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GDP Growth, Unemployment, and Indexes of Financial Stress

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Abstract: This project employs a baseline trivariate vector auto-regression (VAR) model to generate forecasts of real GDP growth and the unemployment rate. In addition to the two aforementioned variables, this project also includes an index of financial stress. Estimations reported in this project indicate that measures of financial stress can be useful in forecasting important macroeconomic variables. Out-of-sample forecasts are generated for a horizon of six years.

Key words: financial stress; vector auto-regressions; impulse response functions

JEL codes: E1, E3

1. Introduction

The current recovery from the *great recession* of 2008-09 has been called both slow in terms of economic growth rates, and a jobless recovery. The meaning of this statement is that the economic growth that has taken place in recent quarters has not been robust enough to result in a great deal of job creation, and the growth has done relatively little to lower the unemployment rate toward "normal" levels.

It is commonly acknowledged that the great recession had its roots in the financial sector, and that continued financial stress has been one of the causes of the slow recovery from the recession. Most models of the economy, based on data since the 1950s, predicted faster rates of economic growth and a more rapid rate of recovery of employment.

Because of the focus on the financial sector as a proximate cause of both the recession and slow recovery, many researchers have constructed new indexes of financial stress (see Kliesen, Owyang, & Vermann, 2012 for a summary). Most of these indexes do not extend back very far in time—often only to the early 1990s. Such a short time frame does not provide sufficient data for convincing tests of whether these indexes will be helpful in predicting important macroeconomic variables such as GDP growth and unemployment rates. There are, however, two indexes that extend to the early 1970s. One of the indexes is produced by the Federal Reserve Bank of Chicago, and is termed the National Financial Conditions Index (NFCI). The other is produced by Hatzius et al. The former is available on-line from the FRB Chicago. The latter was not available for us to use in the project. These indexes cover a period of time that includes six recessions. That time frame is sufficiently long to judge whether the index can be helpful in predicting growth and unemployment.

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2. Measuring Financial Stress

Because of the focus on the financial sector as a proximate cause of both the recession and the slow recovery, many researchers have constructed new indexes of financial stress. The composition and performance of eleven such measures are described in detail by Kliesen et al. (2012). These measures are categorized as financial stress indexes (FSIs) and financial conditions indexes (FCIs). FSIs attempt to identify evidence of exogenous shocks to the financial sector by combining time series data on varieties of interest rate spreads and asset prices. For example, greater interest rate spreads between forms of debt involving different degrees of risk could indicate more stress. Lower stock prices could be an indication of lower expected earnings or smaller dividends. FCIs include many of the same variables as FSIs and a larger set of variables, including various economic indicators since many of them are intended to map directly onto changes in real GDP and other macroeconomic conditions. So for the purposes of this paper, FCIs would be the preferred type of measure of financial stress to be employed.

Most of these FCIs do not extend back very far in time—often only to the early 1990s. Such a short time frame does not provide sufficient data for convincing tests of whether these indexes will be helpful in predicting important macroeconomic variables such as GDP growth and unemployment rates. There are, however, two indexes that extend to the early 1970s, covering a period of time that includes six recessions. That time frame is sufficiently long to judge whether the indexes can be helpful in predicting growth and unemployment. One of these indexes, which is produced by Hatzius et al., was not available for use in this project. The other, which is produced by the Federal Reserve Bank of Chicago and is termed the National Financial Conditions Index (NFCI) is available on-line.

The NFCI is a comprehensive weekly update on U.S. financial conditions that includes data on 100 variables reflecting conditions in money markets (28), debt and equity markets (27), and traditional and “shadow” banking systems (45). These data include prices, volumes, and surveys of financial activity. The index is a weighted average of quarterly (25), monthly (34), and weekly (41) indicators of U.S. financial activity.

The money markets reflected in the NFCI are repurchase agreements, treasuries, commercial paper, and interbank lending. The corresponding variables include total repo market volume, the 2-year interest rate swap/Treasury yield spread, the 1-month nonfinancial commercial paper A2P2/AA credit spread, and the 3-month TED spread (LIBOR-Treasury).

The debt and equity markets are corporate bonds, securitized debt, stock markets, municipal bonds, and collateral prices. Examples of associated variables include the Merrill Lynch High Yield/Moody’s Baa corporate bond yield spread, the Citigroup Global Markets ABS/5-year Treasury yield spread, CBOE S&P 500 Volatility Index (VIX), the Municipal Bonds Bond Market Association Municipal Swap/20-year Treasury yield spread, and the MIT Center for Real Estate Commercial Property Price Index.

