Essays in asymmetric empirical macroeconomics

by

Mohammad Iqbal Ahmed

B.A., University of Delhi, 2000

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AN ABSTRACT OF A DISSERTATION

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Abstract

This dissertation consists of three essays in asymmetric empirical macroeconomics. Making macroeconomic policies has become increasingly difficult because of intricate relationships among macroeconomic variables. In this dissertation, we apply state-of-the-art macroeconometric techniques to investigate asymmetric relationships between key macroeconomic aggregates. Our findings have important macroeconomic policy implications.

An analogue to the Phillips curve shows a positive relationship between inflation and capacity utilization. Some recent empirical work has shown that this relationship has broken down when using data after the mid-1980s and several popular explanations for this changing relationship, including advancements in technology and globalization, were put forward as possible explanations. In the first essay, we empirically investigate this issue using several threshold error correction models. We find, in the long run, a 1% increase in the rate of inflation leads to approximately a 0.0046% increase in capacity utilization. The asymmetric error correction structure shows that changes in capacity utilization show significant corrective measures only during booms while changes in inflation correct during both phases of the business cycle with the corrections being stronger during recessions. We also find that, in the short run, changes in the inflation rate do Granger cause capacity utilization while changes in capacity utilization do not Granger cause inflation. The Granger causality from inflation to capacity utilization can be interpreted as supporting recent calls made in the popular press by some economists that it may be desirable for the Federal Reserve Bank to try to induce some inflation in an effort to stimulate the economy.

In the second essay, we examine the role of consumer confidence on economic activities like households' consumption in good and bad economic times. We consider the "news" versus "animal spirit" approach interpretation of consumer confidence. In the wake of the

Great Recession of 2008-09, many have called for confidence-boosting policies to help speed up the recovery. A recent study has reinforced these policy calls by showing that the Michigan Consumer Confidence Index contains important information about "news" on future productivity that has long-lasting effects on economic activities like aggregate consumption. Using US data, we show this conclusion is more nuanced when considering an economy that has different potential states. We investigate regime-switching models which use the National Bureau of Economic Research US business cycle expansion and contraction data to create an indicator series that distinguishes bad and good economic times and use this series to investigate impulse responses and variance decompositions. We show the connection between consumer confidence to some types of consumer purchases is important during good economic times but is relatively unimportant during bad economic times. We also use this type of model to investigate the connection between news and consumer confidence and this connection is also shown to be state dependent. In the context of the animal spirits versus news debate, our findings show that during economic expansions, consumer confidence shocks likely reflect news, while during economic contractions, consumer confidence shocks are consistent with animal spirits. These findings also have important implications for recent policy debates which consider whether confidence boosting policies, like raising inflation expectations on big-ticket items such as automobiles or business equipment, would lead to a faster recovery.

The third essay investigates expectation shocks and their effect on the economy. For instance, this essay investigates whether the economy responds to expectation shocks in an importantly asymmetric way. A growing literature shows that agents' expectation about the future can lead to boom-bust cycles. These studies so far ignore the transmission effects of expectations on current economic activities across the policy regimes. Using the Survey of Professional Forecasters and Livingstone Survey data, this study empirically investigates the effects of expectation shocks on macroeconomic activities when policy regimes shift. Identifying a structural shock to expectations by using the timing of information in the forecast surveys and actual data releases, we show that the effects of agents' expectations about the future on current macroeconomic activities are asymmetric across the policy regimes. In particular, we find that a perception of good times ahead typically leads to a significant rise in current measures of economic activity in a hawkish regime relative to a dovish regime. We also find that monetary policy's reactions to agents' expectations are asymmetric across the policy regimes. Our findings do not support the views of critics of the central banks, who argued that keeping monetary policy too easy for too long is responsible for fueling the booms. Instead, our findings support the traditional view that a positive (negative) expectation about the future coincides with an anticipatory tightening (easing) of monetary policy.

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Approved by:

Major Professor
Steven P. Cassou

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Dedication

To my parents, Sultana Kashem and Abul Kashem.

Chapter 1

Threshold cointegration between inflation and US capacity utilization[1]

1.1 Introduction

The popular Phillips Curve in traditional as well as New Keynesian models shows a short-run connection between inflation and output. This connection has led the Federal Reserve Bank (Fed) policy makers, who are on the lookout for inflation, to study the connection between capacity utilization and inflation with the expectation that capacity utilization may serve as a useful leading indicator for inflation.[2] Although some of the earlier papers seemed to find a connection, this connection appeared to drop off in the mid 1980s and several popular explanations for this changing relationship, including advancements in technology and globalization were put forward as possible explanations.[3] This decoupling can be under-

[1]A paper is published in *Applied Economics* from this chapter. See Ahmed and Cassou (2017).

[2]Among the numerous Federal Reserve Bank economists' papers are McElhattan (1978, 1985), Bauer (1990), De Kock et al. (1996), Corrado and Mattey (1997), Emery and Chang (1997), Dotsey and Stark (2004).

[3] Garner (1994), Shapiro et al. (1989), Cecchetti (1995) and Stock and Watson (1999), Corrado and Mattey (1997), Brayton et al. (1999) and Nahuis (2003) show that capacity utilization has significant positive relationship with inflation, thus predicting inflation better than the unemployment rate while Shapiro et al. (1989) shows that high capacity utilization has a small, insignificant, and sometimes negative impact on prices. Finn (1995), Aiyagari (1994), Bansak et al. (2007) examined the effects of technological change on

stood anecdotally by noting the stable inflation that settled into the US economy beginning around 1983, which has come to be known as the Great Moderation, despite the economy still traveling through boom and recession episodes. In this study, we use modern time series econometric methods to show that there continues to be both long run and short run linkages between capacity utilization and inflation.

Despite the mature nature of cointegration econometric methods, which are perfectly suited to studying short and long run connections between variables, there are few papers that have used these methods for investigating the potential long run connection between capacity utilization and inflation.[4,5] Several factors could account for this dearth of research, but perhaps one important one is how to undertake unit root tests on bounded series such as capacity utilization. Granger (2010) argues that although bounded time series cannot be integrated in the usual sense, in many theoretical and applied studies they are modeled as pure I(1) processes. He argues that if the bounded nature of a bounded process is not taken into account, the standard unit root test results will be biased.[6] Work by Cavaliere (2005) and Cavaliere and Xu (2014) has shown this to be true, that conventional unit root tests tend to over reject the null hypothesis of a unit root, even asymptotically, and they are potentially unreliable in the presence of bounds.[7] A second important factor for the lack or research may be the inability of the traditional cointegration methods to handle changes in

capacity utilization, while Gamber and Hung (2001) and Dexter et al. (2005) show that international trade has a significant downward impact on US inflation, which might have obscured the relationship between capacity utilization and inflation in 1990s.

[4]The cointegration literature dates back to Engle and Granger (1987) and has seen many important contributions over the years including Johansen (1988), Johansen and Juselius (1990), Hansen and Seo (2002) and of particular interest to this paper, Enders and Siklos (2001).

[5]One paper that does investigate cointegration is Mustafa and Rahman (1995) who use traditional cointegration methods. Unlike our results, they did not find a cointegration relationship between capacity utilization and inflation.

[6]Examples of econometric studies with bounded time series variables are numerous. For example, in their influential paper Nelson and Plosser (1982) reject the unit root hypothesis of the U.S. unemployment rate and studies which link unemployment rates and other variables are quite commonplace. Several empirical models of the European Monetary System exchange rates have been specified by using cointegrated vector autoregressive (VAR) models without taking account of the presence unit root such as Anthony and MacDonald (1998), Svensson (1993).

[7] Cavaliere (2005) explains how the concept of I(1) can coexist with the constraints of a bounded process. Further, Cavaliere and Xu (2014) shows that the presence of bounds affects the standard unit root tests. Using the now popular, Monte Carlo methods to simulate correct critical values, they show that when bounds are taken into account, the Augmented Dickey Fuller tests is much less likely to reject the null of a unit root.

the nature of the relationship between variables.[8] Balke and Fomby (1997) argue that the tendency towards long-run equilibrium might not occur at each point of time as adjustments toward the long-run could be asymmetric. In this paper, we not only use the methods developed by Cavaliere and Xu (2014) to investigate unit roots, but we also use methods developed by Enders and Siklos (2001) to allow a switching structure in the relationship between the variables.

Using these methods, we show that both inflation and capacity utilization have unit roots and they are cointegrated. The cointegrating vector can be interpreted to show the long run relationship between these variables. We show that the momentum threshold autoregression model (M-TAR) suggested by Enders and Siklos (2001) fits the data best, thus showing that the cointegration structure requires a switching structure. Using a switching structure to estimate error correction models, we show that again asymmetries are present. The error correction models show both long run and short run dynamics are in play with the long run dynamics determined by the cointegration vector and the short run dynamics determined by the lagged differences of the two variables in the error correction structure.

We can summarize some of the economic results as follows. The results are largely the same when measuring capacity utilization by either manufacturing capacity utilization or total capacity utilization.[9] A 1% increase in the rate of inflation leads to a 0.0046% increase in capacity utilization in the long run.[10] The error correction structure shows that changes in capacity utilization show significant corrective measures only during booms while changes in

[8]For instance, asymmetric changes in the relationship between capacity utilization and inflation can be associated with the typical Keynesian story. According to this theory, a non-linearity in aggregate supply implies that when the overall resources in the economy are underutilized, firms can increase output without rising the price level because of sticky wages. But when rising aggregate demand pushes output beyond a certain threshold, the increasing marginal cost of resources causes prices to rise. Such an asymmetry was often found in the data from the 1970s and early 1980s where inflation was tame until capacity utilization exceeded a value around 82%.

[9]We studied both types of capacity utilization data to investigate robustness. However, because the results are largely the same between these to measures, in this paper we only report the results for total capacity utilization. Results for manufacturing capacity utilization can be obtained from the authors upon request. From this point on, we will frequently leave off the adjective “total” and simply say capacity utilization rather than total capacity utilization.

[10]By 1% increase in the rate of inflation, we mean a calculation of $0.01\times$inflation, not $0.01+$inflation. Similarly, by a .0046% increase in capacity utilization we mean the same type of calculation.

inflation correct during both phases of the business cycle with the corrections being stronger during recessions. In addition, the error correction structure shows that in the short run, increases in the change in capacity utilization portend further increases in the change in capacity utilization but do not imply a significant impact on the change in the inflation rate while increases in the change in the inflation rate portend further increases in the change in the inflation rate and decreases in the change in capacity utilization. Changes in the inflation rate do Granger cause short term changes in capacity utilization while changes in capacity utilization do not Granger cause short term changes in inflation. The short term Granger causality from inflation to capacity utilization can be interpreted as supporting recent calls made in the popular press by some economists that it may be desirable for the Fed to try to induce some inflation in an effort to stimulate the economy.[11] However, it is also possible to interpret these Granger causality results as arising because both variables respond to some more fundamental set of variables with the inflation rate simply responding sooner. The lack of short term Granger causality from capacity utilization to inflation casts doubt on the older view that capacity utilization could be a leading indicator for future inflation.

The rest of the chapter is organized as follows. In Section 1.2 we describe various econometric techniques for estimating cointegration and error correction models used in this paper and how they relate to the application we are investigating. Section 1.3 undertakes the econometric analysis and summarizes results of the various econometric steps. The conclusion is presented in Section 1.4.

[11]For example, on NPR on October 7^{th}, 2011, Rogoff (2011) is quoted as saying, "They need to be willing, in fact actively pursue, letting inflation rise a bit more. That would encourage consumption. It would encourage investment...," while in The New York Times on October 29^{th}, 2011, Romer (2011) said, "In the current situation, where nominal interest rates are constrained because they can't go below zero, a small increase in expected inflation could be helpful. It would lower real borrowing costs, and encourage spending on big-ticket items like cars, homes, and business equipment."

1.2 Empirical cointegration methodology

Our empirical cointegration methodology follows methods used in Enders and Siklos (2001), who investigated threshold cointegration between short term and long term interest rates.[12] Such investigations start by showing that the variables of interest are integrated of the same order. The methods used in this study to test unit roots are discussed below in the Empirical Results section so that we can focus on the cointegration and error correction methods in this section. For now, we proceed as though this initial result has been established.

Our application investigates whether the log of capacity utilization, which we denote generically by c_t, is cointegrated with the log of the inflation rate which we denote by π_t.[13] Such investigations start by showing that the variables of interest are integrated of the same order. For now, we proceed as though this initial result has been established. The potential cointegrating relationship we investigate is given by

$$c_t = \alpha + \beta\pi_t + \mu_t \tag{1.1}$$

where α and β are parameters and μ_t is an error term. The cointegration methodology suggested by Engle and Granger (1987) and embraced by Enders and Siklos (2001) begins by using OLS to estimate (1.1), then recovering the residuals, which we denote by $\widehat{\mu}_t$, and then estimating a regression of the form

$$\Delta\widehat{\mu}_t = \rho\widehat{\mu}_{t-1} + \sum_{i=1}^{p}\gamma_i\Delta\widehat{\mu}_{t-k} + \varepsilon_t \tag{1.2}$$

where ρ and γ_i, for $i = 1, ..p$, are parameters and ε_t is an error term. In this regression, the lag length p is typically chosen by some type of information criterion so that the model is well specified and results in ε_t being white noise. Using the estimated parameter $\widehat{\rho}$ one

[12]The Threshold Autoregressive and Momentum Threshold Autoregressive models were first described by Tong (2012), Enders and Granger (1998).

[13]In Section 3 we investigate two types of capacity utilization including total and manufacturing, but to keep notation simple we denote them both with a single generic notation c_t.

tests the null $H_0 : \rho = 0$. If this is rejected, then one concludes that μ_t is stationary and thus c_t and π_t are cointegrated. There are some subtle aspects of testing hypotheses in this model, which are well known, and so we do not describe them in detail here. However, one important subtlety that is relevant for this research is that the distribution for the test statistics, including the t-statistic for $H_0 : \rho = 0$ are not standard and need to be generated through Monte Carlo methods.

Enders and Siklos (2001) extend the early cointegration literature to investigate whether there is a threshold structure for the error term μ_t. For now we will describe their simplest extension, called a threshold aggressive (TAR) model, but later we will also discuss their so call momentum threshold autoregressive (M-TAR) model. The TAR model modifies (1.2) to include an asymmetry and is given by

$$\Delta\widehat{\mu}_t = I_t\rho_1\widehat{\mu}_{t-1} + (1 - I_t)\rho_2\widehat{\mu}_{t-1} + \sum_{i=1}^{p}\gamma_i\Delta\widehat{\mu}_{t-k} + \varepsilon_t \tag{1.3}$$

where ρ_1, ρ_2 and γ_i, for $i = 1, ..p$, are parameters and ε_t is an error term and I_t is an indicator function defined by

$$I_t = \begin{cases} 1 & \text{if} \quad \widehat{\mu}_{t-1} \geq 0 \\ 0 & \text{if} \quad \widehat{\mu}_{t-1} < 0 \end{cases} \tag{1.4}$$

As in the Engle and Granger (1987) the lag length p is typically chosen by some type of information criterion so that the model is well specified and results in ε_t being white noise. Testing for cointegration is analogous to the earlier procedure and requires testing $H_0 : \rho_1 = \rho_2 = 0$. Enders and Siklos (2001) call this test statistic Φ, while a simpler statistic that looks at the largest of the two t-statistics for $H_0 : \rho_i = 0$, $i = 1, 2$,they call the t-max statistic. As with the Engle and Granger (1987) method, the test statistics do not have standard distributions and Enders and Siklos (2001) describe methods for generating proper critical values for them.

Once the presence of an asymmetric cointegration relationship is confirmed, one can investigate threshold vector error correction models (VECM) using $\widehat{\mu}_{t-1}$ by estimating

$$\Delta c_t = \alpha_c + \rho_{c,1} I_t \widehat{\mu}_{t-1} + \rho_{c,0}(1 - I_t)\widehat{\mu}_{t-1} + \sum_{i=1}^{p} \beta_{c,c,i} \Delta c_{t-i} + \sum_{i=1}^{p} \beta_{c,\pi,i} \Delta \pi_{t-i} + \varepsilon_{ct} \tag{1.5}$$

and

$$\Delta \pi_t = \alpha_\pi + \rho_{\pi,1} I_t \widehat{\mu}_{t-1} + \rho_{\pi,0}(1 - I_t)\widehat{\mu}_{t-1} + \sum_{i=1}^{p} \beta_{\pi,c,i} \Delta c_{t-i} + \sum_{i=1}^{p} \beta_{\pi,\pi,i} \Delta \pi_{t-i} + \varepsilon_{\pi t} \tag{1.6}$$

where α_j, $\rho_{j,1}$, $\rho_{j,0}$, $\beta_{j,c,i}$, and $\beta_{j,\pi,i}$ for $j = c, \pi$ and $i = 1, ...p$ are parameters to be estimated and ε_{jt}, for $j = c, \pi$, are error terms. In this specification, the subscripts make use of the following mnemonics. The first subscript indicates which equation the parameter or error term is from, the second subscript in the $\rho_{j,1}$and $\rho_{j,0}$ parameters indicates the value for I_t (e.g. 1 or 0), while the second and third subscripts attached to the lagged differenced variables correspond to the type of variable that is differenced (i.e. c or π) and the lag value for that differenced variable. In typical applications, the lag length p is chosen based on some sort of information criterion so that the model is well specified and results in the error terms being white noise.[14]

The various $\rho_{j,1}$, $\rho_{j,0}$ for $j = c, \pi$ are known as the speed of adjustment parameters. Like the speed of adjustment parameters in the basic Engle and Granger interpretations, they show how fast and in what direction the variables adjust to errors in the equilibrium relationship (1.1). However, here, the speed of adjustments not only depend on the equation of interest, but they also depend on whether the switching variable, $\widehat{\mu}_{t-1}$, is above or below the threshold 0. Also of note, is that Granger causality tests which examine the lead-lag relationship between changes in capacity utilization and changes in inflation rate can be investigated. The null hypothesis that changes in inflation do not Granger cause changes in

[14]These empirical models make use of some standard notations such as α, β, ρ and ε in the different equations. However, these parameters and error terms do differ in the different equations and the subscripts should make things easy to see where each came from.

capacity utilization can be formalized mathematically using a null given by

$$H_0 : \beta_{c,\pi,i} = 0 \;\; \text{for} \;\; i = 1, ...p, \tag{1.7}$$

whereas the null hypothesis that changes in capacity utilization does not Granger cause changes in inflation can be formalized mathematically using

$$H_0 : \beta_{\pi,c,i} = 0 \;\; \text{for} \;\; i = 1, ...p. \tag{1.8}$$

There are also various ways to extend the TAR model described above. One is an endogenous TAR model which redefines the switching indicator by

$$I_t = \begin{cases} 1 & \text{if} \quad \widehat{\mu}_{t-1} \geq \tau \\ 0 & \text{if} \quad \widehat{\mu}_{t-1} < \tau \end{cases} \tag{1.9}$$

where τ is a threshold parameter to be estimated. A popular algorithm, due to Chan (1993) estimates τ jointly with the other parameters of the model by considering the middle 70% of the ordered observed values of $\widehat{\mu}_t$ (i.e. all the candidate $\widehat{\mu}_t$ values are ranked from highest to lowest and the top 15% and the bottom 15% are excluded from consideration) and then estimating the model for each of these possibilities. Among the many estimated models, the one with the lowest sum of squared residuals is then chosen as the best fitting model and its parameter estimates become the estimates used for the endogenous TAR model.

A second extension is known as a momentum threshold autoregressive (M-TAR) model. Here we also focus on an endogenous threshold version of this model, but in our analysis below we also consider one with an exogenous threshold with $\tau = 0$. This model has very similar properties to the TAR model, but shows more momentum during some portions of the correction process. The M-TAR model has only one small formal difference relative to the endogenous TAR model in that it defines the switching dummy by

$$I_t = \begin{cases} 1 & \text{if} \quad \Delta\widehat{\mu}_{t-1} \geq \tau \\ 0 & \text{if} \quad \Delta\widehat{\mu}_{t-1} < \tau \end{cases} \tag{1.10}$$

instead of by (1.9). For both of these alternative models, the mechanical details are the same as the TAR model as well as the error correction formulation.

1.3 Empirical results

Our empirical analysis uses monthly data for capacity utilization which is tabulated by the Federal Reserve Bank. Our preliminary analysis used two different measures for capacity utilization in order to investigate whether results are consistent between these different utilization measures. These included Total Capacity Utilization, which can be found at the Board of Governors of the Federal Reserve System website and is given by the series CAPUTL.B50001.S and Manufacturing Units Capacity Utilization, which can be found at the same website and is given by the series CAPUTL.B00004.S. Results for these series were consistent with each other and to save space we only report the total capacity utilization results which we will simply refer to as capacity utilization from this point onward. We used the full set of available data which was collected on a monthly basis and covered the interval 1967:1 to 2013:12.

The inflation rate was computed by using the core consumer price index (CPI) based on the formula, $Inflation\,Rate_i = Log\left[\frac{CPI_t}{CPI_{t-12}}\right] * 100$. We use the core inflation rate in part because of it is a preferred measure of inflation by the Fed, and in part because studies, such as Finn (1996), have shown that fuel prices have a negative impact on capacity utilization. The particular CPI series used was Consumer Price Index for All Urban Consumers: All Items Less Food and Energy Inflation Series (CPILFESL) which was downloaded from the Federal Reserve Bank of St. Louis Economic Data (FRED) base. This data is available on a monthly basis for a longer period than the capacity utilization data, so in effect the complete set of data for our study was also over the interval 1967:1 to 2013:12.

