NEW ZEALAND INSTITUTE FOR THE STUDY OF COMPETITION AND REGULATION INC.

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21 December 2002

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Abstract

In this paper we develop a new approach to understanding the behavior of high frequency electricity spot prices. It treats electricity delivered at different times of the day as different commodities, while recognizing that these commodities may be traded on a small number of intra-day markets. We first present a detailed analysis of the high frequency dynamics of prices at a key New Zealand node. Our analysis, which includes the use of a periodic autoregression model, supports the treating of electricity as multiple commodities and also reveals intrinsic correlation properties that indicate the existence of distinct intra-day markets. Conventional models cannot adequately capture properties that have important implications for derivative pricing and real options analysis. We therefore extend the literature by introducing a state space model of high frequency spot prices that preserves this intra-day market structure.

1 Introduction

Deregulation has been a dominant trend in world electricity markets, with countries such as Australia, New Zealand, Spain, the U.K., as well as many major U.S. states, all deregulating to varying degrees. Furthermore this trend looks set to continue with many others on the verge of restructuring their markets.[1] Yet while deregulation is usually accompanied by the promise

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[1]According to the official energy statistics from the U.S. Government, as of October 2002 "twenty-four states and the District of Columbia have either enacted enabling legislation or issued a regulatory order to implement

of better performance, it also presents new and major challenges for the restructured industry. The combination of the unique characteristics of electricity and the move from regulatory price controls to market-determined prices results in significantly increased price volatility and consequently greater market price risk. Also, deregulation decentralizes decision-making and opens markets to entry, so whereas in the past a central regulator controlled generation, industry entry and investment decisions, now individual firms make their own decisions.

In response to these new challenges the industry has seen the proliferation of financial style derivatives, to mitigate risk, and the increased use of real option analysis (ROA), to enhance the quality of generation decision-making and investment valuation. Yet the precision of both derivative pricing and ROA is conditional on having an accurate stochastic model of the spot price process. This reliance, together with electricity's distinctive properties, make stochastic modeling of electricity spot prices an important and challenging area of research.

There are two approaches to modeling electricity prices: Some authors (e.g. Bessembinder and Lemmon, 2002) build models to describe the demand and supply of electricity in order to calculate market-clearing electricity prices, while other authors (e.g. Deng, 2000) specify an exogenous process for the electricity spot price. Whichever approach is adopted, empirical work has identified properties that the price process should exhibit, including mean reversion, spikes, time-varying volatility, and certain seasonal, day of the week and time of day effects.

The majority of the recent literature uses daily data (for example Lucia and Schwartz, forthcoming; Bessembinder and Lemmon, 2002; Escribano et al. 2002). However, while there is a clear need for higher frequency modeling — for example, pricing certain derivatives and making very short term generation decisions — few studies look at high frequency spot price data. One notable exception is Knittel and Roberts (2001), who fit various financial models of asset price processes to an hourly time series of electricity spot prices from California.[2] Yet while these processes have been successfully applied to other commodity prices, they are not necessarily suitable for electricity. Unlike other commodities, which can be bought in one period and held and sold in another, electricity must be consumed in the period in which it is delivered. This prevents arbitrage between periods and allows prices at different times of the day to behave differently. Therefore it may be difficult to find a single process that can adequately describe all of these prices.[3]

In contrast, our approach treats electricity delivered at different times of the day (and potentially, different days of the week) as different commodities. For example, if the day is divided up into half hourly trading periods then there would be 48 commodities a day. This is consis-

retail access." (Source: Energy Information Administration) With respect to the European Union (E.U.), E.U. directive 96/92 requires member countries to open up their electricity markets.

[2]Knittel and Roberts (2001) use the following models: mean-reverting, time-varing mean, jump-diffusion, time dependent jump intensity, ARMAX, EGARCH, and ARMAX with temperature data

[3]In fact, Knittel and Roberts conclude that "forecasting performance . . . is relatively poor for most standard asset pricing models" (p. 19).

tent with electricity's limited storability and the consequent inability of arbitrage to eliminate persistent price differentials across periods.[4] However the forces which drive demand and supply are similar from one day to the next, so that the behavior of prices in any single trading period is likely to be similar across days. For this reason, daily observations can be taken of each commodity price.[5]

In addition, our approach incorporates the relationships between the prices of different commodities. Although there are many commodities each day, there may be a smaller number of distinct intra-day markets operating, for example one for overnight off peak electricity, and another for morning peak electricity etc. These intra-day markets comprise commodities that share similar demand and supply characteristics, and thus can be identified by the strong positive correlations of their prices.[6] This intertemporal segmentation could not exist in a conventional market — if such a market was segmented in this way, there would be periods during which prices in the various market segments diverge, creating arbitrage opportunities. Exploiting these arbitrage opportunities requires the traded asset to be storable, a condition with is satisfied in conventional markets, but not in electricity markets.

One of the aims of this paper is to build a dynamic model of high frequency electricity prices that is suitable for use in derivative pricing and real option analysis. To do this we group commodities into markets based on the correlation structure, and preserve this intra-day market structure by employing state space modeling. In this model we have one state variable for each intra-day market, which we interpret as a market price. The signal variables are the observed commodity prices, and we assume that each commodity price is a noisy signal of the corresponding state variable. This allows prices of different commodities to behave differently, but ensures prices of commodities in the same market are highly correlated.

In the next section we investigate the properties of prices at a key node in the New Zealand Electricity Market (NZEM). We first analyze the behavior of each commodity price separately, and find heterogeneous behavior. Next we look at the unconditional correlation structure, which suggests the existence of intra-day markets.[7] This heterogeneity and intertemporal segmentation strengthens after day of the week and monthly trends have been accounted for. In the final part

[4]Although electricity cannot be stored, in some cases the generation fuel can be, making limited arbitrage possible. Although New Zealand (the source of the data used in this paper) has large amounts of hydro generation, the amount of storage in the system is relatively low.

[5]Knittel and Roberts (2001) effectively treat electricity as one commodity, regardless of the time of day, employing a single long time series with one observation per hour. In contrast, the approach we use would split their series into 24 shorter time series, each with one observation per day. Kellerhals (2001) and Bhanot (2000) use variations of this approach: Kellerhals (2001) looks at the relationship between spot prices and day-ahead forward prices, for particular trading periods, using Californian data; Bhanot (2000) takes a high and low peak price each day and uses their average as that day's observed peak price. Off-peak prices are calculated similarly. Bhanot analyzes peak and off-peak prices separately.

[6]Examining correlations is a reasonable first step in defining markets. Subsequent analysis should look at the substitutability of the commodities. (Carlton and Perloff 1994, p. 806)

[7]We obtained qualitatively similar results when analyzing prices from other markets, including California.

of Section 2 we look at the dynamic structure in more detail utilizing a periodic autoregression (PAR) model. We then use the uncovered intra-day market structure to build a dynamic model of electricity prices in Section 3. Concluding remarks are presented in Section 4.

2 Behavior of prices

2.1 Data

The New Zealand Electricity Market (NZEM) is a nodal market comprising 244 nodes. Each day is split into 48 half-hourly trading periods, with the market generating a price for each node in each trading period. Our study uses all 48 final spot prices each day at the Haywards Node.[8] This node is chosen as it is one of the key nodes in the NZEM and other studies (for example, Escribano et al., 2002) also examine the behavior of prices at the Haywards node.[9]

The evolution of the NZEM complicates the choice of sample period, as the market has seen many fundamental changes since its inception in 1996. Initially the government-owned generator (ECNZ) competed with a single, privately-owned generator (Contact) in a duopoly. Then, in April 1999, ECNZ was split into three competing state-owned firms, which joined Contact in a competitive wholesale market. The Otahuhu B generation facility was opened in January 2000. This relieved congestion in the north of the North Island, changing the market structure of the NZEM, and thus potentially impacting on prices. In the winter of 2001, New Zealand witnessed a particularly severe drought, which heavily affected hydroelectric generation, the dominant form of generation in New Zealand. The most recent change is generation companies' acquisitions of retail firms, which anecdotal evidence and theory suggest has altered price behavior.

