A Multivariate Dynamic Factor Analysis of Permanent and Transitory Components of the U.S. Economy and the Stock Market[†]

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Abstract

In this paper we analyze the permanent and transitory components of the U.S. economic activity and the stock market using dynamic factor models, which yield multivariate decompositions of trend and cycle in each sector. We capture asymmetries over the phases of economic and stock market trends and cycles by modeling individual Markov-switching processes for each component. We find that both output and stock prices contain significant transitory components. In addition, consumption provides a natural trend for income consistent with the permanent income model whereas dividends represent the trend in prices based on the present value model with dividend smoothing. Our results indicate a strong and persistent bilateral relationship between the real economy and the stock market. In particular, we find that it is the transitory stock market factor that predicts recessions, whereas both the permanent and transitory components of the economy are useful in predicting where the market is headed in the longer run. This mechanism works through the effect of recessions on expectations of future dividends and earnings, which determine the long-run market trend.

Keywords: Business Cycles, Stock Market, Permanent and Transitory Components, Dynamic Factor Models, Markov Switching.

JEL Classification: C32, E32, E44

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1. Introduction

The literature on the relationship between the real economy and the stock market suggests that there exists a bilateral predictive association between these sectors. Several studies document that financial variables are leading indicators of the business cycle while some others find that properties of financial variables are influenced by business cycle phases.[1] However, there is much to be investigated regarding the nature of this relation and the mechanism behind these findings.

The longest expansion in the American history experienced in the 1990s coincided with a prolonged and soaring bull market. This revived an interest in the extent to which variations in the stock market phases are explained by economic fundamentals. Some associate the sharp increase in prices to the faster productivity growth and expanding IT investment, (Hobijn and Jovanovic (2001)), whereas others attribute the stock market performance to the low discount rate prevailing during most of the 1990s (Fama and French (2002)). On the other hand, Poterba (2000) and Jermann and Quadrini (2007) have studied how the wealth generated by the boom in the stock market might also have fueled the economy during this period.

Distinguishing between long-run and short-run variations in the real economy and stock market is crucial in understanding their relationship and explaining potential patterns. A powerful method to investigate this issue is the analysis of how variations in major aggregate macroeconomic and finance series are related to changes in their trends and cycles. This paper proposes multivariate dynamic factor models featuring Markov switching asymmetry to study the permanent and transitory components of the U.S. economic activity and of the

[1] See for example Fama and French (1989), Perez-Quiros and Timmermann (1995), Hamilton and Lin (1996), Chauvet (1998, 1999), Chauvet and Potter (2000), Lettau and Ludvigson (2001) among many others.

stock market. The models provide estimates of the long run trends of the economy and of the stock market as well as their short run cycles. Inferences obtained from the proposed framework are used to analyze the interrelations between economic and financial market trends and cycles without any *a priori* restriction on their relationship.

There is an extensive literature that provides statistical evidence of the sources of transitory components in output and stock prices. For example, Fama (1992) finds that short run deviations of investment from its stochastic trend shared with consumption is the source of the transitory component in output. This is based on the evidence that consumption dynamics are very close to a random walk, and output, consumption and investment grow at the same rate in the long-run. Furthermore, Cochrane (1994) shows that consumption represents the trend in output, which implies that shocks to output – holding consumption fixed – are transitory. These findings are consistent with the permanent income hypothesis, which forms the basis of many macroeconomic models.[2]

Cochrane (1994) also finds that a similar relationship holds between stock prices and dividends, with the latter representing the stochastic trend of the former. If dividends account for all trend movements in stock prices, this implies that shocks that do not affect dividends can be viewed as temporary. This evidence is in accord with the present value dividend smoothing model, which states that if the price-dividend ratio is stationary and dividends follow a random walk process, then shocks to stock prices are transitory. Summers (1986) proposes a model that corroborates this result, in which stock prices correspond to the sum of the fundamental market value and a transitory component. Empirically, the result that stock prices vary more than justified by fundamentals implies that they contain a mean reverting

[2] The Permanent Income Hypothesis states that consumption varies less than measured income because consumers smooth out their consumption based on their permanent income. The implication is that transitory changes in income have no effect on consumption spending.

transitory component. The existence of a significant transitory component that causes deviations in stock price from its long-run trend is supported by overwhelming empirical evidence in the finance literature.[3]

In this paper, we model the U.S. economy through the cointegration relationship among output, consumption, and investment. Motivated by the macroeconomic models of permanent income and empirical findings of Fama (1992) and Cochrane (1994), we assume that consumption represents the trend in output, which allows us to separate out transitory variation common to output and investment.

For the stock market, we model the permanent variation in stock prices using the information contained in dividends in a similar way. In particular, we find that stock prices, dividends, and earnings are cointegrated, which allows us to extract the stochastic trend common to the underlying financial variables and use the remaining transitory component to analyze deviations of stock market valuations from fundamentals. Theoretical models of transitory component in stock prices, also referred to as fad models, form the basis of our formulation.

The methodology we use is different from that of the aforementioned studies, mainly because we explicitly model the permanent and transitory variations in the series and also allow for asymmetric behavior in a nonlinear framework. We study potential asymmetries over the economic and stock market phases by incorporating independent two-state Markov switching processes in the permanent and transitory components. The Markov processes represent low or high growth phases in both components of each sector. We propose a

[3] See for example Shiller (1981), LeRoy and Potter (1981), Campbell and Shiller (1988a, 1988b), Fama and French (1988a, 1988b) and Poterba and Summers (1988), among several others. In particular, Shiller (1981) and LeRoy and Potter (1981) find that no price movements beyond changes in trend growth have ever been rationalized by movements in dividends.

flexible framework that allows identification of the shocks with respect to persistence without forcing the permanent and transitory components to have the same weight across states. We then use inference from these models to study the relationship between permanent and transitory components of the economy, permanent and transitory components of the stock market, and their interrelationships.

Our results are in line with Fama (1992) and Cochrane's (1994), which find that consumption and dividends represent the trend in output and in stock prices, respectively. There is evidence of significant transitory variation in all series even though at a small scale for consumption.

For the model of the real economy, all nine recessions in the post-war sample are identified by the permanent and transitory components, although the relative importance of each component varies across recessions. Turning point analysis reveals that all recessions, except for the last one in 2001, start with a switch in the permanent component in the form of a decline in the trend growth rate. Following this switch, economic activity is plucked down due to a shift in the transitory component.[4] Thus, its permanent component generally leads NBER recessions, whereas the transitory component roughly coincides with them.

Regarding the stock market, we find evidence of a stationary but persistent transitory component in prices. All bear markets identified by both temporary and permanent components are associated with NBER recessions. We also find a striking relation between the stock market and the economic activity not documented before. It is the transitory stock market factor that predicts economic turning points, with an average lead of two quarters. On the other hand, the permanent stock market factor tends to react to recessions rather than

[4] This finding is consistent with a recent result from Kim et al. (2007), which find that switches in the permanent component lead the switches in the transitory component when entering recessions.

predict them, suggesting that stock market is affected by economic slowdowns through expectation on dividends and earnings, which determine the long-run market trend.

In summary, the results support that economic activity, particularly downturns, are useful in predicting the stock market long-run trend. On the other hand, we also find that short term variations in the stock market are leading indicators of the business cycle.

The rest of the paper is organized as follows. Section 2 introduces the real economy model and the stock market model for the post-war U.S. sample. Section 3 presents and interprets the empirical findings for each model, as well as an in-sample analysis of the interrelations between them. Section 5 concludes.

2. The Models

Since our modeling strategy depends on the existence of common stochastic trends for the macroeconomic (GNP, investment, and consumption) and financial (stock prices, dividends, and earnings) series studied, we begin by implementing unit root and cointegration tests. The macroeconomic variables used in the economic model are quarterly real GNP (Y), personal consumption on non-durables and services (C), and private fixed investment (I).[5] For the stock market model we use quarterly real S&P 500 composite stock price index (P), S&P 500 dividends (D), and S&P 500 earnings (E).[6] The sample period is from 1952:Q1 to 2006:Q3 for the real economy model, and from 1952:Q1 to 2004:Q2 for the stock market model.

Table 1 presents the results for unit root tests. The Augmented Dickey Fuller and Phillips-Perron's tests are applied assuming a constant as well as a constant with linear trend.

