Do Asset Prices Reflect Fundamentals?
Freshly Squeezed Evidence from the OJ Market

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Abstract

The behavioral finance literature cites the frozen concentrated orange juice (FCOJ) futures market as a prominent example of the failure of prices to reflect fundamentals. In contrast, we show that when theory clearly identifies the fundamental, e.g., at temperatures close to or below freezing, there is a close link between FCOJ prices and that fundamental. Using a simple, theoretically-motivated, nonlinear, state dependent model, we can explain approximately 50% of the return variation on days with freezing temperatures. Moreover, while these observations represent less than 4.5% of the winter sample, they account for two-thirds of the entire winter return variability.

1 Introduction

There has been considerable research that investigates whether asset prices reflect their fundamental values.[1] The general conclusion from this research is that the variability of returns is much greater than that implied by news about assets' fundamentals, i.e., new information about assets' cash flows and expected returns. Specifically, regressions of asset returns on *ex post* information (relevant for pricing the assets) have low explanatory power. Explanations for the empirically documented lack of a relation between asset returns and fundamental news can be found in the growing literature on behavioral finance. For example, DeLong et al. (1990, p.724-726) explicitly cite the above evidence as support for their noise trading model. However, it seems premature to view this evidence as definitive. There is the alternative explanation that the relation between asset prices and fundamental information is incorrectly measured or not measured at all (e.g., omitted variables). We provide evidence supporting this latter view by analyzing a market where existing empirical results have been interpreted as being consistent with market irrationality, and we illustrate how looking at the data in a new way can overturn this interpretation. By necessity, we choose an example where at least some of the relevant fundamental information is easy to identify, and where theory provides strong intuition about the functional form of the relation between fundamentals and returns. The fact that even in this simple setting it is easy to erroneously conclude that fundamentals have little explanatory power for returns is an important warning to researchers who attempt to interpret the evidence in markets where both fundamentals and their relation to prices are more complex.

Our example comes from one of the forerunners of the excess volatility literature–Roll's (1984) seminal paper on frozen concentrate orange juice (FCOJ) futures prices. His paper is unique and clever in that the fundamental information appears to be identifiable and exogenous. A critical aspect of this market is that 95% of the total U.S. processed orange production takes place in central Florida in and around the Orlando area. Thus, the weather in this region should be a primary determinant of supply and thus of futures prices. Roll (1984, p.876) states that "weather is the most identifiable factor influencing FCOJ returns"; however, he finds little explanatory power in

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[1]For example, see Shiller (1981), Meese and Rogoff (1983), Black (1986), Campbell and Shiller (1987), Frankel and Meese (1987), Roll (1988), Cutler et al. (1989), Lev (1989), and Mitchell and Mulherin (1994) to name just a few.

the relation between FCOJ futures prices and weather. In his conclusion, Roll (1984, p.879) states that

> ...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... There is a large amount of inexplicable price volatility.

Weather's apparent lack of explanatory power for FCOJ returns has become a popular citation in the behavioral literature precisely because the fundamental information seems to be so clear. However, it is important to note that at the time when it was published the paper was seen as being supportive of market efficiency in that it also focused on how prices rationally incorporate all the information in weather forecasts. Moreover, while Roll identifies the puzzling lack of explanatory power, he does not argue that this evidence implies market irrationality. Nevertheless, recent surveys of behavioral finance have a different view of the results.

- Shleifer (2000, p.20), in a discussion of empirical challenges to efficient markets, asks "what about the basic proposition that stock prices do not react to non-information? Here again there has been much work, but three types of findings stand out... many sharp moves in stock prices do not appear to accompany significant news... A similar conclusion has been reached in two striking studies by Richard Roll (1984, 1988)...He finds that, although news about weather helps determine future price movements, they account for a relatively small share of these movements."

- Hirshleifer (2001, p.1560) writes, in a section covering mispricing effects, that "little of stock price or orange futures price variability has been explained empirically by relevant public news."

- Ross (2001, p.11) argues that "the regressions themselves have low power even when run with the return as the dependent variable and past returns and weather forecasts as well as contemporaneous weather changes. The R^2 of these regressions is on the order of 1 or 2%. In other words, while there is no evidence that prices do not fully incorporate past information,

we are pretty much at a loss to say why they move at all! If it's not weather - which is obviously the biggest determinant of supply changes - then what could it be?"

- Daniel et al. (2002, p.172) state "only a small fraction of stock prices or orange juice futures prices has been explained by the arrival of relevant public news. Roll (1984) finds that the volatility of OJ futures prices was hard to explain by news about the weather".

In this paper, we show 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. Thus, most temperature surprises should have no impact on prices at all. For example, an unexpected 30 degree drop in temperature from 80 to 50 degrees in late December might affect the tourism industry in Orlando, but it will have no impact on the FCOJ market. In contrast, a much smaller unexpected 5 degree drop from 30 to 25 degrees will have a devastating effect on the Florida orange crop and a large effect on FCOJ prices. Consistent with this intuition, we document 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^2s on the order of 50% using a relatively simple model. The magnitudes of these R^2s are economically important even though freezing temperatures are relatively uncommon. Over one-half of all variation in FCOJ returns occurs in the winter season, and of this variation two-thirds comes from just 4% of the observations. Not surprisingly, these are the days with temperatures close to or below freezing. There is only one conclusion that can be drawn from these results–there is absolutely no puzzle concerning the relation between FCOJ returns and temperature.

