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International Journal of Forecasting 22 (2006) 317–339

international journal
of forecasting

www.elsevier.com/locate/ijforecast

When Wall Street conflicts with Main Street—The divergent movements of Taiwan's leading indicators

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Abstract

This paper argues that the simultaneous use of all leading indicators may result in the blending of two different sets of information, which could lead to less accurate predictions of a future recession. We divide six of Taiwan's leading indicators into two different sectors, the real and financial sectors, and distinctly demonstrate that the two sectors may very well reveal different information. Three inconsistent, or even divergent, movements are found for 1988, 1991 and 1994, implying that the factor extracted from the real side may be different from that from the financial side. Thus, in contrast to the one-factor model typically used, we suggest a two-factor model. We compare four Markov Switching models, and it is evident that the predicted recessions based on the two-factor one-state model seem to outperform other models. The second best is the one-factor model which is only based on the real side variables, followed by the one-factor model with four variables. The worst model is that which simply uses financial variables. The results support our argument to use the two-factor model.

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JEL classification: C22; E32.1

Keywords: Wall Street; Main Street; Business cycle; Markov Switching model

1. Introduction

Dating a business cycle's turning point has long been not only in the interest of the public but also in that of both academic and government circles. The

first approach can be traced back to 1920 when the National Bureau of Economic Research (hereafter NBER) identified business cycle chronology in the United States. Since then, the stylized fact about asymmetric adjustment (that a recovery takes up more time than a recession) has often been reported. Hamilton (1989) recently applied a Markov Switching model to the U.S. GNP to date the business cycle turning point and found a remarkably consistent pattern in the generated recessionary and recovery periods to that of the NBER-defined chronology of

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the business cycle. He also confirmed the characteristic asymmetric adjustment.

The use of a single univariate process, either GNP or an industrial production index, was soon found to be too narrow to capture broad fluctuations in economic activity even when a time-varying transition probability was used (see [Filardo, 1994](#)). In fact, it is highly possible that a univariate process may ignore extraneous non-trivial information, a fact which compelled researchers to begin to employ more macro time series. To cite one example, [Stock and Watson \(1989, 1991\)](#), for instance, assumed that the co-movements of four coincidence indicators share a common element that can be captured by a single unobservable latent variable and that represents an economy's state. After combining the concepts of [Hamilton \(1989\)](#) and [Stock and Watson \(1991\)](#), [Diebold and Rudebusch \(1996\)](#) proposed a dynamic factor Markov Switching model to capture the asymmetry and co-movement features of business cycles. [Chauvet \(1998\)](#) and [Kim and Nelson \(1998\)](#) meanwhile applied the Markov Switching factor model to investigating coincident indicators for predicting turning points in the U.S. business cycle. In addition, [Chauvet and Potter \(2000\)](#) applied the model to the construction of coincident and leading indicators of the U.S. stock market.²

A single unobservable common factor extracted from various multivariate processes indeed captures more information than that from a univariate process. The use of "a single" or "one" common factor, however, implicitly assumes that inconsistent movements among coincident and leading indicators are random and can be averaged out. Such an assumption ignores the fact that the coincident and leading indicators typically contain two distinct groups of variables, i.e., financial and non-financial ones. While two groups often do reveal the same information regarding the dating of a business cycle, which justifies the use of a single factor, some cases certainly provide conflicting information. The often-heard asset

bubble, where asset prices exceed the intrinsic value of the fundamentals, may be one case which exemplifies that different information may be contained in the two types of variables. With this in mind, [Chauvet \(1998/1999\)](#) proposed a two-factor regime switching model to identify the U.S. business cycle. [Kim and Murray \(2002\)](#) and [Kim and Piger \(2002\)](#) also used a similar model to extract common permanent and transitory factors within the U.S. business cycle.

The major purpose of this paper is in line with that of [Chauvet \(1998/1999\)](#) which is to extract the two unobservable common factors from two groups of leading indicators. The first common factor, which is referred to as the "Wall Street Factor" (hereafter WSF), extracts information from the financial variable group. The second common factor, on the other hand, is referred to as the "Main Street Factor" (hereafter MSF) and it extracts information from real variables. The co-movements of these two sectors are often seen, yet, as we argue above, the inconsistent movements do also occur.

The implications of our two-street factor hypothesis are crucial from two perspectives. Firstly, if the Wall Street factor suggests a boom but the Main Street sector does not, then the asset price may be overvalued, and an asset bubble may form. Pricking the bubble or letting the economy land softly may then become an urgent concern for authorities. Secondly, if Wall Street suggests a recession but Main Street does not, then although the financial market may be pessimistic about the future, the manufacturing market is not endangered. Restoring the confidence of investors by adopting a credible and transparent policy may, at this point, become necessary.

In this paper, we use Taiwan's leading indicators as our example since Taiwan has experienced inconsistent episodes. For example, financial deregulations starting in 1987 stimulated asset prices to a historically unprecedented high level in 1989, whereas manufacturing production remained relatively stable. The "missile tests" of Mainland China over Taiwan Island during 1995 and 1996 led to the reverse effect. The missile tests frightened investors, causing stock prices to drop substantially. All the while, the manufacturing industry, however, was only mildly hurt. Although we use Taiwan as our example here, the application of our study to other economies is straightforward.

² [Kim and Yoo \(1995\)](#) also assumed that an unobserved common factor is driven by a Markov Switching process with a time varying transition probability. They found that both the composite index of leading indicators and disaggregate coincident indicators are informative in identifying the state since they reduce the idiosyncratic noise in the business cycle.

The rest of this paper is organized as follows. Taiwan's leading indicators are discussed in Section 2. The model specifications are described in Section 3, and the empirical results and implications are presented in Section 4. Our comparisons of forecasting performance are described in Section 5, while our concluding remarks are summarized in Section 6.

2. Taiwan business cycle indicators

Taiwan's leading indicators include six variables, with the first three being non-financial (real) variables, namely new manufacturing orders (ORDER), exports through customs (EXPORT) and the floor area permitted for building in Taiwan (BUILD). The latter three are financial variables, namely the stock price index (SP), narrowed money supply (M1B) and the wholesale price index (WPI). The two types of variables, real and financial, are also referred to as Main Street and Wall Street variables, respectively. These leading indicators are regularly published by a Taiwan authority, the Council for Economic Planning and Development (hereafter CEPD), which also publishes the dates of a business cycle whenever it is deemed necessary.

Fig. 1 plots the annual growth rates of the six indicators. They are calculated from the formula $y_t = 100 \times (Y_t - Y_{t-12})$, where Y_t is the logarithm of the empirical series and y_t is the corresponding annual growth rate. The Main and Wall Street variables are plotted in the left- and right-hand panels, respectively. All series are taken from the monthly journal Business Indicators distributed by the CEPD. The variables are monthly data from 1983:m1 to 2001:m4 and total 220 observations.³

The conventional aggregate leading indicator is the simple sum of the percentage changes in the six indicators. The aggregate leading indicator assumes that the information contained in each indicator is the same except for a few random variations. This indicator distinguishes neither between the use of the real sector and that of the financial sector, nor the leading economic activities up to 3 or 6 months.

It would therefore be of particular interest to create two sub-aggregate leading indicators and investigate the differences between the two sectors, and this is central to this study. For expositional purposes, we combine the three real variables into one Main Street indicator (or real sector indicator) and the three financial variables into one Wall Street indicator (or financial sector indicator). In the upper and lower panels of Fig. 2, we plot the simple sub-aggregate leading indicators and the spread between them, respectively.

In Fig. 2, three inconsistent movements are noted between the two sectors. The first inconsistent and divergent movement appears in 1988. As shown, the Wall Street indicator increases substantially, while the Main Street indicator drops slightly. In other words, the financial sector indicates that the economy is "too hot", whereas the real sector shows a "mild cool", meaning such a combination of phenomena which is typical of an asset bubble. The reasons for this asset bubble include the effects of the financial deregulation that started in 1987, a slow but steady appreciation of the exchange rate and a lax monetary policy among others. That is, during that period, both stock prices and real estate prices reached historically unprecedented high levels. The exchange rate also appreciated from 38 New Taiwan dollars (NTD) to around 25 NTD per US dollar. The central bank did not adopt any active monetary policy to prick the bubble, causing the growth rate of M1B to also reach 51% in annual percentage terms. The real side, however, was not affected by this financial boom and to a certain extent, even dropped.

The next inconsistent movement occurred in 1991 once the central bank had finally decided to prick the asset bubble at the end of 1990. The Minister of Finance also announced their intention to tax capital gains earned from the stock market.⁴ This simultaneous tightening monetary and fiscal news shattered the confidence of investors. Stock prices plunged from 9800 to 5400 over a period of 19 consecutive days.⁵ At the same time, the growth rate of M1B

⁴ Previously, there had been no tax on profit gains in Taiwan.

⁵ Because Taiwan's stock market has daily price limits, the impact of the bad news often spills over 2 consecutive days. See Shen and Wang (1998) for a description of price limits in Taiwan's stock market.

³ The data can be downloaded from the website of the CEPD: <http://www.cepd.gov.tw/index.jsp> and are available from the author upon request.

