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Razzak, Weshah

Arab Planning Institute

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Predicting Instability

W A Razzak[†]
Arab Planning Institute
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Abstract

Unanticipated shocks could lead to instability, which is reflected in statistically significant changes in distributions of independent Gaussian random variables. Changes in the conditional moments of stationary variables are predictable. We provide a framework based on a statistic for the Sample Generalized Variance, which is useful for interrogating real time data and to predicting statistically significant sudden and large shifts in the conditional variance of a vector of correlated macroeconomic variables. Central banks can incorporate the framework in the policy making process.

JEL Classifications C1 C3 E66

Keywords: Sample Generalized Variance, Conditional Variance, Sudden and Large Shifts in the Moments

[†] Razzakw@gmail.com and weshah@api.org.kw

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1. Introduction

For economists, instability has always been associated with the changes in the distributions of economic variables. There is a statistical literature on changes in the moments, especially the variance of a time series, which has not penetrated the economic literature. The CUSUM tests have been used to locate changes in the variance, for example, see Inlan and Tiao (1994). Chen and Gupta (1997) test for multiple variance change-points in a sequence of independent Gaussian random variables, when the mean remains common. Malik (2003) tests for "sudden" changes in variance in foreign exchange markets using iterated cumulated sums of squares algorithm. And Fernandez (2006) uses the same approach to examine shifts in the conditional volatility during the Asian crisis and 9/11.

Taleb (2007) talks about a "Black Swan", an event that is rare and difficult to predict, which could reflect either *a sudden and large shift* in the variance or the mean of a random variable. A large shift in the mean or the variance of a random variable would mean an observation falling in the tails of the distribution. Regardless of the type of the distribution, they represent rare events because the probability of such an event is extremely small, e.g., it could be 0.0027 in the case of a standard normal distribution.¹ John Taylor and John Williams (2009) use the phrase to describe a jump in the spread of Libor-Overnight Index Swap rates as a "Black Swan in the money market".

So economists who are interested in stability / instability issues should be concerned with a Black Swan. We would assume that a Black Swan is *a large and a sudden* change in the second moment. That is a rare and highly improbable large change in the conditional variance of relevant macroeconomic data.

Financial economists are concerned with conditional volatility, which is a similar concept but with different technical underpinnings, e.g., ARCH and GARCH models. There is a relatively large and growing literature on financial stability. Central banks, also the BIS and the IMF are among the institutions that are most interested in this matter. Not surprisingly, academic interests in financial stability grow after crises, e.g., the Asian financial crisis in 1997/1998 and the recent 2007/todate crisis. Kaminsky *et al.* (1998) provided leading indicators for currency crisis during the Asian crisis in 1997-1998. Also see for example, Reinhart and Rogoff (2008), John Taylor (2008), and Melvin and M. Taylor (2009) among others. Melvin and M. Taylor (2009) examine a number of economic and financial indicators, producing signals when they exceed certain percentile of their distributions to indicate stress. But the difference between the economic and the statistical literature mentioned above is that the economic literature mentioned above does not provide *test statistics*.

In this paper we provide a test statistic, which is also different from the statistical literature cited above. Quality control engineers and statisticians have developed statistics with *prediction intervals*, which could have

applications in economics and financial economics and useful for policymakers.

Manufacturers have systems whereby production processes are monitored and measurements of parts are taken in regular intervals of time. Engineers like to keep a process or a quality variable at a specified level (mean) with variability about the level as small as economically feasible. In most cases, when a change in the data generating process's distribution occurs it will entail a change in either the mean μ or the standard deviation σ .

The test statistics that are available to quality control engineers entail an interrogation of the real time data as they are observed; they sound alarm bells when the moments shift suddenly with high probability, Shewhart's (1939). Following the shift, processes are stopped and correcting actions are taken.

However, we cannot stop the economy when a certain variable such as spread of Libor-OIS experiences a large shift in its moments. However, we could benefit by knowing about instability earlier than later if we think in the same way quality control engineers and statisticians do.

The primary job of the economists in the central banks is to analyze the data as they arrive, to assess the nature and the permanency of the shocks. Central banks might have more information about the economy than an average private agent. For example, almost 70 percent of the component of the actual CPI are available before any forecasting round. They could deploy such an alarm sounding probabilistic test statistics to monitor and interrogate data as they arrive in addition to other tools they have such as modelling and forecasting. The test statistics, which we will introduce next to test for sudden shifts in the conditional variance of economic data, are general such that central banks can use them to analyze both real and financial data. They could be used to analyze time series and panel data as well.

The economy, however, is more complex than a controlled manufacturing process. There are a number of variables that are associated with each other, i.e., highly correlated. Thus, a *univariate* test statistic for a sudden change in the moments of a random variable might be useful, but incomplete. It would not give us enough information about the stability of the economy. What is needed is a *multivariate test statistic*, where the vector includes correlated – not independent – Gaussian random variables.

The contributions of this paper include the introduction of a multivariate test statistic based on the Sample Generalized Variance, where a prediction interval is derived such that sudden and large changes are identified. The test is applied to US data. We use real and nominal variables. The real variables are economic variables. The nominal data are financial data. For the real economy, we use two data vintages. One covers the period 1973 to 2007 published in 2007 and the second vintage covers the period 1973 to 2008 published in 2009.

Section 2 is the statistical theory. Empirical example is given in section 3. We provide a SAS-IML code and an R code to compute the test statistic. Section 4 is a summary.

2. The statistical theory

Let a statistic ω , which could have any distribution, measure certain features of the variable X such as the variance.

If ω_α ($0 < \alpha < 1$) denotes the $(1 - \alpha)^{th}$ fractile of the distribution of ω then ω_α satisfies the equation:

$$1 \quad \text{prob} (\omega > \omega_\alpha) = \alpha$$

We define a zone for ω under some common distribution by defining upper and lower critical limits such that ω stays within. In other words, when ω exceeds the critical limits it is considered a significant value (i.e., falling in the tails of the distribution). This zone is a prediction interval.

Take a multivariate normal variable $X^T = [X_1, X_2 \dots X_p]^T$, where each X is an *iid* Gaussian random variable, but the $Cov(X_1, X_2, \dots X_p) \neq 0$ and the superscript T denotes transpose. If $(1 - \alpha)$ probability is maintained on each component then the probability that all variables $X_1, X_2 \dots X_p$ are simultaneously falling within the upper and lower critical limits is

$$2 \quad 1 - \phi = (1 - \alpha)^p$$

The probability of falling outside the critical limit is

$$3 \quad \phi = 1 - (1 - \alpha)^p$$

To satisfy a probability of $1 - \phi$ that all variables are falling within the critical limits on one sample when the parameters are the nominal values, α must be:

$$4 \quad \alpha = 1 - (1 - \phi)^{1/p}$$

For a multivariate random normal variable where, $X^T = [X_1, X_2 \dots X_p]^T$, the variance (of the population) is a *function* called the *Generalized Variance*, which is the determinant of a matrix, Σ . The determinant of the sample variance matrix S^2 is called the *Sample Generalized Variance*, where S^2 is the sample covariance matrix based on sample of size n . Anderson (1958) shows that the determinant of S^2 is proportional to the sum of squares of the volumes of all *parallelopes* formed by using as principle edges P vectors of

X_1, X_2, \dots, X_p as one set of end points, and the mean of X as the other with $\frac{1}{(n-1)^p}$ as the factor of proportionality.

