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Asset Price Prediction Using Seasonal Decomposition

by

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1 Introduction

The question whether an asset price can be predicted or not is of great importance in managing portfolios. If the efficient market hypothesis is fully at work, then the stock price or return cannot be predicted at all[1]. On the other hand, if we suppose that the efficient market hypothesis has less than a perfect explanatory power, then the use of a regression model with some macroeconomic variables, could significantly improve performances in predicting asset prices and returns[2]. Suppose that we take a realistic view that the asset price is not one hundred percent subject to the efficient market thesis. Then, there may be two alternative approaches to predicting the asset price. One is based upon at least partially on the efficient market type equilibrium models. For example we may augment explanatory variables of a CAPM type equation or the market model, thereby increasing the overall explanatory power of the model within the sample period. To increase model's explanatory power further, we may employ the Kalman filter time-varying paramer models; use the ARCH-M or GARCH-M time varying conditional volatility models, and so on[3]. These improvements in statistical techniques contribute significantly in increasing within sample R^2, coefficient of determination, but not necessarily increase the predictability power out of the sample. The second approach would be to ignore the efficient market equilibrium argument, and model asset price using a time series analysis technique. The time series techniques may include an integrated autoregressive moving average (ARIMA) model and vector autoregressions (VAR) model, among others.

We take the second approach in this paper, and propose a new asset price prediction method that is easy to implement and that allows forecaster's subjective judgement enter into the prediction. Specifically, we propose to decompose given series into various different factors using a seasonal decomposition procedure. Judgemental forecasts are made on the trend part, while somewhat mechanical prediction methods are employed to forecast other factors. Finally, the original series is predicted by aggregating predicted components. The prediction procedure may seem straightforward enough, but there seem to be several questions that need to be answered before we embark on this method. For instance, which seasonal decomposition method to use? Are there differences in the final prediction performances depending on the seasonal decomposition procedures used? Are there any partic-

[1] Granger (1992) discusses some relevance for the efficient market hypothesis in forecasting stock prices, however.

[2] Notice that the recent "predictability of stock prices" type papers, *e.g.*, Fama and French (1988) among others, focus on the issue how much of the total variance of stock price can be attributed to linear combination of various different observable macroeconomic and stock market variables. Hence they are not primarily concerned with the out-of-the-sample prediction.

[3] See Schinasi and Swamy (1989) for a successful prediction of exchange rates using time varying coefficient models. Brock *et al.* (1993, p.201), however, conclude that prediction performances of the nonlinear models are, in general, poor.

ular time series that tend to be forecasted more accurately than the others, when this method is used? These are only a fraction of questions that we may face if we employed the prediction methodology proposed in this paper. We plan to answer these and others questions.

This paper is organized as follows. In Section 2, we describe the prediction method in detail, and pros and cons for using our method are discussed as well. Applications of our method to the Tokyo Stock Exchange Price Index (TOPIX hereafter), some individual stock prices, and yen/dollar spot rate at the Tokyo Foreign Exchange Market, are presented in Section 3. We give concluding remarks and suggestions for future research in Section 4.

2 Prediction Method

As stated in the previous section, we shall use a seasonal adjustment procedure to decompose a time series into various components. There are abundant empirical findings that stock prices contain seasonal elements[4]. The reason for using seasonal decomposition lies in the fact that when decomposed, each component should be nearly orthogonal in terms of respective information content. If we used seasonal dummy variables in a regression equation to seasonally adjust a series, then we would end up with exactly orthogonally adjusted and unadjusted series[5]. We, however, will use seasonal adjustment methods via moving averages, *e.g.*, X-11 and SABL, because they are (i) well established and have good track records, (ii) readily available in software packages hence easy to use[6], and moreover (iii) seasonal adjustment method that use seasonal dummy variables in regression are not generally capable of dealing with varying seasonal patterns[7]. One other seasonal adjustment procedure that we rule out from using in this paper, is the state space approach[8]. We do not use the state space approach mainly because with this method we need to specify a time series structure to the trend part, hence there is little room left for incorporating subjective judgement in forecasts. With easy to use state space modeling programs available in FORTRAN, however, we should compare our method to the state space

[4]From the many empirical papers, let us cite only Eleswarapu and Reinganum (1993).

[5]See Davidson and MacKinnon (1993) for some desirable properties of seasonally adjusting a series by dummy variables in a regression framework.

[6]Performances and comparisons of X-11 and SABL are well documented in Levenbach and Cleary (1981) and Cleary and Levenbach (1982), among others. A practical account of X-11 is found in SAS Institute (1989), while original description of SABL is Cleveland and Terpenning (1982).

[7]Regression methods are capable of dealing with varying seasonal patterns if we introduced terms that are made of seasonal dummies multiplied by the time trend and/or polynomial of it. We need to specify the type and the number of terms *a priori*, however, hence this method lacks flexibility in handling changing seasonal patterns.

[8]Shumway (1988, p.188) cites several pathbreaking papers in area.

approach in the future[9].