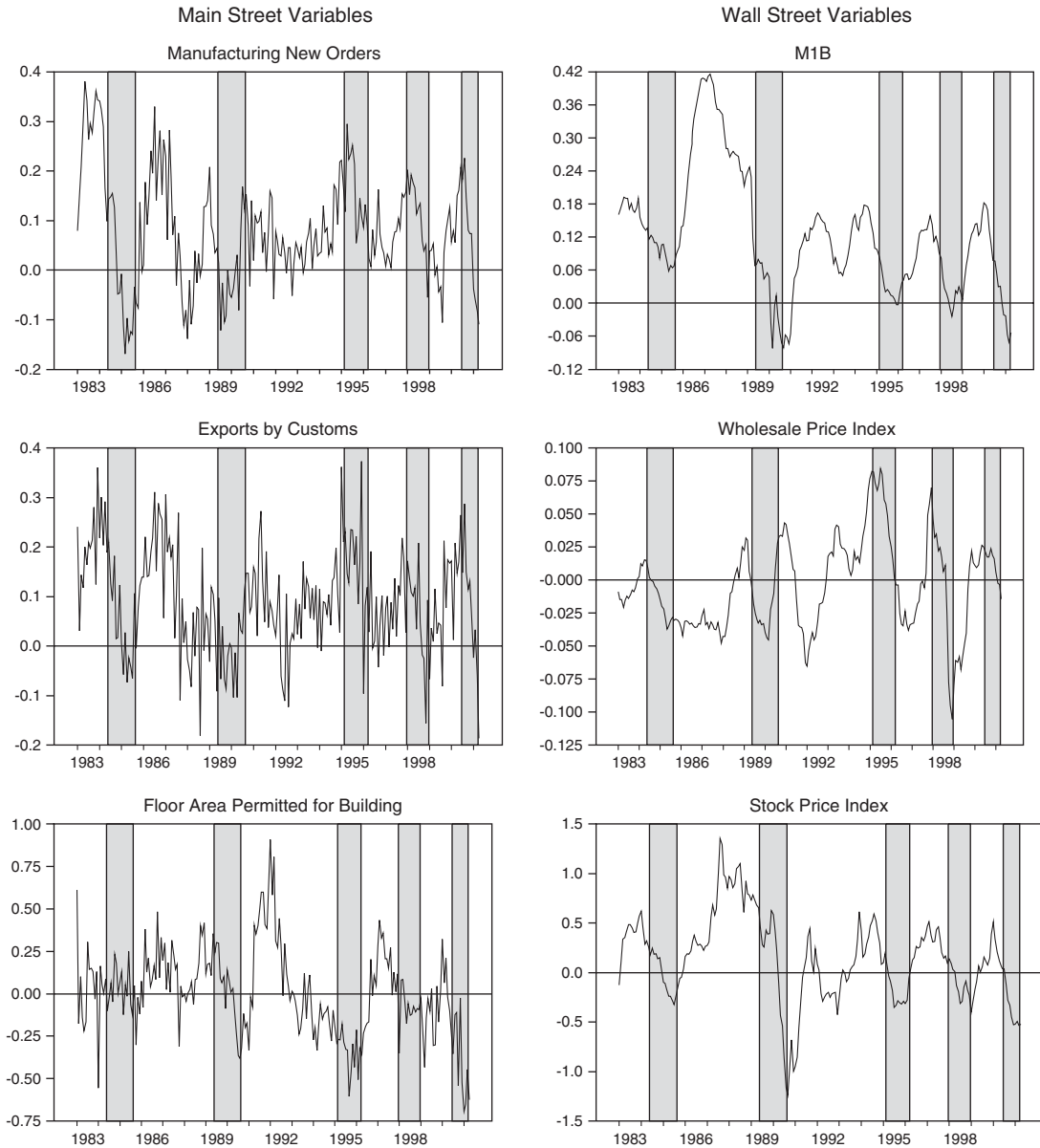


Fig. 1. Scatter plots of the annual growth rates of ORDER, EXPORT, BUILD, M1B, WPI and SP. All series are seasonally adjusted monthly data extending from 1983:m1 to 2001:m4, which amounts to 220 observations.

decreased. The real side, however, was hurt relatively less, meaning that the degree of the response from the two sectors was somewhat different. Thus, from the perspective of the financial side, it was suggested that a recession was approaching, whereas from the standpoint of the real side, it was indicated that no change in the economic condition would occur. The

aggregate index reflected more of a change in the financial side, also indicative of a recession.

The third inconsistent movement appears in 1994 (Fig. 2). In contrast to the above two episodes, we observe that not only do the two sectors move in different directions, but there are also divergent movements inside the real sector (see Fig. 1). As observed in

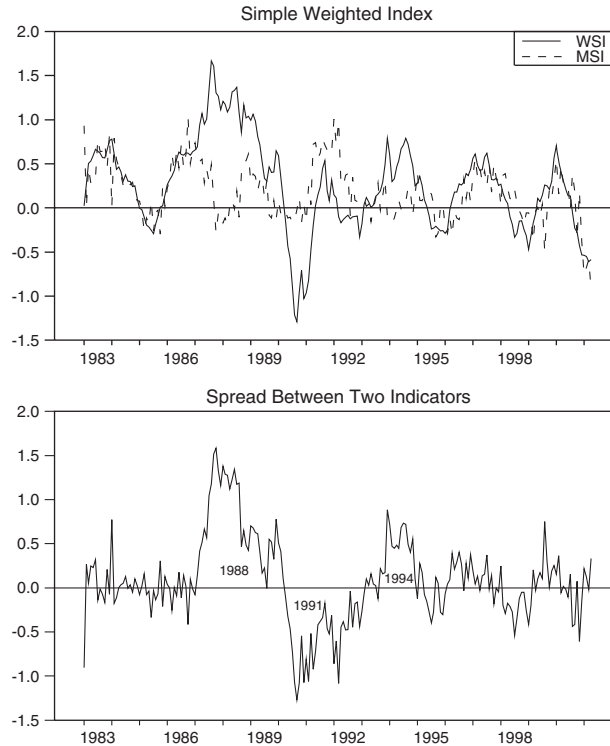


Fig. 2. Simple weighted index of the Main Street and Wall Street variables.

both Figs. 1 and 2, while the first two real components EXPORT and ORDER display an upward trend, their aggregation is pulled down by a strong declining index of the third component BUILD. The Main Street indicator thus decreases although two of the components increase. Unlike the conflicting information inside the real sector, the three financial variables overwhelmingly show a “consistent” prediction of the business cycle. That is, because the growth rate of WPI is countercyclical but the stock return and M1B growth rate are procyclical, the opposite movements between the wage rate and the other two lead to the same prediction vis-à-vis business cycle movements. Hence, based on the prediction of the business cycle direction, all of the three are deemed “consistent” in our paper. By contrast, the inside divergent movements in the real sector lead to the opposite prediction of the business cycle and affect the estimation of the Markov Switching model (which will be discussed shortly).

Because the two sectors may not signal the same directions of future recessions, the conventional

aggregate leading indicator which combines the six variables may result in the annulment of important information. Consequently, the prediction of the business cycle may be imprecise.

3. Econometric model

3.1. The one-factor model

The one-factor Markov Switching model (hereafter the one-factor model) is based on Kim and Yoo (1995) and Kim and Nelson (1998). Let $y_t = [y_{1t}, y_{2t}, \dots, y_{6t}]'$ be a function of a common unobserved dynamic factor F_t and idiosyncratic noises $z_t = [z_{1t}, z_{2t}, \dots, z_{6t}]'$.⁶ The terms y_{it} , where $i = 1, \dots, 6$, are the six Taiwan leading indicators described above, and z_{it} is a vector stationary series with a mean of zero and

⁶ The ranking of the variables in descending order is ORDER, EXPORT, BUILD, M1B, WPI and SP.

variance Σ . All variables are transformed into annual growth rates and deviate from their respective means. Factor F_t captures market-wide co-movements underlying the six leading indices. Thus, the model is:

$$y_t = \gamma(L)F_t + z_t, \quad (1)$$

$$\phi(L)F_t = \beta(S_t) + \eta_t, \quad \eta_t \sim \text{i.i.d.}N(0, \sigma_\eta^2), \quad (2)$$

$$\beta(S_t) = \beta_0(1 - S_t) + \beta_1 S_t, \quad S_t = 0, 1, \quad (3)$$

$$\theta(L)z_t = e_t, \quad e_t \sim \text{MVN}(0, \Sigma), \quad (4)$$

where the boldface variables denote the vectors. Function $\phi(L) = (1 - \phi_1 L - \dots - \phi_k L^k)$ is a scalar lag polynomial; and $\gamma(L)$ and $\theta(L)$ are vector polynomials, as follows: $\gamma(L) = \gamma_0 + \gamma_1 L + \dots + \gamma_q L^q$ and $\theta(L) = 1 - \theta_1 L - \dots - \theta_r L^r$, with L denoting the lag operator, and k, q and r being lag lengths. Σ is the diagonal matrix with diagonal elements equal to $\sigma_1^2, \dots, \sigma_6^2$. Since the factors summarize information common to different variables and cannot be directly observed, a scale must be provided to allow for their interpretation. This is done by setting one of their factor loadings or the factor variance to unity. We adopt the latter approach by setting the factor variance σ_η^2 to unity.

Term S_t is an unobserved latent variable which takes on the value 1 when the economic state is in expansion and 0 when the economic state is in contraction. It is assumed that it follows the following first-order Markov chain:⁷

$$\begin{aligned} \Pr[S_t = 0 | S_{t-1} = 0] &= p_{00}, & \Pr[S_t = 1 | S_{t-1} = 1] &= p_{11}, \\ \Pr[S_t = 1 | S_{t-1} = 0] &= 1 - p_{00}, & \Pr[S_t = 0 | S_{t-1} = 1] &= 1 - p_{11}. \end{aligned} \quad (5)$$

3.2. The two one-factor models

The real and financial variables are separately specified to follow their respective one-factor model since the two types of variables may share various common factors. The first specification involves only real variables, i.e., y_t is an $N_1 \times 1$ vector of monthly real variables containing {ORDER, EXPORT and

BUILD}.⁸ On the other hand, the second specification involves only financial variables, and y_t is an $N_2 \times 1$ vector of monthly financial variables containing {M1B, WPI and SP}. Models (1)–(4) are then repeatedly used by replacing y_t with the real and financial vectors. The common factor F_t resulting from the financial variables is the Wall Street Factor (WSF), whereas when the real variables are used, it is the Main Street Factor (MSF). All variables are transformed into annual growth rates and deviate from their respective means.

