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MEASURING THE ROLE OF FINANCIAL STRESS ON BUSINESS AND FINANCIAL INDICATORS

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ABSTRACT

Owing to how crises in financial markets have historically been documented, i.e. either with an existence of crisis or not, it has been difficult to understand the real intensity and the impact of financial stress on business and financial indicators. We revisit the issues of how financial stress impacts important business and financial indicators such as commercial bank loans, consumer price index, money base, initial jobless claims, stock market index, US Dollar index, Oil index, and home price index, in order to compare realistic intensity of stress and the degree of transmission amongst variables. We use a relatively new indicator for financial stress; St. Louis Federal Reserve financial stress index (STLFSI). Results from our study indicate STLFSI index as a superior indicator in anticipating short-run changes in Business and Finance activity.

1. INTRODUCTION

The sub-prime mortgage led financial crisis, had devastating impact on global economy. U.S. financial crisis which began in 2007 soon spilled over into a global economic downturn creating significant stress on global financial structure. Over this time period, global financial instruments witnessed considerable volatility in their valuation and an increase in counterparty risk which resulted in higher cost of credit and uncertainty among businesses, households, and financial institutions. It was soon apparent that any ability to predict economic events in such uncertain financial environment will serve as an invaluable tool for market participants and policy makers. Economic and financial indicators are more than ever being followed by economists, analysts, policy makers and even individual in their portfolio allocation and valuation decisions. These indicators also serve as important benchmark to evaluate economic outlook, business cycles and market participant sentiments.

In this paper, we examine the usefulness of a relatively new index for economic outlook, The St. Louis Fed's financial stress index (STLFSI)[1] on a number of important business and financial indicators. Researchers have long been involved in the search for a few key indicators which will predict changes in economic activity. To better understand the underlying linkages between economic indicators and business and financial activity, researchers have analyzed monetary and financial variables to predict economic downturns (Palash and Radecki, 1985); term structure of interest rates and economic activity (Harvey, 1988; Estrella and Gikas, 1991;

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Benjimin and Kuttner, 1993; Bernanke and Blinder, 1992; Hu, 1993); interest rates and macro outcomes (Estrella, 1997); financial variables and recession (Estrella and Mishkin, 1995 and 1998; Stock and Watson, 1989, 1992; Watson, 1991; Reinhart and Reinhart, 1996). There have also been studies conducted to analyze relation between monetary and credit aggregates, and economic activity (for e.g. see, Hostland, Poloz, and Storer, 1988; Milton, 1988; and Muller, 1990).

We in our study offer a different standpoint in this paper by noting that majority of these studies employ standalone economic indicators representing a single aspect of economy in predicting economic or financial activities. To investigate the implications on business and financial indicators, one needs economic indicators which are more comprehensive in their construction. Therefore, we employ a unique index that is constructed by the Federal Reserve Board to analyze the economy which is based on broad range of financial factors, such as interest rates, yield spreads, and other variables focusing on counterparty risk. Our study also presents a unique focus in area of business and finance indicator related research which may have received little attention in the literature, i.e. whether these business and financial indicators react differently in terms of speed and magnitude to increase and decrease in financial stress activity as measured by the STLFSI. Another contribution of our study is the focus it presents on near term relation between the variables of interest. A major criticism of conducting research using economic indicator data is that the indicator announcements reported periodically (which are normally reported on a weekly or a monthly basis) may suffer from a problem of endogeneity. By focusing on a near term relationship in this paper, we minimize this affect of endogeneity.

Inspiration for our paper principally arises from the global financial crisis of 2007-08 and the critical role of interest rate, yield spreads, and counterparty risk in that episode. Therefore an understanding of financial stress and leading business and other financial indicators is important. Results from this study will be of an equal importance for investors and policy makers. Purpose of this study is to assess the short-run relation among the monthly database of St. Louis Fed's Financial Stress Index (STLFSI) on changes in commercial and industrial loans at all commercial banks (BUSLN), consumer (Individual) loans at all commercial banks (CONSLN), real estate loans at all commercial banks (REALLN), monetary base (MONBSE), consumer price index (CPI), initial jobless claims (IJCLM), 10-City residential home price index (SHILPIX), Dow Jones industrial average (DJIA), spot oil price (OIL), and the U.S. exchange rate (TWUSEX). We estimate vector auto regression (VAR) model for these financial indicators over 18 year period. Results from our study indicate that, STLFSI index demonstrates as a superior indicator during the sample period of anticipating changes in business and finance activity; since changes in all included indicators, except CONSLN, are explained by STLFSI.