In this paper we shall use SABL to seasonally decompose a series[10]. Let X_t be the original series to be predicted, then SABL assumes a class of power transformed additive processes for transformed X_t, $X_t^{(p)}$:

$$X_t^{(p)} = T_t + S_t + I_t,$$

where the power transformation $X_t^{(p)}$ is defined by

$$X^{(p)} = X^p \quad \text{if } p > 0, \qquad = \log X \quad \text{if } p = 0, \qquad = -X^p \quad \text{if } p < 0,$$

T_t is the trend component, S_t is the seasonal component, and I_t is called the irregular component but we shall call it the residual component in this paper[11]. It makes a great deal of difference whether a component is "irregular" or "residual." The term irregular may seem to imply that the component is supposed to be a white noise, while the term residual may indicate that the component could still involve cyclical factors that have been left out from the trend component and seasonal component[12]. We will demonstrate later that SABL decomposed TOPIX's I_t still contains significant peaks in its spectrum that ought to be modeled and explained by some time series techniques. We suggest that Box-Jenkins type ARIMA model for this purpose[13].

2.1 Estimation and Prediction of the Residual Component

After extracting I_t, the residual series, we should examine its time series graph in order to locate any outliers. We ought to carefully examine each "outlier" since our experience with SABL shows any surprise phenomenon is fully reflected, not in T_t or S_t, but in I_t. There may be two ways of dealing with the outliers in I_t. One is to

[9]See Kitagawa (1993) for a vareity of FORTRAN time series analysis programs that includes state space models.

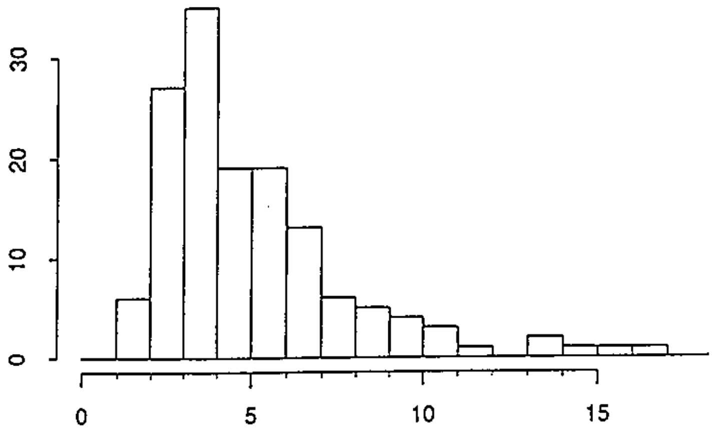
[10]We were inspired by Miura and Uchida (1992) for using SABL in financial time series analysis. Cleveland *et al.* (1982) demonstrate that SABL has certain superiority over such seasonal adjustment methods as X-11. Cleary *et al.* (1982, p.38) document several improvements of SABL that have been made over X-11. In fact we chose SABL because it is in a very versatile data analysis software S. The combination of S's graphics and SABL seems to be ideal for interactive data analysis such as ours. Our experience suggests, however, that X-11, although in its default option assumes a multiplicative process, can be used almost the same way as we use SABL.

[11]SABL automatically selects optimal power p by grid searching p over several prespecified points. The resultant p is optimal in the sense that it has the least cross components' effect in terms of asymptotic t statistics. See Cleveland *et al.* (1982) for details. Needless to say that if $p = 1$ is selected then the original and the power transformed series are the same.

[12]Notice that since SABL uses resistant moving avearge filters iteratively, it essentially belongs to a class of moving average seasonal decomposition methods. In the moving average methods, there is no guarantee that I_t is free of cyclical component. In other words, the trend and seasonal parts may not capture all long waves and seasonal waves.

[13]See Box and Jenkins (1976).

Figure 1: Distribution of Sample Variance Ratios: VR



Note: The vertical axis shows frequency and the horizontal axis is $VR \equiv \hat{Var}(I)/\hat{Var}(S)$.

smooth out the outliers in the I_t series by making interpolation, by such a method as the spline function, by trimming the original I_t at $\pm 2\hat{\sigma}$, where $\hat{\sigma}$ is the sample standard deviation of I_t[14]. The second way is do nothing, *i.e.*, use the original I_t series as is. This will result in poor goodness of fit in the estimated ARIMA model, and could even bias the coefficients depending upon the way outliers are observed. We regard that both of the above methods are worthwhile using. In practice, we do both.

We use non-interpolated original I_t series to compute its sample variance, $\hat{Var}(I)$ along with $\hat{Var}(S)$, that of the seasonal component. Let us note that except for the trend component, the seasonal part, S_t, and the residual I_t, comprise a regression model like framework from which S_t will be forecasted somewhat mechanically using SABL's built in function. That is, S_t amounts to the deterministic part while I_t is the residual part, in a "regression" like framework. If we want to make a reasonable forecast using this framework, we may require that R^2 or $\hat{Var}(S)/(\hat{Var}(S)+\hat{Var}(I))$, to be not too low so that the deterministic part is not overwhelmed by the residual part. There is no rule of thumb as to how large R^2 should be, but we may note that $VR \equiv \hat{Var}(I)/\hat{Var}(S) = 1$ implies $R^2 = 0.5$. In view of the fact that the market model that regresses individual stock return on the market return seldom gives R^2 higher than 0.5, we would argue that individual stock price with $VR \leq 1$ should be a very good candidate for the prediction using the method in this paper. Figure 1 presents a distribution of VR for 146 randomly selected indivudual stock prices in the Tokyo Stock Exchange (T.S.E.) for the sample period from January 1975 to December 1990. We discovered that the minimum is 1.311 with an median of 4.170.