3.3. The two-factor model with regime switching

The two-factor model with regime switching (hereafter referred to as just the two-factor model) is a straightforward generalization of the one-factor regime switching model. Let $Y_t = [y_t, y_t^*]'$ be the 6×1 vector of the leading indices, where the first three terms are the real (or Main Street) sector, i.e., $y_t = [y_{1t}, y_{2t}, y_{3t}]'$, and the last three terms are the financial (or Wall Street) sector, i.e., $y_t^* = [y_{1t}^*, y_{2t}^*, y_{3t}^*]'$. The asterisk (*) denotes the Wall Street sector. The two-factor Markov Switching model is specified as follows:

$$Y_t = \begin{bmatrix} y_t \\ y_t^* \end{bmatrix} = \Gamma(L) \begin{bmatrix} F_t \\ F_t^* \end{bmatrix} + \begin{bmatrix} z_t \\ z_t^* \end{bmatrix} \quad (6)$$

$$\Phi(L) \begin{bmatrix} F_t \\ F_t^* \end{bmatrix} = \begin{bmatrix} \beta_0(1 - S_t) + \beta_1 S_t \\ \beta_0^*(1 - S_t^*) + \beta_1^* S_t^* \end{bmatrix} + \begin{bmatrix} \eta_t \\ \eta_t^* \end{bmatrix} \quad (7)$$

$$\Theta(L) \begin{bmatrix} z_t \\ z_t^* \end{bmatrix} = \begin{bmatrix} e_t \\ e_t^* \end{bmatrix}, \quad (8)$$

where

$$\begin{aligned} F_t &= \begin{bmatrix} F_t \\ F_t^* \end{bmatrix}, & B &= \begin{bmatrix} \beta_0(1 - S_t) + \beta_1 S_t \\ \beta_0^*(1 - S_t^*) + \beta_1^* S_t^* \end{bmatrix}, \\ Z_t &= \begin{bmatrix} z_t \\ z_t^* \end{bmatrix}, & N_t &= \begin{bmatrix} \eta_t \\ \eta_t^* \end{bmatrix}, & E_t &= \begin{bmatrix} e_t \\ e_t^* \end{bmatrix}, \end{aligned}$$

with the latter two noise vectors distributed as:

$$N_t \sim \text{MVN}(0, \Omega); \quad E_t \sim \text{MVN}(0, \Xi) \quad S_t, S_t^* = 0, 1,$$

⁷ After submitting this paper, we found Bandholz and Funke's (2003) paper which is similar to ours.

⁸ Term N_1 is the number of real variables, and N_2 is the number of financial variables.

and

$$\Omega = E(N_t N_t') = E([\eta_t \eta_t^*]' [\eta_t \eta_t^*]) = \begin{bmatrix} \sigma^2 & 0 \\ 0 & \sigma^{*2} \end{bmatrix}$$

$$= \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \quad \text{and} \quad \Xi = \begin{bmatrix} \Sigma & 0 \\ 0 & \Sigma^* \end{bmatrix},$$

where Σ and Σ^* stand for the respective covariance matrix for the Main Street and Wall Street factors. The factor variances σ^2 and σ^{*2} are set to unity.

Eq. (6) states that the vectors Y_t are composed of two sets of leading indices which can be expressed as the stochastic latent factors F_t and the two idiosyncratic terms Z_t . The two latent factors are the Main Street and Wall Street factors, respectively. The factor loading matrix of the observable variables

$$\Gamma(L) = \begin{bmatrix} \gamma(L) & 0 \\ 0 & \gamma^*(L) \end{bmatrix}$$

is a 6×2 diagonal matrix with two vector polynomials. The terms $\gamma(L)$ and $\gamma^*(L)$ are the 3×1 polynomial vectors of loading.

Eq. (7) describes the movement of the latent variable F_t , which consists of an intercept vector B and a white noise vector N_t . The intercept vector is a function of the two different state variables S_t and S_t^* , both of which are unobserved latent variables, taking on a value of 1 when the real and financial factors are in expansion and 0 when they are in contraction. The variance of N_t , which is also the variance of the dynamic factors, F_t , consists of the two variances σ^2 and σ^{*2} . The matrix

$$\Phi(L) = \begin{bmatrix} \phi(L) & 0 \\ 0 & \phi^*(L) \end{bmatrix}$$

is the autoregressive term for the factors.

The states that affect the intercepts and variances are governed by the transition probabilities of the first-order two-state Markov process, $p_{ij} = \text{Prob}(S_t = j | S_{t-1} = i)$ and $p_{ij}^* = \text{Prob}(S_t^* = j | S_{t-1}^* = i)$, with $\sum_{j=0}^1 p_{ij} = \sum_{j=0}^1 p_{ij}^* = 1$, $i, j = 0, 1$. It should be noted that if regime switching in the Wall Street and Main Street types of asymmetry is driven by the same state variable (i.e., $S_t = S_t^*$), then in essence, this assumption would mean all recessions switch synchronously.

Besides this, we allow the Main Street and Wall Street factors to switch non-synchronously over time, that is $S_t \neq S_t^*$. Under this assumption, the two-factor model can be estimated separately, and thus, the log likelihood function corresponds to the sum of the function for each factor derived from the one-factor model (see Chauvet, 1998/1999).

Finally, Eq. (8) specifies the error term of the leading indicators. The term $\Theta(B) = [\theta(B) \theta^*(B)]$ makes up 1×6 vector polynomials, and $E_t = [e_t, e_t^*]'$ represents 6×1 measurement errors with the covariance matrices being Σ and Σ^* for the Main Street and Wall Street factors, respectively.

3.4. Estimation procedure

The estimation procedure is based on Kim's (1994) approximate maximum likelihood method, which requires the conversion of Eqs. (6)–(8) into a state-space representation. We report the state-space in the appendix due to space constraints.

Performing the estimation involves the following steps. First, the ergodic probability must be calculated as the initial value and then the Kalman and Hamilton filters must be applied to the model. The most innovative aspect of the Hamilton filter is its ability to objectively date the state of the economy using the so-called filtered and smoothed probabilities. The filtered probabilities (collected in a $(T \times 1)$ vector denoted as $\xi_{t|t}$, i.e., $\xi_{t|t} = p(S_t = j | \Psi_t)$; $t = 1, \dots, T$, $j = 0, 1$; and Ψ_t which make up the information set) denote the conditional probability that the analyst's inference about the value of S_t is based on information obtained through date t . It is indeed also possible to calculate smoothed probabilities, $\xi_{t|T} = p(S_t = j | \Psi_T)$, $t = 1, \dots, T$, $j = 0, 1$, which are based on the full sample.⁹ Finally, as proposed by Kim (1994), an approximation must be made in order to be able to record the log-likelihood function as follows:

$$\log L = \ln f(Y_T, Y_{T-1}, \dots | \Psi_0) = \sum_{t=1}^T \ln f(Y_t | \Psi_{t-1}). \tag{9}$$

⁹ Hamilton (1989) describes the manner in which to make an inference as to the particular state of the economy at date t .

The unknown parameter estimates of the model can then be obtained by maximizing the log-likelihood with respect to the unknown parameters using the numerical method.

3.5. Prediction criteria

We suggest two criteria to evaluate prediction failures. The first is the missed signal failure, viz., when there is a recession, but the model fails to predict it. The other is the false signal failure, namely, when the model predicts a recession, but one does not actually occur.

Once the conditional regime probabilities are generated, the issue pertaining to a decision rule to translate these probabilities into binary regime predictions remains. Birchenhall, Jessen, Osborn, and Simpson (1999) suggested using two rules to convert a predicted probability into a predicted classification. One is the 0.5 rule and the other is the sample rule. Following the 0.5 rule, a recession is expected if the predicted probability exceeds 0.5. On the other hand, based on the sample rule, a future recession is plausible if the predictive probability exceeds \hat{p} , where \hat{p} is the sample proportion of the recession periods. Conflicting predictions arise when the predictive probability falls between 0.5 and \hat{p} . The probability signals a contraction, but this signal is not strong enough to overturn the overall population information in 0.5. This region delineates a period of market uncertainty. For simplicity, we adopt only the \hat{p} rule for regime prediction.

4. Empirical results

Our empirical results can be categorized into two parts depending on the number of leading indicators used. The first part involves the use of the three Main Street leading indicators, the three Wall Street leading indicators and the six leading indicators. They are all one-factor models.

Bear in mind that our objective is to adopt a two-factor model to extract two possible information sets from our six variables. Hence, a two-factor, six-variable model is expected. We find, however, that

such a model is difficult to implement because of the problem of non-convergence.¹⁰

Also, as we will explain in the next section, one real variable as well as the financial variables are insignificant in the generation of the unobservable factor. Omitting these variables from the six-variable model does not significantly affect the estimated results but does allow us to adopt the two-factor model. For this reason, we downsize the model from six to four variables. This forms the second part of our empirical results.

Thus we use four variables to extract the unobserved factor. The three models in this part are the one-factor (with only four variables) model, the two-factor one-state model and the two-factor two-state model, where the *state* here denotes the state variable, *S*. Hence, one-state means the one state variable with two regimes, while two-state means two state variables with four regimes.

4.1. Three and six leading indicators

Three one-factor models are estimated in this section, with the first two using only three variables and the last one using all six of the variables discussed earlier. All of them are one-factor models. The first two are referred to as the Main Street one-factor (MSF) model and the Wall Street one-factor (WSF) model respectively, depending on whether the real or financial variables are used.

The lag lengths of the factor loading $\gamma(L)$, k , the factor autoregressive terms $\phi(L)$, q , and the idiosyncratic terms $\theta(L)$, r , are determined based on the Schwartz Bayesian Criterion (SBC). The maximum lag length is 2 so as to maintain the degrees of freedom.

¹⁰ All computations of the unknown parameters are performed using the OPTMUM module of GAUSS 3.2 combined with the Broyden–Fletcher–Goldfarb–Shanno (BFGS) algorithm. We impose no constraint on any of the transition probabilities p_{00} and p_{11} other than the conditions that $0 \leq p_{00} \leq 1$ and $0 \leq p_{11} \leq 1$, and that σ is constrained to be positive. For the two-factor model with six variables, we find that the model is extremely difficult to converge, and is sensitive to initial values. When it converges, the results are not reliable; for example, they have very large standard errors. Thus, we reduce the number of variables used from six to four.

For all models, we first examine whether the unobserved factor indeed switches between the two regimes or not. To this end, we estimate the linear dynamic factor model (hereafter DF) of Stock and Watson (1989, 1991, 1993), a model which resembles the MS model but which does not have the switching coefficients, β_0 and β_1 . For simplicity, our model is referred to as the dynamic factor Markov Switching model (DFMS). In other words, both models assume that there is one unobservable factor among the variables, but while the DFMS assumes that the factor switches between two regimes the DF does not. Hence, by imposing a value of zero on the switching coefficients in the DFMS model, we obtain the DF model. Since the DF is nested in the current DFMS, a significant likelihood ratio (LR) implies the rejection of the null hypothesis of no switching.¹¹

There is one econometric issue when LR is used. Because the parameters are not identified under the null, the conventional LR test does not yield the standard asymptotic distribution.¹²

Most researchers, however, still use LR as a useful supporting evidence. LR itself, however, may not be suitable to serve as the sole evidence for the rejection or non-rejection of the null hypothesis. Throughout the paper, our LR tests are considered in this way.

