Factor Analysis of Permanent and Transitory Dynamics of the U.S. Economy and the Stock Market

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SUMMARY

We analyze dynamics of the permanent and transitory components of the U.S. economic activity and the stock market obtained by multivariate dynamic factor modeling. We capture asymmetries over the phases of economic and stock market trends and cycles using independent Markov-switching processes. We show that both output and stock prices contain significant transitory components, while consumption and dividends are useful to identify their respective permanent components. The extracted economic trend perfectly predicts all post-war recessions. Our results shed light to the nature of the bilateral predictability of the economy and the stock market. The transitory stock market component signals recessions with an average lead of one quarter, whereas the market trend is correlated with the economic trend with varying lead/lag times.

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

JEL Classification: C32, E32, E44.

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1. INTRODUCTION

The literature on the real economy and stock market linkages suggests that there exists a bilateral predictive association between them. Several studies document that financial variables are leading indicators of the business cycle while some others find that these variables themselves are influenced by business cycle phases and thus can be predicted by macro variables.[1] This relation has been analyzed from either one of these two perspectives, with no clear-cut conclusion about how the predictive relation goes both ways. There is still much to be investigated regarding the nature of the relation between the real economy and the stock market and the mechanism that drives dynamics of each.

The longest expansion of the American economy experienced in the 1990's coincided with a prolonged and soaring bull market. This revived an interest in the extent to which variations in the stock market phases can be explained by economic fundamentals. Some studies including Cochrane (1994) and Fama and French (2002) associate the sharp increase in stock prices to lower inflation and decline in equity premium whereas Campbell and Shiller (2001) thought the market was highly overvalued and stock prices would eventually fall to normal historical levels. Pastor and Veronesi (2009) analyze the relation between technological innovations and stock prices and conclude that time varying uncertainty about the future productivity of new technologies can generate bubble like behavior in stock prices that is stronger in the new economy than in the old economy. These views have different implications in terms of the roles played by the permanent and transitory factors in driving the stock market and how they are related with the long-run

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

and short-run dynamics in the real economy. Distinguishing between these variations is crucial in understanding the patterns of the real economy and the stock market as well as their interrelations.

In this paper, we use a strategy to take into account the differences in modeling long-run and short-run components of the economy and the stock market, which would also provide insight into their bilateral predictive relation. We propose multivariate dynamic factor models featuring Markov switching asymmetry to model the permanent and transitory components of the U.S. economic activity and of the stock market. These models provide flexible frameworks, not just to sort out common versus idiosyncratic variation in the series but also to capture asymmetries both in the long-run and short-run components, potentially driven by different sources. To account for the asymmetry of trends and cycles, we assume two independent Markov processes in the real economy and in the stock market model, resulting in a four state specification in each model. In the economic model, the transitory component is allowed to go through phases of recessions and expansions while the permanent component switches between low versus high growth phases; similarly in the stock market model, the transitory component captures the temporary ups and downs of the market over bull and bear markets and the permanent component is designed to capture prolonged changes of the long-run market trend. Inferences obtained from this framework are then used to analyze the interaction between the economic and financial trends and cycles without imposing any *a priori* restriction on their relationship.

There is an extensive literature that provides statistical evidence on the sources of transitory components in output and stock prices. 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. 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 macro 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 mean reverting 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 (see Shiller, 1981; LeRoy and Potter, 1981; Campbell and Shiller, 1988a, 1988b; Fama and

[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.

French, 1988a, 1988b; Poterba and Summers, 1988; Dupuis and Tessier, 2003 among several others).[3]

In this paper, we model the U.S. economy through the cointegration relationship of output, consumption, and investment. Motivated by the macro models of permanent income and empirical findings of Fama (1992) and Cochrane (1994), we use the information in consumption to measure the trend in output, but we do not impose any a *priori* restriction. This allows us to separate out the cyclical variation of economic activity from the common trend of macro variables indicated by cointegration tests. 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, allowing us to extract the stochastic trend common to these financial variables and use the remaining transitory component to analyze deviations of stock market valuations from fundamentals. Theoretical models of transitory stock price component, also referred to as fad or bubble models, such as in Summers (1986) and Brunnermeier and Dilip (2003), motivate 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 economy and in the stock market and also allow these components to behave differently during the phases of the business cycles and stock market cycles. We propose a 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. Our models

[3] 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.

are capable of accounting for common versus idiosyncratic variation, permanent versus transitory variation and linear versus nonlinear dynamics in the economy and in the stock market. We then use inference from these models to study the relationship between the trend and cycle of the economy, trend and cycle of the stock market, and their interrelationships.

Our results on the sources of these permanent and transitory variations are in line with that of Fama (1992) and Cochrane (1994), who find that consumption and dividends represent the trend in output and in stock prices, respectively. In the real economy model, all ten recessions in the post-war sample, including the most recent one that started in 2007:Q4, are identified by the permanent and transitory components, although the relative importance of each component varies across recessions. Turning point analysis reveals that all pre-1990 recessions start with a decline in the trend growth rate followed by a switch in transitory component. This pattern seems to have changed recently since the transitory component moves first in the last three recessions. In the stock market, we find evidence of a stationary but persistent transitory component in prices, which is not common to dividends and earnings. All bear markets identified by the permanent component are associated with NBER recessions. The transitory component signals all recessions while it also produces some false signals. Our results uncover a striking relation between the economy and the stock market that, to our knowledge, have not been documented before. We find that it is the transitory stock market factor that predicts all recessions with an average lead of one quarter, whereas the stock market trend identified by dividends and earnings is highly correlated with the economic trend with varying lead\lag times. This suggests that the long-run path of the market tends to influence and also responds to the economic trend.

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 the results of an in-sample analysis of interrelations between the components of the economy and the stock market. Section 4 concludes.

2. THE MODELS

Since our modeling strategy depends on the existence of common stochastic trends for the macroeconomic (GDP, consumption and investment) and financial (stock prices, dividends, and earnings) series studied, we begin by implementing unit root and cointegration tests. The macroeconomic variables used are quarterly real GDP (Y), personal consumption on non-durables and services (C), and private fixed investment (I).[4] These series are seasonally adjusted at the annual rate and are in billions of chained 2005 dollars. 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).[5] The sample period is from 1952:Q1 to 2008:Q2 for both models.

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[4] For consumption on non-durables and services data, we use both the sum of two series and an alternative index constructed by chain subtraction method described in Whelan (2002). The latter produces a Fisher index using data on total consumption and consumption of durable goods. These two methods produced series that are very close to each other. We estimated the macro model using each series and obtained identical estimates.

[5] 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 are obtained from Robert Shiller's website, http://www.econ.yale.edu/~shiller/data.htm, and converted to quarterly frequency by taking three month averages.

Table 1 presents the results of unit root tests. The Augmented Dickey-Fuller, Elliott-Rothenberg-Stock (1996) and Kwiatkowski-Phillips-Schmidt-Shin (1992) tests are applied assuming a constant and a linear trend. Test statistics fail to reject the unit root hypothesis for any of the six series. We proceed to test for possible cointegration relations among the macroeconomic series and among the financial series. Table 2 reports the trace statistic of Johansen for all series, computed with one lag. Each series is assumed to have a linear trend and only intercept is included in the cointegrating equations. The null of no cointegration is rejected at the 1% level for each system, whereas the null of at most one cointegrating vector cannot be rejected. The cointegrating relations for the macro and financial variables imply that each set of series share a stochastic trend. Next, we introduce the models that identify how variations of these series are related to changes in the trends and cycles of the economy and the stock market.