Anderson (1958) also shows that a convenient statistic for the generalized variance is the following form of the Sample Generalized Variance:

$$5 \quad D_k = (n-1)P \left[\frac{|S_k^2|}{|\Sigma|} \right]^{1/P} > 0$$

The matrix S^2 is computed by:

$$6 \quad S_{ij}^2 = \frac{1}{n-1} \sum_{k=1}^m (X_{ki} - \bar{X}_i)(X_{kj} - \bar{X}_j)$$

And Σ is approximately:

$$7 \quad \bar{S}^2 = \frac{1}{N-m} \sum_{k=1}^m (n-1) S_k^2$$

Which is the mean of S^2 .ⁱⁱ A bar on the variable denotes the sample mean. And, k is the number of windows in X for which the statistic is computed. Each window is of size n observations. For a monthly data of a 144 observation, for example, the window could be of size 12, hence $k = 1 \dots 12$, m is 12. If X is a unit root it must be rendered stationary before calculating the moments.

Unfortunately, for $P \geq 3$, the statistic D_k has no exact distribution so we cannot test for the significance level. Ganadesikan and Gupta (1970) approximated the distribution by a Γ (Gamma) distribution with two parameters, a shape and a scale parameter,. They showed that the Γ distribution is best approximated when $n = 10$.

The shape parameter is:

$$8 \quad h = \frac{P(n-P)}{2}$$

And the scale parameter is:

$$9 \quad A = \frac{P}{2} \left[1 - \frac{(P-1)(P-2)}{2n} \right]^{1/P}$$

To simplify the interpretation and the presentation of the statistic D_k , we transform the Γ distribution into a standard normal by computing the following:

$$10 \quad u_k = G_{h,A}(D_k)$$

Where G is the distribution function of the Gamma distribution with the two parameters above, and then the inverse of u_k

$$11 \quad q_i(D_k) = \Phi^{-1}(u_k)$$

$q_i(D_k)$ is distributed standard normal and therefore the values could be $q_i(\cdot) < 0 < q_i(\cdot)$.

The upper and lower control limits, which define the prediction intervals measure the distance from the mean in terms of standard deviations; it could take the value $\pm 3\sigma$ or for a tighter intervals take the value $\pm 2\sigma$. These limits, under a standard normal distribution function, are *prediction* limits for the distributions of $q_i(D_k)$. Note that a $\pm 3\sigma$ control limit constitutes a band of 0.99730 prediction intervals for future values of the statistic $q_i(D_k)$ according to the Tchebysheff's theorem.ⁱⁱⁱ In other words, values that fall in the tails of the distribution are significantly different from values elsewhere under the distribution, and represent inequality of distributions when two regimes are compared. This is the black swan.

3. Empirical example and a framework

In this section we will demonstrate the ability of the multivariate Sample Generalized Variance in predicting sudden and large shifts in the variance of a P-variate system. The economists at the central bank analyze the data as they arrive in real term. Here, for illustration only, they will choose three time series, but they can choose as many as P.

First, prices contain a lot of information. Prices change as demand and supply shift due to shocks and news. The price of oil is an important variable. It could stay unchanged for a long time then experiences a sudden significant change. The variance could change significantly in a short period of time as well. For example, West Texas Oil Price went over 100 US dollars then fell sharply and rose again in a matter of a few years. Between January 1999 and July 2008 the WTO real oil price increased more than 200 percents. See figure 1.

Most of the U.S. post WWII recessions were preceded by sharp increases in crude oil prices. Figure 2 plots the percentage change in the real WTO monthly price and the NBER recessions (shaded areas). After the first and the second oil price shocks in 1973 and 1997 we learned that the increase in the level of the real oil price has adverse effects on the economy. It increases the costs of production thus lowers real output and increases the general price level; it shifts the aggregate supply curve to the left and it could, in a second-

round effect, increase the rate of inflation when it spills-over into other prices. So the oil price is the first time series in the vector X^T .

A second crucial variable is the real exchange rate. The exchange rate is an enigma. It is an asset price, which most models, more or less, fail to explain and predict. Messe and Rogoff (1983) is the first paper to make the case for a random walk. The real exchange rate is even more problematic than the nominal rate. It is also measured in many different ways. When the exchange rate regime is floating and intervention is minimum, the nominal exchange rate acts as a shock absorber, thus large swings. The real exchange rates also convey information about consumer prices and productivity among other things. The question though is whether the swings indicate statistically significant instability.

In addition to prices, central banks must pay a lot of attention to output. In the case of monthly data the industrial production index is used instead of GDP. So $X^T = (X_1, X_2, X_3)^T$ includes these three variables in this paper, but one may want to add other variables such as a measure of money for example.

We will compute the multivariate Sample Generalized Variance and test whether it has significantly, and suddenly shifted over time in the United States. A SAS – IML code and an R code are in the appendix to compute $q_i(D_k)$.

On the other hand, a financial market department's vector X could include different variables. Melvin and Taylor (2009), for example, construct a financial stress index. The variables included in that index are the "beta" of the banking sector; the spread between the interbank rate and the yield on treasury bills; the slope of the yield curve; corporate bond spreads; stock market returns; etc. One can test for sudden changes in the Sample Generalized Variance, regularly and as new data come along.

Financial data are sampled at a much higher frequency than macro data. The financial market department at the central bank could test stock market data several times a day. They could use daily data and test for sudden changes in the Sample Generalized Variance each week. For an example of daily data univariate test statistic for a sudden and large shifts in the distribution see Razzak (1991). In this paper we test monthly data. We use the Moody's Baa yield minus the 10-year Treasury Bond yield; the slope of the yield curve; Nasdaq; and total loans and credits in commercial banks.

A procedure to monitor the whole economy can be established whereby a policymaker is presented with daily, weekly and monthly briefs of statistical tests of sudden, and significant shifts in the conditional variance of variables that convey information about the instability of the economy. This would be a useful piece of information about the health of the economy.

The oil price data are the West Texas, monthly, and from Moody. The price of oil is deflated by the CPI. The industrial production index is from the Federal

Reserve Bank of St. Louis, and the real effective exchange rate is from OECD. All the nominal financial variables are taken from the St. Louis fed.

The data are in log and in first differences, except for the Baa-10 year Treasury Bond differential and the slope of the yield curve, which are in levels and $I(0)$.

We begin with the real variables. We test two vintages of data. One covers the period January 1973 to December 2007, published in 2007. The second vintage covers the period January 1973 to December 2008, published in 2009. We chose an interval of 12 months (one year) to compute the Sample Generalized Variance $q_i(D_k)$ test statistic, thus $n = 12$; $k = 1, 2, \dots, m = 35$ for the first data vintage and $k = 1, 2, \dots, m = 36$ for the second data vintage. We report the values of $q_i(D_k)$ in table 1 second and third columns, and also plot them in figure 3.

The prediction of instability is remarkable. The test picks up all the recessions, the oil price shocks, the stock market crash, the Asian crisis and the recent financial crisis. Except for the 1991 and 2001 recessions, $q_i(D_k) > \pm 3\sigma$. The size of the sudden jumps has clearly been relatively smaller (i.e., between $\pm 2\sigma$) in the 1980s and 1990s compared with the 1970s seem consistent with the Great Moderation story. See Bernanke (2004) on a discussion and full references of the research in this area.

For completeness, a univariate statistic for a sudden and large jumps in the conditional variances could be used in addition to the multivariate statistic to test each of the three time series, individually. This will shed closer light on instability.

We compute the followings in order:

$$12 \quad V_i = (n_i - 1)S_i^2 / \sigma^2 ;$$

$$13 \quad \eta_i = H_{n_i-1}(V_i) ; \text{ and}$$

$$14 \quad R_i(S_i^2) = \Phi^{-1}(\eta_i)$$

Where V_i is the statistic for a sudden shift in the variance, which is distributed chi-squared, S_i^2 is the sample variance, n_i is the number of observation or the window for which the variance is computed; σ^2 is a pooled or overall variance calculated as $(n_i - 1)S_i^2 / \sum_{i=1}^m n_i - m$, where i is the number of samples $= 1, 2, \dots, m$.

We map V_i onto a standard normal distribution to make the presentation of the results easy. $H(\cdot)$ is the distribution function of the chi-squared random variable with $n_i - 1$ degrees-of-freedom and Φ^{-1} is the inverse of the standard normal distribution function.