We look at the data in two sections: 1 March 2000 to 28 February 2001, and 1 March 2001 to 28 February 2002. The sample period begins soon after the opening of Otahuhu B, which gives us a two year sample in which industry structure is reasonably constant. This provides us with a total of 35040 observations.[10] The start date coincides with the start of autumn, allowing eight full seasons in the two-year sample period. The second year of our sample was affected by abnormally dry weather conditions, leading to extremely high prices in the months June–August 2002. Thus, much of our analysis concentrates on the first year of data.

From the raw time series data we extract 48 separate series of prices, each one corresponding to a different trading period, with trading period one beginning at midnight, period two beginning at 12:30 a.m., and so on. This gives us one observation a day for each trading period for

[8] There are three types of prices in the NZEM: forecast prices, which are calculated during the 36 hours before the particular trading period; dispatch prices, which are calculated in the final few hours before electricity is dispatched; and final prices, which are generally available on the following day and are used for settlement. This study uses final prices as they most accurately reflect the prices which industry players face.

[9] We found that prices behave similarly at the other major nodes in NZEM.

[10] We have also studied Californian hourly data at the NP15 zone from 1 April 1999 to 31 March 2000 (a total of 8784 observations) and obtained qualitatively similar results to those reported here for the NZEM.

the two years.

2.2 A first look at the data

We begin this section by investigating the behavior of prices in individual trading periods. This is done in order to ascertain whether they have heterogeneous characteristics and hence should be treated as different commodities. We then look for the existence of intra-day markets by examining the relationships between these prices.

Figure 1 reports some summary statistics of our data set. The top two graphs plot the mean and standard deviation of prices in each trading period, revealing peak periods around trading periods 16 and 36 (8 a.m. and 6 p.m. respectively). The average price is elevated during these peak periods, with volatility moderately elevated during the morning period and even higher in the evening peak. Overall, prices are higher than average in the second year of our sample period. The other two pairs of graphs in Figure 1 split the observations into weekdays (the middle row) and weekends (the bottom row). As expected, the weekday graphs look very similar to the graphs drawn using all observations. However, the weekend graphs display subtly different behavior. The morning peak has almost disappeared, and shifted later in the day. In the first year, the evening peak is much less pronounced than for weekdays, but still significant. During the second year the evening peak appears similar on weekdays and weekends.

Insert Figure 1 here

Figure 2 has the same format as Figure 1, but now the data set is broken up into seasons. The top graphs use all days during the first three months of the sample period (autumn), while the second row of graphs uses all days during the second three months of the sample period (winter), the third row of graphs uses all days during the third three months of the sample period (spring), and the bottom row of graphs uses all days during the fourth three months of the sample period (summer). The effects of the drought are evident in the right hand column, especially in winter (and, to a lesser extent, in autumn), with the mean and volatility being greatly elevated over the rest of our sample. Also of interest is that in the first year, peak periods are most evident in winter and spring, whereas they are much harder to detect in autumn and summer.

Insert Figure 2 here

This shows that prices in different periods behave differently and hence supports the multiple commodity interpretation. We now look at the possibility that these commodities can be grouped into distinct markets. We do this by examining the correlations between different commodity prices. The 48×48 correlation matrix for the first year of our sample is displayed graphically in Figure 3. Each cell in the grid corresponds to an element of the correlation matrix. The shade of the cell indicates the strength of correlation, with black signifying a correlation coefficient of 1 and white a correlation coefficient of 0. The graph reveals a remarkably rich structure, with the 48 commodities falling naturally into 5 groups: overnight (periods 1–14), morning peak (periods 15–18), daytime (periods 19–35), evening peak (periods 36–39), and late evening (periods 40–48). The commodities within each group are highly correlated with each other, yet the correlations between these groups are lower. For example, the average correlation between prices is 0.75 in the overnight period, 0.75 in the morning peak period, 0.59 during the daytime period, 0.40 in the evening peak period, and 0.61 in the late evening period.[11] In contrast, the average correlation between overnight prices and those in the morning peak period is 0.12, and with those in the evening peak period is 0.12. This suggests there are five intra-day markets operating in the NZEM for this section.[12]

Insert Figure 3 here

Figures 1 and 2 show that there is strong seasonality in the data, and this could introduce spurious correlations. Therefore, we adjust for this influence by investigating the correlation structure of the residuals in the following regression:

$$p_{n,t} = \sum_{i=1}^{7} \alpha_{n,i} d_{i,t} + \sum_{i=1}^{23} \gamma_{n,i} m_{i,t} + \varepsilon_{n,t}, \quad \varepsilon_{n,t} \sim N(0, \psi_n^2), \tag{1}$$

where $p_{n,t}$ is the price in trading period n on day t, $d_{j,t}$ is a dummy variable that takes the value 1 on day j and 0 otherwise (Wednesday is day 1, Thursday day 2, and so on), $m_{j,t}$ is a dummy variable that takes the value 1 in month j and 0 otherwise (March 2000 is month 1, January 2002 is month 23). The inclusion of the dummies is designed to eliminate much of the seasonality in the data, while keeping the regression simple. We examine the possibility that the intra-day patterns may be different during weekdays, weekends and the various seasons. Figures 4 and 5 present the de-trended results of the two years of data for these different sample periods.[13]

Insert Figure 4 here

Insert Figure 5 here

Figure 4 describes the correlation structure for the first and second years as a whole and also the weekday and weekend variations. The only major change from the first year's unconditional

[11]We calculate the average correlation coefficient for pairs $(p_{i,t}, p_{j,t})$ with $i \neq j$ in the same group. That is, we do not count the perfect correlation when calculating the averages. Therefore, the numbers reported here actually understate the strength of the correlation within each group.

[12]Lucia and Schwartz (forthcoming) looked at the pair wise correlations of the 24 price time series for the Nord Pool and found them all to be highly correlated($\rho > 0.94$), but did not report the existence of patterns.

[13]The correlation plots for the second year of data are included for completeness. We believe this year was not representative of a regular year as it was affected by a severe drought. Nevertheless, it gives an interesting perspective on how the correlation structure is affected by such an event. Overall the second year's intra-day correlations have increased, thus seemingly merging the patterns into one market. However, a closer look at the graphs of the subsections of the data (for example, weekdays and spring) reveals similarities to the first year of data. While we could change the scale to enhance the patterns, we choose to include the plots with the same scale as the first year so that the graphs of all the sections of data are directly comparable.

correlation structure (Figure 3) is a weakening of the correlations between the intra-day markets; the correlations within the markets remain robust. This suggests that overnight and daytime are distinct markets, not just one market separated by the morning peak. The remaining four graphs present the correlation structure of weekdays and weekends. They show that for the first year the weekend patterns are quite different from the weekday patterns.[14] The daytime off-peak and evening peak periods, which are distinct markets on weekdays, are combined into a single market (the large dark square in the middle of the graph) on weekends. Also the white regions of the weekday graph are absent from the weekend graph. They appear in the weekday graph because peak period prices are practically uncorrelated with all other prices. However, these strong peaks do not appear during the weekend; even the morning peak prices are quite strongly correlated with all other prices on the weekend. Finally, note that the overnight pattern is similar on weekdays and weekends.[15]

Figure 5 has the same format as Figure 4 but the data set is broken into seasons in order to show the seasonal variations in the correlation structure.[16] Autumn 2000 reveals the existence of three distinct intra-day markets (morning, day and night). In this case, the morning and evening peak markets that are present when looking at the year as a whole are highly correlated with the day market, and thus merge to create one large daytime market. Winter and spring 2000 exhibit similar characteristics to the first year as a whole. Summer 2000/2001 displays higher overall correlation, with the overnight market being visible due to its higher internal correlations.[17]

The correlation structures we have found in the data have implications for the dynamic behavior of spot prices. For example, if the price is higher than average in period 1, it is likely to be higher than average in periods 2 to 14, as indicated by the high correlation region in the top left hand corner of the graph. However, the period 1 price reveals little about the price in the morning peak period. The implications for generation decisions are significant. For plants which cannot be turned on and off instantaneously, there is an advantage in delaying generation decisions until after the start of one of these intra-day markets. For example, there is likely to be some value in keeping a moderately inflexible plant operating past the end of the morning

[14] We constructed correlation plots for each day of the week and found that all weekdays shared the same pattern, and that Saturday and Sunday shared the same weekend pattern.