Of course, there is also variability in FCOJ futures returns on days not associated with freezes. This is to be expected since prices reflect changes in expectations, e.g., freeze forecasts prior to freezes. In addition, there are many other factors such as changes in demand, releases of production forecasts, and news about Brazilian production that affect prices. Individually these factors may be less important than freeze-related supply shocks, but collectively they will still be important. While not the main focus of the paper, we present evidence that these fundamentals are also associated with significant variability consistent with economic intuition.

The paper is organized as follows. In Section 2, we provide the theory for how FCOJ prices should be related to supply shocks, and, in particular, freezing temperatures. We shed light on why the literature has misinterpreted the existing findings. Section 3 describes the data and the basic stylized facts about temperature, production and FCOJ futures prices. In Section 4, we then test these links more formally and confirm the theoretical relation empirically. In Section 5, we also explore the effect of other factors on FCOJ prices. Section 6 concludes.

2 Theory of FCOJ and Weather

The fundamental economic determinants of prices in the FCOJ market are the forces of demand and supply. While there could be demand shifts either to or away from FCOJ, we do not address this issue due to lack of data. Instead, we focus on supply shocks to the FCOJ market. Long-run shifts in supply should have little impact on prices because storage costs of FCOJ are high, and therefore only a fraction of the juice gets carried forward from year-to-year. In terms of short-run supply, oranges suitable for FCOJ are produced primarily in the U.S. and Brazil; thus, supply shocks in these two countries should affect returns. U.S. production is concentrated in Florida, and shocks to Florida-based production are primarily attributable to freezing temperatures.[2] Since the temperature is clearly exogenous and the single most important fundamental factor, the FCOJ market allows for a clean examination of the relation between asset prices and fundamentals. However, even in this relatively simple setting there are several reasons why a linear model cannot provide a sufficiently rich framework to address this relation.

First, the effect of temperature surprises (the difference between realized temperatures and forecasts) is state dependent. Roll (1984) documents a statistically significant relation between these surprises and returns, but finds R^2s between 1% and 4%. Returns are informationally efficient

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[2]Other weather-related factors such as rainfall should also influence production, but theoretically the effect should be much more difficult to detect and therefore we do not examine it. However, Roll (1984) runs a regression of returns on rainfall forecast errors and finds no discernible relation, although he acknowledges that its effect "on the crop is much less obvious than the effect of temperature" (p.873). For example, either too little or too much rainfall can have a negative impact on OJ production and quality. Moreover, only extended periods of too little or too much rain are likely to have a significant effect, and the magnitude of the effect will depend on the timing relative to the growing season. Thus, the analysis with rainfall is also suspect in terms of interpreting R^2s due to the presence of similar state dependence and nonlinearity as observed with temperature.

in that forecast errors are not related to future returns, which is arguably the focus of his analysis, but the explanatory power is minimal. However, the relation between returns and temperature surprises depends critically on the existing state, i.e., only freezing temperatures produce supply shocks. Thus, theory implies that the temperature surprise is only relevant to the extent it tells us something about the change in the likelihood and magnitude of a freeze. Somewhat paradoxically, therefore, even if returns were not informationally efficient, Roll's analysis would not necessarily pick this up because forecast errors are important only around freezes.

There are two obvious ways to incorporate state dependence. First, a temperature surprise, or change in temperature, will only matter around freezing temperatures. Therefore, we should exclude fall, spring, and summer months that are unlikely to produce freezing weather in Florida, and even in winter months we should condition on low temperatures. Second, the distribution of the freeze-related supply shock will depend on whether there has already been a freeze during the same growing season. For example, if a freeze has a substantial impact on orange production, then a second freeze may have less impact to the extent that the damage is already done. Any analysis of R^2s that does not take these state dependencies into account is flawed.

Second, returns are likely to be nonlinearly related to temperature surprises. 30-31 degree temperatures have relatively mild effects compared to temperatures in the 27-29 degree range. In the latter instance, there is severe damage done to both the leaves and fruit, dramatically affecting production (Attaway (1997)). Thus, at freezing levels, as temperatures drop just a degree or two, the supply shock gets worse at an accelerating rate. The effect of ignoring nonlinearity will be to lower the R^2s in a regression analysis of FCOJ returns and in other cases in which asset returns are linked to surprises in the fundamentals, as long as there is nonlinearity in the relation.

A related problem is that implicit in a regression of asset returns on forecast errors is the assumption that a zero forecast error (i.e., the realization of the expectation) should have no effect. While this holds for a linear relation between prices and fundamentals, it does not hold generally, i.e., if $y = f(x)$, then $E[y] = E[f(x)] \neq f(E[x])$ for most nonlinear functions. Thus, prices will likely move even if the temperature surprise is zero, with the magnitude and direction of the change depending on the ex ante distribution of possible temperatures and the functional relation between temperature and price.

While Roll (1984) does not explicitly address the importance of these issues in his analysis,

he does report results from a regression of returns on a temperature freeze variable and seven other variables including exchange rates, oil prices and stock returns (see Roll (1984), Table 10 in a section entitled "Nonweather Influences on OJ Prices"). Though we take issue with the exact form of the specification, the freeze variable is very close to the relevant fundamental because it captures both state dependence and the realization versus expectation issue. Not surprisingly, the explanatory power of this regression is greater, although the R^2 is still only 6.7%. This low R^2 derives from (i) treating all observations the same (e.g., running the regression across all seasons),[3] (ii) not incorporating temperature forecasts, (iii) ignoring nonlinearities between returns and freeze severity, and (iv) ignoring limit price moves (in contrast to Roll's earlier tables).

