interrupted by occasional sharp price increases sufficient to bring positive returns, on average, to those with long positions.[16] The distribution of returns is very skewed to the right.

If the OJ futures market is an efficient information processor, it should incorporate all publicly available long-term and short-term weather forecasts. Any private forecasts should be incorporated to the extent that traders who are aware of those forecasts are also in command of significant resources. The futures price should, therefore, incorporate the predictable part of weather in advance. Unpredicted weather alone should be

[16]An extensive theoretical discussion of this phenomenon is given by Benoit Mandelbrot (1966).

TABLE 5—OJ FUTURES RETURNS AND TEMPERATURE FORECAST ERRORS WITH AND WITHOUT WEIGHTING, OCTOBER 1975–DECEMBER 1981

Seasons	Hours Forecast is Ahead[a]	Return Lead/Lag (Days) b_{-2}	b_{-1}	b_0	b_{+1}	b_{+2}
Maximum (A.M.) Temperature Forecast						
Unweighted	36	.105	−.00414	−.0463	−.00397	−.322
	(1,391)	(1.31)	(−.0507)	(−.567)	(−.0487)	(−3.91)
Weighted		.102	−.0558	−.0894	−.0600	−.490
		(1.15)	(−.624)	(−1.00)	(−.673)	(−5.37)
Unweighted	24	.0639	−.0497	−.0113	.0379	−.247
	(1,408)	(.872)	(−.673)	(−.154)	(.510)	(−3.36)
Weighted		.0374	−.0615	.0224	.0585	−.379
		(.461)	(−.750)	(.275)	(.714)	(−4.71)
Unweighted	12	.000123	−.0715	−.000467	.0565	−.123
	(1,400)	(.00186)	(−1.07)	(−.00699)	(.838)	(−1.84)
Weighted		−.0851	−.0905	.00691	.0295	−.191
		(−1.17)	(−1.23)	(.0936)	(.398)	(−2.62)
Minimum (P.M.) Temperature Forecast						
Unweighted	36	.0822	−.104	−.154	.136	.0570
	(1,407)	(.632)	(−.791)	(−1.17)	(1.03)	.436
Weighted		.101	−.198	−.379	.133	.0561
		(.664)	(−1.30)	(−2.49)	(.874)	(.374)
Unweighted	24	.0412	−.139	−.352	−.238	−.0404
	(1,399)	(.357)	(−1.20)	(−3.03)	(−2.03)	(−.348)
Weighted		.0593	−.220	−.673	−.544	−.139
		(.442)	(−1.62)	(−4.96)	(−3.99)	(−1.09)
Unweighted	12	−.0698	−.152	−.263	−.0849	.104
	(1,398)	(−.677)	(−1.47)	(−2.52)	(−.807)	(.991)
Weighted		−.0796	−.231	−.549	−.217	.133
		(−.678)	(−1.97)	(−4.62)	(−1.83)	(1.13)

Notes: The regression equation is $\log(A/F)_t = a + b_{-2}R_{t-2} + b_{-1}R_{t-1} + b_0R_t + b_1R_{t+1} + b_2R_{t+2}$, where A is actual temperature, F is forecast temperature and R_t is the return on day t of an equally weighted sum of two futures contracts.

T-statistics are shown in parentheses. All Durbin-Watson statistics were in the range 1.6–1.9. Adjusted R^2s were between 1 and 3 percent.

The weighting scheme is January = 7, February = 6, March = 5, April = 4, May = 3, June = 2, July = 1, August = 2, September = 3, October = 4, November = 5, December = 6.

[a]Sample size is shown in parentheses.

contemporaneously correlated with price movements.

To examine the market's information processing ability, a series of empirical tests were carried out relating surprises in temperature to OJ futures price changes. The temperature forecast error, the percentage difference between the actual temperature and the forecast temperature provided by the National Weather Service, was taken as a measure of surprise. Price change was measured by the average of the daily returns on the second- and the third-shortest maturity contracts (see Section I).

Table 5 presents the first results. The regressions there use the temperature forecast error as the dependent variable. The independent variables are the same day's OJ return plus the returns on two leading and two lagged days. (There is no causality implied or intended by choosing the "dependent" and "independent" variables in this way. Causality actually runs from weather to prices.) Results are given separately in Table 5 for the daily maximum and minimum temperatures, for each of the three available forecasts, and for observations weighted and unweighted by season.

