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A FORECAST OF THE U.S. BUSINESS CYCLE USING THREE DIFFERENT APPROACHES

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Different approaches to policy issues have suggested different approaches to predicting business cycle fluctuations. The Keynesian approach maintains that consumption, investment, and government spending, along with net exports are the driving factors in changing the business cycle, while the Political model approach maintains that the distribution of power among political parties can be used to predict fluctuations. The purpose of this paper is to examine an alternate approach to predicting business cycles that employs a new measure of economic shocks and volatilities derived from survey forecast data, and to compare the results using this approach to those achieved via the Keynesian and Political model approaches.

Key words: business cycle, Keynesian, consumption, investment, government spending, net exports, political, economic shocks, volatilities, forecast

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1. Introduction

Economists' views of the business cycle change over time and approaches regarding the fluctuation of the business cycle have evolved. There is evidence that within the past ten to fifteen years there has been an evolution in the field of macroeconomic policy, or as Taylor (2000) states it, "a new normative macroeconomics." During the period of the Great Depression, the Keynesian belief was prominent (Mankiw 1993). Towards the 1970s, the Nixon administration caused economists to have considerable interest in the "political business cycle theory" (Fair 1988), and with today's recent study by Davies (2006), the economic shock and volatilities approach is on the rise.

The Keynesian approach asserts the importance of aggregate demand as the ultimate driving force in the economy. Mankiw (1993) writes that the Keynesian belief shows an emphasis on how shifts in aggregate demand cause economic fluctuations. The sum of consumer (C), investment (I), government (G) and net exports spending ($X – M$) are, according to the Keynesian approach, the catalysts that stimulate the fluctuations of the business cycle. Economists who employ a Keynesian approach also focus on consumer spending and saving as principal predictors of turning points (Johnson 2005). Mankiw (1989) states this in broader terms when he says, "Many of the macroeconomic disturbances that receive much attention among Keynesian macroeconomists will also have important effects in real (predictive) business cycle models." According to Keynesian belief, macroeconomic disturbances are consumer, investment, and government spending along with net exports.

The political business cycle theory is an alternative approach to understand why business cycles change. Taylor (2000) states that there is a simple political need to be observed of doing something "positive" during a recession, which may include to "increase spending or to cut taxes to stimulate the economy in the short run, even though such stimulus would be inflationary in the long run." It is in the politicians' best interest to influence policies in order to stimulate the economy during times of election to win favor of the voters.

For example, the Nixon Administration deliberately aimed for a recession during the early part of its administration so that the economy would be on the upswing going into the subsequent election cycle (Nordhaus, 1975). Fair (1988) demonstrated a correlation between conditions in the economic environment and how the economic environment affects a particular party's vote shares. Using the growth rate of real per capita GNP (somewhere between six months to a year before the election), Fair concluded that the incumbent party would receive a 1.02 percentage point increase in the vote share for every one-percentage point increase in the growth rate. Fair also concluded that the incumbent party would receive a 0.34 percentage point decrease in the vote share for every one-percentage point increase in the inflation rate. Fair's model successfully predicted fifteen out of sixteen presidential elections through the years 1916 – 1978. Fair proves that the politicians in office manipulate monetary and fiscal policy in order to increase their vote shares during times of election.

Zuk and Woodbury (1986) investigated "whether U.S. defense spending has been systematically increased (or decreased) during national election years for the presumed purpose of influencing the economy in general and the electorate in particular." Zuk and

Woodbury, however, found that military spending is most likely not used as a policy instrument for winning elections. They did state, however, that their findings are based on a short time-series, therefore "the number of variables that can be meaningfully analyzed is fairly small," and they left room for further investigation on the subject.

Recent research has constructed new inflation and real GDP forecast data from the ASA-NBER Survey of Professional Forecasters (Davies 2006). The traditional approach on shocks showed that in the short run, nominal shocks matter more, while in the long run, real shocks matter (Roberts 1993). Engle and Ng (1993) created a news impact curve based on the traditional approach showing negative shocks having more of an impact than positive shocks on the overall environment (see Figure 1). The traditional approach on shocks was to regard any change in a variable as a shock. If inflation was three percent for a particular quarter and four percent in the following quarter, economists said there was a one percent shock. If, however, this one percent change in inflation was anticipated, there is no shock according to the new view. If inflation was anticipated to rise from three to six percent, but only rose three to four percent, then, according to the new view, there is a negative two percent shock in the environment. Similarly, volatility has traditionally been measured as the variance of a variable. The volatility of inflation shocks has been measured as the variance of inflation over time. The approach is flawed because it assumes that "shock" equals a change in the variable which when using the new approach is incorrect. The Davies framework addresses this issue by using forecasts to measure shocks, or in other words, it assumes that "shock" equals changes in the forecast.