The remainder of this paper is organized as follows: Section two presents the data and descriptive statistics while section three describes the econometric methodology. Section four presents the empirical findings and section five provides concluding remarks.

2. DATA AND DESCRIPTIVE STATISTICS

We obtain all data in monthly intervals from January 1994 to February 2012. The choice of sample length and frequency of the data is based on availability and to ensure adequate variations in the economic cycle. To measure financial stress, we employ the St. Louis Fed's Financial Stress Index (STLFSI) provided by the Federal Reserve Bank of St. Louis. This index is more comprehensive and overcomes the potential criticisms of focusing solely on one indicator. In combining several indicators, it has a broad coverage as it covers three important areas: (a) interest rates (such as federal fund rate; 2 year, 10 year, and 30 year treasury; and corporate bond yield); (b) yield curve (such as 10 year minus 3-month treasury; corporate bond minus 10 year treasury; 3 month TED spread); and (c) other counterparty risk indicators (such as J.P. Morgan emerging markets bond index, Chicago board options exchange market volatility index, Merrill lynch bond market volatility index).

In order to analyze the effect of financial stress we employ the data for a broad range of business and finance related indicators. In case of outstanding loans held by all commercial banks in the U.S., we have commercial and industrial loans (BUSLN), consumer (individual) loans (CONSLN), and real estate loans (REALLN). We also have monetary base (MONBSE), consumer price index (CPI), initial jobless claims (IJCLM) as other important business activity indicators. Finally for financial indicators we have residential home price index (SHILPIX), Dow Jones industrial average (DJIA), spot oil price index (OIL), and the U.S. exchange rate (TWUSEX). These data are obtained from *Federal Reserve Bank of St. Louis.*

Table 1 reports the descriptive statistics on the period to period change on data of the above- mentioned variables. From the table it can be observed that mean for STLFSI and TWUSEX are all negative while for BUSLN, CONLN, REALLN, MONBSE, CPI, IJCLM, SHILPIX, DJIA and OIL are positive. The maximum for all variables are positive while the minimums are negative. There is significant presence of asymmetry in data which can be observed from skewness (for e.g. BUSLN, CPI, SHILPI, DJIA, OIL, and TWUSEX report a negative skewness or longer left tail). All these indices are known to been impacted —and continued to be impacted— with significant decline in their values since the 2007financial crisis. For e.g., business loans made by commercial banks had significantly dropped following increase in counterparty risk observed in aftermath of the financial crisis. Similarly there was a drop in CPI attributed to the recessionary period also following the 2007 financial crisis. On the other hand positive skewness is observed for STLFSI, CONLN, REALLN, and MONBSE. A large Kurtosis figure (>3) is observed, indicating a relatively peaked distribution. Presence of theses observed Skewness and Kurtosis characteristics further motivate the use of time-series methodology for any result inference. The table also show that the data do not support the supposition that each variable has a normal distribution which is rejected (except for TWUSEX) based on the Jarque-Bera test results, for all variables reporting a p-value = 0.0000.

3. ECONOMETRIC METHODOLOGY

Since these business and financial indicators and financial stress index may act as a system (Brown and Cliff, 2004 & 2005; Lee *et al.*, 2002), we choose the VAR model developed by Sims (1980) as an appropriate econometric approach to investigate the postulated short-run relationships. Moreover, since the unit root tests confirm the series of interest in our paper are stationary we can apply the VAR model.

We express the VAR model as:

Table 1
Descriptive Statistics

Table 1 reports the descriptive statistics for variables of interest. In the table are, St. Louis Federal Reserve stress index (STLFSI), Business loans by all commercial banks (BUSLN), Consumer (individual) loans by all commercial banks (CONSLN), Real estate loans made by all commercial banks (REALLN), Monetary base (MONBSE), Consumer price index (CPI), Initial jobless claims (IJCLM), S&P Shillers 10-city home price index (SHILPIX), Dow Jones industrial average (DJIA), Spot oil price (OIL), and Trade weighted U.S. Dollar index (TWUSEX). All data are sourced from the Federal Reserve Bank of St. Louis.

