A Reexamination of Real Stock Returns, Real Interest Rates, Real Activity, and Inflation: Evidence from a Large Dataset

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Abstract

Using the informational sufficiency procedure from Forni and Gambetti (2014) along with data from McCracken and Ng (2014), we update the results of Lee (1992) and find that his Vector Autoregression (VAR) is informationally deficient. To correct this problem, we estimate a Factor Augmented VAR (FAVAR) and analyze the differences once informational deficiency is corrected with an emphasis on the relationship between real stock returns and inflation. In particular, we examine Modigliani and Cohn's (1979) inflation illusion hypothesis, Fama's (1983) proxy hypothesis, and the "anticipated policy hypothesis." We find that the "anticipated policy hypothesis" is the most plausible explanation for our results.

Key words: Informational Sufficiency, FAVAR, Stock Returns.
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1. Introduction

The emergence of large datasets over the past decade has allowed researchers to incorporate more information in empirical analysis than ever before. Many relationships reported in previous studies could potentially be misleading or incorrect if relevant information is missing. Structural Vector Autoregressions (SVARs) have been standard for econometric analysis ever since first being introduced in Sims (1980). However, a crucial assumption in any SVAR model is that all relevant information (i.e. a sufficient number of variables) is accounted for within the VAR. Hansen and Sargent (1991), Lippi and Reichlin (1993), (1994), and Chari et al. (2008) show that if all relevant information is not included, the VAR can lead to incorrect conclusions. To test whether all relevant information is included in a VAR, Forni and Gambetti (2014) propose an informational sufficiency test along with a way to correct for a deficient VAR.

One relationship that has been explored extensively using SVARs is the relationship between real economic activity, inflation, and real stock returns. Originally, Fama (1981, 1983), based on a money demand model, suggested a negative association between inflation and real economic activity in conjunction with a positive association between stock returns and real economic activity leads to a spurious negative relationship between stock returns and inflation. Subsequently, many empirical studies have suggested that that the observed negative stock return–inflation relation is not a direct causal relation but rather reflects other fundamental relationships in the economy (Lee 1992). Another strand of literature suggests that the stock return-inflation relationship depends on whether the source of inflation is derived from supply or demand factors (Geske and Roll, 1983; Danthine and Donaldson, 1986; Lee, 1989). The negative relationship between asset returns and inflation may exist due to the source of inflation being related to nonmonetary factors such as real output shocks (Danthine and Donaldson, 1986; Stulz, 1986; Marshall, 1992; Bakshi and Chen, 1996).

Related, Hess and Lee (1999) build upon the SVAR approach in Lee (1992) and use a SVAR model to identify aggregate demand and supply shocks that drive the stock return–inflation relation. Aggregate demand shocks drive a positive relationship between asset returns and inflation while aggregate supply shocks primarily result in a negative relationship. Hess and Lee (1999) report that aggregate demand shocks dominate in the pre-war period whereas aggregate supply shocks dominate in the post-war period. Lee (2010), using a SVAR, extends the Hess and Lee (1999) two regime framework to demonstrate that the Modiglinani and Cohn (1979) inflation illusion hypothesis is not compatible with pre-war data.

The primary aim of this paper is to update Lee's (1992) seminal paper which was one of the first to use a SVAR to examine the relationship between inflation and asset returns. Using the informational sufficiency procedure of Forni and Gambetti (2014) along with data from McCracken and Ng (2014), we update the results of Lee (1992) using generalized impulse responses and generalized variance decompositions to demonstrate the importance of controlling for macroeconomic factors in a VAR.

The central problem in VAR analysis is that the number of estimated parameters in a VAR expands quickly when additional variables are included. This often leads to only a subset of relevant variables being used in the analysis. As Forni and Gambetti (2014, page 124) point out, "The basic problem is that, while agents typically have access to rich information, VAR techniques allow a limited number of variables to be handled. If the econometrician's information set does not span that of the agents, the structural shocks are non-fundamental and cannot be obtained from a VAR."

Fortunately, the emergence of large data sets such as the one organized by McCracken and Ng (2014) and Factor Augmented VARs provide the framework for uncovering true causal relationships between variables. The procedure in Forni and Gambetti (2014) involves estimating the principal components of a large data set containing all available macroeconomic information and testing whether the estimated principal components Granger cause the other variables in the VAR. If the principal components Granger cause the other variables, the original VAR is deemed insufficient if the principal components are not included in the VAR. In order to implement this procedure the econometrician first needs a large dataset. For our analysis we use the dataset created by McCracken and Ng (2014).

McCracken and Ng (2014) develop a large, monthly dataset that has several appealing features. The dataset can be updated in real-time using the FRED database, and the dataset is publicly available allowing for simpler replication of empirical analysis. McCracken and Ng's (2014) dataset is perfectly suited for our analysis since Lee (1992) uses monthly data to determine causal relationships between asset returns, real activity, interest rates, and inflation. By combining the dataset in McCracken and Ng (2014) with the methodology in Forni and Gambetti (2014), we replicate Lee's (1992) seminal *Journal of Finance* article and update the conclusions once we control for the omitted macroeconomic factors. In addition, we examine three of the most popular hypotheses to explain the negative real stock return-inflation relationship. We do not believe our results provide plausible evidence for Modigliani and Cohn's (1979) inflation illusion hypothesis or Fama's (1983) proxy hypothesis. Instead, we find evidence for the "anticipated policy hypothesis" of Park and Ratti (2000) which is a variant of Geske and Roll (1983).

The rest of the paper proceeds as follows. In Section 2, we replicate the results in Lee (1992) and estimate the model over a new sample period, 1960 to 2014. Section 3 looks at the tests for informational sufficiency and explains our methodology using the Forni and Gambetti (2014) testing procedure with the McCracken and Ng (2014) dataset. The following section — Section 4 — lays out the procedure for producing generalized impulse responses and variance decompositions. Section 5 shows our results. Due to the fact that our results do not support either the inflation illusion hypothesis or the proxy hypothesis, we estimate an additional FAVAR in Section 6. Section 7 concludes.

2. Lee's (1992) Model

We use the model of Lee (1992) as our baseline. However, because the McCracken and Ng (2014) monthly dataset begins in 1960, we estimate Lee's (1992) model over the 1960 – 2014 time period. Thus, while some comparisons to Lee (1992) will be made, our primary comparison will be between an estimated SVAR with principal components and one without principal components.

To begin, we obtain data from the Federal Reserve Economic Data (FRED) database. All variables are defined as in Lee (1992).[1] In order to calculate real stock returns and real interest rates, we follow Lee (1992) and estimate the one-step-ahead forecast of inflation based upon the following four variable VAR:

$$Z_t' = \sum_{i=1}^{p} \Phi_{i,t} Z_{t-1}' + \varepsilon_t \tag{1}$$

where Z_t'= [SR_t, IR_t, IPG_t, INF_t]. SR and IR are *nominal* stock returns and *nominal* interest rates while IPG and INF are the growth rate of industrial production and the rate of inflation.

[1] Whereas Lee (1992) uses the one-month T-Bill rate, we use the three-month T-Bill rate due to its data availability.

In order to generate the one step ahead forecast, we estimate (1) using the Kalman filter so that the coefficients in the matrix $\Phi_{i,t}$ are allowed to update as our data window expands. Put another way, the "states" in our SVAR will be the coefficients which will be updated sequentially as the dataset expands so that the coefficients in (1) are allowed to vary with time. As such, the measurement equations will be

$$Z_t' = \sum_{i=1}^{p} \Phi_{i,t}\, Z_{t-1}' + \varepsilon_t \tag{2}$$

where the state vectors follow a random walk:

$$\Phi_{i,t} = \Phi_{i,t-1} + v_t \tag{3}$$

and ε_t and v_t are independent.

As in Lee (1992), we subsequently subtract the inflation forecast from the nominal stock returns and nominal interest rates to obtain the real variables and estimate the following model:

$$Z_t = \sum_{i=1}^{p} \Phi_i\, Z_{t-1} + \varepsilon_t \tag{4}$$

such that Z_t'= [RSE$_t$, RINT$_t$, IPG$_t$, INF$_t$] where RSE, RINT, IPG, and INF are real stock returns, real real interest rates, the growth rate of industrial production, and the rate of inflation, respectively. $\varepsilon_t \sim (0, \Sigma)$ is a vector of independent and identically distributed error terms.

3. Informational Sufficiency and FAVAR Methodology

To begin Section 3, we implement the procedure outlined in Forni and Gambetti (2014) to test whether Lee's (1992) model over the 1960 – 2014 time period is informationally sufficient. As noted in Forni and Gambetti (2014), a necessary requirement for innovation accounting is that the variables used within the VAR convey all the pertinent information. The testing procedure is comprised of the following three steps. First, obtain a large data set X_t^*

containing all relevant information. Second, set a maximum number of factors *P* and compute the first *P* principal components. Third, undertake a multivariate Granger causality test to see if the principal components Granger cause Z_t^* — the variables of interest in the VAR. If the null hypothesis of no Granger causality is rejected, Z_t^* (the VAR) is not sufficient, and Forni and Gambetti (2014) recommend estimating a FAVAR with the *P* principal components added to the original VAR. If we fail to reject the null hypothesis, than the VAR is informationally sufficient. If informational sufficiency is rejected, including the factors in the VAR such that it becomes a FAVAR ensures that informational sufficiency is achieved.

Consider again the four variable VAR from Lee (1992) over the 1960 – 2014 time period shown in equation (4). In order to test for informational sufficiency in (4), we need to obtain a set of principal components from a sufficiently large macroeconomic data set, X_t^*. As such, we obtain 129 monthly macroeconomic and financial time series from McCracken and Ng (2014)[2]. Rather than arbitrarily setting the number of factors in the dataset, we use the Bai and Ng (2002) criterion to determine the number of factors in the dataset. In utilizing the Bai and Ng (2002) criterion, we allow for a maximum of 10 factors. The PCP1, PCP2, ICP1, and ICP2 criterion all suggest seven factors.[3]

Next, we follow McCracken and Ng (2014) and regress the *i*-th series in the dataset on the set of *r* orthogonal factors in order to reveal information about each factor.[4] As such, for each series in our data set we obtain a R-squared value that displays how much of the variation is

[2] We exclude six of the series to ensure we have a balanced panel. They were COGNO (Orders: Consumer Goods), ANDENOx (Orders: Nondefense Capital Goods), TWEXMMTH (Trade Weight U.S. FX Rate), UMCSENTx (Consumer Sentiment Index), HWI (Help Wanted Index for the U.S), HWIURATIO (Help Wanted to Unemployed Ratio)
[3] The principal components were obtained using the @princomp procedure in the RATS software and were demeaned and standardized.
[4] That is, we treated the factors as dependent variables and added the variables sequentially to measure the changes in the r-squared.

explained by the estimated factors. That is, for $k = 1,\ldots,7$, this produces $R_i^2\,(k)$ for each series i. Thus, the marginal explanatory power of each factor k is $mR_i^2\,(k)^2 = R_i^2\,(k)\; - R_i^2\,(k-1)$ with $k = 2,\ldots,7$ where $mR_i^2\,(1)\; = mR_i^2\,(1)$, and the average importance of factor k is $mR_i{}^2(k)\; = \frac{1}{N}\sum_{i=1}^{N} mR_i{}^2\,(k)$. The factors explain 0.5 or more of the variation in 48 of the 129 series, and between 0.25 and 0.50 of 26 of the 129 series.