[5] These series are seasonally adjusted at the annual rate and are in billions of chained 2000 dollars.
[6] All macro series are retrieved from the FRED database at the Federal Reserve Bank of St. Louis. The data on real stock prices, dividends, and earnings deflated with CPI (2004 is taken as the base year) are obtained from Robert Shiller's website and converted to the quarterly frequency (http://www.econ.yale.edu/~shiller/data.htm).

Each test statistic can not reject the null of unit roots in all six series studied. We then test for possible cointegrating relationships among the macroeconomic series and among the financial series. Table 2 reports the trace statistic of Johansen for the series, computed with one lag. For output, consumption, and investment, the null of no cointegration is rejected at the 1% level. This is also the case for stock prices, dividends, and earnings, for which the null of no cointegration is rejected at the 1% level. The cointegrating relationships for the macroeconomic and financial variables imply that each set of series share a stochastic trend.

2.1 A Time Series Model of the U.S. Real Economy

The model for economic activity is specified as a state space system in which the log of real output, consumption, and investment share a common stochastic trend. Deviations from this trend are modeled as arising from a transitory component common to output and investment, and from transitory idiosyncratic shocks to each series. In particular, consider the following decomposition based on the cointegration results:

(1) $$Y_t = \gamma_y x_t + \lambda_y z_t + e_{y,t}$$

(2) $$C_t = \gamma_c x_t + \lambda_c z_t + e_{c,t}$$

(3) $$I_t = \gamma_i x_t + \lambda_i z_t + e_{i,t}$$

where x_t represents the trend factor or permanent component of the series, and z_t is the transitory factor component. Notice that both x_t and z_t are common to all series. The coefficients γ_h and λ_h for $h = Y, C, I$ are the permanent and transitory factor loadings, respectively, which measure to what extent each series is affected by the common components. The factor loadings for output are set to 1 to provide a scale for the factor. This is a necessary identification condition since the latent factors contain information from all series. Notice that the choice of scale does not affect any time series properties of the dynamic factors. In order to capture potential variations that are not explained by common factors, we also allow for idiosyncratic components in each series, denoted by $e_{h,t}$.

Potential nonlinearities in the U.S. economic activity are modeled by assuming two Markov switching processes. First, we assume regime shifts in the growth rate of the trend, as in Hamilton (1989). In particular, we specify the trend, x_t, as a random walk with a Markov switching drift term. High values of the drift are associated with expansions whereas low values characterize recessionary periods. For the transitory component, denoted by z_t, we allow for Friedman-type asymmetry as proposed in Kim and Nelson (1999). In Friedman-type recessions, economic activity is plucked down from its stochastic trend and subsequently reverts back to its previous level. As a result of full economic recovery to its trend, output losses are not persistent. This type of recessions can be viewed as entirely transitory deviations from the trend. Hence, the permanent, transitory, and idiosyncratic components are specified as follows:

(4) $$x_t = \mu_{S_t^P} + x_{t-1} + v_t \qquad v_t \sim N(0, \sigma_v^2)$$

$$\mu_{S_t^P} = \mu_0(1 - S_t^P) + \mu_1 S_t^P$$

(5) $$\varphi(L) z_t = \tau_{S_t^T} + u_t \qquad u_t \sim N(0, \sigma_u^2)$$

$$\tau_{S_t^T} = \tau S_t^T$$

(6) $$\psi(L) e_{h,t} = \varepsilon_{h,t} \qquad \varepsilon_{h,t} \sim N(0, \sigma^2_{\varepsilon_h}) \qquad \text{for } h = Y, C, I$$

where $\varphi(L)$ and $\psi(L)$ are polynomials in the lag operator with roots outside the unit circle. The permanent and transitory common factors, x_t and z_t, are assumed to be uncorrelated with v_t, u_t, $\varepsilon_{h,t}$ at all leads and lags. S_t^P and S_t^T are the first order two-state Markov processes that characterize the phases of the economy for the permanent and temporary components, respectively. In particular, $S_t^P = 1, S_t^T = 1$ label economic contractions whereas $S_t^P = 0,\ S_t^T = 0$ indicate expansions. Thus, μ_0 and μ_1 are the growth rates of the trend during recessions and expansions, while $\tau < 0$ measures the size of the pluck in the common transitory component during recessions. The transition between states is given by the transition probabilities $p_{ij}^P = \Pr[S_t^P = j \mid S_{t-1}^P = i]$ and $p_{ij}^T = \Pr[S_t^T = j \mid S_{t-1}^T = i]$, for $i, j = 0,1$.

The specification for the permanent component has its roots in the works of Cochrane (1994) and Fama (1992), which show that the trend in output is well represented by consumption. It is also consistent with the neoclassical growth models in the Solow-Ramsey tradition, which suggests that output, consumption, and investment exhibit balanced stochastic growth.[7] In our framework, it is straightforward to assess such theoretical propositions since we estimate the factor loadings of the series instead of imposing any *a priori* value.

[7] See King et al. (1988), King et al. (1991) among others.

Kim and Piger (2002) propose a model for the permanent and transitory components of the economy using a similar framework. Our model differs from theirs in three ways: First, we assume separate Markov processes for the two components, which allow them to have different degree of importance over economic phases. Kim and Piger (2002) assume that the permanent and transitory components follow the same Markov process and, hence, are restricted to switch at the same time across economic phases. Kim et al. (2007) relax this assumption in a bivariate model for output and consumption. However, since asymmetry for the transitory variation is incorporated into the idiosyncratic components and assumed to be driven by the same state variable, this results in perfect correlation in the switching of the idiosyncratic variations of the two variables. Since we incorporate asymmetry into the common transitory component, our specification concurs with the assumption that the idiosyncratic terms are uncorrelated with each other, as they are not driven by the same Markov process. Finally, we allow for both permanent and transitory variation in consumption in order to fully explore its dynamics, especially during recessions.

2.2 A Time Series Model of the U.S. Stock Market

For the stock market, we specify the trend as a random walk process that is common to stock prices, dividends, and earnings. If dividends represent the stochastic trend in prices as argued by Cochrane (1994), then the resulting transitory component should represent swings in the stock prices that are not related to fundamentals. Summers (1986) assumes that prices take long temporary swings, which implies a slowly decaying transitory component that can be modeled as a very persistent AR(1) process. The model is based on the proposition that stock prices can be represented as a sum of a random walk and a stationary component. Here we adopt this proposition to define a process for stock prices. We also allow for short-run variation in earnings and dividends by incorporating transitory components. In particular, consider the following models for stock prices, dividends and earnings,

(7) $$P_t = \eta_p \tilde{x}_t + \tilde{z}_t$$

(8) $$D_t = \eta_d \tilde{x}_t + \tilde{e}_{d,t}$$

(9) $$E_t = \eta_e \tilde{x}_t + \tilde{e}_{e,t}$$

where $\tilde{x}_t$ is the permanent component, which can be viewed as a proxy for the fundamental value, and $\tilde{z}_t$ is the mean reverting transitory component of stock prices. The coefficients η_k for $k = P, D, E$ denote the permanent factor loadings. The factor loading of stock prices, η_p, is set to 1 to provide a scale for the factor.

Based on the cointegration results, we extract the permanent component of stock prices by modeling a stochastic trend common to all three series. If dividends provide an estimate of the trend in stock prices as argued in Cochrane (1994), then we can use the remaining transitory component to identify periods in which stock prices exhibit short run movements away from economic fundamentals. We specify the trend as a random walk with a Markov switching drift to capture the different behavior of the common factor over the phases of bull and bear markets.

