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Finance and the Business Cycle: A Kalman Filter Approach with Markov Switching[*]

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Abstract

This paper combines two popular econometric tools, the dynamic factor model and the Markov-Switching model, to consider three segments of the financial system- the stock market, debt, and money- and their contribution to US business cycles over the past four decades. The dynamic factor model identifies a composite factor index for each financial segment, and using Markov-switching models by Hamilton (1989) and Filardo (1994), this paper then estimates the effect of each segment index on business cycle behaviour. This reexamination of the finance-business cycle link provides results which prove strongest for the effect of stock market movements on business cycles.

Keywords: Dynamic Factor Model; Markov-Switching; Business Cycles

JEL Classifications: C22, E32, E44

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[*] We would like to thank Patrick Coe, Steven Fazzari, Avi Goldfarb, Ivan Jeliazkov, (especially) James Morley, Jeremy Piger, Shane Sherlund and Mark Vaughan for comments and support. Members of Washington University's macro group, as well as participants at the 2003 Midwest Economics Association Annual Meeting and 2003 Canadian Economics Association Annual Meeting also provided helpful suggestions. Ricardo would like to acknowledge the financial support of the Banco Central do Brasil and CNPq (Brazilian Council for Scientific and Technological Research). We also gratefully acknowledge the use of GAUSS programs provided by Kim and Nelson (1999). The usual disclaimer applies.

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1. Introduction

Hypotheses abound to explain the ups and downs of the aggregate economy. These include a range of factors such as unexpected exogenous shocks, animal spirits, policy mistakes, technology, and so on. However, with the recent 2001 US recession as well as persistent Japanese stagnation, financial factors have received a good deal of attention of late. In the case of the US, discussion has centered around the run up of NASDAQ, the overvaluation of the stock market in general, and the bursting of the bubble. In Japan, the country's troubles have been going on for more than a decade, but much like the US case, financial factors are cited as possible sources of blame for of the start of their economic downturn, this time centering on its own apparent stock market bubble as well as real estate bubble.

The possibility that financial markets may impact business cycles has not gone unnoticed in the literature. A natural area of study of course is the Great Depression, where a number of authors find evidence the financial crisis of the early 1930s had real economic effects. For example, Bernanke (1983) considers the role of financial factors in the Great Depression, positing that the financial crisis of 1930-1933, over and above its effects via the money supply, had real economic effects largely due to a reduction in credit intermediation by the financial system. Similarly, Coe (2002) also finds positive evidence that the financial crisis of the early 1930s had real economic effects for the Great Depression beyond those operating through the monetary channel.

In addition to work on the Depression, a number of papers have considered the postwar experience of the US more broadly. Friedman and Schwartz's 1963 book represents a classic in the economics literature, as well as providing a basis of the monetarist view of business cycles, while Sims' classic 1972 paper also supports the role of money in GDP. In contrast Eichenbaum and Singleton (1986) find that money does not appear to Granger cause output over the postwar period in the US, suggesting that exogenous shocks to money growth are not sources of output growth variation. Gertler and Hubbard (1988) show that capital market frictions, which they detail are especially binding for small firms, become more significant during downturns, impacting investment by smaller firms and ultimately the severity of recessions. Friedman and Laibson (1989) find evidence supportive of large stock price variation affecting macroeconomic activity for the postwar US. More specifically their story is one where with the passage of time since a financial crisis, investors tend to become less risk averse, opening themselves up to increasingly exposed positions such that extreme movements in stock prices may bring about a downturn in real economic activity. Perry and Schultze (1993) consider the postwar period for the US, with particular interest in explaining the 1990-1991 recession. They find that while fiscal and monetary policies prove to be important for earlier recessions, financial factors in the form of a shortage in bank capital and increased business debt prove to be important for the 1990-1991 recession. Lastly, Brunner and Kamin (1998) focus on the role of financial factors in the recent Japanese recession (1990-1993 specifically). They find falling asset prices appear to have led banks to increase their loan standards and subsequently reduce the supply of loans. As well, while traditional wealth effects cannot be ruled out, the fall in asset prices have also seen firms and households reduce their demand for loans and goods. Coupled together, these contributed to the resulting reduction in economic activity.

This paper picks up on this body of work by combining two popular econometric tools, the dynamic factor model and the Markov-Switching model, to investigate whether three financial factors (debt, money, and the stock market) contribute to US business cycles over the past four decades. More specifically, this paper develops composite measures for these three areas of the US financial market using a dynamic factor model. A composite measure is developed for the stock market, debt, and money respectively. Further, for each composite measure, three different methods are considered to examine the finance-business cycle relationship. First, vector autoregressive models and Granger causality tests are used to test causality between the variables. Second, Hamilton's (1989) Markov-switching model is used to examine the regime switching of each composite measure relative to switching in GDP regimes (i.e. business cycles). Lastly, Filardo's (1994) time varying transition probability model is used to test whether each financial composite measure helps contribute to business cycle turning points. The results indicate that the stock market has strong robust effects on real activity, with weaker evidence pointing to a role for debt and money in business cycles.

In summary, this paper contributes to the literature by:

(1) Combining two popular econometric tools, the dynamic factor model and the Markov-Switching model, to investigate the finance-business cycle relationship.

(2) Rather than relying on a single approach, the decision of whether a given financial market segment contributes to business cycles is based on the body of evidence resulting from the three approaches as a whole.

(3) The recent 2001 US recession is included in the sample, and the results support those who point to the stock market bubble as one of the ingredients that lead to the recent US economic downturn.

The rest of the paper proceeds as follows. Section 2 provides an overview of the empirical methods used in this study. Section 3 outlines the data, as well as our approach to developing composite measures of the respective financial market segments. The empirical results are also detailed. Section 4 concludes.