Table 1 displays the 5 series with the highest $R_i^2\,(k)$ for each factor k. *N*ot surprisingly, we find very similar results to those in McCracken and Ng (2014). As displayed in Table 1, the series with the highest marginal R-squared from the first factor $mR_i(1)^2$ are primarily real activity/output variables so we interpret factor 1 as a real economic activity factor. Factor 2 is primarily governed by interest-rate spreads; thus, we follow McCracken and Ng (2014) and interpret factor 2 as a forward looking or expectations factor. Factor 3 is primarily an inflation factor given that most of the variables are price indices, and Factor 4 is primarily an interest rate factor. Our results differ a bit from McCracken and Ng (2014) for Factor 5 and 6. Our results suggest that its explanatory power is primarily focused on a combination of unemployment, exchange rates, and monetary variables. Factor 7 is clearly an equity factor.

Table 2 displays the Granger causality tests of the principal components on the variables in (4). First, we test for informational sufficiency as outlined above. As can be seen in Table 2, the principal components from X_t^* Granger cause the variables in Z_t^* indicating that the VAR is not informationally sufficient. Therefore, we follow Forni and Gambetti's (2014) recommendation and add the principal components recursively and repeat the above procedure in order to determine if all the principal components are necessary. As can be seen in Table 2, informational sufficiency is rejected even after adding the components recursively into the system. Therefore, we augment the VAR to include the principal components so that Z_t is now expanded to include the principal components such that

$$Y_t = \sum_{i=1}^{p} \Phi_i \, Y_{t-1} + u_t \tag{5}$$

where Y_t'= [PC_1, PC_2, PC_3, PC_4, PC_5, PC_6, PC_7, RSE_t, $RINT_t$, IPG_t, INF_t] and PC_1, PC_2, PC_3, PC_4, PC_5, PC_6, PC_7 are the principal components. Given the uncertainty regarding the proper ordering of the variables in (5), we choose to undertake generalized impulse responses and generalized variance decompositions.

4. Generalized Impulse Responses and Variance Decompositions

Two econometric tools that were not available to Lee (1992) that are available today are the generalized impulse responses of Koop, Pesaran, and Potter (1996) and the generalized variance decompositions of Diebold and Yilmaz (2012).[5] Diebold and Yilmaz (2012) define the own variance shares as the fraction of the H-step-ahead error variances in forecasting z_i that are due to shocks to z_i for $i = 1,2,\ldots\ldots,N$ and cross variance shares as the fraction of the H-step-ahead error variances in forecasting z_i that are due to shocks to z_{ij} for $i,j = 1,2,\ldots\ldots,N$ such that $i \neq j$.

The H-step-ahead forecast error variance decompositions are

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma e_i)} \tag{6}$$

where Σ is the variance matrix for the error vector ε, σ_{jj} is the standard deviation of the error term for the *j*th equation, $A_h$is a symmetric coefficient matrix, and e_i is the selection vector, with

[5] We opted to use generalized variance decompositions and impulse responses rather than the SVAR of Lee (1992) because of the causal uncertainty regarding the ordering of the variables. However, it should be noted that we tested the informational sufficiency of the Lee (1992) model assuming the SVAR and ordering of the variables as Lee (1992).

one as the *i*th element and zeros otherwise. Because the sum of the elements in each row of the variance decomposition table need not equal 1, Diebold and Yilmaz (2012) normalize each entry in the variance decomposition matrix by:

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \tag{7}$$

such that by construction $\sum_{j=1}^{N} \theta_{ij}^{g}(H) = 1$. Diebold and Yilmaz (2012) then use the volatility contributions from the above generalized variance decompositions to construct the total spillover index as:

$$S^{g}(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} * 100\,. \tag{8}$$

Thus, the total spillover index measures the contribution of volatility shocks across the variables in our VAR to the total forecast error variance.[6]

The directional volatility spillovers Diebold and Yilmaz (2012) subsequently layout provide a decomposition of the total spillovers to those coming from (or to) a particular variable. The volatility spillover by variable *i* to all other variables *j* is

$$S_{i}^{g}(H) = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} * 100\,. \tag{9}$$

Similarly, the directional volatility spillovers transmitted by variable *i* to all other variables *j* is

$$S_{i}^{g}(H) = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}_{ji}^{g}(H)}{N} * 100\,. \tag{10}$$

The net spillover from variable *i* to all other variables *j* is

$$S_{i}^{g}(H) = S_{\cdot i}^{g}(H) - S_{i \cdot}^{g}(H)\,. \tag{11}$$

The net pairwise volatility spillovers, are defined as

[6] However, we do not report the total volatility spillover index since that it is not our primary concern.

$$S_i^g(H) = \frac{\tilde{\theta}_{ji}^g(H) - \tilde{\theta}_{ij}^g(H)}{N} * 100\,. \tag{12}$$

Given the uncertainty regarding the ordering of the variables for identification, generalized impulse responses and variance decompositions have the advantage of producing results that are invariant to the ordering of the variables because of the use of the historically observed distribution of the errors.

5. Results

Figures 1 – 4 display the cumulative generalized impulse responses from estimating Lee's (1992) model over the new 1960 – 2014 time period.[7] Panel A does not include the principal components while Panel B displays the impulse responses from the FAVAR for the same four variables.[8] All of the impulse responses in the VAR and the FAVAR are standardized and accumulated to ease the comparison between the two models.

As can be seen in Figures 1 - 4, the results are substantially different after including the principal components. Note in Figure 1, that a one standard deviation positive shock in real stock returns has a statistically significant 0.1 standard deviation contemporaneous positive effect on real interest rates in Panel A and a positive cumulative effect of 0.25 standard deviations after twenty-four months. However, in Panel B of Figure 1 when the principal components are included, a one standard deviation shock in real stock returns has a -0.1 standard deviation contemporaneous effect on real interest rates and a cumulative -0.15 standard deviation effect after twenty-four months.

[7] The scale for the x-axis for all of the graphs is months.

[8] The lag length of two for the VARs was determined by minimizing the multivariate BIC. The results are similar using lag lengths anywhere between two and six.

The results across the two models are different for output as well. In Panel A, a shock to real stock returns increases output by 0.125 standard deviations contemporaneously and ends up increasing output by 0.6 standard deviations twenty-four months after the real stock return shock. In Panel B the results are much more muted. The real stock return shock does not have a contemporaneous statistically significant effect on output and after twenty-four months the cumulative effect is 0.15 standard deviations. As such, our results do not support a large positive wealth effect of real stock returns on output. The results for the shock to real stock returns on inflation are also different. In Panel A, a positive shock to real stock returns does not have any statistically significant effect on inflation. However, in Panel B of Figure 1 the positive shock in real stock returns has a statistically significant -0.15 standard deviation effect on inflation and the effect is quite persistent over the twenty-four months.

In Figure 2, the shocks to real interest rates have quite different effects in the two models. In Panel A, a shock to real interest rates has a positive contemporaneous 0.10 standard deviation effect on real stock returns and remains positive for the next three months before converging to zero. In Panel B, a shock to real interest rates has no contemporaneous effects on real stock returns but has an increasingly negative effect over the subsequent twenty-four months. The shocks to real interest rates are quite similar and persistent in both models. However, the results on output are different. Note that the positive shock to real interest rates has a contemporaneous positive 0.10 standard deviation effect on output in Panel A and the effect continues to increase until three months after the shock resulting in a cumulative statistically significant 0.5 standard deviation effect after twenty-four months. However, in Panel B, there is no contemporaneous statistically significant effect on output but the cumulative effect on output after twenty-four months is -0.5 standard deviations. The effect of the real interest rate shock on inflation is similar in both Panels A and B.

Figure 3 displays the impulse responses of a shock to output, as measured by industrial production, on the four variables examined in Lee (1992). In Panel A, the shock to output has a statistically significant 0.075 standard deviation increase in real stock returns whereas in Panel B the effect is close to zero. Moreover, in Panel A, when the VAR is not informationally sufficient, the shock to output results in a cumulative 0.15 standard deviation increase in real stock returns whereas in Panel B the cumulative effect of the output shock on real stock returns is not statistically different from zero after twenty-four months. Both the contemporaneous and the cumulative effects of the shock to output is similar in Panels A and B. However, note that the effects of the output shock on inflation are different in Panels A and B. Whereas the shock in output results in a statistically significant 0.10 standard deviation increase in the inflation rate in Panel A, we are not able to conclude that the output shock has statistically significant effects in Panel B. Moreover, the point estimate of the output shock on inflation in Panel B is roughly half of that in Panel A.

Figure 4 displays the generalized impulse responses of a shock to inflation on the variables in the system. As can be seen in Panel A, a shock to inflation has a positive statistically significant effect on real stock returns for the first two months and continues to be significant through month twenty-four. However, in Panel B, the shock to inflation has a -0.15 standard deviation effect on real stock returns and continues to have a negative effect over the subsequent twenty-four months resulting in a cumulative effect of -0.3 standard deviations. Additionally, note that in Panel A the shock to inflation results in a cumulative increase of 0.20 standard deviations in real interest rates, whereas in Panel B there is no statistically significant effect after twenty-four months. Moreover in Panel A, the inflation shock results in a 0.20 statistically significant standard deviation increase in output after twenty-four months, whereas in Panel B there is no statistically significant effect. In fact, the point estimate in Panel B from the inflation shock on output is negative rather than positive.

An interesting and important exercise to undertake at this point is to see whether shocks to the factors that correspond to our four variables of interest have similar results; e.g., do shocks to the output factor cause an increase in our output variable? Do the shocks to the factors produce similar results to shocks to our corresponding variables? Figures 5 and 6 provide the answers to these questions. This exercise is an important check on our results; i.e., one would expect a shock to the real interest rate factor would affect the real interest rate. Figure 5 Panel A shows the impulse responses to shock to the equity factor. Recall using the marginal R-squared in Table 1, the variance in the equity factor is explained best by the return on the S&P 500, followed by the return on the S&P 500 industrials, the S&P 500 dividend yield, the S&P 500 price to earnings ratio, and total housing starts. However, the shock to the equity factor leads to an increase in the real stock returns variable although in the contemporaneous period there is very little change. The other three variables react somewhat differently to the equity factor shock compared to the shock to real stock returns in Figure 1 Panel B. This is likely due to the fact that the equity factor incorporates different information besides purely real stock returns.

Figure 5 Panel B displays the impulse responses to a shock to the real interest rate factor. These results correspond very closely to the impulse responses from a shock to the real interest rate presented in Figure 2 Panel B—the real interest rate increases, real stock returns decrease, output decreases, and inflation increases. Figure 6 Panel A shows how the four variables respond to a shock to the real economic activity factor. The results are largely consistent with the results to a shock in our output variable presented in Figure 3 Panel B—output increases, the real interest rate increases, and inflation increases although it is not statistically significant after 24 months. The effect on real stock returns is different between the two shocks; real stock decrease in response to the shock to real economic activity factor, but increase for a period of time in response to a shock to our output shock. Our final responses from a shock to the inflation factor shown in Figure 6 Panel B confirm the main results from the shock to inflation shown in Figure 4 Panel B—real stock returns decrease, the real interest rate increases, output decreases, and inflation increases. Overall, Figures 5 and 6 provide strong evidence that our analysis in Figures 1 – 4 accurately captures the true relationships between real stock returns, real interest rates, output, and inflation. This can be seen in the response to each of our variables when the corresponding factors are shocked. The responses of all of our variables to shocks to the factors is also very similar to the results discussed in Figures 1 – 4 with the possible exception of the shock to the equity factor.[9] The next part of our analysis discusses generalized variance decompositions.