[15] The correlation plots for the second year of data are more obscure as the overall correlations are higher, yet on closer inspection weekdays exhibit a similar pattern to weekdays in the first year. The weekend structure shows the second half of the day forms one market, although the first half of the day is messier.

[16] By breaking the data into seasons the number of observations used to calculate the correlations is greatly reduced and hence the correlations are more susceptible to spikes. For example, on September 18, 2000 the price was \$114.02 in period 32, \$473.75 in period 33, and \$32.93 in period 34. This causes the unusual behavior at period 33 in spring 2000. Another example is period 39 in autumn 2000. On May 2, the price rose from \$61.12 in period 38, to \$544.67 in period 39, and back down to \$36.95 in period 40.)

[17] The graphs for the second year of data are again more obscure, yet similarities to the first year of data can be seen in autumn, spring and, to a lesser extent, winter. The autumn correlations appear to have merged the daytime and evening markets that are present in autumn for the first year.

peak period, since even the price in period 20 reveals a great deal about prices through until at least trading period 35. We examine spot price dynamics in more detail in the following section.

2.3 Spot price dynamics

Suppose that the price in any trading period depends linearly on the prices in the preceding 48 trading periods as well as day of the week and month of the year dummies:

$$
\begin{aligned}
p_{1,t+1} &= \beta_{1,1}p_{48,t} + \beta_{1,2}p_{47,t} + \cdots + \beta_{1,48}p_{1,t} + \sum_{i=1}^{7}\alpha_{1,i}d_{i,t} + \sum_{i=1}^{23}\gamma_{1,i}m_{i,t} + u_{1,t+1} \\
p_{2,t+1} &= \beta_{2,1}p_{1,t+1} + \beta_{2,2}p_{48,t} + \cdots + \beta_{2,48}p_{2,t} + \sum_{i=1}^{7}\alpha_{2,i}d_{i,t} + \sum_{i=1}^{23}\gamma_{2,i}m_{i,t} + u_{2,t+1} \\
&\vdots \\
p_{47,t+1} &= \beta_{47,1}p_{46,t+1} + \beta_{47,2}p_{45,t+1} + \cdots + \beta_{47,48}p_{47,t} + \sum_{i=1}^{7}\alpha_{47,i}d_{i,t} + \sum_{i=1}^{23}\gamma_{47,i}m_{i,t} + u_{47,t+1} \\
p_{48,t+1} &= \beta_{48,1}p_{47,t+1} + \beta_{48,2}p_{46,t+1} + \cdots + \beta_{48,48}p_{48,t} + \sum_{i=1}^{7}\alpha_{48,i}d_{i,t} + \sum_{i=1}^{23}\gamma_{48,i}m_{i,t} + u_{48,t+1}
\end{aligned} \tag{2}
$$

Each equation has the same form as (1), with the addition of 48 lagged prices. Thus, today's price in trading period 1 depends on all 48 prices yesterday, while today's price in trading period 2 depends on today's price in trading period 1 as well as yesterday's prices in trading periods 2–48. Alternatively, this model can be interpreted as the variant of a standard AR(48) model in which coefficients take different values in different trading periods. Known as periodic autoregression (PAR) models, these have been used extensively in hydrology, but not, to our knowledge, in finance. Because of their special structure, each component equation of a PAR model can be estimately separately (McLeod, 1994).

To give some idea of the importance of the lagged variables, in Table 1 we report the R^2s of the regressions for various special cases of equation (2). In column (i), all lags of the spot price are excluded, leaving only the day of the week and the monthly dummies; in column (ii) the first lag is added; in column (iii) the 48th lag is added instead; column (iv) is the unrestricted model. If we treat each series as the price of a separate commodity, then the natural thing to do is to include only the 48th lag, so that each commodity's price is regressed on its value in the previous day. However, while the R^2s are higher in the third column than they are in the baseline case, comparison with the fourth column reveals that including all 48 lagged prices dramatically increases the R^2 in many cases. This shows that we lose useful information if we ignore the relationships between the prices of different commodities.[18] In fact, when we add in all 48 lags, the R^2 only drops below 0.80 during the peak periods.

[18] The second column reveals that the first lag actually provides more information than the 48th lag. The difference between the fourth and second columns gives an indication of the extra information provided by lags 2–48 over that provided by the first lag alone. This difference is greatest in trading periods 15 (7 a.m.), 19 (9 a.m.), 34 (4:30 p.m.), 39 (7 p.m.), and 45 (10 p.m.), which correspond approximately to the beginning of distinct

Insert Table 1 here

We use our estimated model to investigate the dynamics of spot prices in more detail. In particular, we examine the effects of price shocks in individual trading periods and see how they propagate throughout the day. We begin by writing the system (2) as

$$\mathbf{\Gamma p}_{t+1} = \mathbf{A p}_t + \mathbf{B x}_{t+1} + \mathbf{u}_{t+1}, \quad \mathbf{u}_{t+1} \sim N(\mathbf{0}, \mathbf{\Omega}), \tag{3}$$

where $\mathbf{p}_t = (p_{1,t}, p_{2,t}, \ldots, p_{48,t})'$,

$$\mathbf{\Gamma} = \begin{pmatrix} 1 & 0 & \cdots & 0 & 0 \\ -\beta_{2,1} & 1 & \cdots & 0 & 0 \\ \vdots & & & & \vdots \\ -\beta_{47,46} & -\beta_{47,45} & \ldots & 1 & 0 \\ -\beta_{48,47} & -\beta_{48,46} & \ldots & -\beta_{48,1} & 1 \end{pmatrix}, \quad \mathbf{A} = \begin{pmatrix} \beta_{1,48} & \beta_{1,47} & \cdots & \beta_{1,2} & \beta_{1,1} \\ 0 & \beta_{2,48} & \cdots & \beta_{2,3} & \beta_{2,2} \\ \vdots & & & & \vdots \\ 0 & 0 & \ldots & \beta_{47,48} & \beta_{47,47} \\ 0 & 0 & \ldots & 0 & \beta_{48,48} \end{pmatrix},$$

and $\mathbf{x}_{t+1}$ contains dummy variables for the day of the week and the month of the year. We can rearrange equation (3) as follows:

$$\mathbf{p}_{t+1} = \mathbf{\Gamma}^{-1}\mathbf{A p}_t + \mathbf{\Gamma}^{-1}\mathbf{B x}_{t+1} + \mathbf{\Gamma}^{-1}\mathbf{u}_{t+1}. \tag{4}$$

Suppose we wish to forecast the next day's prices at the end of day t. From equation (4), the vector of forecasts is

$$E_t[\mathbf{p}_{t+1}] = \mathbf{\Gamma}^{-1}\mathbf{A p}_t + \mathbf{\Gamma}^{-1}\mathbf{B x}_{t+1}, \tag{5}$$

and the vector of forecast errors is

$$\mathbf{p}_{t+1} - E_t[\mathbf{p}_{t+1}] = \mathbf{\Gamma}^{-1}\mathbf{u}_{t+1}.$$

Price forecasts can be extended further into the future. For example, repeated substitution of equation (4) shows that

$$\begin{aligned} \mathbf{p}_{t+2} &= \mathbf{\Gamma}^{-1}\mathbf{A p}_{t+1} + \mathbf{\Gamma}^{-1}\mathbf{B x}_{t+2} + \mathbf{\Gamma}^{-1}\mathbf{u}_{t+2} \\ &= \mathbf{\Gamma}^{-1}\mathbf{A}\left(\mathbf{\Gamma}^{-1}\mathbf{A p}_t + \mathbf{\Gamma}^{-1}\mathbf{B x}_{t+1} + \mathbf{\Gamma}^{-1}\mathbf{u}_{t+1}\right) + \mathbf{\Gamma}^{-1}\mathbf{B x}_{t+2} + \mathbf{\Gamma}^{-1}\mathbf{u}_{t+2} \\ &= \mathbf{\Gamma}^{-1}\mathbf{A\Gamma}^{-1}\mathbf{A p}_t + \mathbf{\Gamma}^{-1}\mathbf{A\Gamma}^{-1}\mathbf{B x}_{t+1} + \mathbf{\Gamma}^{-1}\mathbf{B x}_{t+2} + \mathbf{\Gamma}^{-1}\mathbf{A\Gamma}^{-1}\mathbf{u}_{t+1} + \mathbf{\Gamma}^{-1}\mathbf{u}_{t+2}. \end{aligned}$$