[14]In fact, older versions of X-11 adopted this type of filtering to filter out outliers.

The figure indicates that about a quarter of all stock prices have $VR \leq 3$, where $VR = 3$ amounts to $R^2 = .25$, hence the number of individual stock prices that are *good* candidates for our prediction method, is not large.

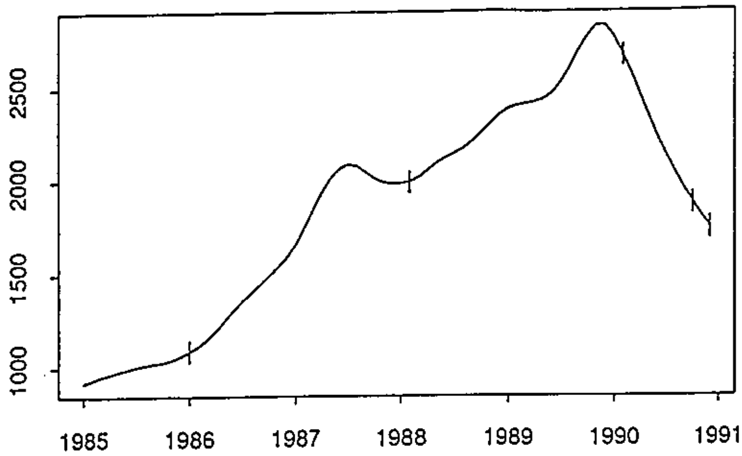
Having obtained rough idea as to what the nature of I_t is, we go on to estimate and make a forecast of the I_t series using an ARIMA (integrated autoregressive moving average) model. A valid question at this point would be: why an ARIMA model instead of an ARMA model, since if I_t were a stationary residual series, then differencing in ARIMA is not needed? To answer this question, we refer the reader again to the argument we developed earlier, *i.e.*, not all cycles and nonstationary factors in the original series are captured by the trend component, T_t, when we used SABL or other seasonal decomposition methods that are based upon moving average.

The possible number of ARIMA(p, d, q) models, where p is the order of autoregression, q is the order of moving average and d is the order of differencing, is not large. In practice we only need to pay attention to $0 \leq p, d, q \leq 3$ excluding $p, q = 0$ cases, hence up to 60 cases. For these 60 cases we recommend that the initial values in the nonlinear maximization be set to the default value of the software used, and delete the non-converging cases. We also recommend that the estimated model should be stationary and invertible in terms of the estimated coefficients. Imposing these criteria, should reduce the number of ARIMA models under consideration, to 1/3 to 1/5 of the 60 at most. For these models, we suggest that we apply such usual criteria as (i) asymptotic t-statistics, (ii) R^2 type goodness of fit statistic, (iii) portmanteau type test[15]. The number of ARIMA models should be very small by then. To decide on the final model, we recommend to carry out (static) simulation of the models under consideration, and compare each model's simulated values with the original I_t's. The comparison of the simulation needs to be done carefully, paying attention to whether turning points of the original I_t series have been captured well or not. It would be better to do static simulations since dynamic simulations tend to uncover model's true explanatory power and thus once the simulated value starts to diverge from the original then it would wander away for good. This is not ideal if our purpose is to make prediction for a relatively short time horizon. Static simulations would do the job satisfactorily.

Using the chosen model, we make a dynamic simulation out of the sample for F months, the number of months that we wish to make forecast. These forecasted I_t values should be kept until predictions of other components are available.

[15]See for example Harvey (1990) for details. Notice that the ARIMA model selection procedure suggested in this paper, is quite different from that in Box and Jenkins (1976), who suggested a step wise approach: first the identification stage, then the estimation and the diagnostic checking stages. After more than 20 years of Box and Jenkins' first development of their modeling methodology, we think that the computer speed is now fast enough for our practical procedure to be implemented.

Figure 2: Inverse Power Transformed TOPIX Trend: p=-.5



Note: The vertical lines on the curve, correspond to the scenarios.

2.2 Scenario on the Trend Component

The trend component, T_t, in SABL is for the power transformed series $X_t^{(p)}$, not for the original series X_t. In predicting stock price or exchange rate, in order to feed in our subjective view about the future course of the series, we need to have the trend component in the original series not in the power transformed series. To this effect, we make an inverse power transformation on the T_t series as $T_t^{[p]} = T_t^{1/p}$ if $p > 0$, $= exp(T_t)$ if $p = 0$, $= (-T_t)^{1/p}$ if $p < 0$. In Figure 2, T_t is seen to be ranging from 500 to 3,000 for the sample period just as the original series, but without the seasonality, other outliers and smaller irregular effects. Hence it would be easier to work with $T_t^{[p]}$ to come up with different scenarios rather than to work with the original series that is contaminated by the various noise.