Table 3 displays the generalized variance decompositions with the principal components included. Note that the last row (entitled *To Others*) and the last column (entitled *From Others*) are summary columns that display the amount of variation that a particular variable explains in other variables (*To Others*), as well as, the amount of variation that the other variables explain (*From Others*). First, it should be noted that we expect the variance decompositions to be dramatically different due to the number of variables included in the FAVAR model versus the Lee (1992) model. The bolded cells are highlighted if a variable explained 5% or more of the variation in a variable.

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[9] Figures of generalized impulse response for all variables and all factors can be obtained upon request of the authors.

As can be seen in row 1, the three variables that explain the most variation in real stock returns are the expectations factor (7.4%), the interest rate factor (10.6%), factor 5 (8.7%), the equity factor (26.5%), and real stock returns itself (37.5%). Somewhat surprisingly, neither the real economic activity factor, the inflation factor, output (IPG), nor inflation explain much of the variation in real stock returns. As can be seen in row 2, the real activity factor explains 6.2% of the variation in real interest rates, with the expectations factor explaining almost 8.5% of the variation, factor 4 explaining 5.5%, and real interest rates itself accounting for 48.7% of the variation. Not surprisingly, note in row 3, that the real economic activity factor explains 26.6% of the variation in industrial production, the expectations factor explains 13% of the variation in industrial production, factor 4 explains 13.1%, factor 5 explains 8.3%, and output explains 32.7% of its own variation. Interestingly, in row 4, the inflation factor explains 39.7% of the variation of inflation, and inflation itself explains 52.1% of its own variation.

The most striking result is that out of the three main conclusions from Lee (1992), only one continues to hold once the principal components are included. The only conclusion which remains valid is that inflation explains little variation in real activity. The other conclusions no longer hold. Real stock returns no longer explain a large portion of real activity, and real interest rates no longer explain a substantial fraction of the variation in inflation.

5.1 Discussion of Results and Relationship to Prior Literature

It certainly should be pointed out that the econometric tools to test for informational sufficiency have only recently been developed. However, our results suggest that it is certainly worth revisiting previous studies that use VARs and SVARs to better understand the relationship between economic activity and real stock returns.[10] We believe that our SVAR suggests the following key results after the inclusion of the principal components. First, real stock returns have a statistically negative effect on real interest rates, a small statistically positive effect on output, and a statistically negative effect on inflation. Second, shocks in real interest rates have a statistically negative effect on output, a statistically negative effect on real stock returns, but a positive statistically significant effect on inflation. Third, shocks to output do not have statistically significant effects on real stock returns but do have statistically positive effects on real interest rates. Finally, shocks to inflation only have a statistically significant effect on real stock returns and on inflation itself.

Many previous empirical studies have documented the negative relationship between inflation and real stock returns post WWII.[11] While many hypotheses have been proposed to explain the relationship, two of the most widely researched have been Modigliani and Cohn's (1979) inflation illusion hypothesis and Fama's (1983) proxy hypothesis. Modigliani and Cohn's (1979) inflation illusion hypothesis essentially states that stock market investors experience an inflation illusion so that as inflation rises, investors discount the expected future earnings (dividends) more because nominal interest rates are higher. As such, stock prices are undervalued when inflation is high and are overvalued when inflation is low. This results in the negative relationship between stock returns and inflation. Fama (1983), on the other hand, argues in the proxy hypothesis that the negative relationship between inflation and real stock returns is spurious and due to the fact that inflation is negatively related to output whereas real stock returns are positively related to output.

[10] For example, see Park and Ratti (2000), Lee (1992, 2003, 2010), and Campbell and Vuolteenaho (2004).

[11] See Nelson and Schwert (1977), Fama and Schwert (1977), and Gultekin (1983).

While our results do confirm the negative relationship between real stock returns and inflation, our results do not really provide support for either Modigliani and Cohn's (1979) inflation illusion hypothesis or Fama's (1983) proxy hypothesis. If the inflation illusion hypothesis were true, one would expect that inflation would explain a substantial portion of the variance decomposition of real stock returns. However, inflation and the inflation factor only explain 3% of the variation in real stock returns. The proxy hypothesis on the other hand posits a negative relationship between output and inflation and a positive relationship between real stock returns and output. Examination of the shocks to output in Figure 3 Panel B do not suggest a statistically significant long-run effect on real stock returns—although the results are positive in months three through twelve—nor a statistically significant effect of output on inflation in the long-run; in fact, the point estimate is positive not negative.

5.2 Time Varying Model

Campbell, Sunderam and Viceira (2009) argue that the effects of macroeconomic variables on real stock returns are likely time-varying.[12] As such, in order to explore that possibility, we estimated a time-varying FAVAR using a rolling 300 month window. As such, our first window spans the 1960 - 1986 time period. However, one complicating issue is that we had 11 variables in the FAVAR. As such, we did not have enough observations in each window to estimate an 11 variable SVAR. That being the case, we estimated the Lee (1992) VAR with the rolling window but added the 7 principal components (2 lags of each principal component) as exogenous variables in the time-varying VAR. Our thinking was that by including the principal components as exogenous variables in the time-varying VAR, the information contained in the principal components would still be present for every window in our time-varying estimation.

[12] We are grateful to the referee for making the suggestion of a time-varying model.

For each rolling window, we standardized the responses as above and then accumulated the impulse responses for 12 months. We subsequently estimated the model 1000 times for each window to obtain one standard deviation confidence intervals. Figures 7 and 8 displays the cumulated 12month impulse responses for the original Lee (1992) variables.

Panel A of Figure 7 displays the time varying impulse responses to a shock in real stock returns. As can be seen in Panel A of Figure 7, shocks to real stock returns have consistently had negative effects on real interest rates; from 1986 - 200, the effect is relatively constant at -0.3 standard deviations and statistically significant. However, the negative effect begins to dissipate beginning in early 2000s and is close to 0 from mid-2004 through mid-2006 but remains negative through 2014. Note that the effects of a real stock return shock on output are 0 until the year 2000 when the effect increases to 0.3 standard deviations (however, it should be noted that the effect is not statistically significant until 2006). The effects of real stock returns on inflation are consistently negative at -0.10 standard deviations but are not really statistically significant until 2008 when the negative effect essentially doubles. The effects of a shock to real interest rates are shown in Panel B of Figure 7. Note that the effect of a shock to real interest rates has no statistically significant effects on the other variables in the system except for inflation beginning after the financial crisis. Note that the effect increase from 0 standard deviations in 2008 to 0.3 standard deviations in 2014. Figure 8 displays the time varying responses to output shocks in Panel A and inflation shocks in Panel B. Note that shocks to output have a statistically significant effect on real stock returns by approximately 2 standard deviations from 1986- 2000, increases to 3 standard deviations and gradually falls until an abrupt fall in 2008 when the effect falls to 1 standard deviation. Somewhat surprisingly, shocks to output do not have a statistically significant effect on real interest rates or inflation rates throughout the time period. Shocks to inflation are shown in Panel B of Figure 8. Note that inflation shocks do not appear to have statistically significant effects on the other variables in the system. The results in Figures 7 and 8 should be interpreted cautiously due to the rolling window used as well as the choice to accumulate the responses for 12 months. However, we do believe they are somewhat informative. First, the examination of the results does indicate that the relationships between the variables in the VAR changed in 2000 during and after the dotcom bust as well as after the financial crisis in 2008. While

6. Monetary Policy FAVAR

A third hypothesis that has seen a substantial amount of attention in the literature is called the "anticipated policy hypothesis."[13] Under this hypothesis, higher inflation leads to expectations of tighter monetary policy and these expectations lead to a decline in the stock market. In order to examine this hypothesis we repeat the methodology outlined above. That is we first consider the following three variable VAR over the 1960 – 2014 time period:

$$X_t = \sum_{i=1}^{p} \Phi_i X_{t-1} + e_t \tag{13}$$

such that X_t'= [RSE_t, $RINT_t$, IPG_t, FF_t, INF_t] where RSE, RINT, IPG, FF, and INF are real stock returns, real real interest rates, the growth rate of industrial production, the federal funds rate, and the rate of inflation. $e_t \sim (0, \Sigma)$ is again a vector of independent and identically distributed error terms. We repeat the Forni and Gambetti (2014) informational sufficiency tests, and Table 4 displays the results. As can be seen, the three variable VAR is not informationally sufficient. As such, we again add the factors recursively and repeat the sufficiency tests. Our results suggest that all the components should be included in the VAR to ensure informational sufficiency. Thus,

[13] As described in Park and Ratti (2000) which builds upon Gesk and Roll (1983), James, Koreisha, and Partch (1985), Kaul (1987) and Patelis (1997) and Thorbecke (1997).

we augment the VAR to include the principal components so that X_t is now expanded to include the principal components:

$$W_t = \sum_{i=1}^{p} \Phi_i \, W_{t-1} + u_t \tag{14}$$

where W_t'= [PC_1, PC_2, PC_3, PC_4, PC_5, PC_6, PC_7, RSE_t, $RINT_t$, IPG_t, FF_t, INF_t] and PC_1, PC_2, PC_3, PC_4, PC_5, PC_6, PC_7 are the principal components.

Figure 9 displays the standardized cumulative generalized impulse responses from estimating (14). Panel A displays the results from a shock to real stock returns. Panel B displays the shocks to the federal funds rate, and Panel C displays the shocks to inflation. The first thing to note, is that if one compares the shocks to RSE and inflation in Panels A and C in Figure 9 to those in Panel B of Figure 1 and Panel B of Figure 4, the results are very similar. We believe the similarity in the results strongly supports the recommendations and results of Forni and Gambetti (2014). In Panel A of Figure 9, a shock in real stock returns does not have a statistically significant effect on the federal funds rate after twenty-four months. However, the point estimate is negative over the corresponding twenty-four months. In Panel B of Figure 9, the shock in the federal funds rate has a statistically significant negative effect on real stock returns. While the contemporaneous effect is zero, beginning three months after the shock, the effect is negative and statistically significant, and after twenty-four months real stock returns are 0.4 standard deviations lower. Note that the shock to the federal funds rate has a 0.2 statistically significant positive effect on inflation one month after the shock but dissipates towards zero and is not statistically significant twenty-four months after the shock. In Panel C, the shock to inflation has a negative effect on real stock returns. However, shocks in the inflation rate do not have statistically significant effects on the federal funds rate.

Given the lack of evidence for the inflation illusion hypothesis and the proxy hypothesis, we interpret our negative significant effects of the federal funds rate on real stock returns as being supportive of the "anticipated policy hypothesis." The fact that shocks to the federal funds rate have positive statistically significant effects on inflation for the first ten months after the shock could be interpreted as the Federal Reserve reacting to contemporaneous inflation but monetary policy affecting inflation with a lag. Based on the results of both of our FAVAR models, we believe that the "anticipated policy hypothesis" seems to be the most plausible of the three hypotheses.