Since

$$\begin{aligned} E_t[\mathbf{p}_{t+2}] &= E_t[\mathbf{\Gamma}^{-1}\mathbf{A\Gamma}^{-1}\mathbf{A p}_t + \mathbf{\Gamma}^{-1}\mathbf{A\Gamma}^{-1}\mathbf{B x}_{t+1} + \mathbf{\Gamma}^{-1}\mathbf{B x}_{t+2} + \mathbf{\Gamma}^{-1}\mathbf{A\Gamma}^{-1}\mathbf{u}_{t+1} + \mathbf{\Gamma}^{-1}\mathbf{u}_{t+2}] \\ &= \mathbf{\Gamma}^{-1}\mathbf{A\Gamma}^{-1}\mathbf{A p}_t + \mathbf{\Gamma}^{-1}\mathbf{A\Gamma}^{-1}\mathbf{B x}_{t+1} + \mathbf{\Gamma}^{-1}\mathbf{B x}_{t+2}, \end{aligned}$$

it follows that the two-day-ahead forecast error is

$$\mathbf{p}_{t+2} - E_t[\mathbf{p}_{t+2}] = \mathbf{\Gamma}^{-1}\mathbf{A\Gamma}^{-1}\mathbf{u}_{t+1} + \mathbf{\Gamma}^{-1}\mathbf{u}_{t+2}.$$

intra-day markets. This suggests that a (periodic) AR(1) model might do quite a good job of modeling prices within an intra-day market, but be unsuitable for modeling the relationships between prices in different markets.

More distant forecast errors can be calculated in the same way.

Suppose, for example, that $\mathbf{u}_{t+1} = (1, 0, \ldots, 0)'$, so that the only price shock occurs in period 1. Then the prices that day exceed their forecasts by

$$\mathbf{p}_{t+1} - E_t[\mathbf{p}_{t+1}] = \mathbf{\Gamma}^{-1}(1, 0, \ldots, 0)',$$

which is just the first column of the matrix $\mathbf{\Gamma}^{-1}$. The following day, prices exceed their forecasts by

$$\mathbf{p}_{t+2} - E_t[\mathbf{p}_{t+2}] = \mathbf{\Gamma}^{-1}\mathbf{A}\mathbf{\Gamma}^{-1}(1, 0, \ldots, 0)',$$

which is just the first column of the matrix $\mathbf{\Gamma}^{-1}\mathbf{A}\mathbf{\Gamma}^{-1}$. The shocks to prices further in the future can be calculated in the same way. These shocks are plotted in the top panel of Figure 6. It shows what happens if the midnight price receives a \$10 shock. The shock persists for approximately seven hours, with the effect slowly weakening for the first three hours, and remaining constant for the next four hours. The shock disappears during the morning peak period, although a very weak effect returns for the remainder of the day. The graph suggests that there is a small positive effect over days 2 and 3, although it is probably not statistically significant.

Insert Figure 6 here

Similarly, if the shock occurs in period 15, the extent to which prices exceed their forecasts is given by the fifteenth column of $\mathbf{\Gamma}^{-1}$. The effect of a \$10 shock at 7 a.m. (period 15) is shown in the second panel of Figure 6. The initial shock is large, but it has practically died out by 9 a.m. The graph suggests that it never returns. The remaining two panels of Figure 6 show the effect of a \$10 shock at 10 a.m. (period 21) and 6 p.m. (period 37) respectively. The mid-morning shock lasts throughout the day, only dying out after the evening peak. In contrast, the shock at the start of the evening peak period only lasts for two trading periods, although it reappears in the following day's evening peak period.

These graphs provide compelling evidence that the intra-day dynamics are richer than can be captured by standard models. Equation (2) could form the basis of a spot price model, suitable for derivative pricing and ROA, but the large number of parameters to be estimated poses problems given the relatively short history of deregulated electricity markets. What is needed is a more parsimonious model that captures the same dynamic properties. In the next section we present such a model, which is motivated by the intra-market structure uncovered in this paper.

3 State space model

Our starting point in this paper was to treat electricity over the course of the day as 48 distinct commodities. This means we need to model 48 separate prices, yet it is clear from the evidence presented in Section 2 that these commodities can be grouped into only 4 or 5 different intra-day markets. We postulate that the price of electricity in any given trading period is the sum of a base price and a disturbance and that this base price is constant across each market. Any change in this base price affects all prices in the same market in the same direction, generating the high correlations observed in Figure 3. Since prices in other markets are not directly affected by such a change in this base price, correlations between markets would be relatively low, as in Figure 3.

We suppose there are four intra-day markets and that the base price in any market depends on the base prices in the previous four intra-day markets and a noise term. That is,

$$\begin{aligned}
s_{1,t} &= \beta_{1,1}s_{4,t-1} + \beta_{1,2}s_{3,t-1} + \beta_{1,3}s_{2,t-1} + \beta_{1,4}s_{1,t-1} + \varepsilon_{1,t}, \\
s_{2,t} &= \beta_{2,1}s_{1,t} + \beta_{2,2}s_{4,t-1} + \beta_{2,3}s_{3,t-1} + \beta_{2,4}s_{2,t-1} + \varepsilon_{2,t}, \\
s_{3,t} &= \beta_{3,1}s_{2,t} + \beta_{3,2}s_{1,t} + \beta_{3,3}s_{4,t-1} + \beta_{3,4}s_{3,t-1} + \varepsilon_{3,t}, \\
s_{4,t} &= \beta_{4,1}s_{3,t} + \beta_{4,2}s_{2,t} + \beta_{4,3}s_{1,t} + \beta_{4,4}s_{4,t-1} + \varepsilon_{4,t}, \\
\varepsilon_{k,t} &\sim N(0, \sigma_k^2),
\end{aligned} \tag{6}$$

where $s_{k,t}$ is the state variable in market k on day t and $\mathrm{Cov}[\varepsilon_{i,t}, \varepsilon_{j,t}] = 0$ for all $i \neq j$. The long run average value of each state variable is zero. We allow the noise terms to have different volatilities in different intra-day markets. We model the trading period n price on day t by

$$p_{n,t} = \delta_n + \sum_{i=1}^{6} \alpha_i d_{i,t} + \sum_{i=1}^{11} \gamma_i m_{i,t} + s_{k_n,t} + \theta_{n,t}, \quad \theta_{n,t} \sim N(0, \phi_n^2), \tag{7}$$

where k_n gives the market containing trading period n. Based on the evidence from the first year of our sample, we choose[19]

$$k_n = \begin{cases} 1, & \text{if } n = 1, \ldots, 14, \\ 2, & \text{if } n = 15, \ldots, 18, \\ 3, & \text{if } n = 19, \ldots, 33, 38, \ldots, 48, \\ 4, & \text{if } n = 34, \ldots, 37. \end{cases}$$

The price in period n can be decomposed into five distinct components: The first, δ_n, is a constant which takes different values in different trading periods; the second, $\sum_{i=1}^{6} \alpha_i d_{i,t}$, is a constant which takes different values in different days of the week; the third, $\sum_{i=1}^{11} \gamma_i m_{i,t}$, is a constant which takes different values in different months of the year; the fourth, $s_{k_n,t}$, is the state variable in the appropriate intra-day market; the fifth, $\theta_{n,t}$, is a noise term.[20] We assume the noise term is independently distributed across trading periods and across days of the week, but allow heteroskedasticity. In particular the variance of the noise term is a function of the trading

[19] Note that the daytime period is interrupted by the evening peak period. This is consistent with the correlation structure in Figure 3 and is necessary to keep the state variables down to a manageable number.