TABLE 6—OJ FUTURES RETURNS AND TEMPERATURE FORECAST ERRORS WITH AGGREGATION OF LIMIT MOVES, OCTOBER 1975–DECEMBER 1981, OBSERVATIONS WEIGHTED BY SEASON

Hours Forecast is Ahead	Return Lag/Lead (Days) b_{-2}	b_{-1}	b_0	b_{+1}	b_{+2}
Maximum (A.M.) Temperature Forecast					
36	.0692	.0671	−.102	.0449	−.0341
(1,257)	(1.46)	(1.25)	(−2.31)	(1.01)	(−.686)
24	.0654	−.00721	−.111	.0234	−.0545
(1,272)	(1.48)	(−.165)	(−2.74)	(.570)	(−1.33)
12	.0518	.0196	−.0121	.0482	−.0368
(1,263)	(1.30)	(.495)	(−.327)	(1.30)	(−.987)
Minimum (P.M.) Temperature Forecast					
36	.0542	−.101	−.236	.167	.0291
(1,272)	(.652)	(−1.23)	(−3.08)	(2.16)	(.377)
24	−.0955	−.00879	−.622	−.0395	−.00346
(1,263)	(−1.32)	(−.122)	(−9.25)	(−.584)	(−.0510)
12	−.00910	.0641	−.143	.0226	.106
(1,262)	(−.138)	(.981)	(−2.37)	(.375)	(1.74)

Notes: For regression and weights, see Table 5. All Durbin-Watson statistics were in the range 1.50–1.95. Adjusted R^2s were between 1 and 4 percent.

Given the preceding discussion, it might seem that the only relevant temperature observations would be for winter evenings (since freezes do not occur at other times); but the futures market deals in anticipations, so forecast errors during the morning hours or even errors during the summer months could conceivably contain meaningful information about the *probability* of a freeze later. The unweighted regressions with A.M. temperature errors do indeed contain some statistical significance. But the P.M. regressions weighted[17] by season are more significant. In the P.M. weighted cases, the contemporaneous OJ return is always statistically significant with the anticipated negative sign.

The P.M. temperature results indicate that the OJ futures price on a given day at the close of trading (2:45 P.M.) is a statistically significant predictor of the forecast *error* of the minimum temperature later that evening (from 7:00 P.M. until 7:00 A.M. the following morning). The price appears to be a slightly better predictor of the error in the forecast issued by the National Weather Service at 5:00 A.M. that same morning than of the errors made by the two other forecasts (5:00 P.M. the previous evening and 5:00 P.M. later the same day).

The futures price is not informationally efficient, however, because several later returns are statistically significant in some regressions. The significant negative coefficient b_{+1} in the P.M. 24-hour ahead case might be consistent with efficiency since trading ceases on day zero before the evening period begins and recommences on day +1 after the evening period ends (see Figure 1). However, the significant two-day later negative coefficients (b_{+2}) for the A.M. temperatures cannot be so easily dismissed.

There is ample a priori reason to suspect some effective informational inefficiency induced by limit move rules. There were 160 limit moves during the sample and prices on these days cannot reflect all information (see Section I). In a first attempt to eliminate this source of inefficiency, limit moves were "aggregated." The results are given in Table 6. For data used in this table, if a particular day registered a limit price move, the "eco-

[17]The weighting scheme is rather arbitrary but is was the only one I tried. January observations, in the middle of winter, receive the highest weight; July observations, in the middle of summer, receive the lowest. January observations are weighted seven times more heavily than July observations, intervening months are weighted linearly between January and July; i.e., February = 6, March = 5, ... June = 2, ... December = 6.

nomic" closing price for that day was assumed to be the price on the next subsequent day which did not have a limit move.

On Tuesday, January 6, 1976, for example, the March contract closed at 59.75 cents per pound. The next day registered a limit move of 3 cents; the reported closing price was 62.75 cents. On Thursday (January 8), which was not a limit move day, the settlement price was 64.4 cents. This was taken as an estimate of what the price would have been the preceding day (January 7) if the exchange had imposed no limits. Thus, the daily return for January 7 used in the regression was $\log_e(64.4/59.75) = 7.5$ percent. There was no observation used for January 8.

