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 use of all leading indicators simultaneously may mix two different sets of information and thus provide a less accurate prediction of a future recession. We divide six Taiwan's leading indicators into two different sectors, real and financial sectors, and show that the two sectors may reveal different information. Three divergent movements are found in 1988, 1991 and 1994. We use a Markov switching model to extract the common factor for each sector and find that the predicted recessions based on the two sectors are different in these three periods. Using financial variables seem to outperform the real variable in predicting a future recession. Finally, a modified two-factor Markov switching model is proposed which can produce business chronologies as accurate as the official contraction dates.

Keywords: Wall Street, main street, business cycle, Markov switching model
JEL classification: C22, E32

1 Introduction

Dating a business cycle's turning point has been the interest of the public, both academic and government, for a long time. The approach can be traced back to 1920 when the National Bureau of Economic Research (hereafter NBER) first identified business cycle chronology in the United States. The stylized fact of asymmetric adjustment that a recovery takes up more time than a recession is often found. Hamilton (1989), recently, applied a Markov switching model to the U.S. GNP to date the business cycle turning point. Hamilton (1989) found a remarkably similarity in the generated recessionary and recovery periods with the NBER-defined chronology of the business cycle. The asymmetric adjustment is also confirmed. This similarity has also been confirmed by Durland and McCurdy (1994), Ghysels (1994), Lahiri and Wang (1994).

While the Markov switching model has proven to be a useful tool in characterizing the business cycle, Filardo (1994) pointed out that Hamilton's (1989) estimated posterior probability exhibited low correlation with the NBER business cycle dates. Using an industrial production index, Filardo (1994) extended Hamilton's constant transition probabilities to the varying transition probability, which leads to a high correlation between the NBER business cycle dates and the estimated posterior probability. Layton (1998) also used the time-varying probability and reached the similar results.

The use of a univariate process, either GNP or an industrial production index, is soon found to be too narrow to capture the broad fluctuation of economic activity even when using a time-varying transition probability. It is plausible that the univariate process may ignore other non-trivial information and thus researchers start to use more macro time series. Stock and Waston (1989, 1991) assumed that the co-movements of the four coincidence indicators share a common element that can be captured by a signal unobservable latent variable which represents the economy's state. Kim and Yoo (1995) further assumed that this unobserved common factor is driven by a Makrov 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 by reducing the idiosyncratic noise in the business cycle.

A single unobservable common factor extracted from the multivariate processes indeed captures more information than that of the univariate process, however, the use of "one" common factor implicitly assumes that divergent movements among leading and coincident indicators are random and can be averaged out. This assumption ignores the fact that the coincidence and leading indicators typically contain two distinct groups of variables, i.e., financial and non-financial variables. While the two groups often reveal the same information regarding the dating of the business cycle, which justifies the use of a single factor, there are cases that providing conflict information. The often heard asset bubble, where asset prices exceed the intrinsic value of the fundamentals, may be one example of different information contained in these two types of variables.

The purpose of this paper is to extend the one unobservable common factor to two unobservable common factors from the 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 is referred to as the "Main Street Factor" (hereafter MSF), which extracts information from real variables. The co-movements of these two sectors are often seen, yet, as we argued above, the divergent movements also exist.

The implications of our two-street factors hypothesis are crucial in two aspects. If the Wall Street suggests a boom but the main street sector does not, then the asset price may be over-valued and an asset bubble may form. Pricking the bubble or letting the economy land softly may be an urgent errand for authorities. Alternatively, if Wall Street suggests a recession and main street does not, then the financial market may be pessimistic about the future but the manufacturing market is not endangered. Restoring the confidence of investors by adopting a credible and transparent policy may be necessary.

We use Taiwan's leading indicators as our example since Taiwan has experienced conflicting episodes. For example, financial deregulations starting in 1987 stimulated the asset prices to historically unprecedented high level in 1989 whereas manufacturing production remained relatively stable. The China missile tests over the Taiwan island during 1995 to 1996 provided the opposite case. The missile tests frightened investors, dropping stock prices substantially. The manufacturing industry, however, was only mildly hurt. While we use Taiwan as an example, the application of our study to other countries is immediate.

2 Taiwan Business Cycle Indicators

Taiwan's leading indicators include six variables, where the first three are non-financial (real) variables, containing manufacturing new orders (ORDER), exports by customs (EXPORT), and floor area permitted for building in Taiwan (BUILD), while the latter three are financial variables, containing stock price index (SP), narrowed money supply (M1B) and wholesale price index (WPI). The two types of variables, real versus 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), who also publishes the dates of a business cycle when it is deemed necessary.

Figure 1 plots the percentage changes of six indicators. The main and Wall Street variables are plotted on the left and right-hand sides, respectively. The indicators display strong seasonality and fluctuations. All series are taken from the monthly journal of *Business Indicators* distributed by the CEPD. The variables are monthly data from 1981:m1 to 2001:m4 which amount to 232 observations.

The conventional aggregate leading indicator is a simple sum of the percentage changes of the six indicators. The aggregate leading indicator assumes information contained in each indicator is the same except for the random variations. This aggregate leading indicator does not distinguish between using real from financial sectors, and supposedly leading economic activities up to three or six months.

It would be interesting to create two sub-aggregate leading indicators and investigate the differences between two sectors. For expositional purposes, we sum the three real variables into a main street indicator (or real sector indicator) and the three financial variables into a Wall Street indicator (or financial sector indicator). In the top and bottom panels of Figure 2, we plot these two sub-aggregate leading indicators and their spread.[1]

In Figure 2, three divergent movements are found between the two sectors. The first divergent movement appeared in 1988. As we observe in the figure, the Wall Street indicator increases substantially, but the main street indicator slightly drops. In other words, the financial sector indicates that the economy is "too hot", but the real sector shows a "mild cool", meaning a combination of both is a typical phenomenon of the asset bubble. The reasons for this asset bubble include the financial deregulation that started in 1987, a slowly but steadily exchange rate appreciation, and a lax monetary policy, etc. That is, during the period both stock prices and real estate prices reached historically unprecedented high levels. The exchange rate also appreciated from 38 New Taiwan dollars (NTD) per US dollar to around 25 NTD to one US dollar. The central bank did not adopt any active monetary policy to prick the bubble, making the growth rate of M1B also reaching to 51% in annual percentage terms. The real side, however, was not affected by this financial boom and even dropped to some extent.

The next contrast movement occurred in 1991 when the central bank decided to prick the asset bubble at the end of 1990. The minister of finance also announced the possibility of taxing capital gains earned from the stock market.[2] The simultaneous tightening monetary and fiscal news destroyed the confidence of investors. The stock prices dropped for nineteen consecutive days from 9,800 to 5,400.[3] The growth rate of M1B also decreased. The real side, however, hurt relatively

[1]Note that the negative percentage change of WPI is added into the main street indicator to be consistent with other variables.

[2]There was no tax on profit gains in Taiwan before 1989.

[3]Because Taiwan's stock market has daily price limits, the impact of the bad news often spilled over to consecutive

less, making the two sectors move toward different directions again.

The third divergent movement appeared in 1994. In contrast to the above two episodes, we observe that not only do the two sectors move toward different directions (also see Figure 2), but there are divergent movements inside the real sector (shown in Figure 1). As can be observed in both Figures 1 and 2, while the first two real components EXPORTS and ORDER display an upward trend, their aggregation is pulled down by the strong declining index of the third component BUILD. The main street indicator thus decreases even though two of them are increasing. In contrast to the conflicting information inside the real sector, the three financial variables overwhelmingly show an upward trend during this year. We find that this inside divergent movement in real sector affects the estimation of Markov switching model (will be discussed shortly).