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

Based on the cointegration test results, we specify a model for economic activity in state space form where the logs of real output, consumption, and investment share a 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, we consider the following decomposition:

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

$$C_t = \gamma_c x_t + e_{c,t} \tag{2}$$

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

where x_t denotes the trend or the permanent component of the series, and z_t denotes the transitory component. Notice that x_t is common to all series whereas z_t is common to output and investment. Our prior estimations suggested that consumption has different short-run dynamics than output and investment as also found in the earlier literature, e.g. Fama (1992). Therefore, we model its' transitory variation separately. The coefficients γ_h for $h = y, c, i$ are the permanent factor loadings, which measure to what extent each series is affected by the common trend. The transitory factor loadings for output and investment are given by λ_y and λ_i respectively. In order to capture potential remaining variation that is not explained by the common factors, we also incorporate idiosyncratic components in each series, denoted by $e_{h,t}$.

Standard identification conditions are imposed to conduct the unobserved components (UC) decomposition: (i) Factor loadings for output are set to 1 to provide a scale for the factor that contains information from multiple series. The choice of scale does not affect any time series properties of the dynamic factors. (ii) Error terms of all factors are assumed to be uncorrelated with each other.[6]

It has long been discussed in the business cycle literature that recessions are generated by a different regime than that of the expansions, as they are usually abrupt, sharp and shorter than expansions. Since our modeling strategy distinguishes between permanent and transitory components, potential asymmetries in each component should be

[6] This implies that the trend and cycle also has a zero correlation. This assumption has been rejected by Morley *et al*. (2003), whereas Perron and Wada (2009) find evidence in favor of it and show that once the structural break in 1973 is incorporated, same decomposition can be obtained under either assumption. I find that the break in 1973 is significant. Thus, I proceed with the zero correlation assumption which also guarantees identification regardless of the specification for the transitory component.

incorporated separately, i.e. by assuming independent Markov processes to model the phases of the trend and the cycle. 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, implying that recessions have permanent effects on output. High values of the drift are associated with high growth phases of the trend whereas low values are associated with low growth phases. For the transitory component, z_t we allow for Friedman-type asymmetry by adopting Kim and Nelson's (1999) version of the plucking model. In these recessions, the transitory component captures the temporary plucks in the economic activity from its trend growth path. Since output subsequently reverts back to its long-run level, output losses are entirely transitory deviations from the long-run trend. If there is any remaining variation in the series, we capture it via autoregressive idiosyncratic components. Hence, the permanent, transitory, and idiosyncratic components are specified as follows:

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

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

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

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

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

where $\varphi(L)$ and $\psi_h(L)$ are polynomials in the lag operator with roots outside the unit circle. The error terms of the factors, v_t, u_t and $\varepsilon_{h,t}$ are assumed to be uncorrelated with each other. 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, when $S_t^P = 1, S_t^T = 1$, both components indicate a low-growth state or a recession for the economy. On the other hand, we can think of the case where $S_t^P = 0,\ S_t^T = 0$ as a high-growth state or an expansion identified by both components. Thus, μ_0 and μ_1 are the growth rates of the trend during low growth and high growth phases and $\tau < 0$ measures the size of the pluck in the common transitory component during recessions. We will be able to fully infer these states after estimating the mean growth rates.

Given that the permanent and the transitory components in our model are driven by independent state variables, they are not restricted to switch from one state to the other at the same time. This provides us great flexibility as it makes possible to analyze the lead-lag relation between the long-run and the short-run components of the economy. The transition between states is governed by first order Markov chains, which imply that the current state includes all relevant information to predict the future state, i.e. transition probabilities are given by $p_{ij}^P = \Pr[S_t^P = j \mid S_{t-1}^P = i]$ 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 output trend is well represented by consumption. It is also consistent with the neoclassical growth models in the Solow-Ramsey tradition, which suggest 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.

Kim and Piger (2002) estimate a similar model of the economy with the assumption that the permanent and transitory components follow the same Markov process and, hence, are restricted to switch at the same time across economic phases. Our model differs in the sense that we assume separate Markov processes for the two components, which allow them to have different degrees of importance over the phases of trends and cycles. Kim *et al*. (2007) uses the same assumption in a bivariate model for output and consumption. However, they incorporate transitory asymmetry into the idiosyncratic components, which are assumed to be driven by the same state variable. This results in perfect correlation in the switching of the idiosyncratic components. Since we incorporate transitory asymmetry into the common component instead, our specification concurs with the assumption that the idiosyncratic terms are not correlated.

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

Summers (1986) states that stock prices take long temporary swings, implying a slowly decaying transitory component that can be modeled as a persistent AR(1) process. His model is based on the proposition that stock prices can be represented as a sum of a random walk and a stationary component. 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. Building on these

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

works, we specify the stock market trend as a random walk process that is common to stock prices, dividends, and earnings. The transitory stock market component is specified as an autoregressive process that is designed to capture long swings of stock prices. We model short-run variation in earnings and dividends through idiosyncratic transitory components, as prior estimations suggest that these variables do not move together in the short-run. In particular, we establish the link between the observable series and the unobservable components as follows:

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

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

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

where $\tilde{x}_t$ is the permanent component that 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 our cointegration test results and also the empirical evidence provided by Shiller (1981), Poterba and Summers (1988), and Cochrane (1994) among others, we extract the permanent component of stock prices by incorporating a stochastic trend common to all three series. Once we have a proxy for the stock market trend, we can use the remaining transitory component of stock prices 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 dynamics of the common trend over the phases of bull and bear markets. After running different specifications and starting values, we could not find statistical evidence of different variances over the stock market phases implied by the permanent component, suggesting that heteroskedasticity across stock market phases is arising from the transitory variation instead.

Even though the permanent component is common to all variables, the transitory components are found to be different for each variable.[8] This result is in line with that of the aforementioned studies, which find that long swings in stock prices are movements away from its trend and thus, cannot be explained by dividends or earnings. Therefore, we model the transitory variation of each series via idiosyncratic components. Based on specification test results, we choose a stationary AR(1) process with state dependent intercept and variance for the transitory component of stock prices.

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.[9] We specify linear autoregressive processes to capture transitory variation in dividends and earnings, denoted by $\tilde{e}_{k,t}$ where *k=D,E*. The specifications for the permanent, transitory and idiosyncratic components are as follows:

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

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

[8] All our prior estimations that allow for a common transitory component produced factor loading estimates which are very close to zero and insignificant. Alternative specifications have been considered and this particular decomposition has been chosen based on model selection criteria.

[9] Anticipating the empirical results, we find that the Friedman type of asymmetry is significant for the real economy, but not for the stock market.

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

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

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

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

where $\theta(L)$ and $\xi_k(L)$ are polynomials in the lag operator with roots outside of the unit circle. The error terms in the factor equations are uncorrelated with each other at all leads and lags for the identification of the model. $\tilde{S}_t^P$ 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 our models by numerical optimization. We first cast them 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 from the filter. The state space representation for each model is given in the Appendix.