2. Empirical Methodology

2.1 Dynamic Factor Model

A contribution of this paper is that rather than relying on a single variable for each segment of the financial market, we use the information provided by a number of financial variables within a given segment to develop composite measures for the respective financial market segment. We use a dynamic factor model with the Kalman filter based on Stock and Watson (1991)[1].

[1] Chapter three of Kim and Nelson (1999) provides a nice overview of the Kalman filter.

The dynamic factor model in this paper rests on the notion that the comovements of the individual financial variables in a given financial market segment have a common underlying source which can be captured by a single unobservable variable. This allows us to abstract from "noisy" variables to capture a common underlying factor with which to examine the finance-business cycle relationship. The dynamic factor model is based on deviation from means of the following general form:

$$\Delta y_{it} = \gamma_i \Delta c_t + e_{it}, \qquad i = 1,2,3,4 \tag{1}$$
$$\Delta c_t = \phi_1 \Delta c_{t-1} + \phi_2 \Delta c_{t-2} + w_t, \qquad w_t \sim i.i.d.N(0,1)$$
$$e_{it} = \psi_{i1} e_{i,t-1} + \psi_{i2} e_{i,t-2} + \varepsilon_{it}, \qquad \varepsilon_{it} \sim i.i.d.N(0,\sigma_i^2), \qquad i = 1,2,3,4$$

where $\Delta y_{it} = \Delta Y_{it} - \Delta \overline{Y}_i$ and $\Delta c_t = \Delta C_t - \delta$, Y_{it} represents the financial variable *i* for each respective financial market segment at time *t*, C_t is the unobserved common component which underlies the comovement of the financial variables for a given financial market segment, and σ_w^2 is set to 1 in order to normalize the common component.

2.2 State Dependent Markov-Switching Model

Numerous time series models exist to analyze the behaviour of macroeconomic variables, however many of them are limited by their linear form. To highlight this limitation, an example commonly cited, and relevant for our paper, is GDP, which appears to exhibit different dynamics during expansions versus recessions. With a linear model, this asymmetry is unlikely to be captured. The Markov switching model however is well suited for this type of dynamics as it permits the switching of regimes and allows the model to better capture non-linear dynamics inherent in the series. For our purposes of examining a causal relationship from finance to business cycles, we are interested in seeing whether movements in financial markets contribute to movements in GDP. As such, capturing regime changes in financial markets and seeing if resulting regime changes occur in GDP provides a useful source of evidence for investigating the finance-business cycle link. The Markov switching model is therefore a natural choice for this paper.

The base Markov-switching model we use is based on Hamilton's (1989) state-dependent Markov-switching model. In this paper, all variables used in the Markov-switching model are modelled as first-difference AR (4) processes as follows:

$$(\Delta y_t - \mu_{st}) = \phi_1(\Delta y_{t-1} - \mu_{st-1}) + \phi_2(\Delta y_{t-2} - \mu_{st-2}) + \phi_3(\Delta y_{t-3} - \mu_{st-3}) + \phi_4(\Delta y_{t-4} - \mu_{st-4}) + e_t \qquad (2)$$

$$e_t \sim i.i.d. N(0, \sigma^2)$$

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

$Pr\ [S_t = 1 |\ S_{t-1} = 1] = p$, $Pr\ [S_t = 0 |\ S_{t-1} = 0] = q$

whereÄy_t represents the first difference of real GDP when business cycles are considered and the first difference of the respective composite measure when the financial segment is considered. We denote S_t as an unobservable state variable which takes on the value one or zero. Further, ì $_{st}$ represents the means of the variable being studied, assumed here to be ì $_0$ in state 0 and ì $_1$ in state 1, while p indicates the probability of being in state 1 at time t, given that you are in state 1 at time $t-1$, and q indicates the probability of being in state 0 at time t, given that you are in state 0 at time $t-1$. The AR(4) lag-length is chosen primarily due to this paper's use of quarterly data, as well as the fact that Hamilton's Markov-switching model is generally based on an AR(4) lag length in the literature.

2.3 Time Varying Transition Probability Model

An extension of the Markov switching model discussed above is the time varying transition probability model (TVTP) of Filardo (1994). The TVTP model in our paper is used to examine GDP Markov switching, with GDP regime switching modelled as a first difference AR(4) process with common variance across regimes and two states as detailed previously in equation 2. However there is a key difference. Hamilton's Markov switching model is premised on a fixed transition probability from one regime to another. More explicitly, the Hamilton model has transition probabilities as follows:

$$Pr\ [S_t = 1 |\ S_{t-1} = 1] = p = \frac{\exp(\theta_{p0})}{1 + \exp(\theta_{p0})}$$

$$Pr\ [S_t = 0 | S_{t-1} = 0] = q = \frac{\exp(\theta_{q0})}{1+\exp(\theta_{q0})}$$

where θ_{p0} and θ_{q0} are constants.

In the case of the TVTP model, however, we assume that the probability of switching regimes may depend on some underlying economic fundamentals, in the case of this paper, a given financial segment composite measure. Thus the transition probabilities in the TVTP case are of the following form:

$$Pr\ [S_t = 1 | S_{t-1} = 1, Z_{t-j}] = p = \frac{\exp(\theta_{p0} + \sum_{j=1}^{J} \theta_{pj} Z_{t-j})}{1+\exp(\theta_{p0} + \sum_{j=1}^{J} \theta_{pj} Z_{t-j})}$$

$$Pr\ [S_t = 0 | S_{t-1} = 0, Z_{t-j}] = q = \frac{\exp(\theta_{q0} + \sum_{j=1}^{J} \theta_{qj} Z_{t-j})}{1+\exp(\theta_{q0} + \sum_{j=1}^{J} \theta_{qj} Z_{t-j})},$$

where Z_{t-j} is the lagged financial segment composite measure, j indicates the number of lags, and θ_{pj} and θ_{qj} are the coefficients that determine the effect of the jth lag of the financial segment composite measure on the time variation of p and q respectively.