The second reason why we use T_t or its inverse power transformed counterpart $T_t^{[p]}$, for scenario construction and why we do not model T_t by the ARIMA process, say, is in the fact that T_t or $T_t^{[p]}$ is usually nonstationary. Stock return, $r_t = log(P_t) - log(P_{t-1})$, where P_t is the stock price at time t, in principle, may be predicted using the same forecasting method proposed in this paper. But we prefer to work with P_t since, compared to the P_t series, it will not be easy to construct scenarios for the r_t series to be used on $T_t^{[p]}$[16]. If P_t has nonlinear trend part then the bulk of it should be represented in the $T_t^{[p]}$ series.

[16]Serial correlation in stock prices tend to be higher as frequency of observation increases. Thus whether a monthly r_t series is a random walk process or not is an issue to be determined empirically. We, however, regard that a monthly P_t series is close to a "trend stationary" process with possibly a nonlinear trend and that of r_t is more like a "difference stationary" process. See Davidson and MacKinnon (1993) for definition of these terms.

Due to the two reasons we stated above, we select $T_t^{[p]}$ to be the component where we inject our subjective view of the prediction period. Notice however, that our method is quite different from what usually is known as the judgemental forecasting method despite the fact that it incorporates scenario or subjective judgement, in the trend component[17]. We could generate projections of the T_t series by some regression techniques such as the error correction models. The main reason we do not employ a regression technique in our prediction process is that we need predicted values of all the right hand side variables, and thus the prediction is *conditional* on the values[18]. Although the same applies for our method, (*i.e.*, our method is a forecasting procedure that is *conditional* on the scenario used) we feel that working with the scenarios is better than finding values for the right hand side variables. .

It now remains to answer how to construct reasonable set of scenarios for $T_t^{[p]}$. We just suggest one way of doing this. Take, for example, the stock price index. We usually have some opinion as to what phase of a cycle we are in; beginning of a boom or just hitting the bottom of a cycle. These views may be quantified by using avearge rate of change of the past $T_t^{[p]}$. If we are optimistic that we are just in the beginning of a boom, then we may compute the average monthly rate of change during the past boom to extrapolate $T_t^{[p]}$. In this way we may construct optimistic, moderate and pessimistic cases, or any other possible cases. An important thing to note at this stage, is that a high resolution graphics of SABL either on screen or in hardcopy form should be utilized to the fullest extent in constructing scenarios. Numerical values of the average rate of change should not be used without checking their graphics. Graphical methods and numerical values need to interact to decide on a reasonable set of scenarios.

2.3 Predicting the Original Series

The seasonal component is predicted automatically for one year if SABL is used. We put predicted values of the three components, T_t, S_t and I_t, together and make an inverse power transformation, to obtain the final forecasts on the original series, X_t,

$$X_t = (T_t + S_t + I_t)^{[p]} \text{ for } t = 1, \cdots, F,$$

where F is the forecast horizon. Notice that the only stochastic component in the right hand side is I_t for $t = 1, \cdots, F$. A $100(1-\alpha)$ percent asymptotic prediction confidence interval for individual I_t is given by $I_t \pm Z_{\alpha/2}\sqrt{Var(e_t)}$, where $Var(e_t)$

[17]See Holden *et al.* (1990) for several business forecasting methods including judgemental forecasting technique.

[18]In reality, however, we may point out that many regression based forcasts are presented and regarded as if unconditional forecasts without the detailed description of what have been assumed to produce certain predictions. We feel that this is a great disservice to both forecasters and to the people who use forecasts. In the forecasting methodology proposed in this paper, we claim outright that our method is a method that produces conditional forecasts.

is the forecast error variance at time t, $Z_{\alpha/2}$ is such that $\Pr(|Z| > Z_{\alpha/2}) = \alpha$, and $Z \sim N(0,1)$, a standard normal variate. Therefore, a $100(1-\alpha)$ percent asymptotic prediction confidence interval for individual X_t becomes

$$(T_t + S_t + I_t \pm Z_{\alpha/2}\sqrt{Var(e_t)}\ )^{[p]}.$$

This formula does not give a symmetrical interval around the point prediction, X_t, because of the inverse power transformation[19].

3 Examples of Prediction

Let us apply the prediction method discussed in the previous section, to several asset prices. Note that our prediction method is not appropriate for forecasting such variables as an individual bond yield with fixed maturity. Such a price series usually has smaller volatility near the maturity, and moreover its price is exactly equal to the prespecified level on the maturity date.