Limit moves often occur one after another. In such cases, the price on the first day with no limit move was brought back to the day of the first limit move and all intervening days were discarded.[18]

This procedure obviously overestimates the ability of the market to predict temperatures. Hindsight was used in that no one could know for sure on the first limit move day how many additional days with limit moves would follow. Thus, the results in Table 6 are biased in favor of finding market efficiency, as opposed to those in Table 5 that are biased against finding efficiency because of the exchange's own rules.

In Table 6, there is no longer a significant negative relation of temperature forecast error and later OJ returns. This indicates that the statistical significance of the lagging coefficients found in Table 5 was indeed due to the exchange's limit rules and not to some other possible source of informational inefficiency.[19] Notice that five of the six contemporaneous coefficients are significant and negative.[20]

To estimate the predictive content of OJ prices without resorting to hindsight, while at the same time including the extra information known to market participants that particular days had limit moves, the regressions in Table 7 were computed. A contemporaneous return and a lagged daily return were included as predictors along with slope dummies for limit move days.

Slope dummies are more appropriate than intercept dummies because the size of a limit move changed during the sample period (see Table 2).[21] Before January 1, 1979, the limit was 3 cents while it was 5 cents thereafter. As a consequence, only 39 out of 160 limit move days occurred during 1979–81 even though almost one-half of the sample observations were in those years. Thus, during 1979–81, the settlement price was more informationally efficient and the news that a particular day displayed a limit move constituted more material information. Slope dummies may not perfectly capture the greater importance of limit moves in the last three years of the sample, but at least they do weight these observations more heavily (by approximately 67 percent).

The F-statistics for these regressions indicate that the A.M. forecast errors cannot be predicted by the current and lagged OJ returns plus a limit move slope dummy. This is also true for the P.M. 36-hour ahead forecasts. However, both the 24- and 12-hour ahead forecast errors can be improved by prior OJ returns.

The lack of predictive content of A.M. temperatures is, perhaps, not all that surprising because A.M. temperatures are relevant only to the extent that they predict freezes that evening. Apparently, this link is too weak to be picked up with statistical reliability by OJ returns.

The low predictive content for P.M. temperatures may be a disappointment until one reflects upon the scope of *possible* predictive ability. As shown in Table 3, about 90 percent of the variability in temperature is removed by the National Weather Service's forecast. The OJ prices predict a very small but still significant part of the remaining 10 percent.[22]

B. *Rainfall*

Orange juice prices are replotted in Figure 4 along with the day's total rainfall[23] (in tenths of inches) at Orlando. Unlike the earlier plot of price and temperature (Figure 3), no relation between the two series in Figure 4 is apparent to the naked eye.

The effect of rainfall on the crop is much less obvious than the effect of temperature. Most of the groves in Florida are not irrigated, so a long dry spell might be damag-

TABLE 7—PREDICTIVE MODEL OF TEMPERATURE FORECAST ERRORS USING SLOPE DUMMY VARIABLES FOR LIMIT MOVE DAYS OCTOBER 1975–DECEMBER 1981, WEIGHTING BY SEASONS

Hours Forecast is Ahead	Contemporaneous b_0	Contemporaneous d_0	Lagged One Day b_{-1}	Lagged One Day d_{-1}	F^a
Maximum (A.M.) Temperature Forecast					
36	−.0636	−.0839	.0750	−.348	2.80
(1,391)	(−.495)	(−.475)	(.580)	(−1.91)	
24	.0992	−.213	−.0989	.0422	.897
(1,408)	(.835)	(−1.34)	(−.845)	(.254)	
12	.0198	−.0581	−.0807	−.0859	1.16
(1,400)	(.186)	(−.386)	(−.766)	(−.576)	
Minimum (P.M.) Temperature Forecast					
36	−.672	−.418	.0282	−.276	2.71
(1,407)	(−.329)	(−1.39)	(.131)	(−.898)	
24	.119	−1.55	.184	−.588	23.9
(1,399)	(.616)	(−5.82)	(.961)	(−2.17)	
12	−.119	−.643	.217	−.781	14.7
(1,398)	(−.697)	(−2.78)	(1.30)	(−3.32)	

Notes: The regression equation is $\log(A/F)_t = a + b_0R_t + d_0\delta_tR_t + b_{-1}R_{t-1} + d_{-1}\delta_{t-1}R_{t-1}$, where A is actual temperature, F is forecast temperature, R_t is return on day t, $\delta_t = 1$ if there was a limit move on day t and zero otherwise.

See weighting scheme in Table 5.

T-statistics are shown in parentheses. Durbin-Watsons were in the range 1.59 to 1.99. Adjusted R^2s were in the range .0018 to .038.