The lag structure of the models is chosen based on specification tests. We settle down to parsimonious AR(1) processes for all transitory components, 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 (2009) show that neglecting this change in the trend affects the trend-cycle decomposition. 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, which is accepted as the beginning of Great Moderation. 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, and neither the parameter estimates nor the resulting decomposition are affected by their inclusion.

Finally, note that we're not modeling interactions of the economy and the stock market directly, as one first needs to have sufficient information about how dynamics of each are related in order to correctly specify a joint model. Our first objective is to understand the nature of variation in major series of the economy and the stock market, and measure the permanent and transitory components by taking into account possible asymmetries. Then, we use inference from these two models to analyze the link between the economy and the stock market and to understand how their predictive relation goes two ways. Our representations allow the underlying processes for the economy and the stock market to switch nonsynchronously over time, so that they can capture the lead/lag relations between the trends and the cycles of each.

3.1 Real Economy Model

Estimation results for the real economy model are reported in Table 3. The factor loading for consumption in the permanent component is estimated to be 1.01, which is consistent with the theoretical models such as the permanent income hypothesis. In line with the previous literature, we find that consumption does not move together with output and investment in the short-run. Instead, it has significant transitory component of small magnitude that is not common with the other variables. The idiosyncratic components of consumption and investment display persistent serial correlation with estimated AR coefficients equal to 0.97.

The asymmetric behavior of U.S. GDP over the trend and cycle phases has been modeled with two types of Markov processes that have different implications for the long-run effects of recessions. Hamilton's (1989) model identifies expansions and recessions assuming that recessions have permanent effects on output. On the other hand, Friedman type asymmetry suggests that during recessions, output is plucked down by transitory shocks from its trend and then reverts back to its previous level with no permanent output loss. We incorporate the first type of asymmetry into the trend and the second one into the cycle. The drift terms for trend regimes, μ_1 and μ_0, are statistically significant and estimated to be 0.65 and 1.17 respectively, separating out phases of permanent low and high growth rates in the trend component. The parameter estimate for τ, which measures how much the economy is temporarily plucked down during recessions, implies that the economic activity is reduced by 0.54% on a quarterly basis during recessions. For both components, expansions are found to be of longer duration than recessions, as depicted by the higher transition probabilities of the expansion state. The innovation standard error of the transitory component is more than two times higher than that of the permanent component and the estimates of both significantly decrease after 1984, once the structural break in variance due to Great Moderation is taken into account.

Figure 1 plots the smoothed probabilities of low growth state for the common permanent component together with the NBER dated recessions. The permanent component clearly identifies every recession in the sample. Figure 2 shows the smoothed probabilities of plucks in the transitory component. The probabilities call every NBER dated recessions including the one in 2001, which is harder to be identified as it is the mildest of all post-war recessions. 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.

A comparison of Figures 1 and 2 inform us about the relative importance of each component during recessionary periods. For example, the recession that started in 1973:Q4 is usually thought of as a recession caused by a permanent shock due to the OPEC policy at the time. This is also supported by EP_t, which signals this recession two quarters in advance, whereas the probabilities of ET_t stay low until after the recession has officially started. In the 1979-1980 recession, during which the real interest rates has risen, the probabilities from ET_t barely exceed 0.5 in the middle of this recession and then declines before the recession ends whereas EP_t again signals the peak two quarters in advance.

In general our results suggest that both components contribute to output fluctuations over the phases of the business cycle, whereas the permanent component seems to be the one that is more useful in monitoring the business cycle turning points. This is mainly because it signals every recession in the sample with probabilities higher than 80% and provides timely and consistent information about the official beginning date of recessions. We further analyze this issue in Section 3.3 where we measure the accuracy of the estimated probabilities.

An interesting observation from Figure 1 is 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 are milder, short-lived, and not followed by fast recovery that is typical of other post-war recessions. Although both permanent and transitory components in our model identify these two recessions, smoothed probabilities of the permanent component indicate that the low growth state 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 official ending of these recessions, as also implied by our probabilities.

Figure 3 shows the estimated trend of output along with the log of real GDP series multiplied by 100. The estimated trend closely resembles the observed level of the original series, whereas the estimated cycle plotted in Figure 4 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 presents the parameter estimates for the stock market model. The permanent factor loading of dividends is estimated to be 1.55, supporting Cochrane's proposition that dividends represent the trend in stock prices. In that sense, the relation is similar to that between output and consumption. Moreover, this trend is also shared by the long-run component of earnings for which the factor loading is estimated to be 1.79.

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 components are negative in State 1 and positive in State 0, indicating negative returns during bear markets and positive returns in bull markets. Our prior estimations suggest that the variance of the permanent component do not exhibit regime switching behavior, however the volatility implied by the transitory component tends to be different between the two regimes identified by the transitory component. The estimated variance for bear markets is higher than the one estimated for bull markets.[10] We also observe that significant part of innovations comes from the transitory component.

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. The longest bear market that started at the beginning of 1966, encompasses two recessions and lasts for 10 years. The other long one that started in 1977 includes the double recessions of 1980 and 1981. 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 March 1975, stock prices were around 60% lower than their value in early 1966. The average real return in the stock market was -1.8% a year during the bear market that ended around 1976.[11]

[10] In order to gain further insight as to which type of asymmetry is more important over bull and bear markets, we also estimate the models allowing for only one type of asymmetry in the transitory component. In the mean switching model, smoothed probabilities identify the same stock market phases with slightly higher values. In the variance switching version, the transitory component lags NBER recessions, possibly reflecting the uncertainty prevailing in the stock market around the end of periods of weak economic activity.
[11] The information is taken from Shiller (2005).

Note that these are prolonged bear markets identified by the long-run component of stock prices that is also common to dividends and earnings. Thus, they distinguish high return and low return phases in a broad sense by considering the path of the stock market trend. The regime classification that determines the phases of the cycles in the market is the one from the transitory component. Smoothed probabilities of bear markets as captured by the transitory component are plotted in Figure 6. The probabilities increase around all economic recessions. For most of the recessions, probabilities start rising before the beginning of recessions, i.e. the transitory stock market component is a leading indicator of NBER recessions. How well can the stock market predict the economy? We provide some answers in the next section based on the in-sample evaluation of our models. At this point a glance at Figure 6 reveals that the stock market has forecast 15 of the last 10 recessions, which is in line with the famous observation by Paul A. Samuelson.[12]

The times at which the probabilities of bear markets increase but recessions do not follow, are the 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.

During 1990's, stock prices have increased dramatically. Traditional measures such as the dividend yield and price earnings ratios have reached record levels by 2000. In an

[12] The original quote from Samuelson is, "The stock market has forecast nine of the last five recessions".

effort to understand what drives stock prices to historically high levels, economists questioned whether these measures are still valuable tools in this so-called "new era". The question of whether stock prices reflect rational expectations of future cash flows or that they are driven by mean reversion divided researchers into two groups. Cochrane (1994), Fama and French (2002) among others believe that these high values are associated with lower inflation rate and decline in the equity premium, whereas Veronesi and Pastor (2009) argue that the time-varying uncertainty about future productivity of new technologies can produce the observed stock price pattern. Both views emphasize the role of permanent factors in driving stock prices to the observed high levels. On the other hand, behavioral economists interpret bubbles as evidence that markets are irrational as they reflect psychological bias through transitory movements. Campbell and Shiller (2001) drew attention to the mean reverting temporary component in driving the stock market in the recent episode. Dupuis and Tessier (2003) argue that transitory shocks have a much larger impact on stock prices than on dividends in the short-run. They also find evidence of overvaluation during the stock market boom of late 1990's.