4.1.1. The Main Street one-factor model (MSF)

We use both DF and DFMS approaches to estimate coefficients for all models considered. For the sake of space, however, we only report one of the results based on the LR test. Except for the third one, i.e., the six-variable with one-factor model, the models reject DF and prefer the DFMS approach.¹³

¹¹ See Kim and Yoo (1995), Kim and Nelson (1998), and Chauvet (1998).

¹² The problem comes from two sources: under the null hypothesis, some parameters are not identified, and the values are set to zero. Hansen (1992, 1996) proposed a bound test that addressed these problems, but its computational difficulty has limited its applicability. See Hansen (1992, 1996) and Garcia (1998) for a detailed explanation of these problems.

¹³ The estimated results of both approaches are available from the website http://www.geocities.com/chen_shyhwei/cv/wallmain.pdf and are also available from the author on request.

The first column of Table 1 presents the estimated results of the MSF model using only DFMS. The three variables from the real sector are {ORDER, EXPORT and BUILD}. The lag lengths of k , q and r are selected as 1, 2 and 2. The switching coefficients β_0 and β_1 in the two regimes are first examined in the DFMS. While the intercept of regime 0, $\beta_0 = -0.670$, is insignificant, the intercept of regime 1, i.e., $\beta_1 = 0.404$, is significant at the 5% level. Also, the null of no switching coefficients, i.e., $\beta_0 = \beta_1 = 0$, is rejected by the LR test ($= 19.032$). The DFMS model is thus the preferable one, and the discussion below is based on this model.

There are three factor loading vectors, γ_0 , γ_1 and γ_2 on F_t , F_{t-1} and F_{t-2} , respectively, in generating the unobserved factor. The factor loadings, γ_{10} , γ_{11} and γ_{12} of ORDER_{*t*}, ORDER_{*t-1*} and ORDER_{*t-2*} are 0.523, -0.293 and 0.020, respectively, with the first two significant at the 5% level but the last one insignificant. The factor loadings, γ_{20} , γ_{21} and γ_{22} , of EXPORT_{*t*}, EXPORT_{*t-1*} and EXPORT_{*t-2*}, are 0.168, 0.018 and 0.063 with the first one significant but the last two insignificant. In contrast to the above significant coefficients, none of the factor loadings of BUILD is significant. Thus, ORDER has the strongest effect in generating the factor, followed by EXPORT. BUILD has no effect on generating the factor whatsoever. BUILD is thus the candidate that could be removed from the model for the following four-variable model.

The three plots on the right panel of Fig. 3 are consistent with the results that indicate that ORDER and EXPORT respectively have the strongest and second strongest influence on the factor and that BUILD has no influence. The pair-wise scatter plots of the generated factor against either ORDER or EXPORT are clearly shown to be positively sloped. By comparison, the scatter plot of the factor against BUILD is less clear. The respective correlation coefficients of the three pair-wise plots are 0.904, 0.761 and -0.032 , respectively.

The panel on the left in Fig. 3 presents the graphs of the filtered and smoothed probabilities of the MSF model, and the results are mainly analyzed on the basis of the smoothed probability. The shaded areas are the contraction periods, as determined by the CEPD, and serve as the benchmarks for the comparisons. Based on the p prediction criterion, two

Table 1
Estimated results of five models

	MSF: 1-factor	WSF: 1-factor	MSF+WSF (6 Var) 1-factor	Four-variable: 1-factor	Four-variable: 1-factor ($S=S^*$)
	Coeff. (S.D.)	Coeff. (S.D.)	Coeff. (S.D.)	Coeff. (S.D.)	Coeff. (S.D.)
ϕ_1	0.879 (0.061)	0.925 (0.156)	0.925 (0.026)	1.141 (0.167)	0.715 (0.111)
ϕ_2		-0.214 (0.072)	0.074 (0.026)	-0.226 (0.155)	0.186 (0.097)
θ_{11}	1.848 (0.056)	1.788 (0.044)	0.345 (0.073)	0.339 (0.073)	0.128 (0.104)
θ_{12}	-0.896 (0.052)	-0.800 (0.039)	0.208 (0.072)	0.209 (0.071)	0.015 (0.088)
θ_{21}	-0.391 (0.079)	1.398 (0.059)	-0.472 (0.084)	-0.387 (0.080)	1.574 (0.104)
θ_{22}	-0.038 (0.015)	-0.467 (0.059)	-0.055 (0.020)	-0.037 (0.015)	-0.620 (0.082)
θ_{31}	0.393 (0.063)	1.279 (0.064)	0.400 (0.062)	1.755 (0.049)	0.499 (0.408)
θ_{32}	0.444 (0.063)		0.433 (0.062)	-0.770 (0.043)	-0.062 (0.102)
θ_{41}			1.399 (0.060)	1.317 (0.063)	1.208 (0.064)
θ_{42}			-0.426 (0.061)	-0.376 (0.063)	-0.328 (0.064)
θ_{51}			1.500 (0.120)		
θ_{52}			-0.546 (0.114)		
θ_{61}			1.336 (0.063)		
θ_{62}			-0.393 (0.063)		
σ_1	0.044 (0.012)	0.064 (0.009)	0.525 (0.028)	0.517 (0.026)	0.481 (0.029)
σ_2	0.627 (0.033)	0.251 (0.012)	0.595 (0.035)	0.625 (0.033)	0.062 (0.020)
σ_3	0.653 (0.031)	0.268 (0.012)	0.657 (0.031)	0.084 (0.014)	0.066 (0.029)
σ_4			0.169 (0.008)	0.271 (0.013)	0.256 (0.012)
σ_5			0.175 (0.033)		
σ_6			0.269 (0.013)		
γ_{10}	0.523 (0.035)	-0.092 (0.008)	0.263 (0.033)	0.105 (0.039)	-0.108 (0.035)
γ_{11}	-0.293 (0.050)	0.028 (0.015)		0.085 (0.049)	-0.074 (0.038)
γ_{12}	0.020 (0.038)			-0.027 (0.035)	-0.076 (0.037)
γ_{20}	0.168 (0.045)	-0.013 (0.010)	0.274 (0.024)	0.107 (0.048)	0.316 (0.054)
γ_{21}	0.018 (0.068)	0.041 (0.011)		-0.022 (0.083)	-0.786 (0.054)
γ_{22}	0.063 (0.051)			0.072 (0.051)	0.284 (0.060)
γ_{30}	-0.010 (0.039)	-0.038 (0.011)	-0.010 (0.017)	-0.088 (0.012)	-0.127 (0.043)
γ_{31}	-0.016 (0.047)			0.051 (0.016)	0.002 (0.071)
γ_{32}	0.062 (0.041)			0.059 (0.012)	0.073 (0.031)
γ_{40}			0.023 (0.014)	-0.039 (0.017)	-0.067 (0.022)
γ_{41}				0.018 (0.018)	0.002 (0.036)
γ_{42}				0.019 (0.017)	0.019 (0.028)
γ_{50}			0.183 (0.032)	-0.039 (0.017)	
γ_{60}			-0.061 (0.022)	-0.039 (0.017)	
β_0	-0.670 (0.313)	-4.078 (1.203)		-1.122 (0.358)	-0.364 (0.108)
β_1	0.404 (0.272)	3.267 (1.161)		0.463 (0.184)	1.438 (0.301)
ρ_{00}	0.882 (0.080)	0.970 (0.017)		0.843 (0.075)	0.944 (0.024)
ρ_{11}	0.914 (0.050)	0.981 (0.011)		0.920 (0.033)	0.813 (0.071)
ϕ_1^*					1.817 (0.052)
ϕ_2^*					-0.826 (0.048)
β_0^*					-0.040 (0.071)
β_1^*					0.263 (0.169)
logL	-43.770	669.563	591.629	434.372	446.44

MSF contains (ORDER, EXPORT, BUILD), WSF contains (M1B, WPI and SP), Four-variable contain ORDER, EXPORT, M1B and SP. Coeff=coefficient; S.D.=standard error.

“strong” false signals occurred in 1987 and 1992, when the smoothed probabilities are larger than 0.8. Aside from this, two “mild” false signals occur in 1993 and 1996, when the smoothed probabilities are

higher than p but lower than 0.65. There are no missed signals. This model is aggressive in the sense that it generates only type II errors (false signals) but no type I errors (missed signals). The average lead

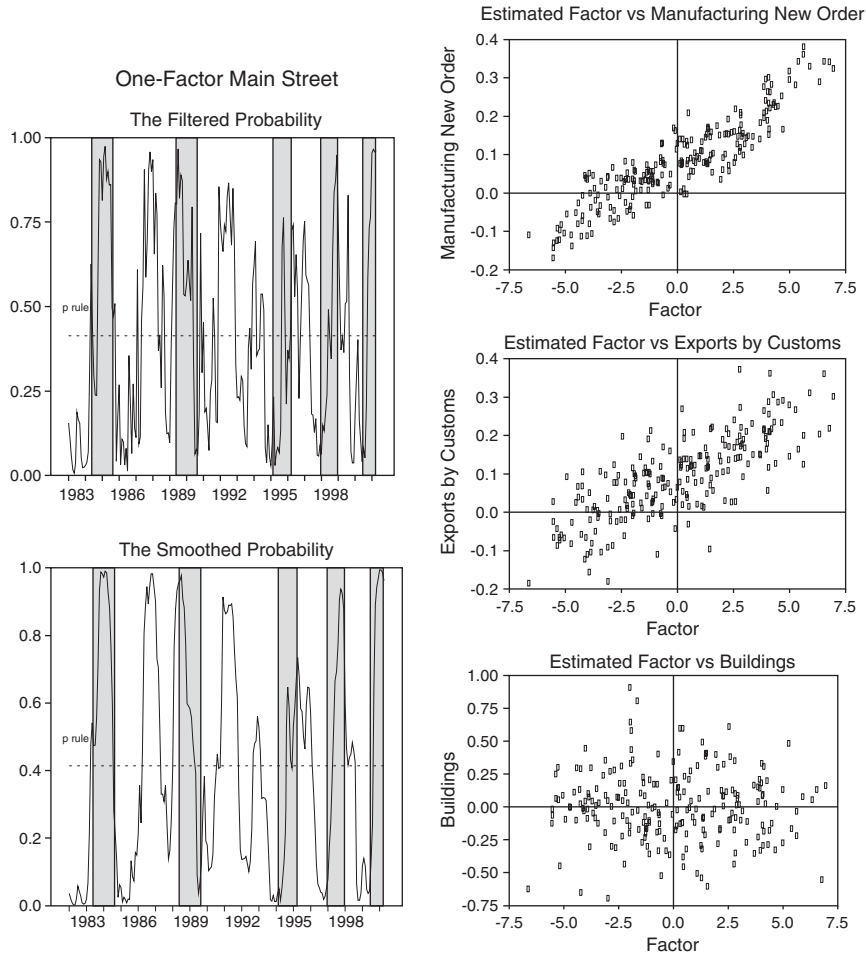


Fig. 3. The panels on the left are the plots of the filtered and smoothed probabilities of the Main Street variables used in the one-factor model. The shaded areas are the contraction periods as determined by the CEPD. The panels on the right are scatter plots of estimated factors and the three Main Street variables.

time in predicting troughs is also calculated.¹⁴ The average lead time for correct signals is five months. The transition probability estimates $p_{11}=0.914$ are greater than $p_{00}=0.882$, showing that the duration(s) of the boom periods are longer than the period during which the economy is in contraction.