[20] Thus δ_n is the expected price in trading period n on a Tuesday (day 7) in February 2001 (month 12). Prices rise, on average, by α_1 on Wednesdays, by α_2 on Thursdays, and so on. They rise, on average, by γ_1 in March 2000, by γ_2 in April 2000, and so on.

period: $\mathrm{Var}[\theta_{n,t}] = \phi_n^2$. The form of the signal equation means the average price curve moves up or down on different days of the week and months of the year. We imposed this, admittedly restrictive, structure on the data in order to keep the number of parameters to a manageable level.[21]

We estimate this as a state space model with four state variables and 48 signals (the observed prices), using the Kalman filter. Our estimates of the process driving the state variables are given in Table 2. For the price in the overnight market ($s_{1,t}$), only the 1st and 4th lag are statistically significant — the overnight price depends mainly on the overnight price of the previous day ($\beta_{1,4} = 0.50$). In contrast, the price in the morning peak market ($s_{2,t}$) depends strongly on the immediately preceding overnight price ($\beta_{2,1} = 0.85$), as well as the previous day's evening peak price ($\beta_{2,2} = 0.39$). The price during the daytime market behaves differently again: it is determined primarily by the morning peak price ($\beta_{3,1} = 0.73$), although the previous day's prices also have a minor role. Finally, the price in the evening peak period ($s_{4,t}$) is influenced mainly by the daytime price ($\beta_{4,1} = 0.49$). Not surprisingly, the state variables corresponding to the two peak periods are the most volatile, while the overnight price is least volatile.

Insert Table 2 here

Table 3 gives the estimated signal equations. As we expect, prices are higher on average in the peak periods, as shown by the high values of δ_n in the corresponding trading periods, and more volatile, as shown by the high values of ϕ_n. The wide variation in the estimates of ϕ_n confirms the heteroskedasticity found by other authors in electricity spot prices. Finally, Table 4 reports the seasonal influences. There are no statistically significant variations over days of the week, but we find significant monthly variations. Prices are lowest in the spring months of September–November.

Insert Table 3 here

Insert Table 4 here

4 Conclusion

In this paper we argued that electricity's unique characteristics demand that a new approach to modelling spot price behavior be adopted. Because of the lack of arbitrage, we treated electricity delivered at different times of the day as different commodities. Daily time series of the prices of these commodities exhibit heterogeneous behavior. Further, our analysis revealed remarkable structure that suggests the existence of a small number of intra-day spot markets for electricity.

[21] The seasonal and weekend variation in correlations could be modelled by introducing time-variant slope coefficients in the state equations, but this dramatically increases the number of parameters to be estimated. For this reason, we ignore these effects.

We used a periodic autoregression model to reveal some interesting dynamic behavior of prices, which we believe impacts on both derivative pricing and real options analysis. The implications of our findings for short-run generation decisions are potentially quite significant. For example, plants which cannot be turned on and off instantaneously benefit from delaying generation decisions until after the start of one of these intra-day markets — because spot prices are highly correlated within these markets, the first few observations reveal a great deal of information about prices during the remainder of the market.

The periodic autoregression model could be used to value electricity derivatives with payoffs depending on high frequency spot price dynamics. The PAR's principal limitation is the large number of parameters which need to be estimated. For example, with half-hourly trading periods each of the 48 equations has 48 slope coefficients, in additional to the coefficients of various dummy variables. However, much of the dynamic structure would remain if only a subset of the lagged prices (for example 1, 2, 47 and 48 lags) is used instead. This parsimony might allow us to introduce jumps and other relevant properties into the price process. This is a promising line of inquiry.

Rather than develop the PAR model in this way, we pursued an alternative approach involving a state space model. This is easily motivated from the intra-day market structure, and has the added advantage of requiring a relatively small number of parameters to be estimated. It divides the day into distinct periods based on the correlation structure. Figures 4 and 5 suggest that the structure of intra-day markets varies between weeks and weekends, and across seasons. Future research will reveal whether these patterns are stable over time and the extent to which they appear in other electricity spot markets. We ignored this seasonality in intra-day market structure when estimating the state space model in order to keep our model to manageable proportions. If more efficient means of estimating the state space model can be found, then this extra level of detail can be incorporated into dynamic models of spot prices.

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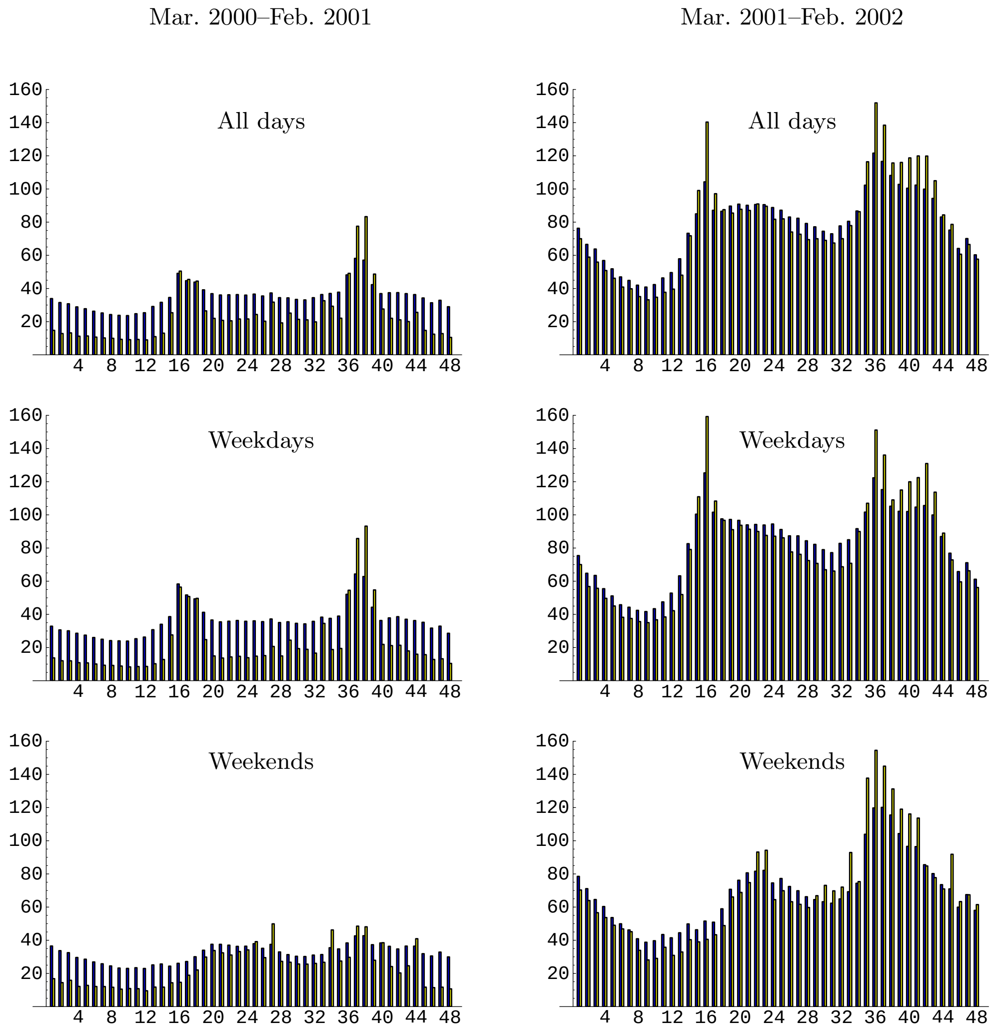
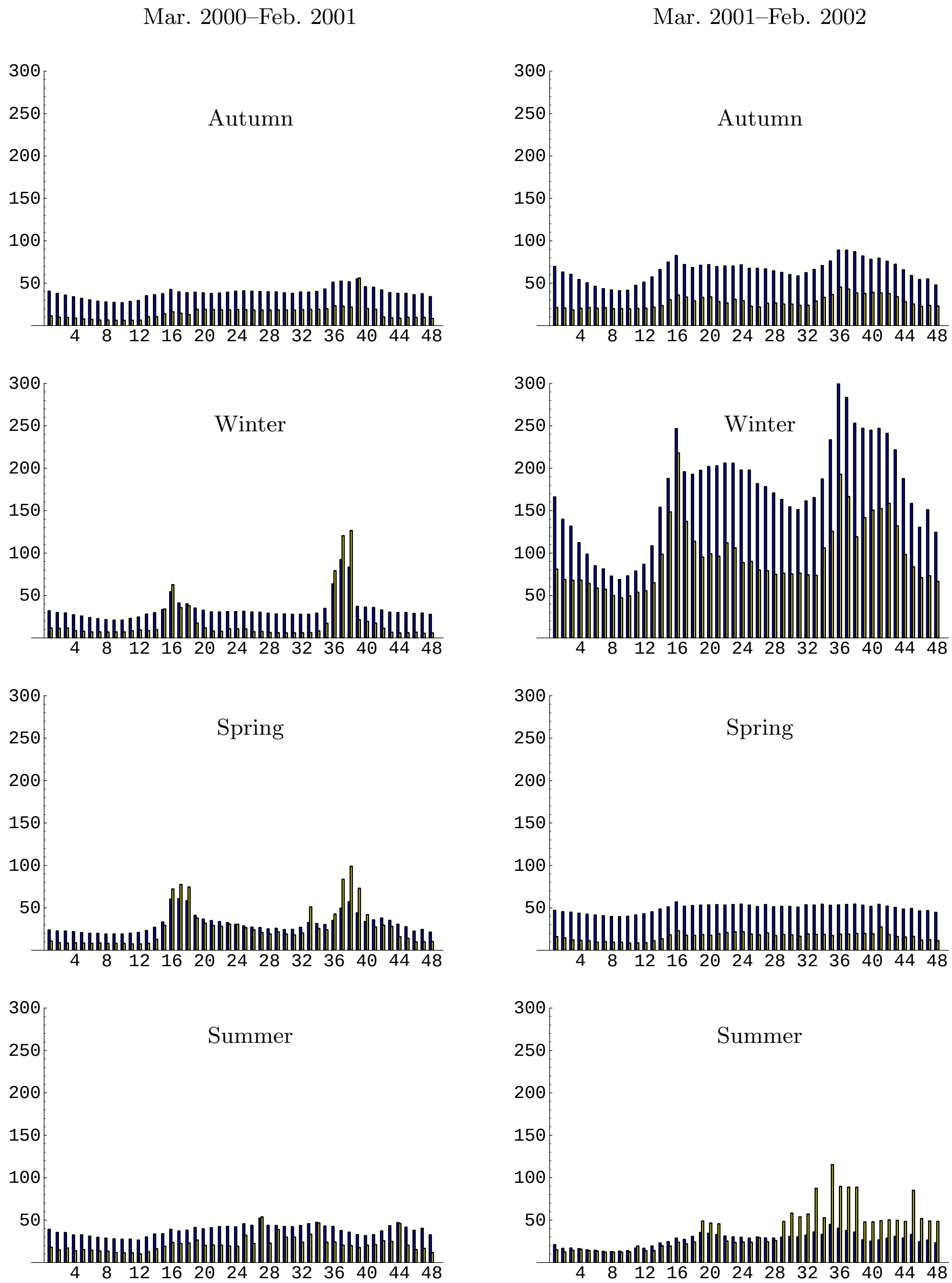
Figure 1: Summary statistics: day of the week variations