3   Data Description and Stylized Facts

We use three primary data series in our empirical analysis: (i) daily minimum temperatures in the Orlando area, (ii) daily FCOJ futures prices, and (iii) monthly USDA production forecasts. The sample period for the temperature and futures data is September 1967 to August 1998, and the production data cover the period October 1967 to July 1997.

With respect to temperature, 25 of the 31 winters experienced one or more nights when the minimum temperature dipped to 32 degrees or below, and many of these years had multiple separate episodes of freezing temperatures. However, not every freeze has material consequences for the orange crop. According to Attaway (1997), there are 11 such freeze seasons during the 1967-1998 sample period, some of which have multiple freezes. In a separate study, Hebert (1993) identifies similar freezes using a different freeze identification methodology. These freezes form the basis for our comparison between freeze and non-freeze years.

To measure production forecasts, we use the United States Department of Agriculture (USDA) crop forecasts for the current season that are provided on a monthly basis from October to July. At the beginning of each month, the USDA sends out surveys to growers who report their expected production as of the first of the month. The production forecasts are compiled from the survey data and released in the second week of the month. The initial forecasts are conditioned on a non-freeze

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[3]Elsewhere in his paper Roll attempts to adjust for the importance of freezes by giving greater weight to observations in winter, but this correction is inadequate to capture the degree of state dependence in the data. The weight on non-winter data must be zero by theory.

season, that is, the USDA does not take into account the possibility of a freeze when forming its forecast. If a freeze occurs, subsequent forecasts take into account the resulting damage and its effect on production.

Finally, to capture movements in FCOJ prices, we collect daily closing prices for the three near maturity FCOJ futures contracts from Bridge/CRB and Datastream.[4] The near maturity contracts are invariably the most liquid, but liquidity diminishes rapidly as the contracts approach expiration. Thus, we usually average the price changes in the two closest to maturity contracts, but we switch out of the closest to maturity contract in the expiration month. Our procedure is complicated by futures price limits imposed by the exchange. Since these limits delay the incorporation of information into prices, we use the standard procedure of aggregating daily returns until the limits no longer bind. For example, if a freeze causes the price to hit the upper limit for four consecutive days, we use the five-day return that includes the first no-limit day as a one-day return.[5] The results are insensitive to the precise mechanism for measuring price changes as long as changes are aggregated over limit days.

To better understand the impact of freezes on prices via their effect on supply, we first examine the production of FCOJ. Table 1A documents the mean and standard deviation of the percentage difference between the October USDA forecast and final production across the 11 freeze years and 19 non-freeze years. The USDA's October forecasts in non-freeze years are nearly unbiased, with only a 1.3% difference on average between the forecast and the realization. More important, there is a considerable reduction in orange production in freeze years, with 12.7% less production than forecast. However, there is also substantial variation in production forecast errors in both freeze and non-freeze years, with standard deviations of 9.1% and 4.1%, respectively. The former is attributable, in part, to the fact that freezes vary in their severity. The latter illustrates that there is considerable production uncertainty even in years when no freeze occurs.

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[4]Futures contracts in frozen concentrated orange juice (FCOJ) have traded on the New York Cotton Exchange since September of 1967. At any given time, there are usually nine to eleven contracts outstanding with expiration schedules every second month (January, March, May, etc.) and with at least two January months listed at all times. The contract is for 15,000 pounds of frozen concentrated orange juice, which represents about 2,400 ninety-pound field boxes of oranges, with specific requirements for color, favor, and defects.

[5]Strictly speaking, this aggregation means that the returns are no longer daily returns in all cases, although we continue to use the terminology "daily returns" in the text. Any additional information that comes out during the limit period will also be reflected in the aggregated return.

Whatever the cause, if the demand curve for oranges is downward sloping and there is no perfect substitute for Florida oranges (at the prevailing price), then the spot price of oranges and FCOJ futures prices should rise in response to a decline in supply. Table 1A provides evidence to this effect. We report the cumulative average return over the winter season (December through February) for freeze and non-freeze years. The average return in freeze years is 12.7% versus - 6.1% in non-freeze years, a difference of almost 19%, consistent with economic intuition. The volatility of cumulative returns is also higher across freeze years than non-freeze years. Interestingly, cumulative return and production forecast error volatility are roughly proportional across the two samples and appear to be related.

If supply shocks caused by freezes are a primary determinant of price movements, then there should be a distinct seasonal pattern to return variability. To verify this intuition, Table 1B reports the volatility of daily FCOJ returns in different seasons. The variance of FCOJ futures returns in winter months is four times that of returns in spring and summer months and three times higher than in the fall season. We also divide the winter season into two separate periods: pre-freeze and post-freeze. The pre-freeze period includes days up to and including the first freeze of the season in a freeze season and all the days in a non-freeze season; the post-freeze period includes the days subsequent to a freeze in a freeze season. Note that the post-freeze period can include a second freeze, and, in fact, two seasons had multiple freezes. The variability in winter months is greater pre-freeze than post-freeze in spite of the fact that freeze frequencies are similar in the two periods. This phenomenon may be due to the fact that the second freeze in a season happened to be less severe in our sample. Alternatively, the second freeze in a season may be less important because damage has already been done to the orange crop. Due to uncertainty surrounding the impact of multiple freezes, the remainder of the paper focuses on the period up to and including the first freeze of the season, i.e., the pre-freeze period.