	STLFSI	*BUSLN*	*CONSLN*	*REALLN*	*MONBSE*	*CPI*	*IJCLM*	*SHILPIX*	*DJIA*	*OIL*	*TWUSEX*
Mean	-0.0034	0.0039	0.0048	0.0061	0.0088	0.002	0.0009	0.0032	0.0056	0.0089	-0.001
Median	-0.2535	0.0061	0.0031	0.006	0.0043	0.002	-0.0029	0.0042	0.0105	0.0182	0.0006
Maximum	5.124	0.0391	0.271	0.0457	0.2427	0.0137	0.3365	0.0186	0.1008	0.2031	0.0647
Minimum	-1.245	-0.0286	-0.0344	-0.0164	-0.0919	-0.0181	-0.2164	-0.022	-0.1641	-0.3367	-0.0478
Std. Dev.	1.0013	0.0099	0.0209	0.0077	0.0292	0.0028	0.0657	0.0088	0.0449	0.0833	0.017
Skewness	2.5113	-0.4604	9.9198	0.8821	4.7398	-1.6902	1.0171	-0.8738	-0.748	-0.7994	-0.022
Kurtosis	11.5541	3.8689	124.564	7.5879	36.5284	16.3628	7.4064	3.4229	4.2962	4.8235	3.6685
Jarque-Bera	893.7875	14.4925	137174.8	218.4543	10976.72	1717.825	213.9526	28.9595	35.4282	53.1766	4.058
Probability	0	0.0007	0	0	0	0	0	0	0	0	0.1315

$$Z(t) = C + \sum_{s=1}^{m} A(s)Z(t-m) + \varepsilon(t) \tag{1}$$

where, $Z(t)$ is a column vector of variables under consideration, C is the deterministic component comprised of a constant, $A(s)$ is a matrix of coefficients, m is the lag length and $\varepsilon(t)$ is a vector of random error terms.

The VAR specification allows the researchers to do policy simulations and integrate Monte Carlo methods to obtain confidence bands around the point estimates (Doan, 1986; Enders, 2003). The likely response of one variable to a one time unitary shock in another variable can be captured by impulse response functions. As such they represent the behavior of the series in response to pure shocks while keeping the effect of other variables constant. Since, impulse responses are highly non-linear functions of the estimated parameters, confidence bands are constructed around the mean response. Responses are considered statistically significant at the 95% confidence level when the upper and lower bands carry the same sign.

It is well known theoretically that traditional orthogonalized forecast error variance decomposition results based on the widely used Choleski factorization of VAR innovations may be sensitive to variable ordering (Pesaran and Shin, 1996; Koop, Pesaran and Potter, 1996; Pesaran and Shin, 1998). To mitigate such potential problems of misspecifications, we employ the recently developed *generalized impulses* technique as described by Pesaran and Shin (1998) in which an orthogonal set of innovations which does not depend on the VAR ordering.

4. ESTIMATION RESULTS

Before proceeding with the main results, we first check the time series properties of each variable by performing unit root tests using Augmented Dickey Fuller (ADF) test (Dickey and Fuller, 1979, 1981). This is done to avoid regressions with spurious results and to detect the presence of unit root. Based on the consistent and asymptotically efficient *AIC* and *SIC* criteria (Diebold, 2003) and considering the loss in degrees of freedom, the appropriate number of lags is determined to be two. In the case of the ADF test, the null hypothesis of non-stationarity is rejected. The inclusion of drift/trend terms in the ADF test equations does not change these results (Dolado, Jenkinson, and Sosvilla-Rivero, 1990). The Unit root test results are reported in table 2. The stationarity in series confirm that there is no conintegrating relation between the series, which implies that series have unique stochastic trends. Given that there is no long-run statistical relationship between STLFSI and other indices, the nature of the near term relationship, which is the purpose of this study can be explored.