The statistics are reported in table 1, columns 4-6 and plotted in figures 4, 5 and 6. They are the prediction intervals for the instability in the price of oil, the real exchange rate and the industrial production index individually.

In figure 4, the conditional variance for the real price of oil jumps high showing significant instability during the first and second oil price shocks as expected. A very large spike is recorded in 1986 and the stock market crashed in October 1987 then it signalled a sudden large shift in 1990 the year Iraq invaded Kuwait and the collapse of the USSR. It signalled a shift $> \pm 2\sigma$ in 1992 and again in 1995. The statistic did not signal the recessions except 1991 and the recent one related to the financial crisis. From 1996 onward the statistic predicted no significant instability in the price of oil.

Figure 5 plots the prediction intervals for the real exchange rate depreciation. Relatively fewer sudden and large jumps in the conditional variance are recorded. Again, the period up to 1982 shows significant activities at $\pm 2\sigma$ and $\pm 3\sigma$, which include the oil price shocks and the switching from the Bretton-Woods to free floating. In 1985 it reacted again, but only by $\pm 2\sigma$. This period is during the Reagan administration when the US appreciated significantly. Followed by another small signal in 1993 and by a large jump in 1996. These were followed by more less significant sudden shifts in 1999 – 2001 recession.

Both the price of oil and the real exchange rate exhibited more or less similar instability. The real exchange rate instability continued to the mid and late 1990s while oil's instability ceased in mid 1990s as if it is no longer an interesting variable. More intriguing is that neither the price of oil nor the real exchange rate signalled the recent financial crisis. This result does not seem to be consistent with Melvin and Taylor's (2009) who identified a foreign exchange crisis. Note that Melvin and Taylor (1) do not examine the real exchange rate but rather an index; (2) they do not provide a test statistic for conditional volatility. Thus they could have reported changes, but they did not test for their significance.

Figure 6 plots the univariate $R(S_i^2)$ statistic for the industrial production. It signalled all the recessions except the 1991 recession. It reacted significantly to the recent crisis signalling in 2007 and more significantly so in 2008. Like the other two variables it reacted to the first and the second oil price shocks with significant sudden and large increase. Then nothing significant happened until 2001 and 2006-2008. In between, the real economy seemed only agitated, with less significant sudden increases in the conditional variance in 1993-1994.

A few interesting observations emerge from all these tests (univariate and multivariate), which underscore the importance of using all of them for completeness. First, In 1984 and 1985 during the Reagan administration the US dollar appreciated to its highest level, the multivariate $q_t(D_k)$ test statistic showed no significant change in the conditional variance of the system. However, both the price of oil and the real exchange rate signalled significant

instability in 1984 and in 1985 respectively. Second, the multivariate statistic $q_i(D_k)$ signalled the Asian crisis in 1998 with a jump $> \pm 2\sigma$, but none of the three univariate statistics were significant in 1998. This finding might be consistent with Fernandez (2006). Fernandez (2006) like Malik (2003) uses an iterated Cumulated Sums of Squares (ICSS) logarithm and find no significant permanent change in volatility after the Asian crisis and 9/11. The real exchange rate only signalled a large jump in 1996, but one cannot be sure whether this was related to the Asian crisis because nothing happened until it jumped again at the $\pm 2\sigma$ level in 1999. Third, most intriguing is that the tests signalled a jump in 2001 with different levels of significance, except the price of oil, and none of the tests picked up the US invasion of Iraq in 2003 obviously because it was an anticipated shock. Fourth, while the multivariate test statistic picked up signs of the current crisis from 2006 and showed significant jumps in the conditional variance of the system in 2006-2008, the univariate test statistic for the industrial production reacted significantly, but no signals came from the univariate test statistics for oil prices and the real exchange rate.

Figure 7 plots the $q_i(D)$ Multivariate Sample Generalized Variance for four financial variables, the Baa yield minus the 10-year Treasury Bond yield; the slope of the yield curve that the short-term 30-day Treasury bill rate minus the 10-year Treasury Bond rate; Nasdaq; and the quantity of loans and credits in the commercial banks. The first two variables are $I(0)$. The last two variables are in log-difference form. The time series are from January 1973 to December 2009. We keep $n = 30$, thus $k = 1 \dots m = 37$.

Interestingly, the test showed no significant change during the first oil shock period while all other variables reacted significantly. However, it picked up the 1980; 1990 and the most recent recession. The signal of the recent financial crisis is particularly large. It signalled the stock market crash and the Asian crisis.

Figure 8, combines the test statistics for the real economic and the nominal financial data. There is a general agreement among the two. They signalled, albeit with different degrees of significance, the second oil shock. The real variables reacted stronger. Both the real and the nominal variables reacted to the 1980's recession; to the stock market crash; the Asian and the recent financial crisis.

In addition to these monthly frequency sudden large shifts in the conditional variance (either multivariate or univariate), the central bank staff can analyze daily data. Most of the useful daily data are financial market data. Then they match the daily predictions and the monthly predictions, see Razzak (1991).

4. Conclusion

We introduce univariate and multivariate test statistics to test for sudden and large shifts in the conditional variance of some stationary Gaussian random

variables. The multivariate statistic is based on the Sample Generalized Variance, Anderson (1958) extended to handle P-variates.

We used US monthly real data from two vintages from 1973 to 2008. We argued that central banks could use these machinery to predict and study instability. They might be able to be ready for crisis since the probabilistic prediction intervals provided by the statistics are very accurate.

Our test of West Texas real oil price, the effective real exchange rate depreciation and the industrial production index for the periods 1973 to 2007 (first vintage of the data) and 1973 to 2008 (the second vintage of the data) show that the 1970s and 1980s are statistically significantly less stable than the rest of the sample, which is consistent with the Great Moderation story, e.g., Bernanke (2004). The statistics accurately predicted the first and the second oil shocks. They also predicted the US recessions. They sent alarms before the stock market crash, the Asian crisis and the most recent financial crisis. The multivariate statistic began, unlike the univariate test statistics, to sound a series of alarm signals regarding the recent crisis. The first signal went off in 2006, 2007 and finally a very large signal in 2008.

These tests are easy to use. They could be used to test a single time series, a bi-variate system of two time series, and a multivariate system of more than 2 and up to P-variates. It could be applied to panel data too. We used monthly data, but one can easily use them to test daily financial market data. Razzak (1991) is an example for using daily foreign exchange rate data. Results can easily be incorporated in policy briefing of the policymakers.

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Table 1: Multivariate Sample Generalized Variance and Univariate Test Statistic for Sudden and large shifts in the conditional variance