Even though the permanent component is common to all variables, the transitory components are idiosyncratic to each variable. We adopt this modeling strategy since there is no evidence of common transitory variation among these three variables based on our prior estimations.[8] Thus, we model the transitory components in each series as idiosyncratic processes. We assume a stationary AR(1) process with state dependent intercept and variance for the transitory component of stock prices.[9] However, we do not restrict the mean of the transitory component to follow only one state, as the plucking effect introduced in the economic model. Instead, we allow it to potentially display phases of high and low growth and let the data tell whether this assumption holds.[10] We specify linear autoregressive processes to capture transitory variation in dividends and earnings, denoted by $\tilde{e}_{k,t}$ for $k=D,E$. The specifications for the permanent, transitory and idiosyncratic components are as follows:

(10) $$\tilde{x}_t = \delta_{\tilde{S}_t^P} + \tilde{x}_{t-1} + \tilde{v}_t \qquad \tilde{v}_t \sim N(0, \tilde{\sigma}_v^2)$$

$$\delta_{\tilde{S}_t^P} = \delta_0(1-\tilde{S}_t^P) + \delta_1 \tilde{S}_t^P$$

(11) $$\theta(L)\tilde{z}_t = \alpha_{\tilde{S}_t^T} + \tilde{u}_t \qquad \tilde{u}_t \sim N(0, \tilde{\sigma}^2_{u_{\tilde{S}_t^T}})$$

$$\alpha_{\tilde{S}_t^T} = \alpha_0(1-\tilde{S}_t^T) + \alpha_1 \tilde{S}_t^T$$

$$\sigma^2_{u_{\tilde{S}_t^T}} = \sigma_0^2(1-\tilde{S}_t^T) + \sigma_1^2 \tilde{S}_t^T$$

(12) $$\xi(L)\tilde{e}_{k,t} = \tilde{\varepsilon}_{k,t} \qquad \tilde{\varepsilon}_{k,t} \sim N(0, \tilde{\sigma}^2_{\varepsilon_k}) \quad \text{for} \quad k = D, E$$

[8] All estimations that allow for a common transitory component of the financial variables produced factor loading estimates which are very close to zero and insignificant. The results from these models are available from the author upon request.
[9] After running different specifications and starting values, we could not find statistical evidence of different variances over the stock market phases arising from the permanent component. The results suggest instead that heteroskedasticity across stock market phases comes from the transitory component only.
[10] Anticipating the empirical results, we find that the Friedman type of asymmetry is significant for the real economy, but not for the stock market.

where $\theta(L)$ and $\xi(L)$ are polynomials in the lag operator with roots outside of the unit circle. The common permanent factor is assumed to be uncorrelated with the idiosyncratic terms at all leads and lags.

$\tilde{S}_t^P$ and $\tilde{S}_t^T$ represent bull and bear market phases in the permanent and transitory components, respectively. In particular, $\tilde{S}_t^P = 1, \tilde{S}_t^T = 1$ denote bear markets, whereas $\tilde{S}_t^P = 0,\ \tilde{S}_t^T = 0$ indicate stock market booms. For the permanent component equation, $\delta_{\tilde{S}_t^P}$ determines the growth rate of the stock market trend. For the transitory component, $\alpha_{\tilde{S}_t^T}$ and $\sigma^2_{u_{\tilde{S}_t^T}}$ determine the state dependent drift and volatility over the phases of stock market cycles, respectively. Both state variables are assumed to follow first-order Markov processes with transition probabilities given by $q_{ij}^P = \Pr[\tilde{S}_t^P = j \mid \tilde{S}_{t-1}^P = i]$ and $q_{ij}^T = \Pr[\tilde{S}_t^T = j \mid \tilde{S}_{t-1}^T = i]$ where $i, j = 0,1$.

3. Empirical Analysis

We estimate the models by numerical optimization. We first cast the models in state space form and then combine a nonlinear discrete version of the Kalman filter with Hamilton's (1989) filter using Kim's (1994) approximate maximum likelihood method. This allows the estimation of the unobserved state vector and the Markov state probabilities using the observable data. A nonlinear optimization procedure is used to maximize the likelihood function, which is based on the probabilities of the Markov states. Predictions of the factors and the Markov probabilities are obtained as a product of the filter. The state space representation and the details of the estimation procedure are given in Appendices A and B.

The lag structure of the models is chosen based on likelihood ratio tests. We assume that all transitory components follow AR(1) processes, as higher order lags are found to be insignificant. In addition, we incorporate two well documented structural breaks in the post-war U.S. data in the model of economic activity. As suggested by Perron (1989), we allow the drift of the permanent component to change in 1973:1, in order to capture the slowdown in output growth in the early 1970s. In a recent study, Perron and Wada (2006) show that neglecting this change in the trend significantly affects the decomposition of trend and cycle. The second structural break we consider is in the variance of output. McConnell and Perez-Quiros (2000), among several others, find strong evidence of a reduction in output volatility since 1984. Thus, we allow for a potential break in the variance of both permanent and transitory components in 1984:1.

With respect to the stock market model, we have investigated the existence of several structural breaks documented in Timmermann and Pettenuzzo (2005). However, we do find that these breaks are not statistically significant within our model specification. For the stock market model, neither the parameter estimates nor the resulting decomposition are affected by inclusion of breaks.

3.1 Real Economy Model

Table 3 reports the estimation results for the real economy model. Estimates of regime switching parameters clearly support the presence of asymmetry over the phases of economy. First, the drift terms, μ_1 and μ_0 are statistically significant and estimated to be 0.63 and 1.13 respectively, separating out phases of permanent low and high growth rates in the trend component. The parameter τ, which measures how much the economy is temporarily plucked down during recessions, is estimated to be equal to -0.55. For both the temporary and permanent components, expansions are found to be of longer duration than recessions, as depicted by their transition probabilities. Finally, we find that a significant portion of innovations is coming from the transitory component since $\sigma_u > \sigma_v$. Notice that the estimates of these two variables significantly decrease after 1984 once the variance break is taken into account.

The factor loading for consumption in the permanent component is estimated to be 1.018, which is consistent with the theoretical models such as the permanent income hypothesis. Prior estimations suggest that the common transitory factor loading for consumption is very close to zero, which is in line with the results of previous literature. However, we find significant transitory variation in consumption that is not shared with output. Therefore, we estimate the model by allowing only idiosyncratic transitory variation in consumption.

Figure 1 plots the smoothed probabilities of low growth for the common permanent component and NBER dated recessions. The permanent component identifies every recession in the sample with probabilities increasing above 0.7. Figure 2 shows the smoothed probabilities of low growth from the transitory component. The probabilities call every NBER dated recessions including the one in 2001, which is not identified by the transitory component in other recent studies (see for example Kim and Murray 2002, Kim et al. 2007). Notice, that there are times at which the probabilities from the transitory component increase above 0.5 but these are not associated with recessions. Instead, they indicate periods in which output temporarily lowers below its long-run path. The most significant case occurs between

1984 and 1986, reflecting a slowdown in the U.S. economy that was also experienced in Europe.

Notice that the characteristics of the last two U.S. recessions (1990-1991 and 2001) are different from the previous ones in the sample. These recessions were milder, short-lived, and were not followed by a fast recovery. Although both permanent and transitory components in our model identify these two recessions, their smoothed probabilities indicate that the low growth in the permanent component lasted for a couple of quarters after the NBER troughs. In addition, fast subsequent recovery periods that were typical in the previous recessions are not found in these last two recessions. In fact, the economy remained weak for quite some time after the end of these recessions.

Figures 3 and 4 show the estimated trend and cycle of output, respectively. The estimated trend closely resembles the observed level of the original series. By the same token, the estimated cycle is highly correlated with NBER recessions. In particular, we observe abrupt decreases during recessions, with 1982 being the deepest one. On the other hand, expansions are characterized by gradual increases. Notice that the exceptional long expansion of the 1990s, when the economy grew well above the trend, is clearly represented by the model as shown in Figure 4.

3.2 Stock Market Model

Table 4 reports the parameter estimates for the stock market model. The mean reverting transitory component of stock prices is very persistent, supporting the well-documented fact that stock prices take long swings away from fundamentals. Even though there is no evidence of short-run transitory variation that is common to all three series, the results point out to persistent idiosyncratic transitory variation for dividends and earnings as well.

Estimates of the intercepts of both the permanent and temporary components are negative in State 1, indicating negative returns during bear markets, and positive in State 0 reflecting positive returns in bull markets. The sample also identifies regime switching in the volatility of the transitory component, with estimates of higher variance during bear markets than during bull markets.[11]

The permanent factor loading of dividends is estimated to be 1.12, supporting Cochrane's proposition that dividends represent the trend in stock prices. In this sense, the relation is similar to that between output and consumption. Moreover, in line with the findings of the economic model, a significant part of innovations also comes from the transitory component since $\tilde{\sigma}_{u_0}$ and $\tilde{\sigma}_{u_1}$ are much larger than $\tilde{\sigma}_v$ (almost seven and nine times larger, respectively).

Figure 5 plots the smoothed probabilities of bear markets in the permanent component. Every bear market arising from a lower trend growth in stock prices is associated with economic recessions. In particular, the first two bear markets in the sample lead NBER recessions whereas the third one is almost coincident. The longest bear market started in the beginning of 1966, encompassed two recessions and lasted for 10-years. Historical data shows that the price-dividend ratio reached a peak in January 1966 following a strong increase in real prices that had lasted for five years. By the end of the economic recession in

[11] In order to gain further insight as to which type of asymmetry is more important over bear and bull markets, we also estimate models allowing only one type of asymmetry in the transitory component. For the model in which only the mean switches, smoothed probabilities identify the same stock market phases, but with slightly higher values. For the specification in which only the variance switches, the transitory component lags NBER recessions, possibly reflecting the uncertainty prevailing in the stock market right around the end of periods of weak economic activity.