Since all these discussions are centered on the behavior of permanent versus transitory variation in the stock market, our results contribute to the ongoing debate about the sources of the prolonged bull market of late 1990's. The estimated permanent component of the stock market and the log of S&P 500 index multiplied by 100 are plotted in Figure 7. The permanent stock market component bears a resemblance to the path followed by the index and captures the smooth component of stock prices shared by dividends and earnings. The transitory component plotted in Figure 8 is more volatile and exhibits mean reversion since it captures the dynamics of the stock market apart from the behavior of dividends and earnings. The remarkable stock market boom that started in mid 1990's and ended in 2000 is clearly observable in the transitory component. In addition to the surge of the transitory component, 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. The probabilities from the transitory component point out to an uninterrupted bull market following the 1991 crisis until the end of 2002. The dynamics implied by the permanent and transitory component in our model provides a relatively stronger support for the view that the stock market boom of 1990's cannot be justified by fundamentals as much as by short-run deviations from the long-run trend.

3.3 Turning Point Analysis

We further investigate the relationship between the stock market and the economy 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, EP_t, for the most part leads economic recessions, whereas the transitory component, ET_t, on average coincides with the NBER recessions. More specifically, 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, is leading some recessions including the last three, whereas it also lags four of them in the sample. Second, the transitory component of the stock market, SMT_t that contains leading information on the economic activity anticipates all recessions with a median lead of one quarter. 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 (see for example Stock and Watson, 1989; Chauvet, 1998/1999; Estrella and Mishkin, 1998). This is also implied by our model, with SMT_t predicting more recessions than the ones documented by the NBER. The information from the permanent component of the stock market is not that clear though. Even though SMP_t is associated with every NBER recession in the sample, lead/lag times vary substantially. Especially when we consider the prolonged bear markets that include not just one but two recessions (1969-1974 and 1980-1981), we see that probabilities start to rise a few years before recessions begin and remain high quite some time until after the latter of the two recessions end, in which case it makes it harder to conclude that they actually signal recessions. In order to gain more information about the predictive power of the factors, we proceed with an in-sample analysis using smoothed probabilities, which contain information about the factor dynamics that are representative of the entire sample.

We use the Quadratic Probability Score (QPS), as proposed in Diebold and Rudebusch (1989) in order to evaluate the accuracy of the implied probabilities in predicting NBER peaks. 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 $\{N_t\}_{t=1}^{n}$ denote a 0/1 dummy representing the NBER chronology, with N_t equals 1 at NBER recessions and equals 0 otherwise. Then, the QPS at lead/lag i is given by:

$$QPS_i = \frac{2}{n}\sum_{t=1}^{n}(\hat{N}_t - N_{t+i})^2 \tag{13}$$

where i indicates lead/lag horizon in quarters up to a year, $i = -4,\ldots,0,\ldots 4$. 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 economic transitory component (EP_t), coincides with the NBER chronology with a smallest QPS value of 0.22 at i = 0, which is still higher than the smallest two QPS values achieved by EP_t. This suggests that the recession signals of EP_t are on average more accurate than the signals of ET_t and it also has a consistent lead time of 1 quarter. The smallest QPS value for the stock market transitory component (SMT_t) is also achieved at i = 1, indicating a lead of the NBER reference cycle by one quarter. We also find that on average the permanent component, SMP_t, lags it by 2 quarters with a lowest QPS value of 0.8. However, when we compare the QPS values of SMP_t with that of the other components, we see that they are well above even the highest values achieved by all other components. This indicates that the relation between the NBER chronology and SMP_t is less accurate than the other components.

In order to further analyze the interactions between the permanent and transitory components, we also perform turning point analysis across the factors extracted from the real economy and the stock market models. The QPS statistic we use here is a slightly modified version of equation (13) given by,

$$QPS_i = \frac{2}{n}\sum_{t=1}^{n}(\hat{N}_{1t} - \hat{N}_{2t+i})^2 \tag{14}$$

where $\hat{N}_{1t}$ and $\hat{N}_{2t}$ refer to the estimated smoothed probabilities of any two factors. Table 7 presents the QPS values of factors in anticipating each others' turning points cross factor turning point signals and Table 8 provides a general summary of these results. The stock market cycle, SMT_t is found to be a leading indicator for both the permanent and transitory components of the economic model (EP_t and ET_t) with 1 and 2 quarters lead time, respectively. The trend of the market, SMP_t, seems to lag economic components by 2 quarters when we consider the average lead/lag times in the sample. However, most of the switches in this component to the low mean state take place before recessions start. Overall, given highly varying lead/lag times, we cannot extract reliable signals from SMP_t.

To sum up, the results of the turning point analysis uncover a striking relation between the stock market and economic activity. It is the transitory stock market factor that predicts economic turning points with an average lead of one quarter. The permanent stock market factor is found to be highly correlated with the economic trend with varying lead/lag times. The stock market trend seems to affect and in return is influenced by the long-run economic trend. Since dividends and earnings are used to measure the stock market trend, we conjecture that the prospects about economic growth are transmitted to the stock market trend through future dividend and earning streams.

4. CONCLUSION

We analyze long-run and short-run dynamics of the U.S. economic activity and the stock market by modeling their permanent and transitory components. We estimate these components via multivariate dynamic factor models, which utilize information in major macro and financial series. We incorporate asymmetries over the phases of the trends and cycles of the economy and the stock market using independent Markov switching processes, to allow for time-varying leads and lags of switching. These models can account for common versus idiosyncratic variation, permanent versus transitory variation and linear versus nonlinear dynamics in the economy and in the stock market.

We find that the trend in GDP is well represented by consumption, as argued in Cochrane (1994) and Fama (1992), but there is also fairly small idiosyncratic variation in consumption. The permanent and transitory components of the economic model identify all post-war NBER recessions with a varying degree of importance. Our turning point analysis reveals that all pre-1991 recessions start with a switch in the permanent component followed by a switch in the transitory component. The extracted economic trend perfectly signals all post-war recessions with an average lead of one quarter.

All bear markets identified by the permanent stock market factor are associated with NBER recessions. As argued by Cochrane (1994), dividends provide a proxy for the long-run component of the stock market. There is no evidence of a common transitory component in the stock market as we find that the short-run dynamics of stock prices cannot be explained by dividends or earnings. These findings reinforce that of Shiller (1981), Summers (1986), Poterba and Summers (1988), and more recently Brunnermeier and Dilip (2003) who show that asset bubbles can be very persistent even in the presence of rational arbitrageurs.

Finally, our results on interrelations of the economy and the stock market point out to a strong and persistent bilateral link that, to our knowledge, has not been documented before. We find that the transitory component of the stock market predicts all post-war recessions with an average lead of one quarter and is therefore a useful leading indicator of business cycles. On the other hand, the stock market trend is highly correlated with the permanent economic component with varying lead/lag times. Our results suggest that the economy affects and also influenced by where the market is headed in the long-run. This may take place through the stream of dividends and earnings that not only determine the stock market trend, but are also influenced by expectations of economic trend. A potential direction for future work would be to further analyze this relation by jointly modeling the trends of the economy and the stock market.