4.1.2. The one-factor Wall Street model (WSF)

The second column of Table 1 presents the estimated results of the WSF model. It repeats the

calculations for column 1 but uses the three Wall Street variables {M1B, WPI and SP} instead of the three Main Street variables. The lag lengths k, q and r change slightly and are 2, 1 and 2, respectively. The two switching coefficients, β_0 and β_1 , are -4.078 and 3.267 , respectively. The null of the no switching restriction is significantly rejected by the LR test (LR statistic is 38.141), again suggesting that the factor taken from the Wall Street variables switches. The DFMS is thus preferable to the DF and the following report is based on the DFMS. It is worth noting that the difference between the two switching coefficients is much larger here than that in column 1, suggesting that fluctuations in the

¹⁴ We do not calculate the average lead time in predicting peaks because our smoothed probabilities are related to the probability of a recession.

factor from Wall Street are larger than those from Main Street.

All factor loading estimates are significant except for γ_{20} which is the coefficient of the current WPI, but although the coefficients are significant, their values are much smaller than those reported in the case of Main Street. Most of the values here are less than 0.1, in contrast to an average of 0.5 in the Main Street case. Put briefly, though the generated factor is also affected by the financial variables, their relative influence is small.

The right panel of Fig. 4 presents the pair-wised scatter plots of the generated factor against the three

Wall Street variables. From the naked eye, except for the M1B, the scatter plots are less clear in direction on account of the above reported low values of the factor loadings. The corresponding correlation coefficients of the three pairs of {M1B, WPI and SP} against factor are 0.742, -0.272 and 0.548, respectively. Because the WPI has the lowest correlation with the factor and due to its insignificant factor loading, the WPI is the other candidate which should be removed when the four-variable model is attempted.

The panels on the left in Fig. 4 show the graphs of the filtered and smoothed probabilities. Based on the latter probabilities, the WSF model characterizes the

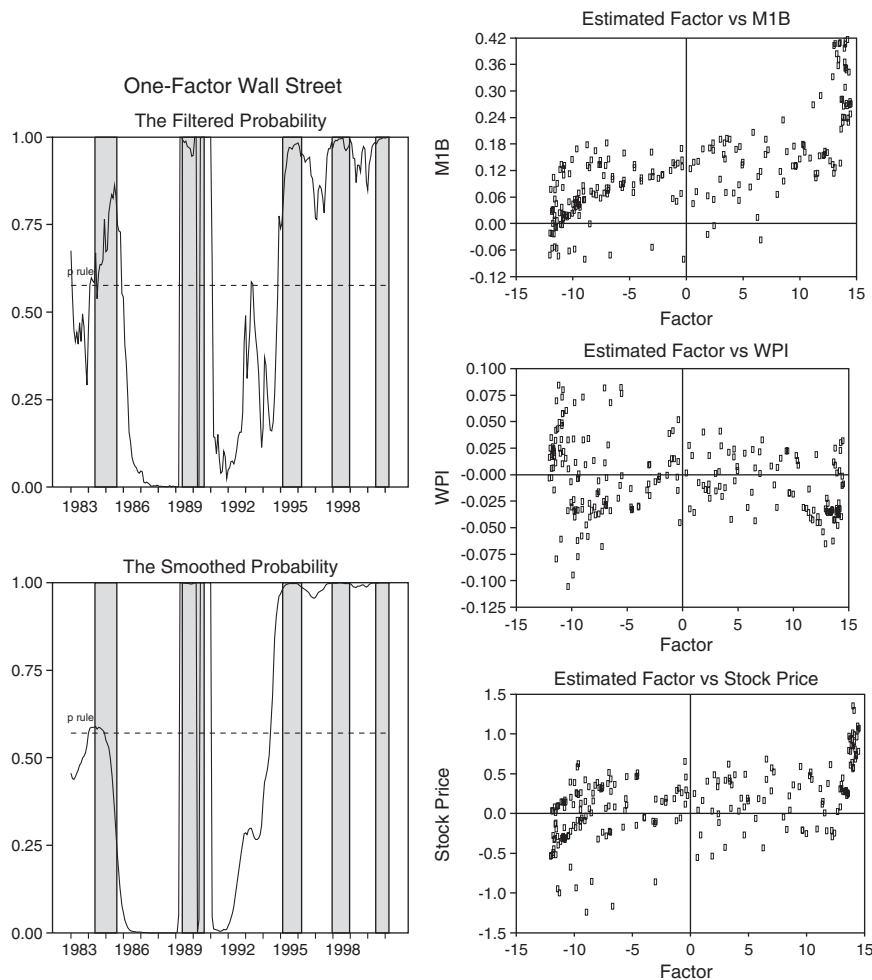


Fig. 4. The panels on the left show the plots of the filtered and smoothed probabilities of the Wall Street variables used in one-factor model. The shaded areas are the contraction periods as determined by the CEPD. The panels on the right are scatter plots of the estimated factor and the three Wall Street variables.

entire post-1995 period as a recession. This should not seem surprising because, in Taiwan, the financial market performed relatively badly after 1995 for the following reasons. First, two banking runs and one bill company scandal occurred in 1995.¹⁵ Second, during the same period, at the end of 1995 and 1996, China launched two “missile tests” against Taiwan. Third, the Asian crisis broke out in mid 1997 lasting until 1999 and was followed by the worldwide recession in 2000, largely owing to the burst of the bubble within the Internet industry. The continuing bad news and other incidents destroyed shattered investors’ confidence, making them pessimistic about the economy. Accordingly, although the economy had not dipped into a recession throughout the whole 1995 period, the factor extracted from the financial leading indicators falsely shows such a downturn in the economy. Because of this, the average lead time in predicting a recession is difficult to determine. Another “mild” false signal is seen in 1983 as evidenced by the smoothed probabilities which are just higher than p , but less than 0.6. This, together with the fact no missed signals are found, suggests that the model is also too aggressive. The continuing errors in dating the recession for the entire 1995-period indicate that the financial variables may over-react to any negative incidents. Thus, the Wall Street sector alone is likely not to be an ideal leading indicator.

Moreover, unlike the case of Main Street, the transition probability estimates predict that the periods of duration are longer during contraction ($p_{11}=0.981$) than in expansion ($p_{00}=0.97$).

4.1.3. *The one-factor six-variable model*

This subsection puts the six leading indicators into the one-factor model without distinguishing Wall Street from Main Street. The third column of [Table 1](#) summarizes the estimated results. Both of the switching coefficients β_0 and β_1 are insignificantly different from zero, strongly suggesting that there is no switching when six variables are used simultaneously. This is confirmed by the LR test which does not reject the null

of no switching. Thus, the DF model is more acceptable than the DFMS. This evidence may reflect some inconsistent, or even divergent, movement between the two sets of variables. To some extent, the information content for the six variables here is inconsistent, if not contradictory. The predicted business cycle chronologies may also be affected.

In the DF model, the loading factors are mostly significant with the exception of γ_{30} and γ_{40} , implying that a common factor may exist but does not switch.

Although no switching occurs in this model, we summarize the filtered and smoothed probabilities but do not report them here. This shows that several false signals occur in mid-1987, throughout 1988, from 1992 to 1994 and at the beginning of 1999. Nevertheless, we still plot the generated factor against the six leading indicators, as shown in [Fig. 5](#). Not surprisingly, the previous clearly sloped patterns of ORDER, EXPORT and the M1B disappear because the factor is not significantly affected by any of the variables. The correlation between the estimated factor and ORDER, EXPORT, BUILD, the M1B, WPI and the SP are 0.253, 0.308, 0.765, 0.389, -0.224 and 0.223, respectively, values which are much lower than their respective three-variable counterparts. This further motivates us to adopt the two-factor model.

4.2. *The four leading indicators*

The discussion above shows that BUILD and WPI might help a little to generate the common factor. These results, along with the fact that the two-factor, six-variable model is not easy to converge, provide us with an even greater incentive to adopt a four-variable model. In this section, therefore, we repeat the above exercises, but we simultaneously employ the four variables, {ORDER, EXPORT, M1B and Stock}. We also plot the simple weighted index of the two Main Street and two Wall Street variables, and the spread between them. Their patterns are similar to those shown in [Fig. 1](#), and hence are not reproduced here.

4.2.1. *The one-factor model*

The fourth column of [Table 1](#) reports the estimated results from using the one-factor model with four variables. Compared to the case with six variables, it is most interesting to note that the previously insignificant switching coefficients end up being significant. The

¹⁵ The two banking runs were the KauChi and DonChi Small and Medium Enterprise Banks, while the bill company was the International Bill Company. The former two arose from the relationship lending and the proxy fights for the controlling shares, respectively, whereas the latter is attributed to a scam of more than 10 billion New Taiwan Dollars by one employee.