1.3.1 Preliminary analysis

Before considering more formal unit root and cointegration testing, we first carry out some looser preliminary analysis to get a sense for the data. In this subsection we describe a few of these investigations.

Figure 1.1 shows a plot of capacity utilization and inflation over the period from 1967:1. to 2013:12, with the shaded areas representing the NBER recessionary periods. The figure shows the moderating inflation rate after 1983 which has confounded some of the work trying to link capacity utilization and inflation. The figure also shows that capacity utilization tends to decline sharply during recessions and slowly increase during recoveries and boom periods. Recognizing this pattern is useful later on when we discuss how to interpret the cointegration results.

Table 1.1 shows autocorrelation values for capacity utilization and inflation over two intervals of time. Autocorrelation functions are traditional methods that are used for measuring persistence and potentially identifying unit roots. For comparison purposes we have also included the autocorrelations for a popular measure for the dollar exchange rate which is widely viewed as having a unit root. The exchange rate series is tabulated by the Board of Governors of the Federal Reserve System and is reported in Table H.10 under the name Price-adjusted Broad Dollar Index- Monthly Index. This broad dollar index is only available starting in January of 1973, so for comparison purposes, we have started the statistical calculations for Tables 1.1 - 1.3 at this date. We also used a start date of January 1990 as an alternative in order to focus on behavior during more recent times and perhaps detect different behavior during the recent period. Table 1.1 shows all three series to be highly persistent over both data intervals. The comparable level of persistence for the two series of interest in this study, capacity utilization and inflation, with the exchange rate provides preliminary

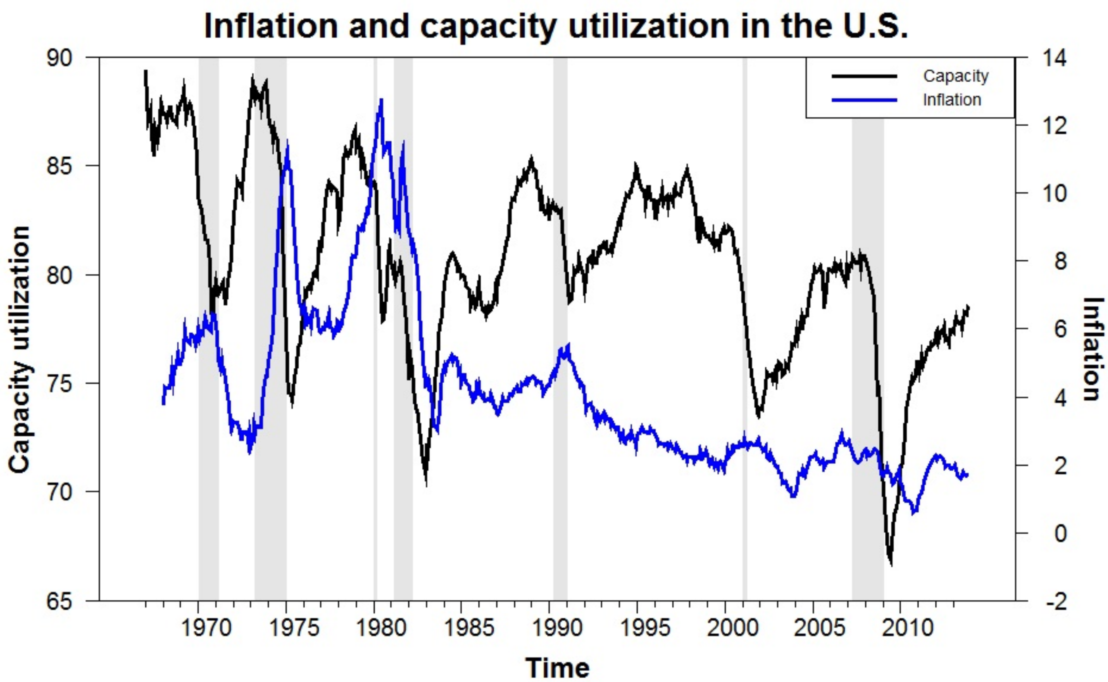

Figure 1.1: Inflation and Capacity Utilization in the U.S.

evidence that capacity utilization and inflation may also contain unit roots. Furthermore, there does not appear to be obvious differences in behavior for the series of interest during more recent dates.

A related measure of persistence is the so called half-life measure for a unit shock. The half-life of a shock measures the number of years for a unit impulse to dissipate by one-half. The computation is based on the assumption that the series is stationary and estimates AR(1) models that contain an intercept or an intercept and a trend. The half-life is then computed using $HL = \frac{ln(0.5)}{\ln(\widehat{\alpha})}$, where $\widehat{\alpha}$ is the estimated coefficient for the AR(1) term. Table 1.2 reports the half lives for capacity utilization, inflation and the exchange rate in various rows, where the first column lists the names of the various variables. The table is organized into two panels with the left panel reporting half-lives for models estimated over the 1973:1 to 2013:12 period and the right panel reporting half-lives for models estimated over the 1990:1 to 2013:12. For each of the time intervals, we estimate the AR(1) models without a trend and with a trend. The first and third column of each panel lists the AR(1)

Table 1.1: *A*utocorrelation functions values

Lag	1973:1 to 2013:12 Cap Ut	Inflation	Ex rate	1990:1 to 2013:12 Cap Ut	Inflation	Ex rate
1	0.986	0.994	0.988	0.983	0.990	0.988
2	0.964	0.985	0.972	0.962	0.976	0.970
3	0.935	0.973	0.956	0.939	0.957	0.952
4	0.902	0.959	0.939	0.915	0.932	0.934
5	0.863	0.944	0.922	0.891	0.903	0.918
6	0.824	0.927	0.905	0.864	0.871	0.901
7	0.781	0.910	0.890	0.833	0.836	0.885
8	0.739	0.891	0.874	0.798	0.801	0.870
9	0.694	0.872	0.857	0.761	0.764	0.855
10	0.648	0.851	0.834	0.726	0.727	0.840
11	0.601	0.830	0.821	0.691	0.691	0.823
12	0.555	0.791	0.800	0.655	0.656	0.805

coefficient estimates for each model, while the second and fourth column of each panel lists the implied half-life. Table 1.2 shows that the half-life values for capacity utilization and inflation are similar to those for the exchange rate. Because the exchange rate is widely viewed as having a unit root, this similar level of persistence for capacity utilization and inflation point to these variables as also having unit roots.

Table 1.2: Half-lives of a unit shock

	(1973:1 to 2013:12)				(1990:1 to 2013:12)			
Variables	Without trend		With trend		Without trend		With trend	
	$\widehat{\alpha}$	HL	$\widehat{\alpha}$	HL	$\widehat{\alpha}$	HL	$\widehat{\alpha}$	HL
Cap Ut	0.991	76.67	0.987	52.97	0.990	68.97	0.986	45.86
Inflation	0.995	138.28	0.993	98.67	0.993	98.67	0.976	28.53
Ex rate	0.992	86.30	0.99	68.97	0.989	62.67	0.989	62.67

Another useful preliminary data analysis is to investigate the comovement between the data series. If the data series are cointegrated then there should be comovement between the series. Table 1.3 shows how these three series comove over the two data intervals. Again the real exchange rate as a reference series. Table 1.3 shows that capacity utilization and inflation are highly positively correlated on a contemporaneous basis which indicates that they could possibly be cointegrated. Furthermore, in most instances, neither series is very correlated with the exchange rate, which is consistent with a lack of cointegration with the exchange rate. However, one notable instance where there is higher correlation is for the inflation rate and the exchange rate over the full 1973:1 to 2013:12 period. This likely arises because the high inflation during the 1970s resulted in a steady decline in the exchange rate. Overall, Table 1.3 shows evidence that capacity utilization and inflation are highly correlated and that the correlation has actually increased during more recent years. This further motivates a formal cointegration analysis.

Table 1.3: Contemporaneous cross-correlation values

	1973:1 to 2013:12			1990:1 to 2013:12		
Variable	Cap Ut	Inflation	Ex rate	Cap Ut	Inflation	Ex rate
Cap Ut	1			1		
Inflation	0.218	1		0.461	1	
Ex rate	-0.016	-0.191	1	-0.118	-0.106	1

1.3.2 Formal analysis

The first step in a cointegration investigation is to investigate whether the series are individually integrated. We ran a battery of different unit root tests to investigate this issue and Table 1.4 summarizes some of these results. The table is organized into two vertical panels, with the left-most panel showing results using inflation data and the right-most panel showing the results for capacity utilization as indicated in the first row of the table.[15] Each vertical panel has three horizontal subpanels which report results for the Augmented Dickey-Fuller tests (ADF), Phillips-Perron (PP) tests and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests. These are among the most popular unit root tests, with the ADF and PP tests using a null of nonstationarity and the KPSS using a null of stationarity. For each series, models with different deterministic variables were run, with one including both a deterministic trend and a constant term, one with only a constant term and one without either a deterministic trend or a constant. These three alternatives are marked in the second row of the table and summarized with mnemonic column notations of Trend, for models with a deterministic time trend and a constant, Cons, for models with just a constant and None for models with neither a deterministic trend or a constant. For the ADF tests, a preliminary analysis to determine the number of lags on the differenced terms using the Schwarz Crite-

[15] The data interval in this table for inflation was 1967:1 to 2013:12.

rion or Bayesian Information Criterion (BIC) was undertaken and as indicated in the table, the inflation series best fit with 13 lagged differenced terms while the capacity utilization series best fit with 4 lagged difference terms. For comparison purposes, this number of lags was used for the other tests as well.

The first row with numbers shows the value of the t-statistic for the ADF test. In particular, the ADF test statistic for the inflation series in a model with a deterministic time trend and a constant was -3.16, for a model with just a constant term was -1.89, and for a model with no deterministic trend or constant term was -1.24. As noted at the bottom of the table, we use a convention of including asterisks to indicate significance levels, with one asterisk indicating significance at the 10% level, two asterisk indicating significance at the 5% level and three asterisks indicating significance at the 1% level. This convention is also used in Tables 1.5 and 1.6 below. For the ADF tests, we used the conventional critical values in applying the significance notations. As can be seen in the table, all of the inflation models could not reject the null of nonstationarity using the ADF tests. These results are consistent with those in Ng and Perron (2001) who also could not reject the null of nonstationarity.[16] Table 1.4 also provides the 5% critical values directly below the coefficients in parenthesis terms, which may be a useful reference for reinforcing ones thinking about these tests. So as indicated in the table, the conventional 5% critical values for the ADF test on inflation for the model with deterministic trend and a constant is -3.41, for the model with only a constant is -2.86, and for the model without a deterministic trend or constant is -1.95.

For the capacity utilization series, we report the conventional ADF critical values in the second line and the Cavaliere and Xu (2014) bounded series adjusted critical values in the third line for the model in which there is a constant term. Based on arguments in Cavaliere (2005), Granger (2010) and Cavaliere and Xu (2014), conventional unit root critical values are inappropriate for bounded series. Furthermore, Cavaliere (2005) and Cavaliere and Xu (2014) argue that conventional unit root critical values are inappropriate for series which are influenced by a policy control exercise. Both of these rationals play a role with capacity

[16] Ng and Perron (2001) proposed a class of modified unit root tests that focus on concerns about the low power of the standard unit root tests.

utilization. In particular, capacity utilization indices are by construction bounded between 0 and 100. In addition, policy makers indirectly target capacity utilization since capacity utilization is the analogue of labor unemployment which they directly target. In other words, by targeting labor unemployment directly, policy makers are also targeting capacity utilization indirectly and this binds capacity utilization even more than the simple 0 and 100 values. Based on these arguments, in the presence of construction bounds as well as policy bounds, the conventional unit root test statistics are biased in favor of rejecting the null hypothesis of stationarity. This issue is perfectly illustrated here for the models with constant terms, where we see that using the conventional ADF critical values we reject the null hypothesis of nonstationarity, but when using bounded series adjusted critical values we fail to reject nonstationarity.[17]

The next horizontal panel shows the results for the PP test, which is a popular alternative to the ADF test. Unlike the ADF test, there are only two variations of the PP. In particular, there is no version that does not have a deterministic trend and a constant. This panel is organized in a similar fashion to the ADF test panel, with the t-statistics reported in the first row of the panel, the conventional 5% critical values in the second row of the panel and the bounded series adjusted critical values reported in the third row. This panel also shows that we can never reject the null hypothesis of nonstationarity for either of the series using either the conventional critical values or the bounded series adjusted critical values.

The last horizontal panel shows the results for the KPSS test, which is a popular alternative to conventional unit root tests because it has a null that the series is stationary. Like the PP test, there is no version of the test for a model without a constant. Like the other two panels, the first row of the panel shows the test statistic results while the second row shows the 5% critical values for the test. Unlike the other two panels, there are no Cavaliere and Xu (2014) bounded series adjusted critical values. For all three series, the KPSS tests

[17] Cavaliere and Xu (2014)'s simulation based tests are applicable when bounds are known. Based on their arguments a reasonable range for the bounds can often be inferred from historical observations. We choose the lower and upper bounds of the capacity utilization rate, respectively, at 60 percent and 90 percent as the historical data shows that the capacity utilization rate never lies beyond this range. See also Herwartz and Xu (2008) for further details.

are always rejected at the 5% level which shows consistency with the other tests in that this test also concludes that all three series are nonstationary.

Taken as a whole, these results show strong evidence that the series are nonstationary. Although the ADF critical values for capacity utilization indicated this series was stationary, when using what we consider to be the more reliable Cavaliere and Xu (2014) critical values, the ADF tests show this series is nonstationary. This nonstationary result is further confirmed using the PP and KPSS tests. Since the series are nonstationary, this means there is a chance they can be cointegrated. We now turn to that analysis.

Table 1.4: Unit root tests

Inflation			Capacity Utilization		
Trend	Cons	None	Trend	Cons	None
Lags = 13			Lags = 4		
Augmented Dickey-Fuller - H_0: Nonstationarity					
-3.16	-1.89	-1.24	-4.39**	-3.78**	-0.23
(-3.41)	(-2.86)	(-1.95)	(-3.41)	(-2.86)	(-1.95)
				(-3.83)	
Phillips-Perron Test - H_0: Nonstationarity					
-3.25	-2.02		-3.03	-2.85	
(-3.42)	(-2.87)		(-3.42)	(-2.87)	
				(-3.71)	
KPSS Test -H_0: Stationarity					
0.21**	2.35***		0.36***	3.07***	
(0.15)	(0.46)		(0.15)	(0.46)	

Notes: Values in parenthesis are 5% critical values. For Tables 1.4 - 1.6, ***, ** and * denote the significance at the 1%, 5% and 10% level respectively. ADF tests significance are based on conventional (nonbounded series adjusted) critical values.

To investigate cointegration we now estimate (1.1) for the capacity utilization series and recover the residuals for unit root analysis and later error correction estimation. The estimated long-run relationships are given by

$$c_t = \underset{(0.0049)}{4.37} + \underset{(0.0009)}{0.0046}\pi_t + \widehat{\mu}_t \tag{1.11}$$

where the notations c_t, π_t and $\widehat{\mu}_t$ were described above. The standard errors for the estimated coefficients are presented directly below the parameter estimates in parenthesis. These regression results show highly significant parameter estimates. The estimated slope coefficients show the elasticity of capacity utilization with respect to inflation and indicate that if the inflation rate goes up by 1% then capacity utilization will go up by 0.0046%.

Also of interest are the Regression Error Specification Tests (RESET) which test the null hypothesis of linearity against the alternative hypothesis of nonlinearity. In particular, if the residuals of the linear cointegrated variables are independent, they should not be correlated with the regressors used in the estimating equation or with the fitted values. Thus a regression of the residuals on these values should not be statistically significant. For the capacity utilization data, the RESET test has a value of 8.26 which is highly significant. Because the RESET test has a general alternative hypothesis, the test is helpful in determining whether a nonlinear model is appropriate but not in determining the nature of the nonlinearity. Even so, these results can be interpreted as providing evidence of a nonlinearity in the cointegration relationship between capacity utilization and inflation as well as evidence that the error correction term has a nonlinear relationship for the adjustment towards long-run equilibrium.

We now turn to investigating the structure for the cointegration relationship. Table 1.5 summarizes the estimation results for several different models described earlier. The table shows the results for five models. The first is the standard structure given by (1.2), which we denote by E-G since this is the form used in the original Engle and Granger approach. The next four are various forms of the TAR models, with the second model given by (1.3) and (1.4), the third model given by (1.3) and (1.9) with τ estimated based on an algorithm suggested by Chan (1993), the fourth model given by (1.3) and (1.10) with $\tau = 0$, and the fifth model given by (1.3) and (1.10) with τ also estimated endogenously as in the third model. One clarification about the structure of the table is useful to note. In particular, for the basic model given by (1.2), which we denote E-G, there is only one ρ term with no subscript. To save space, for this model, we listed this estimated parameter in the same row as the ρ_1 terms in the various TAR models. Using either the Akaike Information Criterion

(AIC) or the BIC to chose the lag length for the standard E-G model, we found 5 lags was best. We went ahead and used the same lag lengths for the various TAR models in part to maintain comparability across models.

Table 1.5: Testing for threshold cointegration

	E-G	TAR	TAR	M-TAR	M-TAR
Threshold		$\tau = 0$	$\tau = -0.0414$	$\tau = 0$	$\tau = -0.0053$
ρ_1	-0.024***	-0.020**	-0.017***	-0.024***	-0.031***
	(0.006)	(0.009)	(0.008)	(0.008)	(0.007)
ρ_2		-0.027***	-0.032***	-0.025***	-0.001
		(0.008)	(0.008)	(0.008)	(0.012)
γ_1	0.256***	0.255***	0.254***	0.256***	0.238***
	(0.042)	(0.042)	(0.042)	(0.042)	(0.043)
γ_2	0.149***	0.149***	0.151***	0.149***	0.141***
	(0.044)	(0.044)	(0.0435)	(0.044)	(0.045)
γ_3	0.153***	0.153***	0.156***	0.153***	0.142***
	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)
γ_4	0.113**	0.115***	0.117***	0.114***	0.110**
	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)
γ_5	-0.025	-0.023	-0.019	-0.025	-0.034
	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)
AIC	-2030.20	-2028.62	-2029.98	-2028.21	-2033.32
$H_0 : \rho = 0$	-4.16**				
Φ		8.86**	9.55**	8.64**	11.26***
$t - Max$		-2.27**	-2.01**	-2.92***	-0.06
$H_0 : \rho_1 = \rho_2$		0.41	1.76	0.01	5.08***

In addition to the parameter coefficient estimates, Table 1.5 reports AIC values, and various cointegration test statistics. For the standard E-G model, the relevant statistic is the ADF hypothesis $H_0 : \rho = 0$ while for the TAR and M-TAR models the relevant statistics are the Φ and $t - Max$ statistics suggested by Enders and Siklos (2001). The Φ statistic tests the null $H_0 : \rho_1 = \rho_2 = 0$ while the $t - Max$ statistic is the largest t-statistic among the two nulls of $H_0 : \rho_1 = 0$ and $H_0 : \rho_2 = 0$. As pointed out by Enders and Siklos (2001), one advantage of the $t - Max$ statistic is that it never rejects the null of nonstationarity of the residual (and thus concludes there is cointegration of the variables) when either ρ_1 or ρ_2 are positive, while the Φ statistic could reject the null even when one of the ρ_i values are positive.[18] However they argue the Φ statistic does have improved power and thus they

[18]The desirability of having both ρ_i values negative is motivated by Petruccelli and Woolford (1984), who

place more faith in its value.[19] Because of this greater faith in the Φ statistic, we will focus our discussion on it.[20]

Focusing on the E-G model, we see that $\rho = -0.024$ which implies a t-statistic of -4.16. The statistic is beyond (in the negative direction) the 5% critical value of -1.96 and implies that we reject the null of nonstationarity of the residual series, which is typically interpreted to mean the residuals are stationary and thus the variables in the first step regression are cointegrated.[21] Next focusing on the TAR model we see that both of the ρ_i values are negative, as required for stationarity, and the preferred Φ statistic also rejects the null of nonstationarity of the residuals and thus implies the first step regression variables are cointegrated.[22] Recognizing this pattern, we see that the two M-TAR models have ρ_i values with the appropriate negative signs and Φ statistics that point to cointegration of the variables in the first step regression. Overall, these results all show that the variables in the first step regression are cointegrated.

The next task is to decide which of these candidate models fit the best. One criterion is to use the AIC values which are reported toward the bottom of the table. This statistic picks the M-TAR with endogenous threshold model. Another result that also provides insight into making this choice is to investigate the null that the two ρ_i coefficients are equal in the various TAR and M-TAR models. This test is reported in the last line of the table and shows the M-TAR model with endogenous threshold rejects the null of symmetric adjustment, while the TAR and the constrained threshold M-TAR model do not. This indicates that an endogenous threshold does a better job of fitting the data.

To interpret this asymmetric result, several background details must be recognized first.

showed that necessary and sufficient conditions for stationarity are $\rho_1 < 0$, $\rho_2 < 0$ and $(1+\rho_1)(1+\rho_2) < 1$.

[19]This can be seen on page 169 of Enders and Siklos (2001) where they say, "However, as will be shown, the phi statistic is quite useful because it can have substantially more power than the t-Max statistic." It can also be seen in Table 7 of their paper, where they do not even report the $t - Max$ statistic values.

[20]This preference for the Φ statistics can also be seen in the literature. For instance, Shen et al. (2007) only mention the Φ statistic results and do not mention the $t - Max$ results.

[21]Here we use the conventionally Engle and Granger cointegration adjusted ADF statistics rather than a bounded series ADF statistic. We do this because, even though it is reasonable that c_t is bounded, because π_t is not, any linear combination of the two may not be bounded, so the Cavaliere and Xu (2014) adjustment is not needed.