Because the two sectors may move divergently, the conventional aggregate leading indicator, summing up the six variables, may average out the important information. The resulting business cycle prediction may also 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 $\mathbf{y}_t = [y_{1t}, y_{2t}, \ldots, y_{6t}]'$ be a function of a common unobserved dynamic factor F_t and idiosyncratic noises $\mathbf{z}_t = [z_{1t}, z_{2t}, \ldots, z_{6t}]'$. The terms y_{it}, $i = 1, \ldots, 6$ are the six Taiwan leading indices described above and $\mathbf{z}_{it}$ is a vector stationary series with mean zero and variance Σ. All variables are transformed into annual growth rates and deviate from their respective means. The factor F_t captures market-wide co-movements underlying the six

days. See Shen and Wang (1998) for a description of Taiwan's stock market.

leading indices. The model is thus:

$$\mathbf{y}_t = \gamma(L)F_t + \mathbf{z}_t, \tag{1}$$

$$\phi(L)F_t = \beta(S_t) + \eta_t, \;\; \eta_t \sim \text{i.i.d.N}(0, \sigma^2_{\eta(s_t)}), \tag{2}$$

$$\beta(S_t) = \beta_0(1 - S_t) + \beta_1 S_t, \;\; S_t = 0, 1, \tag{3}$$

$$\theta(L)\mathbf{z}_t = \varepsilon_t, \;\; \varepsilon_t \sim \text{MVN}(\mathbf{0}, \Sigma), \tag{4}$$

where boldface variables denote the vector. Function $\phi(L) = (1 - \phi_1 L - \cdots - \phi_k L^k)$ is a scalar lag polynomial and $\gamma(L)$ and $\theta(L)$ are vector polynomials as follows: $\gamma(L) = \gamma_0 + \gamma_1 L + \cdots + \gamma_q L^q$ and $\theta(L) = 1 - \theta_1 L - \cdots - \theta_r L^r$, with L denoting the backward operator and k, q and r are the lag length. While Σ is the diagonal matrix with diagonal elements equal to $\sigma_1^2, ..., \sigma_6^2$.

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 to follow a first-order Markov chain as follows:

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

3.2 Two One-Factor Models

The real and financial variables are separately specified to follow their respective one-factor models since the two types of variables may share different common factors. The first specification involves only real variables, i.e., $\mathbf{y}$ is an $N_1 \times 1$ vector of monthly real variables, containing {ORDER, EXPORT, BUILD}.[4] Alternatively, the second specification involves only financial variables, and $\mathbf{y}$ is an $N_2 \times 1$ vector of monthly financial variables, containing {SP, M1B, WPI}. Models (1) $\sim$ (4) are then repeatedly used by replacing $\mathbf{y}_t$ with the real and financial vectors. The common factor F_t resulting from the financial variables is the Wall Street Factor (WSF) and the Main Street Factor

[4] Term N_1 is the number of real variables and N_2 is the number of financial variables.

(MSF) when real variables are used. All variables are transformed into annual growth rates and deviate from their respective means.

The two one-factor models, which implicitly assume that two sectors are independent of each other, use brute force to divide the sample. While this exogenous method reduces the burden of estimation, it incurs inefficiency by ignoring the interaction between the two sets of variables. The next subsection relaxes this assumption by endogenizing the two-factor model.

3.3 The Two-Factor Model with Regime Switching

The two-factor model with regime switching (hereafter, just the two-factor model) is a straightforward generalization of the one-factor regime switching model. This new specification encompasses different interactions among the mean and variance states of both factors.

Let $\mathbf{Y}_t = [\mathbf{y}_t \ \mathbf{y}_t^*]' = [y_{1t} \ y_{2t} \ y_{3t} \ y_{1t}^* \ y_{2t}^* \ y_{3t}^*]'$ be the 6×1 vector of leading indices, where the first three terms are the real (or main street) sector and the last three terms are the financial (or Wall Street) sector. The superstar (*) hence denotes the Wall Street sector. The two-factor Markov-switching model is specified as follows.

$$\mathbf{Y}_t = \begin{bmatrix} \mathbf{y_t} \\ \mathbf{y_t^*} \end{bmatrix} = \Gamma(L) \begin{bmatrix} F_t \\ F_t^* \end{bmatrix} + \begin{bmatrix} \mathbf{z_t} \\ \mathbf{z_t^*} \end{bmatrix} \tag{6}$$

$$\Phi(B) \begin{bmatrix} F_t \\ F_t^* \end{bmatrix} = \begin{bmatrix} \beta_0(1-S_t) + \beta_1 S_t \\ \beta_0^*(1-S_t^*) + \beta_1^* S_t^* \end{bmatrix} + \begin{bmatrix} N_t \\ N_t^* \end{bmatrix} \tag{7}$$

$$\Theta(B) \begin{bmatrix} \mathbf{z_t} \\ \mathbf{z_t^*} \end{bmatrix} = \begin{bmatrix} \mathbf{e_t} \\ \mathbf{e_t^*} \end{bmatrix}. \tag{8}$$

When

$$\mathbf{F}_t = \begin{bmatrix} F_t \\ F_t^* \end{bmatrix}, \mathbf{B} = \begin{bmatrix} \beta_0(1-S_t) + \beta_1 S_t \\ \beta_0^*(1-S_t^*) + \beta_1^* S_t^* \end{bmatrix}, \mathbf{Z}_t = \begin{bmatrix} \mathbf{z_t} \\ \mathbf{z_t^*} \end{bmatrix}, \mathbf{N}_t = \begin{bmatrix} N_t \\ N_t^* \end{bmatrix}, \mathbf{E}_t = \begin{bmatrix} \mathbf{e_t} \\ \mathbf{e_t^*} \end{bmatrix},$$

then the latter two noise vectors are distributed as

$$\mathbf{N}_t \sim \mathbf{MVN}(\mathbf{0}, \Omega_{S_t,S_t^*}), \mathbf{E}_t \sim \mathbf{MVN}(\mathbf{0}, \Xi), S_t, S_t^* = 0, 1,$$

where

$$\Omega_{S_t,S_t^*} = \mathrm{E}(\mathbf{N}_t\mathbf{N}_t^{'}) = \mathrm{E}([\eta_t \ \eta_t^*]'[\eta_t \ \eta_t^*]) = \begin{bmatrix} \sigma_{S_t}^2 & \cdot \\ \sigma_{12}^2 & \sigma^{*2}_{S_t^*} \end{bmatrix},$$

and

$$\Xi = \begin{bmatrix} \Sigma & \cdot \\ \Sigma_{12} & \Sigma^* \end{bmatrix}.$$

Equation (6) states that the vectors $\mathbf{Y}_t$ are composed of two sets of leading indices, which can be expressed as the stochastic latent factors $\mathbf{F}_t$ and the two idiosyncratic terms $\mathbf{Z}_t$. The two latent factors are our main street and Wall Street factors, respectively. These two sectors affect the leading indicator through Γ, which is the matrix of factor loading the observable variables. That is,

$$\Gamma(B) = \begin{bmatrix} \gamma(L) & \cdot \\ \gamma_{12}(L) & \gamma^*(L) \end{bmatrix}$$

is a 6×6 diagonal matrix with two vector polynomials. The terms $\gamma(L)$ and $\gamma^*(L)$ are the 3×3 polynomial vectors of loading. The two factors are interacted through $\gamma_{12}(L)$.

Equation (7) describes the movement of the latent variable $\mathbf{F_t}$, which consists of an intercept vector $\mathbf{B}$ and a white noise vector $\mathbf{N}_t$. The intercept vector is the function of two different state variables S_t and S_t^*, both which are unobserved latent variables, taking on 1 when real and financial factors are in expansion and 0 when they are in contraction, respectively. The variance of $\mathbf{N}_t$, which is also the variance of the dynamic factors, $\mathbf{F}_t$, consists of the two variances $\sigma_{S_t}^2$ and $\sigma_{S_t^*}^2$ and one covariance σ_{12}. Both variances are also affected by the states.

The states that affect the intercepts and variances are governed by the transition probabilities of the first-order two-state Markov process, $p_{ij} = \mathrm{Prob}(S_t = j|S_{t-1} = i)$, with $\sum_{j=0}^{1} p_{ij} = 1$,

$i, j = 0, 1$. Notice that the regime switching in the Wall Street and main street types of asymmetry are driven by the same state variable, S_t. In essence, this assumption enforces all recessions to have the same relative importance. This assumption can be motivated as an extension of Hamilton (1989) and Kim and Nelson (1999).

Equation (8) specifies the error term of the leading indicator. Term $\Theta(B) = [\theta(B), \theta^*(B)]$ makes up 1×6 vector polynomials and $\mathbf{E}_t = [\varepsilon_t, \varepsilon_t^*]'$ are 6×1 measurement errors with the covariance matrix Σ and Σ^* for the main street and Wall Street factors, respectively.