Scatter Plots of the Factor and Variables

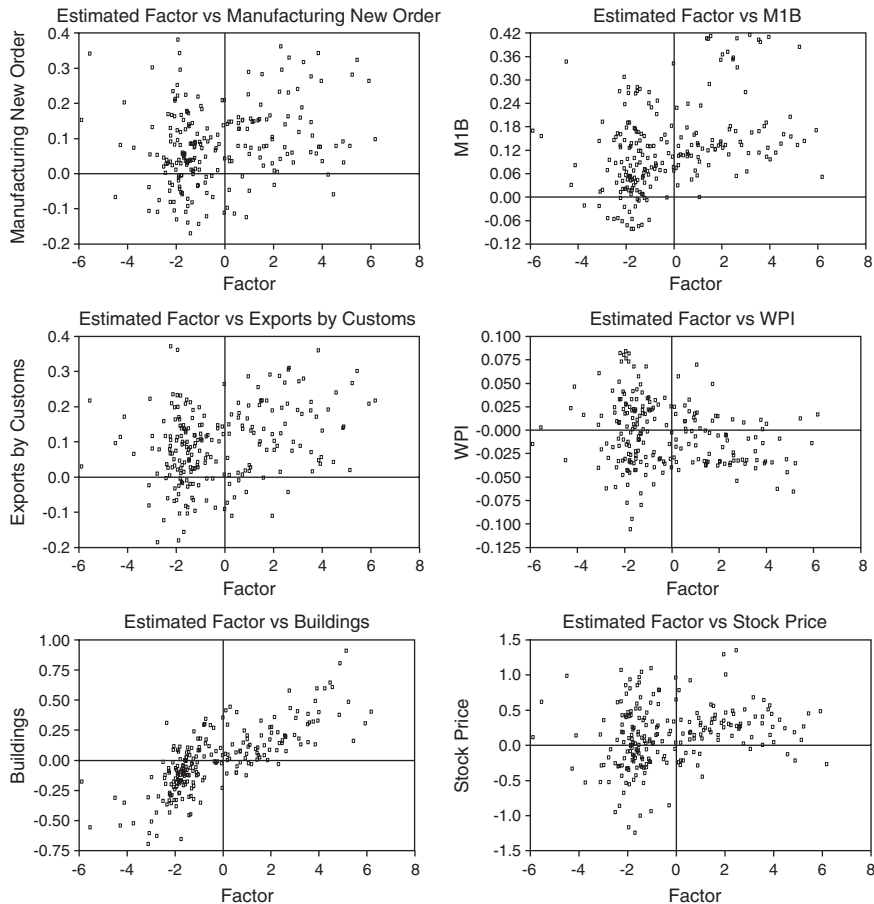


Fig. 5. The panels on the left are scatter plots of the estimated factor and the three Main Street variables. The panels on the right are the scatter plots of the estimated factor and the three Wall Street variables.

two switching coefficients $\beta_0 = -1.112$ and $\beta_1 = 0.463$ are significant at the 5% level here. Unfortunately, the LR test ($=4.642$) cannot reject the null of no switching. As mentioned earlier, the findings obtained from the LR should be considered along with those from other tests in light of the LR's non-standard distribution. Since the finding of the individual t is significant and the LR test is indecisive, we tend to rely more on the results from the individual t tests. Hence, we said that “on the margin” the DFMS is acceptable in predicting the turning points in the Taiwan business cycle.

The graphs of the filtered and smoothed probabilities are plotted in Fig. 6. The smoothed probabilities here predict two “strong” false signals in 1987 and 1992 and two “mild” false signals in 1993 and 1996.

Mild here means that these two false signals are around 0.4 and seem like replications of those of the MSF (Fig. 3), which are around 0.6. In this sense, removing BUILD and WPI from the model improves the prediction to some extent. As a general rule, the correlation estimates between the generated factors increase and are 0.878, 0.798, 0.197 and 0.489 for {ORDER, EXPORT, the M1B, and the SP}, respectively.¹⁶ Based on these coefficients, the generated factor seems to be affected more by the real than by the Wall Street variables. The average lead time in predicting troughs is around 3 months.

¹⁶ The scatter plots are not shown due to space considerations but are available from the authors on request.

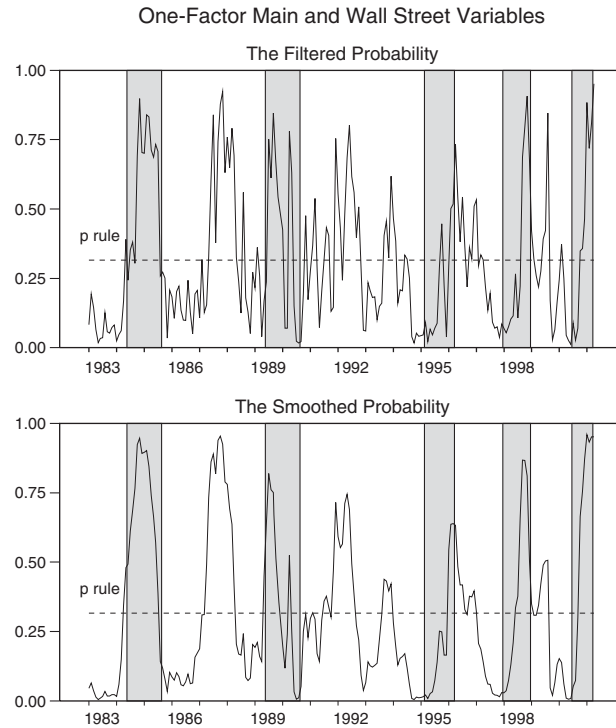


Fig. 6. Plots of the filtered and smoothed probabilities of the four variables of the leading indicator, i.e., ORDER, EXPORT, M1B and SP, used in the one-factor model. The shaded areas are the contraction periods as determined by the CEPD.

4.2.2. The two-factor one-state variable

There are two designs in our two-factor model depending on whether one or two state variables are used. The fifth column of Table 1 reports the estimated results of using one state variable, and assume that the state variable, S_t , generated by Main Street is equal to the state variable, S_t^* , generated by Wall Street. Hence, there is only one smoothed probability, making all recessions obtained by the two types of variables switch synchronously. In the table, the two switching coefficients of the real sector, β_0 and β_1 , are found to be significantly different from zero, whereas the two coefficients of the financial sector, β_0^* and β_1^* , are insignificant. These findings are consistent with those above which state that Main Street variables have a greater effect on the generated factor. These results also suggest that the smoothed probabilities are impacted more by the real than by the financial sector. The LR test, however, rejects the null of no switching. Our discussion is based on the DFMS.

The loadings estimates of the variables are also improved. The loadings of ORDER and EXPORT at t , $t-1$ and $t-2$ are significant at the 10% level, those of the M1B at t and $t-2$ are significant, while only the loading of the current SP is significant. This evidence again suggests that the Main Street variables dominate Wall Street ones.

Fig. 7 plots the posterior probabilities of the model. In contrast to the two strong and two mild false signals using the Main Street variables, along with the false signals for the whole post-1995 period using the Wall Street variables, the new model has only one strong false signal, namely the one in 1987. It is noteworthy is that the predicted probabilities are around 0.4 in 1995 and 1998, values which are only slightly higher than p . Recessions are predicted if the p rule is followed but not if the 0.5 rule is followed. Because the former is adopted here, we feel that it is reasonable to suggest that there were recessions in the two periods. Thus, it correctly forecast these two

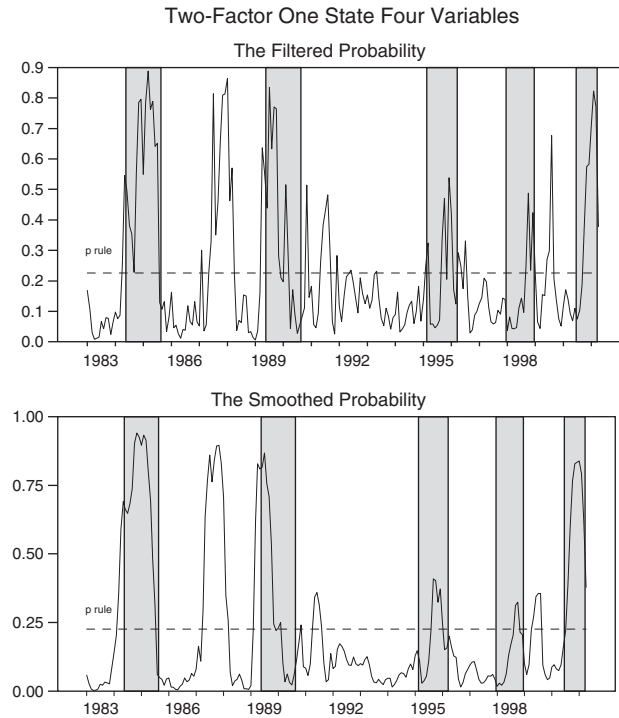


Fig. 7. Plots of the filtered and smoothed probabilities of the four variables of leading indicator, i.e., ORDER, EXPORT, MIB and SP, used in the two-factor model with $S_t = S_t^*$. The shaded areas are the contraction periods, as determined by the CEPD.

recessions in the margin. This could be explained by the uncertainty in our predictions, as we mention above. Thus, in sharp contrast to the aggressive nature of the previous models, for the most part, using the two-factor with the one-state variable model mitigates the aggressive nature. The average lead time in predicting troughs is around 4 months.

4.2.3. The two-factor two-state variables

The estimates of the two-factor model with two-state variables, S_t and S_t^* , are not reported here but are available from our website. The smoothed probabilities of the Main Street and Wall Street factors in this model are allowed to switch non-synchronously over time. Some factor loading estimates for the Wall Street variables are, again, still not significant, but this is most often true of the Main Street variables. The regime estimates for both Main and Wall Street are significant at the 5% level. The null hypothesis of no switching by the LR is also rejected by the LR test (the LR statistic is 40.590).

Fig. 8 represents the plots of the filtered and smoothed probabilities with $S_t \neq S_t^*$ for the Main and Wall Street variables. The smoothed probabilities of Main Street here are similar to the MSF model (Fig. 3), and the smoothed probabilities of Wall Street are similar to the WSF model (Fig. 4). The resulting false signals here are therefore almost the same as theirs.

To sum up, all the models produce more than four false signals and have no missed signals except for the two-factor one-state variable model. Simply put, the model seems to lessen the “aggressiveness” to some extent.