The TVTP model is extremely useful for our purposes. As seen in the next section, the Hamilton Markov switching results are somewhat limited, as we must determine if there is a relationship from finance to business cycles by comparing the regime switching graphs of the respective financial composite measures with that of GDP regime switching. This more or less involves “eyeballing” the graphs to see whether regime switching in a given composite measure seems to correspond with regime switching in GDP. As well, the way a financial segment affects business cycles is through a regime change, however the effect of financial factors on business cycles may be subtler. With the TVTP model, we no longer rely on “eyeballing” of regime switches, nor do we require the composite measure to actually switch regimes. Rather, we consider only GDP regime changes, and can test statistically whether a given financial composite measure (Z_t) helps predict business cycle turning points. To the extent it does not, we can interpret this as evidence against a causal relationship from that particular financial segment to economic fluctuations. However to the extent that it does, this points towards a causal relationship. This involves considering whether the coefficients of the financial composite measure, θ_{pj} and θ_{qj}, are statistically significant, as well as testing the null hypothesis of no time variation in the transition probabilities through the use of a likelihood ratio test. The results of the TVTP model therefore can lead to fairly powerful conclusions.

We should note that Filardo's model is generally used for predictability purposes, and in fact his 1994 paper uses the case of business cycle predictability as the application of the model. While Filardo (1994) tests for the ability of financial variables to predict turning points, our paper differs significantly from Filardo's in that the goal is not predictability, but rather we are interested in causality. By using the dynamic factor model to identify the common components for each financial sector, this paper interprets the results using the Filardo model not as predictability but as causality.

2.4 Vector Autoregression Model and Granger Causality

In addition to the use of Hamilton's Markov-switching model and the TVTP model discussed above, a vector autoregression model (VAR) is used in conjunction with Granger causality tests to further examine the possible finance-business cycle relationship. The general form of the VAR models used in this paper is as follows:

$$\begin{aligned} \Delta F_t &= C_1 + \sum_{j=1}^{\rho} a_{1j}\Delta F_{1t-j} + \sum_{j=1}^{\rho} a_{2j}\Delta Y_{1t-j} + \sum_{j=1}^{\rho} A_{3j}\Delta X_{t-j} + \varepsilon_{1t} \\ \Delta Y_t &= C_2 + \sum_{j=1}^{\rho} b_{1j}\Delta F_{1t-j} + \sum_{j=1}^{\rho} b_{2j}\Delta Y_{1t-j} + \sum_{j=1}^{\rho} B_{3j}\Delta X_{t-j} + \varepsilon_{2t} \end{aligned} \tag{3}$$

where *F* represents the financial composite measure, *Y* is real GDP, *X* includes a number of control variables, C_1 and C_2 are constants, and ε_1 and ε_2 represent the error terms which are normally distributed with mean 0 and variance σ_1^2 and σ_2^2 respectively.

In order to test for causality between the respective financial measure and GDP, Granger causality tests are considered, which use an F-test to test the hypothesis that $b_{1j}=0$ for $j=1$ to ρ, in the case of the financial measure "Granger causing" GDP, and that $a_{2j}=0$ for $j=1$ to ρ, in the case of GDP "Granger causing" the financial measure.

3. Empirical Results and Discussion

3.1 Debt Market Factor

As detailed earlier, four variables are used in the dynamic factor model to construct each composite measure. The debt market composite measure (or debt market factor) is developed using the log-difference of the following variables: the debt-equity ratio, real consumer credit outstanding, real credit market instruments of non-financial firms outstanding, and real US financial liabilities outstanding (all sectors)[2]. These variables, and all variables used to develop the respective financial segment composite measures are quarterly for the period 1959:1 to 2001:4[3].

A graph of the resulting debt composite measure is seen in figure A1, while the coefficients of the respective dynamic factor models are detailed in table A. Looking at the debt factor column of table A, the loading factors $\tilde{\alpha}$ all enter positively, such that an increase in the debt composite measure positively affects the four debt variables. One can think of this composite measure as a general measure of debt in the economy.

Recall that this paper uses a number of approaches to examine the finance-business cycle relationship (in this case, debt and the business cycle). A first look at this involves Granger causality tests. More specifically, two VARs with tests for Granger causality are employed. One is a simple bi-variate model consisting of the log differences of the debt composite measure and real GDP. The other extends the basic model to include control variables in the form of the quarterly change in oil prices (to proxy for supply shocks), as well as the quarterly return of the Standard and Poor's 500 and a quarterly term spread based on the 10-year Treasury and 3-month Treasury[4]. Table B details the Granger causality results for all of the respective composite measures. In the case of debt and GDP, the Granger causality results indicate one-way Granger causality from the debt factor to GDP in both models.

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[2] For data sources please see appendix 1. Also unit root tests can be obtained by contacting the authors.
[3] Note that the money variables are an exception, with a slightly shorter sample of 1960:1 – 2001:4.
[4] See Stock and Watson (2003) for more on asset prices and output predictability.

Our second approach, using Hamilton's Markov switching model, compares the regime switching of the debt composite measure with that of GDP. Intuitively, if movement in debt contributes to business cycles, one might expect to see a high growth debt regime switch to a low or negative growth debt regime in advance of a downturn in GDP. Figure B1 shows the smoothed probability of a recession for the GDP variable and the smoothed probability of a low or negative growth state for the debt composite measure[5]. Table C details the respective Markov switching parameters.