3.1 Prediction of TOPIX

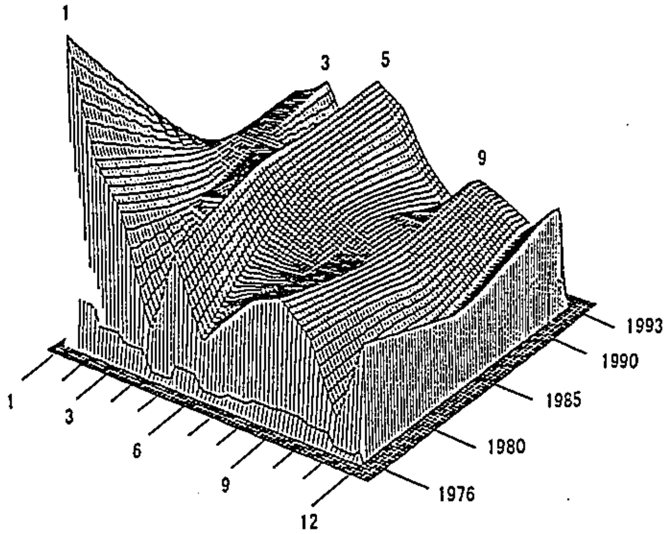
TOPIX is one of the most important price indices that are watched by many portfolio managers. Our sample period is September 1975 to December 1990, while the forecasting period is 1/91 to 12/91, a 12 month period[20]. We first decompose the series using SABL. Selected power is -.5. SABL gives a set of graphs of components in one page, which is convenient. Although this is a useful set of graphs, we suggest singling out the S_t series and make a three-dimensional graph out of it. Take years and months on the X and the Y axis, respectively. This obviously is a byproduct of our prediction exercise. We extend the sample to 11/93, and show the three-dimensional graph in Figure 3. It is interesting to observe that (i) previously observed January effect has faded away recently, rather (ii) what might be called the "kessanki effect" (financial statement time effect) seems to be at work[21], and (iii) November (and also December to some extent) has been always a bad month given the same trend series. In particular, (iii) seems to suggest that the present slump in the stock market is at least partially a seasonal phenomenon. At this stage this, however, is a speculation, and needs to be shown empirically.

[19]For log transformed variables, the above interval is smaller than that of the interval for X_t due to Jensen's inequality.

[20]We shall denote September 1975 as 9/75, and so on hereafter.

[21]Financial statements are due, usually on March and September. Many businesses realize capital gains on their stock holdings for cosmetic reasons, just before the statements are due. After they are made public, those businesses who sold stocks, may buy them back in order to maintain "mochiai" relationship. "Mochiai" is an inter-business stock holdings by businesses that are in close relationships, to hold their stock price at a high level by holding each others' stocks.

Figure 3: TOPIX Seasonality in a 3-Dimension Graph: p=-1



Note: We used the most recent observation available for this graph. Hence its sample period, 1/76 to 11/93, is different from that in the text. The chosen power is also different from the one used in the prediction exercise.

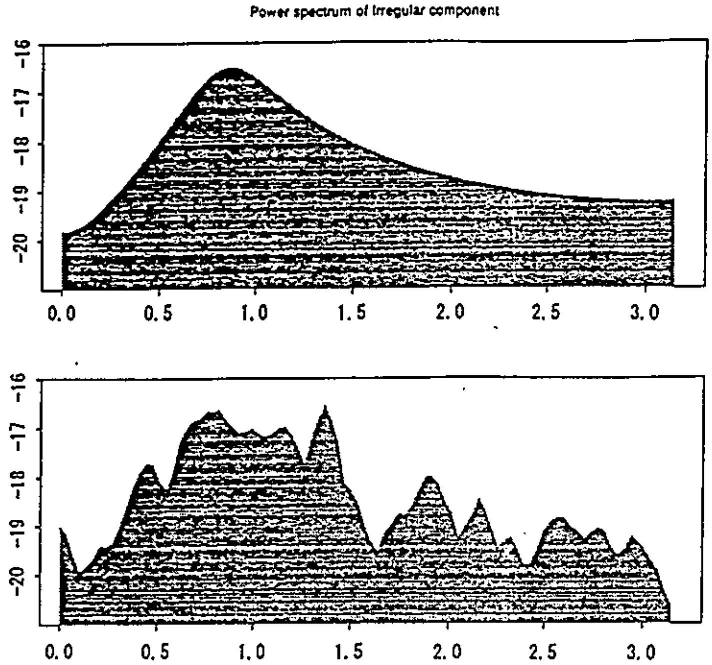
We now go back to the original sample period of 9/75 to 12/90. Various ARIMA models for the I_t series have been estimated following the model selection procedure outlined in Section 2, and the chosen model is

$$(1 - \sum_{i=1}^{2} \phi_i L^i)\Delta^2 I_t = (1 - \sum_{i=1}^{2} \theta_i L^i)\epsilon_t \ ,$$

where L is the lag operator, $\Delta^d \equiv (1-L)^d$ is the dth difference operator, $\epsilon_t \sim$ a white noise, estimated ϕ_i's and θ_i's are given by $\underset{(1.8)}{\hat{\phi}_1 = .50}$, $\underset{(0.5)}{\hat{\phi}_2 = -.47}$, $\underset{(0.9)}{\hat{\theta}_1 = 1.78}$, $\underset{(0.9)}{\hat{\theta}_2 = -.79}$; respectively with asymptotic t value inside $(\cdot)$, and $R^2 = .680$. This is an ARIMA(2,2,2) process and from this we extrapolate I_t for $t = 1, \cdots, F$. It would be of some interest to examine if the chosen model really captured the cycles that are present in the original I_t process. To this effect, we estimated the sample spectrum of the original I_t series, and compared it to the spectrum of the chosen model, and they are stacked up in Figure 4. It seems that some of the significant cycles in the original series have the same peaks in the theoretical spectrum of the chosen model.