We construct the generalized impulse responses from the VAR model to trace the response of one variable to a one-standard-deviation shock to another variable in the system. We employ Monte Carlo methods to construct confidence bands around the mean response (Doan and Litterman, 1986). When the upper and lower bounds carry the same sign, the responses become statistically significant at the 95% confidence level[2].

To analyze the impact of financial stress index on three commercial bank loans indicator categories (i.e. BUSLN, CONLN, and REALLN), we estimate VAR models with two lags

Table 2
Unit Root Results

Table 2 reports the Unit root test for variable of interest. Table 1 reports the descriptive statistics for variables of interest. In the table are, St. Louis Federal Reserve stress index (STLFSI), Business loans by all commercial banks (BUSLN), Consumer (individual) loans by all commercial banks (CONSLN), Real estate loans made by all commercial banks (REALLN), Monetary base (MONBSE), Consumer price index (CPI), Initial jobless claims (IJCLM), S&P Shillers 10-city home price index (SHILPIX), Dow Jones industrial average (DJIA), Spot oil price (OIL), and Trade weighted U.S. Dollar index (TWUSEX). All data are sourced from the Federal Reserve Bank of St. Louis.

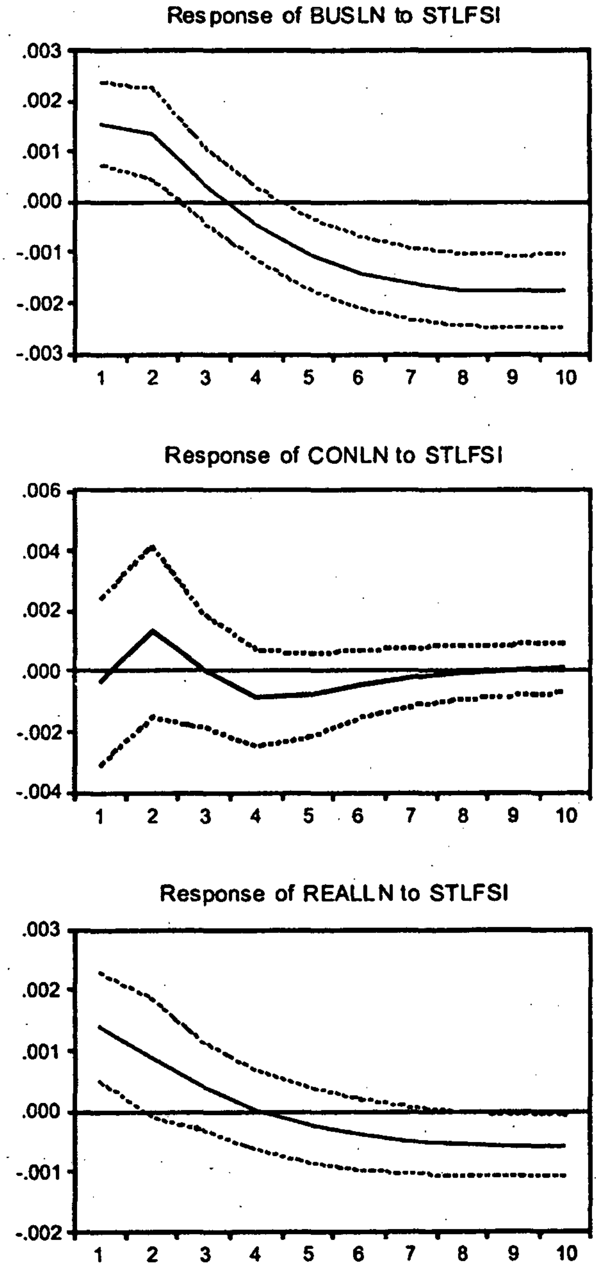
	Augmented Dickey-Fuller	*Phillips-Perron*
	Intercept	*Intercept*
STLFSI	-2.860873	-2.629239
BUSLN	-2.874939	-5.959581
CONSLN	-10.33395	-10.82566
REALLN	-8.507086	-9.252198
MONBASE	-9.255255	-6.365519
CPI	-9.9244	-9.181755
IJCLM	-20.66298	-20.41991
SHILPIX	-8.519835	-14.21136
DJIA	-14.11339	-14.13584
OIL	-11.50196	-11.50196
TWUSEX	-10.44806	-10.31605
1% level	-3.460596	-3.460453
5% level	-2.874741	-2.874679
10% level	-2.573883	-2.57385