[a] F-statistics for the regressors having no effect. The 95 percent fractile is approximately 5.6.

[18] If an up limit was followed by a down limit (or vice versa), day 1 was treated as if the return were zero and day 2 was discarded. The next included observation was then for day 3 (if it was not a limit move). In other words, for any sequence of limit moves followed immediately by another sequence in the opposite direction, the first closing price after reversal was brought back to the first day of the initial sequence. Then the price on the first day with no limit move is brought back to the first day of the second sequence.

[19] The one anomalous coefficient, b_{+1} in the 36-hour P.M. regression, has a positive sign. A single "significant" coefficient such as this is to be expected by chance among so many possibilities.

[20] The reader may notice that the number of observations differs by only one, 1263 to 1262, between the P.M. 24- and 12-hour regressions; yet the t-statistics on the contemporaneous returns are −9.25 and −2.37. Could this be caused by a single observation out of more than 1200? The answer is no. There are actually 138 observations that differed in these two regressions (due to missing data), but almost exactly one-half were missing from each regression. (There were other *common* missing observations.)

[21] Also, a slope dummy preserves the sign of the price change. This could be done, too, with intercept dummies, for example, using +1, 0, and −1 for up limit, normal, and down limit, but the slope dummy accomplishes this feat automatically while allowing for the nonstationarity in the size of a limit move.

[22] It should be noted that all of the contemporaneous slope dummies (d_0) have negative signs. Also, the differences between the last two regressions in the table are intriguing but puzzling. The lagged slope dummy (d_{-1}) is more important for the 12-hour forecast error than for the 24-hour forecast error. Could this be related to the fact that the 12-hour forecast is not issued until after the market closes, while the 24-hour forecast is issued before it opens?

[23] Rainfall data are available only in the categories shown in Table 4. To construct Figure 4, the midpoint of each category was used as an estimate of the actual rainfall in inches. The A.M. and P.M. figures were added to obtain the total precipitation for the day.

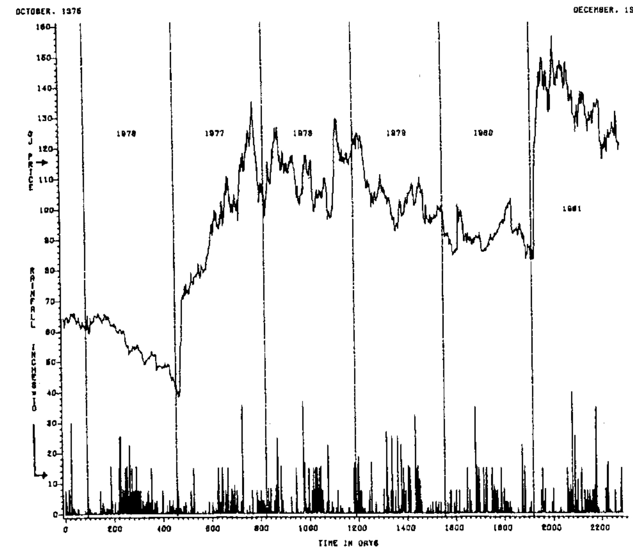

FIGURE 4. OJ FUTURES PRICES AND DAILY RAINFALL AT ORLANDO

ing. On the other hand, the crop could be reduced by extremely heavy rain or by wind damage from tropical storms (that appear in the rainfall time series because they also drop a lot of water).

For example, on November 6, 1981, the *Wall Street Journal* reported higher orange juice prices "...on news of a hurricane off the Florida coast," and on February 18, 1983, prices were purportedly higher due to "...talk of heavy rain." Some confusion about the effect of rainfall is disclosed in the latter story; it included a statement from the Florida Citrus Commission that the orange crop was "unscathed" by the rain. " 'Our oranges are enjoying the weather,' said a department spokesman, 'oranges need a lot of moisture.' " A commodities "analyst" stated that OJ traders drove up prices because they were confused by reports of rain damage to strawberries and tomatoes!

Whether or not the futures market understands the effect of rainfall is rather moot if the empiricist does not understand it well enough to develop a measure of rainfall surprise. With this admission in mind, let us plunge ahead into this turbid subject.