We computed the avearge rate of change of the $T_t^{[p]}$ series for the period 1/86 to 12/90 to obtain the optimistic case; 2/88 to 10/90 to obtain the moderate case, and 2/90 to 12/90 to obtain the pessimistic case. The dates above have been chosen so

Figure 4: Residual Series' Spectrum Compared to that of the Chosen ARIMA Model



that each one is representative of the stock market cycle as seen in the graph of $T_t^{[p]}$ in Figure 2.

Finally we compiled each component together, and made an inverse power transformation to obtain predictions of the TOPIX series for 1/91 to 12/91 as in Figure 6. This figure shows the optimistic case with a 95 percent prediction confidence interval. It turns out that the most optimistic case is the closest to the actual *ex post,* but even this prediction has not captured the major turning points. One peculiar characteristic that we noticed about SABL is that when the forecast is going upwards then any fluctuation around the trend line is amplified; on the contrary when the slope of the forecast is steeply downward then the seasonality and the residual component have far lesser effect on the final prediction. In other words, if we used steeply upward sloping trend line then effects of the seasonal component and the residual component are magnified greatly. This phenomenon is particular to SABL and does not happen with X-11[22].

[22]Let η be $S_t + I_t$, *i.e.*, the components other than the trend, T_t. Then the effect of a small change in η, on the original series, X_t, is given by

$$f(T,p) \equiv \frac{\partial}{\partial \eta} X = \frac{1}{p}(T+\eta)^{\frac{1}{p}-1}$$

if $p > 0$. In fact SABL does not deal $p \geq 1$ case. Hence, for $0 < p < 1$, the power in the above expression is $\frac{1}{p} - 1 > 0$. Consider two values on T such that $T_B \gg T_S$, then the difference $(f(T_B,p) - f(T_S,p))$ is always positive. This implies that the effect of η on X is greater if the trend level is larger, *i.e.*, $T_B \gg T_S$. For $-1 < p < 0$ and $p = 0$ cases, the same conclusion can be

Figure 5: Scenarios on Inverse Power Transformed Trend, $T_t^{[p]}$

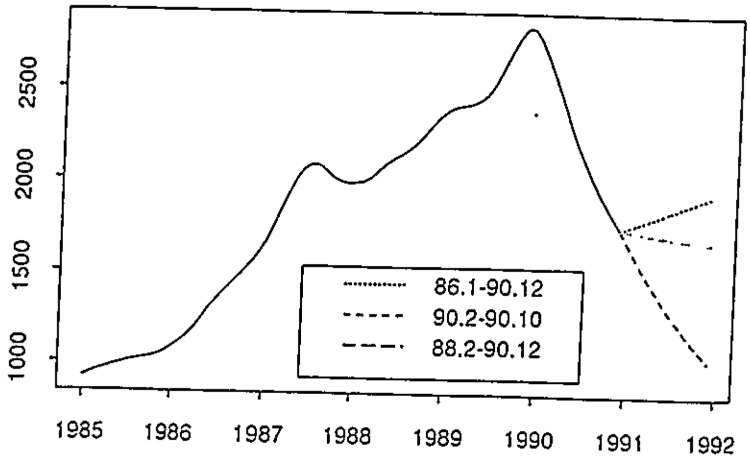


Figure 6: TOPIX Predicted and Its 95% Prediction Confidence Interval

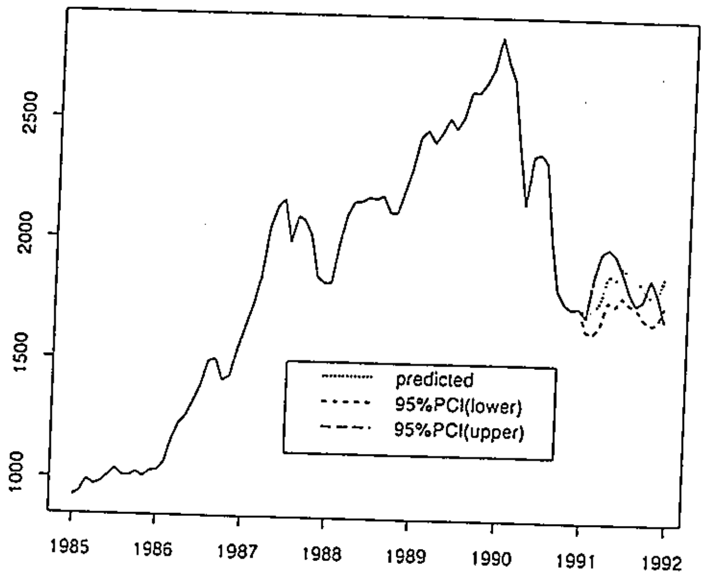
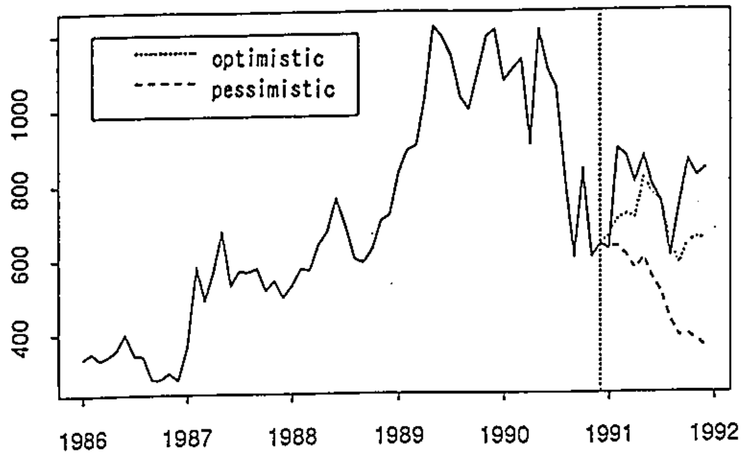