5. Out-of-sample forecasting

This section conducts out-of-sample forecasting to determine exactly which model is superior. A good in-sample may have a bad out-of-sample forecast because of over-fitting (Clements & Krolzig, 1998). We employ the quadratic probability score (QPS), as defined by Hamilton and Perez-Quiros (1996), to

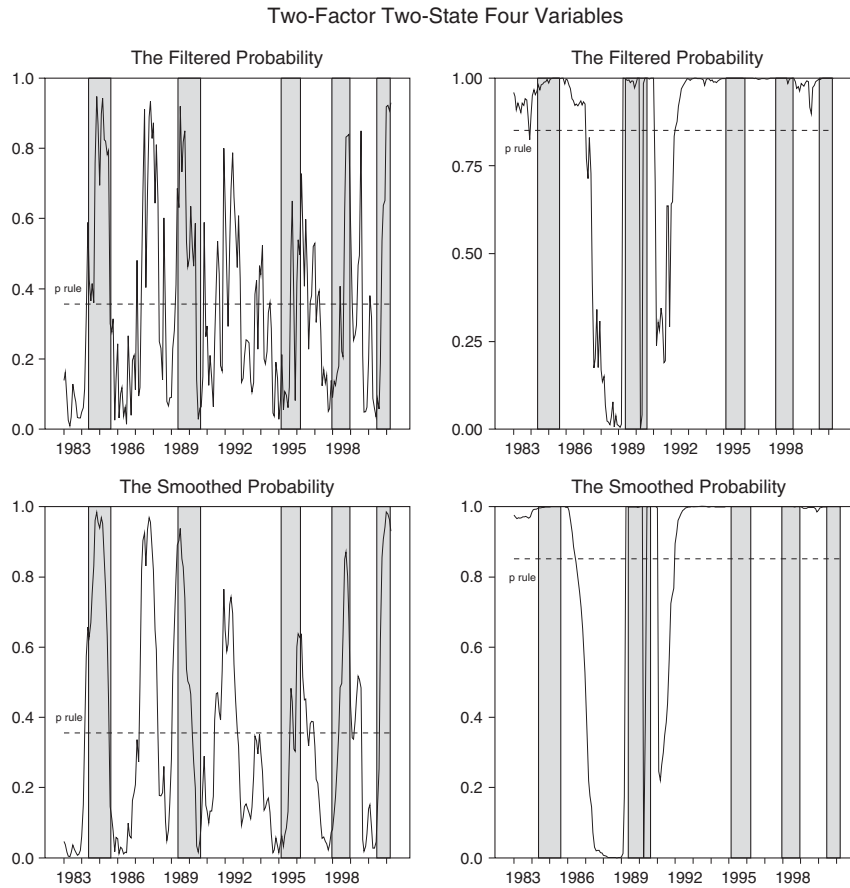


Fig. 8. Plots of the filtered and smoothed probabilities of the four variables of the leading indicators, i.e., ORDER, EXPORT, M1B and SP, used in the two-factor model with $S_t \neq S_t^*$. The shaded areas are the contraction periods as determined by the CEPD.

evaluate the forecasting performances in-sample and out-of-sample.¹⁷ The QPS is:

$$\text{QPS} = K^{-1} \sum_{t=1}^K \{\text{prob}(S_t = 0 | \Psi_T) - d_t\}^2, \quad (10)$$

where $d_t=1$ if dated as a period within the CEPD-defined contraction. The closer the QPS is to zero, the more consistent the model-generated regime is with the chronology of an official business cycle.

¹⁷ The QPS was first suggested by Diebold and Rudebusch (1989), who used the QPS as a measure of correspondence between turning point probabilities and actual turning points. By contrast, Filardo (1994) and Hamilton and Perez-Quiros (1996) used it in conjunction with the actual NBER phase dates and the model-generated regime probabilities for each data point in the series.

Only four models, the MSF, the WSF, the one-factor four-variable and the one-factor one-state variable models are compared. We do not consider the one-factor six-variable since it rejects the switching hypothesis. The two-factor two-state model is also not considered as it produces almost the same results as the first two models.

The QPS of the in-sample and out-of-sample comparisons is calculated in the following. The in-sample QPS covers the period from 1983:m1 to 2001:m4 and totals 220 observations. The calculation of the out-of-sample QPS requires more work as it necessitates defining the estimation period first and then making an out-of-sample forecast. We conduct one- and two-period-ahead forecasts but only report the former. The explanation below is based on the one-step-ahead forecast. Also, given the eruption of the

Table 2
Forecasting performance: in-sample and out-of-sample

Models	In-QPS ^a	Out-QPS ^b	Out-QPS ^c
MSF (3 variables): 1-factor	0.185	0.234	0.138
WSF (3 variables): 1-factor	0.524	0.324	0.448
MSF+WSF (6 variables): 1-factor	0.200	0.312	0.222
Four variable: two-factor, one state	0.180	0.322	0.099

^a The in-sample QPS runs from 1983: m1 to 2001: m4, totaling 220 observations.

^b The out-of-sample QPS runs from 1997: m11 to 2001: m4, totaling 42 observations.

^c The out-of-sample QPS runs from 1999: m1 to 2001: m4, totaling 28 observations.

1997 Asian crisis, we consider two starting periods of the prediction, namely, 1997:m11 and 1999:m1, for our out-of-sample forecast.

The results of the in-sample forecasting (Table 2) show that the (four-variable) two-factor one-state model leads to the best recession predictions, followed by the MSF model and the one-factor six-variable model. This should not come as a surprise since the two-factor one-state model is less aggressive. That the WSF model has the worst in-sample forecasting performance is also not astonishing as the Wall Street sector alone (Fig. 4) produces continuous false signals for the whole post-1995 period.

As stated above, we conduct two out-of-sample forecasts using both 1997:m11 and 1999:m1 as the starting periods. When 1997:m11 is used as the starting period of the forecast, the initial estimation covers 1983:m1 to 1997:m10. Upon obtaining the estimates, we conduct a one-step-ahead forecast. Once

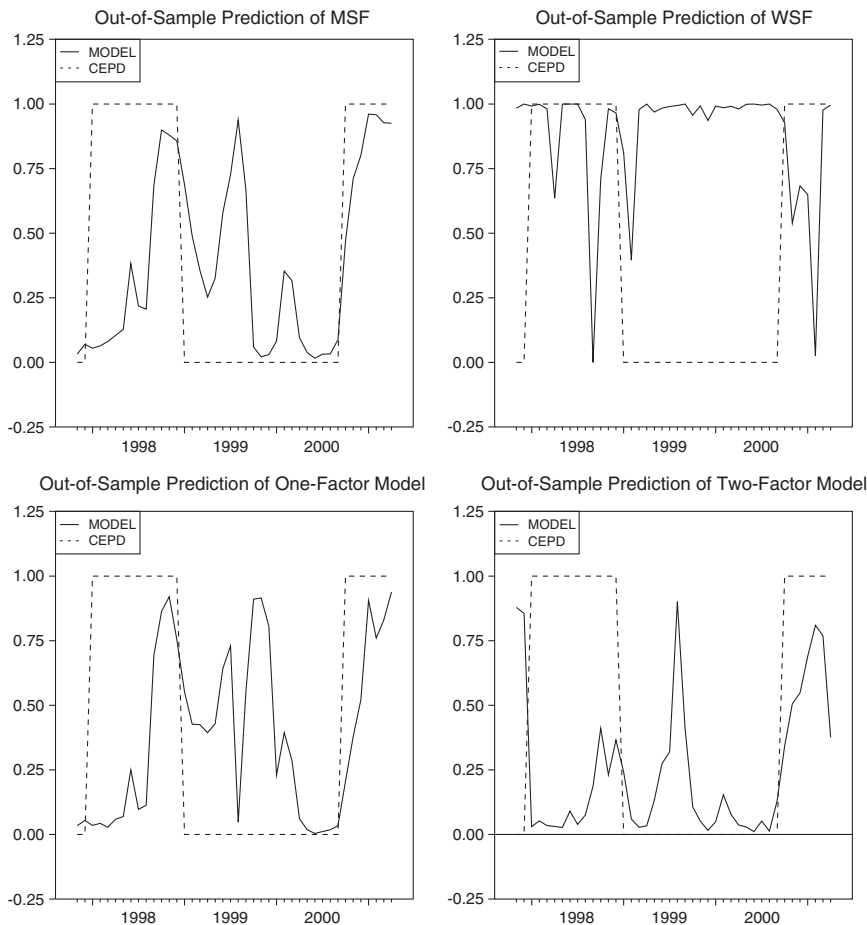


Fig. 9. The out-of-sample posterior probabilities for various models. The dashed lines are the contraction dates as determined by the CEPD.

these estimate-forecast steps are performed, we move one period forward and re-estimate the model. We then make a new one-step-ahead forecast using the new estimates. In the next stage, we repeat these steps until we reach the last sample. In this way, we recursively estimate the parameters throughout the out-of-sample period. There are $K=42$ out-of-sample forecasts, from 1997:m11 to 2001:m4. In Table 2, the resulting QPSs are almost the same as those in the four models. This is probably because the abruptly burst Asian crisis changed the stable relationship between the leading indicators and the business cycle. That is, the leading indicators may have predicted a boom before a crisis but this is inaccurate since the sudden crisis changed the relationship. It is obvious then that the four models perform similarly when 1997:m11 is used as the starting period of the prediction.

The use of the second starting period of the forecast helps us to determine the forecasting ability of the models. The estimation period is from 1983:m1 to 1998:m12, yielding 28 out-of-sample forecasts. We find that the out-of-sample forecasts in this case produce a similar ranking of forecasts to that from the in-sample forecasts. Not unlike what we observe with other models, the two-factor one-state model has the best predicting performance, reaching the minimum out-of-sample QPS ($=0.099$). Furthermore, its QPS is far less than the second best model, the MSF (0.138). Once more, the WSF model shows the worst performance. Fig. 9 summarizes the corresponding out-of-sample filtered probabilities for the recession regime. These plots clearly demonstrate the superiority of using the two-factor one-state model if the samples are run from 1999:m1 to 2001:m4.

6. Concluding remarks

This paper argues that the simple sum of all the leading indicators may combine conflicting information and, therefore, provide less than accurate predictions. We strongly suggest that, based on their inherent characteristics, the leading indicators be divided into two sectors, real and financial sectors. The real sector contains new manufacturing orders, exports through customs, and the floor space available for building in Taiwan. The financial sector contains the stock price index, a narrowed money supply and

the wholesale price index. The rationale for this separation is that the two sectors may not share the same information with respect to future recessions.