As shown previously in Section II (Table 4), National Weather Service rainfall forecasts are statistically significant but imperfect predictors of actual precipitation. I experimented with several different models of rainfall forecasts (including "probit" and logarithmic models), in order to find the most reliable predictor. It turned out that the largest reduction in variance was obtained with the simplest of regression models,

$$A_t = a + bF_t,$$

where $A_t = 1,\ldots,9$ is the actual rainfall by category on day t and F_t is the forecast "probability of rain." The adjusted R^2 of this regression ranged between .118 and .332 (see Table 8). It is interesting to note that predictive ability for rainfall rises more rapidly as the prediction period approaches than it does in the case of temperature (compare Table 3).

Table 8 contains F-statistics from regressions relating the rainfall forecast error to the contemporaneous and lagged OJ return plus a slope dummy for limit moves, that is, the same purely predictive model as the one for temperature in Table 7. As might have been anticipated in light of the preceding discussion, OJ returns appear to have no significant predictive power for rainfall.[24] There was not a single significant coefficient out of the 24 possible and no F-statistic is significant in any of the six regressions.

TABLE 8—PREDICTIVE MODEL OF RAINFALL FORECAST ERRORS USING SLOPE DUMMY VARIABLES FOR LIMIT MOVE DAYS OCTOBER 1975–DECEMBER 1981, NO WEIGHTING

Hours Forecast is Ahead	Adjusted R^2 of Weather Service Forecast[a]	F-Statistic of OJ Return Predictive Power[b,c]
A.M. Rainfall		
36 (1,371)	.239	.362
24 (1,393)	.265	.410
12 (1,372)	.332	.417
P.M. Rainfall		
36 (1,393)	.118	.388
24 (1,374)	.165	.230
12 (1,384)	.225	.629

[a]Actual rainfall A_t by category, ($A_t = 1,2,\ldots 9$), was predicted by the Weather Service's "probability of rain," F_t, in the simple regression model $A_t = \hat{a} + \hat{b}F_t + \varepsilon_t$; the forecast error ε_t was then used as the dependent variable in another regression model with OJ returns as predictors (see fn. c below).

[b]The 95 percent fractile of the F-statistic is approximately 5.6.

[c]The regression model was $\varepsilon_t = a + b_0 R_t + d_0\delta_t R_t + b_{-1}R_{t-1} + d_{-1}\delta_{t-1}R_{t-1}$, where ε_t is the Weather Service's rainfall prediction error, R_t is the OJ return on day t and δ_t is +1 if day t had a limit move, otherwise zero. No coefficient was significant and coefficients are not reported for reasons of space.

C. *Nonweather Influences on OJ Prices*

The small predictive power for temperature and rainfall seems to imply that influences other than weather are affecting OJ returns. What might they be? In an attempt to find out, news stories in the financial press were systematically examined.

From October 1, 1975 through December 31, 1981 (the sample period of the paper), a total of 91 articles related to oranges appeared in the *Wall Street Journal*; 26 articles reported either results of weather (17) or forecasts of weather (9). Of the 26 weather articles, 25 concerned temperature and 1 concerned rainfall. There were 22 articles disclosing crop forecasts by the U.S. Department of Agriculture, 15 articles reporting price movements with no explanation, 7 articles about international conditions (Canadian and Japanese imports and Brazilian exports), 6 articles about supermarket supplies, and 15 miscellaneous articles. In this last category, the subjects ranged from product quality (4) and new products (1) through antitrust action against the Sunkist cooperative in California (3), to such truly unclassifiable stories as orange rustlers in Florida and advertising contracts with Anita Bryant.

The number and content of weather stories shows that weather is considered important and that rainfall is a relatively minor factor compared to temperature. Among the other topics, *ex post* stories about futures price movements per se and most of the miscellaneous stories could not possibly have been about true influences on earlier OJ price variation. Agricultural crop forecasts, though, would seem likely to have moved prices in some direction. Perhaps international news, reports of supermarket supplies, and antitrust actions are also relevant. The variability of returns was computed for periods ending on the *Wall Street Journal* publication date of such articles and including two prior trading days (to allow for news leakage). This variability is compared in Table 9 to the variability of returns on dates with no orange juice news.

[24]A similar model was computed with a dependent variable defined as the *absolute value* of the rainfall forecast's prediction error. Of course, this would not be a legitimate model from an efficient markets perspective since it would not imply predictive ability of the direction of error (even if it had worked). It is, however, suggested by the possibility that either too much or too little rain is bad for the orange crop. As it turned out, the model had even lower explained variance than the model in Table 8 which preserved the sign of the rainfall prediction error.