The fact that winter months produce greater variation in futures prices does not in itself imply a relation between temperature and FCOJ prices. It is the change in the likelihood of a freeze that should move FCOJ futures prices. Table 1C presents the volatility of FCOJ futures prices in winter months conditional on various contemporaneous minimum temperature realizations, namely 35 degrees and below, 36-40 degrees, 41-45 degrees and 46 degrees and above. At or around freezing temperatures (i.e., 35 and below), the daily standard deviation of FCOJ returns is 11.81% compared

to 1.79%, 2.08% and 2.16% for the other temperature buckets. That is, there is over 50 times greater variance in FCOJ futures returns near freezing temperatures than when temperatures are warmer. As a result, in spite of the fact that there are only 77 observations at these low temperatures (5.2% of the winter pre-freeze sample and 1.0% of the total sample), these observations account for almost 70% of the variance in the winter pre-freeze period and over one third of the total variance.[6] This result strongly suggests that freezes have a substantial impact of FCOJ futures prices.

4 FCOJ Prices and Temperature: Empirical Results

As discussed in Section 2, the correct approach to analyzing FCOJ price movements is to project FCOJ returns on the changes in the market's perception of the likelihood and severity of a freeze. While this variable is generally unobservable, there is one exception–when a freeze actually occurs. In this case, the likelihood is probability one and the severity of the freeze maps to the temperature level. If one assumes that the conditional probability of a freeze is constant, then the realization of a freeze and its corresponding temperature level will measure the "freeze surprise" and therefore the supply shock.

Consider the following linear model:

$$R_t = \alpha + \beta W_t + \epsilon_t, \tag{1}$$

where R_t is the close-to-close return and W_t is the contemporaneous realized minimum temperature. We consider this the benchmark model, and it is equivalent to a regression on temperature surprises if there is no temperature forecasting power. The problem with the linear model is that it imposes the same relation between returns and temperature at temperatures both above and below freezing.

A more natural specification given our constant freeze probability assumption is

$$R_t = \alpha + \beta_1 \max[0, \ W^* - W_t] + \beta_2 (\max[0, \ W^* - W_t])^2 + \epsilon_t. \tag{2}$$

FCOJ returns are a second order polynomial in the regressor $Max(0, \ W^* - W_t)$, where W^* represents the critical temperature threshold. In our analysis, we use 32 degrees as this threshold,

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[6]Due to aggregation over limit days, it is slightly deceptive to compare volatilities for samples that contain different numbers of these events. For example, the low temperature sample includes a disproportionate number of these aggregations; therefore, the number of observations somewhat understates the number of underlying days. Nevertheless, the basic result is correct.

although the results are insensitive to any reasonable choice. Since FCOJ prices are not affected by non-freezing temperatures, the regressor is zero in this temperature range by construction. Then, as the temperature gets below a certain level, the regressor rises quickly as the temperature falls. Thus, this model incorporates the nonlinearity implied by the theory of freeze impact.

A more flexible approach is to specify a general functional relation between returns and temperature:

$$R_t = f(W_t) + \epsilon_t. \tag{3}$$

We choose to estimate this functional form using the kernel regression methodology (e.g., see Ullah (1988)) with a bandwidth chosen via cross-validation.

Table 2 presents the estimation results for these specifications using the winter pre-freeze sample. The results are in stark contrast to the current view in the literature of the relation between FCOJ futures prices and temperature. While temperature is statistically significant in the linear model, the R^2s jump from 1.5% for the linear model to as high as 33.3% and 33.6% for the nonlinear model and kernel nonparametric models, respectively. To get a finer partition of the explanatory power of temperature, the table also breaks up the R^2s into different temperature buckets. This partitioning is important because the theory suggests that weather should only matter at low temperatures. The results confirm this theoretical prediction, with the more general models capturing close to 50% of the return variation for temperatures of 35 degrees and below. Above 35 degrees there is almost no relation between temperature and FCOJ futures returns. Of course, the nonlinear model in equation (2) has little or no explanatory power in temperature ranges above the specified temperature threshold by construction. The nonparametric model in equation (3) exhibits the same pattern in explanatory power, but this result is not imposed by the specification and results from the theoretically predicted relation (or lack thereof) between temperature and returns.

This breakdown of R^2s for different temperature ranges requires some discussion because it is not a standard technique. First, note that we are not snooping the data by conditioning on large returns (the dependent variable). Instead, we are conditioning on the temperature (the independent/exogenous variable) that should, in theory, lead to large returns. Thus the R^2s we report are not overstated; they accurately reflect the true explanatory power (asymptotically) in this region of the data. Second, this kind of analysis is only interesting in a nonlinear/state dependent context. In the case of a standard univariate linear regression model with homoscedasticity, the

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R^2s increase as the deviation of the independent variable from its mean increases. In the general nonlinear case this is no longer true, and the R^2s can take on any pattern conditional on the level of the independent variable. In our sample, conditioning on large deviations *above* the mean (i.e., the high temperature region) produces R^2s of zero. The point of the analysis is to confirm that the data are consistent with the theoretical predictions and to examine the magnitude of explained variation in the regions where the fundamental should matter.