March 1975, stock prices were almost 60% lower than their January 1966 value. The average real return in the stock market was -1.8% a year for the entire bear market that ended in 1976.[12]

The smoothed probabilities of bear markets as captured by the transitory component are plotted in Figure 6. The probabilities increase around all economic recessions. Moreover, for all recessions, except the first one in the sample, the probabilities start to rise before the beginning of recessions, with an average lead of two quarters. That is, the transitory stock market component is found to be a leading indicator of NBER recessions.

There are also times in which the probabilities of bear markets increase but recessions do not follow. Invariably, these are periods when either the economy is relatively weak and displays mild low growth, or predictions of recessions are widespread. For example, following the oil shock in 1975, the U.S. economy experienced a slowdown but not a full recession. Similarly, the stock market crash in October 1987, which was the largest one-day stock market crash in history, increased the uncertainty in the economy and gave rise to expectations of a future recession. However, the swift Fed's intervention decreasing short-term interest rates may have contributed to prevent a recession following the crash.

The permanent and the transitory components of the stock market are plotted in Figures 7 and 8, respectively. The permanent component moves very closely with the level of the index, whereas mean reversion is more evident in the transitory component. The steep upward movement in prices starting in the mid 1990s is observable in both components. This remarkable stock market boom ended in 2000. Some economists argue that the sharp increase in prices during this time can be justified by economic fundamentals such as faster productivity growth and expanding IT investment, whereas others believe that this was due to

[12] The information is based on Shiller's (2005) findings.

lower equity premium and discount rate. Comparison of figures 5 and 6 suggests that the bull market identified by the permanent component is not as strong and persistent as the one identified by the transitory component. This may be interpreted as a stronger evidence for the view that the stock market boom of 1990s can not be justified by fundamentals as much as by short-run deviations from long run trend, as evinced by the dynamics of the permanent and transitory component in our model.

3.3 Turning Point Analysis

The relationship between the stock market and the economy is further investigated using turning point analysis. In order to identify the beginning of economic recessions, we adopt the following criterion: a peak indicating a transition from regime 0 to regime 1 for the r^{th} component occurs at time t if $\Pr[S_{t-1}^r = 1] < 0.5$, $\Pr[S_t^r = 1] \geq 0.5,$ and $\Pr[S_{t+1}^r = 1] \geq 0.5$ where $r = P,T$. We use the same criterion to find the beginning of bear markets, replacing the state variable with $\tilde{S}_t^r$.

Table 5 reports the peak signals from all four factors and the reference chronology of the NBER Business Cycle Committee. We find some striking results. First, the permanent component of the economy for the most part leads economic recessions, whereas the transitory component roughly coincides with the NBER recessions. Second, it is the transitory component of the stock market that contains leading information on the economic activity, whereas the permanent component of the stock market lags the economic activity and short run deviations in prices.

More specifically, the permanent component of the economy, EP_t, displays a perfect fit with the NBER peaks, matching all recessions with zero false signals. It coincides with three

NBER peaks (1953:Q2, 1990:Q3, 2001:Q1) and leads the other six recessions by around one quarter. On the other hand, the transitory component of the economy, ET_t, roughly coincides with NBER recessions.

The stock market transitory component, SMT_t, also anticipates all recessions, with a median lead of two quarters. A well known feature of the stock market as a leading indicator of the economy is that it signals not only recessions, but also milder low economic growth. This is also found by our model, with SMT_t predicting more recessions than the ones documented by the NBER.

In order to further evaluate the accuracy of the implied probabilities in predicting NBER peaks, we use Quadratic Probability Score (QPS), as proposed in Diebold and Rudebusch (1989). QPS is a counterpart metric for the mean squared error measure. Let $\{\hat{N}_t\}_{t=1}^{n}$ denote the model generated probabilities, which take values in the [0, 1] range, and let $\{N_t\}_{t=1}^{n}$ denote a 0/1 dummy representing the NBER chronology, with N_t equals 1 at NBER recessions and equals 0 otherwise. Then the QPS is given by:

$$QPS = \frac{2}{n}\sum_{t=1}^{n}(\hat{N}_t - N_t)^2$$

The QPS ranges from 0 to 2, with zero corresponding to perfect accuracy. It achieves its minimum value when the loss function associated with event timing forecast is minimized.

Table 6 compares the accuracy of the factors in predicting NBER recessions using this metric. The economic permanent component (EP_t) yields the lowest QPS for horizons 0 to 4 with a minimum at i = 1 indicating that EP_t leads the NBER reference cycle by 1 quarter. The smallest QPS for the stock market transitory component (SMT_t) is found at $i = 2$, indicating a lead of the NBER reference cycle by 2 quarters. Even though SMT_t leads the NBER cycle, we find that the permanent component, SMP_t, lags it by 2 quarters.

Table 7 presents the results of the analysis of cross factor turning point signals using QPS. SMT_t leads the permanent and transitory components of the economic model (EP_t and ET_t) with 1 and 2 quarters, respectively. On the other hand, SMP_t lags EP_t by 1 quarter and ET_t by 2 quarters.

The results of the turning point analysis uncover a striking relation between the stock market and economic activity not documented before. It is the transitory stock market factor that predicts economic turning points, whereas both the permanent and transitory components of the economic activity are useful in predicting where the market is headed in the longer run. Considering the variables used to estimate the permanent stock market factor, it is apparent that this mechanism works through the effect of recessions on expectations of future dividends and earnings, which determine the long-run market trend (see Table 8 for a summary of the findings).

4. Conclusion

We characterize permanent and transitory components of U.S. economic activity and the stock market by modeling the permanent and transitory components of GNP and stock prices. The proposed multivariate dynamic factor models featuring Markov switching asymmetry allows identification of these components by exploring the information contained in several macro and financial series. The permanent income model forms the basis of the model formulated to analyze the US economic activity. The specification for the stock market has its roots in the present value model with dividend smoothing.

We find that the trend in GNP is well represented by consumption, as argued in Cochrane (1994). However there is also evidence of fairly small idiosyncratic variation in consumption. The permanent and transitory components of the economic model identify all post-war NBER recessions. Our turning point analysis reveals that except for the 2001, all recessions start with a switch in the permanent component followed by a switch in the transitory component in the form of a pluck.

With respect to the stock market, we find that all bear markets identified by the model are associated with NBER recessions. The trend in stock prices can usefully be represented by dividends. On the other hand, there is also persistent transitory variation in stock prices that cannot be explained either by dividends or by earnings. Even though there is no evidence of a transitory component common to all financial series, we find significant variable specific variations for dividends and earnings as well.

In terms of the nature of the interrelations, we find a strong and persistent bilateral link between the real economy and the stock market: transitory stock market factor predicts economic turning points, whereas both the permanent and transitory components of the economic activity are found to be useful in predicting the market behavior in the long-run.

The results from this study lay the foundation for further analysis of the relation between the two sectors in a joint framework, which poses different challenges mainly due to the unsynchronized regime switches in the trend and cycle components. Since this is beyond the scope of this paper, we are pursuing this line of research in a different project.