	Multivariate $q_i(D_k)$		Univariate $R(S_i^2)$		
	Vintage 1	Vintage 2	Oil	Real Exchange Rate	Industrial Production
1973	0.939	0.406	1.482	-2.750 [#]	1.580
1974	3.719 [*]	3.719 [*]	-8.272 [*]	-0.373	-4.651 [*]
1975	-5.208 [*]	-5.541 [*]	8.099 [*]	0.892	-3.462 [*]
1976	-2.353 [#]	-1.653	2.345 [#]	4.158 [*]	0.795
1977	-3.962	-4.169 [*]	4.423 [*]	2.425 [#]	0.407
1978	-5.255 [*]	-5.537 [*]	4.753 [*]	4.753 [*]	-1.536
1979	0.192	0.075	1.001	0.996	0.365
1980	3.067 [*]	2.349 [#]	2.179 [#]	-2.340 [#]	-4.826 [*]
1981	-0.765	-1.284	4.055 [*]	-1.835	-0.393
1982	3.996 [*]	3.758 [*]	0.393	-3.410 [*]	-1.808
1983	-1.642	-1.929 [#]	3.055 [*]	1.283	-0.249
1984	-1.135	-1.087	3.064 [*]	0.064	0.522
1985	-0.078	-0.200	1.829	-2.019 [#]	1.328
1986	4.161 [*]	2.788 [#]	-5.187 [*]	-1.068	0.959
1987	0.840	0.039	0.755	-0.595	1.231
1988	-0.217	-1.049	0.693	-0.857	3.097 [*]
1989	0.397	0.291	1.538	0.473	0.715
1990	2.389 [#]	1.920 [#]	-3.962 [*]	0.113	0.175
1991	1.635	1.596	-0.162	-0.485	0.312
1992	-0.673	-0.700	2.329	-0.673	0.963
1993	-2.251 [#]	-2.093 [#]	1.563	1.943	2.673 [#]
1994	-1.071	-1.967	1.317	1.018	2.503 [#]
1995	-0.502	-0.515	2.044 [#]	-1.407	1.558
1996	-1.346	-1.350	0.777	3.763 [*]	0.056
1997	-0.506	-0.720	0.995	0.279	1.672
1998	2.372 [#]	1.985	0.554	-0.786	-0.583
1999	-0.790	-0.793	0.091	2.167 [#]	1.330
2000	-0.528	-0.333	-1.037	1.430	2.241 [#]
2001	-2.768 [#]	-2.709 [#]	0.972	1.953 [#]	3.731 [*]
2002	-0.038	0.149	0.477	1.315	1.394
2003	0.907	1.207	-0.371	-0.502	1.267
2004	1.159	1.304	-0.057	-0.300	0.591
2005	0.733	0.860	0.591	1.740	-0.889
2006	-2.295 [#]	-1.534	0.690	1.371	2.509 [#]
2007	-2.804 [#]	-2.136 [#]	0.579	1.549	1.740
2008	#N/A	3.719 [*]	1.572	0.931	-4.634 [*]

The Prediction intervals are $\pm 3\sigma$ and $\pm 2\sigma$.

* Values of the tests $> \pm 3\sigma$ denote significant sudden and large shifts in the conditional variance.