The NFCI data on the banking system include measures of consumer credit conditions, banking system conditions, shadow bank assets and liabilities, business credit conditions, and commercial bank assets and liabilities. These measures include the Consumer Credit Conditions Senior Loan Officer Opinion Survey: Tightening Standards on RRE Loans, the Credit Derivatives Research Counterparty Risk Index, total assets of funding corporations/nominal GDP, Senior Loan Officer Opinion Survey: Tightening Standards on Small C&I Loans, and commercial bank C&I loans/total assets.

The 100 variables included in the NFCI are expressed relative to their sample averages and scaled by their sample standard deviations. The index itself is measured in standard deviations from its historical mean, where positive values denote tight financial market conditions and negative values denote loose conditions. So an increase in the index is an indicator of increasing financial stress.

See http://www.chicagofed.org/webpages/publications/nfci/index.cfm for the NFCI data and detailed descriptions of the index and its construction.

3. Data and Method

The data set for this project begins in the early 1970s and extends through the most recently available data (first quarter, 2013). The variables are the growth rate (annualized) of real GDP, the unemployment rate, and the index of financial stress. The index of financial stress from the FRB Chicago is a weekly measure. We averaged the weekly values over the course of each quarter, producing the desired quarterly index. The unemployment rates are quarterly averages of monthly data. These series are available from the FRED economic database of the Federal Reserve Bank of St. Louis, and the FRB Chicago. Figure 1 depicts the series on unemployment, real GDP growth, and the NFCI for the sample period.

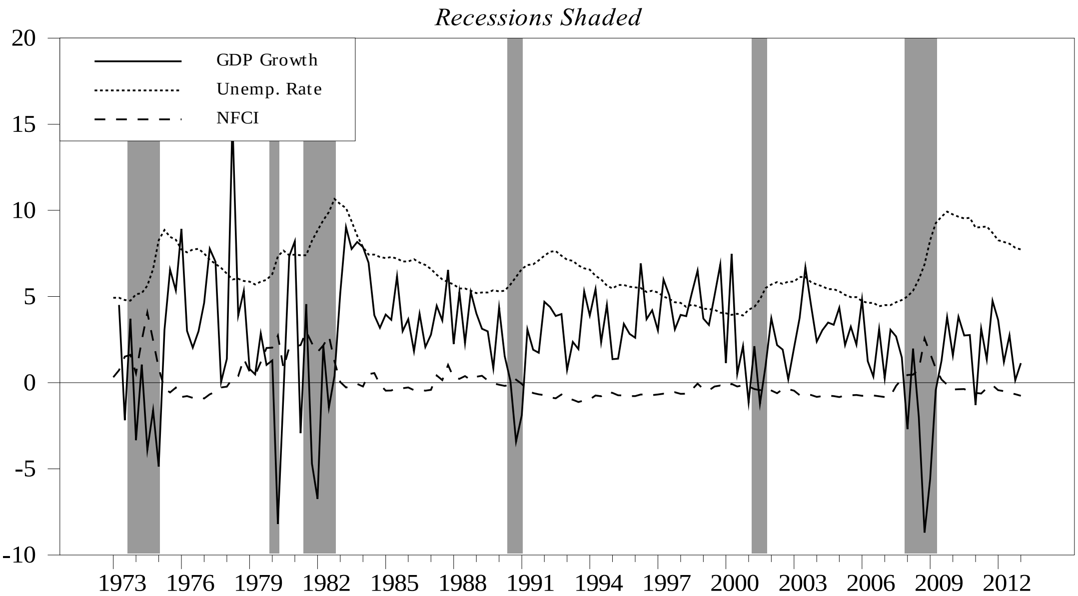

Figure 1 US GDP Growth, Unemployment Rate, and NFCI

From inspection of the figure, in which recessions are shaded, it is reasonably clear that the periods following negative real GDP growth are periods of rising unemployment, and that recoveries produce declines in the rate of unemployment with a significant lag. Note also that with the exceptions of the 1990-1991 and the 2001 recessions, each of the other four recessions was also accompanied by significant financial stress as measured by the NFCI. It is further clear that the 1990-1991 and the 2001 recessions were relatively mild in comparison to other recessions over the time frame depicted in the figure, lending support to the view that financial stress is associated with deeper and more prolonged recessions.