7. Conclusion

A critical assumption in a VAR model is that the included variables are able to account for all relevant information. If all relevant information is not included, the VAR can lead to incorrect conclusions. To test whether all relevant information is included in a VAR, Forni and Gambetti (2014) propose an informational sufficiency test and a procedure to correct a deficient VAR. Using this procedure along with data from McCracken and Ng (2014), we update Lee's (1992) seminal *Journal of Finance* article and find substantially different results once we control for macroeconomic factors. We find that real stock returns have a negative effect on real interest rates, a small positive effect on output, and a negative effect on inflation. Shocks to real interest rates have a statistically negative effect on output, a statistically negative effect on real stock returns, but a positive statistically significant effect on inflation. Shocks to output do not have statistically significant effects on real stock returns but have positive effects on real interest rates. Finally, shocks to inflation only have a statistically significant effect on real stock returns.

Given the negative relationship observed between real stock returns and inflation we review our results considering Modigliani and Cohn's (1979) inflation illusion hypothesis and

Fama's (1983) proxy hypothesis as possible explanations. However, we do not believe either one of these hypotheses are plausible explanations for our results. Thus, we estimate a second FAVAR and examine the "anticipated policy hypothesis" by examining how monetary policy shocks affect real stock returns. We find the "anticipated policy hypothesis" to be the most plausible hypothesis that is consistent with both of the FAVARs. Finally, we believe our paper has significant implications for the macroeconomics-finance literature. We believe that illustrating the differences between the shocks from a VAR that is not informationally sufficient with a FAVAR that is informationally sufficient illustrates the importance of using FAVARs to correctly identify macroeconomic-finance relationships. We believe that ultimately, our paper provides a better understanding about the true relationships between stock returns, interest rates, real activity, and inflation while controlling for many macroeconomic factors. Using information in large datasets, such as McCracken and Ng (2014), can provide new insights into the relationships between macroeconomic variables and financial variables.

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Table 1: Identification of Factors Using Marginal R-Squares ($mR_i(k)^2$)

$mR_i(1)^2$	0.26	$mR_i(2)^2$	0.19	$mR_i(3)^2$	0.36
All Employees: Goods-Producing	0.75591	5 yr. - FFR spread	0.46127	CPI: Commodities	0.81672
All Employees: Manufacturing	0.73388	10 yr. - FFR spread	0.4297	PCE: Nondurable goods	0.79797
All Employees: Durable goods	0.67753	1 yr. - FFR spread	0.39259	CPI inflation	0.76672
IP: Manufacturing	0.66929	6 Mo. - FFR spread	0.33531	CPI: All items less medical care	0.72492
Capacity Utilization: Manufacturing	0.64892	Aaa - FFR spread	0.29401	CPI: All items less shelter	0.695

$mR_i(4)^2$	0.25	$mR_i(5)^2$	0.05	$mR_i(6)^2$	0.05
1-Year T-bond	0.50889	Retail and Food Services Sales	0.08603	IP: Consumer Goods	0.14133
5-Year T-bond	0.50311	Credit to PI ratio	0.04668	Ave. Hourly Earnings: Manufacturing	0.04298
10-Year T-bond	0.46398	Average Duration of Unemployment	0.04627	Total Nonrevolving Credit	0.03456
6-Month T-bill	0.44706	Japan / U.S. FX Rate	0.0451	St. Louis Adjusted Monetary Base	0.03223
Aaa Corporate Bond Yield	0.42458	Ave. Hourly Earnings: Construction	0.02873	Ave. Hourly Earnings: Manufacturing	0.01391

$mR_i(7)^2$	0.15
Return on the S&P 500	0.4717
S&P: Industrials	0.4638
S&P div yield	0.40026
S&P: Price-Earnings Ratio	0.36816
Starts: Total	0.15437

Table 1 displays the 5 series that load the most on the 7 factors. In addition, we have included the R-squared of a series on the factor. For example, the first factor explains 0.751 of the variation in the variable USGOOD. In addition, we have included the marginal R-squared for each factor in explaining the total variation of the data.

Table 2: Forni and Gambetti (2014) Informational Sufficiency Tests (1960 – 2014)

	Principle Components Included in the Sufficiency Test	*Sufficiency Test F-Statistic*
Sufficiency Test 1	All	805.66*** (0.00)
Sufficiency Test 2	PC1	808.42*** (0.00)
Sufficiency Test 3	PC1, PC2	823.47*** (0.00)
Sufficiency Test 4	PC1, PC2, PC3	784.23*** (0.00)
Sufficiency Test 5	PC1, PC2, PC3,PC4	670.54*** (0.00)
Sufficiency Test 6	PC1, PC2, PC3,PC4,PC5	639.79*** (0.00)
Sufficiency Test 7	PC1, PC2, PC3,PC4,PC5, PC6	436.14*** (0.00)

Notes: The null hypothesis for each test is that there is no granger causality. If we cannot reject the null hypothesis, the VAR is informationally sufficient. If the null hypothesis is rejected, the VAR is not informationally sufficient and the VAR must be estimated with the principal components. Each Prob-value is given in parenthesis. * represents significance at the 10% level; ** represents significance at the 5% level; *** represents significance at the 1% level.

Table 3: FAVAR Generalized Variance Decompositions

Variables Explained	By Innovations in											
	Real Activity Factor	Expect. Factor	INF Factor	Interest Rate Factor	Factor 5 (real act. and monetary)	Factor 6 (real act. and monetary)	Equity Factor	RSE	RINT	IPG	INF	*From Others*
RSE	1.3	**7.4**	2	**10.6**	1	**8.7**	**26.5**	**37.5**	2.4	1.5	1.1	*63*
RINT	**6.2**	**8.5**	0.8	**22**	**5.5**	4.1	1.4	0.7	**48.7**	1.7	0.5	*51*
IPG	**26.6**	**13.1**	0.5	2.8	**13.1**	**8.3**	0.7	0.4	1.4	**32.7**	0.3	*67*
INF	0.2	0.2	**39.7**	0.8	0.2	2.1	3.1	0.8	0.4	0.3	**52.1**	*48*
To others	*81*	*79*	*49*	*57*	*48*	*32*	*44*	*8*	*57*	*72*	*50*	

Note: Table 3 displays the generalized variance decompositions from estimating the FAVAR model. The column entitled *From Others* is simply the amount of total variation explained by the other variables in the system excluding its own variation. The *To Others* row explains the amount of total variation that the column variable explains of the other variables in the system excluding itself. The other columns and rows display the generalized variance decompositions.

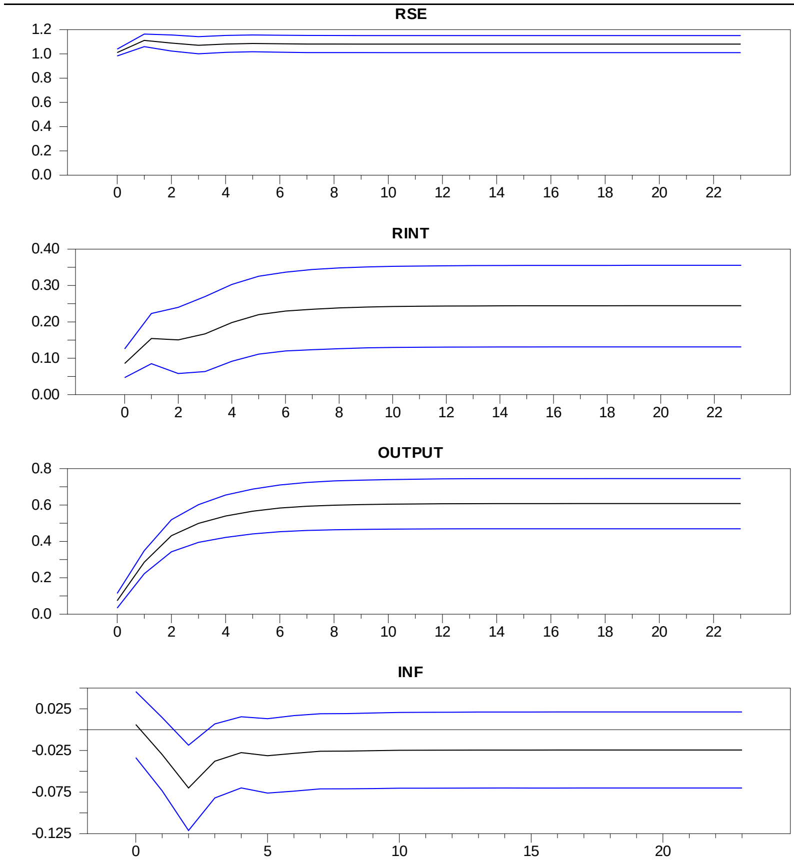
Table 4: Forni and Gambetti (2014) Informational Sufficiency Tests (1960 – 2014)

	Principle Components Included in the Sufficiency Test	*Sufficiency Test F-Statistic*
Sufficiency Test 1	All	617.18*** (0.00)
Sufficiency Test 2	PC1	694.38*** (0.00)
Sufficiency Test 3	PC1, PC2	804.28*** (0.00)
Sufficiency Test 4	PC1, PC2, PC3	791.45*** (0.00)
Sufficiency Test 5	PC1, PC2, PC3,PC4	652.47*** (0.00)
Sufficiency Test 6	PC1, PC2, PC3,PC4,PC5	579.93*** (0.00)
Sufficiency Test 7	PC1, PC2, PC3,PC4,PC5, PC6	418.01*** (0.00)

Notes: The null hypothesis for each test is that there is no granger causality. If we cannot reject the null hypothesis, the VAR is informationally sufficient. If the null hypothesis is rejected, the VAR is not informationally sufficient and the VAR must be estimated with the principal components. Each Prob-value is given in parenthesis. * represents significance at the 10% level; ** represents significance at the 5% level; *** represents significance at the 1% level.