TABLE 9—VARIABILITY OF OJ FUTURES RETURNS ON DAYS WITH NEWS ABOUT ORANGE JUICE IN THE *WALL STREET JOURNAL*, OCTOBER 1975–DECEMBER 1981

	No News (1)	Weather (2)	Crop Forecast (3)	Supplies, Antitrust, International (4)	Miscellaneous (5)
Standard Deviation of Returns	1.53 (1361)	2.86 (64)	2.01 (60)	1.97 (34)	1.37 (34)

	Comparisons Among	F-Statistic	Tail Probability
Levene's Test for Equal Variances[a]	Cols. (1)-(5)	22.5	0.0000
	Cols. (1), (3), (4), (5)	9.83	.0018
	Cols. (2), (3), (4).	8.99	.0033

Notes: Standard deviation of returns are shown in percent per day, with sample size shown in parentheses; returns on an equally weighted index of the second and third from the shortest maturity contracts on the day of the news story and on the two preceding trading days.

Sample sizes are smaller than the number of possible days because of overlapping dates among articles. For overlapping dates, returns were assigned hierarchically to category (2) (Weather) first, then to categories (3), (4), and (5), respectively.

[a]See Brown and Forsythe.

The miscellaneous category has a low volatility. It is even lower than the variability of returns on days with no news stories. Volatility of returns is highest during periods when stories about weather were published. During periods associated with stories about crop forecasts, retail supplies, antitrust actions, and international events, volatility is higher than during "no news" periods. However, it is significantly *lower* than during periods with weather-related news stories.

From this evidence, weather remains as the most important identifiable factor influencing OJ returns. Crop forecasts and other newsworthy events have an influence, but their frequency is too small and their impact too slight to explain a material part of the variability in returns left unexplained by weather. As Table 9 shows, there is substantial volatility (a daily standard deviation of returns of 1.53 percent per day), on days that are not associated with *any* story about oranges in the *Wall Street Journal*; and these days constitute about 87 percent of the sample observations.

In addition to events important enough to appear in special orange juice stories in the financial press, other influences on supply and demand might be directly measurable. For instance, stock market returns could measure general economic activity and thus provide a proxy for consumer demand. Canada is the largest customer for U.S. orange juice, so the Canadian dollar/U.S. dollar exchange rate might have a measurable impact on orange juice because it would proxy for Canadian demand. Energy prices could affect short-term supply because they influence the cost of operating farm equipment and the costs of processing and distributing the product. Petroleum is also a direct ingredient of fertilizer and a major component of fertilizer production costs.

Table 10 offers evidence about the influence of these and other variables on OJ price movements. Two regressions were computed. The first involves the OJ return as dependent variable. It shows that cold temperatures indeed cause OJ price movements, but general stock market returns, changes in the Canadian dollar exchange rate, and oil stock returns (a measure of energy prices), have no significant influence.

The second regression in Table 10 uses the squared OJ return as dependent variable. This was done because the objective here is merely to identify sources of price movements in either direction, as opposed to testing the direction of influence of particular variables. Using the squared return permits the inclusion of dummy variables on news story dates without having to decide whether the story should be associated with a positive or negative price change. To illustrate the problem, take the case of crop forecast stories. It would be very hard to know whether a particular forecast by the Department of Agriculture is above or below the previously expected production level without looking at the OJ price movement itself.

TABLE 10—*T*-STATISTICS OF EXPLANATORY FACTORS FOR OJ RETURNS, NO CONSIDERATION OF LIMIT MOVES, DAILY DATA, OCTOBER 1975–DECEMBER 1981

Explanatory Variable	Dependent Variable: OJ Return	Dependent Variable: Squared OJ Return
Max $(32-T_{-1},0)$[a]	5.40	7.99
Max $(32-T_{-0},0)$	3.69	8.09
(Oil Stock Return)$_{-1}$[b]	−.618	.385[g]
(Oil Stock Return)$_0$	.624	2.11[g]
(VW Market Return)$_{-1}$[c]	.525	−1.05[g]
(VW Market Return)$_0$	−.120	−1.53[g]
(Δ CDN exch. Rate)$_{-1}$[d]	−.417	−.759[g]
(Δ CDN exch. Rate)$_0$	.577	.938[g]
Monday[e]	−2.18	4.23
Weather-Related News Story[f]	–	9.36
Crop Forecast News Story[f]	–	3.35
Supplies or Int'l News Story[f]	–	−.563
Miscellaneous News Story[f]	–	−1.47
Multiple Adjusted R^2	.0668	.268
F-Statistic for Regression	13.4	45.0
Durbin-Watson	1.81	1.39
Number of Observations	1,559	1,559

[a]T_t is the minimum temperature at Orlando on day t.