The in- and out-of-sample forecasts are not conducted for either the one-factor six-variable or the two-factor two-state models because the former rejects the switching hypothesis, as mentioned above, and the datings from the latter are very similar to the results of the MSF and WSF models, respectively. As a consequence only four models are repeated in the prediction comparisons. The ranking of the forecasting ability of the remaining four models is explained below.

First, the two-factor one-state model performs the best in both in- and out-of-sample forecasts. It produces fewer false signals than do the other models. The model is, in fact, the least aggressive as it only produces one false signal. The runner-up for both forecasts is the one-factor Main Street model, followed by the one-factor four-variable model. The former is aggressive in the sense that there are no missed signals, but it produces two strong and two mild false signals, whereas the latter has only two strong and two even milder false signals. The worst performing model is the Wall Street model since it suggests that the whole post-1995 period was in a recession caused by continuous bad news in the financial markets studied here.

Our results have three central implications. First, the concept of the two-factor model is important because the two sectors may have conflicting information, which somewhat lessens the degree of forecast aggressiveness. The aggressiveness may be due to overfitting, but that is another issue. Next, the Wall Street sector tends to over-react to news, especially bad news which makes investors overly pessimistic, and causes the financial leading indicators to perform badly. Third, we can downsize the model if it is too difficult to converge because of the complexities inherent in the model. Removing those variables that have insignificant factor loadings changes the results very little.

Acknowledgements

We would like to thank the associate editor and two anonymous referees for helpful comments and suggestions. The usual disclaimer applies.

Appendix A. State-space representation and algorithm

In this appendix, we briefly describe how to restate the two-factor model with regime switching, i.e., Eqs. (6)–(8), into a state-space representation and then apply Kim’s (1994) algorithm with regard to the approximate maximum likelihood method to calculate unknown parameter estimates. Basically, Kim’s algorithm is a synthesis of Hamilton’s and Kalman’s filters. Eqs. (6)–(8) can be transformed into the measurement Eq. (11) and the transition Eq. (12) as follows:

$$Y_t = H_t \xi_t \tag{11}$$

$$\xi_t = T_t \xi_{t-1} + \beta_{S_t} + u_t \tag{12}$$

with

$$H_t = \begin{bmatrix} \gamma_1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \gamma_2 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \gamma_3 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \gamma_1^* & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \gamma_2^* & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \gamma_3^* & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix},$$

$$T_t = \begin{bmatrix} \phi_1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \theta_{11} & \theta_{12} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \theta_{21} & \theta_{22} & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \theta_{31} & \theta_{32} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \phi_1^* & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \theta_{11}^* & \theta_{12}^* & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \theta_{21}^* & \theta_{22}^* & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \theta_{31}^* & \theta_{32}^* \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix},$$

$$\xi_t = [F_t \ z_{1,t} \ z_{1,t-1} \ z_{2,t} \ z_{2,t-1} \ z_{3,t} \ z_{3,t-1} \ F_t^* \ z_{1,t}^* \ z_{1,t-1}^* \ z_{2,t}^* \ z_{2,t-1}^* \ z_{3,t}^* \ z_{3,t-1}^*]'$$

$$\beta_{S_t} = [\beta(S_t) \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ \beta^*(S_t^*) \ 0 \ 0 \ 0 \ 0 \ 0 \ 0],$$

$$u_{S_t} = [\eta_t \ \varepsilon_{1t} \ 0 \ \varepsilon_{2t} \ 0 \ \varepsilon_{3t} \ 0 \ \eta_t^* \ \varepsilon_{1t}^* \ 0 \ \varepsilon_{2t}^* \ 0 \ \varepsilon_{3t}^* \ 0]'$$

$$\mathbf{Q}_t = \begin{bmatrix} \sigma_\eta^2 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \sigma_{\varepsilon_1}^2 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \sigma_{\varepsilon_2}^2 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \sigma_{\varepsilon_3}^2 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \sigma_{\eta^*}^2 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \sigma_{\varepsilon_1^*}^2 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \sigma_{\varepsilon_2^*}^2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \sigma_{\varepsilon_3^*}^2 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix},$$

where $\mathbf{Q} = E(\mathbf{u}_t \mathbf{u}_t')$. Under the restriction of $S_t = S_t^*$ (given the realization of the state variables at times t and $t - 1$ ($S_t = j$ and $S_{t-1} = i$, where $i, j = 0$ or 1)) and using the notation $\mathbf{Z}_{t|t-1}^{(i,j)}$ to denote the variable \mathbf{Z} conditional on the information available up to $t - 1$ and the realized states j and i , the Kalman filter can then be represented as:

$$\boldsymbol{\xi}_{t|t-1}^{(i,j)} = \mathbf{T}_t \boldsymbol{\xi}_{t-1|t-1}^{(i)} + \boldsymbol{\beta}_{S_t}^{(j)}; \tag{13}$$

$$\mathbf{P}_{t|t-1}^{(i,j)} = \mathbf{T}_t \mathbf{P}_{t-1|t-1}^{(i)} + \mathbf{T}'_t + \mathbf{Q}_t; \tag{14}$$

$$\boldsymbol{\xi}_{t|t}^{(i,j)} = \boldsymbol{\xi}_{t|t-1}^{(i,j)} + \mathbf{K}_t^{(i,j)} \boldsymbol{\eta}_{t|t-1}^{(i,j)}; \tag{15}$$

$$\mathbf{P}_{t|t}^{(i,j)} = \left(\mathbf{I} - \mathbf{K}_t^{(i,j)} \mathbf{H}_t \right) \mathbf{P}_{t|t-1}^{(i,j)}; \tag{16}$$

$$\boldsymbol{\eta}_{t|t-1}^{(i,j)} = \mathbf{Y}_t - \mathbf{H}_t \boldsymbol{\xi}_{t|t-1}^{(i,j)}; \tag{17}$$

$$\mathbf{W}_{t|t-1}^{(i,j)} = \mathbf{H}_t \mathbf{P}_{t|t-1}^{(i,j)} \mathbf{H}'_t; \tag{18}$$

$$\mathbf{K}_1^{(i,j)} = \mathbf{P}_{t|t-1}^{(i,j)} \mathbf{H}'_t \left(\mathbf{W}_{t|t-1}^{(i,j)} \right)^{-1}, \tag{19}$$

where Eqs. (13) and (14) are the prediction formulae, Eqs. (15) and (16) are the updating formulae, and Eq. (19) is the Kalman gain. Term $\boldsymbol{\eta}_{t|t-1}^{(i,j)}$ is the conditional forecast error of \mathbf{Y}_t based on information up to $t - 1$, and $\mathbf{W}_{t|t-1}^{(i,j)}$ is the conditional variance of the forecast error $\boldsymbol{\eta}_{t|t-1}^{(i,j)}$.

As noted by Harrison and Stevens (1976), each iteration of the above Kalman filtering produces a two-fold increase in the number of cases to consider. Kim (1994) provides a fast approximation algorithm which can be

applied to this problem. The crux of the issue is in collapsing the dimensions of the (2×2) posteriors $(\xi_{it}^{(i,j)})$ and $P_{it}^{(i,j)}$ to the two posteriors $(\xi_{it}^{(j)})$ and $P_{it}^{(j)}$ by taking the weighted averages over the states at $t-1$. That is,

$$\xi_{it}^{(j)} = \frac{\sum_{S_{t-1}=0}^1 \Pr[S_t = j, S_{t-1} = i | \Psi_t] \times \xi_{it}^{(i,j)}}{\Pr[S_t = j | \Psi_t]} \quad (20)$$

$$P_{it}^{(j)} = \frac{\sum_{S_{t-1}=0}^1 \Pr[S_t = j, S_{t-1} = i | \Psi_t] \times \left\{ P_{it}^{(i,j)} + \left(\xi_{it}^{(j)} - \xi_{it}^{(i,j)} \right) \left(\xi_{it}^{(j)} - \xi_{it}^{(i,j)} \right)' \right\}}{\Pr[S_t = j | \Psi_t]} \quad (21)$$

where Ψ_t refers to the information available at time t . Following Hamilton (1989), the filter can be obtained by Bayes's theorem. That is:

$$\begin{aligned} \Pr[S_t = j, S_{t-1} = i | \Psi_t] &= \frac{\Pr[\mathbf{Y}_t, S_t = j, S_{t-1} = i | \Psi_{t-1}]}{\Pr[\mathbf{Y}_t | \Psi_{t-1}]} \\ &= \frac{f[\mathbf{Y}_t | S_t = j, S_{t-1} = i, \Psi_{t-1}] \times \Pr[S_t = j, S_{t-1} = i | \Psi_{t-1}]}{\Pr[\mathbf{Y}_t | \Psi_{t-1}]} \end{aligned} \quad (22)$$

where

$$f[\mathbf{Y}_t | S_t = j, S_{t-1} = i, \Psi_{t-1}] = (2\pi)^{-N/2} |\mathbf{W}_{it-1}^{(i,j)}|^{-1/2} \times \exp \left\{ -\frac{1}{2} \boldsymbol{\eta}_{it-1}^{(i,j)'} \left(\mathbf{W}_{it-1}^{(i,j)} \right)^{-1} \boldsymbol{\eta}_{it-1}^{(i,j)} \right\}. \quad (23)$$

The smoothed probabilities, $p(S_t | \Psi_T)$, on the other hand, stand for the conditional probability based on data available through the whole sample at future date T , which amount to

$$\Pr[S_{t+1} = k, S_t = j | \Psi_T] \approx \frac{\Pr[S_{t+1} = k | \Psi_T] \times \Pr[S_t = j | \Psi_t] \times \Pr[S_{t+1} = k | S_t = j]}{\Pr[S_{t+1} = k | \Psi_t]} \quad (24)$$

$$\Pr[S_t = j | \Psi_T] = \sum_{S_{t+1}=0}^1 \Pr[S_{t+1} = k, S_t = j | \Psi_T]. \quad (25)$$

The approximate sample conditional log-likelihood is:

$$\log L = \ln f(\mathbf{Y}_T, \mathbf{Y}_{T-1}, \dots | \Psi_0) = \sum_{t=1}^T \ln f(\mathbf{Y}_t | \Psi_{t-1}). \quad (26)$$

The approximate maximum likelihood estimates of the model can be obtained by maximizing the log-likelihood with respect to the unknown parameters.

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