Figure 7: *Mitsubishikakouki* Predicted for One Year



3.2 Individual Stock Price Prediction

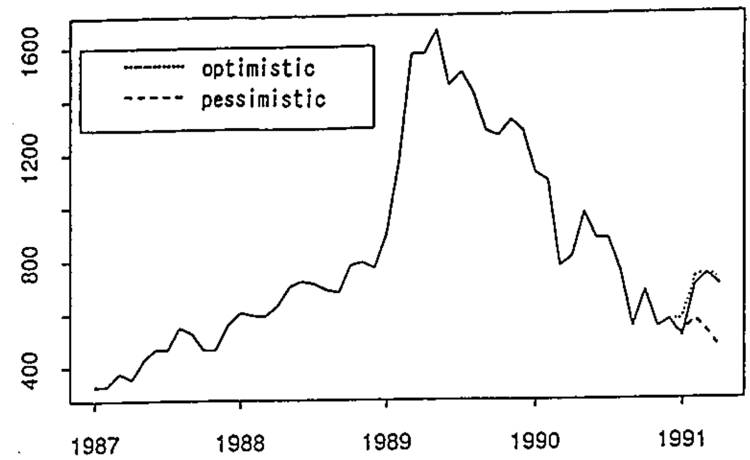
We have carried out prediction exercises on a number of individual stocks traded in the T.S.E. In this subsection we present only two of them. We have selected them for presentation here not because their prediction performances are outstanding or particularly poor. Rather, they are representative of what we obtain from many individual stock prices. The first one is *Mitsubishikakouki* with which we made one year forecast, and the second is *Daidoutokushukou* whose four months' prediction is presented[23]. They are in Figures 7 and 8, respectively. In Figure 7 we see that some turning points of the original series are predicted fairly well by the forecast, but not the level. A possible way of improving the forecast performance may be to change the scenario we have given[24]. As indicated in the last paragraph of the previous subsection, this would have changed the way the forecasts of the S_t series and the I_t series affect the final forecast through the trend. In Figure 8, an example of better than the average shortrun prediction performance is given. When this is extended to one year, then the difference between our forecast (whichever the case is) and the actual, becomes larger. An obvious remaining task for us then, is to find the way to identify *a priori* the type of time series that is suitable for shortrun prediction rather than the one year prediction.

established easily.

[23]For the two figures, only the optimistic case and the pesimisstic case are presented. Average rate of change on the $T_t^{[p]}$ series have been computed for the period of 9/88 to 12/90 and 2/87 to 10/89, respectively for *Mitsubishikakouki* and *Daidoutokushukou*, to construct the optimistic cases, while 1/90 to 12/90 and 11/89 to 12/90, respectively to obtain the pesimisstic The entire sample periods for the two stocks are 3/75 to 12/90 for *Mitsubishikakouki* and 3/80 to 12/90 for *Daidoutokushukou*.

[24]This would require a justification on the new scenario. What we are doing is an *ex ante* forecasting, not a forecasting exercise using *ex post* available data for forecast.

Figure 8: *Daidoutokushukou* Predicted for 4 Months



3.3 Yen/Dollar Exchange Rate and Long Term Bond Price Index

Other than the stock prices, an asset price that is suitable for our method, is hard to come by. This is so, since there are not many series that have definite linear or nonlinear trend component, to which we inject our subjective view of prediction. Thus, such important series as the exchange rate, EXC, or the long term goverment bond price index, $BOND$, cannot serve as good examples of our method. This is confirmed by computing the VR ratio which was defined as $\hat{Var}(I)/\hat{Var}(S)$. VR for EXC is 1.58 while that of $BOND$ is 6.09[25]. The $BOND$ series, in particular, is on the higher side, and thus we suspect that this is not a suitable series for our method. Let us hence present some preliminary results on them in this subsection.