While the two-factor Markov-switching model generalizes the one-factor model, it substantially increases the computation loading. To keep the system tractable and to facilitate convergence of the maximum likelihood procedure, we assume that all off-diagonal elements of the unknown parameters matrix are equal to zero. That is,

$$\gamma_{12} = \sigma_{12} = \Sigma_{12} = 0.$$

These restrictions substantially reduce the number of unknown parameters. Thus, the two sectors are affected by each other only through the interaction of the transition probability. Note that imposing this restriction does not result in the problem of model identification, since the growth rate of the common component is assumed to be regime-switching.

3.4 Estimation Procedure

The estimation procedure is based on Kim's (1994) approximate maximum likelihood method, which requests converting equations (6) to (8) into the state-space representation. We report the state-space in the appendix to save space.

The estimation contains the following several steps. First, we need to calculate the ergodic probability as the initial value and then apply the Kalman filter and the Hamilton filter to this model. The Hamilton filter's most innovative aspect is its ability to objectively date the economy's states by the so-called filtered and smoothed probabilities. The filtered probabilities (collected in a $(T \times 1)$ vector denoted $\xi_{t|t}$, i.e., $\xi_{t|t} = p(S_t = j|\Psi_t)$, $j = 1, \ldots, T$, and Ψ_t is 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 also indeed possible to calculate smoothed probabilities, $\xi_{t|T} = p(S_t = j|\Psi_T)$, $j = 1, \ldots, T$, which are based on the full sample.[5] Finally, we must do an approximation proposed by Kim (1994) in order to write down the log-likelihood function as follows.

$$\text{logL} = \ln f(\mathbf{Y}_T, \mathbf{Y}_{T-1}, ...|\Psi_0) = \sum_{t=1}^{T} \ln f(\mathbf{Y}_t|\Psi_{t-1}). \tag{9}$$

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

3.5 Prediction Criteria

Two criteria are suggested 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, viz, the model predicts there is a recession, but it never happens.

Having generated conditional regime probabilities, there remains the issue of a decision rule to translate these probabilities into binary regime predictions. Birchenhall et al. (1999) suggest 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. A recession is expected if the predicted probability exceeds 0.5 following the 0.5 rule. Alternatively, future recessions are plausible if the predictive probability exceeds $\hat{p}$, where $\hat{p}$ is the sample proportion of recession periods based on the sample rule. Conflicting predictions arise when the predictive probability falls between 0.5 and $\hat{p}$. The probability signals a contraction, but this signal is not sufficiently strong enough to overturn the overall population information in 0.5. This region defines the period of market uncertainty.

[5] Hamilton (1989) describes how to make an inference about the particular state the economy was in at date t.

4 Empirical Results

We compare three models in our empirical studies. The first is the conventional one-factor model utilizing all leading indices. The two one-factor models make up the next one, which separates the six variables into two set of three variables. The two models are referred to as the main-street-one-factor and Wall-Street-one-factor models if real and financial sectors are used, respectively. The last one is the two-factor model suggested in this paper.[6]

4.1 The One-Factor Model

Table 1 presents the results of using six variables and assumes only one factor. Except for regime 0's intercept, β_0, the other coefficients are overwhelmingly significantly different from zero. However, because switching states appear only in the intercept and the corresponding residual variances, using the six variables by assuming one factor tends to reject the two-regime assumption. For example, when we normalize the standard deviation of σ_{η_0} to be unity, the standard deviation of σ_{η_1} is only 1.124. Thus, the two regimes almost have the same dispersions.[7] Next, because β_0 is insignificantly different from zero, and β_1 is significant at only the 10% level, both intercepts nearly crash to zero. Since both the variance and intercept show little evidence to switch, the model is closer to a one-regime model.

Figure 3 displays the estimated filtered and smoothed probabilities, where missed and false signals are found frequently. The two horizontal lines in the figures are the two corresponding

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[6]All computations of the unknown parameters are implemented by using the OPTMUM module of GAUSS 3.2 with a combination of 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.

[7]We, however, cannot examine the validity of two regimes under the restriction of $\sigma_{\eta_0} = \sigma_{\eta_1}$ since the null is not identified under this condition. See Hansen (1996) for details.

prediction criteria, the 0.5 rule and the sample rule $\hat{p}$ rule. The shaded areas are the business cycle chronologies dated by CEPD, which is the benchmark of comparison. Both posterior probabilities wrongly show that there were no recessions in 1984 and 1989, when in fact the economy was indeed in a recession. Alternatively, the false signals occur in early-1983, 1988, 1992, 1994, 1996, and 1999. Employing the six-variables-one-factor model may mix two conflicting information, and hence does not provide a convincing enough fitting.

4.2 Main-Street- and Wall-Street-One-Factor Model

Empirical results using thee real variables and three financial variables separately with the one-factor regime switching model are reported in Table 2. The regime switching model is evidenced more clearly in the real sector (the left panel of Table 2) than in the financial sector (the right panel of Table 2). With respect to the real sector, it is found that all coefficients are overwhelmingly significantly different from zero at the 5% level, suggesting that the two-regime is non-rejectable. Furthermore, the intercept term β_i is -2.583 in recession and 5.792 in expansion. Hence, the real sector's growth in the two regimes is unlikely to be the same, confirming the existence of the two regimes.[8] The standard deviations in the real sector's two regimes are only slightly different. If we normalize the contractionary regime to be 1.000, the expansionary regime is found to be 1.188. The dispersions of the variances across the two regimes are similar.

The estimation results in the financial sector show similar results. The estimated intercepts are -3.268 in a contraction and 0.872 in an expansion. While the difference is non-trivial, the latter is insignificantly different from zero. This implies a wide variation of intercept in an expansion, rejecting the significance. The standard deviation in expansionary regime is only 0.621 in contrast to 1.000 in a recessionary regime. The small variation in expansion justifies that the volatility in the financial market is larger during a downturn than in a recovery.

[8]Because of non-identification in the null, we cannot test this hypothesis. See footnote 7 for the same reason.

4.3 Three Episodes of Conflicts

The estimated filtered and smoothed probabilities are plotted in Figures 4 and 5, respectively. In each figure, real sector is put on the top panel and the financial sector is put on the bottom panel. These probabilities can be thought of as the proxies for MSF and WSF in the two figures, respectively. The two horizontal lines in the figures are the two corresponding prediction criteria, the 0.5 rule and the sample rule $\hat{p}$ rule. The shaded areas are the business cycle chronologies dated by the CEPD. The model-identified business cycle chronologies are proxied by these probabilities and seem not to match well with the CEPD-defined business dates.

We first compare our two common factors, proxied by the filtered and smoothed probabilities, with the three conflicting episodes mentioned above. In Figure 4, the filtered probabilities in two sectors appear to show different patterns. Recall that the first divergence occurred in 1988, when financial sector indicates a “too hot” economy and the real sector shows a “mild cool”, alternatively. This fact is confirmed here. Because the real sector shows a mild cold in 1988, the filtered probability of top panel in this period exceeds two prediction criteria, indicating a possible recession. In contrast, the same probability of the bottom panel does not predict a recession. The actual recession occurred one year later when the central bank decided to prick the asset bubble. Thus, the financial sector does not yield false signal and outperforms the real sector in 1988. In Figure 5, the smoothed probabilities reveal the similar results as those in Figure 4.

The previous mentioned second episode in 1991 shows an opposite case. The Wall Street factor is in a trough since the central bank raised the discount rate at the end of 1990, whereas MSF is only mildly hurt. Though CEPD does not date 1991 as a recession, it is not surprising to find that the filtered probabilities of WSF stay above 0.9 in 1991, but are near zero using MSF. It also holds true for the smoothed probabilities. That is, the recession in 1991 is wrongly predicted by WSF, but is correctly predicted by MSF.

The reason for the false signal predicted by WSF in 1991 is because of the significant fluctuations of the financial variables. As we have already seen in Figure 2, the financial variables exhibit a big upturn in 1991, followed by a big drop in 1992. Though the percentage change is still positive during the period, the econometric model treats this significant fluctuation as going from expansion to recession. Since the official recession is often dated when the percentage change in the financial variable is below a certain cutoff, for example, zero, the CEPD will not date the year as recession since the growth rate is positive. As a result, the recessions are predicted by the econometric model because of a big fluctuation, but are not officially dated as recessions due to the positive growth rates.