APPENDIX: MODEL SPECIFICATION AND ESTIMATION

We 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. The measurement and the transition equations are given by Equations (A.1) and (A.2) respectively,

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

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

where $E(V_t V_t') = R^*$ and $E(\Lambda_t \Lambda_t') = Q^*$. In the economic model, the matrices (A.1) and (A.2) are specified as follows:

$y_t = (\Delta Y_t, \Delta C_t, \Delta I_t)'$, $\beta_t = (z_t, z_{t-1}, e_{y,t}, e_{y,t-1}, e_{c,t}, e_{c,t-1}, e_{i,t}, e_{i,t-1})'$,

$Z = (\gamma_y \mu_{S_t^P}, \gamma_c \mu_{S_t^P}, \gamma_i \mu_{S_t^P})'$, $K = (\tau_{S_t^T}, \mathbf{0})'$ where $\mathbf{0}$ is a 7x1 null vector, $G = \mathbf{I}_8$,

$$H = \begin{bmatrix} \lambda_y & -\lambda_y & 1 & -1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & -1 & 0 & 0 \\ \lambda_i & -\lambda_i & 0 & 0 & 0 & 0 & 1 & -1 \end{bmatrix}$$

$$\Gamma = \begin{bmatrix} \gamma_y & 0 & 0 \\ 0 & \gamma_c & 0 \\ 0 & 0 & \gamma_i \end{bmatrix}$$

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

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

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

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.

We estimate each model using a synthesis of the Kalman filter and Hamilton's filter. Since the state variables are unobservable, the resulting Kalman filter equations are nonlinear making the calculation of the exact likelihood intractable. Thus, we utilize Kim's approximation method, which is based on the work of Harrison and Stevens (1976). For maximization of 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. As a robustness check, we perform a Monte Carlo experiment by estimating each model 100 times using different sets of starting values. Simulation results show that our maximum likelihood estimates for each model are associated with the highest likelihood value.

REFERENCES

Brunnermeier M., Dilip A. 2003. Bubbles and crashes. Econometrica **71**, 173-204.

Campbell, JY., Shiller RJ. 1988a. Interpreting cointegrated models. *Journal of Economic Dynamics and Control* **12**, 505-522.

Campbell, JY., Shiller RJ. 1988b. The dividend-price ratio and the expectations of future dividends and discount factors. *Review of Financial Studies* **1**, 195-227.

Campbell, JY., Shiller, RJ. 2001. Valuation ratios and the long-run stock market outlook: an update. Cowles Foundation Discussion Paper No. 1295.

Chauvet, M. 1998. An econometric characterization of business cycle dynamics with factor structure and regime switching. *International Economic Review* **39**, 969-996.

Chauvet, M. 1998/1999. Stock market fluctuations and the business cycle. *Journal of Economic and Social Measurement* **25**, 235-258

Chauvet, M., Potter S. 2000. Coincident and leading indicators of the stock market. *Journal of Empirical Finance* **7**, 87-111.

Clark, PK. 1987. The cycle component of the U.S. economic activity. *Quarterly Journal of Economics* **102**, 797-814.

Cochrane, JH. 1994. Permanent and transitory components of GNP and stock prices. *Quarterly Journal of Economics* **109**, 241-263.

Diebold, FX., Rudebusch GD. 1989. Scoring the leading indicators. *Journal of Business* **62**, 369-391.

Dupuis, D. and Tessier D. 2003. The U.S. stock market and fundamentals: a historical decomposition, Bank of Canada working papers.

Elliott, G., Rothenberg, TJ., Stock, JH. 1996. Efficient tests for an autoregressive unit root. *Econometrica* **64,** 813–836.

Estrella, A., Mishkin FS. 1998. Predicting U.S. recessions: financial variables as leading indicators. *The Review of Economics and Statistics* **80**, pp. 45-61.

Fama, EF., French KR. 2002. The equity premium. *The Journal of Finance* **57**, 637-659.

Fama, EF. 1992. Transitory variation in investment and output. *Journal of Monetary Economics* **30**, 467-480.

Fama, EF., French KR. 1988a. Permanent and temporary components of stock prices. *Journal of Political Economy* **96**, 246-273.

Fama, EF., French K.R. 1988b. Dividend yields and expected stock returns. *Journal of Financial Economics* **22**, 3-25.

Friedman, M. 1993. The plucking model of business fluctuations revisited. *Economic Inquiry* **31**, 171-177.

McConnell, MM., Perez-Quiros G. 2000. Output fluctuations in the United States: what has changed since the early 1980s? *American Economic Review* **90**, 1464-1476.

Hamilton, JD. 1989. A new approach to the economic analysis of nonstationary time series and business cycles. *Econometrica* **57**, 357-384.

Hamilton, JD, Lin G. 1996. Stock market volatility and the business cycle. *Journal of Applied Econometrics* **11**, 574-593.

Harrison, PJ., Stevens CF. 1976. Bayesian forecasting. *Journal of the Royal Statistic Society* Series **B 38**, 205-247.

Kim, CJ. 1994. Dynamic linear models with Markov-switching. *Journal of Econometrics* **60**, 1-22.

Kim, CJ., Murray CJ. 2002. Permanent and transitory components of recessions. *Empirical Economics* **27**, 163-183.

Kim, CJ., Nelson CR. 1999. Friedman's plucking model of business fluctuations: tests and estimates of permanent and transitory components. *Journal of Money, Credit and Banking* **31**, 317-334.

Kim, CJ., Nelson CR. 1999. *State-Space Models with Regime Switching: Classical and Gibbs- Sampling Approaches with Applications*. MIT: Cambridge, MA.

Kim, CJ., Piger J. 2002. Common stochastic trends, common cycles, and asymmetry in economic fluctuations. *Journal of Monetary Economics* **49**, 1189-1211.

Kim, CJ., Piger J., Startz R. 2007. The dynamic relationship between permanent and transitory components of U.S. business cycles. *Journal of Money, Credit and Banking* **39**, 187-204.

King, RG., Plosser CI., Rebelo ST. 1988. Production, growth and business cycles. *Journal of Monetary Economics* **21**, 309-341.

King, RG., Plosser CI., Stock JH.,Watson MW. 1991. Stochastic trends and economic fluctutations. *The American Economic Review* **81**, 819-840.

Kwiatkowski D, Phillips PCB, Schmidt P., Shin Y. 1992. Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root? *Journal of Econometrics* **54**, 159-178.

LeRoy, SF., Porter RD. 1981. The present-value relation: tests based on implied variance bounds, *Econometrica* **49**, 555-574.

Lettau M., Ludvigson S. 2001. Consumption, aggregate wealth and expected stock returns, *The Journal of Finance* **56**, 815-849

Pastor L., Veronesi P. 2009. Technological revolutions and stock prices. *American Economic Review* **99**, 1451-1483.

Perez-Quiros, G., Timmermann A. 1995. Variations in the mean and volatility of stock returns around turning points of the business cycle. In: *Forecasting Volatility in the Financial Markets*, Knight J., Satchell S. (eds.). Butterworth-Heinemann: Oxford.