A.1 Appendix A: Representation

We first cast both models in state-space form and then estimate the parameters by Maximum Likelihood using a combination of the Kalman Filter and the Hamilton Filter. We employ the following specification for the real economy model,

(A.1) $$y_t = Z_{S_t^P} + H\beta_t + \Gamma V_t$$

(A.2) $$\beta_t = K_{S_t^T} + F\beta_{t-1} + G\Lambda_t$$

$$E(V_t V_t') = R^*$$

$$E(\Lambda_t \Lambda_t') = Q^*$$

where (A.1) is the measurement equation and (A.2) is the transition equation. In our nonlinear and multivariate framework, the estimation of the trend and cycle becomes fairly complicated mainly due to the different order of magnitudes of the variables. To overcome this difficulty, we take the difference of equations 1-3 for the economic model and 7-9 for the stock market model to write down the state space forms in first differences. However, all the processes for the components are still defined for the levels of the variables, not for the differences. This strategy allows us to drop the trend component of each model, x_t and $\tilde{x}_t$, from the state vectors. Thus, matrices in Equations (A.1) and (A.2) are specified as follows: For the real economy model, $y_t = (\Delta Y_t, \Delta C_t, \Delta I_t)'$, $\beta_t = (z_t, z_{t-1}, e_{y,t}, e_{y,t-1}, e_{c,t}, e_{c,t-1}, e_{i,t}, e_{i,t-1})'$, $K = (\tau_{S_t^T}, \mathbf{0})'$, $Z = (\gamma_y \mu_{S_t^P}, \gamma_c \mu_{S_t^P}, \gamma_i \mu_{S_t^P})'$, where $\mathbf{0}$ is a 7x1 null vector, $G = \mathbf{I}_8$,

$$H = \begin{bmatrix} \lambda_y & -\lambda_y & 1 & -1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & -1 & 0 & 0 \\ \lambda_i & -\lambda_i & 0 & 0 & 0 & 0 & 1 & -1 \end{bmatrix} \qquad \Gamma = \begin{bmatrix} \gamma_y & 0 & 0 \\ 0 & \gamma_c & 0 \\ 0 & 0 & \gamma_i \end{bmatrix}$$

$$F = \begin{bmatrix} \varphi & 0 & & & & \cdots & & 0 \\ 1 & 0 & \ddots & & & \cdots & & 0 \\ 0 & 0 & \psi_y & & & \cdots & & 0 \\ 0 & 0 & 1 & 0 & \ddots & \cdots & & 0 \\ 0 & 0 & 0 & 0 & \psi_c & & & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & \ddots & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \psi_i & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix}$$

with $Q = G\,Q^{*}G'$ where $Q^{*} = diag(\sigma_u^2, 0, \sigma_{\varepsilon_y}^2, 0, \sigma_{\varepsilon_c}^2, 0\ , \sigma_{\varepsilon_i}^2, 0)$ and $R = \Gamma R^{*}\Gamma'$ where R^{*} is a 3x3 matrix with all elements are equal to σ_v^2.

For the stock market model, we again use the state space representation in Equations (A.1) and (A.2) by replacing the state variables with $\tilde{S}_t^P$ and $\tilde{S}_t^T$, and Q^{*} with $Q^{*}_{\tilde{S}_t^T}$. The state vectors and the parameter matrices are now specified as follows: $y_t = (\Delta P_t, \Delta D_t, \Delta E_t)'$, $\beta_t = (z_t, z_{t-1}, e_{d,t}, e_{d,t-1}, e_{e,t}, e_{e,t-1})'$, $K = (\alpha_{\tilde{S}_t^T}, \mathbf{0})'$, $Z = (\eta_p \delta_{\tilde{S}_t^P}, \eta_d \delta_{\tilde{S}_t^P}, \eta_e \delta_{\tilde{S}_t^P})'$, where $\mathbf{0}$ is a 5x1 null vector, $G = \mathbf{I}_6$,

$$H = \begin{bmatrix} 1 & -1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & -1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & -1 \end{bmatrix} \qquad F = \begin{bmatrix} \theta & 0 & & \cdots & & 0 \\ 1 & 0 & \ddots & \cdots & & 0 \\ 0 & 0 & \xi_d & & & 0 \\ 0 & 0 & 1 & 0 & \ddots & 0 \\ 0 & 0 & 0 & 0 & \xi_e & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix}$$

with $Q_{\tilde{S}_t^T} = G Q^{*}_{\tilde{S}_t^T} G'$ where $Q^{*}_{\tilde{S}_t^T} = diag(\tilde{\sigma}^2_{u_{\tilde{S}_t^T}}, 0, \tilde{\sigma}^2_{\varepsilon_d}, 0, \tilde{\sigma}^2_{\varepsilon_e}, 0)$, R^{*} is a 3x3 matrix with all elements equal to $\tilde{\sigma}_v^2$ and Γ is as defined above.

A.2 Appendix B: Estimation

Estimation Procedure

There are two independent unobservable state variables both in the real economy and in the stock market model. We can define one state variable that summarizes the information content of these two variables for each model, which helps to construct the algorithm in a more straightforward way. Suppose S_t represents the dynamics of S_t^P and S_t^T in the economic model in the following way,

$$\begin{aligned} S_t &= 1 \text{ if } & S_t^P &= 0 \text{ and } S_t^T = 0 \\ S_t &= 2 \text{ if } & S_t^P &= 0 \text{ and } S_t^T = 1 \\ S_t &= 3 \text{ if } & S_t^P &= 1 \text{ and } S_t^T = 0 \\ S_t &= 4 \text{ if } & S_t^P &= 1 \text{ and } S_t^T = 1 \end{aligned}$$

with $\Pr[S_t = j \mid S_{t-1} = i] = p_{ij}$ and $\sum_{j=1}^{4} p_{ij} = 1$.

We estimate both models using a synthesis of the Kalman filter and Hamilton's filter. Since the state variables are unobservable, the resulting Kalman filter equations are nonlinear. This makes the calculation of the exact likelihood intractable since the number of cases to consider increases exponentially with sample size. For instance if we assume *k* states with a sample size of *T*, this would lead to k^T cases to consider. In order to deal with this dimensionality problem we utilize Kim's approximation method, which is based on the work of Harrison and Stevens (1976).

Optimal estimates of the unobserved state vector, $\beta_{t|t}^{(i,j)}$ and the associated mean squared error matrices, $M_{t|t}^{(i,j)}$ are computed recursively given $S_t = j$, $S_{t-1} = i$ and the information set available at time t -1 denoted by $\Im_{t-1}$,

$$\beta_{t|t-1}^{(i,j)} = E(\beta_t | \Im_{t-1}, S_t = j, S_{t-1} = i)$$

$$M_{t|t-1}^{(i,j)} = E[(\beta_t - \beta_{t|t-1})(\beta_t - \beta_{t|t-1})' | \Im_{t-1}, S_t = j, S_{t-1} = i]$$

The prediction equations of the Kalman filter algorithm applied to the above specified model are given by,

$$\beta_{t|t-1}^{(i,j)} = Z_{S_j} + F\beta_{t-1|t-1}^{i}$$

$$M_{t|t-1}^{(i,j)} = FM_{t-1|t-1}^{(i,j)}F' + Q_{\tilde{S}_j}$$

and the updating equations are as follows:

$$\beta_{t|t}^{(i,j)} = \beta_{t|t-1}^{(i,j)} + M_{t|t-1}^{(i,j)}\ H'[\,f_{t|t-1}^{(i,j)}]^{-1}\,\zeta_{t|t-1}^{(i,j)}$$

$$M_{t|t}^{(i,j)} = (I - M_{t|t-1}^{(i,j)}\ H'[\,f_{t|t-1}^{(i,j)}]^{-1}H)\ M_{t|t-1}^{(i,j)}$$

where $\zeta_{t|t-1}^{(i,j)} = y_t - H\beta_{t|t-1}^{(i,j)} - Z_{S_j}$ denotes the conditional forecast error of y_t based on $\Im_{t-1}$ and given $S_t = j$, $S_{t-1} = i$, and $f_{t|t-1}^{(i,j)} = H_t M_{t|t-1}^{(i,j)} H_t' + R_{\tilde{S}_j}$ denotes its variance.