With respect to the third case of 1994, the probabilities in Figures 4 and 5 show the same pattern, although the two simple average indicators in Figure 2 are different. Both common indicators correctly predict the expansion. The reason that they do not provide conflicting information as one would expect is possibly owing to the one "betrayed" variable in the main street sector. Recall that all three Wall Street variables are in a downward trend in 1994, but not all main street variables are in a upward trend in the same year. That is, the permitted BUILD for Taiwan, being different from the remaining two real variables, displays a strongly downward trend pattern, making the estimated two common factors co-move.

When the main street sector and Wall Street sector move toward the same direction, we find their predicted outcomes coincide. For most of time, their co-movements indeed increase the predictabilities but it is not always true. For example, they both shrink in 1998 and 2000 and hence both sectors correctly predict the coming recessions in these two years. Both sectors, however, also shrink in 1993, suggesting a recession in that year, which never comes out.

We also find that the real sector makes two more false signals than the financial sector. Two additional false signals made by the real sector are 1987 and 1991. Alternatively, we find that the financial sector makes one more missed signal than the real sector, viz. In 1983 there is a recession, but it is not predicted by the financial sector. Except for this missed signal and the common false signal in 1993, the financial sector predicts correctly the remaining recessions. The financial sector seems superior to the real sector in predicting future recession.

4.4 The Two-Factor Model

Table 3 presents the estimation results using the six leading indices by allowing interactions of the two common factors. The coefficient of β_1, which is insignificant from zero in Table 2, is also insignificant here. Except for this coefficient, all coefficients are overwhelmingly found to be significantly different from zero at the 5% level.

The intercept term of main street factor F_t is $\beta_0 = -1.030$ in contraction and $\beta_1 = 1.590$ in expansion, while it is $\beta_0^* = -4.155$ in contraction and $\beta_1^* = 0.796$ in expansion for Wall Street factor F_t^*. Allowing interactions of the two sectors change the intercept estimates to some extent. The difference of two intercepts for the main street factor is smaller than that in main-street-one-factor model, whereas the difference for the Wall Street factor is larger than that in Wall-Street-one-factor model.

The transition probabilities are $p_{00} = 0.923$ and $p_{11} = 0.874$, suggesting that the duration times for the contraction periods is longer than the expansion times. The log-likelihood value rises significantly from 440.298 (six-variables-one-factor model) to 474.447. The likelihood ratio statistics becomes $-2 \times (440.298 - 474.298) = 68.298$ which is far larger than the 5% level of $\chi^2_{0.05}(2) = 5.99$, suggesting that the two-factor Markov-switching model is preferable.[9]

If the unobservable state variables of the real variables and financial variables are independent, i.e., S_t is independent of S_t^*, then the associated log-likelihood value is a simple sum of the log-likelihood functions such as $571.858 - 137.689 = 434.169$. The log-likelihood value of the two-factor model which imposes $S_t = S_t^*$ is also significantly greater than the two-factor model with state variables S_t and S_t^* imposed exogenously.

[9] It should be noted that our six-variable-one-factor and two-factor Markov-switching models are not entirely nested, and the likelihood ratio statistic is used only for reference.

Figure 6 plots the posterior probabilities using the two-factor model. While two false signals still occurred for 1983 and 1994, there are no missed signals. The turning points yielded by the two-factor model are hence much more accurate than those yielded by the one-factor model. The two-factor model also providing ambiguous information from two sectors, as exhibited in Figures 4 and 5. This two-factor model can resist the pitfall of the one-factor model that mixes all financial and non-financial variables together and provides better turning points' dating.

4.5 Out-of-Sample Forecasting

It is interesting to compare the forecast performances of these empirical models. We adopt the turning point (TP) criterion, defined by Hamilton and Perez-Quiros (1996), to evaluate the in-sample and out-of-sample forecasting performance. This TP criterion is defined as follows.

$$\mathrm{TP} = K^{-1} \sum_{t=1}^{K} \{\mathrm{prob}(S_t = 0|\Psi_T) - d_t\}^2, \tag{10}$$

where $d_t = 1$ if dated as a period of CEPD-defined contraction.[10] The closer TP is to zero, the more consistent are the model-generated regime probabilities with the official business cycle chronology.

The equation TP contains in-sample and out-of-sample comparisons. The in-sample TP covers the period 1983:m1 to 2001:m4 which amounts to 220 observations. The out-of-sample TP needs to define the estimation and forecast periods, where the former ranges from 1983:m1 up to 1998:m5 and the latter starts from 1998:m6 to 2001:m4 ($K = 36$). We obtain the estimated parameters using the sample in the estimation period. These estimated parameters are then used to generate out-of-sample forecasts of the filtered probabilities.

The in-sample forecasting results in Table 4 show that the Wall-Street-one-factor model per-

[10] This turning point criterion, which is referred to as the quadratic probability score (QPS), was first proposed by Diebold and Rudebusch (1989). They use 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) use it in connection with the actual NBER phase dates and the model-generated regime probabilities for each data point in the series.

forms the best recession prediction, followed by the two-factor model and the one-factor model. The main-street-one-factor model is the worst one for in-sample forecasting performance.

The out-of-sample forecasting performances provide different scenarios. The two-factor model performs the best among the four models, by reaching the minimum out-of-sample TP (= 0.128). Furthermore, its TP is far less than the second best Wall-Street-one-factor model, which is = 0.251. The main-street-one-factor model continuous to show the worst performance. Figure 7 also summarizes the corresponding out-of-sample filtered probabilities for the recession regime. These plots clearly demonstrate the superiority of using the two-factor model.

5 Concluding Remarks

This paper argues that the simple sum of all leading indicators may mix conflicting information and provide less accurate predictions. We suggest dividing the leading indicators into two sectors, real and financial sectors, based on their inherent characteristics. The real sector, contains manufacturing new orders, exports by customs, and floor area permitted for building in Taiwan. The financial sector contains stock price index, a narrowed money supply and wholesale price index. The two sectors may not share the same information for the future recessions.

There are three episodes of divergent movements, which occurred in 1988, 1991 and 1994, between the two sectors. The predicted recessions in these three periods are thus expected to be different. We use a Markov switching model to extract the common factor for each sector. Basically, the filtered and smoothed probabilities of both sectors confirm this conjecture. When both sectors move toward the same direction, the predicted probabilities roughly overlap. When the two sectors move divergently, the predicted recessions become different.

We also find that the real sector makes two more false signals than the financial sector. Two additional false signals made by the real sector are in 1987 and 1991. Alternatively, we find that the financial sector makes one more missed signal than the real sector. That is, in 1983 there is a recession, but it is not predicted by the financial sector. Except for this missed signal, our sample shows that the financial sector correctly predicts more often than the real sector.

We propose a modified two-factor Markov-switching model to exploit these characteristics, which are ignored by past studies. The in-sample prediction shows that the one-factor model utilizing only financial variables performs the best, followed by our two-factor model, the conventional one-factor model, and the one-factor model using only real variables.

The out-of-sample prediction demonstrates that our two-factor model produces business chronologies as accurate as the contraction dates determined by official dating. The one-factor model using financial variables provides the second best dating, followed by the conventional one-factor model. The worst performance remains to be the one-factor model using real variables.

Utilizing all leading indices to forecast future recessions, assuming a one-factor, may be less accurate when the underlying information is generated by two sectors. While this paper uses Taiwan data as the example, our model can be applied to almost all countries since asset bubbles and asset crashes have been very common recently.