[22]The critical values for the Φ statistic can be found in Enders and Siklos (2001).

First note that (1.1) implies

$$\mu_t = c_t - \alpha - \beta\pi_t,$$

which implies that the state $\Delta\mu_t$ is above the threshold when either Δc_t is sufficiently positive or $\Delta\pi_t$ is sufficiently negative or some combination of the two and conversely $\Delta\mu_t$ is below the threshold when either Δc_t is sufficiently negative or $\Delta\pi_t$ is sufficiently positive or some combination. Because the relative sizes of Δc_t and $\Delta\pi_t$ impact whether $\Delta\mu_t$ is above or below the threshold, it is useful to start by looking at Figure 1.1. There it can be seen that the most rapid changes in either direction for c_t and π_t occur in c_t when the economy is in recession. Figure 1.1 shows that c_t falls at a very high rate in recessions which will produce a large negative Δc_t which overwhelms any values for $\Delta\pi_t$. Figure 1.2 both μ_t and $\Delta\mu_t$ for the capacity utilization series and it shows this to be true. In particular, it shows that negative values for $\Delta\mu_t$ tend to occur in recessions and positive values in booms. Next note that ρ_1 corresponds to above threshold $\Delta\mu_t$ and ρ_2 corresponds to below threshold $\Delta\mu_t$. Also note that because ρ_1 is more negative than ρ_2, it implies that when the economy is in the ρ_1 state, there is less persistence than when the economy is in the ρ_2 state. Taken together, the larger value of ρ_1 indicates that there is less persistence in booms than in recessions. Although this may seem counterintuitive to general business cycle facts, that intuition would be wrong, because that intuition is not appropriate for M-TAR models. What is important in the M-TAR is the momentum, so here, the momentum of the recession is so violent that it sustains itself, i.e. it is highly persistent, until the economic bottom is reached and the economy then switches out of the negative state and recovers. But the recovery is more uneven in terms of momentum, with some minor switches out of the positive momentum state during the recovery, which can be interpreted as lower persistence.

A useful alternative exercise is to look at the TAR model which does not have the momentum interpretation. So in the TAR models, positive values of μ_t tend to occur when c_t is large and π_t is small which tend to be booms. Looking at the coefficients we see the more negative coefficient is associated with ρ_2 or the recession periods and this more negative coefficient indicates less persistence during the recession.

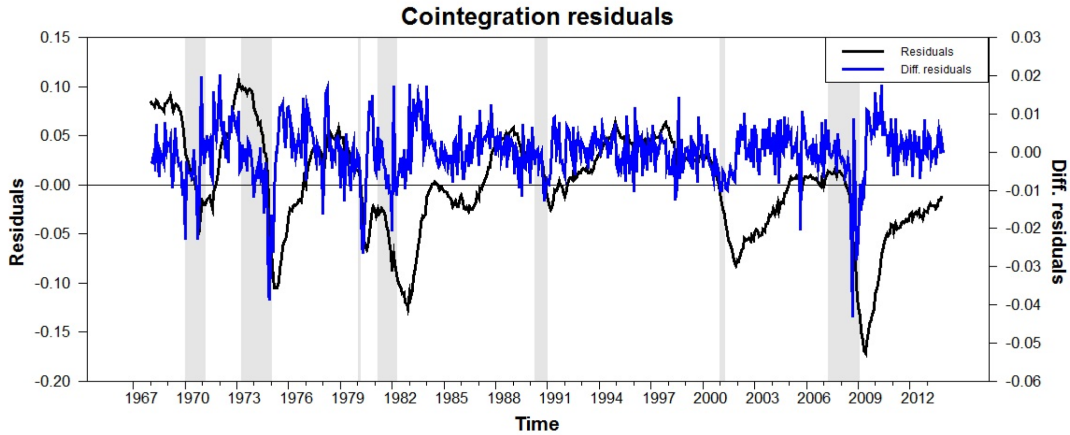

Figure 1.2: Cointegration residuals: TCU

Because we found that the variables are cointegrated with asymmetric adjustments of the error correction terms, investigating the VECM models given by (1.5) and (1.6) using the endogenous threshold M-TAR model is justified. We used two lags in the error correction term, which is justified by the AIC. Table 1.6 shows the results of this threshold VECM estimation. As in the Table 1.5, the first column shows a list of the variables in the VECM equations (1.5) and (1.6), while the second and third columns show the estimated coefficients for the variables in (1.5) and (1.6). Coefficients on Δc_{t-k} and $\Delta \pi_{t-k}$ represent the short run adjustments, while the coefficients on $I_t\widehat{\mu}_{t-1}$ and $(1 - I_t)\widehat{\mu}_{t-1}$ represent the speed of adjustment for the error in the cointegrating vector under the two states of the word. In addition, the t-statistics for each estimated parameter are listed below the estimates.

Interpreting the error correction coefficients in Table 1.6 is a bit more complicated than a TAR model, because each variable in each row consists of an error term $\widehat{\mu}_{t-1}$ and an indicator variable which is defined from $\Delta\widehat{\mu}_{t-1}$. As we noted above, negative values of $\Delta\widehat{\mu}_{t-1}$ are associated with recessions, so we next need to consider the error term $\widehat{\mu}_{t-1}$. As can be seen in Figure 1.2, negative values are generally associated with recessions too, but not to the extent that $\Delta\widehat{\mu}_{t-1}$ is, with $\widehat{\mu}_{t-1}$also covering part of the initial phase of the recovery when c_t is still relatively low. For simplicity, it is may be easier to think of negative $\widehat{\mu}_{t-1}$ as associated with low c_t rather than simply associated with recessions even though the exact details are a bit more nuanced. Looking at the coefficients on $I_t\widehat{\mu}_{t-1}$, we see that for Δc_t they are significantly negative and for $\Delta\pi_t$ they are significantly positive. So economically we could say that during booms ($I_t = 1$), positive values of $\widehat{\mu}_{t-1}$, which are associated with high c_t, result in Δc_t correcting downward (or c_t decreasing). Similarly, we would say that during booms ($I_t = 1$), positive values of $\widehat{\mu}_{t-1}$, which are associated with high values of c_t, result in $\Delta\pi_t$ correcting upward (or π_t as increasing). Looking at the coefficients on $(1 - I_t)\widehat{\mu}_{t-1}$, we see that for Δc_t they are insignificantly positive and for $\Delta\pi_t$ they are significantly positive. So economically we could say that during recessions ($I_t = 0$), there is no significant impact on the rate at which Δc_t corrects, but positive values of $\widehat{\mu}_{t-1}$, which are associated with high c_t, result in $\Delta\pi_t$ correcting upward (or π_t is increasing). This last sentence may seem counterintuitive, but that is simply because we were looking at positive values of $\widehat{\mu}_{t-1}$. Alternatively, we can make the same statements with a negative value of $\widehat{\mu}_{t-1}$ and say that during recessions ($I_t = 0$), there is no significant impact on the rate at which Δc_t corrects, but negative values of $\widehat{\mu}_{t-1}$, which are associated with low c_t, result in $\Delta\pi_t$ correcting downward (or π_t decreasing). Furthermore, it is possible to put some asymmetric interpretations on the error corrections. So for instance, one could say that during booms, firms are more willing to slow capacity utilization toward its long run than to increase capacity utilization toward its long run during recessions. Their reluctance to increase capacity utilization during recessions could be due to the violent nature of recessions and the unease about where the bottom might be. On the other hand, the relative sizes of the error correction coefficients for $\Delta\pi_t$ show that the speed of the correction in $\Delta\pi_t$ is larger in recessions ($I_t = 0$), than the speed of the correction during booms ($I_t = 1$). Put differently, inflation slows much more quickly during recessions than it speeds up during booms.

The other coefficients not associated with the error correction term provide information about the short term adjustments in the economy. These coefficients show that in the short run, increases in the change in capacity utilization portend further increases in the change in capacity utilization but do not imply a significant impact on the change in the inflation rate while increases in the change in the inflation rate portend further increases in the change in

Table 1.6: Estimated threshold VECM

Variables	Δc_t	$\Delta \pi_t$
$I_t \widehat{\mu}_{t-1}$	-0.015**	0.651***
	(0.007)	(0.234)
$(1 - I_t)\widehat{\mu}_{t-1}$	0.004	1.518***
	(0.012)	(0.384)
Δc_{t-1}	0.272***	-1.608
	(0.043)	(1.415)
Δc_{t-2}	0.194***	1.279
	(0.043)	(1.421)
$\Delta \pi_{t-1}$	-0.001	0.244***
	(0.001)	(0.042)
$\Delta \pi_{t-2}$	-0.003***	0.193***
	(0.001)	(0.042)
$\overline{R}^2$	0.19	0.22
F-statistic	3.77**	0.83

Notes: Constant terms are not reported.

the inflation rate and decreases in the change in capacity utilization.

The error correction models given by (1.5) and (1.6) can also shed light on some recent economic commentary. In particular, following the financial crisis and the recession it precipitated, some economists have suggest that raising inflation expectations might help speed up the recovery. To investigate this hypothesis, we conducted Granger causality tests to see if changes in inflation can Granger cause changes in capacity utilization. In addition we also investigated whether changes in capacity utilization can Granger cause changes in inflation. These hypothesis were described formally in (1.7) and (1.8) where $p = 2$ for this application. The last row of Table 1.6 shows the value of the F-statistics for these tests in the different models. These tests show that we are able to reject the null given by (1.7) at the 5% level for the capacity utilization model with an F-statistic 3.77. This result shows that changes in inflation do Granger cause changes in capacity utilization which can be interpreted as showing that inducing changes in inflation will result in changes in capacity utilization. On the other hand, these tests also show that we are unable to reject the null given by (1.8) at even the 10% level that changes in capacity utilization cause changes in inflation with an F-statistic of 0.83. Intuitively this means that changes in capacity utilization do not Granger cause changes in inflation. However, it is also possible to interpret these Granger causality results as arising because both variables respond to some more fundamental set of variables with the inflation rate simply responding sooner.

1.4 Conclusion

In this chapter, we investigate the short term and long term connections between capacity utilization and inflation. Contrary to much of the recent literature, which has shown that the relationship between capacity utilization and inflation has broken down since mid 1980s, we show that both series continue to have short term and long term connections. We argue that part of the reason for these different results is the theoretical nature of capacity utilization which entails a switching structure and by using the M-TAR model developed by Enders and Siklos (2001) we are better able to econometrically model the data and capture the nature of the short run and long run connections. We find, in the long run, a 1% increase in the rate of inflation leads to a 0.0046% increase in capacity utilization. The error correction structure shows that changes in capacity utilization show significant corrective measures only during booms while changes in inflation correct during both phases of the business cycle with the corrections being stronger during recessions. Asymmetric interpretations on these error corrections are as follows. During booms, firms are more willing to slow capacity utilization toward its long run than to increase capacity utilization toward its long run during recessions. Their reluctance to increase capacity utilization during recessions could be due to the violent nature of recessions and the unease about where the bottom might be. On the other hand, the relative sizes of the error correction coefficients for inflation show that the speed of the correction is larger in recessions, than the speed of the correction during booms. Put differently, inflation slows much more quickly during recessions than it speeds up during booms.

We also find that in the short run, changes in the inflation rate do Granger cause short term changes in capacity utilization while changes in capacity utilization do not Granger cause short term changes in inflation. The short term Granger causality from inflation to capacity utilization can be interpreted as supporting recent calls made in the popular press by some economists that it may be desirable for the Fed to try to induce some inflation in an effort to stimulate the economy. However, it is also possible to interpret these Granger causality results as arising because both variables respond to some more fundamental set of variables with the inflation rate simply responding sooner. The lack of short term Granger causality from capacity utilization to inflation casts doubt on the older view that capacity utilization could be a leading indicator for future inflation.

Chapter 2

Does consumer confidence affect durable goods spending during bad and good economic times equally?[1]

"It is unfortunate that most economists and business writers apparently do not seem to appreciate this [role of animal spirits] and thus often fall back on the most tortured and artificial interpretations of economic events. They assume that variations in individual feelings, impressions, and passions do not matter in the aggregate and that economic events are driven by inscrutable technical factors or erratic government action." - George A. Akerlof and Robert J. Shiller[2]

[1] A paper is published in the *Journal of Macroeconomics* from this chapter. See Ahmed and Cassou (2016).

[2] "Animal spirits: How human psychology drives the economy, and why it matters for global capitalism". 2010. *Princeton University Press.*

2.1 Introduction

In the wake of the Great Recession of 2008-09, many have called for confidence-boosting policies to help speed up the recovery. A recent empirical paper by Barsky and Sims (2012) has reinforced these policy calls by showing that the Michigan Consumer Confidence Index contains important information about "news" on future productivity that has long lasting effects on economic activities like aggregate consumption.[3] In this study, we investigate the robustness of the news content interpretation for consumer confidence by asking whether there could be differences in the connection between consumer confidence and consumer consumption during bad and good economic times.

To explore this issue, we use regime switching models to distinguish the response of consumption to confidence shocks during recessions from the response during expansions. We also decompose consumption into its subcomponents to see if different parts of consumption respond differently. Our regime-switching models use the National Bureau of Economic Research (NBER) US business cycle expansion and contraction data to create the indicator series which distinguishes bad and good economic times. We rely on the local projections methods of Jordà (2005) to estimate the responses; these methods are well-suited for the complicated switching structures used in this paper which could not be carried out using standard Vector Autoregression (VAR) methods.[4] We consistently find that the impact of consumer confidence shocks on consumption of durable goods is strongly state dependent while consumption of nondurable goods is more moderately state dependent. This may help explain the relatively weak economic recovery since the Great Recession of 2008-09, despite the improvements in consumer confidence, and can be interpreted as supporting the

[3]Other relevant academic papers include Blanchard (1993), Carroll et al. (1994) and Ludvigson (2004) who argue that one of the leading causes of the 1990-92 recession was weak household and business confidence. In addition, Barsky and Sims (2012) and Petev et al. (2012) suggest the slow recovery since the Great Recession of 2008-09 is in part due to weak confidence.

[4]This approach also has several advantages over other new methods, such as the smooth transition vector autoregressive (STVAR) method used by Auerbach and Gorodnichenko (2012b) which also incorporates nonlinear features, because the local projection method provides greater flexibility in terms of estimation. See, for instance, Auerbach and Gorodnichenko (2015), Stock and Watson (2007), Owyang et al. (2013) and Ramey and Zubairy (2014) for additional discussion on this topic.

alternative view that is skeptical of whether confidence boosting policies would help the recovery.

The connection between consumer confidence and macroeconomic performance has become an important area of inquiry in recent years, with early work by Blanchard (1993) attributing the 1990-1991 recession as arising from an exogenous rise in consumer pessimism. This view is often called the "animal spirits" view connecting consumer confidence and macroeconomic performance, with a distinguishing feature suggesting that consumer confidence shocks only lead to temporary changes in consumer spending.[5] Later work by Cochrane (1994) and Beaudry and Portier (2004) describe an alternative news view approach of business cycles which leads to a connection between consumer confidence and consumer spending. In this scenario, news is regarded as signalling changes in future productivity, with positive news leading to a rise in consumer confidence and thus consumer consumption, while negative news has the opposite effects. In contrast to the animal spirits view, changes in consumer spending in the news view are long lasting. Barsky and Sims (2012) investigated the connection between news, consumer confidence and consumer consumption and found evidence in support of the news view. In this chapter, we investigate this issue using regime-switching models and show that the connection between consumer confidence and some types of consumption, as well as the connection between various popular measures of news and consumer confidence, depend on whether the economy is in an economic expansion or an economic recession. In particular, we find evidence that supports the news view during economic expansions, but the evidence during economic contractions is more consistent with the animal spirit view.

The fact that consumers respond differently during bad economic times is not new to the economic literature, with important contributions arising in the investment under uncertainty literature.[6] But so far, to the best of our knowledge, there has been no work

[5]Animal spirit interpretation of consumer confidence and its implications to economic fluctuations are investigated by Akerlof and Shiller (2010), Farmer (2010, 2012), Benhabib et al. (2015).

[6]Papers by Bernanke (1985) and Berger and Vavra (2014, 2015) show that few households purchase durable goods during recessions. In addition, papers by Katona (1968), Mishkin et al. (1978), Blanchard (1993), Carroll et al. (1994), Cochrane (1994), Acemoglu and Scott (1994), Matsusaka and Sbordone

which has used state of the art regime-switching models to investigate whether the link between consumer confidence and consumer spending is the same during economic expansions and economic contractions.

We further explore the robustness of these results by trying alternative measures of consumer confidence, various subcomponents of the durable goods data, alternative measures for asset holdings, alternative switching variables, an alternative structural shock identification method (i.e. an alternative Cholesky ordering), an alternative subsample and an alternative lag length and find the results continue to hold up. Finally, we explore the news origins of consumer confidence by extending the approach used in Barsky and Sims (2012) to include switching structures. Again we find that the connection between news and consumer confidence is state dependent.

2.2 Econometric method

All models use four basic variables including one of several measures for consumer confidence, one of several measures for consumption, a measure of income and one of several measures of financial assets, which we will denote generically by cc_t, c_t, y_t and f_t respectively. Inclusion of these variables is motivated by Lettau and Ludvigson (2001, 2003) and Carroll et al. (1994), who built on a model described in Campbell and Mankiw (1989, 1990, 1991). The Campbell and Mankiw model includes two types of consumers, one which follows a dynamic consumer optimizing structure and another which follows a rule of thumb. Carroll et al. (1994) extend this model to include consumer confidence, showing that in an economy in which some consumers are not life-cycle optimizers, consumer sentiment will forecast a household's spending on durable and nondurable goods. Their empirical model controls only for household labor income. Inclusion of financial assets can be motivated by Ludvigson

(1995), Batchelor and Dua (1998), Howrey (2001), Ludvigson (2004), Berry and Davey (2004) and Starr (2012) have investigated the connection between confidence and consumption.

(2004) and Leeper (1992).[7]

2.2.1 Linear model

For now, we will focus on a simple linear model in which there is no threshold behavior, which we will regard as the current frontier for the literature in this area. Because one of our objectives is to show differences in the impulse response function (IRF) once thresholds are added, this will be a useful baseline for comparisons. To generate the IRFs we make use of the local projection method suggested by Jordà (2005) which has the advantage over the more common vector autoregression (VAR) method because it only requires projecting one period at a time, rather than an increasingly distant horizon as in the VAR method. This method generates IRFs by running a sequence of forecast equations given by

$$x_{t+s} = \alpha^s + \sum_{i=1}^{p} B_i^{s+1} x_{t-i} + u_{t+s}^s \qquad s = 0, 1, ..., h, \tag{2.1}$$

where $x_t = [cc_t \quad c_t \quad y_t \quad f_t]'$ is a vector of the model variables which we wish to forecast s steps ahead for h different forecast horizons using a forecasting model consisting of only p lags of the variables in the system. The parameters in the model are straight forward, with α^s denoting a 4×1 vector of constants and B_i^{s+1} denoting 4×4 square matrices of parameters corresponding to the ith lag, x_{t-i}, in the s step ahead forecasting equation and u_{t+s}^s is a moving average of the forecast errors from time t to time $t+s$. This method is robust to situations with nonstationary or cointegrated data, so for our application the components of x_t are level data.

Jordà (2005) shows that IRFs generated by the local projections are equivalent to the ones that are calculated from a VAR when the true data generating process (DGP) is a VAR, but that the IRFs for other DGPs that are not true VARs are better estimated using this

[7] Leeper (1992) finds that consumer sentiment is weekly correlated with other economic variables such as unemployment and industrial production once financial indicators are included in the regression model.

local projection method. The IRFs are defined as

$$\widehat{IR}(t,s,d_i) = \widehat{B}_1^s d_i \qquad s = 0,1,...,h \tag{2.2}$$

where $B_1^0 = I$ and d_i is an $n \times 1$ column vector that contains the mapping from the structural shock for the ith element of x_t to the experimental shocks.[8] We construct this mapping matrix using methods suggested in Jordà (2005), which essentially follows methods used in the traditional VAR literature, and begins by estimating a linear VAR and applying a Cholesky decomposition to the variance-covariance matrix. We discuss this below in the next subsection.

One can compute confidence bands using estimates of the standard deviations for the impulses. One issue that needs to be recognized in doing this is that because the DGP is unknown, there could be serial correlation in the error term of (2.1) induced by the successive leads of the dependent variable. We address this issue by using Newey and West (1987) standard errors which correct for heteroskedasticity and autocorrelation (HAC). Letting, $\widehat{\sum}_s$ be the estimated HAC corrected variance-covariance matrix of the coefficients $\widehat{B}_1^s$, a 68% (or one standard deviation) confidence interval for each element of the IRF at horizon s can be constructed by $\widehat{IR}(t,s,d_i) \pm \sigma(d_i^{'}\widehat{\sum}_s d_i)$, where σ is a $n \times 1$ column vector of ones.