The Markov switching results indicate that the debt factor switches two quarters after the beginning of the NBER dated recession of 1960-61, one quarter after the beginning of the 1973-75 recession and in line with the start of the 1980 recession. The debt factor indicates no regime switching near the 1969-70, 1981-82 or 2001 recessions, and only a weak spike a quarter after the 1990-1991 recession begins (perhaps due partly to the credit crunch occurring at that time). Regime switching in the debt market factor does not appear to be related to recessions over this period, at least as far as a causal story would require.

A final examination of a possible debt-business cycle relationship involves Filardo's time varying transition probability model. Recall from Section 3, that with the TVTP model we no longer rely on "eyeballing" of regime switches or the requirement that the composite measure actually switch regimes. Rather, when considering GDP regime changes, the TVTP model allows us to test whether GDP regime switching exhibits time variation through the inclusion of a given financial composite measure. Table D details the TVTP estimation results for all of this paper's composite measures [6].

Column 2 of table D details the estimated transition probabilities for the inclusion of our debt composite measure, where the parameters of interest are $\grave{e}_{q1}$ and $\grave{e}_{p1}$. $\grave{e}_{q1}$ proves to be negative and statistically insignificant, while $\grave{e}_{p1}$ is positive and statistically significant. The fact that these parameters exhibit opposite signs eases interpretation, as the transition

[5] The regime switching of the GDP variable does not coincide exactly with all of the NBER dated recessions however the switching is inline generally with these recessions.

probabilities move in opposite directions when our debt measure (Z_t) changes. Thus intuitively an increase in the debt composite measure increases the probability of being in an expansionary state next period as both p and 1-q increase. Keep in mind this is limited by the fact that θ_{q1} is statistically insignificant. Taking into account only θ_{p1} we can say an increase (decrease) in the debt composite measure increases (decreases) the probability of remaining in an expansionary state. That is, high debt flows help keep the economy going, but "credit crunches" contribute to a downturn. This evidence indicates the inclusion of the debt composite measure provides some predictive power to the model of GDP regime switching and supports debt contributing to whether the economy remains in an expansionary state or not. The test for time variation further points in this direction, where with the likelihood ratio test, the null of no time variation is rejected at the 5 percent level[7].

3.2 Money Factor

The second financial market segment considered, the money composite measure, is estimated based on the log difference of the following variables: real M1 Divisia, a spread based on M2 and M0, velocity based on M0, and real M3. The money factor column of table A indicates the loading factors γ all enter positively with the exception of γ_3 (the loading factor for velocity), which is statistically insignificant.

Granger causality tests indicate that both the simple and extended VAR find support for Granger bicausality between the money composite measure and GDP at the 5 percent level.

Figure B2 details the smoothed probability of a recession for GDP and the smoothed probability of a low or negative growth regime for the money composite measure. The money factor switches to a low growth regime in 1966 coinciding with the credit crunch of that period, while switching two quarters before the 1969-70 recession, two quarters

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[6] Please see figures C1-C4, for TVTP graphs of the probability of GDP being in a low growth state.

[7] Time variation is tested by using a likelihood ratio test and restricting the coefficients of the financial composite measure in the transition probabilities to be zero. Rejecting this restriction indicates that changes in the financial composite measure affect the transition probabilities.

before the 1973-75 recession, and one quarter before the 1980 recession. The money factor then fails to switch in the neighbourhood of any of the recessions of the past twenty years. Money switches regimes to a low growth state twice over the 1987-1990 period. This latter regime switch at best coincides loosely with the first half of the 1989-1992 credit crunch. The results appear supportive of the view of money as a contributor to business cycles, where the change from a high growth state to a tightening of money (a low or negative growth state) leads to recessions, however this is only the case for the first half of the sample. Any relationship between money and business cycles falls apart after the 1980 recession.

Lastly, in terms of the TVTP results, column 3 of table D details the estimated coefficients given the inclusion of the money composite measure in the transition probabilities. The TVTP coefficients indicate θ_{p1} is positive and θ_{q1} negative, where an increase in the money measure increases the probability of being in an expansionary state the next period regardless of the current state of the economy. This is in line with what one would intuitively expect from a money influencing business cycles story. However these coefficients are not statistically significant, tempering the extent of their power in predicting business cycles. That said the likelihood ratio test of the zero restrictions is rejected at the 5 percent significance level, providing some empirical support for money in business cycles.

3.3 Stock Market Factor

It is well known that financial market prices tend to be forward looking. This is potentially problematic in the stock market, where stock market prices through their incorporation of all available information, can price-in coming changes in the economy. This forward-looking price effect clearly needs to be addressed when one is interested in identifying causality rather than simply predictability. As discussed earlier, the Kalman filter is an important part of this exercise. It enables us to filter the noisy variables of a financial segment in order to capture the underlying factor which drives the comovement of the variables in that segment. Therefore, in order to control for the forward looking price problem, we include a non-price variable as one of the variables in the stock market dynamic factor model. The non-price variable is the New York Stock Exchange margin account debt balance. A potential drawback of this measure is it may have some price component to it as movements in the NYSE may impact the margin debt. However, we are fairly comfortable that our stock market factor is not picking up this forward-looking price effect. If it were, we would expect the loading factors of the three other variables ($\tilde{\alpha}_1$, $\tilde{\alpha}_3$, $\tilde{\alpha}_4$) to be much larger than they are in table A.