The theory also predicts that the relation between FCOJ futures returns and the temperature should be nonlinear. As the temperature drops further below freezing, the impact on production (the duration of the freeze aside) should be more severe. The regression results in Table 2 strongly support the nonlinear nature of the theoretical relation. The coefficient on the nonlinear term in the polynomial regression is highly significant with a t-statistic of approximately 7. Figure 1 graphs the fitted relations implied by the models and shows a highly convex relation between FCOJ returns and freezing temperature levels.

Note that the empirical models above ignore potentially important information by assuming that the actual temperature describes the entire shift in the likelihood of there being a freeze and its magnitude. One issue, highlighted by Roll, is the fact that the market also has access to temperature forecasts. Roll looks at the relation between returns and temperature surprises (the difference between the realized temperature and the forecast), but he does not focus on just the days when freezing temperatures are either predicted or realized, i.e., when they will tell us something about the market's change in perception of the likelihood of a freeze. Theory suggests that this is the only time when forecasts should matter.

The intuition for the role of forecasts is simple. First, forecasts measure the current expectation, though not the entire distribution, of the future temperature and thus contain information about the likelihood and severity of a future freeze. As a result, FCOJ futures returns might move prior to the realization of a freeze if there is a credible forecast of impending freezing temperatures. Second, the realization of the temperature might be a surprise relative to the forecast. For example, when a freeze is forecast but does not materialize, we would expect to see negative returns as prices drop to reflect the fact that a expected negative supply shock did not occur. Neither of these price effects will be picked up in the empirical analysis reported in Table 2, which relates returns to contemporaneous temperatures. The former effect is a relationship between returns and contemporaneous forecasts

of future temperatures. The latter effect is a relationship between returns and contemporaneous temperature surprises, which will be uncorrelated with the realized temperature if the forecast is conditionally unbiased.

In order to investigate the explanatory power of forecasts over and above that of temperature realizations, we regress the residuals from the kernel regression in equation (3) on forecasts of one-day ahead temperatures, and contemporaneous temperature surprises (the realized temperature minus the previous day's forecast). In principle, we could incorporate both forecasts and temperature surprises in the original nonparametric model of FCOJ returns, but the added dimensionality makes this approach uninformative with our sample size. Instead, we consider the following regression and special cases thereof:

$$\epsilon_t = \alpha + \beta_1 \max[0, 32 - F_t(W_{t+1})] + \beta_2 I_{1,t}(32 - F_{t-1}(W_t)) + \beta_3 I_{2,t}(W_t - F_{t-1}(W_t)) + \nu_t , (4)$$

where

$$I_{1,t} = \begin{cases} 1 & \text{if } F_{t-1}(W_t) < 32^o \text{ and } W_t \geq 32^o \\ 0 & \text{otherwise} \end{cases} ,$$

$$I_{2,t} = \begin{cases} 1 & \text{if } F_{t-1}(W_t) < 32^o \text{ and } W_t < 32^o \\ 0 & \text{otherwise} \end{cases} ,$$

and $F_{t-1}(W_t)$ is the forecast on day $t-1$ of the minimum temperature on day t.

This specification incorporates a critical temperature/forecast threshold of 32 degrees as in the nonlinear specification in equation (2). The first term captures the effect on returns of forecasts of future freezing temperatures. The second and third terms capture the effect of the temperature surprise (i.e., the difference between the realized temperature and the forecast) on days for which a freeze was forecast. Because the temperature surprise may have a different effect depending on whether or not a freeze occurs, we separate out these states of the world using the dummy variables $I_{1,t}$ and $I_{2,t}$. When a freeze is forecast and occurs we use the temperature surprise, $W_t - F_{t-1}(W_t)$, since both variables are below 32 degrees. When a freeze is forecast but fails to materialize, we use the truncated value of the temperature surprise, $32 - F_{t-1}(W_t)$, since for orange production it does not matter whether the realized temperature is 35 degrees or 55 degrees.

The minimum temperature forecasts come from the National Weather Service (NWS), and we have data that covers a limited 10-year sample. Importantly for our purposes the NWS has some,

though clearly imperfect, ability to predict freezes during this period, with freezing temperatures occuring 40% of the time that they are predicted. Lagged temperatures have little or no marginal predictive power for freezes; therefore, we do not include them in our analysis.

As reported in Table 3, the results from the regression analysis indicate that, consistent with theory, forecasts have economically and statistically significant incremental explanatory power for returns. The first row of the table reports the results from regressing unexplained returns on the contemporaneous truncated forecast for the winter, pre-freeze sample for which we have forecast data. As expected the coefficient is positive, i.e., forecasts of future freezes cause prices to increase in proportion to the severity of the forecast. As in Table 2, we report the explanatory power over different regions of the data; however, for this specification the relevant variable is the temperature forecast. The overall R^2 of the regression is small, but by construction explanatory power is limited to days with forecasts of freezing temperatures. In this region the R^2 is 17%. Note that these days do not, in general, coincide with low temperature days used in the first analysis. Thus, this model provides explanatory power for observations associated with higher temperatures, which have R^2s close to zero in the original analysis (see Table 2).