2.2.2 Threshold local projection model

Our extension of this baseline model is to incorporate threshold behavior to the impulse response structure that allows the possibility that the IRF may differ during different phases of the business cycle. We use the NBER business cycle index to define the two states of the

[8] Here we use Jordà's experimental shock terminology, but the terminology reduced form shock is also appropriate.

economy and define our extension to (2.1) by

$$x_{t+s} = I_{t-1}\left[\alpha_R^s + \sum_{i=1}^{p} B_{i,R}^{s+1} x_{t-i}\right] + (1 - I_{t-1})\left[\alpha_E^s + \sum_{i=1}^{p} B_{i,E}^{s+1} x_{t-i}\right] + u_{T,t+s}^s \qquad s = 0, 1, ..., h, \tag{2.3}$$

where most of the notation carries over from above, but subscripts of R or E have been added to the various parameters to indicate recession or expansion dates respectively and we use a different notation of $u_{T,t+s}^s$ to denote the error process for this model where the added subscript indicates this is the error for the threshold model. The threshold dummy variable, denoted by I_t, is defined by using the NBER business cycle index according to,

$$I_t = \begin{cases} 1 & \text{when the economy is in a recession} \\ 0 & \text{when the economy is in an expansion.} \end{cases} \tag{2.4}$$

By analogy to (2.2), we define the IRFs for the two states of the economy by

$$\widehat{IR}^R(t, s, d_i) = \widehat{B}_{1,R}^s d_i \qquad s = 0, 1, ..., h, \tag{2.5}$$

and

$$\widehat{IR}^E(t, s, d_i) = \widehat{B}_{1,E}^s d_i \qquad s = 0, 1, ..., h, \tag{2.6}$$

with normalizations $B_{1,R}^0 = I$ and $B_{1,E}^0 = I$. The confidence bands for the impulse responses of the threshold model are simple extensions of the methodology discussed above.

The primary advantage over the standard VAR approach is its lack of structure from one horizon to the next. This can be understood by reviewing the IRF computation from the typical VAR model. The VAR approach uses the VAR parameters to generate the moving average form from which the IRFs are generated at each horizon. Thus the IRFs at all horizons are directly connected to these VAR parameters. On the other hand, the local projection method computes the IRFs from a different forecast equation (here (2.1) or (2.3)) and thus the structure of the IRFs can vary over the horizon. This allows flexibly when the DGP is nonlinear. So for instance, if the DGP is given by the highly nonlinear structure in (2.3), the linear VAR structure will not be able to handle this as well as the local projection approach which imposes less structure on the IRF. The local projection method also is attractive relative to the smooth transition VAR (STVAR) method used by Auerbach and Gorodnichenko (2012b).[9] In the STVAR approach suggested by Auerbach and Gorodnichenko (2012b), it is assumed that the economy stays in the current state over the horizon in which the impulse responses are calculated. Ramey and Zubairy (2014), for example, argues that this type of assumption is inconsistent with the fact that the average NBER recession period typically last 3.3 quarters, much shorter than the horizons over which one estimates IRFs. On the other hand, the local projection approach estimates parameters that are based on data that can be in either state of the world. Thus these parameters have an averaging effect, and the projections based on these estimates can be interpreted as weighted averages of the two separate state IRFs.

2.2.3 Identifying the structural shocks

As suggested in Jordà (2005), the mapping from the structural shocks to the experimental shocks uses the traditional VAR approach described in Sims (1980) which makes use of the Cholesky decomposition. This approach begins with what is called a structural form VAR given by

$$A_0 x_t = \sum_{i=1}^{p} A_i x_{t-i} + \varepsilon_t, \tag{2.7}$$

where A_i, for $i = 0, ...p$ are 4×4 matrices, p is the lag length for the model and ε_t is a 4×1 vector of structural shocks and we have left out the vector of constant terms to keep things simple. The structural form VAR is not directly estimable without making identification assumptions, so the traditional VAR approach recasts it as a reduced form VAR given by

$$x_t = \sum_{i=1}^{p} A_0^{-1} A_i x_{t-i} + e_t, \tag{2.8}$$

[9] See Ramey and Zubairy (2014) and Auerbach and Gorodnichenko (2012a, 2015) for details.

where $e_t = A_0^{-1}\varepsilon_t$ is a 4×1 vector of experimental (or reduced form) shocks.[10] Because the reduced form model has fewer parameters than the structural form model, if one wishes to consider structural model implications, identifying restrictions need to be imposed on the structural parameters and the original suggestion in Sims (1980) was to use the Cholesky decomposition which requires that A_0 be lower (sometimes upper) triangular and this structure implies a contemporaneous causal ordering among the variables, with the variable listed at the top of the vector x_t potentially having contemporaneous causal effects on the remaining variables, the variable listed second from the top potentially having contemporaneous causal effects on all the variables except the first and so on down the list. So, to use this algorithm we must make decisions about how to order the variables in our vector.

We use the ordering that was described earlier in the paper with $x_t = [cc_t \quad c_t \quad y_t \quad f_t]'$. This ordering, for the most part, follows Barsky and Sims (2012) who in a three variable model ordered consumer sentiment first, consumption second and Gross Domestic Product (GDP) third.[11] Here we use labor income rather than GDP, but national income accounts imply the two are similar. To this list, we add financial assets which was ordered last. Ordering financial assets last seems reasonable since impulses in income may have contemporaneous implications for how much people decide to invest, but it is less likely that impulses in financial assets have a contemporaneous impact on income. In other words, because financial assets are highly unpredictable, it is unlikely that agents make short term changes in working decisions as a result of a good or bad year for asset returns.

With these decisions in hand, we can now describe the construction of the d_i vectors used in the impulse response calculations. First note that $e_t = A_0^{-1}\varepsilon_t$ implies that the experimental shock variance is given by

$$e_t e_t' = A_0^{-1}\varepsilon_t\varepsilon_t' \left(A_0^{-1}\right)' = A_0^{-1}\Omega_\varepsilon (A_0^{-1})' \tag{2.9}$$

[10] To be consistent with the linear projection approach methods, we use level data for these calculations too. Hamilton and Susmel (1994) has shown that VAR methods are robust to unknown forms of cointegration. Using level data is quite common and was used by Barsky and Sims (2012) as well.

[11] Barsky and Sims (2012) chose this as their preferred ordering because they identified confidence innovations as "news" on future productivity, which is exogenous to the economy, and has long lasting effects on economic activities like aggregate consumption.

where Ω_ε and A_0 are given by

$$\Omega_\varepsilon = \begin{bmatrix} \sigma_{cc}^2 & 0 & 0 & 0 \\ 0 & \sigma_c^2 & 0 & 0 \\ 0 & 0 & \sigma_y^2 & 0 \\ 0 & 0 & 0 & \sigma_f^2 \end{bmatrix} \quad \text{and} \quad A_0 = \begin{bmatrix} 1 & 0 & 0 & 0 \\ \beta_{21} & 1 & 0 & 0 \\ \beta_{31} & \beta_{32} & 1 & 0 \\ \beta_{41} & \beta_{42} & \beta_{43} & 1 \end{bmatrix}.$$

Next note that $e_t = A_0^{-1}\varepsilon_t$ can also be interpreted as showing the mapping from an arbitrary vector of structural shocks given by ε_t into a vector of experimental shocks given by e_t, and that A_0^{-1} provides this mapping. Now, if we define d_i by

$$d_i = A_0^{-1}\Omega_\varepsilon\delta_i, \tag{2.10}$$

where δ_i is a column vector with a one in the ith position and zeros elsewhere, then d_i has a special interpretation. First note that the term $\Omega_\varepsilon\delta_i$ gives a vector with a one standard error shock for the ith variable in only the ith position, with zeros elsewhere. So by multiplying by A_0^{-1}, d_i can be interpreted as a vector of experimental shocks that arise from a one standard deviation structural shock in the ith variable. This means the impulse response functions given by (2.2), (2.5) and (2.6) show how the vector of variables x_t respond to a one standard deviation shock in the ith structural variable at various forecast horizons.

2.3 Empirical results

Our empirical analysis uses quarterly data for the US economy from 1960:Q1-2014Q2.[12] We used three different measures of consumer confidence published by the University of Michigan, which were obtained from various tables available on the Michigan Consumer Survey (MCS) webpages. These include, the Index of Consumer Sentiment (ICS), which

[12]We focus on quarterly data because, as noted above, our model includes household financial assets and this data is only available on a quarterly basis. It should also be noted that many of the papers in this literature, including Barsky and Sims (2012) use quarterly data.

is an overall measure of consumer sentiment and was obtained from Table 1 of the MCS webpages, C12M, which is a measure of consumer confidence with a twelve month horizon and was obtained from Table 28 of the MCS webpages and C5Y which is a measure of consumer confidence with a five year horizon and was obtained from Table 29 of the MCS webpages.[13]

For most of our analysis, we focus on the ICS series, but we look at the others in a robustness investigation later. Our measure of labor income starts with the Bureau of Economic Analysis (BEA) personal income and its disposition database series. We use Line 37 of Table 2.1 that includes wages, salaries, transfer payments and other labor income minus personal contributions for social insurance and personal current taxes. This series is converted to a per capita constant dollar measurement by dividing by the seasonally adjusted personal consumption expenditure chain-type deflator (PCECTPI) obtained from the Federal Reserve Bank of St. Louis (FRED) data base and the population, which comes from the BEA personal income and distribution Table 2.1 line 40, and reflects the mid-period total population. Financial assets were tabulated using the Flow of Funds Account of the Federal Reserve Board. Our calculation uses line 9 of Table B.101 for financial assets and subtracted from this was line 31 of the same table which are the liabilities to get our measure for financial assets. This series was then adjusted over time by using the price deflator and the population series described above to get a per capita measure in real terms. We use three measures for consumption which are also obtained from the FRED database, including per capita real personal consumption expenditures of durable goods (A795RX0Q048SBEA), per capita real personal consumption expenditures of nondurable goods (A796RX0Q048SBEA) and motor vehicles (DMOTRC1Q027SBEA). The first two series are the primary focus of our analysis, while the motor vehicles series is used to investigate robustness of the results. The motor vehicle series is a nominal aggregate series and was converted to real per capita terms using the same methods as used for converting nominal financial assets. Finally, our

[13]To be more specific, C12M and C5Y are compiled based on a question which asks whether economic conditions would be good or bad over the next twelve months or five years respectively. Details on the construction of these indices can be found at http://www.sca.isr.umich.edu.

switching variable is the NBER US business cycle expansion and contraction index. This series (USRECQM) was also downloaded from the Federal Reserve Bank of St. Louis data base.

Some preliminary insights into the business cycle aspects this study investigates can be obtained by plotting the various consumer sentiment indexes over time. Figure 2.1 does this and also provides shaded regions which indicates the NBER recession periods. As one would expect, consumer confidence is generally higher during expansionary periods than during contractionary periods.

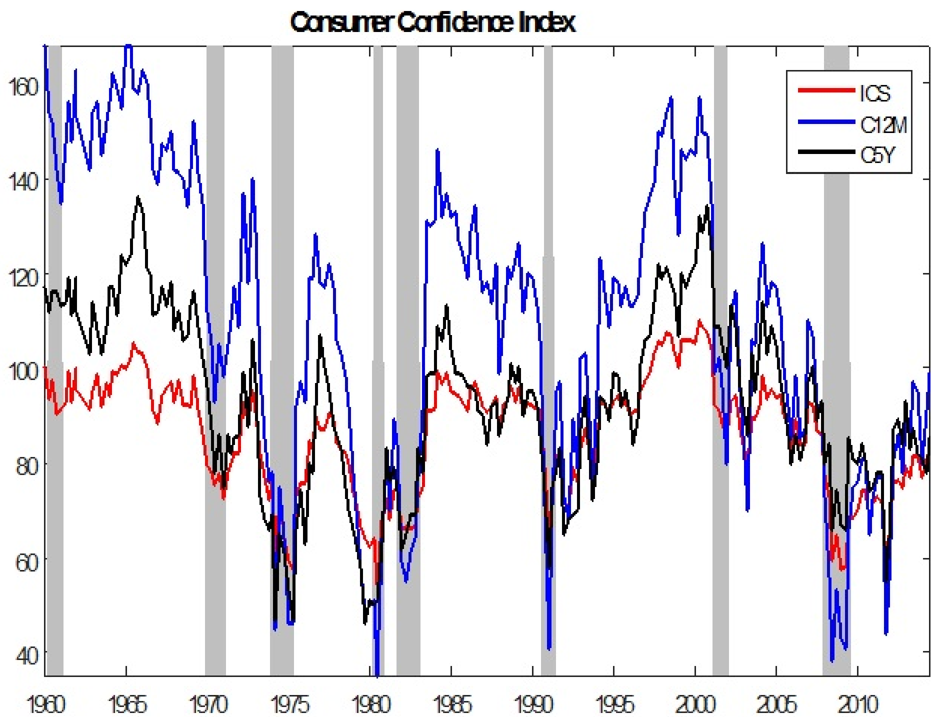

Figure 2.1
Different measures of Consumer confidence: ICS, C12M and C5Y.
Shaded regions are NBER recession

2.3.1 Linear model

We begin by looking at the impulse response functions in the linear model given by (2.1), which we regard as the baseline model that summarizes the current frontier of the literature. We focus on only the confidence shock results since this is where we want to contribute to the literature by showing that differences arise when considering a threshold model. Using the Akaike Information Criterion (AIC), we find that two lags are appropriate in (2.1).

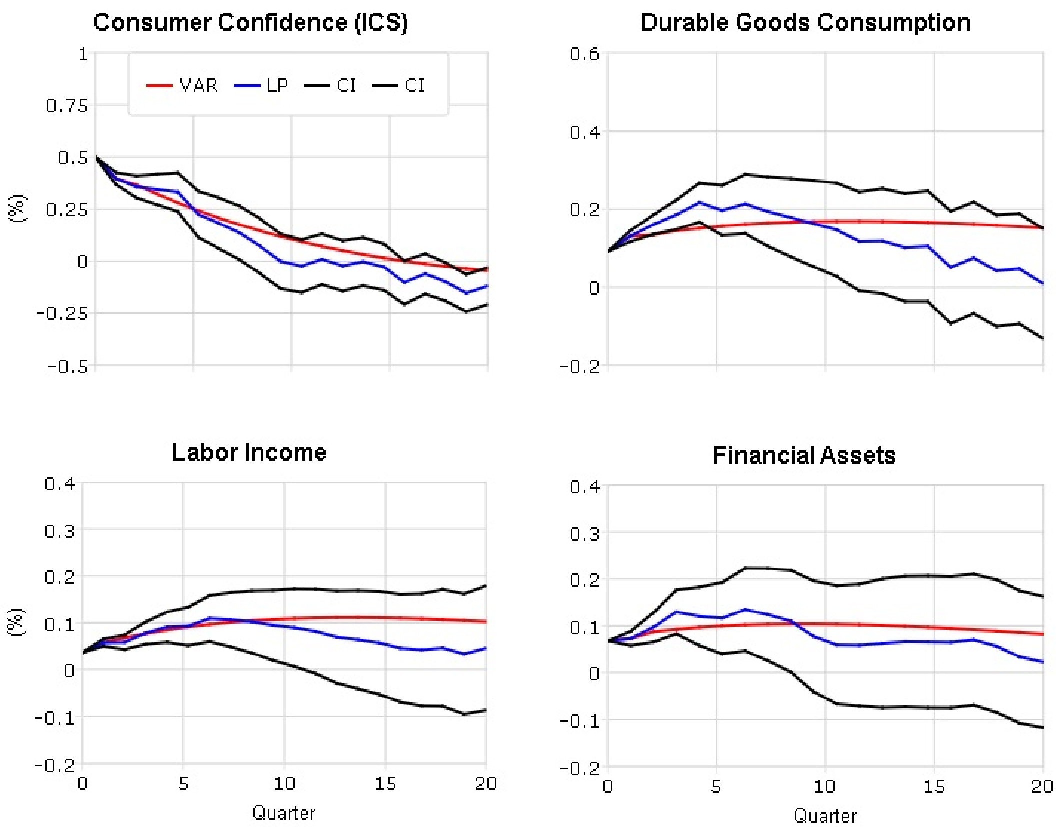

Figure 2.2
Impulse responses from one standard deviation confidence shock
Model with durable goods

Figures 2.2 and 2.3 show the results for models that use ICS as the measure of confidence with Figure 2.2 using durable goods as the consumption variable and Figure 2.3 using nondurable goods as the consumption variable.[14] In each figure four lines are plotted for

[14]The results are unchanged with other measures of confidence as discussed in the robustness analysis below.

twenty quarters, or five years. The blue line represents the impulse response obtained from the local projection model given by (2.1), the red line represents the impulse response based on a two lag VAR model using the same Cholesky ordering to identify the structural shocks as in the local projection model, and the two black lines represent the one standard deviation bands around the local projection impulse response function using the Newey-West method for computing standard errors described earlier.

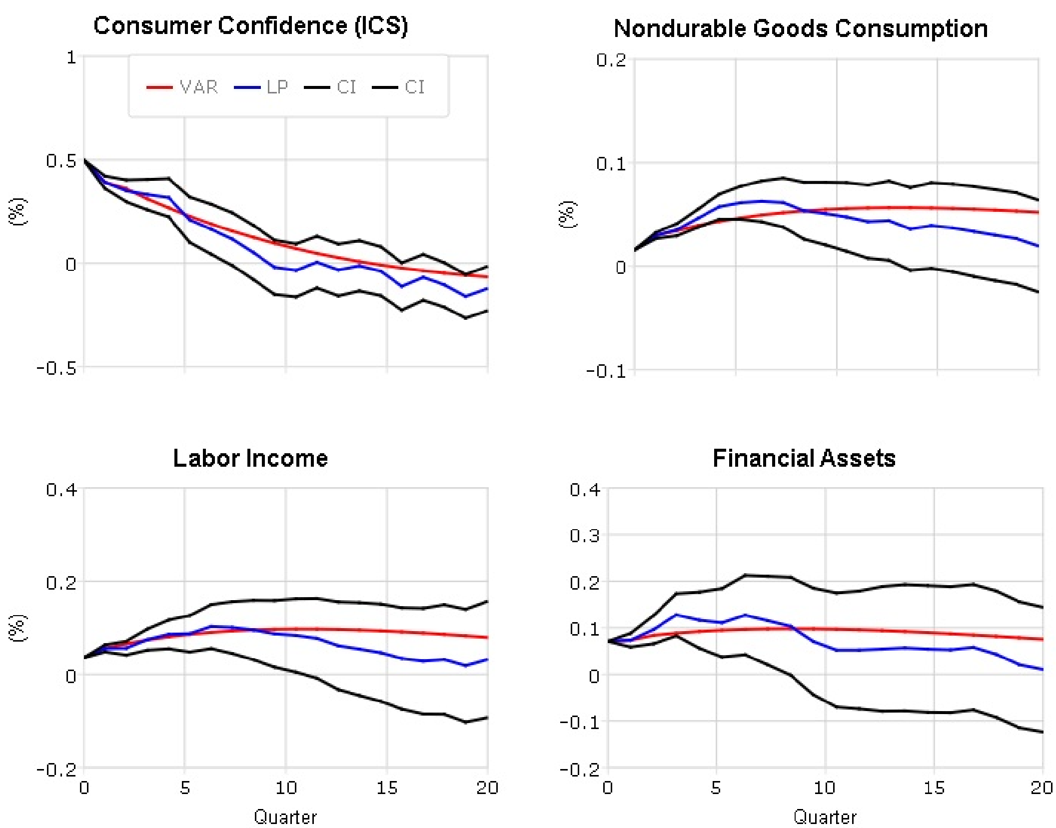

Figure 2.3
Impulse responses from one standard deviation confidence shock
Model with nondurable goods

Both figures show similarities between the impulse response patterns using the local projection method and the VAR method with the solid line mostly tracking the short dashed line over the twenty quarter horizon, and, with the exception of very few instances, always remaining inside the one standard error bands. However, there are two notable differences. First, the VAR method impulses are smoother, and this reflects the construction process where the vector moving averages used to find the impulse response functions are always functions of the same estimated VAR coefficients, while the local projection method does not impose any construction relationships between impulses at different horizons. Second, and more importantly, when looking at both the durable goods and nondurable goods response functions as well as the income response functions, one sees that toward the end of the twenty quarter horizon, the responses are nearly zero for the local projection responses, thus indicating less permanence, while the responses are more permanent looking for the VAR method. However, because the linear projection impulses only reach zero after twenty quarters, or five years, we believe that these results do show important effects. In the context of the animal spirits versus news debate, the VAR methods are most consistent with the news view while the local projection results are less clear but are likely consistent with the news view as well.

Comparing the different figures, we see that, confidence responses start near 0.5 and decline slowly toward zero, reaching it after about thirteen quarters; the response of consumption goods have a hump-shaped pattern, with very modest humps for both goods; the response of both income and financial assets also have humped patterns with the former increasing for about twelve quarters to about 0.1 before starting to decline and the latter also increasing to about 0.1 but only for about eight quarters before declining. One notable difference is that the response for durable goods is much larger in magnitude.[15] The response for durable goods consumption is roughly three times the size of nondurable goods. We interpret these findings as illustrating the following economic processes. The initial jump in confidence results in an increase in consumption spending which has a multiplier effect on income and financial assets and thus results in all of these responses exhibiting hump shaped patterns.

[15]This fact can be easily missed because we use different vertical scales to plot these series. The scales for the other three impulse responses are identical across the exercises.

2.3.2 Threshold local projection model

Figures 2.4 and 2.5 show the impulse response plots for the threshold regression model (2.3). Although these figures use the same four line types as in Figures 2.2 and 2.3 and use the same scales on the vertical axis, there are a few differences in the plotting notations relative to the plots in Figures 2.2 and 2.3. In particular, we use a convention of plotting the impulse responses for the state when the NBER indicator shows an expansion using a short dashed line and its one standard deviation confidence band using long dashed lines, and then for the state when the NBER indicator shows a recession, we plot it as a solid line without confidence bands. Thus in these figures, the expansion state takes the previous role used by the local projection model and the recession state takes the previous role used by the VAR model.

Figures 2.4 and 2.5 show some big differences between the good state and bad state impulses. We see that the stimulative effects of a confidence shock on durable and nondurable consumption goods during an expansion is considerably higher than the stimulative effects during a recession. For durable goods, the recessionary confidence shock to durable consumption goods is outside the one standard error bands for roughly the first eleven quarters, whereas for the nondurable goods, it is outside the one standard error bands for quarters four to eight. These differences in consumption good behavior arise despite very similar impulse responses for the other three variables in the system. Overall, these results show that the stimulative effects of a confidence shock has a considerable smaller effect on consumption during recessions and this diminished effect is more pronounced for durable goods.