A simple VAR (vector autoregression) model is estimated in the form of Equation (1):

$$UR_t = \alpha_0 + \sum_{i=1}^{p} \beta_i UR_{t-i} + \sum_{i=1}^{p} \delta_i GDP_{t-i} + \sum_{i=1}^{p} \varphi_i FS_{t-i} + \varepsilon_t \tag{1}$$

where UR is the unemployment rate, GDP is the annualized quarterly growth rate of real GDP, FS is an index of financial stress, t indexes time, ε_t is a white noise disturbance term and the $\beta_i, \delta_i, \varphi_i \ (i=1,\ldots,p)$ are the lag coefficients, and p indicates the order of the lags. Each variable serves as the left-hand side of (1) in a VAR. We are, of course, interested primarily in forecasts of real GDP growth and the unemployment rate. For comparison purposes we also estimated a bivariate VAR model excluding the financial stress index.

The number of lags to be included in the model may be selected by complexity penalized likelihood criteria such as the Akaike information criterion *(AIC)*. The *AIC* can be represented as

$$\boldsymbol{AIC} = (2k/T) + \log(\sigma) \qquad (2)$$

where k is the total number of estimated coefficients in the equation, T is the number of usable observations, and σ is the scalar estimate of the variance of the equation's disturbance term. In this case the *AIC* chooses only two lags. Most VAR practitioners suggest that the AIC is likely to choose lag structures that are too parsimonious to capture the dynamics of the relationships between the variables included in the model. It is generally recommended that at least a year's worth of lags (four with quarterly data) should be included in the estimated model (Doan, 2010, p. 206). We choose to include a year's worth of lags in the results that follow.

4. Results

4.1 Estimation and Analysis

Tables 1, 2, and 3 are the traditional F-tests of "Granger causality" (Granger, 1969) for the individual equations in the VAR model, where p = 4 (lags = 4). Table 1 suggests that real GDP growth is unrelated to its own lags, perhaps weakly related to the unemployment rate, but significantly related to financial conditions. These results are not particularly surprising given: (1) that real GDP growth does not exhibit smooth persistence, (2) unemployment lags rather than leads real GDP growth, (3) the depth and duration of the recessions are clearly associated with heightened levels of financial stress (see Figure 1). Table 2 indicates that the unemployment rate is related to its own lags as well as those of real GDP growth and the NFCI. Finally, from Table 3, the NFCI is related to the unemployment rate, its own lags and (more weakly) to real GDP growth.

Table 1 F-Tests, Dependent Variable: GDP Growth

Variable	F-Statistic	Significance
GDP Growth	0.6072	0.65812
UR	1.5197	0.19966
NFCI	6.8331	0.00005

Table 2 F-Tests, Dependent Variable: Unemployment Rate

Variable	F-Statistic	Significance
GDP Growth	2.6769	0.034305
UR	1306.96	0.000000
NFCI	14.7610	0.000000

Table 3 F-Tests, Dependent Variable: NFCI

Variable	F-Statistic	Significance
GDP Growth	2.01540	0.095516
UR	6.3833	0.000095
NFCI	113.2846	0.000000

Figure 2 contains the impulse response functions computed from the VAR model. The lighter lines are 95% confidence bands for the variable responses. The impulse response functions simulate the dynamic response of the variables to a one-standard deviation change (shock) to one of the variables. Here the horizon over which the responses are evaluated is four years (16 quarters). For example, the first column represents the responses of the three variables to a (positive) shock to real GDP growth. A shock to GDP growth has a relative short term effect on itself, a persistent effect on the unemployment rate (GDP growth lowers the unemployment rate as expected), and little short-term effect on NFCI.

A shock to the unemployment rate has relatively little effect on GDP, a short term effect on itself that raises unemployment (as expected) and a longer term effect to *lower* the rate of unemployment. Interestingly, a shock to the unemployment rate has a negative effect on the NFCI (middle panel at the bottom). We suspect the latter result represents an easing of monetary policy due to a rise in the unemployment rate, which by extension could explain why unemployment ultimately declines following an initial shock to the unemployment rate. Finally, the third column represents the effect of a shock to the NFCI. A one standard deviation change in the NFCI (a worsening of financial conditions) results in a sharp short-term decline in real GDP growth and a persistent rise in the rate of unemployment. These effects are, of course, in line with economic theory and the motivation for constructing such indexes. The bottom right panel might suggest that worsening financial conditions are not short-lived.