In order to make inferences on the probabilities, Hamilton's (1989) filter is used. First, consider the marginal density of y_t, which is obtained from the joint density of y_t, S_t, S_{t-1}:

$$f(y_t \mid \Im_{t-1}) = \sum_{i=1}^{4}\sum_{j=1}^{4} f(y_t, S_t = j, S_{t-1} = i \mid \Im_{t-1})$$

$$= \sum_{i=1}^{4}\sum_{j=1}^{4} f(y_t \mid S_t = j, S_{t-1} = i, \Im_{t-1}) \times \Pr[S_t = j, S_{t-1} = i \mid \Im_{t-1}]$$

where $\Pr[S_t = j, S_{t-1} = i \mid \Im_{t-1}]$ is calculated with given $\Pr[S_{t-1} = i \mid \Im_{t-1}]$ and the conditional density is constructed from the Kalman filter recursion using conditional forecast error and its variance:

$$f(y_t \mid S_{t-1}, S_t, \Im_{t-1}) = \frac{1}{\sqrt{2\pi}} \mid f_{t|t-1}^{(i,j)} \mid^{-1/2} \exp\left\{ -\frac{\zeta_{t|t-1}^{(i,j)\prime} (f_{t|t-1}^{(i,j)})^{-1} \zeta_{t|t-1}^{(i,j)}}{2} \right\}$$

After y_t is observed at the end of time *t*, probability terms are updated.

$$\Pr[S_t = j, S_{t-1} = i \mid \Im_t] = \Pr[S_t = j, S_{t-1} = i \mid y_t, \Im_{t-1}]$$

$$= \frac{f(S_t = j, S_{t-1} = i, y_t \mid \Im_{t-1})}{f(y_t \mid \Im_{t-1})}$$

$$= \frac{f(y_t \mid S_t = j, S_{t-1} = i, \Im_{t-1}) \Pr[S_t = j, S_{t-1} = i \mid \Im_{t-1}]}{f(y_t \mid \Im_{t-1})}$$

and

$$\Pr[S_t = j \Im_t] = \sum_{i=1}^{4} \Pr[S_t = j, S_{t-1} = i \mid \Im_t]$$

Without any approximation, the number of cases to consider would be multiplied by *m* at each iteration. To overcome this computational burden, we use the following approximations,

$$\beta_{t|t}^{j} = \frac{\sum_{i=1}^{4} \Pr[(S_{t-1} = i, S_t = j) \mid \Im_t] \beta_{t|t}^{(i,j)}}{\Pr[S_t = j \mid \Im_t]}$$

$$M_{t|t}^{j} = \frac{\sum_{i=1}^{4} \Pr[(S_{t-1} = i, S_t = j) \mid \Im_t] \{ M_{t|t}^{(i,j)} + (\beta_{t|t}^{j} - \beta_{t|t}^{(i,j)})(\beta_{t|t}^{j} - \beta_{t|t}^{(i,j)})' \}}{\Pr[S_t = j \mid \Im_t]}$$

The filtered estimate of the state vector is then given by

$$\beta_{t|t} = \sum_{i=1}^{4} \sum_{j=1}^{4} \Pr[(S_{t-1} = i, S_t = j) \mid \Im_t] \beta_{t|t}^{(i,j)} .$$

Computational Details

For the numerical estimation of the models, we used both optmum and cml procedures based on BFGS and Gauss-Newton algorithms. All computations are done in Gauss 7.0. The tolerance for the gradient change is set to 1e-5. In maximizing the likelihood we employ transformations such that the resulting autoregressive processes are stationary, innovation covariance matrices are positive definite and the transition probabilities are in the (0,1) range. For the initial values of the Kalman filter we use the steady state values of $\beta_{t|t}^{(i,j)}$ and $M_{t|t}^{(i,j)}$.

It is known that estimation of regime-switching models can be problematic due to the existence of many local maxima. As a robustness check, we perform a Monte Carlo experiment by estimating each model 100 times using different sets of starting values. For the economic model, the convergence of the optimization routine is found to be sensitive to the choice of γ_c, the permanent factor loading of consumption. Thus, in order to increase the chances of convergence, we set it to a reasonable value for each trial, i.e. $\gamma_c = 1$, which is the value imposed by the theory. Then we randomly draw the starting values for all other parameters from a standard normal distribution. For the stock market model, we set the starting value of permanent factor loading of dividends, η_d, to 1 to minimize convergence problems. We randomly draw the starting values for all other parameters from a generated distribution, $N \sim (0,3)$. Whenever an inverse of a matrix cannot be calculated, we skip the estimation and move on to the next trial. Simulation results indicate that our maximum likelihood estimates for each model are associated with the highest likelihood value.

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TABLES

Table 1: Tests for Unit Root

Test	Test Statistics						Critical Values	
	Y	C	I	P	D	E	5%	1%
ADF_1	3.162	3.819	0.975	-0.678	-1.248	-1.712	-2.875	-3.461
ADF_2	-0.389	0.196	-1.384	-1.532	-2.233	-3.204	-3.431	-4.001
PP_1	4.573	7.682	1.990	-0.811	-1.491	-2.145	-2.875	-3.460
PP_2	-0.082	1.003	-0.772	-1.630	-2.057	-3.400	-3.431	-4.001

ADF and PP denote the Augmented Dickey Fuller and Phillips-Perron tests. ADF_1 and PP_1 are performed using a constant term and ADF_2 and PP_2 are performed using a constant and a linear trend. Lags used in the computation of statistics are automatically chosen by Eviews with respect to SIC criterion. The asymptotically equivalent critical values for the test statistics are taken from MacKinnon (1996). * and ** denote the significance at 5% and 1% levels.

Table 2: Tests for Cointegration

	Trace Test Statistics		Critical Values	
H_0	Data Set 1: Y,C, I	Data Set 2: P,D,E	5%	1%
$r = 0$	81.456**	53.164**	29.68	35.65
$r \leq 1$	25.682**	6.637	15.41	20.04
$r \leq 2$	3.469		3.76	6.65

The critical values for Johansen's trace statistics are taken from Osterwald and Lenum (1992). Consistent with the specification chosen for the models, 1 lag is used for both data sets. * and ** denote the significance at 5% and 1% levels.

Table 3: Maximum Likelihood Estimates: Real Economy Model (1952:Q2 to 2006:Q3)

Transition Probabilities					
p_{11}^P	0.794	p_{11}^T	0.695		
	(0.085)		(0.111)		
p_{22}^P	0.927	p_{22}^T	0.883		
	(0.032)		(0.068)		
Regime Dependent Intercepts					
μ_1	0.624	μ_0	1.130	μ^*	-0.283
	(0.120)		(0.093)		(0.090)
τ	-0.553				
	(0.104)				
AR parameters					
φ	0.925				
	0.034				
ψ_y	0[b]	ψ_c	0.965	ψ_i	0.975
			(0.035)		0.020
Factor Loadings					
γ_y	1[a]	γ_c	1.018	γ_i	1.296
			(0.013)		(0.058)
λ_y	1[a]	λ_c	0[b]	λ_i	2.414
					(0.245)
Innovation Standard Deviations					
σ_v	0.359	σ_u	0.782		
	(0.041)		0.075		
σ_v^*	0.149	σ_u^*	0.165		
	(0.048)		(0.077)		
σ_{ε_y}	0.275	σ_{ε_c}	0.216	σ_{ε_i}	1.461
	0.042		(0.034)		(0.105)
Log-L	-154.581				

Standard errors of the parameter estimates are reported in parenthesis.
[a] Restricted to 1 for identification
[b] Restricted to 0 based on prior estimations suggesting that these coefficients are either zero or insignificant.

Table 4: Maximum Likelihood Estimates: Stock Market Model
1952:Q2 to 2004:Q2

Transition Probabilities					
q_{11}^{P}	0.935	q_{11}^{T}	0.765		
	(0.025)		(0.098)		
q_{22}^{P}	0.922	q_{22}^{T}	0.870		
	(0.032)		(0.061)		
Regime Dependent Intercepts (Permanent)					
δ_1	-0.462	δ_0	1.166		
	(0.259)		(0.607)		
Regime Dependent Intercepts (Transitory)					
α_1	-3.337	α_0	4.191		
	(2.670)		(2.165)		
Regime Dependent Standard Deviations					
$\tilde{\sigma}_{u_1}$	5.530	$\tilde{\sigma}_{u_0}$	4.282		
	(0.666)		(0.420)		
AR Parameters					
θ	0.985	ξ_d	0.982	ξ_e	0.961
	(0.019)		(0.023)		(0.016)
Permanent Factor Loadings					
η_p	1[a]	η_d	1.120	η_e	1.777
			(0.586)		(0.922)
Innovation Standard Deviations					
$\tilde{\sigma}_v$	0.617	$\tilde{\sigma}_{\varepsilon_d}$	0.621	$\tilde{\sigma}_{\varepsilon_e}$	4.583
	(0.304)		(0.227)		0.237
Log-L	-1011.30				

Standard errors of the parameter estimates are reported in parenthesis.
[a] Restricted to 1 for identification.