Some further insights can be obtained by comparing the magnitudes of the changes between Figures 2.2 and 2.3 with the magnitudes of the changes in Figures 2.4 and 2.5. This comparison shows that the stimulative effect on both types of consumption from a confidence shock during an economic expansion (contraction) is much larger (smaller) than the average stimulative effect given in Figures 2.2 and 2.3. In addition, the multiplier effect on income during an economic expansion (contraction) is also larger (smaller) than the average effect in Figures 2.2 and 2.3. Overall, these results also show that the stimulative effects of a confidence shock are different than the simple average effects in Figures 2.2 and 2.3 and further show the need for using a threshold model to investigate this issue.

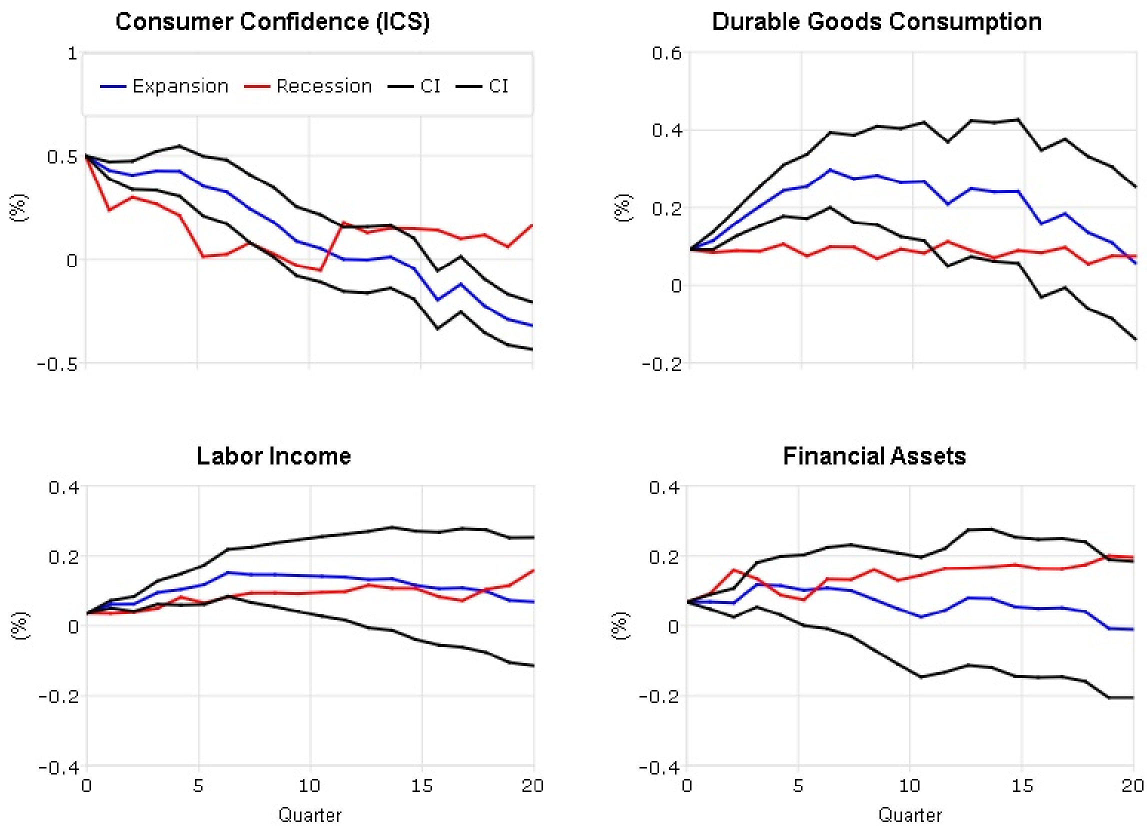

Figure 2.4
Impulse responses from one standard deviation confidence shock
Model with durable goods

Economically we can interpret these differences as showing that during economic expansions, confidence has an amplifying effect on the economic condition, while during economic recessions, confidence shocks are not strong enough to generate lasting improvements in the economic condition. In the context of the debate between the animal spirits and news views for consumer confidence shocks, these results show that during economic expansions, a consumer confidence shock has a large and fairly long duration impact on both types of spending. However, by the end of the twenty period horizon, the impact on consumption does approaches zero as in the local projection findings in Figures 2.2 and 2.3. Again we interpret these findings as consistent with the news view. On the other hand, during economic contractions a consumer confidence shock has a much smaller effect on consumption with the impact on durable goods consumption measuring roughly one third of the magnitude seen during economic expansions. During this phase of the business cycle, the results are more consistent with the animal spirits view. This recessionary finding is consistent with findings in Berger and Vavra (2014, 2015) who show that fewer households purchase durable during recessions because of substantial adjustment costs that exist with this type of purchase, leading aggregate durable goods spending to be relatively less sensitive to confidence shocks.

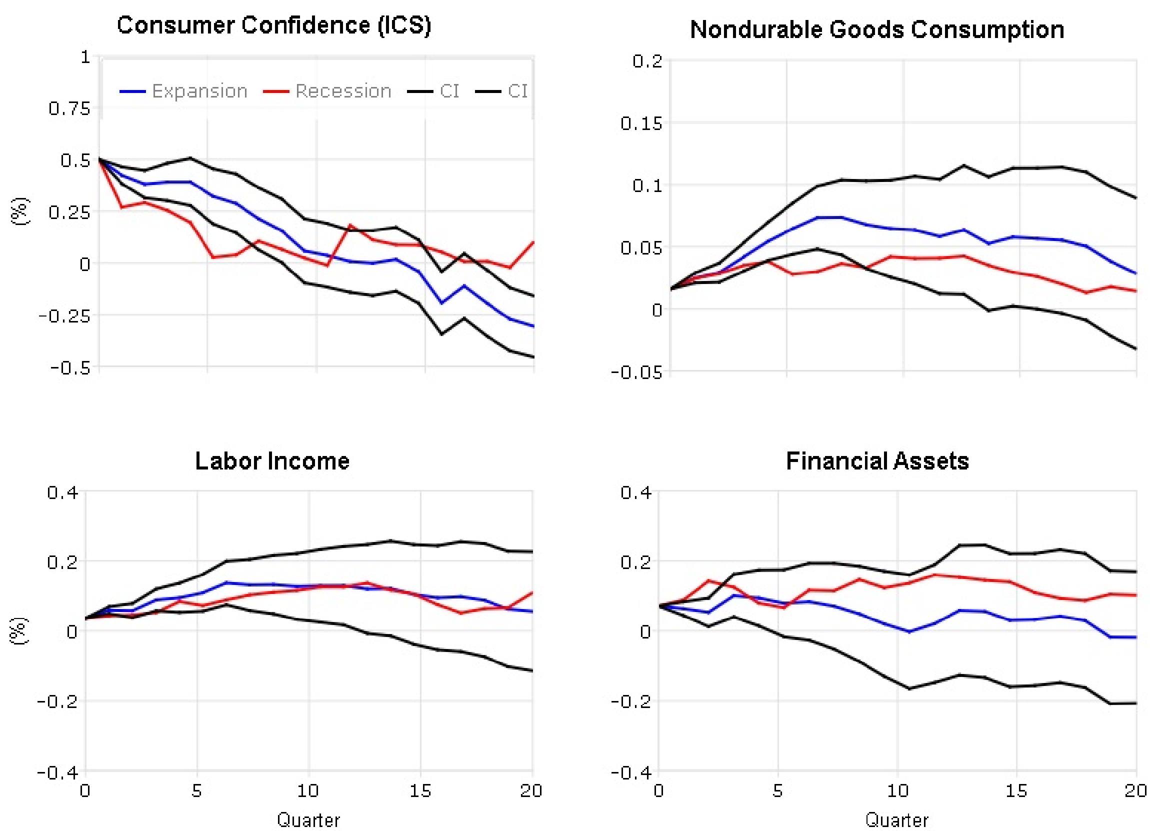

Figure 2.5
Impulse responses from one standard deviation confidence shock
Model with nondurable goods

It is also useful to recognize how these results would differ from the STVAR methods, such as those used in Auerbach and Gorodnichenko (2012b). In the STVAR approach the model assumes that the economy remains in whatever state it begins in. This would have an amplifying effect on the expansionary results found here. The results here can be interpreted as showing coefficients that are weighted averages for the economic outcomes going forward. Although the persistence of an economic expansion is relatively high, this model does not assume that the economy will remain in an expansion for the next twenty quarters, but instead builds in an average transition to the recessionary state. Because of this averaging effect, the impulse responses are going to be more modest relative to a model that assumes that the economy remains in an economic expansion. By the same token, the STVAR model which assumes remaining in a recession for twenty quarters will have a more negative outcome than this model which assumes an average transition back to an expansionary state.

2.3.3 Variance decomposition results

It is also possible to make a case for the threshold models by using variance decomposition analysis, which is a popular tool from the traditional VAR analysis. To understand the variance decomposition method using local projections, we provide a brief overview of the procedure. For theoretical detail, we refer the reader to Jordà (2005).

The mean squared error of the forecast error is given by

$$MSE_u(E(x_{t+s}|X_t)) = E(u^s_{t+s}u^{s'}_{t+s}) \qquad s = 0, 1, ..., h. \tag{2.11}$$

This can be estimated by using $\widehat{\Sigma}_{u^s} = \frac{1}{T}\sum_{t=1}^{T} \widehat{u}^s_{t+s}\widehat{u}^{s\prime}_{t+s}$ where $\widehat{u}^s_{t+s} = x_{t+s} - \widehat{\alpha}^s +_{i=1}^{p} \widehat{B}^{s+1}_i x_{t-i}$. The diagonal elements of this will be the variance of the s step ahead forecast errors for each of the elements in x_t. Next, defining the $n \times n$ experimental choice matrix D by the columns d_i from the mapping described above. Renormalizing MSE_u by the choice matrix D into

$$MSE(E(x_{t+s}|X_t)) = D^{-1}E(u^s_{t+s}u^{s'}_{t+s})D^{'-1} = D^{-1}\Sigma_{u^s}D^{'-1} \qquad s = 0, 1, ..., h. \tag{2.12}$$

From (2.12), we can calculate the traditional variance decompositions by directly plugging in the sample-based equivalents from the projections in (2.1). Extensions of this calculation to the threshold models can be done using a straightforward extension of the vector x_t by putting terms $I_{t-1}x_t$ in the upper half of the new vector and $(1 - I_{t-1})x_t$ in the lower half of the new vector.

Table 2.1 shows the results of this exercise. To save space, only the results showing the percent of the total forecast error variance attributable to confidence innovations are reported. The table is organized into two vertical panels, with columns two through four showing the results when using durable goods as the consumption variable and columns five through seven showing the results when using nondurable goods as the consumption variable. The table is also organized into four horizontal panels each of which corresponds to a different forecast horizon. Only the variance decompositions for forecast horizons of four, eight, twelve and twenty quarters are reported. Focusing on the top horizontal panel, which summarizes the variance for the four quarter horizon, we see it is organized into three rows, with the first row showing the results for the linear model given by (2.1) and the next two rows showing the results for economic expansions and economic contractions as found in the threshold model given by (2.3).

To get a more concrete sense for the organization of the table, focus on the durable goods models at the four quarter forecast horizon. The linear model shows that confidence innovations account for 32.07% of the forecast error variance for durable goods, 20.71% of the forecast error variance for labor income and 11.05% of the forecast error variance for financial assets. Similarly, the durable goods threshold model shows that during economic expansions confidence innovations account for 31.90% of the forecast error variance for durable goods, 22.06% of the forecast error variance for labor income and 8.47% of the forecast error variance for financial assets at the four quarter forecast horizon, while during economic recessions confidence innovations account for 16.93% of the forecast error variance for durable goods, 16.03% of the forecast error variance for labor income and 36.87% of the forecast error variance for financial assets for the forecast horizon of 4 quarters. The remaining sub panels

Table 2.1: Percent of total forecast error variance attributable to confidence innovations

	Durable Goods Models			Nondurable Goods Models		
States	Dur Good	Lab Income	Fin Asset	Nondur Good	Lab Income	Fin Asset
			Forecast horizon of 4 quarters			
Linear	32.07	20.71	11.05	23.81	19.46	10.69
Expansion	31.90	22.06	8.47	18.06	19.62	6.66
Recession	16.93	16.03	36.87	22.84	20.91	35.95
			Forecast horizon of 8 quarters			
Linear	39.64	29.67	15.91	39.66	27.78	14.35
Expansion	43.02	35.83	12.47	41.17	32.23	8.46
Recession	16.19	27.44	31.73	20.32	31.86	32.64
			Forecast horizon of 12 quarters			
Linear	39.63	30.93	16.43	43.58	28.75	14.55
Expansion	44.42	40.11	11.04	47.56	35.90	7.00
Recession	13.84	28.20	34.05	18.62	34.91	36.09
			Forecast horizon of 20 quarters			
Linear	35.78	20.69	15.48	43.44	18.73	13.18
Expansion	43.20	34.61	10.11	46.16	31.06	6.16
Recession	12.65	26.17	39.31	15.30	27.19	34.04

of the table have a similar organization.

Next moving down the table, the linear model shows that confidence innovations account for 32.07% of the forecast error variance of durable goods at the four quarter horizon, then rises to 39.64% and 39.63% at the eight and twelve quarter horizons, before falling to 35.78% at the twenty quarter horizon. These percentages are similar to those reported in Barsky and Sims (2012). However, the threshold model shows there are differences in the variance decomposition according to whether the current state corresponds to good or bad economic times. Moving down the table, we see that during economic recessions the portion of the forecast error variance of durable goods attributable to confidence innovations is considerably smaller at all forecast horizons than the portion of the forecast error variance of durable goods attributable to confidence innovations during economic expansions.[16] This shows that a proper modeling structure for this set of variables is the threshold model.

[16]In some results not presented here to keep space down, a model using motor vehicles produced very similar variance decompositions to the durable goods models in Table 2.1.

Next comparing the durable and nondurable good panels with each other we see that the main differences arise in the first four quarters. In particular, when comparing the eight, twelve and twenty quarter horizons, the two sides of the table show very similar percentages. This arises because by construction the local projection method has an averaging effect as one moves forward from the initial economic state. However, at the four quarter horizon, the two panels show differences because the averaging effect has not fully worked out. At this four quarter horizon we see that there is little difference between the forecast error variance across the states for the nondurable goods in contrast to the durable goods case which show quite difference forecast error variance values. These findings are consistent with those in Figures 2.4 and 2.5 where it was seen that the nondurable goods responses during the expansion and recession cases tracked each other for the first four quarters pretty closely, while the durable goods responses showed difference between the expansionary and recessionary cases right off the bat beginning in the first quarter.

It is also useful to note the outcomes for labor income and financial assets. Looking at the columns for the variance decompositions for labor income, we see that the linear model and the threshold model in both the good and bad economic times are relatively (i.e. relative to the durable goods results) similar at the different forecast horizons. This is not surprising since the impulse response functions in Figures 2.4 and 2.5 showed the labor impulses to be similar in the two regimes. On the other hand, the variance decompositions for financial assets do show greater difference between the linear model and the threshold model results with the threshold models showing large percentages during economic recessions.

2.4 Robustness

The results above suggest that the effects of a confidence shock on consumption goods spending are state dependent with considerably smaller effects during weak economic times, and these differences are more sizable for durable consumption goods. This section discusses some alternative specifications for the model that were investigated in order to determine the robustness of the results. For the most part, the impulse response patterns for these alternative exercises were similar to those above, so rather than provide all the plots, we only describe the exercises and some of the results. An online appendix with additional details is available at this journal's website.

The first exercise was to consider alternative measurements for consumer confidence. For this exercise we used the previously noted indexes C12M and C5Y as well as another question on the Michigan consumer confidence survey which asks whether now is a good time to buy major household items and we denote by CDUR. For this exercise we redefine x_t as $x_t = [AltConf_t \quad c_t \quad y_t \quad f_t]'$, where $AltConf_t$ denotes a vector using either $C12M_t$, $C5Y_t$ or $CDUR_t$. The results of this exercise produced virtually identical impulse response plots to those in Figures 2.4 and 2.5 and indicate that during good economic times, the impulse has favorable effects on both durable and nondurable good consumption spending, while during bad economic times, the impulse has very little effect on durable goods and modest effects on nondurable goods.

The next exercise was to consider some of the subcomponents of the durable goods index. Here we considered motor vehicle purchases and the other durable goods subcomponents of the durable goods series. For this exercise we redefine x_t to have these alternative consumption series. The impulse response results were qualitatively the same as those discussed above.[17] Using a subsample from 1960:01 to 2007:03, which was chosen to exclude data that included the financial crises and its recovery, also resulted in qualitatively the same results. Next, an alternative Cholesky ordering in which consumer confidence was ordered last was considered and again the impulse response functions where qualitatively unchanged and again showed large effects during good times, and weak effects during bad times. A one lag model, which is optimal by the Schwarz Bayesian lag length selection criterion, did produce some changes. But these changes showed even stronger differences between the good times and bad times impulse responses. Alternative measures for asset holdings also showed qualitatively the same results. Finally, we investigated a model that used the unemploy-

[17]This result is consistent with Bram and Ludvigson (1997) who found that motor vehicles and durable goods spending are highly correlated.

ment rate as an alternative switching variable. Here two models were considered. One used an exogenous unemployment rate threshold with values above 6.5% considered to be bad economic times and rates below 6.5% considered to be good economic times and another used an endogenous unemployment rate threshold. These alternative structures resulted in qualitatively similar impulse response functions.

Overall, the conclusion that consumer confidence innovations lead to increases in consumption spending during good economics times, but have small effects during bad economic times proved to be robust.

2.5 Connections between news and confidence

Another insightful exercise is to extend the analysis connecting news and confidence done in Barsky and Sims (2012) to include threshold behavior. For this exercise we begin by generating a structural confidence innovation series using analogous methods to those in Barsky and Sims (2012). Here we run a four variable VAR using the same data used in the earlier exercises and then use that VAR to construct the structural confidence shock series using a Cholesky ordering with confidence ordered first.[18] This series is then used as the dependent variable in several regressions connecting various news items on economic conditions that the respondents report in the Michigan Consumer Confidence Survey.[19] As in Barsky and Sims (2012), the question is whether the news about economic conditions impact innovations in consumer confidence. The interpretation is that if news about economic conditions impact innovations in consumer confidence, then it seems natural to establish the connection between news and consumer confidence. We are thus motivated to investigate whether the news view approach holds in an economy that has different potential states.

[18] Here we use ICS as our confidence series, but the results described below are robust with other measures of confidence.

[19] The Michigan Survey asks respondents to report any recent "news heard" concerning the economy. The specific question is *"During the last few months, have you heard of any favorable or unfavorable changes in business conditions?"* If the answer is yes, the follow up question is *"What did you hear?"* The Survey documents the percentage of respondents reporting having heard either favorable and unfavorable news concerning different macroeconomic variables including price, employment, stocks etc.

Table 2.2 shows the results of regressions analogous to those in Barsky and Sims (2012) in columns 2 through 4 while columns 5 through 7 show the results from running a threshold regression with the NBER business cycle index as the threshold variable. To reduce the amount of space that the table contains, the first 18 rows serve double duty in that they report the coefficient estimates and standard errors for those variables in the nonthreshold regression and they report the coefficient estimates for those variables in the above threshold (i.e. expansionary) case for the threshold model. The below threshold (i.e. recessionary) values are given in the next 18 rows of the table.

The nonthreshold regressions mostly confirm the results in Table 4 of Barsky and Sims (2012) showing that favorable employment news, favorable and unfavorable price movements are significant in the baseline model. Adding unfavorable government spending news is also significant, but adding favorable government, favorable or unfavorable stock price news or energy crises does not produced significant coefficients.

Shifting over to the threshold models, the table shows that during economic expansions, all of the variables that were significant in the nonthreshold model continue to be significant in this state of the economy. In addition, unfavorable employment has become significant in two of the models. Looking at the bottom of the table we see that there are a few instances in which favorable employment and unfavorable prices are significant during recessions. But these are only significant at the 10% level in contrast to the high levels of significance, typically at the 1% level, seen during economic expansions or in the models without threshold behavior. Overall, these results show that news has important implications for confidence during economic expansions, but are generally not very important during economic recessions. This can be interpreted as showing that news about economic conditions only signal improvements in consumer confidence and thus economic activities during economic expansions as shown in the previous section, and that during economic recessions, the news view approach to consumer confidence is weak.

2.6 Conclusion

This chapter investigates whether consumer confidence innovations have long lasting effects on various types of consumption. We find that the connection between consumer confidence and consumption is not robust when considering the state of the economy and some measures of consumption. In particular, during economic recessions, the results of impulse response analysis and variance decomposition investigations show that consumer confidence innovations do not imply the same magnitude increase in durable and nondurable good consumption as was seen during economic expansions, and this difference is particularly large for durable goods. These results proved to be robust to alternative measurements of consumer confidence, alternative subcomponents of durable goods, alternative measures for asset holdings, alternative measurements for the switching variable, alternative Cholesky orderings, an alternative subsample and an alternative lag structure. We also investigated the connection between news and consumer confidence and found it is also state dependent.