The stock market composite measure is developed using the log difference of the following stock market variables: the two-year New York Stock Exchange equal weighted return, the one-year change in the NYSE margin account debt, the six-month equal weighted return on the CRSP NYSE-AMEX-NASDAQ index, and the two-year Standard and Poor's excess return. The loading factors for the four stock market variables all enter positive and significantly. Considering the Granger causality results for the stock market composite measure and GDP, the evidence supports a one-way Granger causal relationship from the stock market measure to GDP at the 5 percent level in both models.

Figure B3 details our Markov switching results, where in the case of the stock market composite measure, the graph indicates the smoothed probability of a bear market. The stock market factor switches to a bear market regime two quarters after the beginning of the 1969-70 recession, two quarters in advance of the 1973-75 recession, two quarters in advance of the 1990-1991 recession, and one quarter ahead of the 2001 recession. The stock market factor fails to switch regimes with the 1980 and 1981-1982 recessions, however these recessions are often considered monetary induced, so this is not surprising. The graph of course also picks up the 1987 stock market crash. As a whole, the Markov switching results provides fairly favourable evidence that downturns in the stock market may have played some role in a number of the recessions experienced over the past forty years.

In terms of the TVTP results, Column 4 of table D indicates θ_{q1} is negative and statistically insignificant, while θ_{p1} proves to be positive and statistically significant. The positive value of θ_{p1} indicates that an increase (decrease) in the stock market measure increases (decreases) the probability of staying in an expansionary state. This evidence supports the notion that a strong stock market increases the probability of remaining in an economic expansion, while a downturn in the stock market contributes to the economy moving into a recession. Providing further support, the likelihood ratio test rejects the null of no variation at the 5 percent level.

4. Conclusion

The recent US and Japanese recessions both raise the possibility of financial factors as sources of the respective economic downturns, and this paper uses these events as motivation to re-examine the link between financial factors and business cycles. This paper adds to the existing literature on a number of margins. First, this paper considers the finance-business cycle question via a number of approaches rather than a single approach, basing decisions on the results as a whole. Second, this paper uses composite measures estimated using the dynamic factor model in order to abstract from noisy single measures typical in earlier research, in order to capture the underlying state of the financial sector Finally, data which includes the 2001 recession is used, which allows us to consider finance's role in that most recent recession.

The basic question then is do financial factors contribute to business cycles? The answer is yes, however this depends on the aspect of finance considered and largely if one considers moving from an economic expansion to a recession rather than a recession to a recovery. In the case of the debt composite measure, Granger causality tests provide evidence of a one-way relationship from debt to GDP, and the TVTP model indicates that the debt composite measure contributes to whether the economy remains in an expansionary state or moves into recession. This is coupled with the likelihood ratio test evidence, which supports time variation. That said, the Markov switching results do little to support these results as debt regime switching bears little relation to that of business cycles.

In the case of the money composite measure, the Granger causality results indicate a bicausal relationship between money and GDP, however the Markov switching results over the first half of the sample appear to exhibit a close relationship between money and business cycles. While the TVTP parameters exhibit the intuitively correct signs, they are statistically insignificant (the likelihood ratio test for time variation does however support time variation). Overall, the evidence points in the right direction intuitively, however it does not stand up to tests of statistical significance.

Clearly the strongest results come from the stock market composite measure. The Granger causality results support a one-way relationship from stock markets to GDP, while the TVTP results indicate that stock market movements play a role in whether the economy continues to grow or moves into a downturn (tests for time variation results further substantiate this). Finally the Markov switching results indicate the stock market measure moves into a bear market regime in advance of a number of recessions over the sample. One of the factors which motivated this research is the 2001 recession and the notion that the stock market crash contributed to it. Our results support this view.

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Dynamic Factor Model Coefficients

Table A: Parameter Estimates of the Respective Dynamic Factor Models						
	Debt		Money		Stock	
	Estimate	SE	Estimate	SE	Estimate	SE
Ö_1	0.5370	(0.0778)	0.7331	(0.0874)	1.0525	(0.089)
Ö_2	0.2714	(0.0781)	0.0118	(0.09)	-0.2536	(0.0844)
Ø_{11}	0.0515	(0.0764)	0.5002	(0.0803)	-0.1409	(0.2264)
Ø_{12}	0.1738	(0.0841)	0.3217	(0.0811)	-0.005	(0.016)
Ø_{21}	0.5300	(0.0781)	0.3337	(0.2031)	1.0659	(0.0672)
Ø_{22}	0.2016	(0.0768)	-0.0278	(0.0339)	-0.284	(0.0358)
Ø_{31}	-0.0279	(0.0752)	0.3213	(0.0764)	0.5889	(0.0886)
Ø_{32}	0.9685	(0.0756)	0.1765	(0.0808)	-0.0867	(0.0261)
Ø_{41}	-0.0293	(0.0891)	0.7459	(0.1667)	1.5329	(0.0905)
Ø_{42}	-0.0002	(0.0013)	0.0184	(0.1662)	-0.5874	(0.0696)
ó_1	0.8606	(0.0932)	0.3174	(0.0381)	0.0554	(0.0227)
ó_2	0.2463	(0.0269)	0.0794	(0.0232)	0.227	(0.025)
ó_3	0.0016	(0.0017)	0.8292	(0.0908)	0.6398	(0.0722)
ó_4	0.7175	(0.0783)	0.0694	(0.0194)	0.0355	(0.0131)
ã_1	0.1700	(0.0627)	0.5239	(0.0535)	0.5061	(0.0419)
ã_2	0.3573	(0.0447)	0.6397	(0.0448)	0.1907	(0.0399)
ã_3	0.6062	(0.0335)	-0.0447	(0.0707)	0.2855	(0.068)
ã_4	0.3468	(0.0470)	0.573	(0.0403)	0.3306	(0.0287)
LL	-102.2744		-0.8821		122.8380	