Values of the tests $\geq (\pm 2\sigma)$

Vintage 1 are data published in 2007

Vintage 2 are data published in 2009

**Figure 1: West Texas Oil Price dollar per barrel
October 1972-September 2009**

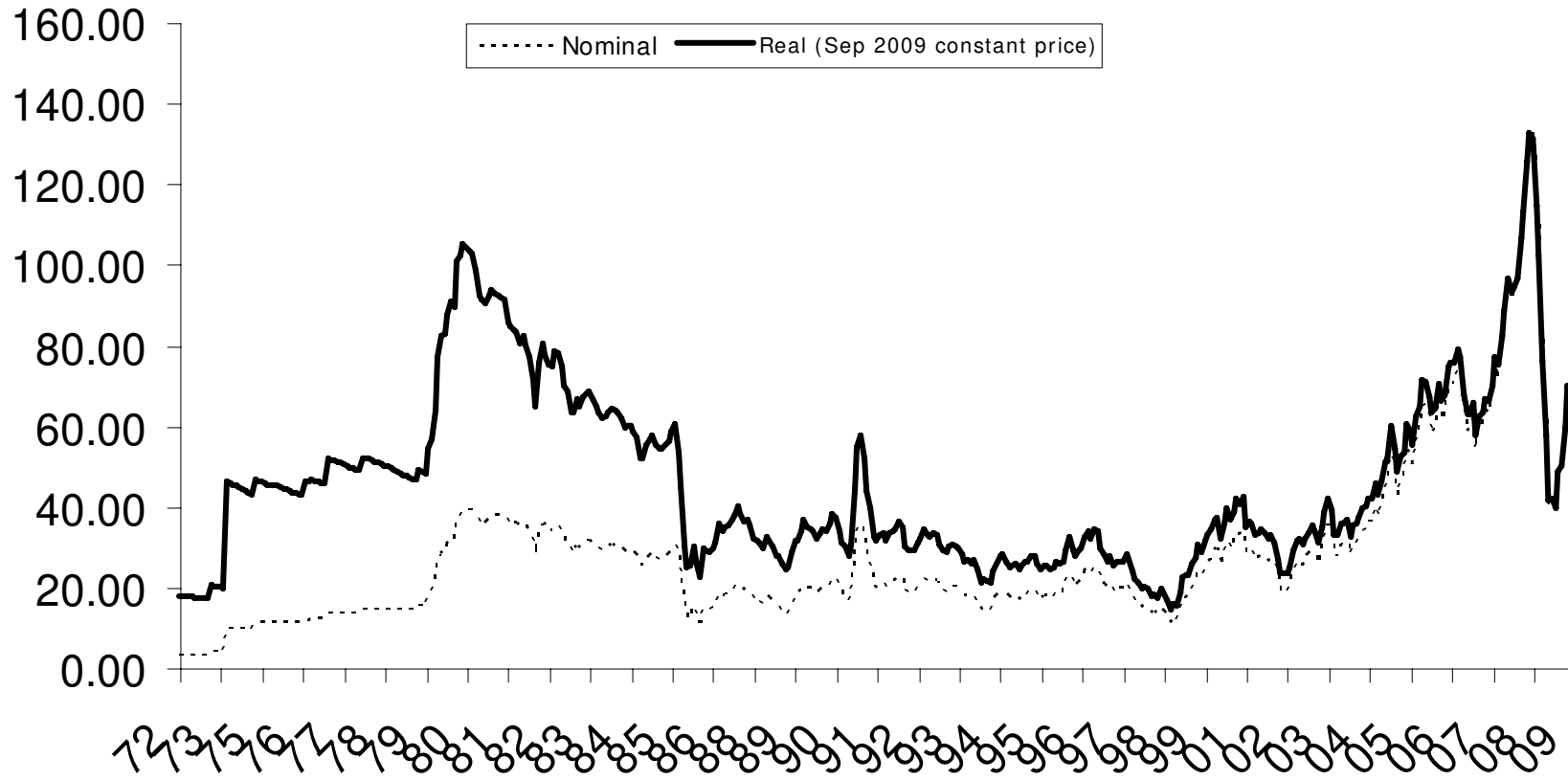


Figure 2: Real West Texas Oil Price Changes and U.S. Recessions

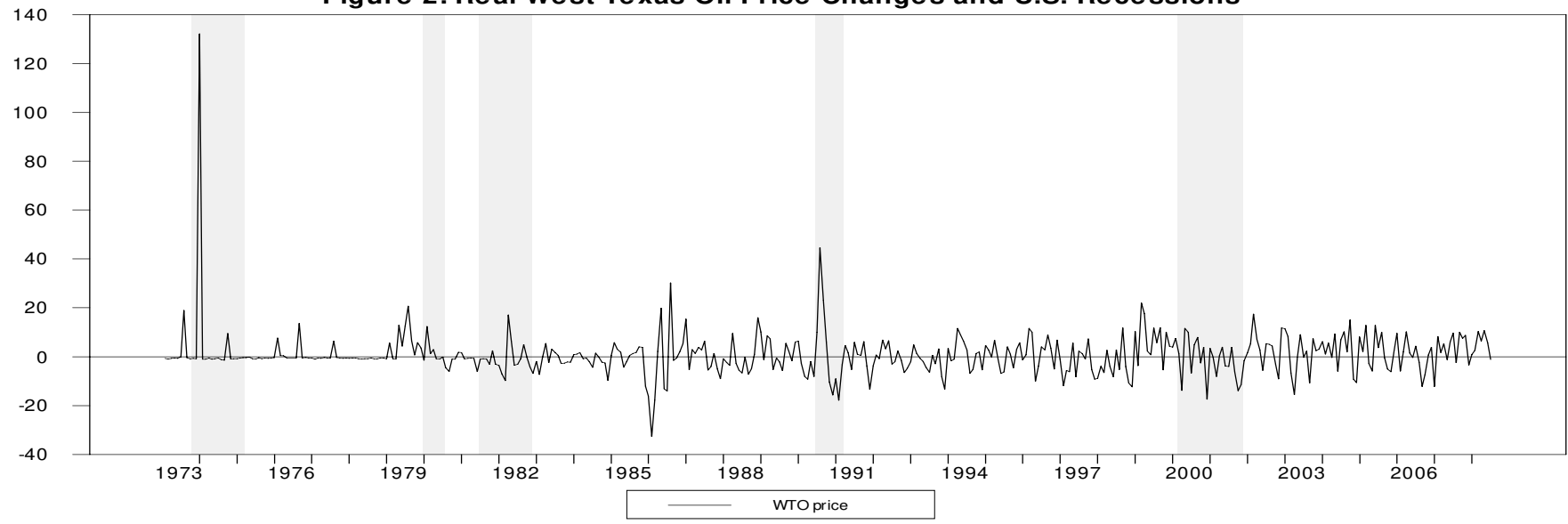


Figure 3

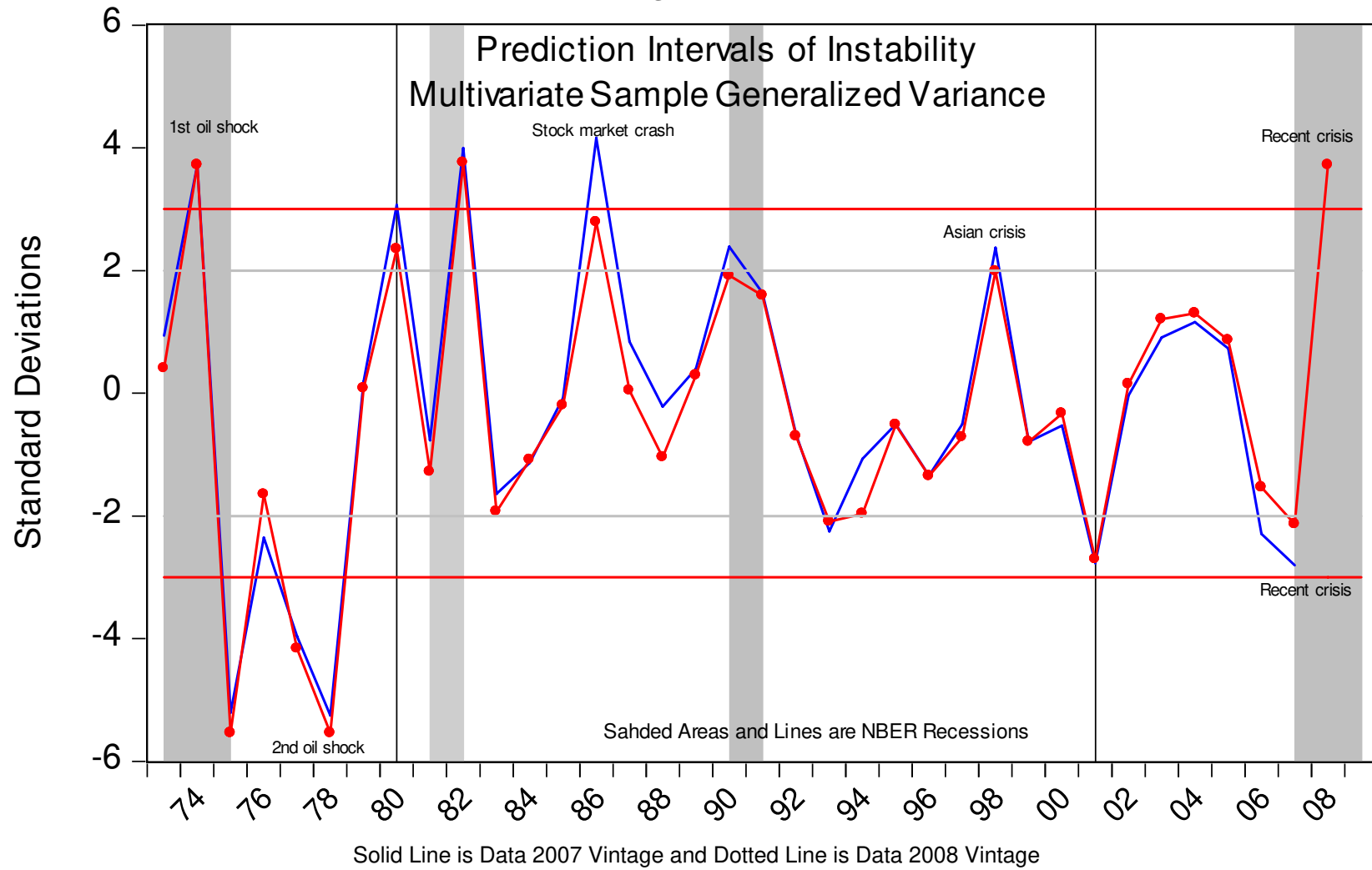


Figure 4

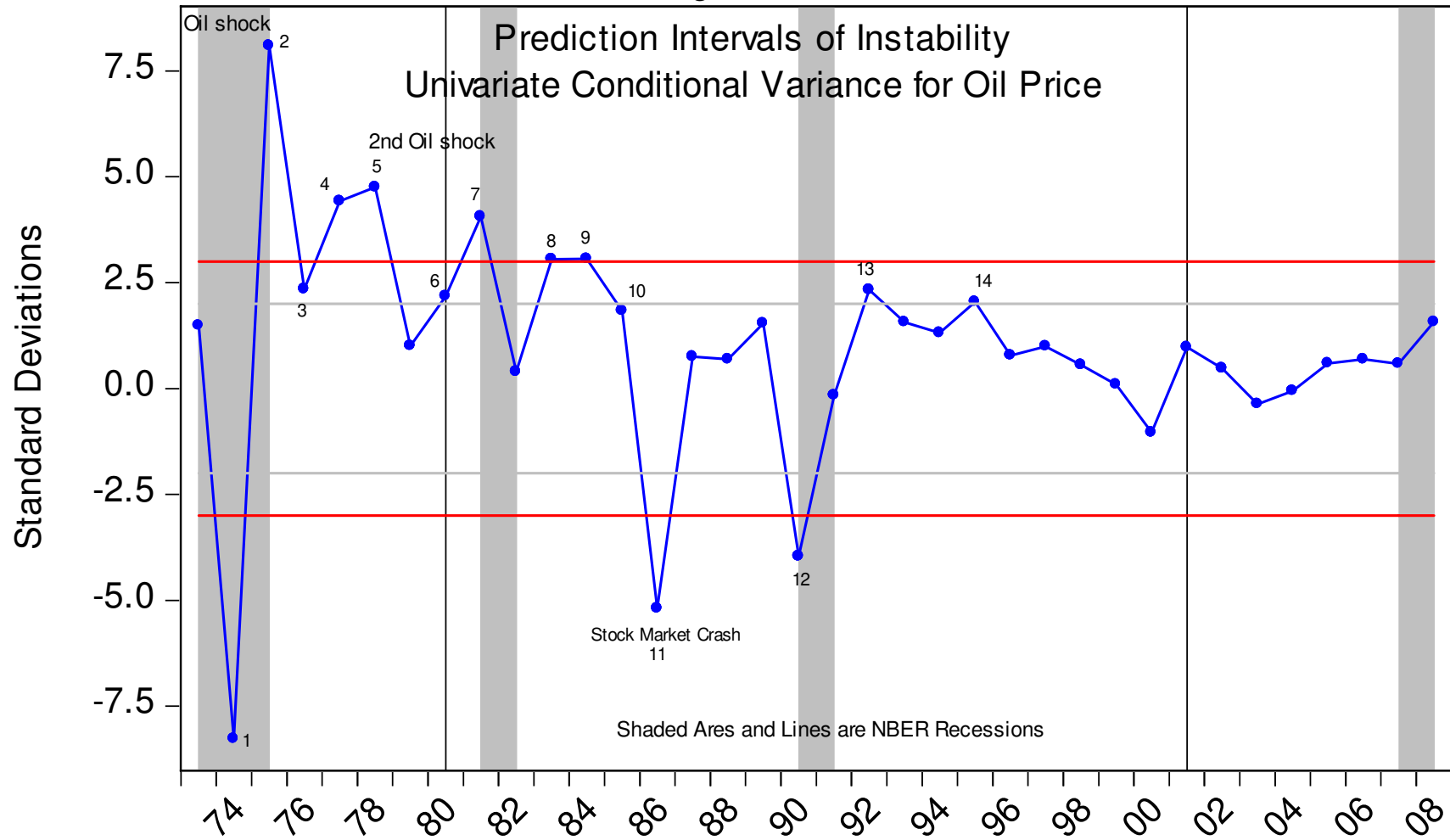