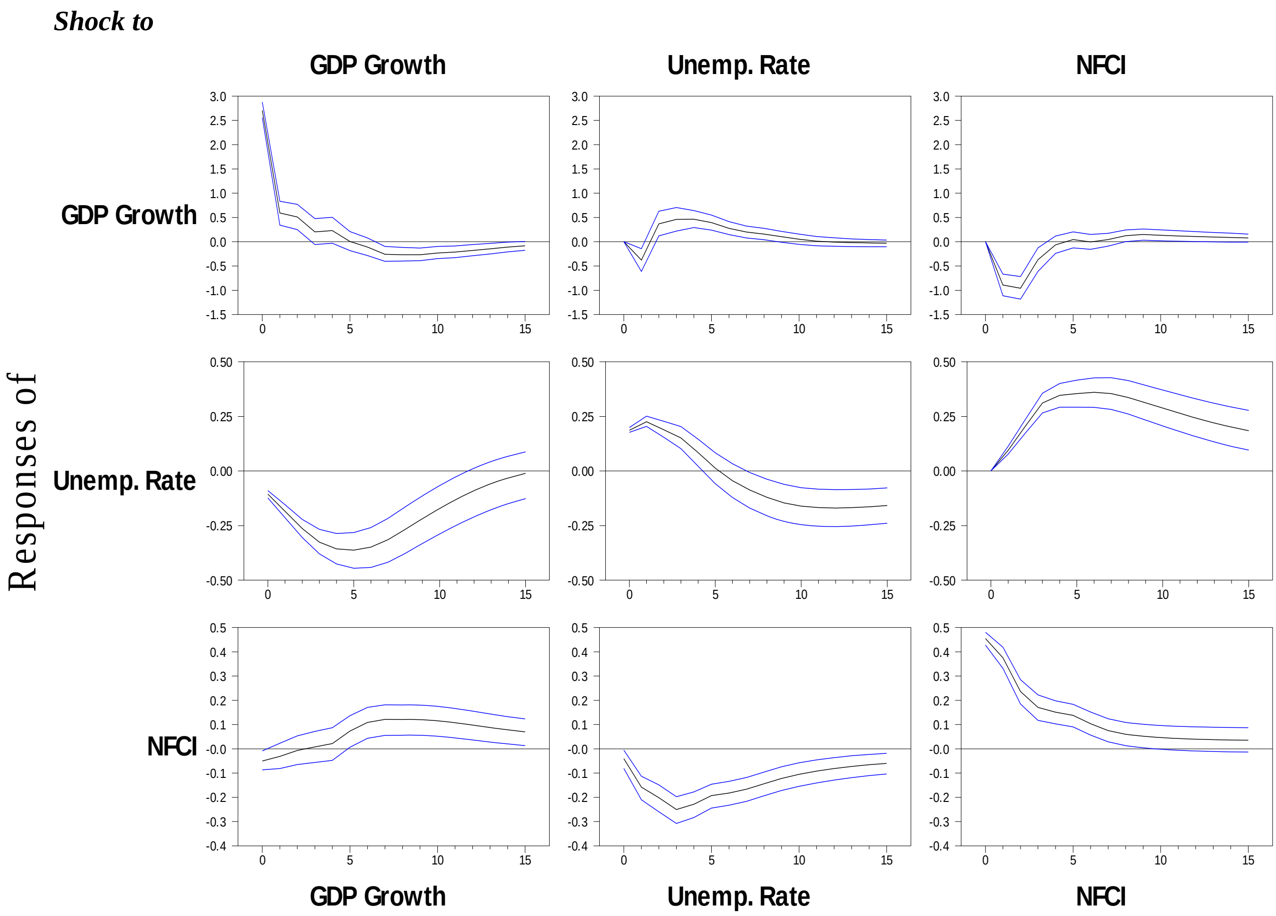

Figure 2 Impulse Response Functions

4.2 Forecasts

Table 4 contains out-of-sample forecasts for all three variables for six years, based on the data available at the time of this writing. Though the model predicts the absence of stress, most forecasters would agree that only the GDP growth and the unemployment rate are of primary interest as forecasts.