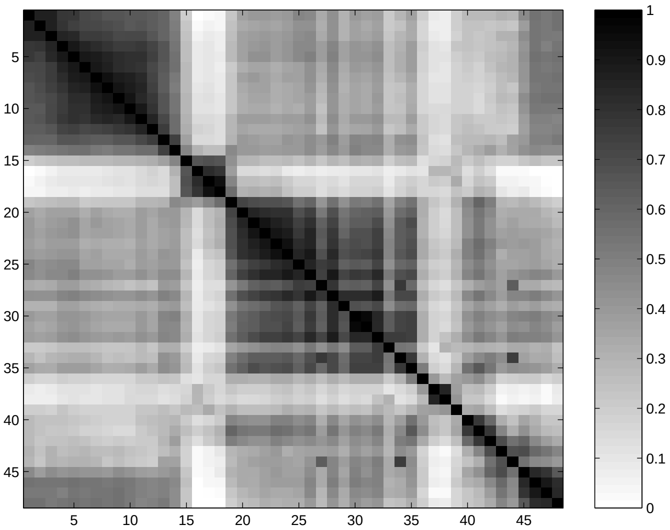
Notes. Each graph shows the mean (dark shading) and standard deviation (light shading) of electricity prices for each trading period. Graphs in the left column use data from the Haywards node during the period 1 March 2000 to 28 February 2001, and graphs in the right column use data from the same node during the period 1 March 2001 to 28 February 2002. The top graphs use all days during the sample period, while the middle graphs use only weekdays, and the bottom graphs use only weekends.

Figure 2: Summary statistics: seasonal variations



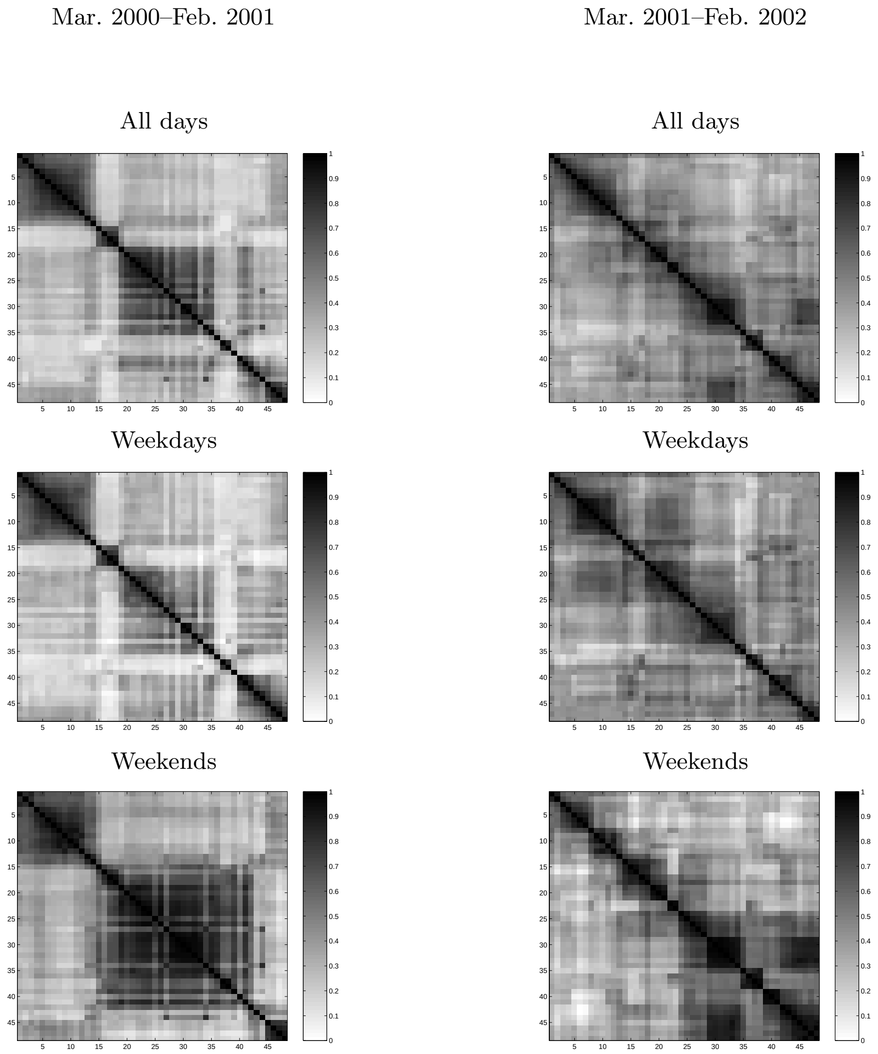
Notes. Each graph shows the mean (dark shading) and standard deviation (light shading) of electricity prices for each trading period. Graphs in the left column use data from the Haywards node during the period 1 March 2000 to 28 February 2001, and graphs in the right column use data from the same node during the period 1 March 2001 to 28 February 2002. The top graphs use all days during the first three months of the sample period (autumn), while the second row of graphs uses all days during the second three months of the sample period (winter), the third row of graphs uses all days during the third three months of the sample period (spring), and the bottom row of graphs uses all days during the fourth three months of the sample period (summer).

Figure 3: Correlation structure



Notes. The graph displays the correlation matrix for prices at the Haywards node, with black cells having a correlation coefficient of 1 and white cells a correlation coefficient of 0, using all observations during the period 1 March 2000 to 28 February 2001.