The second and third regressions examine the explanatory power of the temperature surprise. On days when a freeze was forecast but did not occur (the second regression), the estimated coefficient on the truncated temperature surprise is negative (albeit not statistically significant), indicating that prices fall if the forecasted freeze does not materialize. However, the explanatory power is minimal, even for days preceded by a forecast of freezing temperatures. In contrast, on days when a freeze was forecast and did materialize (the third regression), the coefficient is larger in magnitude and very significant. Moreover, the temperature surprise explains not only 25% of the variance on days preceded by a forecast of freezing temperatures, but also 7% of the variance over the full winter pre-freeze sample.

The last regression in Table 3 combines the three explanatory variables and examines the R^2 bucketed by temperature. The estimated coefficients change little from the separate regressions because the sets of relevant observations for each explanatory variable are close to disjoint. Of greater note, the regression explains 21% of the variation in the residuals from the original regression for observations with low temperatures (0-35 degrees). In other words, when a freeze occurs the realized temperature explains 48% of the resulting return (see Table 2), and the temperature

surprise explains an additional 11% (i.e., one fifth of the remaining variation).

The R^2s documented above demonstrate that FCOJ futures prices do react significantly, and in the correct direction, to fundamental information about freezes. However, it is still possible that prices are either under- or over-reacting to news. Without a formal structural model relating freezes to supply shocks and thus price movements, it is impossible to know exactly how large returns should be when freezes occur. Nevertheless, the time series properties of returns do provide important information about the potential existence of under- or over-reaction. For example, under-reaction to a news event implies a positive serial correlation in returns (at some horizon) as prices eventually reflect the fundamental information. Similarly, over-reaction implies negative serial correlation in returns. We do not find any evidence of reversals or continuations. As reported in Table 1B, the autocorrelations at lags 2 through 20 for daily returns are generally small and insignificant,[7] and average returns (measured over various intervals) after large price moves tend to be small regardless of the direction of the original move.[8]

5   What's Missing?

Weather in Florida is not the only factor affecting the demand and supply of orange juice–or that should affect FCOJ prices. To explore this issue, we examine price volatility associated with days on which the Wall Street Journal (WSJ) has an article about orange juice futures during the period January 1, 1984 to November 11, 1998, in the spirit of Roll (1984). We classify each article into one of six categories based on the content, i.e., news about (i) weather, (ii) production, (iii) Brazil, (iv) demand, (v) technical factors, and (vi) miscellaneous. In all cases we look at the return on the day prior to the day on which the story appears in the WSJ. While this scheme is not perfect, it appears to pick up the relevant return in many cases based on a examination of a representative sample. As with our earlier analysis, we aggregate returns over days on which the futures price hits its limit. Thus, for stories with large price implications there is not a perfect correspondence between return observations and days.

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[7]The small but positive first order autocorrelation is due to nonsynchronous trading in the two contracts whose returns we average.

[8]For brevity, we do not report the results from this analysis. However, the complete analysis and additional analyses referred to in the next section appear in Boudoukh et al. (2003).

Of the 381 relevant articles during our sample period, which are summarized in Table 4, 118 (31%) are about the weather in Florida. The standard deviation of returns on the days with weather articles, 3.298%, is only slightly higher than the standard deviation on days with other articles about orange juice, 3.155%. Both estimates are about twice the estimated volatility for days without WSJ articles, 1.550%. Of course, the higher volatility on days with WSJ articles does not prove that it is news causing price changes. Perhaps the WSJ searches for stories to report during periods of high volatility, so the causality is reversed, i.e., volatility causes news articles. However, the nature of the stories suggests this is not the case. For example, consider non-weather stories related to production. The volatility associated with these stories, 3.853%, is higher than the volatility associated with weather stories. Moreover, many of these stories concern the USDA's forecasts of orange production. Since the dates on which these monthly forecasts are released are predetermined, stories about them (or, more precisely, the forecasts themselves) are the cause, not the result, of price volatility.

Volatility is particularly high when the USDA announces its October forecast, the first official government forecast of production for the forthcoming season. Although there are about 240 observations a year, the announcement day in October accounts for more than 7% of the annual return variance (see Table 1B).[9] The government crop forecasts later in the growing season are less important, but the variance on these days is still up to 3 to 4 times that of a normal day.[10] Interestingly, this information about U.S. production does not generally come out in the winter months, which helps explain other seasonal volatility. Table 4 documents that 70% of the stories about production appear in non-winter months in contrast to a mere 21% of weather related stories in these seasons.

So far our analysis has focused only on the production of oranges in Florida, but FCOJ prices are determined by global supply and demand. And supply and demand are global. Since 1984

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[9]Note that is not possible to impute this variance decomposition directly from the results in Table 4 for three primary reasons: (1) the WSJ articles do not encompass all the relevant events due to selective reporting, (2) the timing of the article relative to the associated return is not always consistent with the assumption underlying the analysis, and (3) the sample period for our WSJ analysis is shorter than the full sample used in Table 1.

[10]The direction of these FCOJ futures return movements are also consistent with theory. For example, Bauer and Orazem (1994) look at the relation between production surprises and FCOJ futures returns and find a strong negative correlation.