Figure 1: Generalized Impulse Responses of Variables to a Shock in Real Stock Returns

***Panel A**: Lee's (1992) Model using Generalized Impulse Responses *without* Principal Components included in the VAR*



Panel B: FAVAR using Generalized Impulse Responses *with* Principal Components

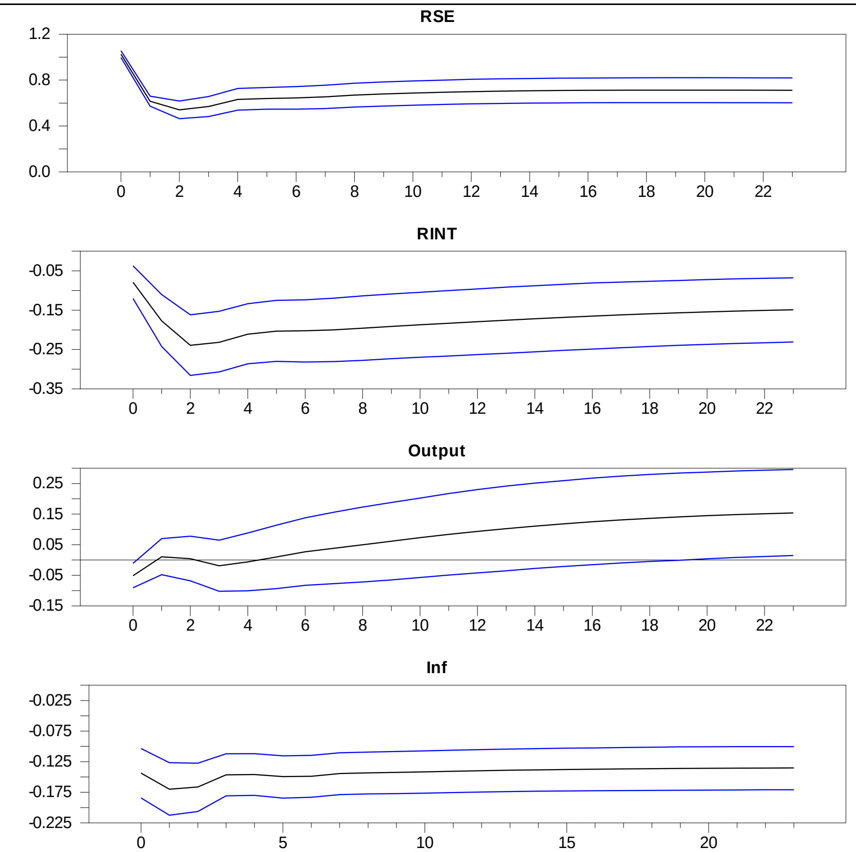


Figure 2: Generalized Impulse Responses of Variables to a Shock in Real Interest Rates

***Panel A**:* Lee's (1992) Model using Generalized Impulse Responses *without* Principal Components included in the VAR

Panel B: FAVAR using Generalized Impulse Responses *with* Principal Components

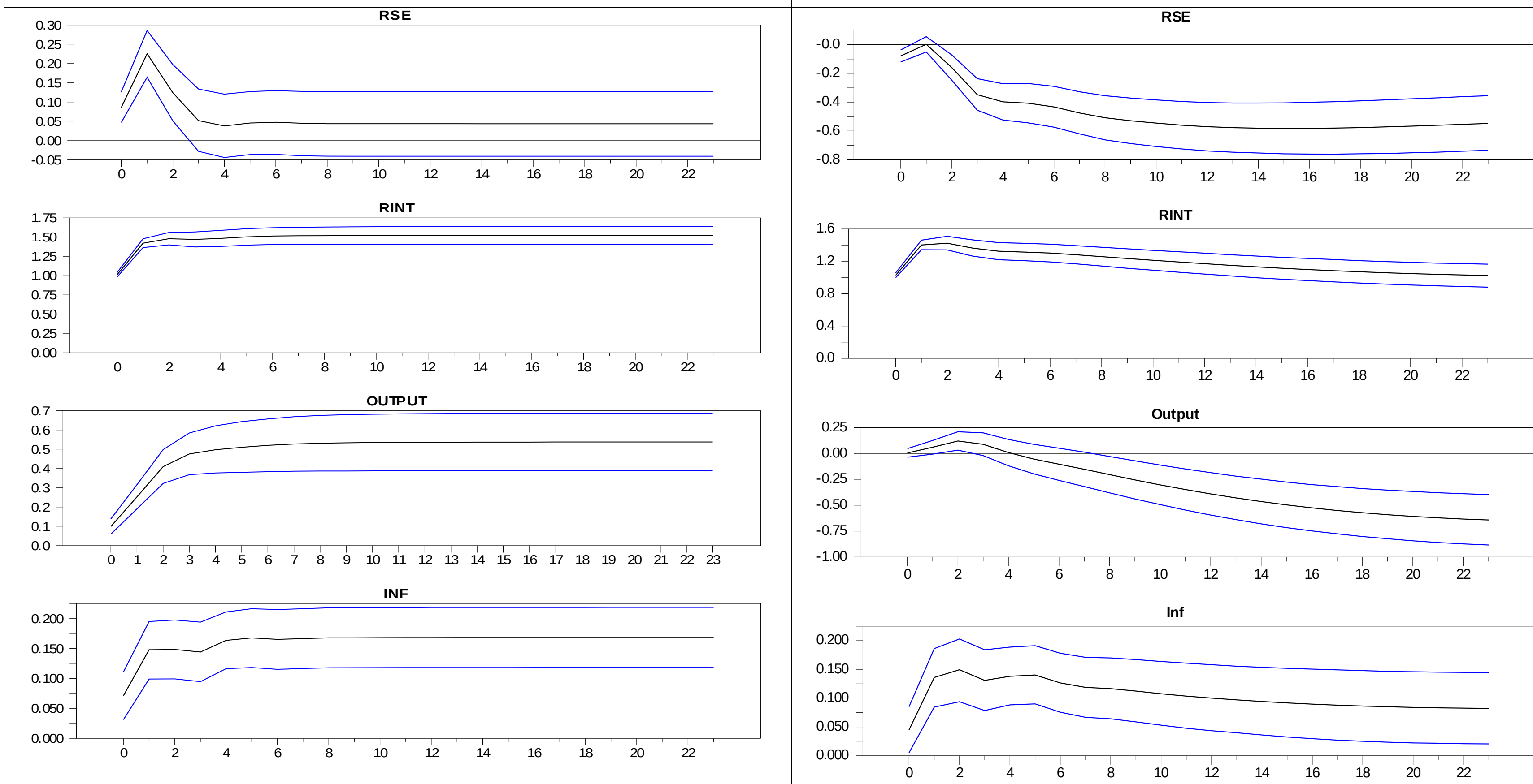


Figure 3: Generalized Impulse Responses of Variables to a Shock in Output

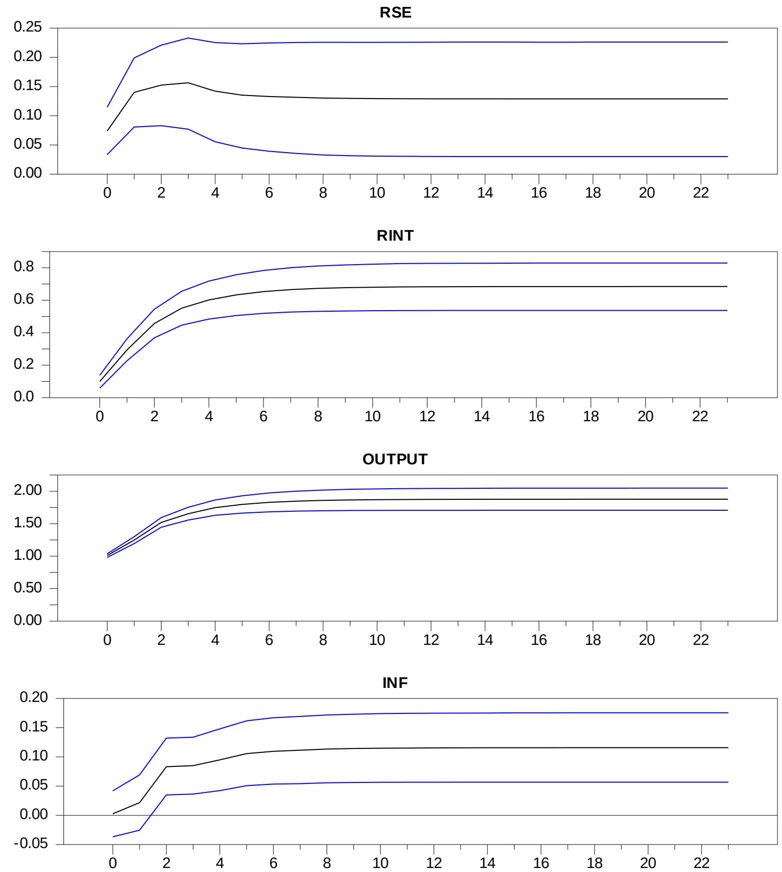
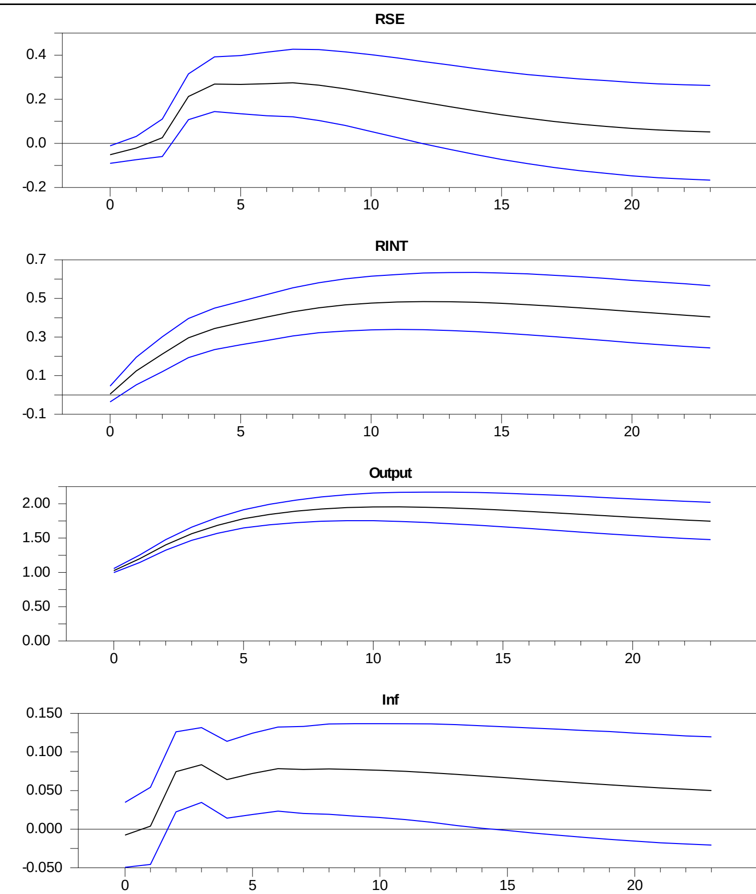
***Panel A**: Lee's (1992) Model using Generalized Impulse Responses *without* Principal Components included in the VAR*	**Panel B:** FAVAR using Generalized Impulse Responses *with* Principal Components
	

Figure 4: Generalized Impulse Responses of Variables to a Shock in Inflation

Panel A: Lee's (1992) Model using Generalized Impulse Responses *without* Principal Components included in the VAR