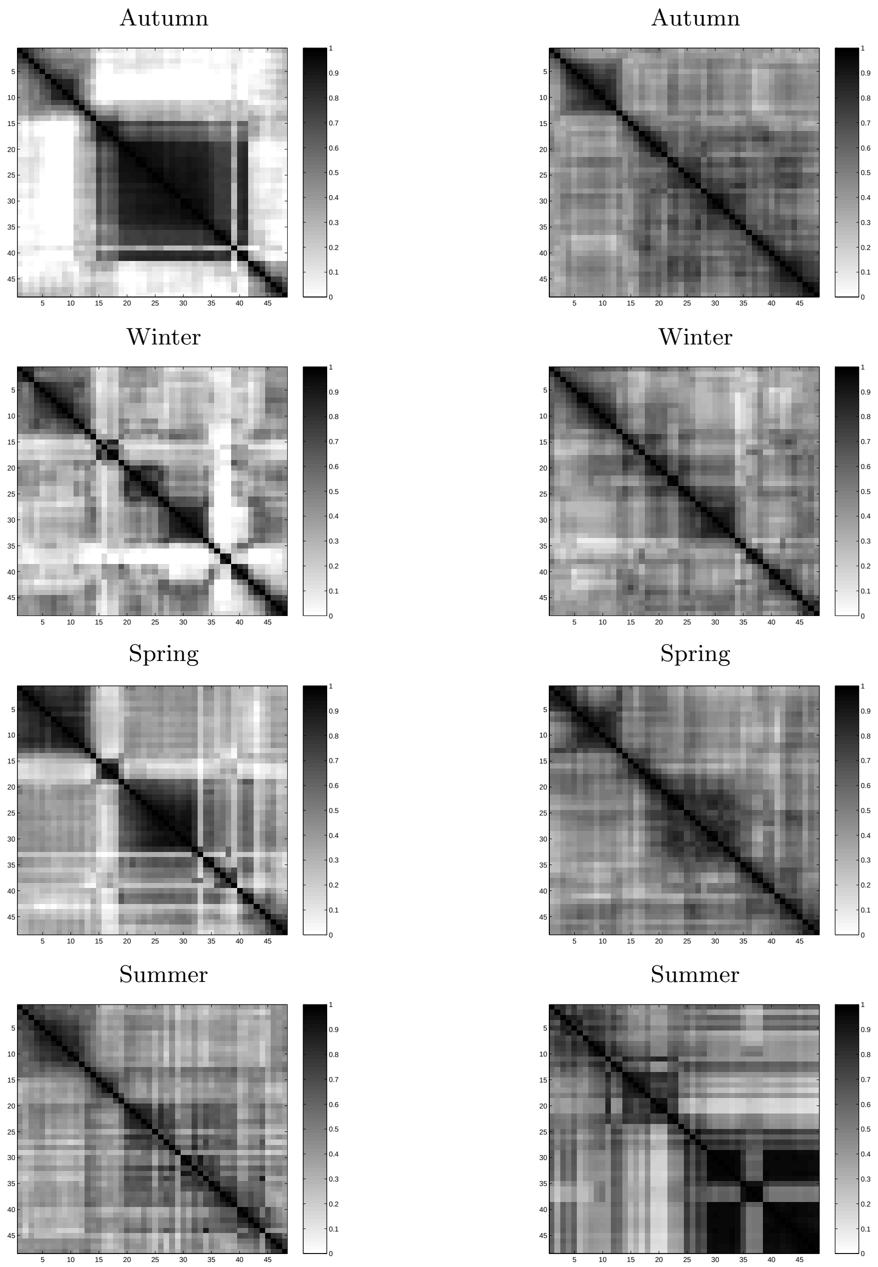
Figure 4: Correlation structure: day of the week variations



Notes. Each graph displays the correlation matrix for the residuals in equation (1) using prices at the Haywards node, with black cells having a correlation coefficient of 1, and white cells a correlation coefficient of 0. Graphs in the left column use observations during the period 1 March 2000 to 28 February 2001, and graphs in the right column use data from the same node during the period 1 March 2001 to 28 February 2002. The top graphs use prices on all days in the relevant sample period, the middle graphs use weekday prices, and the bottom graphs use weekend prices.

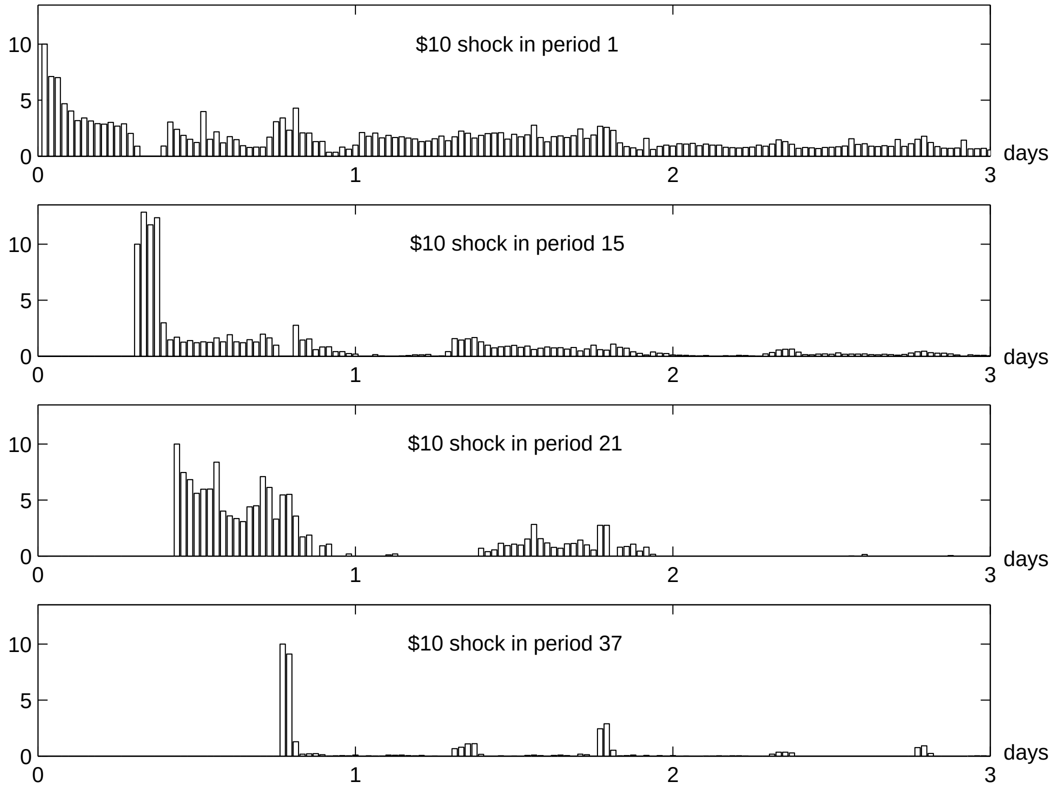
Figure 5: Correlation structure: seasonal variations

Mar. 2000–Feb. 2001 | Mar. 2001–Feb. 2002



Notes. Each graph displays the correlation matrix for the residuals in equation (1) using prices at the Haywards node, with black cells having a correlation coefficient of 1, and white cells a correlation coefficient of 0. Graphs in the left column use observations during the period 1 March 2000 to 28 February 2001, and graphs in the right column use data from the same node during the period 1 March 2001 to 28 February 2002. The top graphs use all days during the first three months of the sample period (autumn), while the second row of graphs uses all days during the second three months of the sample period (winter), the third row of graphs uses all days during the third three months of the sample period (spring), and the bottom row of graphs uses all days during the fourth three months of the sample period (summer).

Figure 6: Impulse response functions



Notes. Each panel shows what happens if the price in the indicated trading period receives a $10 shock. The impulse response functions are derived from our estimates of equation (3) using prices at the Haywards node for the period 1 March 2000 to 28 February 2001.