Appendix: State-Space Representation and Algorithm

In this appendix we briefly describe how to re-write the two-factor model with regime switching, i.e., equations (6) to (8), into a state-space representation and then apply the algorithm of Kim's (1994) approximate maximum likelihood method to calculate unknown parameter estimates. Basically, Kim's algorithm is synthesis of Hamilton's filter and Kalman filter. Equations (6) to (8) can be transformed into measurement equation (11) and transition equation (12) as follows.

$$\mathbf{Y}_t = \mathbf{H}_t \boldsymbol{\xi}_t \tag{11}$$

$$\boldsymbol{\xi}_t = \mathbf{T}_t \boldsymbol{\xi}_{t-1} + \boldsymbol{\beta}_{S_t} + \mathbf{u}_t \tag{12}$$

with

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

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

$$\boldsymbol{\xi}_t = \begin{bmatrix} F_t & z_{1,t} & z_{1,t-1} & z_{2,t} & z_{2,t-1} & z_{3,t} & z_{3,t-1} & F_t^* & z_{1,t}^* & z_{1,t-1}^* & z_{2,t}^* & z_{2,t-1}^* & z_{3,t}^* & z_{3,t-1}^* \end{bmatrix}',$$

$$\boldsymbol{\beta}_{S_t} = \left[\begin{array}{cccccccccccccc} \beta(S_t) & 0 & 0 & 0 & 0 & 0 & 0 & \beta^*(S_t^*) & 0 & 0 & 0 & 0 & 0 & 0 \end{array} \right]',$$

$$\mathbf{u}_t = \left[\begin{array}{cccccccccccccc} \eta_t & \varepsilon_{1t} & 0 & \varepsilon_{2t} & 0 & \varepsilon_{3t} & 0 & \eta_t^* & \varepsilon_{1t}^* & 0 & \varepsilon_{2t}^* & 0 & \varepsilon_{3t}^* & 0 \end{array} \right]',$$

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

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

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

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

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

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

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

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

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

where equations (13) and (14) are the prediction formula, equations (15) and (16) are the updating formula, and equation (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 forecast error $\boldsymbol{\eta}_{t|t-1}^{(i,j)}$.

As noted by Harrison and Stevens (1976), each iteration of the above Kalman filtering produces an 2-fold increase in the number of cases to consider. Kim (1994) provides a fast approximation algorithm applicable to this problem. The idea is to collapse the dimension of the (2×2) posteriors ($\boldsymbol{\xi}_{t|t}^{(i,j)}$ and $\mathbf{P}_{t|t}^{(i,j)}$) to two posteriors ($\boldsymbol{\xi}_{t|t}^{(j)}$ and $\mathbf{P}_{t|t}^{(j)}$) by taking weighted averages over the states at $t-1$. That is,

$$\boldsymbol{\xi}_{t|t}^{(j)} = \frac{\sum_{S_{t-1}=0}^{1} \Pr[S_t = j, S_{t-1} = i|\Psi_t] \times \boldsymbol{\xi}_{t|t}^{(i,j)}}{\Pr[S_t = j|\Psi_t]} \tag{20}$$

$$\mathbf{P}_{t|t}^{(j)} = \frac{\sum_{S_{t-1}=0}^{1} \Pr[S_t = j, S_{t-1} = i|\Psi_t] \times \{\mathbf{P}_{t|t}^{(i,j)} + (\boldsymbol{\xi}_{t|t}^{(j)} - \boldsymbol{\xi}_{t|t}^{(i,j)})(\boldsymbol{\xi}_{t|t}^{(j)} - \boldsymbol{\xi}_{t|t}^{(i,j)})'\}}{\Pr[S_t = j|\Psi_t]} \tag{21}$$

where Ψ_t refers to information available at time t. Following Hamilton (1989, 1990), the filter can be obtained by Bayes's theorem.

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

where

$$f[\mathbf{Y}_t|S_t = j, S_{t-1} = i, \Psi_{t-1}] = (2\pi)^{-N/2}|\mathbf{W}_{t|t-1}^{(i,j)}|^{-1/2} \times \exp\{-\frac{1}{2}\boldsymbol{\eta}_{t|t-1}^{(i,j)\prime}(\mathbf{W}_{t|t-1}^{(i,j)})^{-1}\boldsymbol{\eta}_{t|t-1}^{(i,j)}\} \tag{23}$$

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

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

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

The approximate sample conditional log-likelihood is

$$\text{logL} = \ln f(\mathbf{Y}_T, \mathbf{Y}_{T-1}, ...|\Psi_0) = \sum_{t=1}^{T} \ln f(\mathbf{Y}_t|\Psi_{t-1}). \tag{26}$$

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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Table 1: MLE Estimates of the One-Factor Model

Parameter	Coefficients	Std. Err.	Parameter	Coefficients	Std. Err.
ϕ_1	-0.292	0.074	σ_3	0.278	0.013
ϕ_2	0.708	0.074	σ_1^*	0.896	0.042
θ_{11}	1.123	0.069	σ_2^*	0.652	0.031
θ_{12}	-0.153	0.069	σ_3^*	0.113	0.051
θ_{21}	1.387	0.059	γ_{10}	0.009	0.006
θ_{22}	-0.452	0.059	γ_{20}	0.008	0.005
θ_{31}	1.307	0.062	γ_{30}	0.003	0.006
θ_{32}	-0.368	0.062	γ_{10}^*	0.062	0.040
θ_{11}^*	0.119	0.064	γ_{20}^*	0.019	0.023
θ_{12}^*	0.375	0.062	γ_{30}^*	0.341	0.070
θ_{21}^*	0.466	0.063	β_0	-1.963	1.079
θ_{22}^*	0.349	0.064	β_1	1.615	0.979
θ_{31}^*	1.654	0.121	p_{11}	0.787	0.149
θ_{32}^*	-0.684	0.100	p_{00}	0.813	0.071
σ_1	0.229	0.010	σ_η	1	—
σ_2	0.259	0.012	logL	440.298	

Table 2: Main Street and Wall Street One-Factor Model

Parameter	MSV	Std. Err.	Parameter	WSV	Std. Err.
ϕ_1	0.012	0.124	ϕ_1^*	1.547	0.043
ϕ_2	-0.000	0.000	ϕ_2^*	-0.598	0.033
θ_{11}	0.877	0.042	θ_{11}^*	0.958	0.018
θ_{21}	0.648	0.058	θ_{21}^*	0.955	0.018
θ_{31}	0.626	0.052	θ_{31}^*	0.942	0.022
σ_1	0.280	0.040	σ_1^*	0.212	0.012
σ_2	0.655	0.031	σ_2^*	0.181	0.020
σ_3	0.760	0.036	σ_3^*	0.292	0.014
γ_{10}	0.143	0.031	γ_{10}^*	0.050	0.021
γ_{20}	-0.027	0.023	γ_{20}^*	-0.075	0.018
γ_{30}	-0.022	0.024	γ_{30}^*	0.017	0.006
γ_{11}	-0.407	0.052	γ_{11}^*	-0.080	0.034
γ_{12}	0.161	0.046	γ_{12}^*	0.052	0.018
γ_{21}	-0.111	0.026	γ_{21}^*	-0.069	0.034
γ_{22}	0.002	0.018	γ_{22}^*	0.143	0.033
γ_{31}	-0.042	0.024	γ_{31}^*	—	—
γ_{32}	-0.065	0.026	γ_{32}^*	—	—
β_0	-2.583	0.840	β_0^*	-3.268	0.981
β_1	5.792	0.950	β_1^*	0.872	0.713
p_{11}	0.915	0.026	p_{11}^*	0.952	0.022
p_{00}	0.903	0.036	p_{00}^*	0.972	0.014
σ_{η_1}	1.188	0.212	$\sigma_{\eta 1}^*$	0.621	0.213
σ_{η_0}	1		$\sigma_{\eta 0}^*$	1	
logL	-137.237		logL	573.194	

Note. WSV and MSV denote Wall Street and main street variables, respectively.

* denotes the coefficients from the Wall Street sector.

Table 3: MLE Estimates of the Two-Factor Model

Parameter	Coefficients	Std. Err.	Parameter	Coefficients	Std. Err.
ϕ_1^*	0.464	0.112	σ_1	0.801	0.057
ϕ_1	-0.134	0.151	σ_2	0.535	0.054
θ_{11}^*	1.783	0.044	σ_3	0.701	0.033
θ_{12}^*	-0.795	0.040	γ_{10}^*	0.106	0.010
θ_{21}^*	1.403	0.060	γ_{20}^*	0.018	0.008
θ_{22}^*	-0.464	0.059	γ_{30}^*	0.015	0.010
θ_{31}^*	1.303	0.063	γ_{10}	0.300	0.080
θ_{32}^*	-0.365	0.063	γ_{20}	0.258	0.067
θ_{11}	0.146	0.072	γ_{30}	0.020	0.044
θ_{12}	0.391	0.073	β_0^*	-4.155	2.102
θ_{21}	0.566	0.096	β_1^*	0.796	2.026
θ_{22}	0.269	0.089	β_0	-1.030	0.543
θ_{31}	0.360	0.060	β_1	1.590	0.631
θ_{32}	0.446	0.062	p_{00}^*	0.874	0.046
σ_1^*	0.075	0.012	p_{11^*}	0.923	0.027
σ_2^*	0.258	0.012	σ_η^*	1	—
σ_3^*	0.276	0.013	logL	474.447	

Note. * denotes the coefficients from the Wall Street sector.