The intent of this analysis is to measure the extent to which new measures of economic shocks and volatilities can predict turning points in the business cycle, and to compare the performance of a model built on the new measures to models constructed based on the Keynesian and political approaches. In this paper, three different models forecast the expansion of business cycles: a Keynesian approach, a political approach, and a shock/volatility approach. The models represent the "evolution" of beliefs over time. The first model in my analysis, based on Keynesian theory, attempts to determine the extent to which spending and labor costs (the wages and salaries of all civilian workers) can predict real GDP changes. I also include the variables in the formula for generating aggregate demand: consumption, investment, government, and net export spending. I will include in my political model variables that represent monetary policy (CPI) and fiscal policy (tax rates) as a result of analyzing Taylor's (2000) research. I will also include the variables of military spending as a percentage of real GDP and the percentage of Congressional seats held by Democrats and Republicans.

In comparison to these established models, I construct a model using new measures of shocks and volatility. This model is constructed based on the proposition that economic shocks affect business cycles, which means that they represent a potential change in peoples' expectations of the future. As people alter their behaviors based on their new expectations, they can induce turning points in the business cycle. I employ Davies' (2006) framework for decomposing the forecasts into implied shock and volatility data (see Davies) to predict the business cycle.

2. The Models

Keynesian Model

I build three forecast models for real Gross Domestic Product. The first model, based on the Keynesian approach, uses data on consumption, investment, government spending, net exports, and consumer spending.[1] Let G_t be real GDP at time *t*. I define the dependent variable Y_t as:

$$Y_t = \begin{cases} 1 & \text{if } \dfrac{G_t - G_{t-1}}{G_{t-1}} > 0.007 \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

For the data on real GDP, through the years 1971:2 to 2006:3, the average growth rate is 0.007 or 0.7%. I set Y_t equal to one if the growth rate for the particular quarter is above the average of the data set, 0.007, and equal to zero otherwise. I train the model to the years 1971:2 to 2001:4, combine the variables with their appropriate lags to form the model with the most significance, and generate the model:

$$Y_t = \alpha + \beta_1 \frac{I_{t-6} - I_{t-7}}{I_{t-7}} + \beta_2 \frac{I_{t-7} - I_{t-8}}{I_{t-8}} + \beta_3 \frac{I_{t-8} - I_{t-9}}{I_{t-9}} + \beta_4 \Delta^2 G_{t-8} + \beta_5 \Delta^2 \left(X - M \right)_{t-6} + \beta_6 \Delta^2 \left(X - M \right)_{t-8} + \varepsilon_t \tag{2}$$

and estimate (2) via probit. The variable *I* is investment spending, *G* is government spending, and *X*-*M* is net exports. The estimated model appears in Table 1 below:

[1] Data ranges from 1971:2 through 2006:3. Data is collected from *Moody's Economy.com*.

$$Y_t = \alpha + \beta_1 \frac{I_{t-6} - I_{t-7}}{I_{t-7}} + \beta_2 \frac{I_{t-7} - I_{t-8}}{I_{t-8}} + \beta_3 \frac{I_{t-8} - I_{t-9}}{I_{t-9}} + \beta_4 \Delta^2 G_{t-8} + \beta_5 \Delta^2 \left(X - M \right)_{t-6} + \beta_6 \Delta^2 \left(X - M \right)_{t-8} + \varepsilon_t$$

Coefficient	Estimate	Standard Error	P-value
α	-0.909	0.477	0.056
β_1	35.857	14.737	0.015
β_2	54.691	18.921	0.004
β_3	25.202	13.458	0.061
β_4	0.037	0.021	0.087
β_5	-0.024	0.014	0.082
β_6	-0.044	0.022	0.043
Mean Dependent Var	0.632	S.E. of regression	0.425

Table 1. Probit estimation of the Keynesian model

At the current level of variables, a one-percentage increase in the growth of investment spending is associated with an eventual increase in the probability of real GDP expansion of 0.184. A one-dollar increase in the acceleration in government spending is associated with an eventual increase in the probability of real GDP expansion of 0.008. A one-dollar increase in the acceleration of net exports is associated with an eventual decrease in the probability of real GDP expansion of 0.015.

Political Model

The second model, based on political business cycle theory, uses data on CPI, tax rates (a proxy for the overall tax rate), the percentage of military spending to real GDP[2], and a variable *S*[3]. The variable *S* consists of the data on the percentage of Republicans and the percentage of Democrats represented in Congress. Based on which political party is in the Presidential office determines which percentage of either Republican or Democrats in Congress I use for the particular quarter.