each. The impact of financial stress index is observed significant for BUSLN and REALLN. The response for BUSLN is positive and significant for 2 time periods and then becomes negative and significant from period 3 onwards. These results are an evidence of BUSLN reducing as STLFSI increases, i.e. this may be because of increase in counterparty risk premium demanded by commercial banks. Also this is amplified by a lack of willingness on part of businesses to borrow and build high interest debt levels during uncertain times. A similar result is observed for REALLN, the response is positive and significant for 3 time periods and then becomes negative and significant from period 4 onwards, i.e. as STLFSI increases, REALLN reduces from period 4 onwards. This can be explained by the fact that there is inter-ruption to the normal functioning of financial markets which in turn also increases uncertainty about fundamental value of assets, such as residential homes. This reduces the demand for consumer real estate and consumer real estate loans from commercial banks. We don't observe any significant impact on consumer (individual) loans at commercial banks.

Now we turn our attention towards other economic indicators, i.e. CPI, IJCLM and MONBSE. The response for CPI is negative and significant for 3 time periods and then becomes insignificant. This is clearly evidence of CPI reducing with an increase in STLFSI. The CPI measures average change over time in the prices for a market basket of consumer goods and services. With increase in financial stress, the economic conditions promote less spending on part of consumers which is reflected in the drop in CPI index. We also observe rise in initial jobless claims with increase in financial stress index, IJCLM (impact of STLFSI is positive and

Figure 1: Response to St. Louis Financial Stress (STLFSI) Index for Variables of Interest*

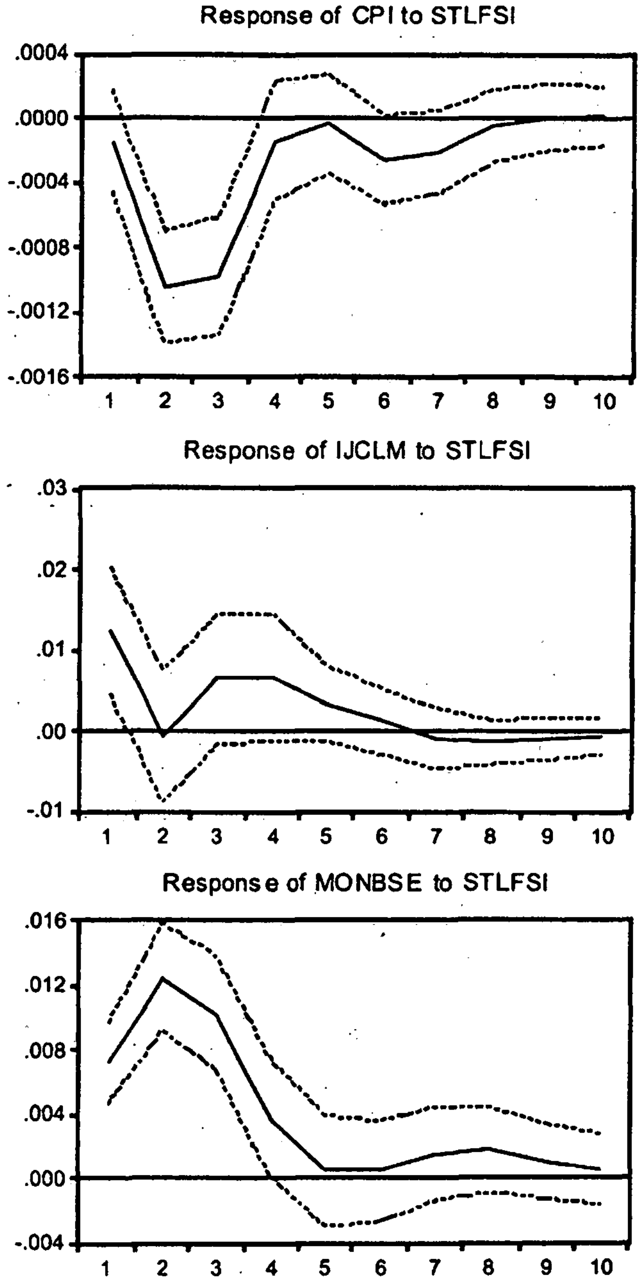
Figure 1 shows the responses to St. Louis financial stress index for variables of interest. In the figure are U.S. business loans at all commercial banks (BUSLN), U.S. consumer loans at all commercial banks (CONLN), and U.S. consumer real estate loan at all commercial banks (REALLN).