Perron, P. 1989. The great crash, the oil shock and the unit root hypothesis. *Econometrica* **57**, 1361-1401.

Perron, P., Wada T. 2009. Let's take a break: trends and cycles in U.S. real GDP. Forthcoming in *Journal of Monetary Economics*.

Poterba, JM., Summers LH. 1988. Mean reversion in stock prices. *Journal of Financial Economics* **22**, 27-59.

Shiller, RJ. 1981. Do stock prices move too much to be justified by subsequent changes in dividends? *American Economic Review* **71**, 421-36.

Shiller, RJ. 2005. *Irrational Exuberance*. Princeton University Press: Princeton.

Summers, LH. 1986. Does the stock market rationally reflect fundamental values', *The Journal of Finance* 41, 591-601.

Stock J., Watson M. 1989. New indexes of coincident and leading economic indicators. *Macroeconomics Annual*, Vol. 4, 1989, MIT. Press.

Timmermann, A., Pettenuzzo D. 2005. Predictability of stock returns and asset allocation under structural breaks. Working Paper.

Whelan, K. 2002. A guide to U.S. chain aggregated NIPA data. *Review of Income and Wealth*, **48**, 217-233.

TABLES

Table 1: Tests for Unit Root

Test	Test Statistics						Critical Values	
	Y	C	I	P	D	E	5%	1%
ADF	-0.389	0.196	-1.384	-1.532	-2.233	-3.204	-3.431	-4.001
ERS	183.439	364.983	39.604	15	18.516	4.277	5.655	4.038
KPSS	0.463	0.468	0.402	0.340	0.206	0.192	0.146	0.216

ADF, ERS and KPSS denote the Augmented Dickey-Fuller, Elliott-Rothenberg-Stock and Kwiatkowski-Phillips-Schmidt-Shin unit root tests respectively. All tests 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 null hypothesis is unit root in the ADF and ERS tests whereas the KPSS evaluates the null of no unit root.

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%
$r = 0$	37.484**	39.553**	29.68	35.65
$r \leq 1$	14.590	6.938	15.41	20.04
$r \leq 2$	5.646*	0.588	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. Each series is assumed to have a linear trend and only intercept is included in the cointegrating equations. * and ** denote significance at 5% and 1% levels.

Table 3: Maximum Likelihood Estimates: Real Economy Model
(1952:Q2 to 2008:Q2)

Transition Probabilities					
p_{11}^{P}	0.827	p_{11}^{T}	0.662		
	(0.065)		(0.136)		
p_{22}^{P}	0.924	p_{22}^{T}	0.873		
	(0.030)		(0.087)		
Regime Dependent Intercepts					
μ_1	0.654	μ_0	1.171	μ^*	-0.317
	(0.115)		(0.102)		(0.101)
τ	-0.538				
	(0.126)				
AR parameters					
φ	0.925				
	(0.035)				
ψ_y	0[b]	ψ_c	0.972	ψ_i	0.971
			(0.041)		(0.020)
Factor Loadings					
γ_y	1[a]	γ_c	1.010	γ_i	1.276
			(0.013)		(0.048)
λ_y	1[a]	λ_c	0[b]	λ_i	2.268
					(0.247)
Innovation Standard Deviations					
σ_v	0.364	σ_u	0.813		
	(0.040)		0.078		
σ_v^*	0.184	σ_u^*	0.200		
	(0.040)		(0.073)		
σ_{ε_y}	0.241	σ_{ε_c}	0192	σ_{ε_i}	1.512
	(0.048)		(0.038)		(0.103)
Log-L	-154.02				

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 very close to zero and insignificant.

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

Transition Probabilities					
q_{11}^{P}	0.941	q_{11}^{T}	0.739		
	(0.023)		(0.120)		
q_{22}^{P}	0.910	q_{22}^{T}	0.886		
	(0.035)		(0.061)		
Regime Dependent Intercepts (Permanent)					
δ_1	-0.266	δ_0	1.012		
	(0.143)		(0.452)		
Regime Dependent Intercepts (Transitory)					
α_1	-3.269	α_0	4.105		
	(3.804)		(3.335)		
Regime Dependent Standard Deviations					
$\tilde{\sigma}_{u_1}$	5.572	$\tilde{\sigma}_{u_0}$	4.314		
	(0.717)		(0.479)		
AR Parameters					
θ	0.985	ξ_d	0.982	ξ_e	0.969
	(0.028)		(0.031)		(0.016)
Permanent Factor Loadings					
η_p	1[a]	η_d	1.553	η_e	1.793
			(0.668)		(0.834)
Innovation Standard Deviations					
$\tilde{\sigma}_v$	0.595	$\tilde{\sigma}_{\varepsilon_d}$	0.120	$\tilde{\sigma}_{\varepsilon_e}$	4.852
	(0.262)		(0.00)		(0.227)
Log-L	-1096.11				

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	2	-4	0
1957:Q3	-5	-1	-3	0
1960:Q2	-1	0	1	-2
1969:Q4	-1	-1	-12	-3
1973:Q4	-1	2	*	-2
1980:Q1	-2	1	-7	-5
1981:Q3	-8	1	*	-2
1990:Q3	0	-1	0	-2
2001:Q1	0	-2	-9	-1
2007:Q4	-2	-5	2	0
Correct Peak	10	10	10	10
Missed Peak	0	0	0	0
False Peak	0	1	1	5
Peak Error	0	1	1	5

EP_t and ET_t stand for the permanent and transitory components of the economy, while SMP_t and SMT_t are the permanent and transitory stock market components, 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. 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.
(*) Starting from 1966:Q4, SMP_t labels a long bear market that encompasses two recessions (1969, 1973). Similarly starting from 1978:Q2 bear market probabilities remain high until 1985:Q4, which includes the double recessions of 1980 and 1981. Given highly varying lead/lag times, we cannot extract reliable recession signals from SMP_t.

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	0.461	0.407	0.910	0.439
i =3	0.364	0.360	0.887	0.341
i =2	0.264	0.315	0.873	0.270
i =1	0.211	0.252	0.851	0.261
i =0	0.215	0.223	0.819	0.338
i =-1	0.286	0.247	0.800	0.446
i =-2	0.374	0.312	0.811	0.547
i =-3	0.468	0.389	0.844	0.593
i =-4	0.543	0.451	0.875	0.602

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	0.373	0.179
i=3	0.351	0.148
i=2	0.331	0.122
i=1	0.311	0.107
i=0	0.293	0.118
i=-1	0.285	0.148
i=-2	0.281	0.182
i=-3	0.289	0.213
i=-4	0.305	0.241
ET_{t+i}	SMP_t	SMT_t
i=4	0.327	0.144
i=3	0.320	0.120
i=2	0.311	0.105
i=1	0.299	0.108
i=0	0.288	0.126
i=-1	0.280	0.148
i=-2	0.279	0.167
i=-3	0.280	0.170
i=-4	0.286	0.165

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 1Q
Cross Factor Leads	
SMT_t	leads ET_t by 2Q
SMT_t	leads EP_t by 1Q
EP_t	leads SMP_t by 2Q
ET_t	leads SMP_t by 2Q

FIGURES

Figure 1: Smoothed Probabilities of Recessions from the Economic Permanent Component