Table 5: Evaluation of In-Sample Peak Signals with respect to the NBER Chronology

NBER	EP_t	ET_t	SMP_t	SMT_t
1953:Q2	0	1	-3	0
1957:Q3	-5	-1	-3	-3
1960:Q2	-1	0	2	-2
1969:Q4	-1	0	-12	-3
1973:Q4	-1	2	(*)	-2
1980:Q1	-1	1	-6	-5
1981:Q3	-7	1	-12	-2
1990:Q3	0	1	2	-2
2001:Q1	0	-2	-7	-1
Average	-1.78	0.33	-4.88	-2.22
Median	-1	1	-4.5	-2
Std.dev.	2.49	1.22	5.46	1.39
Correct Peak	9	9	8	9
Missed Peak	0	0	1	0
False Peak	0	1	0	5
Peak Error	0	1	1	5

EP_t and ET_t stand for the permanent and transitory components of the economy, respectively, while SMP_t and SMT_t are the permanent and transitory components of the stock market, respectively. The criterion adopted to determine peaks in columns (2)-(5) is that a peak occurs whenever the smoothed probabilities of a factor exceeds 0.5 and the new regime persists for at least two quarters. Negative numbers indicate leads and positive numbers indicate lags in quarters with respect to NBER dating.
(*) Starting from 1969:Q4, the stock market model yields a long bear market that encompasses two NBER recessions started at 1969:Q4 and 1973:Q4.
Correct Peak is the prediction of a peak when one occurs. Missed Peak is the prediction of no peak when one occurs. False Peak is the prediction of a peak when one does not occur. Peak Error denotes the total of missed and false peaks. A perfect forecast is obtained when peak error is zero.

Table 6: Evaluation of In-Sample Fit with respect to the NBER Chronology Using QPS

$NBER_{t+i}$	EP_t	ET_t	SMP_t	SMT_t
i =4	0.437	0.440	0.811	0.460
i =3	0.346	0.370	0.786	0.357
i =2	0.246	0.299	0.775	**0.290**
i =1	**0.183**	0.232	0.758	0.292
i =0	0.184	**0.201**	0.738	0.388
i =-1	0.253	0.221	**0.731**	0.509
i =-2	0.341	0.292	0.750	0.614
i =-3	0.429	0.387	0.783	0.663
i =-4	0.496	0.469	0.820	0.671

EP_t and ET_t stand for the permanent and transitory components of the economy, respectively, while SMP_t and SMT_t are the permanent and transitory components of the stock market, respectively. The table reports Quadratic Probability Scores (QPS) for all four factors as a function of horizon, i. Positive values of i indicate leads of the factors compared to NBER peaks, whereas negative values indicate lags in terms of quarters. Highlighted values are the minimum QPS for each factor.

Table 7: Evaluation of the In-Sample Cross Factor Turning Point Signals using QPS

EP_{t+i}	SMP_t	SMT_t
i=4	0.636	0.340
i=3	0.594	0.279
i=2	0.556	0.233
i=1	0.523	**0.210**
i=0	0.502	0.246
i=-1	**0.497**	0.325
i=-2	0.499	0.404
i=-3	0.526	0.469
i=-4	0.566	0.518
ET_{t+i}	**SMP_t**	**SMT_t**
i=4	0.607	0.311
i=3	0.594	0.250
i=2	0.575	**0.217**
i=1	0.550	0.222
i=0	0.522	0.262
i=-1	0.499	0.309
i=-2	**0.491**	0.361
i=-3	0.496	0.383
i=-4	0.518	0.389

Positive values of *i* indicate leads of stock market factors (SMP_t and SMT_t) compared to the economic factors (EP_t and ET_t), whereas negative values indicate their lags in terms of quarters. Highlighted values are the minimum QPS for each stock market factor.

Table 8: Summary Findings of the Turning Point Analysis

Factor leads/lags of NBER	
EP_t	leads NBER by 1Q
ET_t	coincident with NBER
SMP_t	lags NBER by 1Q
SMT_t	leads NBER by 2Q
Cross Factor Leads	
SMT_t	leads ET_t by 2Q
SMT_t	leads EP_t by 1Q
EP_t	leads SMP_t by 1Q
ET_t	leads SMP_t by 2Q

FIGURES

Figure 1: Smoothed Probabilities of Recessions from the Economic Permanent Component, $P[S_t^P = 1|\Im_n]$

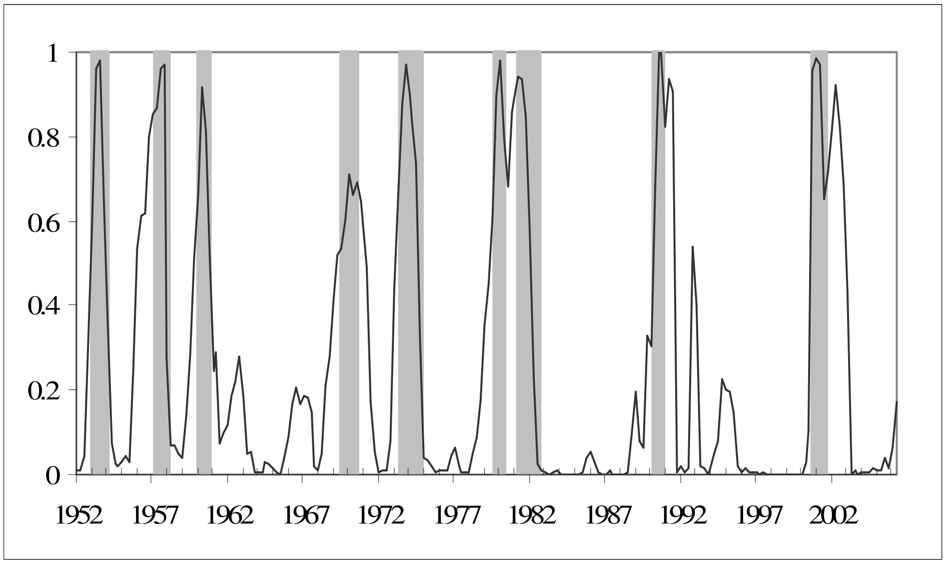

Figure 2: Smoothed Probabilities of Recessions from the Economic Transitory Component, $P[S_t^T = 1|\Im_n]$