The GDP growth predictions are for relatively robust growth in the near term, followed by a smooth return near to mean historical rates (the growth rate of real GDP averaged 2.66% over the sample period). Similarly, the model predicts that the unemployment rate will decline slowly near historical averages based on the sample period (the unemployment rate averaged 6.5% over the sample period). Figure 3 contains the same forecasts, with the actual data displayed going back to 2006. Most professional and government forecasts at the time of this writing are predicting considerably slower growth than our model generates. One set of factors in the differences are likely the effects of the so-called “fiscal cliff” and *sequestration* that are current fiscal factors (July-August, 2013) that are not accounted for in our forecasts.

In comparison to forecasts from a model without the financial stress index, the unemployment rate is a bit slower to converge to the historical mean when accounting for financial stress, while the forecasts of the growth rate of real GDP differ very little between the two models (The results of these comparisons are available from the authors on request.).

Table 4 Forecasts from the VAR

Quarter	GDP Growth	Unemployment Rate	NFCI
2013:02	3.07	7.64	-0.64
2013:03	3.20	7.52	-0.54
2013:04	2.96	7.42	-0.53
2014:01	3.01	7.33	-0.59
2014:02	3.28	7.21	-0.62
2014:03	3.48	7.07	-0.61
2014:04	3.47	6.93	-0.59
2015:01	3.38	6.79	-0.57
2015:02	3.30	6.67	-0.54
2015:03	3.22	6.56	-0.51
2015:04	3.14	6.46	-0.48
2016:01	3.05	6.38	-0.44
2016:02	2.97	6.32	-0.41
2016:03	2.90	6.28	-0.39
2016:04	2.85	6.24	-0.36
2017:01	2.81	6.22	-0.34
2017:02	2.77	6.20	-0.32
2017:03	2.75	6.19	-0.31
2017:04	2.73	6.19	-0.29
2018:01	2.71	6.18	-0.28
2018:02	2.70	6.19	-0.27
2018:03	2.69	6.19	-0.26
2018:04	2.69	6.20	-0.26
2019:01	2.68	6.20	-0.25

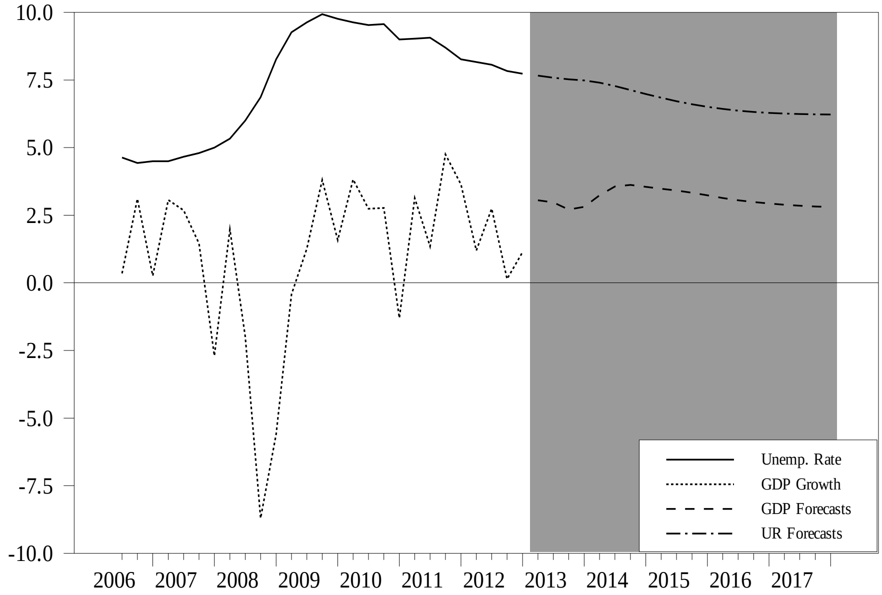

Figure 3 US Forecasts of Unemployment Rate, Real GDP Growth

5. Conclusions

We find that a vector auto regression model including real GDP growth, the unemployment rate, and an index of financial conditions performs as expected in a forecast setting—that is, it produces reasonable forecasts for the macroeconomic variables of interest. Traditional F-tests indicate that a measure of financial conditions can improve forecasts for GDP growth and the rate of unemployment. Since that is one of the primary motivations for such indexes, the results here are encouraging, but not particularly surprising. The financial index we employ is, to our knowledge, the only one of its kind that is available over a sufficient length of time for exercises such as those in the project.

As a further test of the efficacy of indexes of financial stress as important forecasting tools, we plan to produce real time forecasts for the years following the *great recession* from a model that includes the NFCI and a competing model that does not. This will allow us to generate formal tests of the accuracy of the competing forecasts.

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