These results have important implications for recent policy debates which have speculated that improving consumer confidence can lead to a faster economic recovery from the 2008-09 Great Recession. Our results show that improving consumer confidence may not produce the economic benefit that has been speculated unless the fundamentals of the economy improve. These results also are important to the ongoing debate as to whether consumer confidence shocks indicate animal spirits or news about economic fundamentals. We interpret the relatively strong connection between consumer confidence and consumer spending during economic expansions as consistent with the news interpretation. On the other hand, the weak connection between consumer confidence and consumer consumption during economic recessions in both the short term and long term is likely driven by a wave of pessimism as described in Blanchard (1993) and is more consistent with the animal spirits interpretation.

Table 2.2: Regressions of confidence innovations on news about economic conditions

News categories	Linear			Threshold		
Fav employment (Exp)	0.002***	0.001*	0.002***	0.002***	0.002**	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Fav price (Exp)	0.010***	0.010***	0.008***	0.010***	0.010***	0.008***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Unfav employment (Exp)	-0.000	-0.001	-0.000	-0.001*	-0.001**	-0.001
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Unfav price (Exp)	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Fav stocks (Exp)		0.003	0.003		0.003	0.004
		(0.002)	(0.002)		(0.002)	(0.002)
Unfav stocks (Exp)		0.000	0.000		0.000	0.000
		(0.001)	(0.001)		(0.002)	(0.002)
Fav government (Exp)			0.003			0.004
			(0.004)			(0.004)
Unfav government (Exp)			-0.003***			-0.003***
			(0.001)			(0.001)
Energy crisis (Exp)			-0.001			-0.001
			(0.002)			(0.002)
Fav employment (Rec)				0.003*	0.003	0.003
				(0.002)	(0.002)	(0.002)
Fav price (Rec)				0.004	0.006	0.003
				(0.011)	(0.011)	(0.011)
Unfav employment (Rec)				-0.000	-0.001	0.000
				(0.001)	(0.001)	(0.001)
Unfav price (Rec)				-0.004*	-0.003*	-0.003
				(0.002)	(0.002)	(0.002)
Fav stocks (Rec)					0.007	0.005
					(0.010)	(0.009)
Unfav stocks (Rec)					0.002	0.002
					(0.003)	(0.003)
Fav government (Rec)						-0.001
						(0.013)
Unfav government (Rec)						-0.003
						(0.006)
Energy crisis (Rec)						-0.002
						(0.003)
R^2	0.18	0.19	0.24	0.21	0.22	0.27

Terms in parenthesis are white standard errors.

Chapter 3

The asymmetric effects of expectation shocks on macroeconomic activities: Evidence from survey data of professional forecasters

"Explicit modeling of the connection of expectation-formation mechanisms to policy [regime] in an accurately identified model would allow better use of the data." - C. Sims (1982, p. 120)

3.1 Introduction

Recent developments in the expectation driven business cycle literature provides evidence that expectations about the future has led to the boom-bust cycles of the post-war US economy (see Beaudry and Portier (2004, 2007, 2014) and Ladner and Rebelo (2009) among others). According to these studies, optimism about the future growth prospects may help fuel booms and the subsequent revisions in expectations may help precipitate busts. However, in an economic environment, where one set of policy rules is likely to have stronger effects on macroeconomic aggregates than the others, agents' upward or downward revisions in expectations about the future are not likely to be symmetric across the policy regimes. Consequently, their effects on current economic activities are likely to be asymmetric. For instance, according to recent studies, an "inflation-hawk" Fed would act more aggressively when inflation is high than when it is low. Similarly, the Fed's responses are more aggressive to a negative than a positive output gap. Now under such rules of the game, it is reasonable to believe that agents' expectation formation also changes with the regime shifts. Although the effects of expectations about the future on current economic activities are of interest to researchers and policy makers, existing research provides little evidence, if anything, about how the effects of the expectations on economic activities might change when the policy regime shifts. To investigate this, we ask the questions: Does the economy respond to expectation shocks in an importantly asymmetric way? If so, what are the reactions of the monetary policy to the expectation shocks?

Also, the idea of the asymmetric effects of expectation shocks can be motivated from the rational expectation theory. Since the development of Lucas critique in 1976 that put using econometric models for macroeconomic policy evaluations on trial, economists have found it as a challenge empirically examining the effects of expectations on macroeconomic activities.[1] An important caveat of earlier studies is that when the economy enters into a particular policy regime, households naively expect that the regime would prevail indefinitely. However, according to the rational expectation theory, agents should form expectations based on all available information, including possible changes in future. The difference between the equilibrium outcome from a model that ignores the regime shifts and a model that takes into account such expected changes in regimes is due to expectation effects of regime shifts (Liu et al., 2009). Motivated by the epigraph taken from Sims et al. (1982), we construct an

[1] Lucas (1976) has expressed the view that it makes no sense to think of the government as conducting one of the several possible policies while at the same time assuming that agents remain certain about the policy rule in effect.

empirical model that uses the survey of professional forecasters data to measure expectations of the future of the economy.

We consider a couple of issues to motivate our empirical measures of expectations. First, while econometric models are subject to criticisms, rational expectation tools have limitations too. For example, the standard rational expectation models make a tight link between fundamentals and equilibrium prices and allocations through expectations (Ball and Croushore, 1995; Sims et al., 1982). However, this tight connection may not be as obvious as assumed in the rational expectation theory. When agents form an expectation about the future, their revisions of expectations are often subject to an error. For example, Alfred C. Pigou (1927, pg. 122), writes:[2]

"[...] a rise in prices, however brought about, by creating some actual and some counterfeit prosperity for business man, is liable to promote an error of optimism, and a fall in prices an error of pessimism, and this mutual stimulation of errors and price movements may continue in a vicious spiral [...]."

These autonomous revisions to expectations, whether in part due to changes in fundamentals and/or in part due to errors, are not likely to be as tight as depicted in the rational expectation theory, and thus could be a potential source of fluctuations. Or, it could be due to rational inattention that makes agents to take a decision based on incomplete information (Sims, 2003; Sims et al., 2010). Also, there could be a potential tension between a policy announcement and people's skepticism about the policy (Sims et al., 1982). These factors could potentially contribute to macroeconomic fluctuations. However, an empirical aggregation of such revisions of expectations is a tall order. We use the survey data from professional forecasters to measure expectations about the future. In particular, we take data from two sources - the Survey of Professional Forecasters and the Livingston Survey data.[3] While in the views of rational expectation models, the survey measure of expectations is less-than-fully-rational, Carroll (2003) shows that an empirical model can capture

[2]See Arthur (1926).

[3] Bachmann et al. (2013) show that errors in survey measure of professional forecasters produce significance business cycle fluctuations.

the expectational dynamics well using the survey measure of expectations. According to him, households' often form their expectations based on news reports, which are rational in a sense that these reports are prepared based on the views of professional forecasters. Moreover, Ang et al. (2007), Croushore (2010), and Faust et al. (2013) among others documented that the professional survey forecasts systematically outperform other forecasting methods. In addition, Carroll (2003), Leduc et al. (2007), Leduc and Sill (2013) and many others explained the benefit of using survey data to measure expectations of macroeconomic variables. A common argument in favor of using the survey data is that they provide an independent source of information about agents' perceptions of future economic activity.[4] This information, which is often ignored in an otherwise standard VAR models, matters for understanding the movements in macroeconomic variables (Cochrane, 1994). Consequently, VAR models may suffer from misspecification due to omitted variables. This problem could potentially be mitigated by using the survey data of expectations into the VAR framework because professional forecasters and households consider a wide range of variables when predicting the future.[5] Additionally, one should acknowledge the fact that surveys are closely monitored by policymakers, who view them as important indicators of market participants' perceptions of future economic activity.

Second, we use the local projection (LP) technique to estimate our empirical model. Among many other advantages,[6] one attractive feature of the LP technique is that unlike standard VAR that assumed that the economy stays in the current state over the horizon in which the impulse responses are calculated, the LP approach estimates parameters over forecast horizons that are based on data that can be in either state of the world. Thus the estimated parameters take into account the weighted average effects of variables based on the economic conditions. So in an econometric environment where the state of the economy is subject to change due to nonlinear effects of policy shifts, the projections based on the

[4] Also, one can interpret the innovation of this type of information using the arguments provided in Sims (2003)'s rational inattention theory.

[5] For example, Cochrane (1994) argued that consumers have more information about the future, though most of these shocks are idiosyncratic, in aggregates, they are correlated with future GDP.

[6] See Ramey and Zubairy (2014), Auerbach and Gorodnichenko (2012a, 2015), Ahmed and Cassou (2016) for details.

LP method take into account the average effects of the economy, which are robust than the projections based the VAR.

Third, identification of expectation shocks is crucial for our analysis. We use the information of timing of the survey data construction and actual data release dates to identify structural shocks to expectations of future economic activities.[7] We use the Survey of Professional Forecasters and Livingstone Survey forecast data of the unemployment rate, to proxy expectations about future economic activity.[8] Using the unemployment rate has the advantage over other variables. For example, the unemployment rate is subject to only a minor revision, which is limited to changes in seasonal factors. Thus by using forecasts of the unemployment rate, we can bypass difficult questions about the real-time data and the subsequent data revisions that many other macro variables often face.[9] Since the unemployment rate series is unrevised, this gives a window to include both actual and expected unemployment in a system of VAR to recover the structural shocks of agents' expectations (professional forecasters in our case) about the future economy by imposing certain restrictions. We use information of actual and survey data releases to make sure that professional forecasters' predictions about the economy are not contemporaneously affected by the release of actual data. Leduc et al. (2007) and Leduc and Sill (2013) follow the similar kind of strategies using the information of the timing of data releases that are available at the Federal Reserves Bank of Philadelphia. We interpret the shocks as news about future economic fundamentals that drive expectations in a sense that professional forecasters' predictions about the economy often come out in the news media, which eventually influence household expectations.[10]

Finally, we use the regime switching structures of our empirical models to investigate the effects of expectations on macroeconomic activities across the policy regimes. In the baseline specification, we consider two formulations of regime switching structures. In our

[7] We provide a detailed analysis in Section 3.2.

[8] The surveys are well designed and they rank high in terms of accuracy. See Thomas (1999) for instance.

[9] For example, the use of expected and actual real GDP growth would be problematic because real GDP revisions may incorporate information that is unavailable to forecasters at the time their forecasts were being made.

[10] In the near future, we plan to carry out this research to give a more formal interpretation of the shocks.

first formulation, we assume that the Federal Reserve follows the "opportunistic" monetary policy approach such that there is an aggressive anti-inflation policy only when inflation is high relative to that in the recent past. This choice reflects the growing consensus among central bankers that the opportunistic strategy eschews deliberate action to reduce inflation, but instead waits for unforeseen but favorable price surprises to reduce inflation.[11] Another reason of using the "opportunistic" strategy as a threshold indicator is that there exists a gap between people's belief about the Fed's policy announcements and the Fed's inertia to achieve the policy goals, suggesting that there is an asymmetric flow of information between government and private agents. Therefore, it is likely that people's expectation formation and its effects on the economy could be asymmetric across the regimes.[12,13] In our second formulation, we use the unemployment rate as a threshold indicator variable, which the Federal Reserves often takes into consideration in its policy strategy. Motivated from the Fed's recent policy statement, we use a prior threshold value of 6.5 percent of the unemployment rate, in which they begin to consider policy changes.

We provide our results in the form of impulse response functions and forecast error variance analysis. Our main finding is that the effects of expectation shocks on macroeconomic activities are asymmetric in different monetary policy regimes. A perception that good times are ahead manifested as a drop in the expected unemployment rate typically leads to a significant rise in current measures of real economic activities and inflation during a hawkish (high inflation or low unemployment) regime. Consequently, the Fed reacts by raising the short-term interest rate. The Fed's responses are rather accommodative when people expect a good time ahead during a dovish (low inflation or high unemployment) regime. Our results are robust using two survey measures of expectations, using two different samples including the period of Great Recession and using an alternative regime switching structure of mon-

[11] "An opportunistic monetary strategy also assumes an ultimate target of price stability and distinguishes an interim inflation target from the ultimate one. However, except when inflation is high, the opportunistic policy maker's interim inflation target is simply the current rate of inflation. Thus, the opportunistic strategy eschews deliberate action to reduce inflation, but instead waits for unforeseen but favorable price surprises to reduce inflation." (Federal Reserve Bank of San Francisco 1996).

[12] Rudebusch et al. (1996) explains the Fed's credibility and its opportunism strategy.

[13] Sims et al. (1982) provides several examples of such tension between policy announcements and people's skepticism about the policy as he attacks the usefulness of rational expectation theory in policy evaluations.

etary policy. Additionally, recent studies suggest that uncertainty shocks due to uncertain economic and political events cause significant business cycle fluctuations. We augment our baseline regime switching model by including an exogenous dummy variable that controls for the major uncertain economic and political events. The results remain robust. Finally, we provide a comparative analysis of forecast error variance decomposition. We show that the expectation shocks are more important than the monetary policy shocks to explain the economic fluctuations. This finding is consistent with Cochrane (1994) who shows that news about economic fundamentals is more important than other shocks like monetary policy shocks or technology shocks.

Our study contributes to the growing interest in understanding the role of monetary policy in boom-bust cycles. There is a heightened criticism around the world that the central banks' policies of keeping monetary policy too easy for too long are responsible for fueling the booms (Okina and Shiratsuka, 2002; Taylor, 2009).[14] These arguments, however, contradict the conventional views of the central banks. For instance, Bernanke and Gertler (2000) opined that when there is an upward revision to expectations that lead to a boom in current activities and inflation, there is a concomitant rise in the short-term interest rate, which tends to stabilize the economy.

Also, our empirical findings provide important insights into the debate on rational expectation theory as well as the Dynamic Stochastic General Equilibrium (DSGE) models with expectation shocks. The rational expectation theory suggests that effects of monetary policy on real economic activities are neutral. However, an increasing literature suggests that monetary policy has a strong effect on real economic activities, which, in a model economy, agents with rational expectation hypothesis systematically underestimate the effects of monetary policy on aggregate demand (Ball and Croushore, 1995).[15] The debate so far ig-

[14] Okina and Shiratsuka (2002) argued that too loose of the Japanese monetary policy led the burst of the stock market bubble at the beginning of 1990.

[15] The conventional wisdom of rational expectation models is that when policy shifts, a rational agent would change its expectations based on all available information. Consequently, the agent's pattern of behavior would change. Accordingly, the effects of policy on real economic activities are neutral. (See Sims (1985); Sims et al. (1982), Sargent (1984), Cooley et al. (1984), among others, for details).

nores whether the effects of changes in agents' expectations on economic activities are equal across the policy regimes. Liu et al. (2009) build a DSGE model that allows shifts in monetary policy regimes and examine the asymmetric expectation effects on economic activities. In this chapter, we provide new empirical evidence, examining the role of expectations on economic activities and its interaction with monetary policy using regime switching models. To best of our knowledge, our study is the rst attempt to empirically quanties the effects of expectation shocks across the policy regimes.

The rest of the chapter is organized as follows. In Section 3.2 we describe our empirical measure of expectation shocks. Section 3.3 provides econometric models for our analysis. We illustrate our results in Section 3.4, followed by robustness and forecast error variance analysis respectively in Sections 3.5 and 3.6. Finally, we end with a conclusion presented in Section 3.7.

3.2 Expectation shocks

In this section, we further elaborate the timing information of the surveys and data aggregation to get a clear understanding that our expectation shocks are exogenous and not contemporaneously affected by the actual data release. The survey forecasts of the unemployment rate are our proxy expectations about future economic activity. This along with the actual unemployment rate helps us to extract expectation shocks. We use the unemployment rate because this data is subject to only a minor revision. Thus we can avoid difficult questions as exposed in real-time data and subsequent data revisions. Since the forecasters are provided with the information of previous quarter, using a variable, such as, GDP, which is subject to revisions, would be problematic because the revised data may contain information that could be unavailable to forecasters at the time when they prepare the forecasts. For our baseline specification, we use the expected unemployment rate both from the SPF and the LS. It is crucial to know the timing of the surveys and the times when actual data are released in order to make sure that our expectation shocks are exogenous to current economic activities. The quarterly SPF data starts from 1968.[16] About forty to fifty survey participants provide forecasts of variables such as CPI inflation, the unemployment rate, real GDP growth, and nonfarm payroll growth over a five-quarter horizon and annual projections for the current year and the following year.[17]

The SPF is conducted four times a year. For the purpose of illustration, a time-line of the SPF survey design is constructed in Figure 3.1.[18] The survey's schedule is aligned to the Bureau of Economic Analysis's (BEA) advance release of the data from the national income and product accounts. The survey process starts soon after the BEA's releases issued at the end of the first month of each quarter. The BEA's report includes the first estimates of the key macroeconomic variables for the previous quarter.[19] The SPF sends out the survey questionnaires to the forecasters after these data are released to the public. The BEA's report includes first estimates of the key macroeconomic variables of the last quarter.[20] The deadlines for responses, which is used to be the third week of the middle month, were moved up a few days to the second week of the middle month. The SPF releases the results of the survey in the fourth week of the middle month of the quarter.[21] The SPF survey reports always come out before the release of BEA's first revision of GDP and its components for the last quarter.

Based on the survey's timing, we redefine quarters of the year so that the first month of a quarter is the month that survey responses are filled out. Accordingly, the first quarter is redefined from February to April, the second quarter is from May to July, and so on. This

[16] In late 1968, the American Statistical Association and the National Bureau of Economic Research jointly initiated a survey of professional economic forecasters known as the ASA/NBER Economic Outlook Survey. The charge was taken over by the Federal Reserve Bank of Philadelphia in 1990: Q2.

[17] The forecasters are from non-financial businesses, investment banking firms, commercial banks, academic institutions, and from labor, government, and insurance companies.

[18] The information is taken from http://phil.frb.org. One can construct a similar time-line for the LS.

[19] For example, the first release of the BEA's report for 2002: Q4 is in the third week of January 2003.

[20] For some variables, notably those contained in the Bureau of Labor Statistics monthly Employment Situation Report, there could be a revision to the data (and an additional monthly observation) compared with the data the SPF reported on the survey questionnaire. When there is a new release of the data between the time the survey questionnaires are sent out and before the deadline for returning it, the SPF updates the forecasters providing them the new releases. One prime example is the Employment Situation Report, which is almost always released on the first Friday of each month.

[21] Beginning with the survey of 2005: Q1, the SPF advanced the dates of release a few days, to late in the second week of the middle month of the quarter.

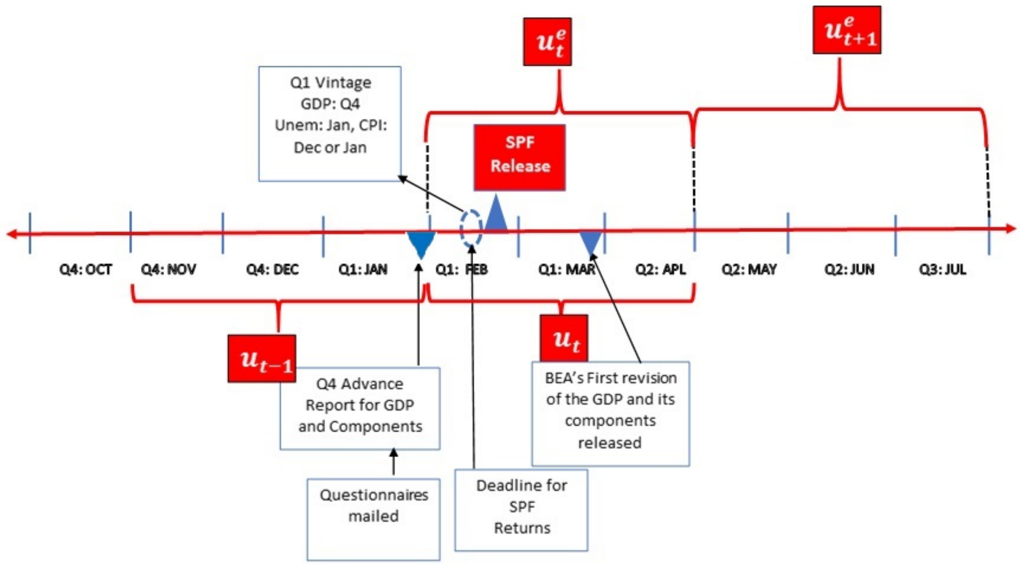

Figure 3.1
Timing information of survey and actual data releases

alignment makes sure that actual data does not have any contemporaneous effects on the forecasted data. Based on the timing and data realignment, we put expected unemployment first in our recursive identification scheme so that there is no contemporaneous response of expected unemployment to other shocks in the system. That is at time t, the forecasters only have information about the variable in time $t-1$; they do not know the information of the variables at t. We adopt this identification strategy in our benchmark model.

We employ a similar strategy to identify the expectation shocks using the Livingston Survey data. Unlike SPF, Livingston Surveys are conducted twice a year. Livingston typically mailed questionnaires in early May and early November, shortly after the BEA reports are released in April and October, respectively. In the questionnaire, Livingston supplied the most recently available BEA reports. Respondents of the June survey were asked to forecast among others the expected unemployment rate for December and June. We take the half-yearly data based on the timing of the Livingston Survey. Since the survey questionnaire is due back in May and November, we redefine half-years as running from April to October and from October to April. We choose this dates such that contemporaneous realizations of current macroeconomic variables can have an influence on forecasters' decisions about future unemployment rates.

3.3 Empirical investigation

Our empirical methodology is similar as described in Section 2.2 in Chapter 2. However, a brief review of the empirical models will help to keep track with the relevant changes and adjustments that we made for our analysis. First, we explain the linear and threshold local projection techniques. Then we explain the regime switching structures of the threshold models.

Our main interest is to gauge the effects of expectation shocks on the dynamic behavior of macroeconomic variables. We first consider a linear econometric model in which agents naively believe that the current regime would prevail indefinitely. We then extended the linear version of the model to a regime-switching model that takes into account the possible switches in future policy regime.