Table 1: Performance of various periodic autoregressive models

	R^2					R^2					R^2			
n	(i)	(ii)	(iii)	(iv)	n	(i)	(ii)	(iii)	(iv)	n	(i)	(ii)	(iii)	(iv)
1	0.36	0.57	0.44	0.67	17	0.17	0.73	0.20	0.82	33	0.11	0.62	0.12	0.77
2	0.33	0.79	0.41	0.83	18	0.12	0.89	0.13	0.92	34	0.11	0.35	0.12	0.83
3	0.32	0.79	0.40	0.87	19	0.09	0.38	0.15	0.62	35	0.22	0.70	0.24	0.82
4	0.30	0.74	0.38	0.79	20	0.12	0.60	0.14	0.79	36	0.14	0.36	0.14	0.43
5	0.32	0.85	0.42	0.90	21	0.13	0.76	0.15	0.83	37	0.21	0.36	0.26	0.55
6	0.30	0.83	0.43	0.87	22	0.15	0.88	0.18	0.91	38	0.20	0.77	0.28	0.87
7	0.27	0.85	0.40	0.89	23	0.13	0.86	0.16	0.90	39	0.15	0.30	0.22	0.53
8	0.27	0.91	0.37	0.93	24	0.14	0.91	0.16	0.94	40	0.13	0.21	0.15	0.56
9	0.26	0.86	0.40	0.88	25	0.16	0.76	0.19	0.85	41	0.16	0.67	0.20	0.81
10	0.26	0.87	0.38	0.90	26	0.20	0.77	0.24	0.92	42	0.14	0.66	0.19	0.79
11	0.24	0.84	0.35	0.90	27	0.14	0.59	0.19	0.77	43	0.15	0.57	0.17	0.69
12	0.24	0.77	0.40	0.84	28	0.22	0.71	0.28	0.91	44	0.12	0.52	0.13	0.89
13	0.32	0.65	0.45	0.74	29	0.15	0.71	0.17	0.77	45	0.29	0.47	0.34	0.78
14	0.28	0.63	0.35	0.74	30	0.20	0.53	0.22	0.76	46	0.38	0.78	0.50	0.84
15	0.17	0.31	0.22	0.59	31	0.20	0.94	0.22	0.96	47	0.34	0.85	0.44	0.89
16	0.21	0.55	0.24	0.60	32	0.21	0.74	0.26	0.88	48	0.35	0.78	0.43	0.85

Notes. The numbers reported in the table are the R^2 for regressions of special cases of equation (2). In case (i), all lags of the spot price are excluded; in case (ii) only the first lag is included; in case (iii) only the 48th lag is included; case (iv) is the unrestricted model. All regressions use observations from the Haywards node during the period 1 March 2000 to 28 February 2001.

Table 2: State space equations

	1st lag	2nd lag	3rd lag	4th lag	σ_k
s_1	0.1104^{**}	-0.0486	-0.0002	0.4952^{***}	6.5958^{***}
	(0.05506)	(0.08581)	(0.07340)	(0.06618)	(0.37379)
s_2	0.8492^{**}	0.3867^{**}	-0.0292	-0.0280	16.6886^{***}
	(0.34403)	(0.17423)	(0.40096)	(0.31326)	(2.04034)
s_3	0.7329^{***}	-0.0449	-0.1783^{**}	0.2226^{***}	7.2119^{***}
	(0.09738)	(0.13918)	(0.07654)	(0.07791)	(0.79723)
s_4	0.4890^{**}	0.1738	0.0547	0.1799^{**}	13.7785^{***}
	(0.24526)	(0.19991)	(0.27352)	(0.08283)	(0.97358)

Notes. The table reports maximum likelihood estimates of the state equations (6) using prices at the Haywards node for the period 1 March 2000 to 28 February 2001. Standard errors are given in brackets. * indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

Table 3: Signal equations

n	δ_n	ϕ_n	n	δ_n	ϕ_n	n	δ_n	ϕ_n	n	δ_n	ϕ_n
1	43.6490	9.6479	13	38.8791	7.4643	25	46.3094	13.3147	37	67.8546	75.3397
	(3.56761)	(0.67986)		(3.48679)	(0.41096)		(7.05194)	(0.26596)		(20.40623)	(4.45104)
2	41.2485	8.0332	14	41.3924	10.4042	26	45.1814	6.8622	38	66.7077	81.0256
	(3.43745)	(0.45717)		(3.47417)	(0.59386)		(6.05186)	(0.33829)		(29.21073)	(5.72752)
3	40.5127	7.5755	15	44.3028	24.0018	27	46.9973	21.1078	39	51.9884	45.8580
	(3.59210)	(0.33873)		(6.55408)	(0.58635)		(12.21826)	(1.11654)		(14.80144)	(1.28646)
4	38.6356	5.2669	16	58.8690	50.0858	28	44.1672	6.5081	40	46.5811	19.2615
	(3.30091)	(0.26856)		(12.53161)	(2.36100)		(6.05655)	(0.49822)		(8.91678)	(0.37778)
5	37.5278	4.4806	17	54.4449	45.0323	29	44.0397	16.0990	41	47.1140	10.6471
	(3.34048)	(0.24149)		(17.85056)	(4.59579)		(7.92420)	(0.39405)		(6.52834)	(0.95114)
6	36.0347	4.1790	18	53.5193	41.0614	30	43.0856	10.6929	42	47.1778	9.2196
	(3.34284)	(0.08446)		(18.22905)	(3.93940)		(6.30588)	(1.63432)		(6.46362)	(1.02913)
7	34.9758	3.1413	19	48.8545	16.3395	31	42.7988	10.7013	43	46.5682	15.3534
	(3.24673)	(0.18642)		(7.74416)	(0.69591)		(6.78962)	(1.67783)		(8.56021)	(0.52735)
8	34.0133	3.0848	20	46.5455	8.8166	32	44.1303	7.8007	44	46.0176	22.0339
	(3.30877)	(0.17790)		(6.56429)	(0.47206)		(6.08932)	(0.50584)		(9.85803)	(2.13526)
9	33.5428	3.3602	21	45.7467	7.3429	33	45.9639	25.0708	45	43.9802	15.5978
	(3.35427)	(0.13058)		(6.78982)	(0.35159)		(10.87791)	(0.73088)		(7.71575)	(1.78131)
10	33.3867	3.4250	22	45.9050	9.9175	34	46.6931	19.2036	46	41.0839	14.7108
	(3.32974)	(0.19709)		(6.32815)	(0.59814)		(8.93379)	(1.34195)		(6.90580)	(3.02994)
11	34.5115	3.9060	23	46.0158	10.0906	35	47.4608	13.2300	47	42.5876	15.3459
	(3.32267)	(0.21697)		(6.16036)	(0.77618)		(6.29031)	(0.75720)		(7.36319)	(3.19522)
12	35.1061	5.2534	24	45.7035	9.2496	36	57.8962	45.4751	48	38.6928	15.5902
	(3.32117)	(0.19337)		(6.24115)	(0.62184)		(10.34780)	(1.21253)		(8.58333)	(2.85700)

Notes. The table reports maximum likelihood estimates of the signal equations (7) using prices at the Haywards node for the period 1 March 2000 to 28 February 2001. Standard errors are given in brackets. All coefficients are statistically significant at the 1% level.

Table 4: Seasonal influences

Mon	Tue	Wed	Thu	Fri	Sat	Sun
α_6	—	α_1	α_2	α_3	α_4	α_5
-1.88448	—	0.15874	1.35218	-0.99956	0.49500	-1.83798
(1.48925)	—	(1.73385)	(2.03003)	(2.28638)	(2.17066)	(1.85788)

Mar	Apr	May	Jun	Jul	Aug
γ_1	γ_2	γ_3	γ_4	γ_5	γ_6
-6.13055	-3.17946	-2.06176	-11.33319^{***}	-12.70774^{**}	-11.21363^{*}
(5.20059)	(4.45181)	(4.29503)	(4.19874)	(5.18452)	(5.73320)

Sep	Oct	Nov	Dec	Jan	Feb
γ_7	γ_8	γ_9	γ_{10}	γ_{11}	—
-12.96581^{**}	-24.62486^{***}	-17.15902^{***}	-7.80929^{**}	-2.99184^{**}	—
(5.15948)	(4.63896)	(4.18619)	(3.56894)	(3.56894)	—

Notes. The table reports maximum likelihood estimates of the coefficients of the dummy variables in the signal equations (7) using prices at the Haywards node for the period 1 March 2000 to 28 February 2001. Standard errors are given in brackets. * indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.