The other difficulty of working with such a series as EXC is the lack of definite seasonality[26]. In Figure 9, however, we present EXC's seasonality in an interesting three dimensional graph. We observe that the July peak has been somewhat spread out recently to August, but the peak still remains. The two troughs of February and November are also observed up to the most recent month. As suspected, predictions of EXC shown in Figure 10, are not so good. The bond series yields the similar results to those of the EXC series, and thus we shall not present them here.

4 Concluding Remarks

In this paper, we have proposed a prediction method that uses a seasonal decomposition method. Among the asset prices, it seems to work well with stock prices or

[25]The sample periods are 9/71 to 8/91 and 2/73 to 12/87, respectively for EXC and $BOND$. EXC is inter-bank monthly average rate at Tokyo Market, while $BOND$ is 10 year Japanese goverment bond rate.

[26]A recent paper, Diebold and Nason (1990) discusses some of the difficulties involved in predicting foreign exchange rate and stocks.

Figure 9: Exchange Rate Seasonality in a 3-Dimension Graph: p=-1

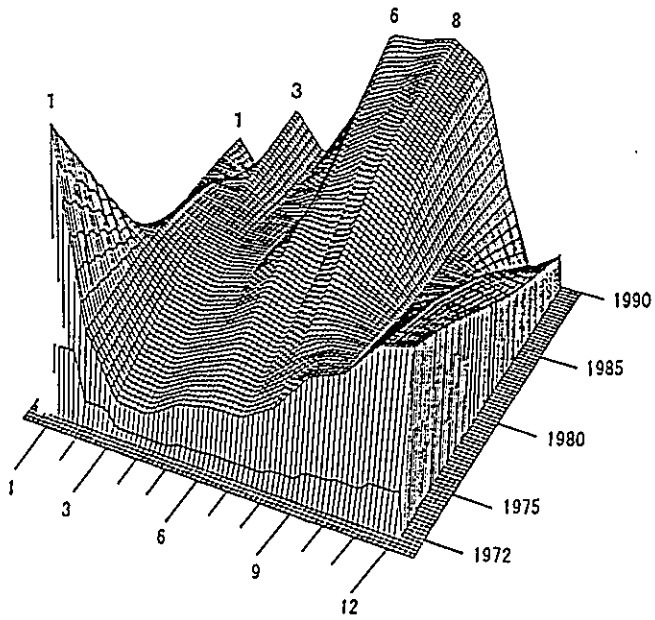
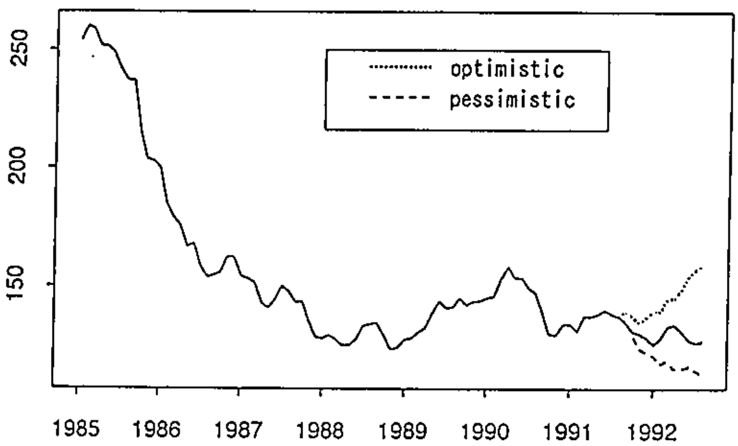


Figure 10: Yen/Dollar Exchange Rate Predicted One Year



indices. Application of this method to other asset prices need more investigation. In addition, there are many other things that remain to be done to improve our forecasting method. We list them in the following.

- SABL has been recently upgraded to STL that uses Locally Weighted Regressions (LOWESS)[27]. We need to investigate whether we can use STL in place of SABL.

- Comparisons of our prediction method based upon SABL to other seasonal decomposition methods have not been presented in this paper. Results that are based upon X-11, are similar to that of SABL. Other seasonal decomposition methods cannot be used transparently to our prediction method, since we do not know how the same scenario could be incorporated in these seasonal decomposition methods. Comparisons to other forecasting methods seem to be somewhat meaningless, since it would be more difficult to use the same scenario as used in our method to the other forecasting method, *e.g.,* a regression method.

- It would be interesting to search all the individual stocks in T.S.E. to find good candidates for our method, in the future. Also, increasing the frequency of observation from monthly to weekly or daily would be very fitting projects since SABL and X-11 easily compute the same set of components as we deal with monthly data.

- Possible application area for this prediction method, is not confined to asset prices. Any series with seasonality and at least 3 to 4 years of sample period, is a candidate for this method. For instance international phone call volume between Japan and the U.S. may be a good series with which to apply this method.

- There is definitely a room for improvement in the way scenarios are constructed for the T_t series. For instance, we could somehow relate this series to some economic variables and use regression analysis. to construct a scenario.

- If a way to divide the trend part to (i) common trend component and (ii) specific trend component, is found, then it would be interesting to devise a multivariate seasonal decomposition, and implement our prediction method on the specific component while using such method as the VAR to forecast the common part.

[27]See Cleveland *et al.* (1990) for details.

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