3.3.1 Linear model

First, we will focus on a simple linear model in which there is no threshold behavior. Our baseline specification for both the linear and threshold models include four variables. Though our main interests are to investigate the asymmetric effects of expectation shocks, the linear specification will help use to understand the effects of expectation shock on economic activities and the concomitant reaction of monetary policy under the assumption that state of the economy will remain same over the forecast horizon.[22] Because our objective is to show differences in the IRF once thresholds are added, technicality linear specification will be a useful baseline for comparisons. To generate the IRFs we make use of methods suggested by Jordà (2005), which have the advantage over the more common vector autoregression (VAR) methods, because they only require projecting one period at a time, rather than an

[22] Leduc and Sill (2013) examine the effect of expectation shock on economic activities using linear VAR. Our estimation technique is different from them.

increasingly distant horizon as in the VAR methods. This method generates IRFs by running a sequence of forecast equations given by

$$x_{t+s} = \alpha^s + \sum_{i=1}^{p} B_i^{s+1} x_{t-i} + \varepsilon_{t+s}^s \qquad s = 0, 1, ..., h, \tag{3.1}$$

where $x_t = [u_t^e \quad u_t \quad \pi_t \quad i_t]'$ is a vector of the model variables which we wish to forecast s steps ahead for h different forecast horizons using a forecasting model consisting of only p lags of the variables in the system. Variables are respectively expected unemployment rate, actual unemployment rate as a measure of economic activity, inflation rate and short term nominal interest rate (three-month treasury bill rate). The parameters in the model are straight forward, with α^s denoting a 4×1 vector of constants and B_i^{s+1} denoting 4×4 square matrices of parameters corresponding to the ith lag, x_{t-i}, in the s step ahead forecasting model and ε_{t+s}^s is a moving average of the forecast errors from time t to time $t+s$. Although all the variables in the baseline models are in percentage change, it is important to note that the local projection technique is robust to situations with nonstationary or cointegrated data, so one can avoid the debate of the true data generating process (DGP) of our variables in interests.

Jordà (2005) shows that IRFs generated by the local projections are equivalent to the ones that are calculated from the VAR when the true DGP is a VAR, but that the IRFs for other DGPs that are not true VARs are better estimated using this linear projection method. The IRFs are defined as

$$\widehat{IR}(t, s, d_i) = \widehat{B}_1^s d_i \qquad s = 0, 1, ..., h \tag{3.2}$$

where $B_1^0 = I$ and d_i is an $n \times 1$ column vector that contains the mapping from the structural shock for the ith element of x_t to the experimental shocks.[23] We construct this mapping matrix using methods suggested in Jordà (2005), which essentially follows methods

[23] Here we use Jordà's experimental shock terminology, but the terminology reduced form shock is also appropriate.

used in the traditional VAR literature and begins by estimating a linear VAR and applying a Cholesky decomposition to the variance-covariance matrix. As described in section 3.2, our recursive ordering of the identification scheme with putting expected unemployment first well suited with the Cholesky ordering. We ordered actual unemployment second followed by inflation and interest rate. Based on the timing information of the survey design and the release dates of the actual data, it is plausible that expectation about the future may have contemporaneous impacts on other variables, but since the current data is not become available to the forecasters when they make the predictions, the other variables will not have contemporaneous impacts on expectation. Our ordering for other variables is reasonable too. For example, it is more likely that unemployment to have contemporaneous impact on inflation but the reverse may happen only with lag effects. We ordered monetary policy variables last because impulses of any of the other variables may cause the monetary policy to react, but it is unlikely that other variables would respond contemporaneously with the monetary policy impulse.

Next, using local projection technique, one can compute confidence bands using estimates of the standard deviations for the impulses. One issue that needs to be recognized in doing this is that because the DGP is unknown, there could be serial correlation in the error term of (3.1) induced by the successive leads of the dependent variable. We address this issue by using Newey and West (1987) standard errors which correct for heteroskedasticity and autocorrelation (HAC). Letting, $\widehat{\sum}_s$ be the estimated HAC corrected variance-covariance matrix of the coefficients $\widehat{B}_1^s$, a 68% (or one standard deviation) confidence interval for each element of the IRF at horizon s can be constructed by $\widehat{IR}(t, s, d_i) \pm \sigma(d_i' \widehat{\sum}_s d_i)$, where σ is a $n \times 1$ column vector of ones.

3.3.2 Threshold local projection model

Our extension of the baseline linear model is to incorporate threshold behavior to the impulse response structure that allows the possibility that the IRF may differ during different across the policy regimes. We define our extension to (3.1) by

$$x_{t+s} = I_{t-1}\left[\alpha^s_{dov} + \sum_{i=1}^{p} B^{s+1}_{i,dov} x_{t-i}\right] + (1-I_{t-1})\left[\alpha^s_{hawk} + \sum_{i=1}^{p} B^{s+1}_{i,hawk} x_{t-i}\right] + \varepsilon^s_{T,t+s} \qquad s = 0, 1, ..., h, \tag{3.3}$$

where most of the notation carries over from above, but subscripts of *dov* or *hawk* have been added to the various parameters to indicate dovish or hawkish regimes respectively and we use a different notation of $\varepsilon^s_{T,t+s}$ to denote the error process for this model where the added subscript indicates this is the error for the threshold model. The threshold dummy variable, denoted by I_t, indicates the distinction between hawkish (high inflation or low unemployment) and dovish regimes (low inflation or high unemployment). We use two formulations for determining the threshold indicator for our baseline estimation, which we explain in the next subsection.

By analogy to (3.2), we define the IRFs for the two states of the economy by

$$\widehat{IR}^{dov}(t, s, d_i) = \widehat{B}^s_{1,dov} d_i \qquad s = 0, 1, ..., h, \tag{3.4}$$

and

$$\widehat{IR}^{hawk}(t, s, d_i) = \widehat{B}^s_{1,hawk} d_i \qquad s = 0, 1, ..., h, \tag{3.5}$$

with normalizations $B^0_{1,dov} = I$ and $B^0_{1,hawk} = I$. The confidence bands for the impulse responses of the threshold model are simple extensions of the methodology discussed above.[24]

3.3.3 Threshold structures

Since agents' expectations about the future are tightly connected with the monetary policy's actions, we choose monetary policy regimes to construct the threshold indicator.[25] We use two formulations to define the regime switching structures of our baseline estimations.

[24]We discuss the advantages of using local projection technique over the standard VAR approach in chapter 2.

[25]For example, an expected rise in real interest rate impacts people's and firm's demand for goods and services.

Our first formulation features the "opportunistic" monetary policy strategy by the Fed, which has become the dominant strategy to conduct monetary policy. An opportunistic strategy aims to gradually ratcheting down the inflation by setting an intermediate target of inflation rate based on the history of recent past but virtually do nothing to achieve the target, waiting instead for a random event to achieve the target.[26] According to Rudebusch et al. (1996), an opportunistic strategy is neither clearly nor believably communicated to the public, which undermines people's expectations about the future. This indeed has different implications for the economy compared to the scenario when monetary policy is credible.[27] We motivate to use the "opportunism" as one of our threshold indicators because of the obvious tension between a "credible" monetary policy and an "opportunism" likely to have important implications to people's expectations about the economy.

We define our "opportunistic" threshold structure following Bunzel and Enders (2010).[28] Accordingly, we assume that the interim target of the Fed depends on the "inherited" or past inflation such that threshold drifts upward or downward from time to time. Accordingly, we set an intermediate target by a simple average of the inflation rate prevailing 1 and 2 years ago. We estimate (3.7) such that the indicator function is

$$I_t = \begin{cases} 1 & \text{for} \quad \pi_{t-1} \geq \pi^T = \frac{\pi_{t-5}+\pi_{t-9}}{2} \\ 0 & \text{for} \quad \pi_{t-1} < \pi^T = \frac{\pi_{t-5}+\pi_{t-9}}{2}, \end{cases} \tag{3.6}$$

where π^T is the interim target of inflation for period $t-1$.

Equation (3.6) characterizes the essential feature of the opportunistic monetary policy.

[26]The FOMC meeting minute in December 1989 quoted a participant, which can be described an opportunistic scenario in the Fed's policy making process: "Now, sooner or later, we will have a recession. I don't think anybody around the table wants a recession or is seeking one, but sooner or later we will have one. If in that recession we took advantage of the anti-inflation [impetus] and we got inflation down from $4\frac{1}{2}$ percent to 3 percent, and then in the next expansion we were able to keep inflation from accelerating, sooner or later there will be another recession out there. And so, . . . we could bring inflation down from cycle to cycle. . . .".

[27]According to a research by the staff of the Federal Reserve Board in 1996, a credible policy to reduce inflation by 1 percentage point would require a 1 percentage point higher unemployment rate for one year than would otherwise be the case. However, the unemployment cost would be over twice as high if the policy were not credible and the disinflation was not anticipated by public (Rudebusch et al., 1996).

[28]Also see Bomfim and Rudebusch (2000).

Since the Fed targets current inflation based on the history of recent past, a decline in inflation causes the threshold to drift down. As a result, the Fed could be relatively inactive when the intermediate target is achieved. In our specification, a regime shift occurs when the current value of inflation rate exceeds the average value of the past two years inflation rate. Another statistical advantage of (3.6) is that the threshold variable $\pi_{t-1} - (\pi_{t-5} + \pi_{t-9})/2$ is clearly stationary. According to Enders and Granger (1998), conditioning the regimes on a stationary variable has better properties than conditioning the regime change on a nonstationary, or highly persistent, variable.[29]

In our second formulation, we use the unemployment rate as an alternative threshold indicator. The Federal Reserve Bank often regarded the unemployment rate as an important indicator of its monetary policy stance. That is, the Fed is more accommodative in a high unemployment regime than the low unemployment regime. Thus the policy regimes switch according to

$$I_t = \begin{cases} 1 & \text{for} \quad u_{t-1} \leq u^T, \\ 0 & \text{for} \quad u_{t-1} > u^T, \end{cases} \tag{3.7}$$

where u^T is the threshold value. We choose 6.5% as the threshold value because it is often mentioned by the Federal Reserve Bank of the United States as an unemployment rate at which they begin to consider any policy changes.[30]

3.4 Empirical results

Our baseline empirical analysis uses the Survey of Professional Forecasters data for the US economy from 1968:Q3-2008:Q4. We take the half-yearly data for the Livingstone Survey;

[29] This feature characterizes the momentum threshold model introduced in Enders and Granger (1998). Also see Bomfim and Rudebusch (2000).

[30] See for instance, the Federal Open Market Committee minutes from December 2012 which states, "In addition, all but one member agreed to replace the date-based guidance with economic thresholds indicating that the exceptionally low range for the federal funds rate would remain appropriate at least as long as the unemployment rate remains above $6\frac{1}{2}$ percent, inflation between one and two years ahead is projected to be no more than a half percentage point above the Committees longer-run goal, and longer-term inflation expectations continue to be well anchored."

the sample period runs from 1961:H2 to 2008:H2. We eschew the post-Great Recession period data to avoid potential misspecification issues in expectation arising from hitting the zero lower bound on nominal interest rates. However, our results are also robust with the full sample which extended to 2016:Q3 and 2016:H2, respectively, for the SPF and the LS. Both the SPF and LS data for unemployment expectation are taken from the Federal Reserve Bank of Philadelphia. The realized unemployment rate is the civilian unemployment rate (UNRATE), the realized CPI inflation rate (annualized) is the seasonally adjusted consumer price index (CPIAUCSL), and the realized interest is the three-month nominal Treasury bill rate (TB3MS). All these variables are obtained from the Federal Reserve Bank of St. Louis (FRED) database. In general, the unemployment rate, CPI index and the Treasury bill rate are hardly subject to any revisions over time. One of our robustness checks also augmented the baseline threshold local projection model by exogenously incorporating the uncertainty shocks resulting from the uncertain economic and political events. We use the implied and realized volatility of the stock market returns to gauge the uncertainty shocks. We use the VXO index and SP500 Index to measure the implied and realized volatility. In the robustness section, we provide a detailed description to our measure of uncertainty shocks.

3.4.1 Linear model

We first focus on the linear model given by (3.1) to gauge economy's response to an unanticipated shock to an expectation of future unemployment rate and how its interaction with monetary policy contribute to fluctuations in macroeconomic aggregates. Our linear specification assumes that whenever the economy enters into a particular policy regime, the agents naively believe that the regime will last forever. We want to contribute to the literature by showing that differences arise when considering a threshold model that allows regime shifts. That is, an appropriate econometric model, which captures the connections to changes in expectations to regime shifts, shows us that whether the effects of expectation shocks on macroeconomic activities are asymmetric across the policy regimes. Given our research interest, we focus on only the effects of expectation shocks on macroeconomic variables.

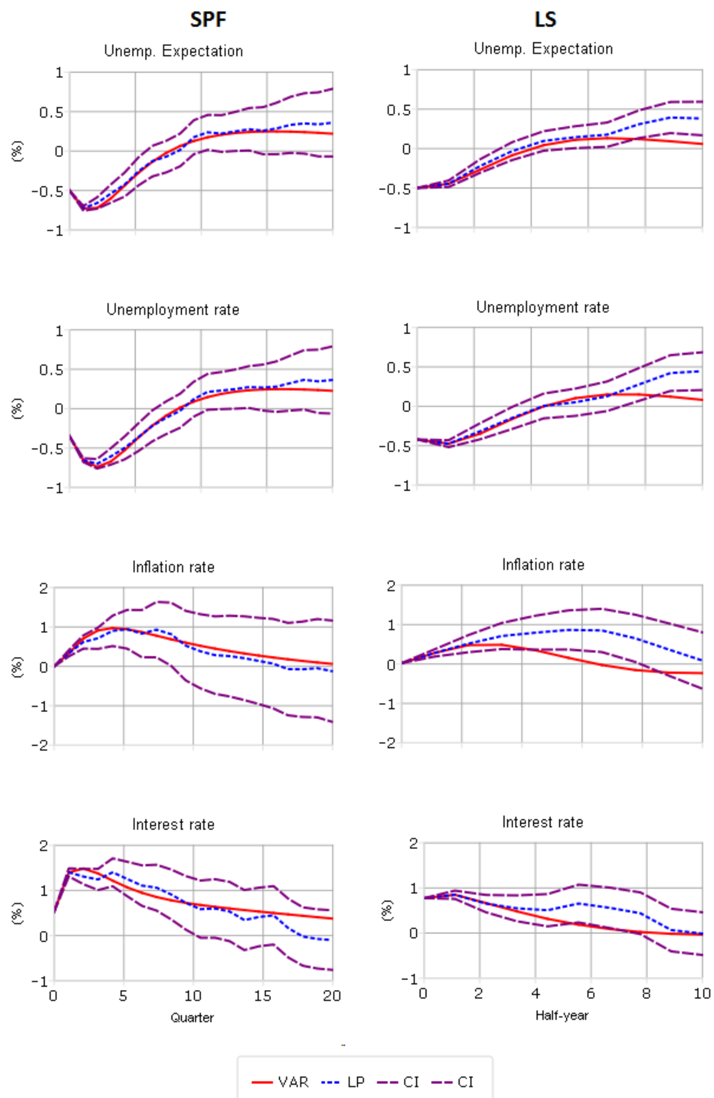

Figure 3.2
Impulse response functions from one standard deviation expectation shock using linear model

Figure 3.2 shows the impulse responses to a one standard deviation negative innovation of unemployment expectation at one-step-ahead. By a one-step-ahead negative shock, we mean that agents expect that the unemployment rate would decline in the next quarter using the SPF data (six-month-ahead forecast using the LS data). In the subsequent sections, we also refer it as a positive expectation about the future economy. The left panel shows the impulse responses from both a linear projection and a VAR using the unemployment expectation measured by the SPF and the panel on the right shows the responses using the

LS data. In each figure contains four lines plotted over the five year horizon. The short dashed line represents the impulse response obtained from the local projection model given by (3.1), the solid line represents the impulse response based on a VAR model. In each case, two lags are chosen based on the AIC. Structural shocks of unemployment expectation are identified using the timing of the surveys, which led us to put the unemployment expectation first in the Cholesky ordering as explained in the previous section. The two long dashed lines represent the one standard deviation confidence intervals around the local projection impulse response function that is generated using the Newey-West method for computing standard errors described earlier.

Both panels show similarities between the impulse response patterns using the local projection method and the VAR method with the solid line mostly tracking the short dashed line over the five year horizon, and, with the exception of very few instances, always remaining inside the one standard error bands. An important difference is that with the VAR method, the impulses are smoother, and this reflects the construction process where the vector moving averages used to find the impulse response functions are always functions of the same estimated VAR coefficients, while the local linear projection method does not impose any construction relationships between impulses at different horizons.

First, consider the impulse response functions presented in the left panel using the SPF data. On impact, both the VAR and local projection indicate that one standard deviation of negative innovation of unemployment expectation that lowers the expected unemployment by about 0.5 percentage point causes to decline the realized unemployment rate by almost similar magnitude. As the realized unemployment rate dips down further at the end of quarter 2, the inflation rate goes up by 1 percentage point over a four quarter horizon. Consequently, a boom driven by a positive expectation is associated with a contractionary monetary policy, reflecting a rise in the interest rate by 0.5 percentage point on impact. It goes up to 1.5 percentage points in the second quarter before it started falling. The impulse responses using the LS data are qualitatively the same.

These findings are consistent with the expectation driven business cycle. Clearly, an optimistic expectation about the future causes a boom in current economic activities with the unemployment rate falling and the inflation rate rising. These responses are consistent with the conventional view that the monetary authority's reaction is aggressive in the wake of rising inflation as interest rate rises more than proportionately. Our findings from the linear projection are similar to Leduc and Sill (2013), which is based on the assumption that the policy regime remains the same over the forecast horizon. However, our main focus is to investigate the macroeconomic effects of expectation shocks when policy regime shifts.

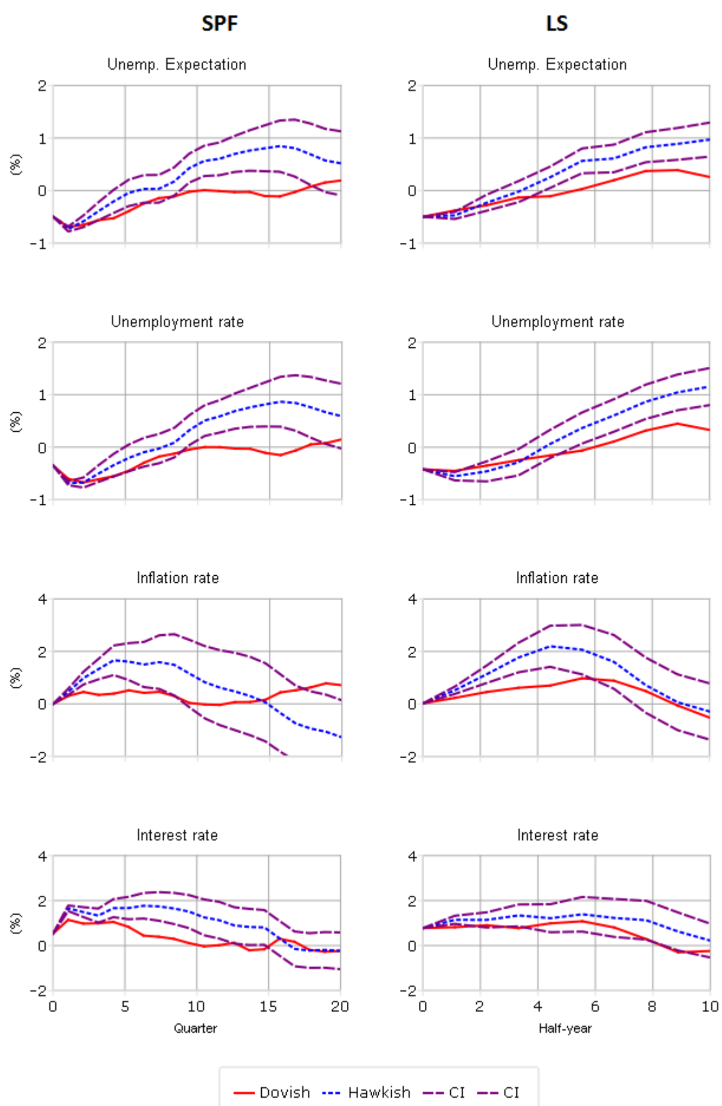

Figure 3.3
Impulse response functions from one standard deviation expectation shock using opportunistic monetary policy strategy as a threshold indicator

3.4.2 Threshold local projection model

Figures 3.3 and 3.4 show the impulse response plots for the threshold model (3.3) such that intensity of agents' expectations and monetary policy response depend on the policy regimes. As described above, our regime switching indicator variables are, respectively, the inflation rate and the unemployment rate. Like Figure 3.2, the left panel corresponds to the IRFs using the SPF data while the right panel shows the IRFs using the LS data. Although these figures use the same four line types as in Figure 3.2, there are a few differences in the plotting notations relative to the plots in Figure 3.2. In particular, we use a convention of plotting the impulse responses for two different policy regimes. Our first formulation is the opportunistic monetary policy strategy that distinguishes the economy into a dovish (or low inflation) regime and a hawkish (or high inflation) regime. The unemployment rate indicator divides the states of the economy into a low unemployment regime and a high unemployment regime as shown in Figures 3.3 and 3.4 respectively. We also refer to the hawkish regime as a low unemployment regime while the dovish regime as a high unemployment regime. The impulse responses in the hawkish (low unemployment) regime use short dashed lines, and its one standard deviation confidence bands use long dashed lines. For the dovish (high unemployment) regime, we plot the impulse responses using solid lines without any confidence bands. Thus in these figures, the hawkish regime takes the previous role used by the local projection model while the dovish regime takes the previous role used by the VAR model.