Granger Causality Results[8]

Table B: Granger Causality Results *(p values)*			
Financial Variable (lags)	Finance does not Granger cause output	Output does not Granger cause business cycles	Two way or one way
Debt (2) *no controls*	0.0001	0.3153	One way
Debt (2) *controls*	0.0011	0.1095	One way
Money (2) *no controls*	0.0000	0.0019	Two way
Money (2) *controls*	0.0001	0.0053	Two way
Stock (1) *no controls*	0.0000	0.7778	One way
Stock (1) *controls*	0.0038	0.6002	One way

Controls include quarterly oil prices and the quarterly return of the Standard and Poor's 500 (both in log-differences) as well as a quarterly spread based on the 10-year Treasury and 3-month Treasury.

[8] All VAR model lag lengths are determined based on the Schwartz Information Criterion and Akaike Information Criterion. White standard errors are used in the VAR estimation.

Markov Switching Coefficients

Table C: Parameter Estimates of the Respective Financial Market Segment Markov Switching Models						
	Factors					
	Debt		Money		Stock	
	Estimate	SE	Estimate	SE	Estimate	SE
p	0.94517	(0.02433)	0.93677	(0.03093)	0.93504	(0.02712)
q	0.40085	(0.18205)	0.76375	(0.09668)	0.56342	(0.15246)
Φ_1	0.11610	(0.07518)	0.34795	(0.09632)	0.94438	(0.09277)
Φ_2	0.50223	(0.07322)	0.11785	(0.08932)	-0.19886	(0.14846)
Φ_3	-0.06676	(0.06676)	0.25019	(0.07414)	0.28523	(0.12708)
Φ_4	0.27331	(0.06944)	0.08912	(0.07308)	-0.32669	(0.08940)
μ_0	-1.51330	(0.54951)	-0.96087	(0.46815)	-0.59351	(0.30460)
μ_1	1.32481	(0.46046)	1.32962	(0.41807)	0.92234	(0.21430)
μ_0^*	1.44707	(0.63437)	0.82720	(0.58140)	0.43610	(0.33959)
μ_1^*	-0.96132	(0.50563)	-0.89280	(0.52272)	-0.19736	(0.23993)
σ_1	0.76760	(0.05858)	0.71645	(0.05918)	0.56551	(0.06571)
σ_2	0.33728	(0.04069)	0.47430	(0.05451)	0.27538	(0.02584)
LL	-166.605		-173.948		-128.629	

Early Markov switching results largely resulted in little or no regime switching for the debt and money composite measures over the latter half of the sample. These results are available from the authors on request. Plotting the log difference in our composite measures, the likely reason for these results became apparent. The dispersion of the data becomes much narrower over the latter half of the sample. In light of research such as Stock and Watson (2002), this is not unexpected. In order to account for this, a dummy variable is used to allow for a change in the variance as well as μ_0 and μ_1 over the latter half of the sample period. The dummy variable coverage is as follows: Debt: 1986.1-2001.4; Money: 1984.1-2001.4; Stock Market: 1984.1-2001.4. As a result, $\mu_{st} = (\mu_0 + \mu_0^*(dmy))(1-S_t) + (\mu_1 + \mu_1^*(dmy))(S_t)$, while $\sigma^2 = \sigma_1^2(1-dmy) + \sigma_2^2(dmy)$.

Time Varying Transition Probability Coefficients

Table D: TVTP Results[9]			
Parameters	Z=Debt	Z=Money	Z=Stock
ì$_0$	-0.87305	-0.23825	-0.53928
	(0.23840)	(0.22424)	(0.29112)
ì$_1$	0.99259	1.05369	1.01721
	(0.07621)	(0.09309)	(0.08683)
è$_{q0}$	-5.59295	0.35075	-1.11564
	(3.74321)	(0.70942)	(1.11814)
è$_{q1}$	-3.61811	-1.22705	-0.71290
	(2.43487)	(0.83419)	(0.88324)
è$_{q2}$	---	---	---
è$_{p0}$	4.79554	5.43969	4.16202
	(1.24066)	(2.39300)	(1.05242)
è$_{p1}$	1.94697	3.19463	3.47484
	(0.80627)	(1.91579)	(1.18895)
è$_{p2}$	---	---	---
LR Test[*]	16.72398[†]	13.99188[†]	17.86352[†]

** Likelihood ratio test of no time variation.*
† Reject the null of no time variation (á=0.05)

[9] AIC and BIC were used to determine the order of lags of the *Z* variables in the TVTP.