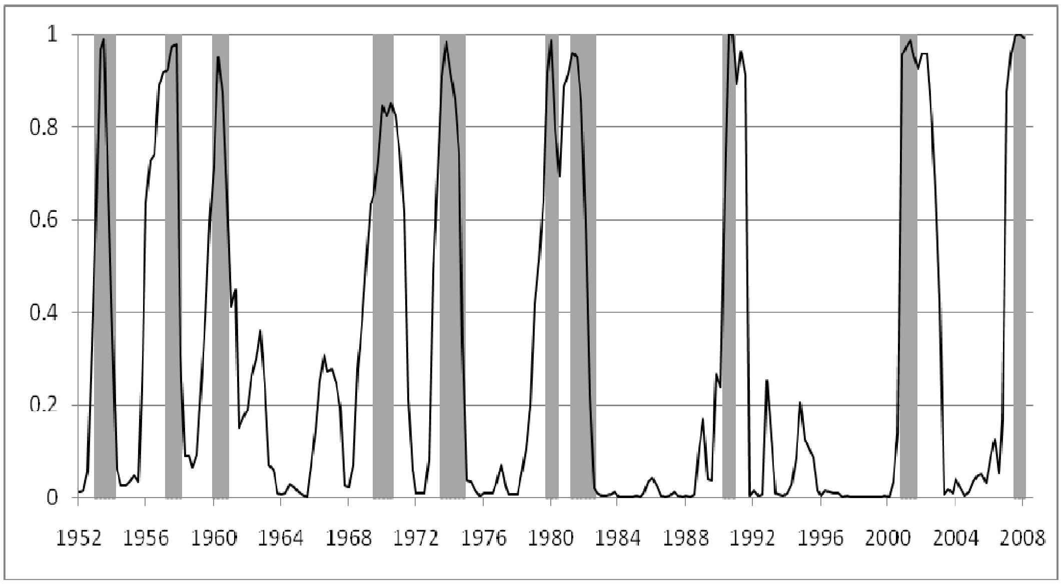

Figure 2: Smoothed Probabilities of Recessions from the Economic Transitory Component

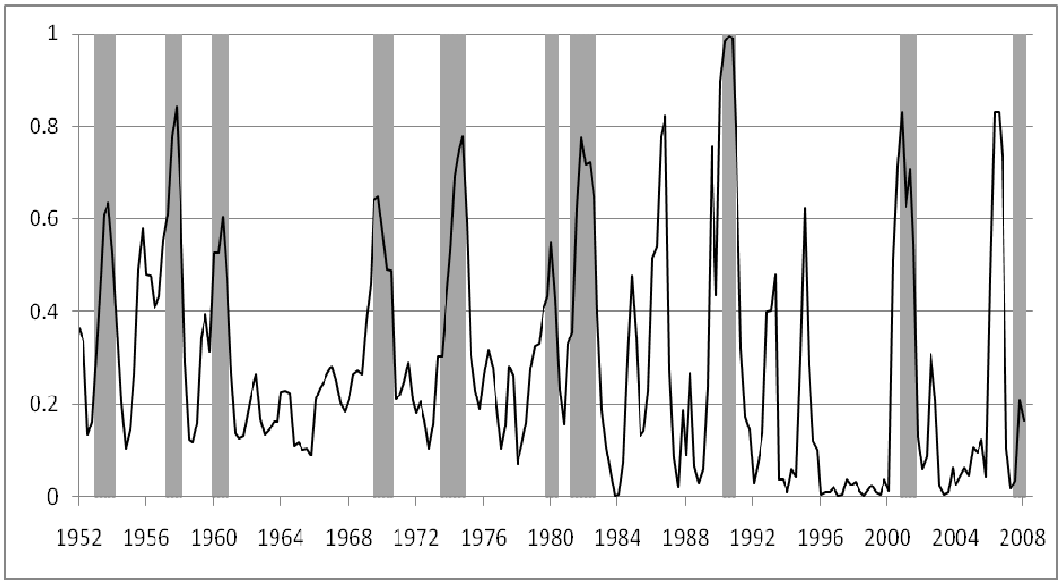

Figure 3: Log GDP (—) and the Estimated Permanent Component (- -)

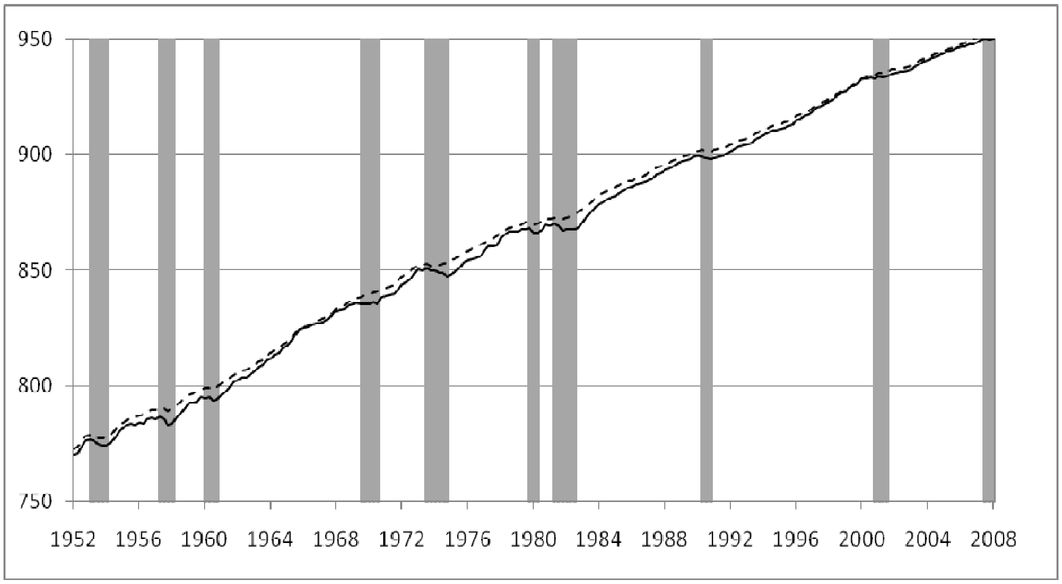

Figure 4: Estimated Transitory Component of GDP

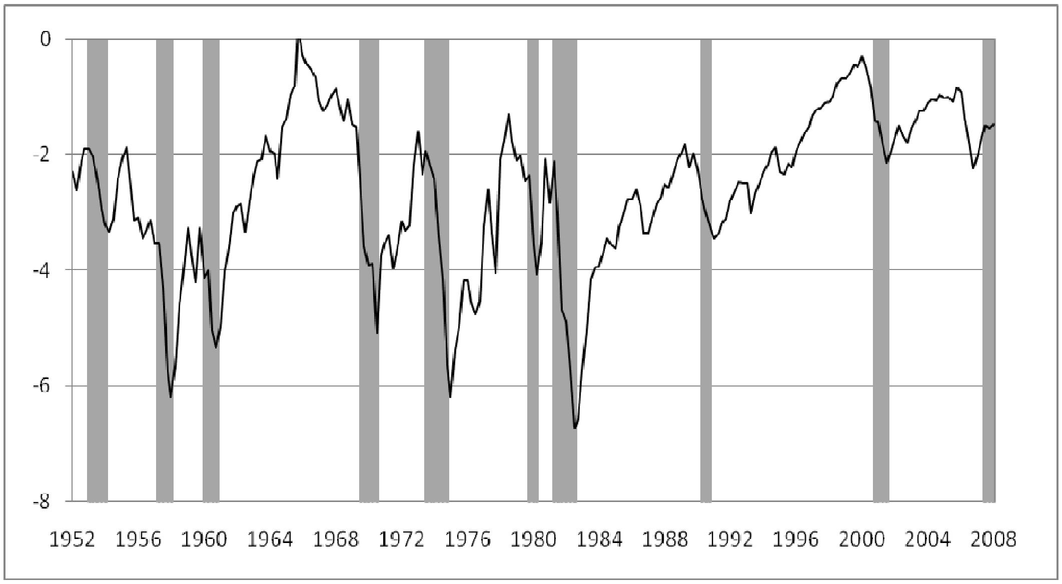

Figure 5: Smoothed Probabilities of Bear Markets from the Stock Market Permanent Component