Figure 5

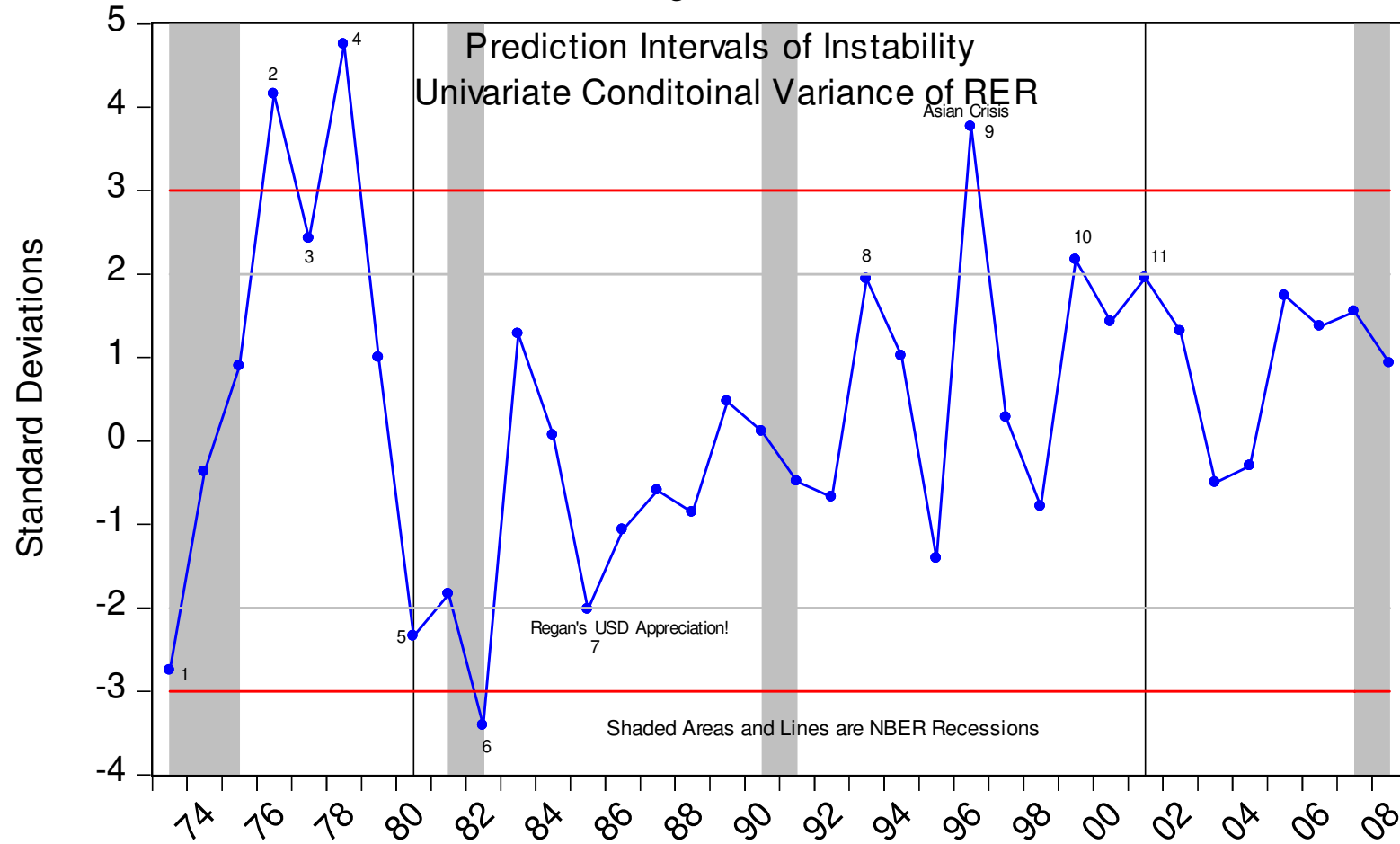


Figure 6

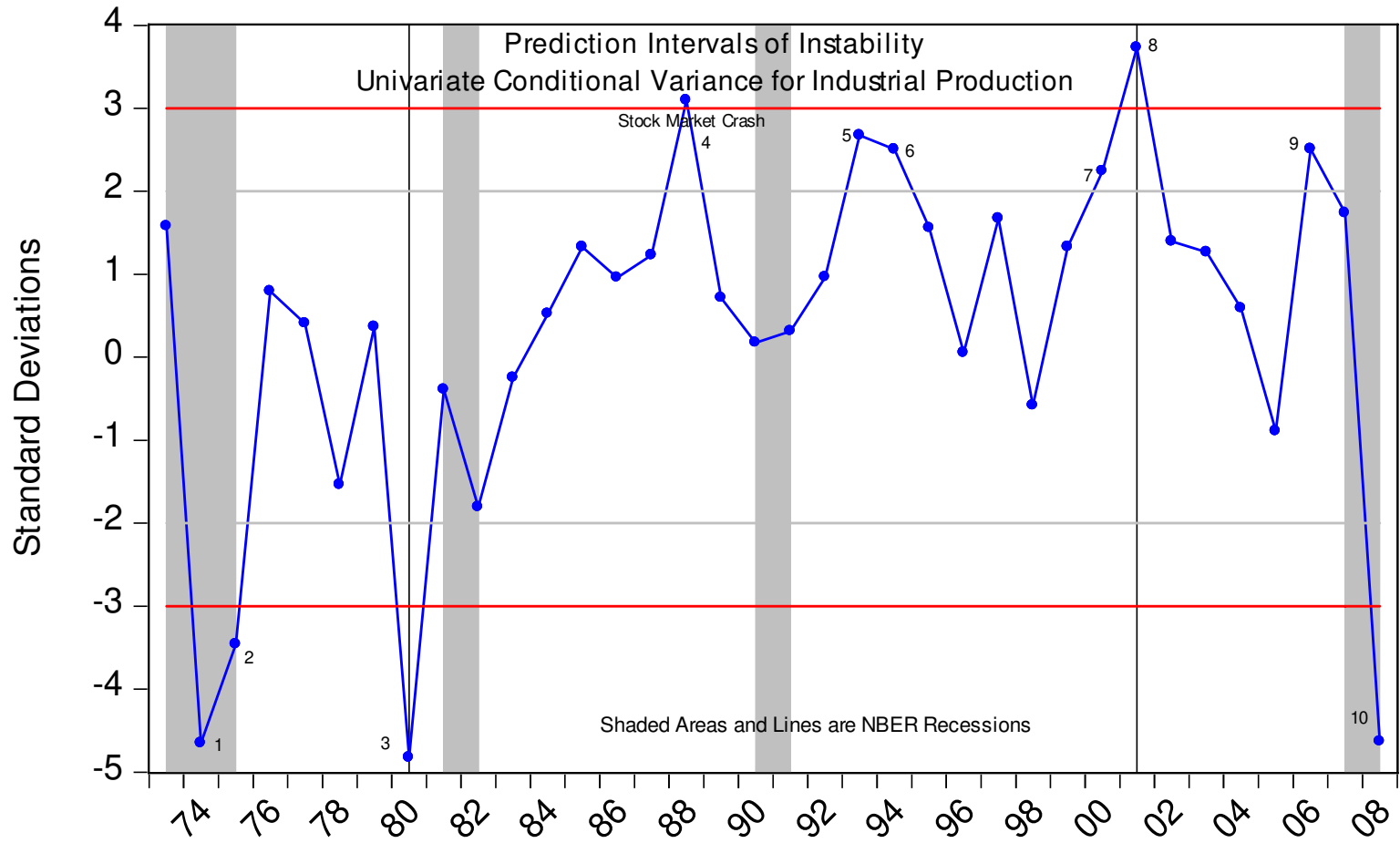


Figure 7

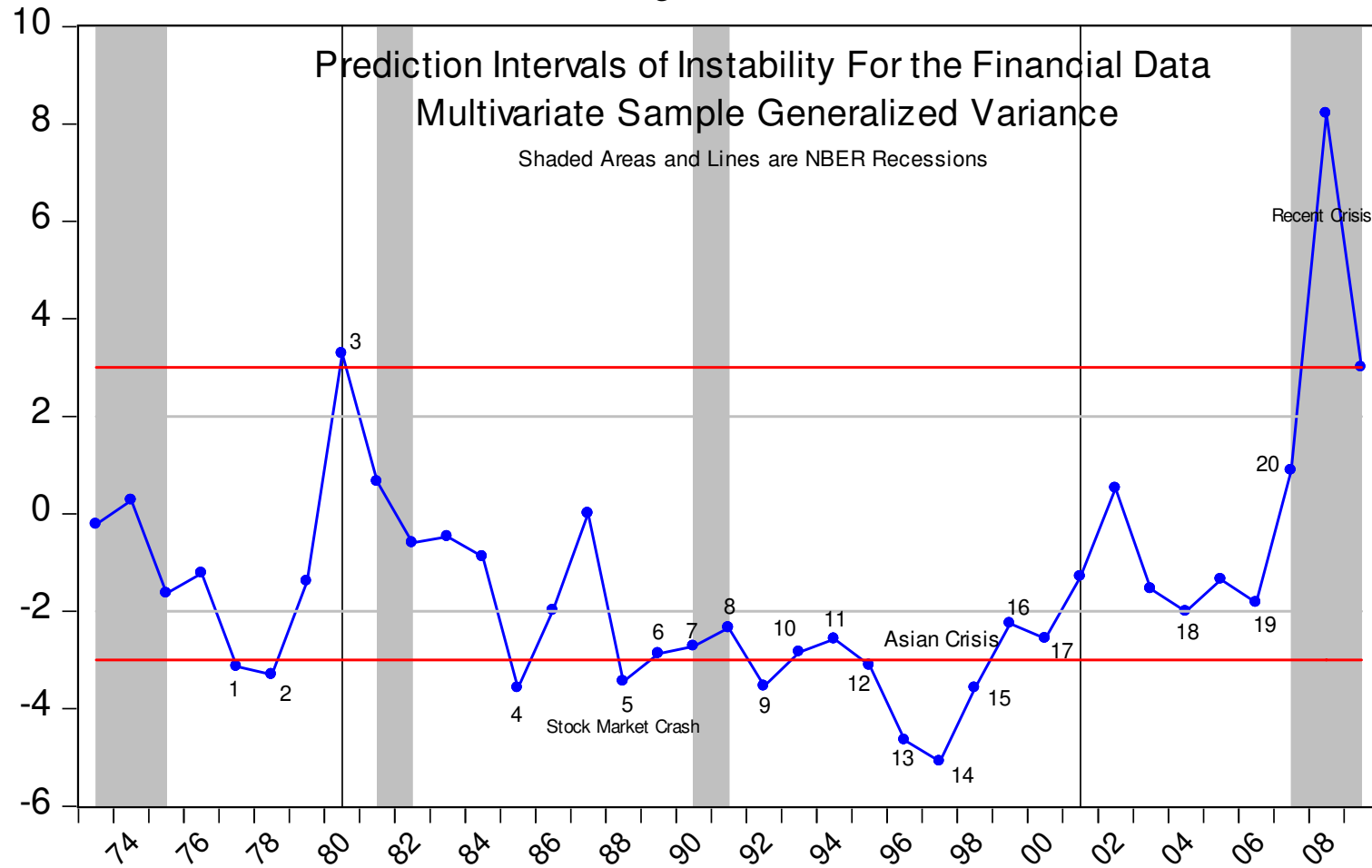
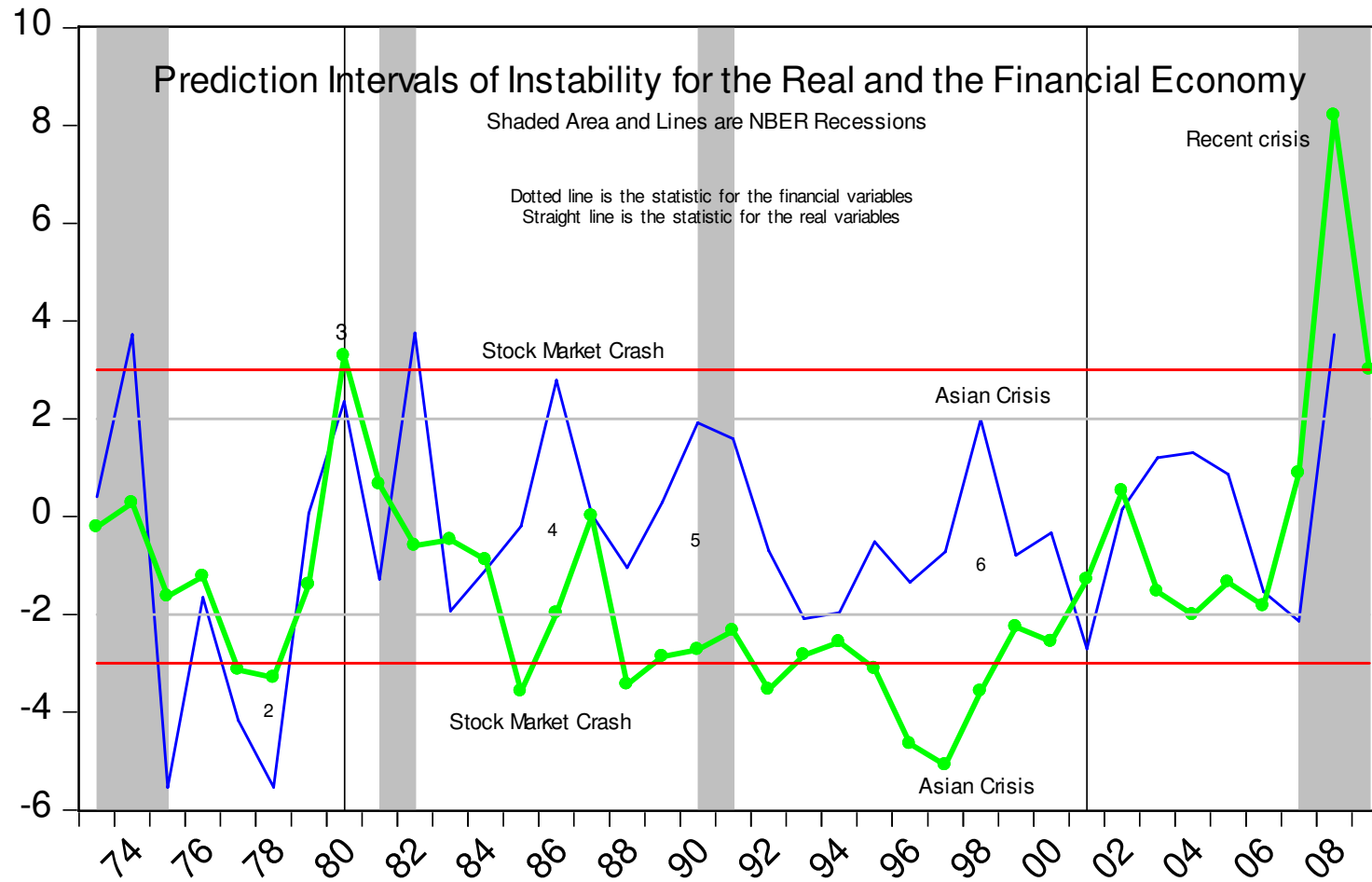