Financial Market Factor Graphs

Figure A1: Debt Factor and GDP

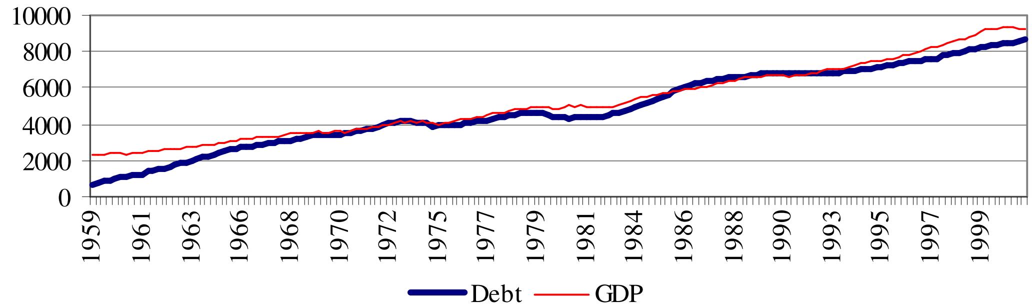


Figure A2: Money Factor and GDP

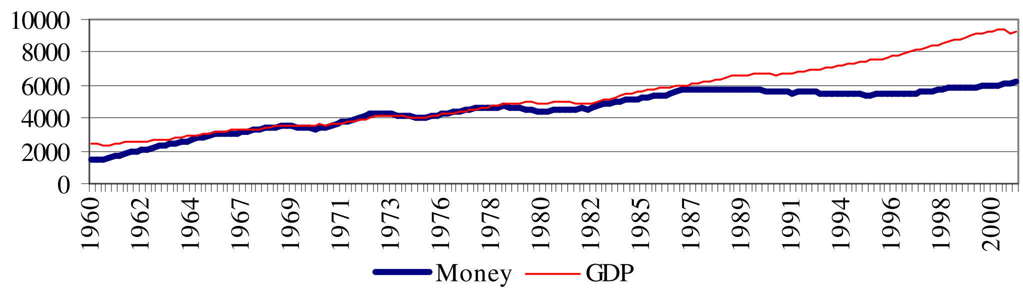
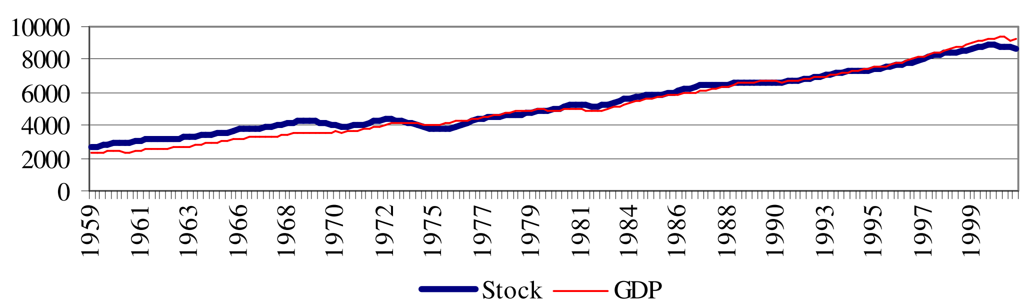


Figure A3: Stock Factor and GDP



Markov Switching Graphs

Figure B1: Debt Factor and Real GDP Markov Switching

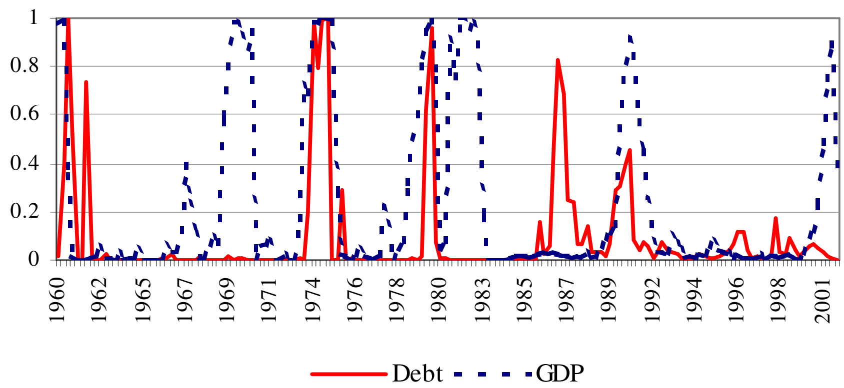


Figure B2: Money Factor and Real GDP Markov Switching

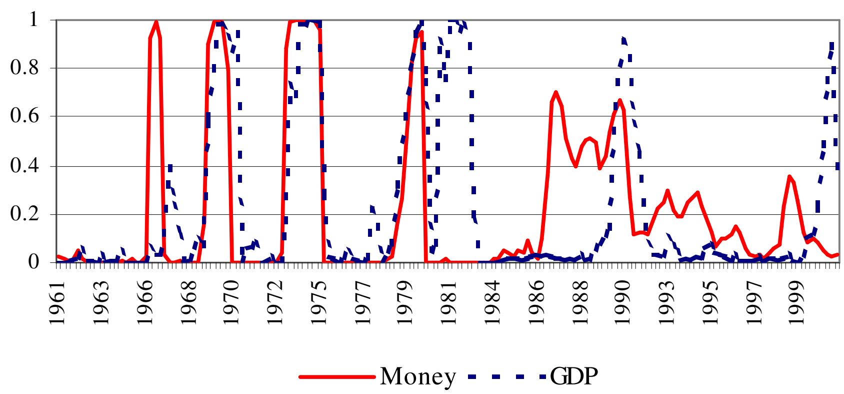
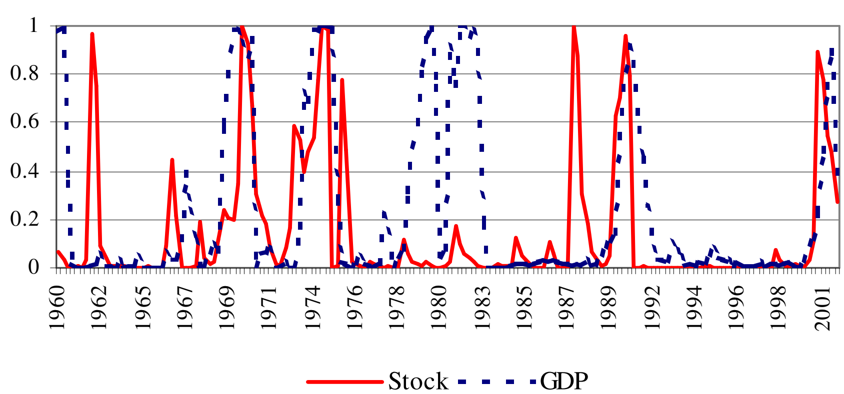