Panel B: FAVAR using Generalized Impulse Responses *with* Principal Components

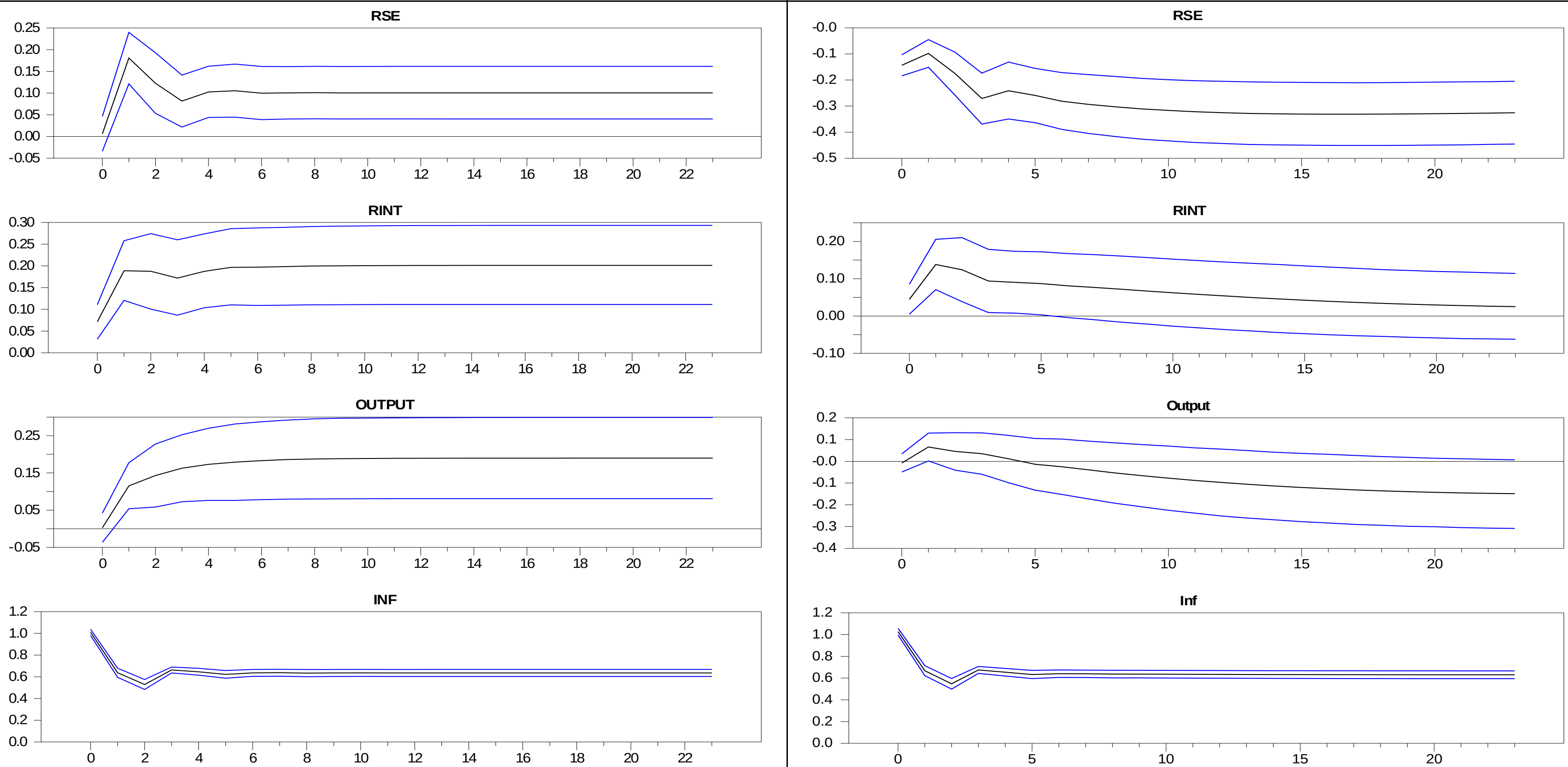
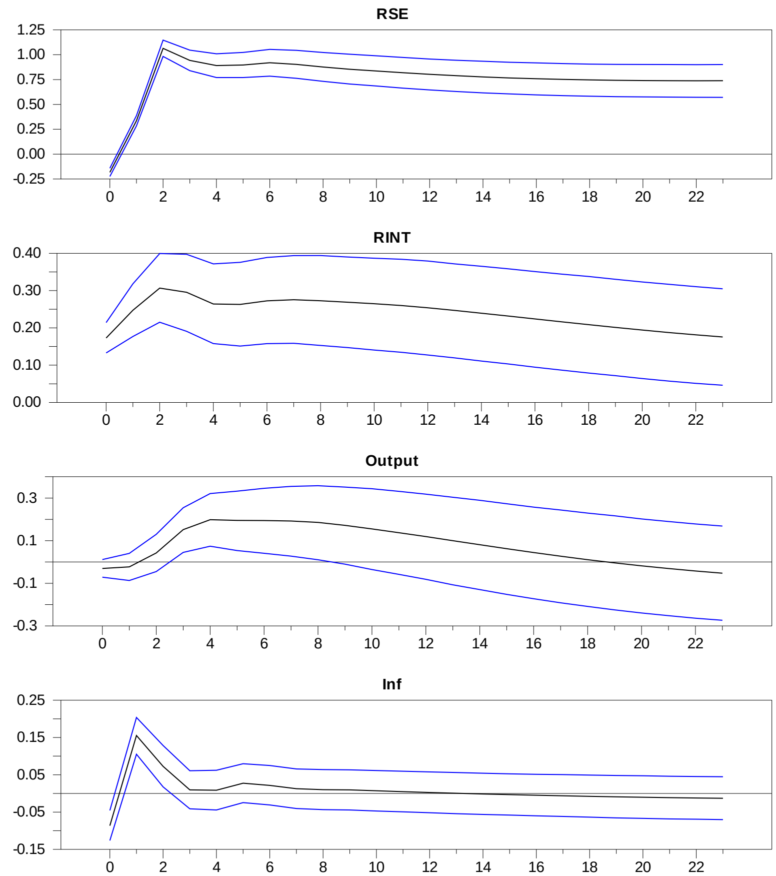


Figure 5: Generalized Impulse Responses of Variables to Shocks to the Factors

Panel A: Responses to a Shock to the Equity Factor



Panel B: Responses to a Shock to the Real Interest Rate Factor

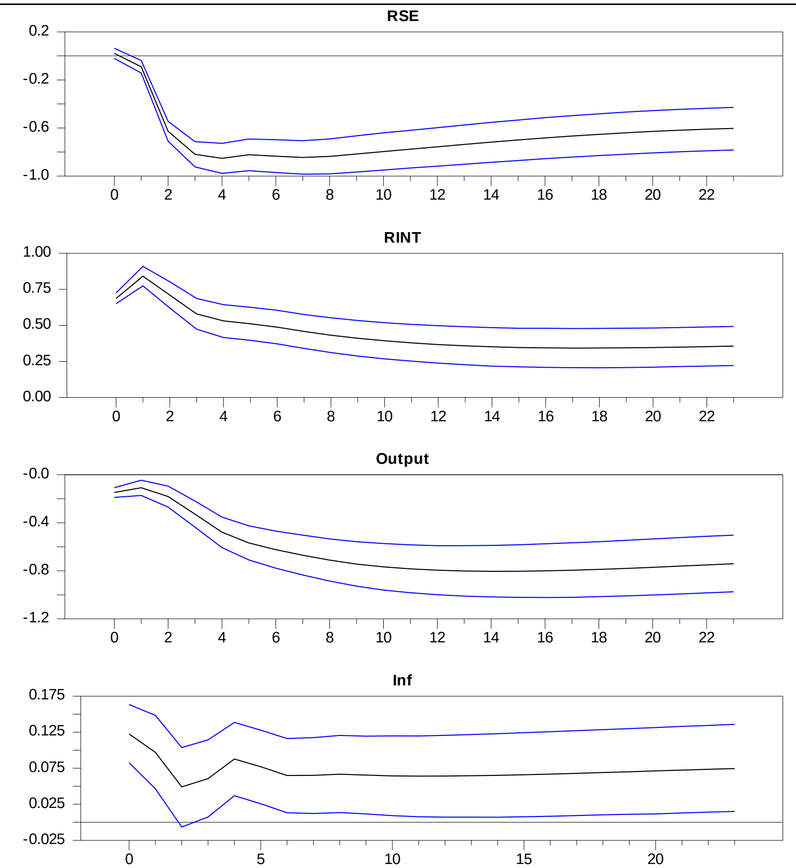
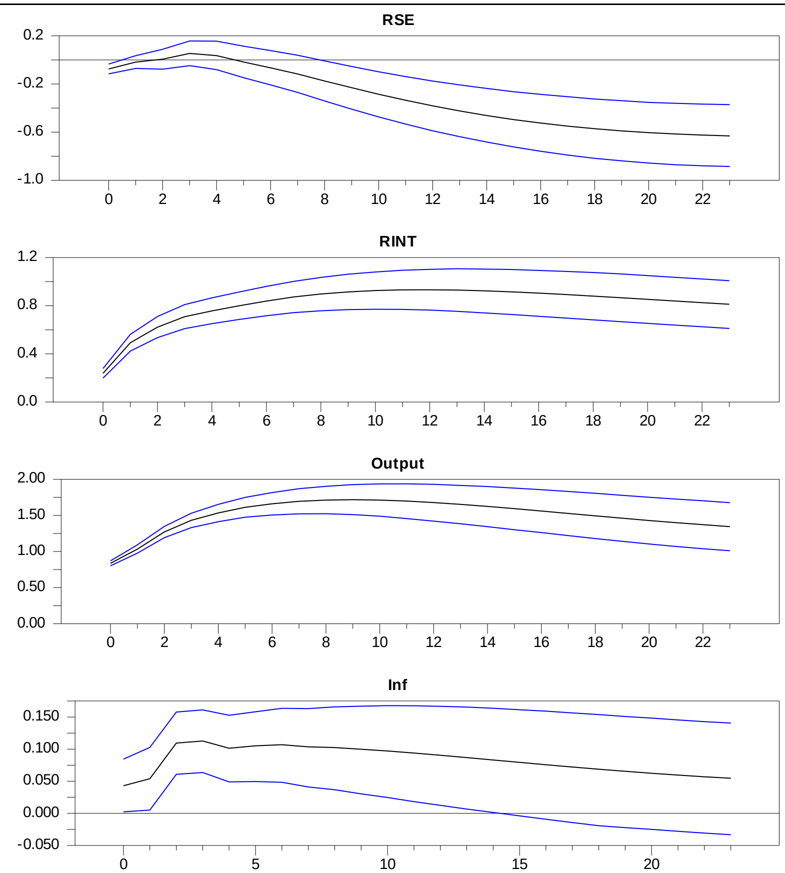