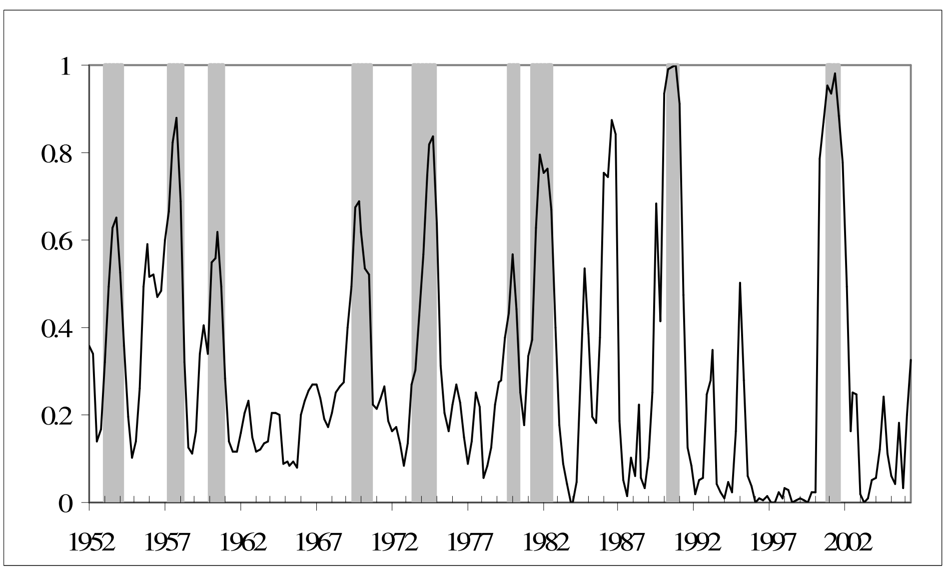

Figure 3: Permanent Component of GDP

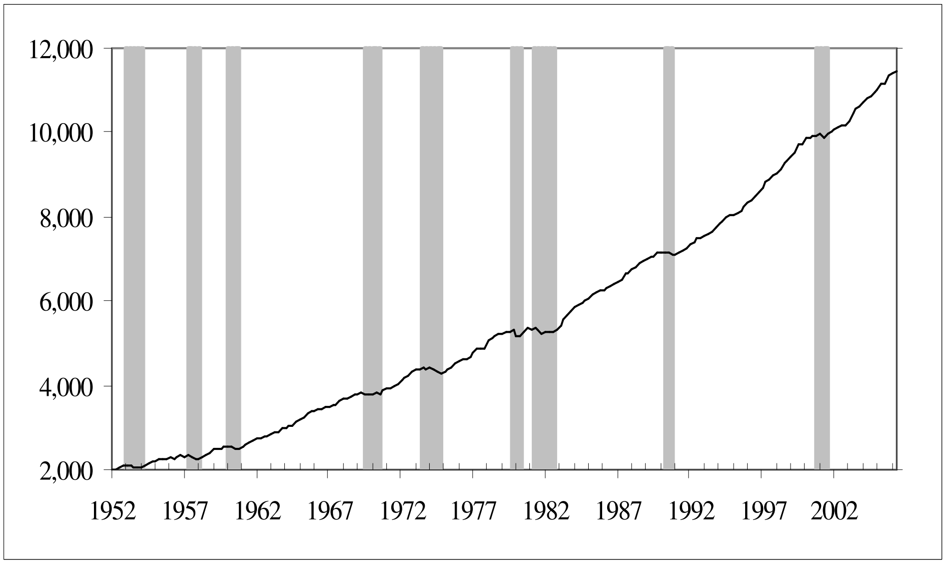

Figure 4: Transitory Component of GDP

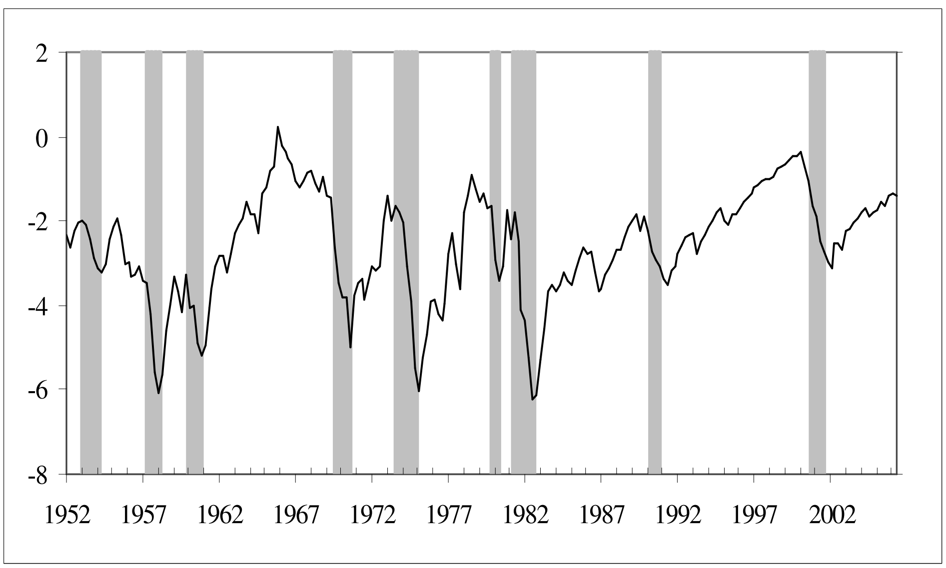

Figure 5: Smoothed Probabilities of Bear Markets from the Stock Market Permanent Component, $P[\tilde{S}_t^P = 1 | \Im_n]$

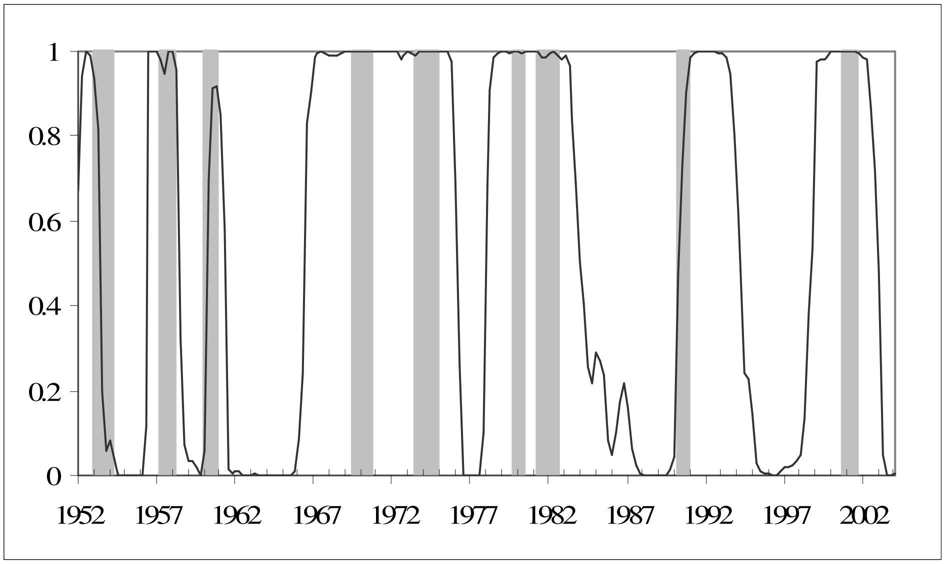

Figure 6: Smoothed Probabilities of Bear Markets from the Stock Market Transitory Component, $P[\tilde{S}_t^T = 1 | \Im_n]$

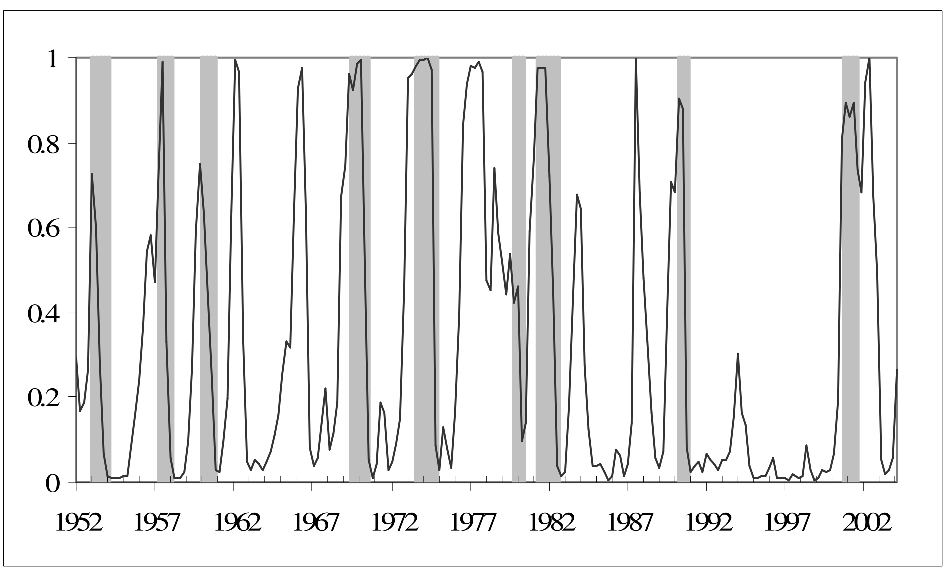

Figure 7: Permanent Component of Stock Prices

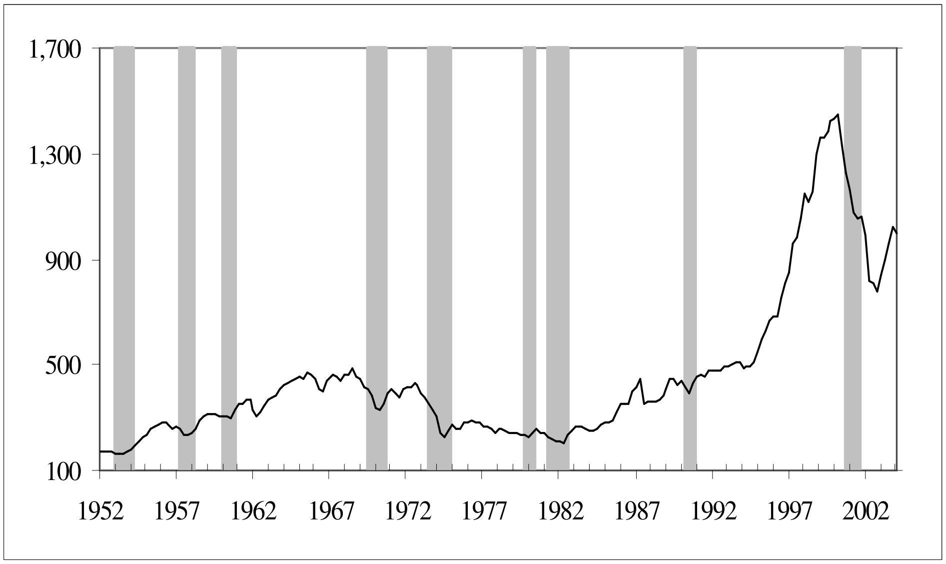

Figure 8: Transitory Component of Stock Prices