Brazil has been the largest producer of orange juice in the world. Moreover, Brazilian FCOJ is a good substitute for U.S. FCOJ. The data suggest that when the U.S. suffers negative supply shocks Brazilian FCOJ replaces about 80% of the lost production. From 1977-1996, in years in which U.S production falls, the average decline is 23.9 million gallons from the previous year, and these years correspond to an average increase in U.S. imports from Brazil of 19.3 million gallons. Thus, we might expect news about Brazil to affect prices in the U.S., and it does. The volatility is 2.951% on the days associated with the 58 WSJ articles about Brazil. Again, the majority (74%) of these articles appear in non-winter months.

Although much less prevalent than supply related stories, there are also WSJ articles about the demand side of the FCOJ market. Again these stories are associated with high volatility in the FCOJ futures market, and their seasonal distribution is even more skewed away from winter months. Overall, the analysis of WSJ articles provides further evidence that much of the variation in prices is driven by news about supply and demand.

6   Concluding Remarks

This paper reexamines the literature's view that FCOJ futures returns are not explained by fundamentals, particularly temperature. We show that when theory dictates that temperature should matter it does and when it should have no effect, it does not. Of course, FCOJ returns also exhibit volatility during times other than those associated with freezing temperatures. However, the futures convenience yield, market microstructure effects, long-run news about weather, news about orange quality, news about Brazil (e.g., production, import quotas, tariffs), production forecasts, and short-run demand shifts, among many other factors, can all have important effects on prices. If an econometrician could build the correct structural model and accurately measure the fundamentals, the vast majority of variability might be explained, just as we have done here with respect to temperature. However, this is a difficult, if not impossible, task. Even in the comparatively simple setting of the FCOJ market, the relation between returns and temperature is nonlinear, multi-dimensional and state and path dependent. In other markets, identifying the fundamentals and modeling their relation to prices is likely to be even more difficult.

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Panel A: Production and Returns					
		Production Change (%)		Cumulative Return (%)	
Type	No. Years	Mean	SD	Mean	SD
Freeze	11	-12.7	9.1	12.7	28.7
Non-Freeze	19	1.3	4.1	-6.1	14.4

Panel B: Seasonal Returns (%)								
Season		Obs	Mean	SD	AC(1)	AC(2-20)	% Obs	% Var
All		7543	0.033	2.105	0.018	0.001	100.0	100.0
Winter		1772	0.009	3.160	0.029	0.001	23.5	52.9
	Pre-Freeze	1475	0.015	3.305	0.005	-0.005	19.6	48.2
	Post-Freeze	297	-0.020	2.315	0.055	0.008	3.9	4.8
Fall		1878	0.068	1.847	-0.016	0.005	24.9	19.2
	Oct. USDA Ann.	30	-0.837	9.258	NA	NA	0.4	7.5
Spring		1939	0.059	1.555	0.030	-0.006	25.7	14.0
Summer		1954	-0.002	1.539	0.009	-0.007	25.9	13.9

Panel C: Temperature-Sorted Returns (%)– Winter Pre-Freeze Sample					
From-To	Obs	Mean	SD	% Obs	% Var
0-99	1475	0.015	3.305	100.0	100.0
0-35	77	2.721	11.815	5.2	69.4
36-40	134	-0.311	2.163	9.1	4.0
41-45	198	-0.273	2.081	13.4	5.4
46-99	1066	-0.086	1.790	72.3	21.3

Table 1: FCOJ Futures Returns

Panel A reports the mean and standard deviation of the percentage difference between the October USDA forecast and final production and of the cumulative winter-season FCOJ futures return across freeze and non-freeze years. Panel B reports means, standard deviations and autocorrelations (at lag 1 and the average over lags 2 to 20) of daily FCOJ futures returns in percent for different seasons, and the percentage of the variance of returns accounted for by the observations in each season. Winter season is defined as December, January and February; Spring is March, April and May; Summer is June, July and August; and Fall is September, October and November. The pre-freeze period includes days up to and including the first freeze of the season, if a freeze occurs, and all the days in the season otherwise. Oct. USDA Ann. is the sample of days coinciding with the annual initial USDA production forecast announcement. Panel C presents the same statistics (with the exception of autocorrelations) for the winter pre-freeze sample for different temperature ranges. Temperatures are the minimum temperature for the Orlando region, contemporaneous with the close-to-close futures return. The data period is September 1967 to August 1998 except for results using USDA production data, which end in August 1997.

Model	α	β	β_1	β_2	R^2 0-99	0-35	36-40	41-45	46-99
Linear	2.187	-0.042			0.015	0.043	-0.137	-0.067	-0.029
	(0.474)	(0.009)							
Nonlinear	-0.135		0.098	0.202	0.333	0.478	0.016	0.015	0.002
	(0.071)		(0.339)	(0.031)					
Kernel					0.336	0.480	0.024	0.019	0.005

Table 2: Model Estimates and R^2s

The table reports estimation results for the three models of FCOJ futures returns (in percent per day) as a function of contemporaneous minimum temperatures (equations (1)-(3)). The sample is the winter, pre-freeze period from September 1967 to August 1998. The winter, pre-freeze period includes days in December, January and February up to and including the first freeze of the season, if a freeze occurs, and all the days in the season otherwise. The models are estimated using all the observations in the sample, but the R^2s are also reported for subsets of the observations grouped by temperature. For example, 0-99 is the standard model R^2 for the full sample, and 0-35 is the R^2 for those observations with temperatures less than or equal to 35 degrees calculated based on the parameter estimates from the full sample. Standard errors are in parentheses under the corresponding coefficient estimates.