Figure 6: Generalized Impulse Responses of Variables of Shocks to the Factors

***Panel A**:* Responses to a Shock to the Real Economic Activity Factor



Panel B: Responses to a Shock to the Inflation Factor

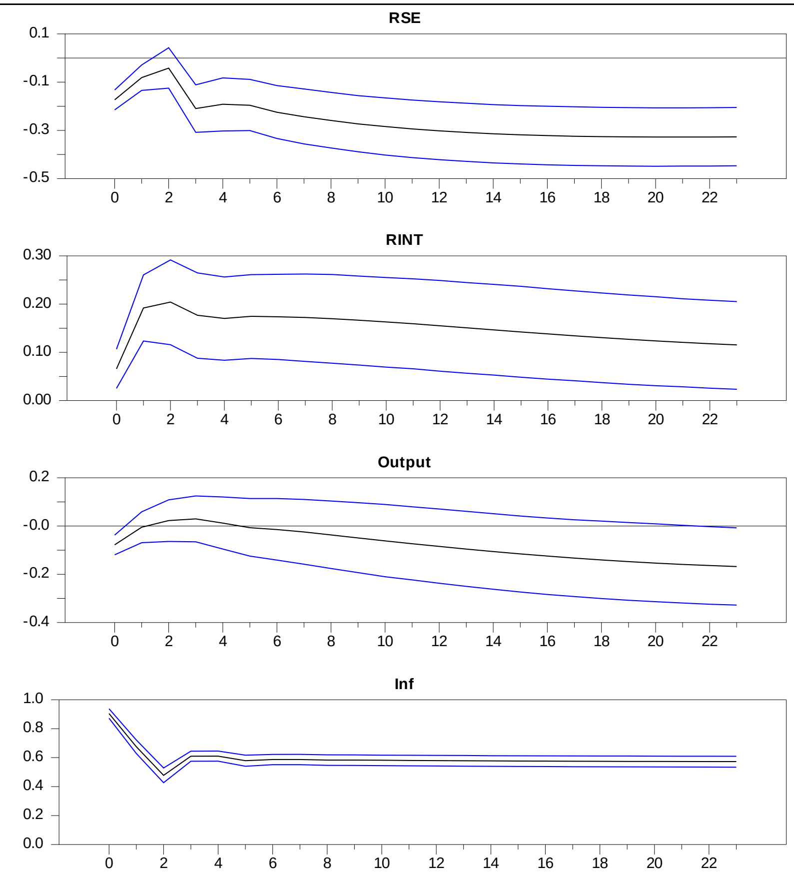
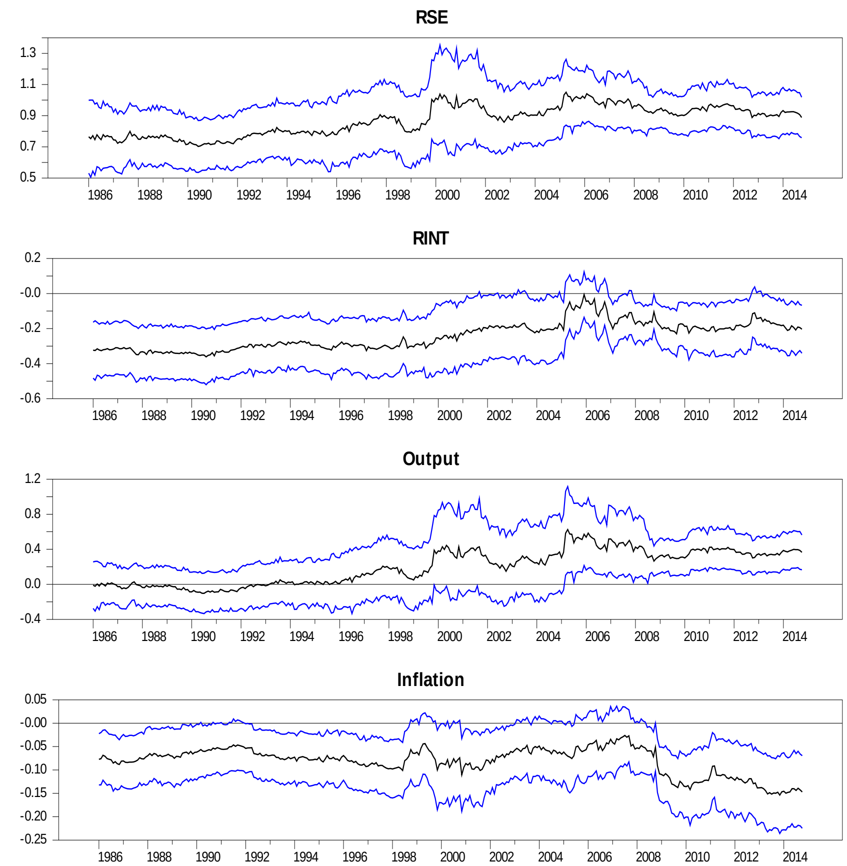


Figure 7: Time Varying 12month Accumulated Generalized Impulse Responses

***Panel A**:* Time Varying Responses to a Real Stock Return Shock



Panel B: Time Varying Responses to a Real Interest Rate Shock

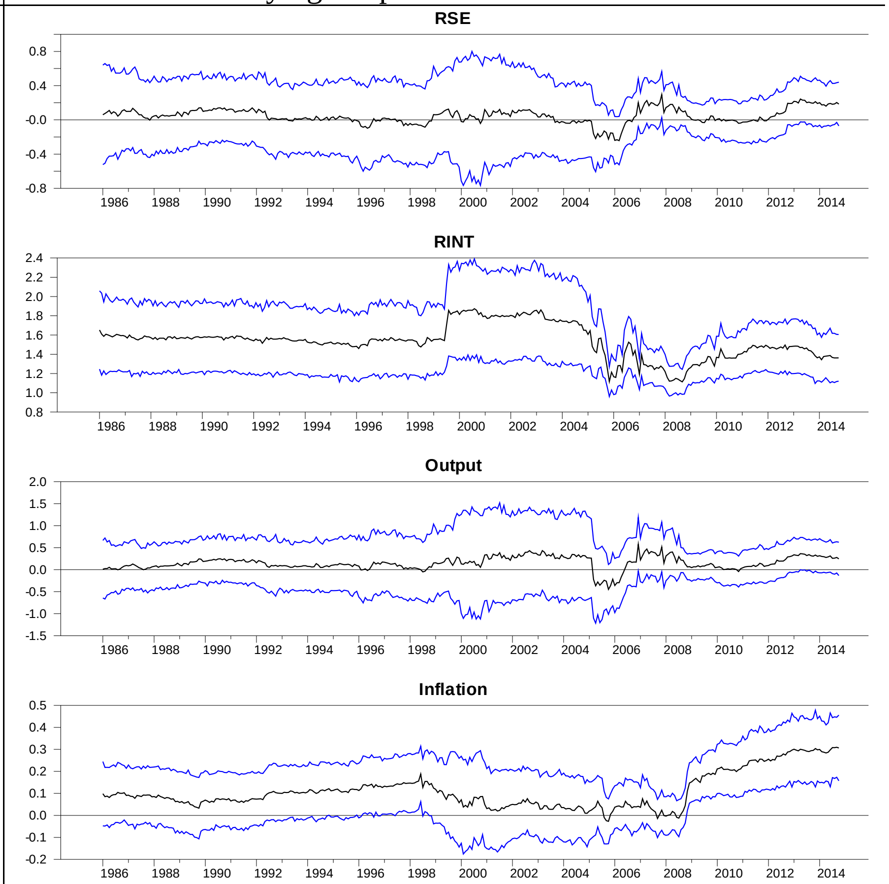
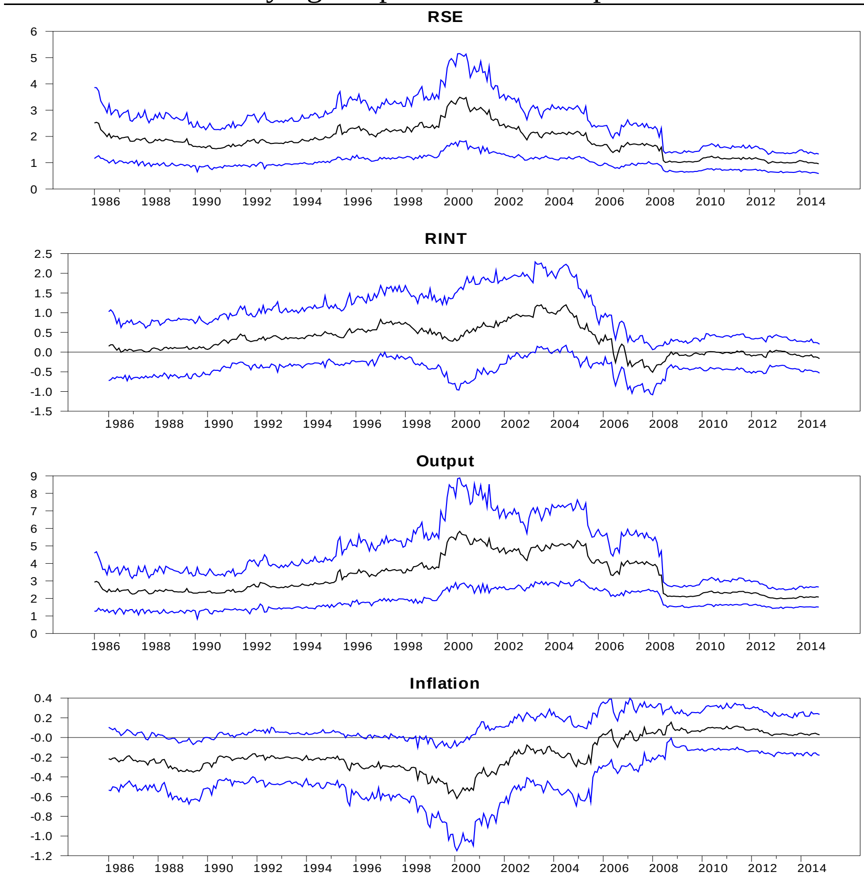