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[2] Data ranges from 1971:2 through 2006:3. Data is collected from *Moody's Economy.com*.
[3] Data ranges from 1971:2 through 2006:3. Data is collected from *Party Divisions*.

Let Y_t equal the equation in (1). I train the model to the years 1971:2 to 1994:4, combine the variables with their appropriate lags to form the model with the most significance, and generate the model:

$$Y_t = \alpha + \beta_1 \Delta^2 C_{t-4} + \beta_2 \Delta^2 C_{t-5} + \beta_3 \Delta^2 C_{t-6} + \beta_4 \Delta^2 M_{t-6} + \varepsilon_t \tag{3}$$

and estimate (3) via probit. The variable *C* is Consumer Price Index, and *M* the percentage of military spending to real GDP. I have the estimated model, using (3) in Table 2 below:

$Y_t = \alpha + \beta_1 \Delta^2 C_{t-4} + \beta_2 \Delta^2 C_{t-5} + \beta_3 \Delta^2 C_{t-6} + \beta_4 \Delta^2 M_{t-6} + \varepsilon_t$			
Coefficient	**Estimate**	**Standard Error**	**P-value**
α	0.138	0.218	0.525
β_1	-0.856	0.607	0.159
β_2	-1.176	0.676	0.082
β_3	-1.231	0.682	0.071
β_4	14972.06	8455.71	0.077
Mean Dependent Var	0.550000	S.E. of regression	0.474713

Table 2. Probit estimation of the Political model

At the current level of variables, a one-dollar increase in acceleration in CPI is associated with an eventual decrease in the probability of real GDP expansion of 0.498. A one-dollar increase in the acceleration in military spending is associated with an eventual increase in the probability of real GDP expansion of 0.458.

Shock-Volatility Model

Finally, the third model uses Davies' (2006) framework for decomposing the forecasts into implied shock and volatility data to predict the business cycle. Theoretically, when the volatility increases (more case of different economical shocks occurring) the shock's effect on inflation and real GDP becomes increasingly unnoticed. Consequently, I created two new variables:

$$w_t = \frac{\text{inflationary shocks at time } t}{\text{volatility of inflationary shocks at time } t} \tag{4}$$

$$z_t = \frac{\text{RGDP shocks at time } t}{\text{volatility of RGDP shocks at time } t} \tag{5}$$

Following Engle and Ng (1993), I split each new variable into two separate variables representing negative and positive shocks, respectively. Thus:

$$w_t^+ = \begin{cases} w_t & \text{if } w_t \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

$$w_t^- = \begin{cases} w_t & \text{if } w_t < 0 \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

$$z_t^+ = \begin{cases} z_t & \text{if } z_t \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

$$z_t^- = \begin{cases} z_t & \text{if } z_t < 0 \\ 0 & \text{otherwise} \end{cases} \tag{9}$$

Let Y_t equal the equation in (1). I train the model to the years 1971:2 to 1994:4, combine the variables with their appropriate lags to form the model with the most significance, and generate the model:

$$Y_t = \alpha + \beta_1 w_{t-7}^- + \beta_2 z_{t-5}^+ + \beta_3 z_{t-6}^+ + \beta_4 z_{t-8}^+ + \beta_5 z_{t-5}^- + \beta_6 z_{t-6}^- + \varepsilon_t \tag{10}$$

and estimate (10) via probit. The estimated model appears in Table 3 below:

$Y_t = \alpha + \beta_1 w_{t-7}^{-} + \beta_2 z_{t-5}^{+} + \beta_3 z_{t-6}^{+} + \beta_4 z_{t-8}^{+} + \beta_5 z_{t-5}^{-} + \beta_6 z_{t-6}^{-} + \varepsilon_t$			
Coefficient	**Estimate**	**Standard Error**	**P-value**
α	1.001	0.440	0.023
β_1	0.023	0.11	0.030
β_2	0.019	0.008	0.015
β_3	-0.020	0.007	0.003
β_4	-0.012	0.006	0.068
β_5	-0.019	0.010	0.064
β_6	0.019	0.007	0.006
Mean Dependent Var	0.581	S.E. of regression	0.435

Table 3. Probit estimation of Shock-Volatility model

At the current level of variables, a one-unit increase in w_t^{-} is associated with an eventual decrease in the probability of real GDP expansion of 0.001. A one-unit increase in z_t^{+} is associated with an eventual increase in the probability of real GDP expansion of 0.0007. A one-unit increase in z_t^{-} is associated with an eventual decrease in the probability of real GDP expansion of 0.001.