α	β_1	β_2	β_3	Bucket	R^2				
					0-99	0-35	36-40	41-45	46-99
-0.09	0.24			$F_t(W_{t+1})$	0.01	0.17	0.00	0.00	0.00
(0.11)	(0.15)								
-0.06		-0.31		$F_{t-1}(W_t)$	0.00	0.01	0.00	0.00	0.00
(0.11)		(0.39)							
-0.10			-1.65	$F_{t-1}(W_t)$	0.07	0.25	0.01	0.00	0.00
(0.11)			(0.29)						
-0.11	0.25	-0.35	-1.65	W_t	0.08	0.21	-0.03	0.02	0.01
(0.11)	(0.14)	(0.37)	(0.29)						

Table 3: Error Analysis using Temperature Forecasts

The table reports estimation results from error analysis regressions, where the errors are from a winter pre-freeze kernel regression of returns on contemporaneous minimum temperatures. The model, given in equation (4), has truncated contemporaneous forecasts and truncated contemporaneous temperature surprises (the temperature less the prior day's forecast) as the explanatory variables. The R^2s are calculated within buckets, sorted by the forecast or the temperature, as denoted in column "Bucket". Data are for days where forecasts are available (443 observations). Standard errors are in parentheses under the corresponding coefficient estimates.

	Sample Size	Mean (%)	SD (%)	Winter (%)	Fall (%)	Spring (%)	Summer (%)
News Day	381	0.214	3.197	40.9	23.1	19.4	16.5
No News Day	3302	-0.008	1.550				
Weather	118	0.320	3.298	78.8	12.7	5.9	2.5
Production	102	-0.034	3.853	30.4	35.3	24.5	9.8
Brazil	58	0.554	2.951	25.9	17.2	29.3	27.6
Demand	21	0.065	2.904	14.3	14.3	38.1	33.3
Technical	49	0.307	2.804	18.4	26.5	28.6	26.5
Miscellaneous	33	-0.042	1.267	15.2	33.3	9.1	42.4

Table 4: FCOJ Futures Returns and WSJ Events

The table reports the sample size, mean, and standard deviation of daily FCOJ futures returns on the day prior to an article appearing in the Wall Street Journal about FCOJ futures in the period January 1, 1984 to November 11, 1998. It also shows the seasonal frequency of these articles. Based on the content of the article, the stories are classified into one of six categories: (i) weather, (ii) production, (iii) Brazil, (iv) demand, (v) technical, or (vi) miscellaneous.
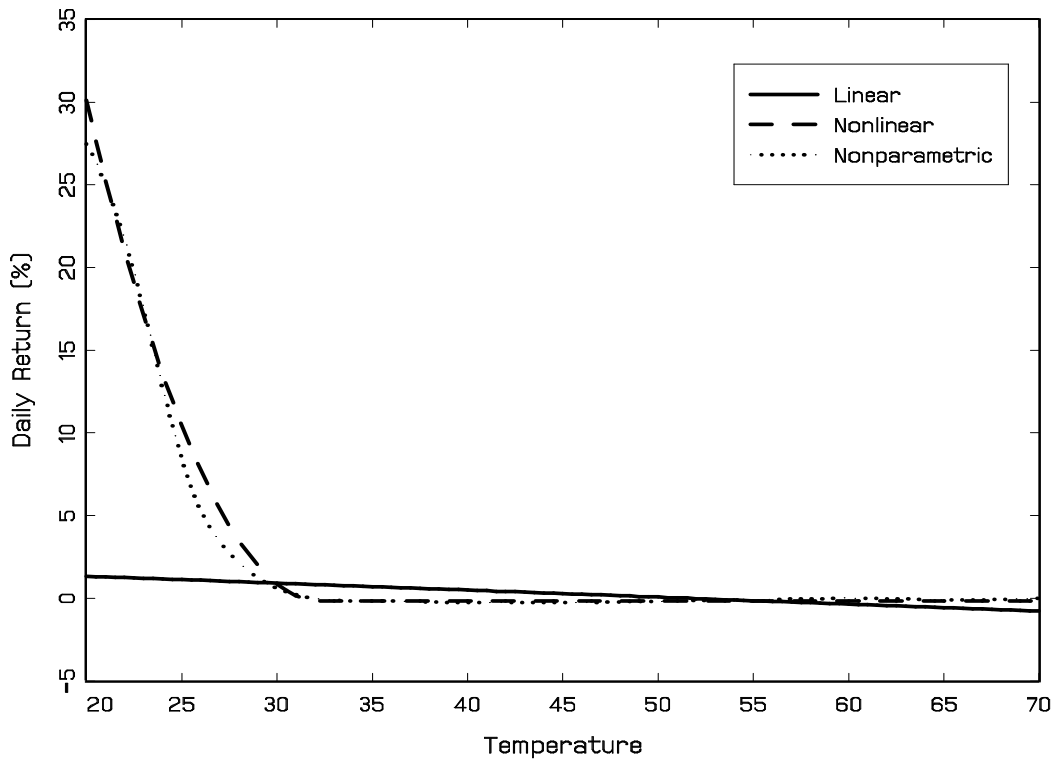
Figure 1: Fitted Returns

The figure shows fitted daily returns versus contemporaneous realized temperature for the three models in equations (1)-(3). The models are estimated using the pre-freeze, winter sample over the period September 1967 to August 1998. See Table 2 for the regression results.