Figure B3: Stock Market Factor and Real GDP Markov Switching



Time Varying Transition Probability Graphs[10]

Figure C1: GDP TVTP; Z=0

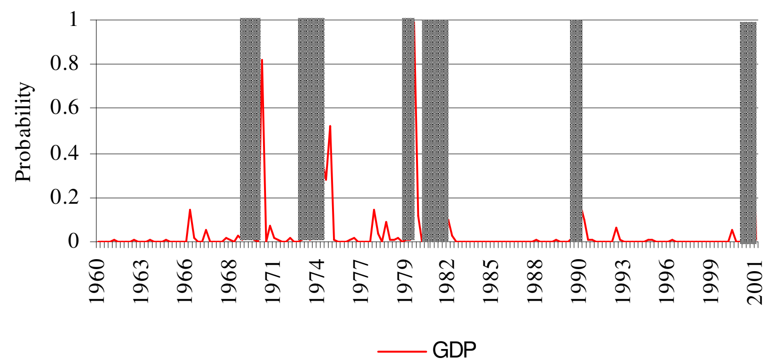


Figure C2: GDP TVTP; Z=Debt

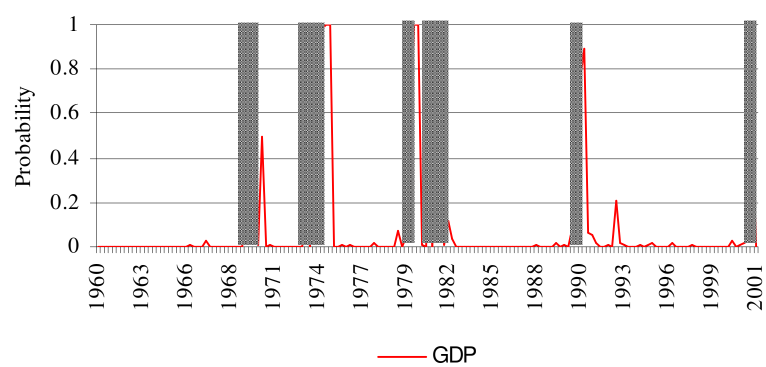
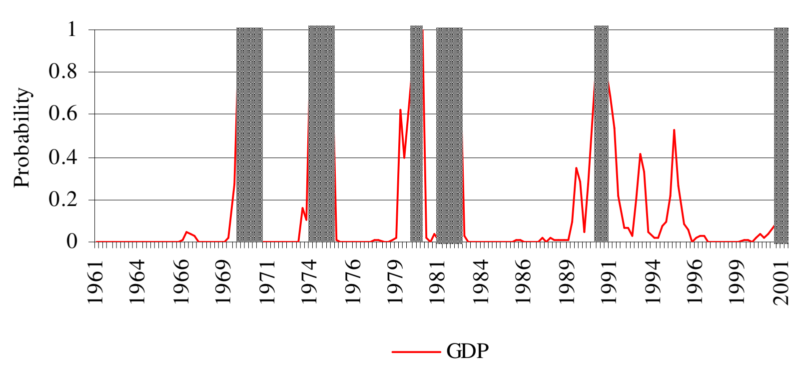
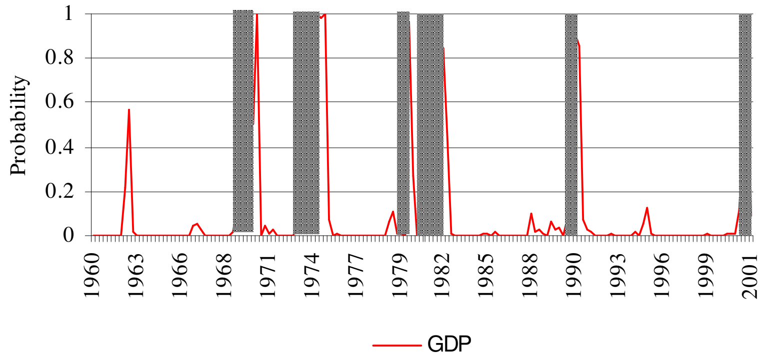


Figure C3: GDP TVTP; Z=Money



[10] The shaded areas indicate NBER-dated recessions.

Figure C4: GDP TVTP; Z=Stock



Appendix 1: Data

Data Sources	
Variables	**Source**
Debt	
Debt (Credit Market Instruments (non-farm non-financial))	Federal Reserve Flow of Funds Accounts of the US
Net Worth Market Value (non-farm non-financial corporations)	Federal Reserve Flow of Funds Accounts of the US
Consumer Credit Outstanding	Datastream
Financial Liabilities (All Sectors)	Datastream
Credit Market Instruments (Private Non-financial Firms)	Datastream
Money	
Monetary Services Index M1 (Divisia)	Federal Reserve Bank of Saint Louis
MO	Datastream
M1	Datastream
M2	Datastream
M3	Datastream
Stock Market	
Standard & Poor' s 500 Index (Common Stock)	Datastream
NYSE-AMEX-NASDAQ Equal Weighted Share Price Index	CRSP
NYSE Debt Balances in Margin Accounts	Financial Market Center*
NYSE Equal Weighted Return	CRSP
Others	
Spot Oil Price: West Texas Intermediate	Dow Jones Energy Services
CPI	Datastream
3 Month Treasury Bill	Datastream
10 Year Treasury Bond Yield (Composite)	Datastream

* Compiled from Federal Reserve Banking and Monetary Statistics, Federal Reserve Annual Statistics and New York Stock Exchange

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