Figure 8



SAS-IML Code to compute $q_i(D_k)$

```
%macro razzak(dataset=stability, Variables=X1 X2 X3, m=36, n=12);
proc iml;

use &dataset;

read all into x var {&variables};

m=&m; /*-number of samples-*/
n=&n; /*- sample sizer-*/

p=ncol(x); /*-number of variables-*/

t=nrow(x); /*-total number of observation-*/

b=j(n,1,1);

j=(p-1)*(p-2)/(2*n);

scale=(p/2)*(1-j)##(1/p);

shape= p*(s-p)/2 ;

start qc;

do h=n to t by n;

gp=x((h-n+1):h,|);

mgp=gp(|:,|);

if h=n then xb=mgp; else xb=xb//mgp;

cssg=gp-(mgp@b);

ssg=(cssg`*cssg);

covg=(cssg`*cssg)/((n)-1);

dcovg=det(covg);

if h=n then do ;

ssp=ssg;;dcov=dcovg ; end;

else do ;ssp=ssp+ssg;dcov=dcov//dcovg; end;
```



```

end;

xdb=x(:,:)|@b;

b=j(m,1,1);

cov=ssp/(t-m);/* this is a S bar matrix*/

dsbar=det(cov);

gamma=((n-1)*p)*(dcov/dsbar)##(1/p);

y=gamma/scale;

gamma=probgam(y,shape);

xdb=x(:,:)|@b;

t2=(n*diag((xb-xdb)*inv(cov)*(xb-xdb`)))(|,+);

sample=(1:m);

colchr={'Z1' 'Z2' 'Z3' 'Z4' 'Z5' 'Z6' 'Z7' 'Z8' };

u=probchi(t2,p);

q=probit(u);

u1=probgam(y,shape);

q1=probit(u1); /* This is q(D) statistic, which is distributed standard normal*/

output2=output2//((sample`||gamma||u1||q1);

colchr2={'Sample' 'Gam' 'u1' 'Q1'};

output=output//((sample`||t2||u||q||dcov);

colchr1={'SAMPLE' 'T SQUARE' 'U' 'Q' 'DET n'};

*print cov(|colname=colchr rowname=colchr|);

* print output(|colname=colchr1|);

* print output2(|colname=colchr2|) ;

create p0 from output(|colname=colchr1|);

```

```
append from output;  
  
close p0;  
  
create p1 from output2(|colname=colchr2|);  
  
append from output2;  
  
close p1;  
finish ;  
start main;  
run qc;  
finish;  
run main ;  
quit;  
proc print data=p0;  
title2'IML OUTPUT Dataset=P0';  
run;  
proc print data=p1;  
title2'IML OUTPUT Dataset=P1';  
run;  
%mend;  
%razzak(dataset=stability , variables=X1 X2 X3, m=36,n=12);
```

An R code in case one does not have SAS. This software is free.

This is the RUN file.

Create a folder Prog in the C drive.

Save the R code written below in boldface in the Prog folder and name it Prog.R

Create a file data.txt and save in the Prog folder in the C drive

Download R from the net and save in the Prog folder in the C drive.

RUN.txt

```
setwd("c:/prog")
source("prog.R")
stability <- read.table("data.txt", header=TRUE)
out <- test(dataset=Name , variables=c("X1", "X2", "X3"),
m=Number,n=Number)
out$p0
out$p1
```

Code: Prog.R

```
test <- function(dataset, variables, m, n) {

  x <- dataset[,charmatch(variables, colnames(dataset))]
  p <- ncol(x)
  t <- nrow(x)
  b <- matrix(1, n, 1)
  j <- (p-1)*(p-2)/(2*n)
  scale <- (p/2)*(1-j)^(1/p)
  shape <- p*(n-p)/2
  for(h in seq(n,t, by=n)) {
    gp <- x[(h-n+1):h,]
    mgp <- colMeans(gp)
    if (h==n) {
      xb <- mgp
    } else {
      xb <- rbind(xb,mgp)
    }
    cssg <- as.matrix(gp-(mgp %x% b))
    ssg <- (t(cssg) %**% cssg)
    covg <- (t(cssg) %**% cssg)/((n)-1)
    dcovg <- det(covg)

    if (h==n) {
      ssp <- ssg
      dcov <- dcovg
    } else {
      ssp <- ssp+ssg
    }
  }
}
```

```

    dcov <- rbind(dcov, dcovg)
  }
}

#xdb=colMeans(x)
cov <- ssp/(t-m) ## this is a S bar matrix*
dsbar <- det(cov);
gamma <- as.vector(((n-1)*p)*(dcov/dsbar)^(1/p))
y <- gamma/scale
gamma <- pgamma(y,shape=shape)
b <- matrix(1, m, 1)
xdb <- t(colMeans(x)) %x% b
t2 <- n*diag((xb-xdb)%*%solve(cov)%*%t(xb-xdb))
sample <- 1:m
colchr <- c('Z1', 'Z2', 'Z3', 'Z4', 'Z5', 'Z6', 'Z7', 'Z8')
u <- pchisq(t2,p)
q <- qnorm(u)
u1 <- pmin(pgamma (y,shape), 0.999999) ##We do this to avoid having U1=1*
q1 <- qnorm(u1)
output2 <- data.frame(gamma=gamma, u1=u1, q1=q1)
colchr2 <- c('Gam', 'u1', 'Q1')
output <- data.frame(t2=t2,u=u,q=q,dcov=as.vector(dcov))
colchr1 <- c('T SQUARE', 'U', 'Q', 'DET N')
colnames(output) <- colchr1
colnames(output2) <- colchr2
return(list(p0=output, p1=output2, xdb = xdb))
}

```

ⁱ Think of a $\pm 3\sigma$ which constitute a probability of 0.9973, hence 1-0.9973.

ⁱⁱ For a two-variable case, i.e., $P = 2$, the appropriate prediction intervals are derived such that the statistic is an approximately chi-squared random variable, when the number of degrees of freedom for estimating the parameters is large. When the number of degrees of freedom is not large, the statistic is an approximately Hotelling T^2 . This is easily computed given the definitions above:

$$T^2 = \frac{n}{1 - \rho^2} \left[\left(\frac{x_1 - \bar{x}}{s_1} \right)^2 + \left(\frac{x_2 - \bar{x}}{s_2} \right)^2 - 2\rho \left(\frac{x_1 - \bar{x}}{s_1} \right) \left(\frac{x_2 - \bar{x}}{s_2} \right) \right]$$
, where ρ is the correlation coefficient and x, \bar{x}, s as defined earlier.

ⁱⁱⁱ Chebyshev's inequality (also known as Tchebysheff's inequality, Chebyshev's theorem, or the Bienaymé-Chebyshev inequality) states that in any data sample or probability distribution, nearly all the values are close to the mean value, and provides a quantitative description of *nearly all* and *close to*. For any $k > 1$, the following example (where $\sigma = 1/k$) meets the bounds exactly. So $\Pr(X = 1) = 1/2k^2$; $\Pr(x = 0) = 1 - 1/k^2$ and $\Pr(X = -1) = 1/2k^2$ for that distribution $\Pr(|X - \mu|) \geq k\sigma = 1/k^2$. Equality holds exactly for any distribution that is a linear transformation of this one. Inequality holds for any distribution that is not a linear transformation of this one.