Table 4: Forecasting Performance

Models	LogL	In-sample	Out-sample
MSF	-137.689	0.449	0.377
WSF	571.858	0.211	0.251
One-Factor	440.298	0.341	0.278
Two-Factor	474.447	0.251	0.128

Figure 1: Growth Rate of Six Leading Indicators

Main Street Variables

Wall Street Variables

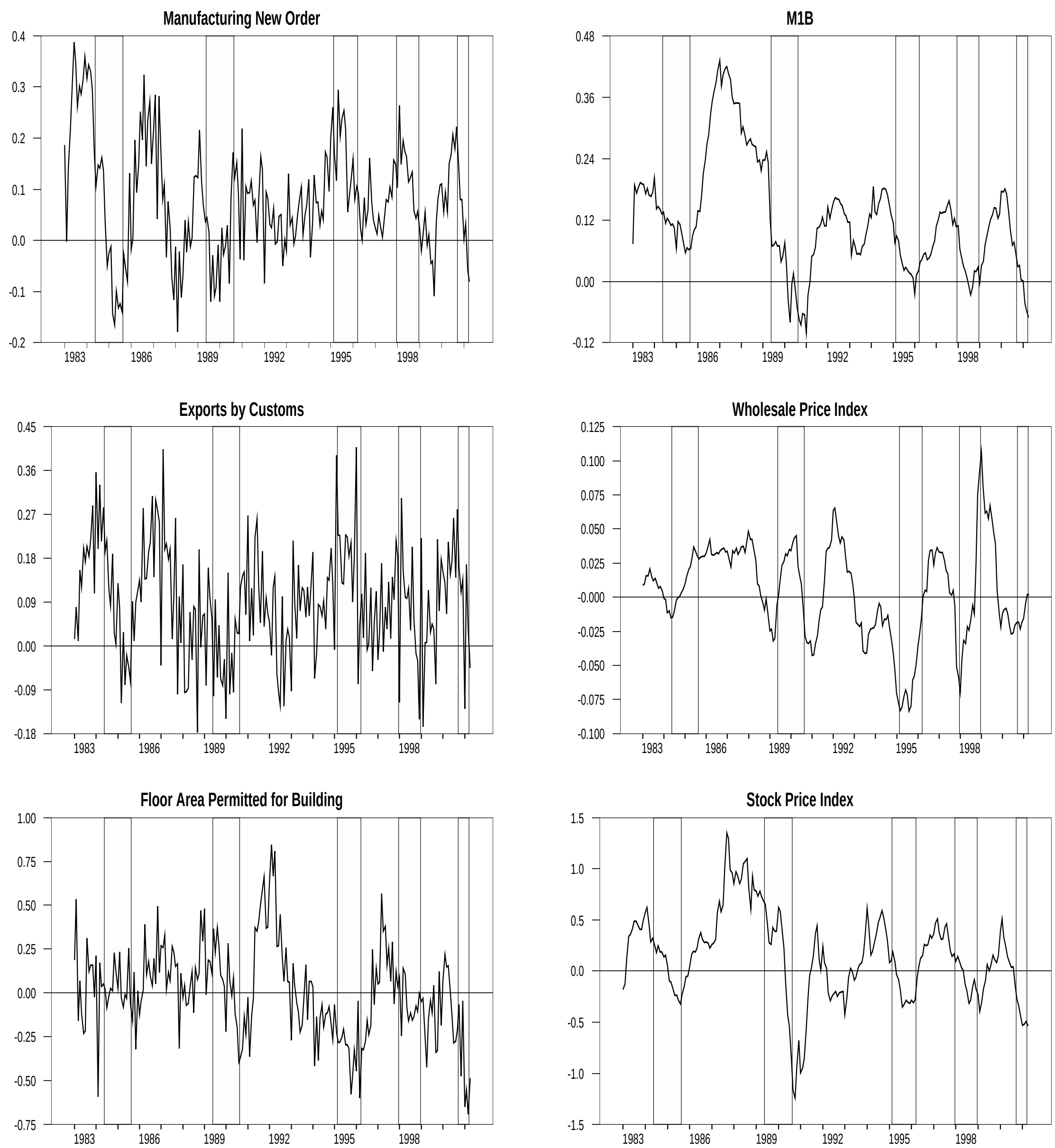
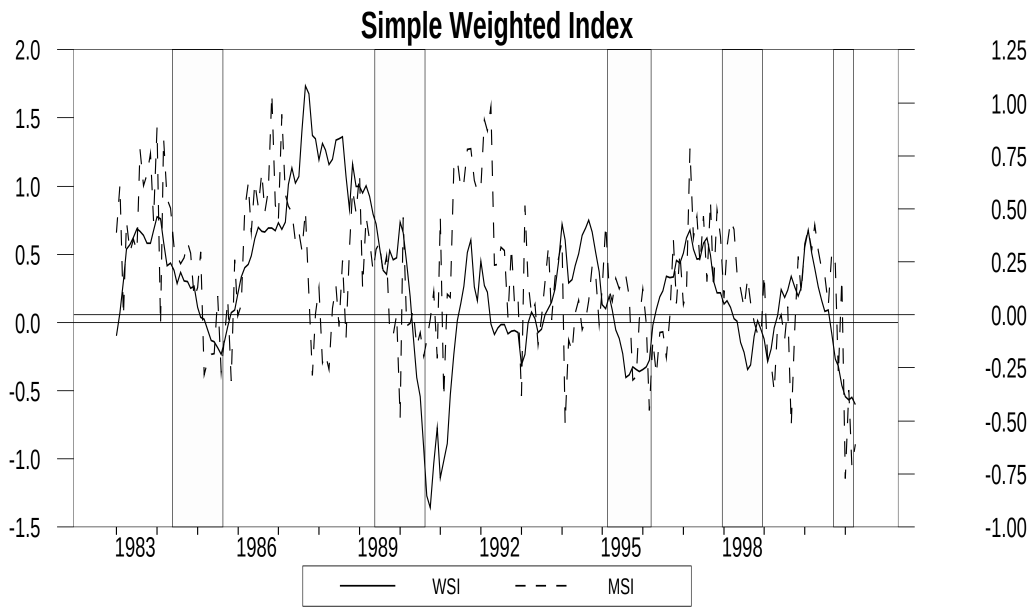