*The dashed lines on each graph represent the upper and lower 95% confidence bands. When the upper and lower bounds carry the same sign the response becomes statistically significant.

Figure 2: Response to St. Louis Financial Stress (STLFSI) Index for Variables of Interest*

Figure 2 shows the responses to St. Louis financial stress index for variables of interest. In the figure are U.S. consumer price index (CPI), U.S. initial jobless claims (IJCLM), and U.S. money based (MONBSE).



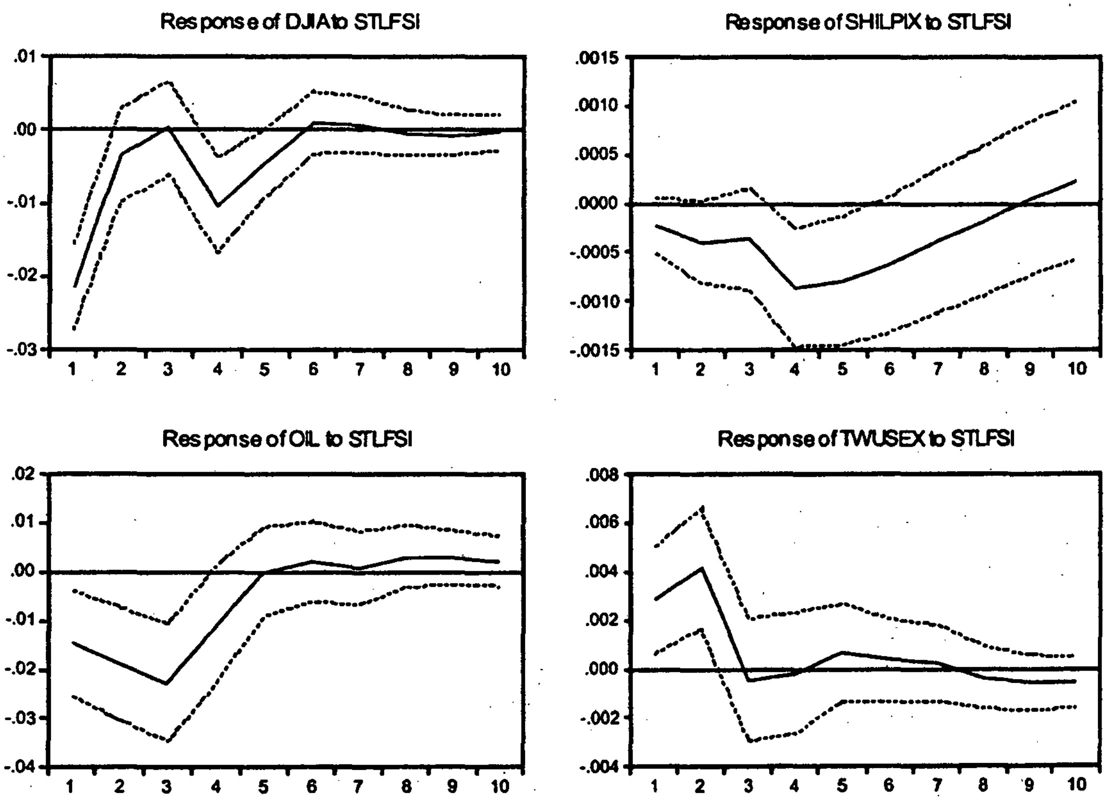
*The dashed lines on each graph represent the upper and lower 95% confidence bands. When the upper and lower bounds carry the same sign the response becomes statistically significant.

significant for 1 time period and then becomes insignificant. For case of MONBSE; we notice the response to be positive and significant for 3 time periods. This can be explained as a result of expansionary monetary policy initiated by the Federal Reserve during such times to infuse liquidity as financial stress increases.