3. Results

Keynesian Model

I first train the model in equation (2) using the sample of the second quarter 1971 to the fourth quarter 2001. I then use the estimated model to forecast the four quarters of 2002. Then, I re-train the model using data from the second quarter 1971 to the fourth quarter of 2002 and forecasted for the four quarters of 2003. I repeat this process until there are forecasts through the second quarter of 2006. At the end, I have five sets of four-quarter-ahead out-of sample forecasts. To translate the probability forecast for expansion into a binary "expansion/recession" forecast, one must select an arbitrary cut-off point for the probability forecast. I select three cut-offs, $c = \{0.5, 0.6, 0.7\}$, and define a binary forecast as follows:

$$\text{Forecast} = \begin{cases} \text{Expansion in quarter } t & \text{if } \hat{Y}_t \geq c \\ \text{Recession in quarter } t & \text{if } \hat{Y}_t \leq 1-c \\ \text{Undecided in quarter } t & \text{if } c \leq \hat{Y}_t \leq 1-c \end{cases} \tag{11}$$

The results appear in Table 4 below:

Keynesian Model		Actual	
	c = 0.5	Expansion	Recession
Forecast	Expansion	4	3
	Undecided	0	0
	Recession	4	7
	c = 0.6		
Forecast	Expansion	3	2
	Undecided	2	3
	Recession	3	5
	c = 0.7		
Forecast	Expansion	2	1
	Undecided	3	4
	Recession	3	5

Table 4. Forecasted vs. Actual results for Keynesian model using equation (2) (2002:1 – 2006:2)

Table 4 shows the Keynesian model at $c = 0.5$ correctly predicting the turning points in real GDP eleven out of eighteen times or sixty-one percent of the time. For $c > 0.5$, the

Keynesian model fails to return forecasts (i.e., has no opinion) some of the time. Ignoring the quarters for which the model has no opinion, at $c = 0.6$, the Keynesian model correctly predicted the turning point in real GDP eight out of thirteen times or sixty-two percent of the time. At $c = 0.7$, the Keynesian model correctly predicted the turning points in real GDP seven out of eleven times or sixty-four percent of the time.

Political Model

I first train the model in equation (3) using the sample of the second quarter 1971 to the fourth quarter 1994. I then use the estimated model to forecast the four quarters of 1995. Then, the model is re-trained using data from the second quarter 1971 to the fourth quarter of 1995 and forecasted for the four quarters of 1996. I repeat this process until there are forecasts through the second quarter of 1999. At the end, I have five sets of four-quarter-ahead out-of sample forecasts. I select three arbitrary cut-off points for the probability forecast of $c = \{0.5, 0.6, 0.7\}$, and define a binary forecast as in equation (11). The results appear in Table 5 below:

Political Model		Actual	
	$c = 0.5$	Expansion	Recession
Forecast	Expansion	5	6
	Undecided	0	0
	Recession	3	4
	$c = 0.6$		
Forecast	Expansion	5	4
	Undecided	1	4
	Recession	2	2
	$c = 0.7$		
Forecast	Expansion	4	2
	Undecided	2	7
	Recession	2	1

Table 5. Forecasted vs. Actual results for Political model using equation (3) (1995:1 – 1999:2)

Table 5 shows the Political model at $c = 0.5$ correctly predicting the turning points in real GDP nine out of eighteen times or fifty percent of the time. Ignoring the periods for which the model had no opinion, at $c = 0.6$, the Political model correctly predicts the turning point in real GDP seven out of thirteen times or fifty-four percent of the time. At $c = 0.7$, the Political model correctly predicts the turning points in real GDP five out of nine times or fifty-six percent of the time.

Shock-Volatility Model

An interesting occurrence appeared in my shock and volatility model when the four variables with their lags were combined into one model. Short run lags for my variable w_t^- were eliminated because of insignificance to the model. My model does not support Roberts' (1993) research in that inflationary shocks have more of an effect in the short run since my variable w_t^- has lags of minus seven. My model shows that nominal, inflationary shocks matter in the long run, adversely to what Roberts' research has shown. Prior research by Engle and Ng (1993) would suggest that negative shocks have a substantial effect on real GDP, more so than positive shocks. According to my model, negative shocks only have slightly more affect on real GDP. Past research uses the "traditional" approach to describing shocks, yet the data set in my model uses Davies' (2006) approach explaining why my findings are inconsistent with prior research.