[b]Return on an equally weighted portfolio of oil stocks listed on the NYSE and the AMEX, consisting of up to 45 firms. The sample consisted of all listed oil firms covered in the 1982 *Value Line* service.

[c]Value-weighted index of all NYSE and AMEX stocks.

[d]Percentage change in the Canadian/U.S. dollar exchange rate.

[e]Dummy variable; 1 if Monday, 0 otherwise.

[f]Dummy variable; 1 if news story in this category in the *Wall Street Journal* on day t or $t+1$, zero otherwise.

[g]*T*-statistic for the squared explanatory variable.

In this second regression, cold weather remains very significant and stories related to weather and to crop forecasts are significant as well (the latter result confirms the implications drawn from Table 9). The contemporaneous squared oil stock return is also significant, though its *t*-statistic indicates a much lower level of influence. (This is something of a curiosity in that oil stock returns are unrelated in direction to OJ returns in the first regression.) Finally, notice that only 27 percent of the variability in squared OJ returns is explained by all of these variables combined. Most of the variability remains unexplained.[25]

D. *Supply Shocks vs. Demand Shocks*

Variability in OJ prices could be caused by shifts in demand induced by changes in the prices of substitute products. The prices of apple juice, tomato juice, and soft drinks, inter alia, should influence the demand for orange juice. We have seen already in Table 10 that general consumer demand and the demand of the largest foreign customer (Canada) are not important relative to the supply shocks of weather, energy prices, and crop forecasts. Table 11 provides information about the relative importance of more micro demand shocks.

For firms in the orange juice business and for certain firms producing substitutes, daily stock returns were related, firm by firm, to OJ returns. In each case, the firm's return was regressed on the contemporaneous OJ return, plus two leading and two lagged OJ returns, plus slope dummies for limit move days on the OJ exchange. The *F*-statistics of the regression were examined for significance. In cases where significance was indicated, the coefficients were examined for direction of comovement between equity and OJ returns.

Two basic types of firms were examined. The first type consists of firms whose SIC (standard industrial classification) code on the CRSP tape indicated that it was in some aspect of the orange juice or a related food-processing business. (It had the same SIC

[25]These regressions are obviously misspecified (for example, notice the Durbin-Watson statistics in the second regression). However, they are intended merely to characterize the data, not to test any particular theory, so it seems doubtful that much can be learned by using more sophisticated econometric methods.

TABLE 11—RETURNS ON AGRICULTURE RELATED EQUITIES AND RETURNS ON ORANGE JUICE FUTURES[a]

Company[b]	Line of Business	Relation to OJ Returns[c]
American Agronomics	Owns 9200 acres of Fl. citrus; Produces and markets OJ	None (+)
CHB Foods	Produces and markets pet food, fish, vegetables and fruit	None
Castle & Cooke	Produces and markets pineapples, bananas, fish, broccoli, sugar; Owns Hawaii land	Positive
Consolidated Foods	Manufactures and distributes coffee, candy, sugar, soft drinks	Positive
Curtice-Burns	Processes and packs fruits and vegetables, soft drinks, Mexican food, frozen vegetables	None
Del Monte[d]	Produces fresh bananas and pineapples; processes seafood	None
Di Giorgio	Diversified food processor including citrus, Italian food, sells OJ in Europe; Has some Fl. land	None
Green Giant[d]	Produces canned and frozen vegetables	None
Norton Simon	Produces tomato-based food products, popcorn, cooking oil, liquor	None (−)
Orange-Co. Inc.	Owns 8100 acres of Fl. citrus; Produces and markets OJ	None
J. M. Smucker	Produces jellies, condiments, syrups, and canned fruit drinks	None (−)
Stokeley Van Camp	Produces Gatorade and canned and frozen vegetables	None
Tropicana[d]	Processes citrus juice; Owns a few Fl. groves which are experimental plantings	Negative
United Foods	Produces frozen vegetables	None

[a]Equities with the standard industrial classification of food manufacturers and processors with the same four-digit SIC codes as Di Giorgio, Orange-Co. or Tropicana, and with at least 100 daily return observations in the period October 1975–December 1981.