Finally, we include important financial indicators, i.e. DJIA, SHILPIX, OIL and TWUSEX in our model. The response for DJIA is negative and significant for 1 time periods and then becomes insignificant and then is again observed negative and significant in time period 3 and 4. The increase in financial stress and implied volatility results in an increase in uncertainty among investors about the fundamental values of financial assets, i.e. stocks and representing firms. The fundamental value of a stock is the present discounted value of future cash flows, such as dividends and prospects of capital growth from owing the stock. Increased uncertainty about these future cash flow values typically translates into greater volatility in the market

Figure 3: Response to St. Louis Financial Stress (STLFSI) Index for Variables of Interest*

Figure 2 shows the responses to St. Louis financial stress index for variables of interest. In the figure are Down Jones Industrial Average (DJIA), 10-city U.S. residential home price index (SHILPIX), and Spot oil price (OIL) and Trade weighted U.S. dollar exchange rate index (TWUSEX).



*The dashed lines on each graph represent the upper and lower 95% confidence bands. When the upper and lower bounds carry the same sign the response becomes statistically significant.

prices of the stock. We also observe a delayed response (significant and negative response in time period 3 and 4) for SHILPIX. This result follows the same explanation as for DJIA which is market uncertainty, and lower demand among market participant for residential homes lead to a drop in home price index value. We had observed a similar response in real estate loans at all commercial banks supporting this finding for U.S. 10-city home real estate values. For OIL we observe a negative and significant response for 4 time periods. It is well know that the energy demand drops in anticipation of lower demand in a weakening economy. Given the CPI dropped with an increase in STLFSI index, this result is not at all surprising. However the reaction in case of OIL is observed significant and immediate, whereas for CPI it was delayed response. Finally for TWUSEX we observe a positive and significant response for 2 time periods. As financial stress leads to uncertainty, investors move to safer investments such as the U.S. Dollar, U.S. treasuries, and precious metals.

5. CONCLUSIONS

The financial crisis of 2007-08 has yet again got academicians and practitioners to focus on idea of using financial and economic indicators to understand changes in economic conditions. In this paper we offer a different standpoint, using a relatively new index which measure financial stress for the U.S. economy, STLFSI (St. Louis Federal Reserve financial stress index). We analyze the impact of STLFSI on several business and finance indicators, such as commercial and industrial loans at all commercial banks (BUSLN), consumer (Individual) loans at all commercial banks (CONSLN), real estate loans at all commercial banks (REALLN), monetary base (MONBSE), consumer price index (CPI), initial jobless claims (IJCLM), 10-City residential home price index (SHILPIX), Dow Jones industrial average (DJIA), spot oil price (OIL), and U.S. exchange rate (TWUSEX). Results from our study indicate that STLFSI has significant, albeit varying impact on all indicators of our study, except CONSLN which does not report a significant response. Thus the STLFSI index has demonstrated to do be a superior indicator during the sample time period in anticipating changes in a host of Business and Finance activity indicators. These findings suggest that the STLFSI can be a useful tool for academicians and market participants, especially during uncertain times.

Notes

2. The St. Louis Fed's Financial Stress Index (STLFSI) is based on 18 weekly data series. The actual index is constructed using a principal components analysis, which is a statistical method of extracting factors responsible for the comovements of the 18 variable group. It is assumed that financial stress is the primary factor influencing this comovement, and by extracting this factor (the first principal component) financial stress index can be created (St. Louis Fed, 2012, available at: http://research.stlouisfed.org/publications/net/NETJan2010Appendix.pdf).

3. Sims (1980) suggests that autoregressive systems like these are difficult to describe succinctly. Especially, it is difficult to make sense of them by examining the coefficients in the regression equations themselves. Likewise, Sims (1980) and Enders (2003) show that the *t*-tests on individual coefficients are not very reliable guides and therefore do not uncover the important interrelationships among the variables. Sims (1980) recommends focusing on the system's response to typical random shocks i.e., IRFs. Given these theories, we analyze the relevant IRFs and do not place much emphasis on the estimated coefficients of the VAR models.

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