I first train the model in equation (10) using the sample of the second quarter 1971 to the fourth quarter 1994. I then use the estimated model to forecast the four quarters of 1995. Then, the model is re-trained using data from the second quarter 1971 to the fourth quarter of 1995 and forecasted for the four quarters of 1996. This process is repeated until I have forecasts through the second quarter of 1999. At the end, I have five sets of four-quarter-ahead out-of sample forecasts. I select three arbitrary cut-off points for the probability forecast of $c = \{0.5, 0.6, 0.7\}$, and define a binary forecast as in equation (11). The results appear in Table 6 below:

Shock-Volatility Model		Actual	
	c = 0.5	Expansion	Recession
Forecast	Expansion	7	2
	Undecided	0	0
	Recession	8	1
	c = 0.6		
Forecast	Expansion	7	2
	Undecided	1	0
	Recession	7	1
	c = 0.7		
Forecast	Expansion	7	2
	Undecided	3	0
	Recession	5	1

Table 6. Forecasted vs. Actual results for Shock-Volatility model using equation (10) (1995:1 – 1999:2)

Table 6 shows the Shock-Volatility model at c = 0.5 correctly predicting the turning points in real GDP eight out of eighteen times or forty-four percent of the time. Ignoring periods for which the model has no opinion, at c = 0.6, the Shock-Volatility model correctly predicts the turning point in real GDP eight out of seventeen times or forty-seven percent of the time. At c = 0.7, the Shock-Volatility model correctly predicts the turning points in real GDP eight out of fifteen times or fifty-three percent of the time.

In reviewing the literature, one would believe that over time, the evolution of beliefs and philosophies would result in better predictive models. My research shows the reverse of this "evolution." The constructed Keynesian model correctly predicts the expansion of real GDP sixty-two percent of the time, while the political and shock models correctly predict fifty-three and forty-eight percent of the time. This paper only intensifies the fact that economists have struggled throughout many years to find accurate predictive models for business cycles.

4. Conclusion

The purpose of this paper is to examine an alternate approach to predicting business cycles that employs a new measure of economic shocks and volatilities derived from survey forecast data, and to compare the results using this approach to those achieved via the Keynesian and Political model approaches. The underlying hypothesis of this paper was to show how an evolution of approaches would result in accurately predicting business cycles, resulting in the shock and volatility model best predicting real GDP. The results, however, were similar for each predictive model and do not promote a growth in accurately predicting business cycles over time. The results actually showed a reverse of "evolution" where the shocks and volatility model predicted below the fifty percentile. The variables w_t^-, z_t^-, and z_t^+ have the smallest affect on the probability of real GDP expanding compared to the other variables in the Keynesian and political models.

This raises the question of why the Keynesian model best predicted the expansion of real GDP. The research by Nordhaus, Alesina, and Schultze (1989) shows strong evidence that refutes the political business cycle theory. Their data on policy inputs do not show a strong political component with predicting business cycles. A possible explanation of why the shock and volatility model predicted the least out of the three models is because the Davies' framework addresses the issue of using forecasts to measure shocks, or in other words, assumes that "shock" equals change in the forecast. This can possibly minimize the "effect" the data can have on the dependent variable, real GDP. As stated earlier in my research, the traditional view claimed that if inflation was three percent for a particular quarter and four percent in the following quarter, economists said there is a one percent shock. If this one percent change in inflation was anticipated, there is no shock according to the new view. Past research shows a significant effect on the business cycle, yet there might not be such a great effect according to the new view. This leaves for future research on the different levels of effect that the traditional and new shock approaches have on business cycles.

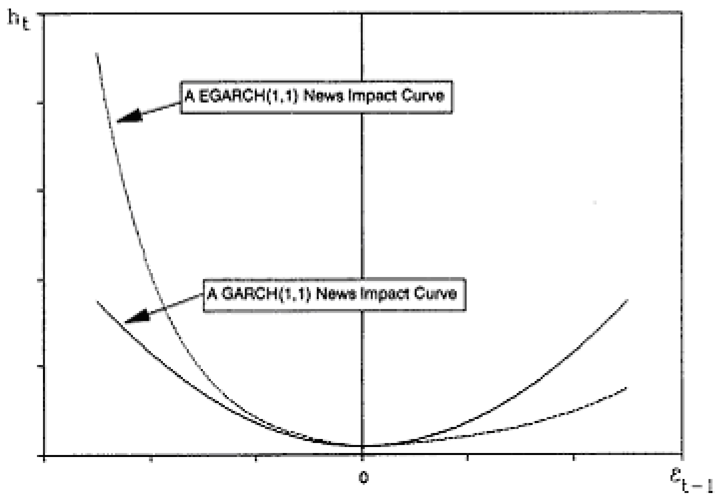

Figure 1. Engle and Ng (1993) News Impact Curve

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