Figure 2: Simple Weighted Index of Main and Wall Street Variables



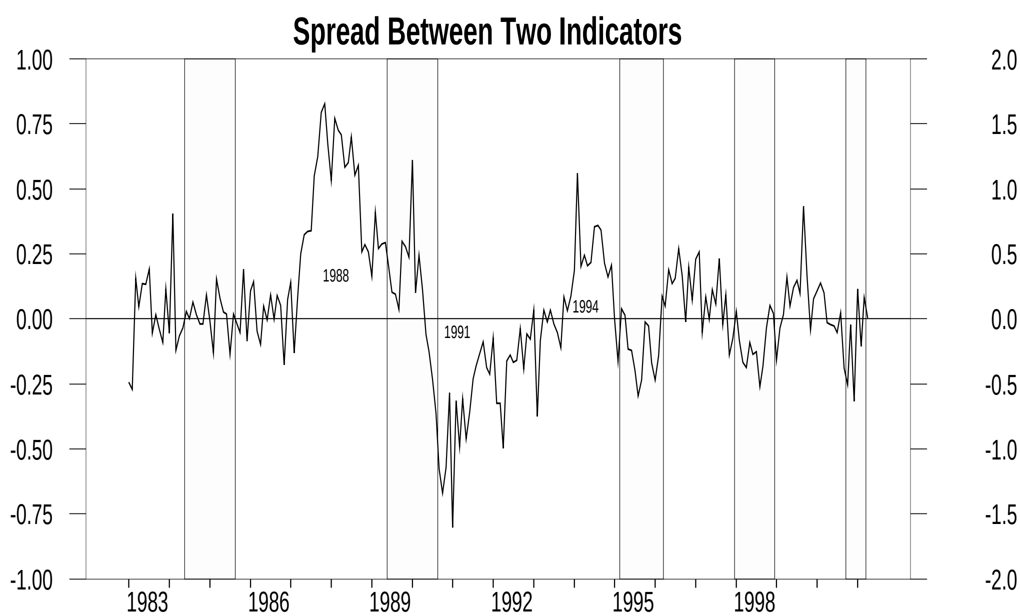


Figure 3: The Posterior Probabilities of the One Factor Model

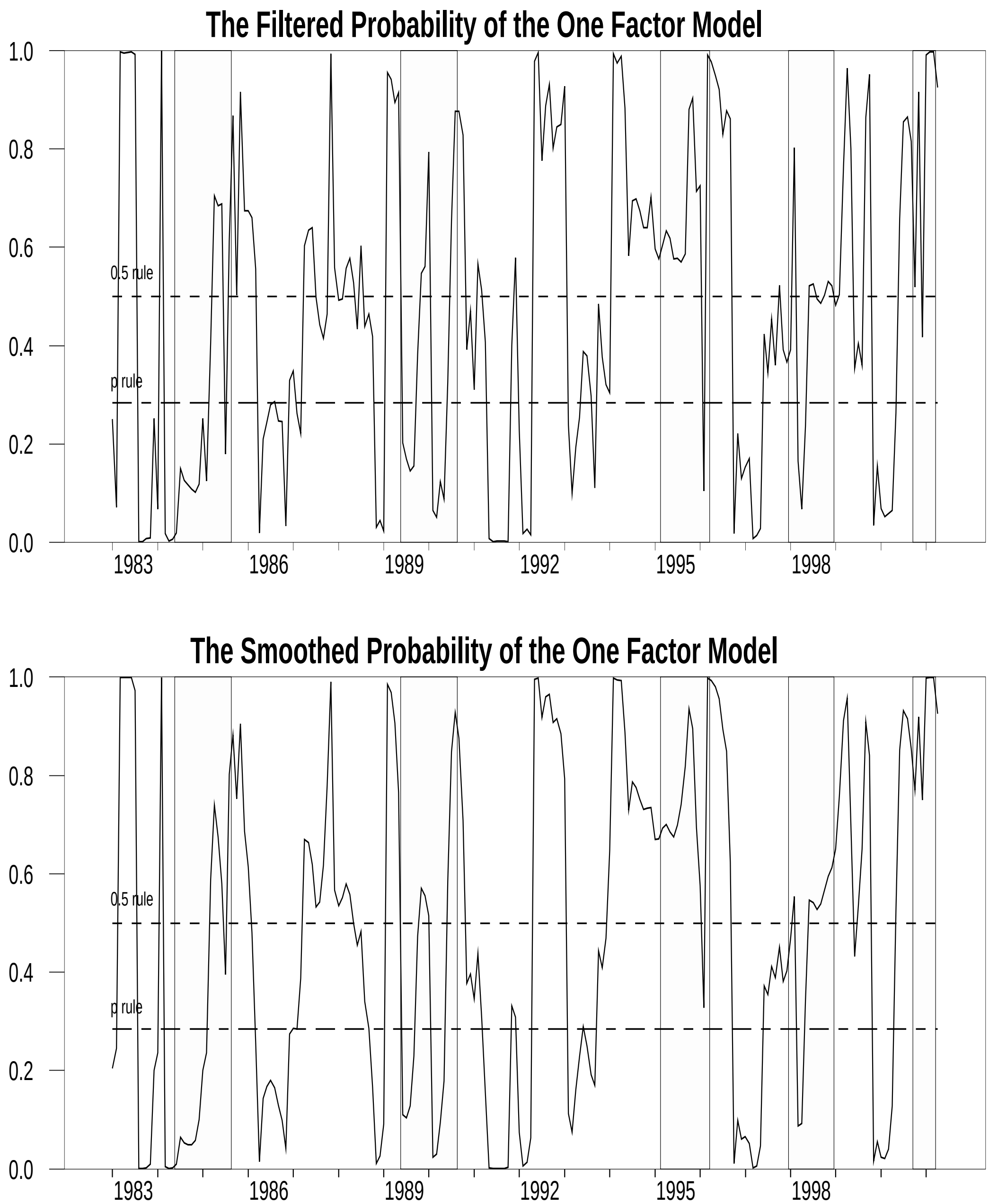


Figure 4: The Filtered Probabilities

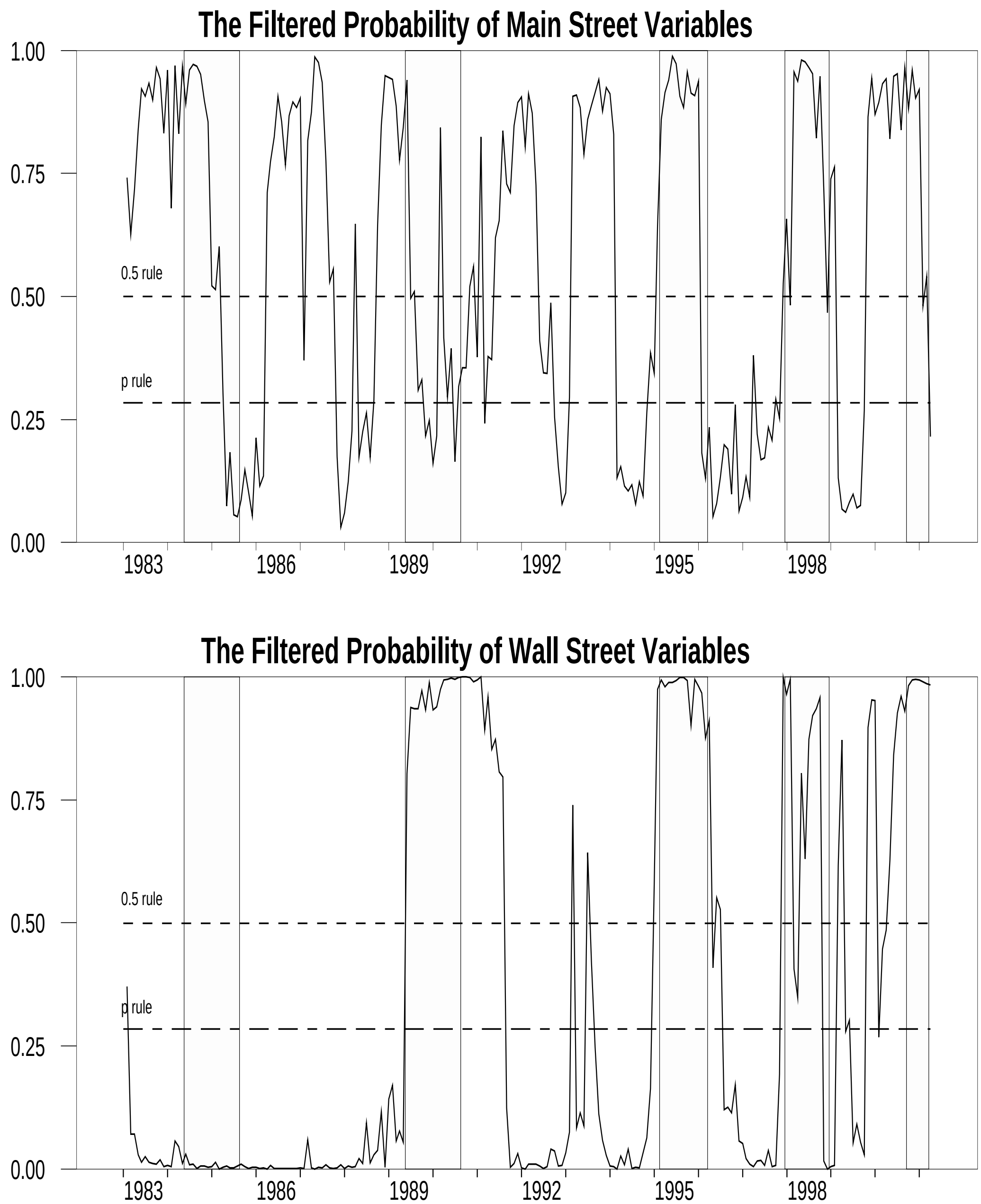
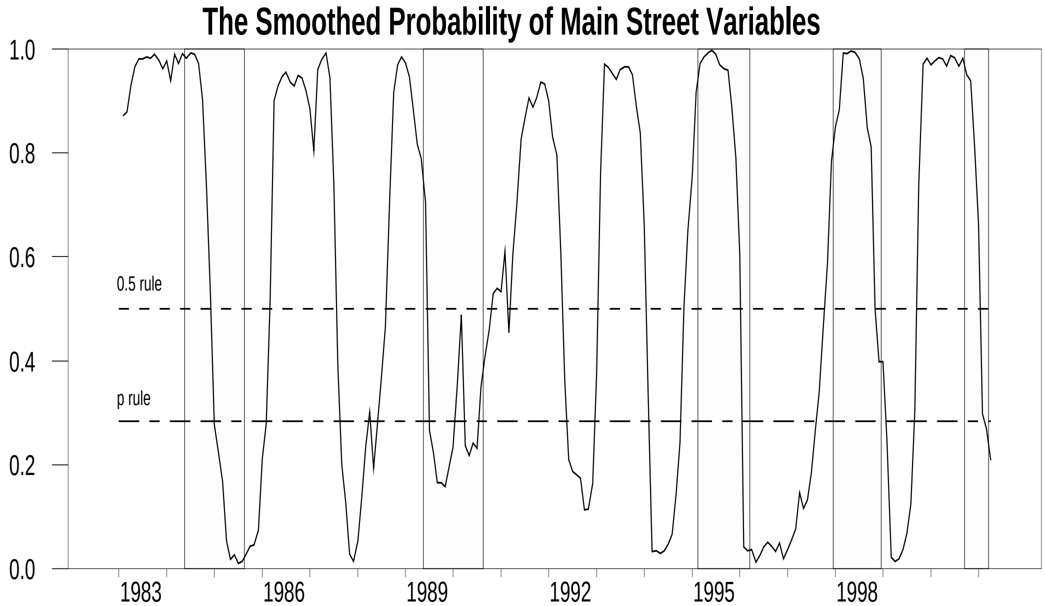