Figure 8: Time Varying 12month Accumulated Generalized Impulse Responses

***Panel A**:* Time Varying Responses to an Output Shock



Panel B: Time Varying Responses to an Inflation Shock

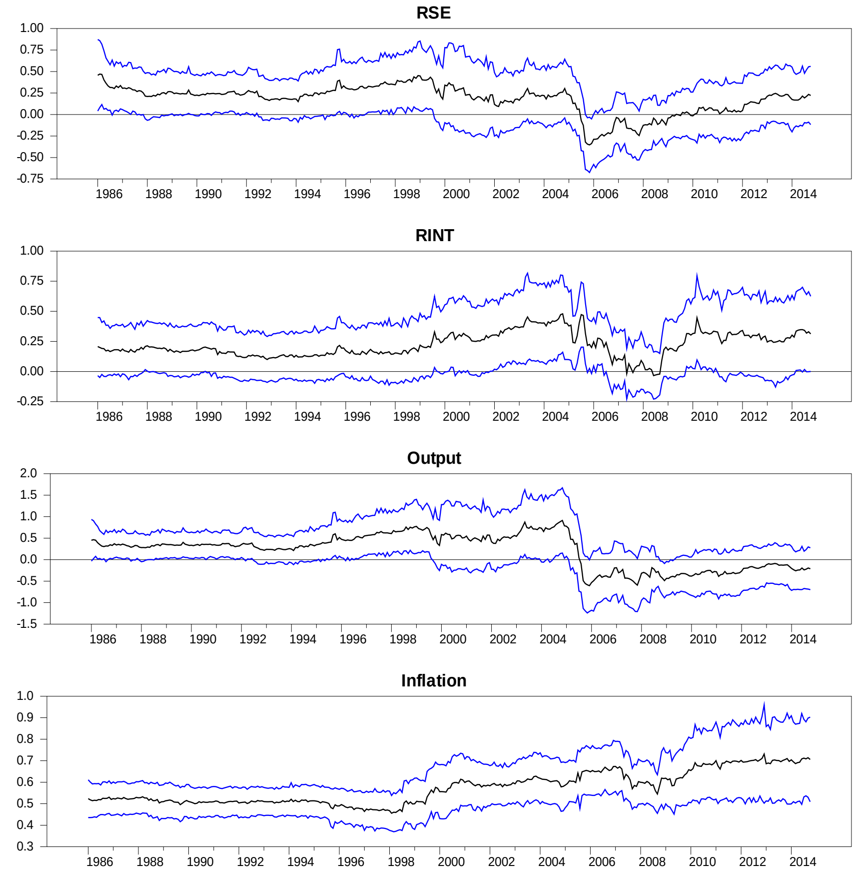
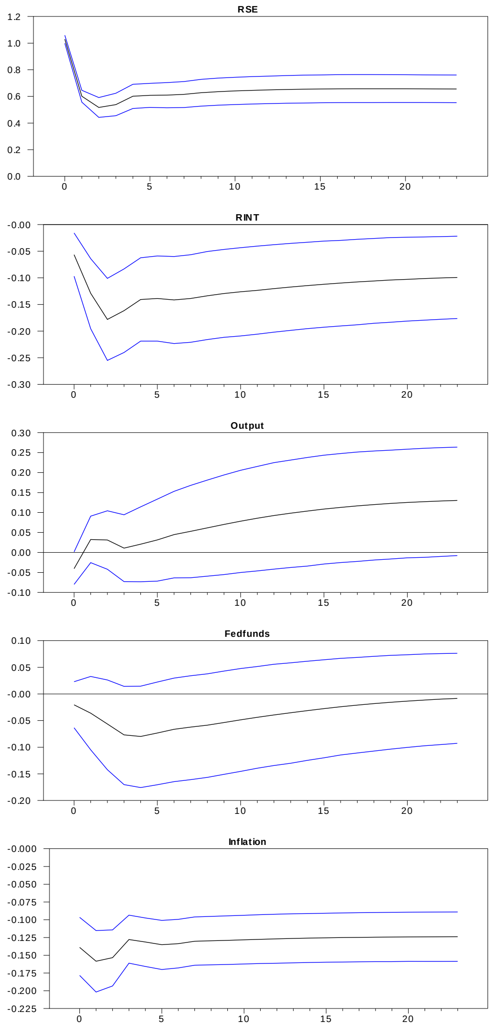
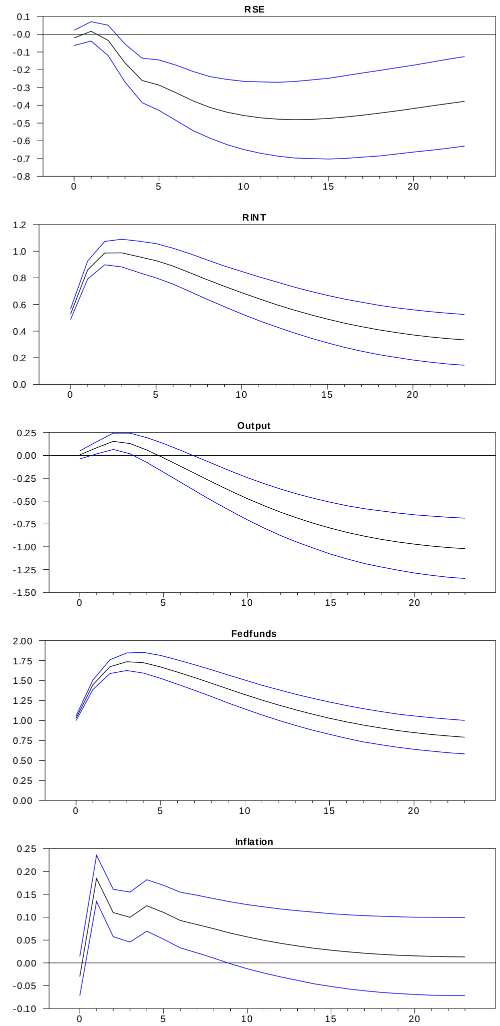


Figure 9: Generalized Impulse Responses of Variables From Second FAVAR: Equation (14)

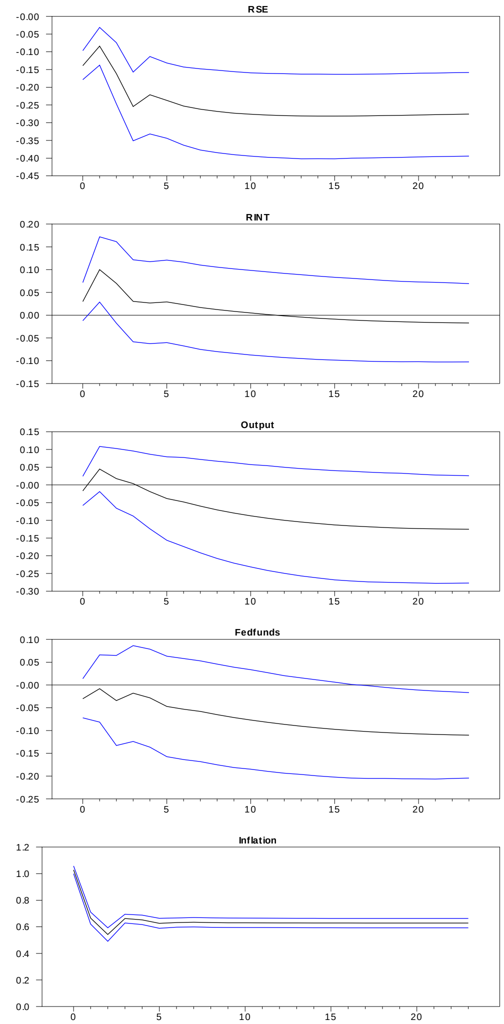
***Panel A**:* Generalized Impulse Responses: Shock to *RSE*



***Panel B**:* Generalized Impulse Responses: Shock to *Fedfunds*



***Panel C**:* Generalized Impulse Responses: *Shock to Inflation*



Variables Used From the McCracken and Ng (2014) Dataset			
Symbol	*Description*	*Symbol*	*Description*
AAA	Aaa Corporate Bond Yield	IPMAT	IP: Materials
AAAFFM	Aaa - FFR spread	IPNCONGD	IP: Nondurable Consumer Goods
AMBSL	St. Louis Adjusted Monetary Base	IPNMAT	IP: Nondurable Materials
AMDMNOX	Orders: Durable Goods	ISRATIOX	Inventories to Sales Ratio
AMDMUOX	Unskilled Orders: Durable Goods	M1SL	M1 Money Stock
AWHMAN	Hours: Manufacturing	M2REAL	Real M2 Money Stock
AWOTMAN	Overtime Hours: Manufacturing	M2SL	M2 Money Stock
BAA	Baa Corporate Bond Yield	MANEMP	All Employees: Manufacturing
BAAFFM	Baa - FFR spread	MZMSL	MZM Money Stock
BUSINVX	Total Business Inventories	NAPM	ISM: PMI Composite Index
BUSLOANS	Commercial and Industrial Loans	NAPMEI	ISM Manufacturing: Employment
CAPUTLB00004S	Capacity Utilization: Manufacturing	NAPMII	ISM: Inventories Index
CE16OV	Civilian Employment	NAPMNOI	ISM: New Orders Index
CES0600000007	Hours: Goods-Producing	NAPMPI	ISM Manufacturing: Production
CES068	Ave. Hourly Earnings: Goods	NAPMPRI	ISM Manufacturing: Prices
CES1021000001	All Employees: Mining and Logging	NAPMSDI	ISM: Supplier Deliveries Index
CES28	Ave. Hourly Earnings: Construction	NDMANEMP	All Employees: Nondurable goods
CES308	Ave. Hourly Earnings: Manufacturing	NONBORRES	Nonborrowed Reserves
CLAIMSX	Initial Claims	NONREVSL	Total Nonrevolving Credit
CLF16OV	Civilian Labor Force	OILPRICE	Crude Oil Prices: WTI
CMRMTSPLX	Real M&T Sales	OUTPUT1	Industrial Production: Bong Soo Lee (1992)
COMPAPFF	CP - FFR spread	PAYEMS	All Employees: Total nonfarm
CONSPI	Credit to PI ratio	PCEPI	PCE: Chain-type Price Index
CP3M	3-Month AA Comm. Paper Rate	PERMIT	Permits
CPIAPPSL	CPI: Apparel	PERMITMW	Permits: Midwest
CPIMEDSL	CPI: Medical Care	PERMITNE	Permits: Northeast
CPITRNSL	CPI: Transportation	PERMITS	PERMITS
CPIULFSL	CPI: All Items Less Food	PERMITW	Permits: West
CUSR0000SA0L5	CPI: All items less medical care	PPICMM	PPI: Commodities
CUSR0000SAC	CPI: Commodities	PPICRM	PPI: Crude Materials
CUSR0000SAS	CPI: Services	PPIFCG	PPI: Finished Consumer Goods
CUUR0000SA0L2	CPI: All items less shelter	PPIFGS	PPI: Finished Goods
CUUR0000SAD	CPI: Durables	PPIITM	PPI: Intermediate Materials
DD_1	PCE: Durable goods	REALLN	Real Estate Loans
DD_2	PCE: Nondurable goods	RETAILX	Retail and Food Services Sales
DD_3	PCE: Services	RINT1	Real Interest Rates: Bong Soo Lee (1992)
DMANEMP	All Employees: Durable goods	RPI	Real Personal Income
DPCERA	Real PCE	RSE1	Real Stock Returns: Bong Soo Lee (1992)
DTCOLNVHFNM	Consumer Motor Vehicle Loans	SP500	Return on the S&P 500

DTCTHFNM	Total Consumer Loans and Leases	SPDIV	S&P div yield
EXCAUS	Canada / U.S. FX Rate	SPINDUST	S&P: Industrials
EXJPUS	Japan / U.S. FX Rate	SPPE	S&P: Price-Earnings Ratio
EXSZUS	Switzerland / U.S. FX Rate	SRVPRD	All Employees: Service Industries
EXUSUK	U.S. / U.K. FX Rate	T10YFFM	10 yr. - FFR spread
FEDFUNDS	FEDFUNDS	T1YFFM	1 yr. - FFR spread
GS1	1-Year T-bond	T5YFFM	5 yr. - FFR spread
GS10	10-Year T-bond	TB3SMFFM	3 Mo. - FFR spread
GS5	5-Year T-bond	TB6MS	6-Month T-bill
HOUST	Starts: Total	TB6SMFFM	6 Mo. - FFR spread
HOUSTMW	Starts: Midwest	TOTRESNS	Total Reserves
HOUSTNE	Starts: Northeast	UEMP15OV	Civilians Unemployed >15 Weeks
HOUSTS	Starts: South	UEMP15T26	Civilians Unemployed 15-26 Weeks
HOUSTW	Starts: West	UEMP27OV	Civilians Unemployed >27 Weeks
INF1	Inflation: Bong Soo Lee (1992)	UEMP5TO14	Civilians Unemployed 5-14 Weeks
INVEST	Securities in Bank Credit	UEMPLT5	Civilians Unemployed <5 Weeks
IPB51222S	IP: Residential Utilities	UEMPMEAN	Average Duration of Unemployment
IPBUSEQ	IP: Business Equipment	UNRATE	Civilian Unemployment Rate
IPCONGD	IP: Consumer Goods	USCONS	All Employees: Construction
IPDCONGD	IP: Durable Consumer Goods	USFIRE	All Employees: Financial Activities
IPDMAT	IP: Durable Materials	USGOOD	All Employees: Goods-Producing
IPFINAL	IP: Final Products	USGOVT	All Employees: Government
IPFPNSS	IP: Final Products and Supplies	USTPU	All Employees: TT&U
IPFUELS	IP: Fuels	USTRADE	All Employees: Retail Trade
IPMANSICS	IP: Manufacturing	USWTRADE	All Employees: Wholesale Trade
		W875RX1	RPI ex. Transfers