[b]In addition to these companies, regressions were also run with soft drink equities, Coca-Cola, Dr. Pepper, MEI, Pepsi Cola, and Royal Crown. None of these regressions were significant.

[c]"Positive" or "Negative" indicates that the regression's F-statistic was significant at the 5 percent level. The regression's dependent variable is the equity's return and independent variables are two leading, contemporaneous, and two lagged orange juice futures returns plus corresponding slope dummies for limit moves. A symbol in parentheses indicates a marginally significant regression (at the 10 percent level).

[d]Companies no longer listed on the New York or American Exchange.

code as Di Giorgio, Tropicana, or Orange-Co., three companies known in advance to be in the orange juice business.) All such companies are listed by name in Table 11.

The second type of company produced soft drinks (see Table 11, fn. b). No soft drink producer had a significant relation to orange juice. So changes in OJ demand due to changes in soft drink prices are not revealed in the data.[26]

Turning back to the first type of firm, Table 11 indicates that many were not related to OJ prices. This was true even for such companies as Orange-Co., whose principal business is growing oranges and producing juice. There are several possible explanations for the lack of significant comovement in such a firm. First, consider the impact of supply shocks: an increase in OJ prices due to, say, cold weather, would not affect the firm if the gain in the value of its Florida land were offset by a reduction in the value of its processing and distribution divisions, or if the firm had hedged its own supply by selling OJ futures.

A demand shock, however, should affect the firm unequivocally unless it overhedged in the futures market. For example, an exogenous increase in OJ demand raises the value of its land and, if there are fixed costs, also raises the value of its production and distribution facilities. Thus, the lack of significant comovement between OJ prices and firms such as Orange-Co., Di Giorgio, and American Agronomics, who grow *and* process juice, suggests that most of the OJ price volatility is due to supply shocks instead of demand shocks.

[26]One of these companies, Coca-Cola, also produces orange juice, so a lack of comovement due to shifts in prices of orange juice substitutes might be expected for this particular firm; roughly, what it gains in the soft drink business might be lost in the orange juice business, or vice versa.

This is reinforced by the case of Tropicana, a processor owning virtually no land. It is the only such firm and also the only firm whose equity comoves negatively and significantly with OJ prices. It is conceivable, of course, that this negative relation is induced by a combination of demand shocks and Tropicana purchasing too many futures contracts (more than its own anticipated requirements), but it seems more plausible that the relation is induced directly by supply shocks that squeeze Tropicana's profit margin.

Two companies, Castle & Cooke and Consolidated Foods, produce OJ substitutes and have positive comovement with OJ prices (as is expected if OJ prices move because of supply shocks). One firm, Smucker, buys oranges for jam and has a marginally negative comovement (also explainable by OJ supply shocks). The only anomalous firm is Norton Simon, a producer of substitutes such as tomato juice and liquor (but its negative comovement is of only marginal significance). Some wits have suggested that Norton-Simon actually produces a complement, not a substitute, product. Vodka, one of its biggest sellers, is often consumed with orange juice.

Overall, the evidence in Table 11 supports the view that supply shocks are the principal cause of OJ price movements. Unfortunately, the identity of such shocks remains at least a partial mystery. Weather is important, but measured weather explains only a small fraction of the volatility in OJ prices.

III. Summary and Conclusion

The market price of frozen concentrated orange juice is affected by the weather, particularly by cold temperatures. A statistically significant relation was found between OJ returns and subsequent errors in temperature forecasts issued by the National Weather Service for the central Florida region where most juice oranges are grown. Orange juice prices are much less related to errors in rainfall prediction. Indeed, no significant statistical association was found between these variables.

The OJ futures price is rendered informationally inefficient by the existence of exchange-imposed limits on price movements. This inefficiency manifests itself in the data by allowing temperature surprises to have apparent predictive power for *later* price changes. When limit moves are taken into account, however, temperature has no remaining predictive content.

There is, nevertheless, a puzzle in the OJ futures market. Even though weather is the most obvious and significant influence on the orange crop, weather surprises explain 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.

Possible sources of orange juice demand and supply movements such as substitute product prices, general demand, export demand, and production costs were also examined here. Yet *no* factor was identified that can explain more than a small part of the daily price movement in orange juice futures. There is a large amount of inexplicable price volatility.

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