Figure 5: The Smoothed Probabilities



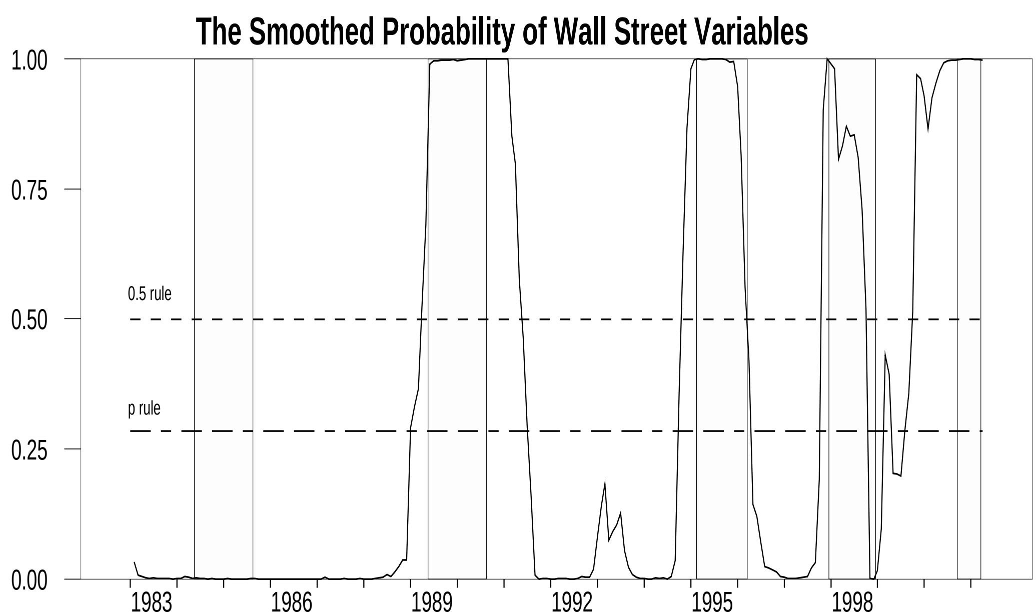


Figure 6: The Posterior Probabilities of the Two Factor Model

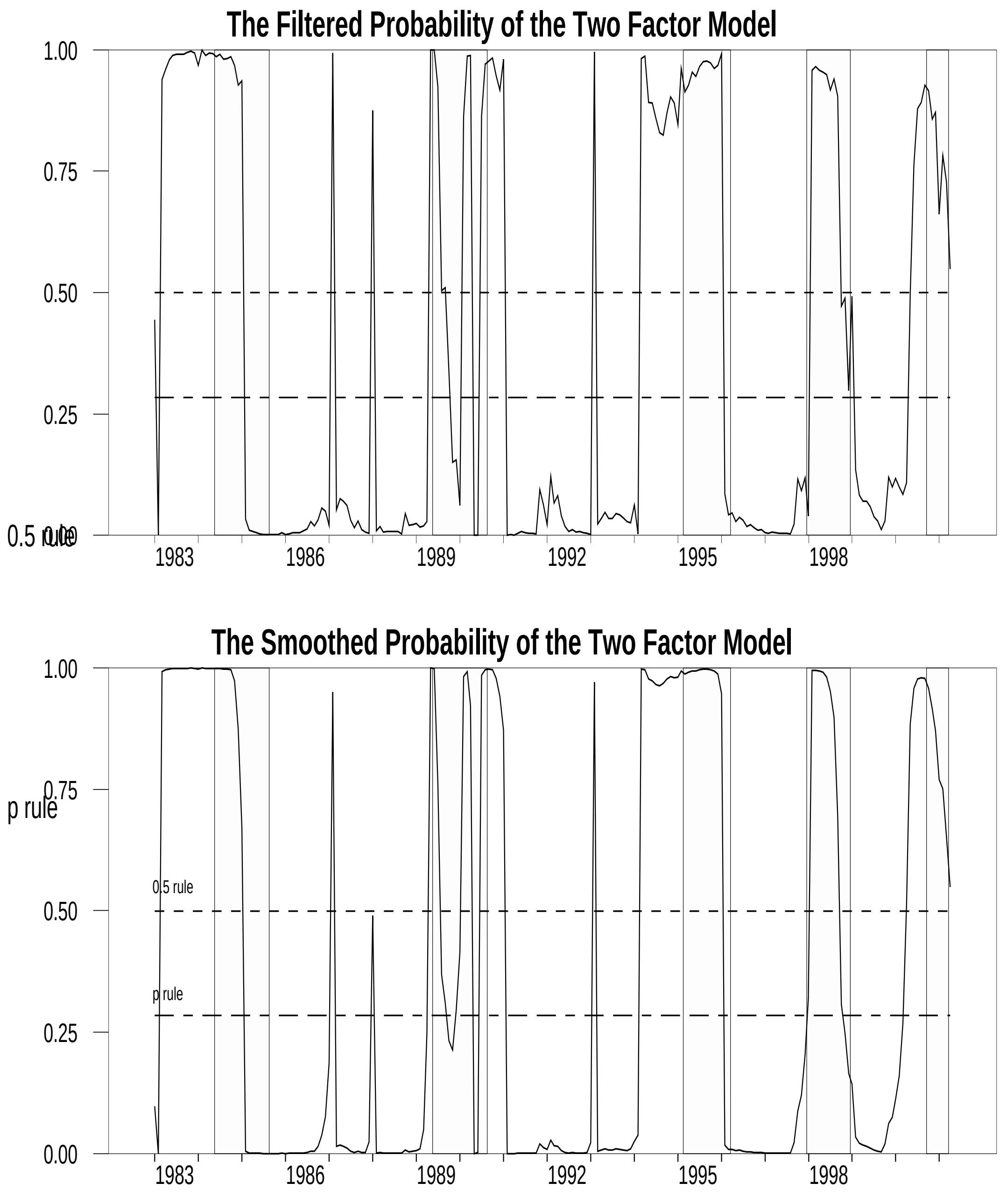


Figure 7: The Out-of-Sample Posterior Probabilities