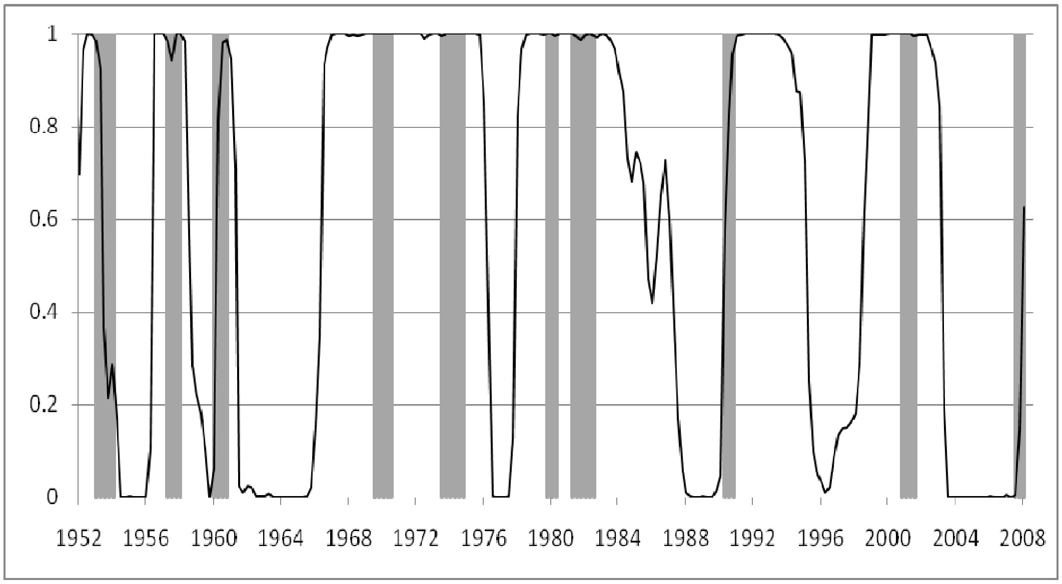

Figure 6: Smoothed Probabilities of Bear Markets from the Stock Market Transitory Component

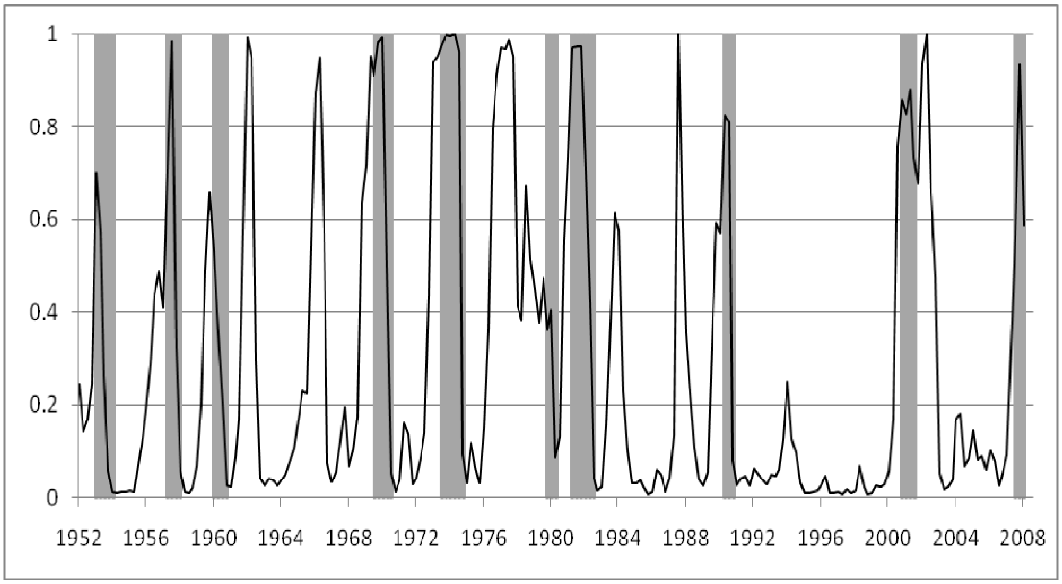

Figure 7: S&P 500 Stock Prices (—) and the Estimated Permanent Component (- -)

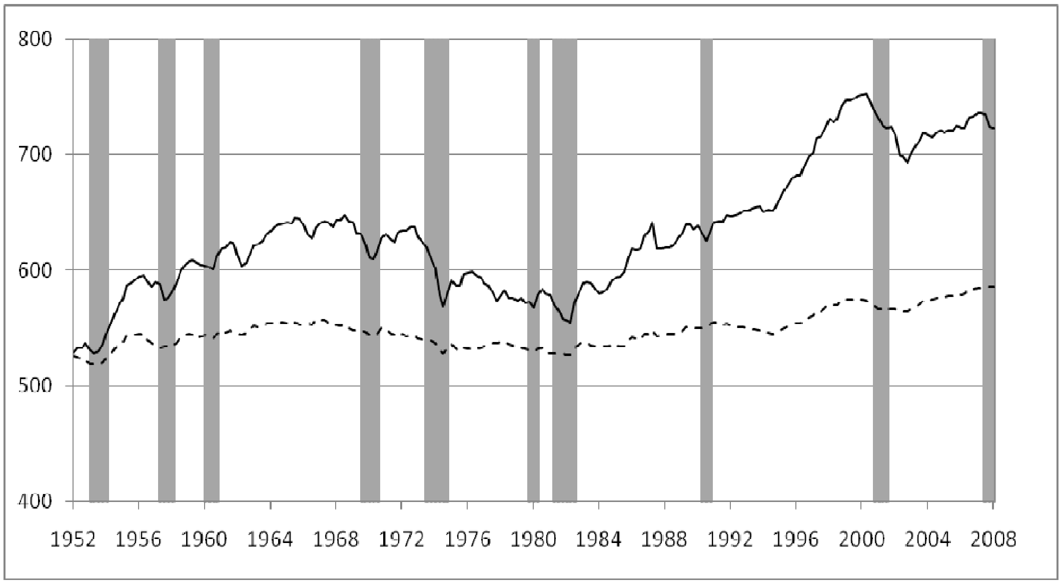

Figure 8: Transitory Component of Stock Prices