Figures 3.3 and 3.4 show that the economy responds significantly asymmetric ways to expectation shocks across the policy regimes. To get a deeper insight of it, let us first consider Figure 3.3, where impulse responses are plotted based on the assumption that the opportunistic Fed is more aggressive in the hawkish than the dovish regime. In other words, the Fed would not be aggressive to any boom unless the current inflation rate exceeds the average inflation rate of the recent past. On the left panel, a one standard deviation of negative innovation of unemployment expectation lowers the expected unemployment by about 0.5 percentage point on impact. Accordingly, the realized unemployment rate declines

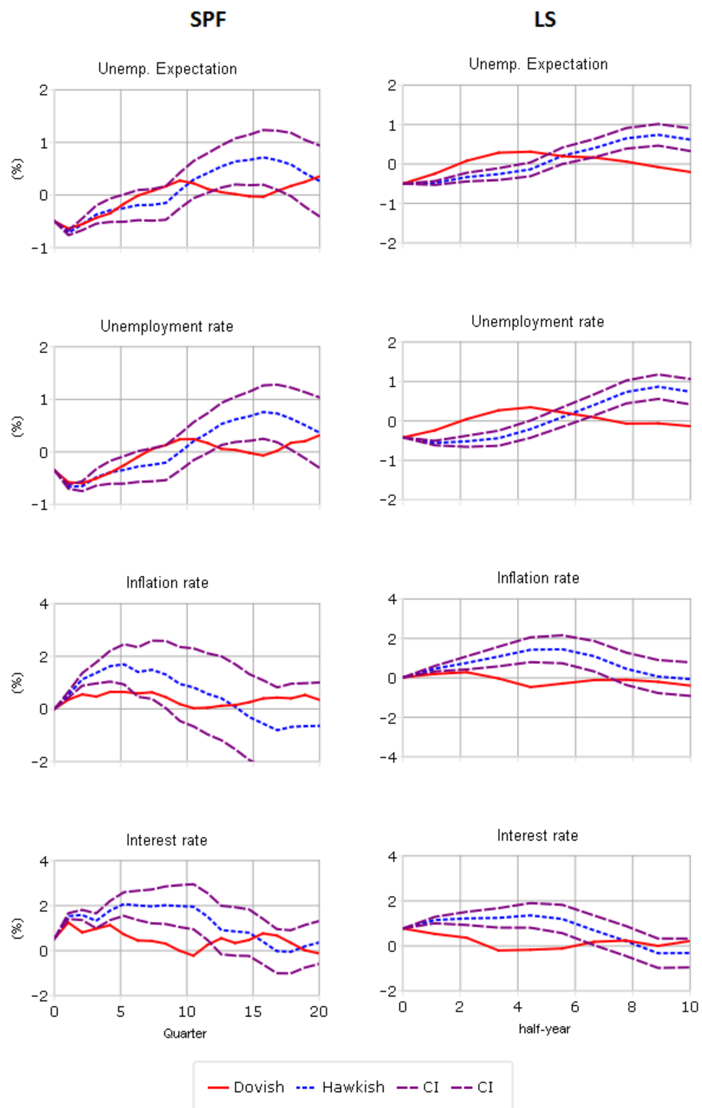

Figure 3.4
Impulse response functions from one standard deviation expectation shock using unemployment as a threshold indicator

by almost similar magnitude in both the regimes. Unemployment rate starts creeping up thereafter. After ten quarters, the unemployment rate increased significantly higher during the high inflation regime than the low inflation regime. The explanation of the asymmetric responses of unemployment rate can be clearer as one moves down further to look at the impulse responses of the inflation rate and the interest rate. The booms led by positive expectations about the future trigger the inflation rate up significantly during the high inflation regime. Consequently, the interest rate increases on impact. Now it is important to look at the aftermath-shock-dynamics of inflation and interest rate. Following the shock, as inflation accelerates significantly at high inflation regime, the interest rate goes up more than proportionately, reflecting the Fed's aggressive policy to fight inflation. Eventually, inflation cools down after eight quarters, which is associated with lowering down the interest rate. On the other hand, at the dovish regime, an expectation leads to booms in current economic activities with unemployment falling at the same magnitude as in the hawkish regime during the first two quarters. The opportunistic Fed, who relies on the state of the economy to take care of inflation, seems to be less aggressive.

Now moving to the right panel that uses the Livingstone survey data, an unanticipated expectation shock tells the similar story. However, few issues to note here. First, in few instances, the responses of interest rate in the hawkish regime are not as strong as the ones with the SPF data. Second, the impulse responses with the Livingstone survey data seem to be more persistent. One potential reason for this differences could be that the LS data considers a longer horizon (half-yearly) to forecast the variable and while the SPF data is quarterly.

We now focus on Figure 3.5 to get a more clear picture of the asymmetric effects of expectation shocks on macroeconomic activities. It shows a comparison between the impulse response plots for both the linear model and the threshold models as reported in Figures 3.3 and 3.4. To keep the plots simple, we ignore the confidence bands. The solid line shows the impulse responses using the linear model while small dashed line and the big dashed line represent the impulse responses respectively in the hawkish and dovish regime. All the four panels show that the impulse responses using the linear models lie in between the hawkish and dovish regimes while a big difference exists in the impulse responses in the hawkish and dovish regimes. In the top panels, the asymmetric effects of a one standard deviation negative unemployment expectations on the expected unemployment rate and the actual unemployment rate are more prominent at the end of about eight quarters. As we focus on the inflation rate, we find that the rise of inflation rate is higher in the hawkish regime than

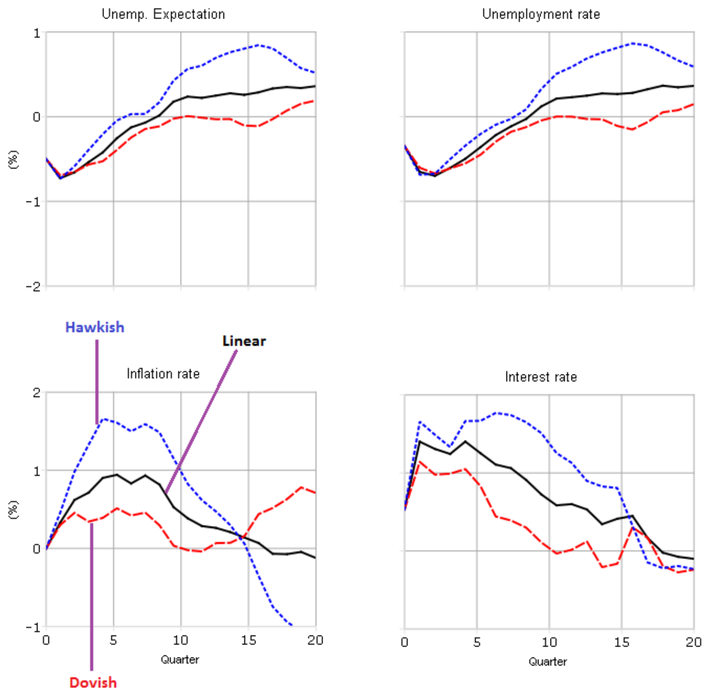

Figure 3.5

IRFs: Differences in the expectation effects of regime shifts on economic activities

the dovish regime for up to 15 quarters. This difference is maximum at the end of 5 quarters when the inflation rate is more than 4 times higher in the hawkish regime than the dovish regime. Now moving to the interest rate, we yet again find a big difference in the impulse responses between the hawkish regime and the dovish regime with the interest rate is almost always higher in the high inflation regime than the low inflation regime. This difference is maximum at the end of 10 quarters when the interest rate is 14 times higher in the hawkish regime than the dovish regime. Overall, it shows that the effects of expectation shocks on the macroeconomic activities are asymmetric across the policy regimes.

It would be interesting to look at how the effects of expectation shocks and the monetary policy's reaction change when we use an alternative regime structure. We plot the impulse responses in Figure 3.4 using unemployment rate as an alternative threshold indicator. We construct this threshold indicator based on the assumption that, usually, the Fed pursues an accommodative monetary policy during a high unemployment (dovish) regime while it conducts a contractionary monetary policy in a low unemployment (hawkish) regime. Let us focus on the impulse responses using both the SPF and LF data simultaneously since they follow the same dynamics. On impact, a positive expectation shock about the future leads to decline both the expected and actual unemployment to almost an equal magnitude. In the subsequent periods, the unemployment rate started rising. But the increase of unemployment rate is slower in the hawkish regime than the dovish regime. Next, we focus on the dynamics of the inflation and interest rates to an expectation shock. On impact, the inflation rate does not respond to an expectation shock. However, in the subsequent periods, a positive expectation shock that leads to a boom in current economic activities with falling unemployment rate also causes a substantial increase in inflation rate during the hawkish regime while the responses of inflation rate are weak during the dovish regime. As the Fed anticipates a potential boom, on impact, it reacts to an expectation shock by raising the interest rate. Later on, as the shock realized, the Fed looks to be more aggressive in the hawkish regime than the dovish regime. We can see it from the difference in responses of the interest rate across the policy regimes. The difference in responses of the interest rate is significant roughly for more than three years using both the SPF and LS data. Overall, these findings are consistent with the ones in which we determine the policy regime shifts using the Fed's opportunistic monetary policy strategy. That is, the effects of an unanticipated expectation shock on current economic activities and its interaction with the monetary policy are asymmetric when the policy regime shifts.

3.5 Robustness

This section provides robustness exercises to check the consistency of our baseline results. We only focus on regime-switching models since our main interests are to investigate the asymmetric effects of expectation shocks when policy regime changes. First, we control for exogenous uncertainty shocks that may play a significant role in the system's dynamic behavior. Second, we conduct the analysis using the full sample that includes the period of the Great Recession of 2008-09.

Figure 3.6

Measuring uncertainty shocks from the realized and implied volatility of the U.S. stock market

3.5.1 Controlling for uncertainty shocks

Bloom (2009) shows that heightened "economic uncertainty" due to uncertain economic and political shocks have a significant impact on economic activities.[31] We control for such exogenous uncertainty shocks that may play a significant role in our system's dynamic behavior as we want to make sure that agents' expectation shocks solely depend on policy regimes. We follow Bloom (2009) using the observed and implied stock market volatility to identify the uncertainty shocks as plotted in Figure 3.6.[32] The measure of implied volatility is the VXO index, which corresponds to the volatility implied by a synthetic 30-day option

[31] Jones and Enders (2016) show that effects of uncertainty shocks on economic activities are asymmetric. However, the estimated the generalized impulse response functions.

[32] Since the seminal contribution of Bloom (2009), a significant number of studies used the US stock market volatility as a measure of uncertainty. See Jones and Enders (2016), Bekaert et al. (2013) among others for example.

on the S&P100 stock index, obtained from the Chicago Board of Options Exchange which is available from June 1986 onward. For pre-1986 data, realized monthly returns volatility are calculated from the daily S&P500 index, which is then normalized with the same mean and variance of the VXO index when the overlap from 1986 onward.[33] Note that 19 major political and economic events are labeled with the sudden jumps of stock market volatility in Figure 3.6.[34] Evidence suggests that these major events caused significant downturn of economic activities. To control for exogenous uncertainty shocks we augment our regime-switching model in equation (3.3) employing dummy variable that takes a value of 1 for each of the uncertain events and 0 otherwise. Fourteen out of 19 events lie within our baseline samples that use the SPF data while 17 events lie within the baseline sample that uses the LS data. Note that baseline estimations exclude the periods of the Great Recession. Our results are also robust that include uncertainty shocks using the full sample.[35]

Figures 3.7 and 3.8 show the impulse response functions of our baseline regime switching models that are modified to incorporate the dummy variable to control for the uncertainty shocks. Like before we use the same recursive ordering and adopt both types of regime switching formulations. Figure 3.7 corresponds to model with opportunistic monetary policy strategy as a threshold indicator while Figure 3.8 is the with one with the unemployment rate as a threshold indicator. Organization of the figures is the same as before.

Comparing our results with those illustrated in Figures 3.3 and 3.4 we find that controlling for uncertainty shocks has only a minor effects on the dynamic behavior of expectation shocks on unemployment, inflation rate and its interaction with the monetary policy. The impulse responses follow a similar dynamic path as shown in Figures 3.3 and 3.4. That is an unanticipated decrease in the expected unemployment rate has stronger effects in the hawk-

[33] We take the uncertainty data from Bloom (2009) and updated it from July 2008 using the CBOE's VXO index.

[34] Bloom (2009) identified these events from stock market volatility with more than 1.65 standard deviations above the Hodrick-Prescott ($\lambda = 129,000$) mean of the stock market volatility series.

[35] Our findings considering all the 19 events using the full sample is also robust. Also, note that in their estimation, Leduc and Sill (2013) control for exogenous oil and fiscal shocks identifying 5 major events including OPEC I, OPEC II, Gulf War I, Carter-Reagan Military buildup (which also coincides with Afghanistan, Iran hostages) and 9/11. Our analysis takes into account all of these events.

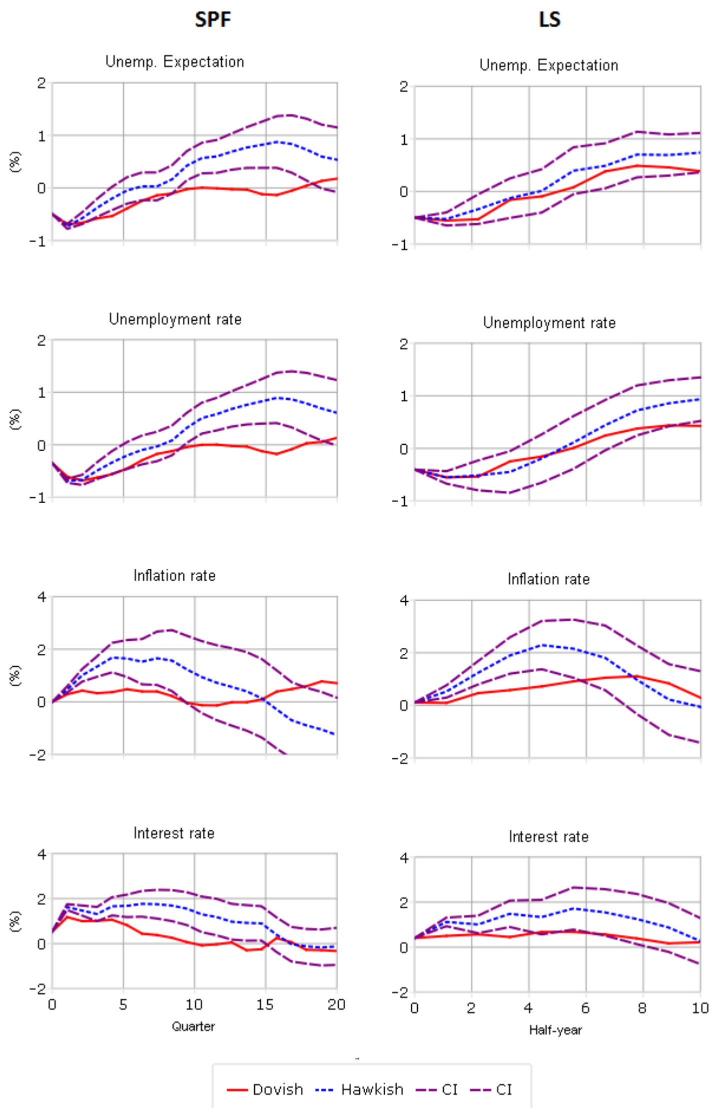

Figure 3.7
Impulse response functions from one standard deviation expectation shock using opportunistic monetary policy strategy as a threshold indicator with controlling the uncertainty shocks

ish regime than the dovish regimes under both formulations. Consequently, the monetary policy's reaction is more aggressive in hawkish regime than the dovish regime.

3.5.2 Full sample

We also redo our baseline analysis using the full sample as one wonders how our results might change if we incorporate the period of financial crisis. We re-estimate the baseline

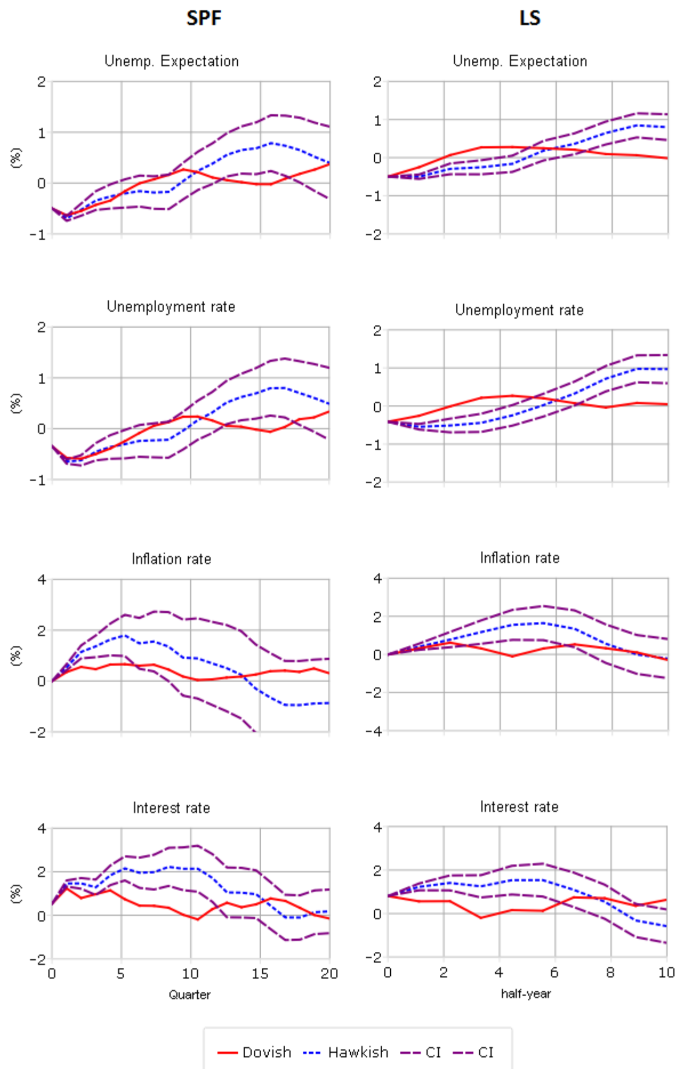

Figure 3.8
Impulse response functions from one standard deviation expectation shock using unemployment as a threshold indicator with controlling the uncertainty shocks

regime-switching models over 1968:Q3-2016:Q3 for the SPF and 1961:H2-2016:H2 for LS data.

The results, shown respectively in Figures 3.9 and 3.10, show little difference from those displayed in Figures 3.3 and 3.4. The asymmetric effects of expectation shocks on the inflation rate and the interest rate are stronger when we consider the full sample. That is the responses of inflation and interest rates are stronger in hawkish regime than the dovish regime. This is not surprising because the financial crisis indeed has weighed down agents'

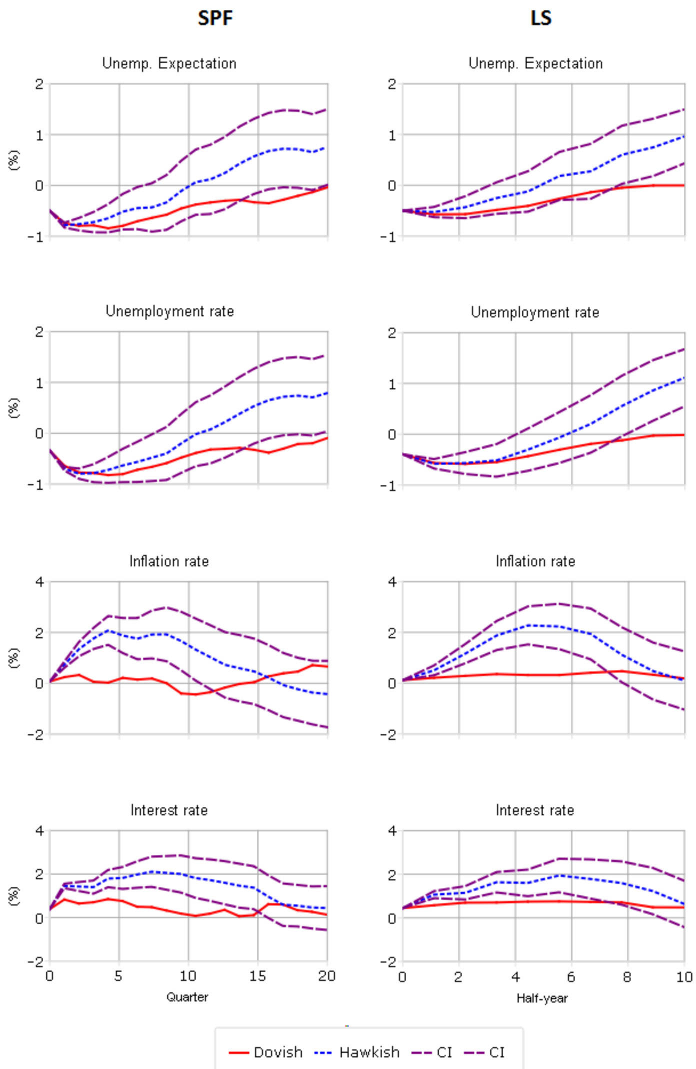

Figure 3.9
Impulse response functions from one standard deviation expectation shock using opportunistic monetary policy strategy as a threshold indicator. Threshold model using full sample that includes the Great Recession of 2008-09.

expectation during the dovish regimes.

3.6 Variance decomposition analysis

Finally, we assess how the shocks to the expected unemployment rate contribute to the dynamics of the variables of interest across policy regimes by using variance decomposition

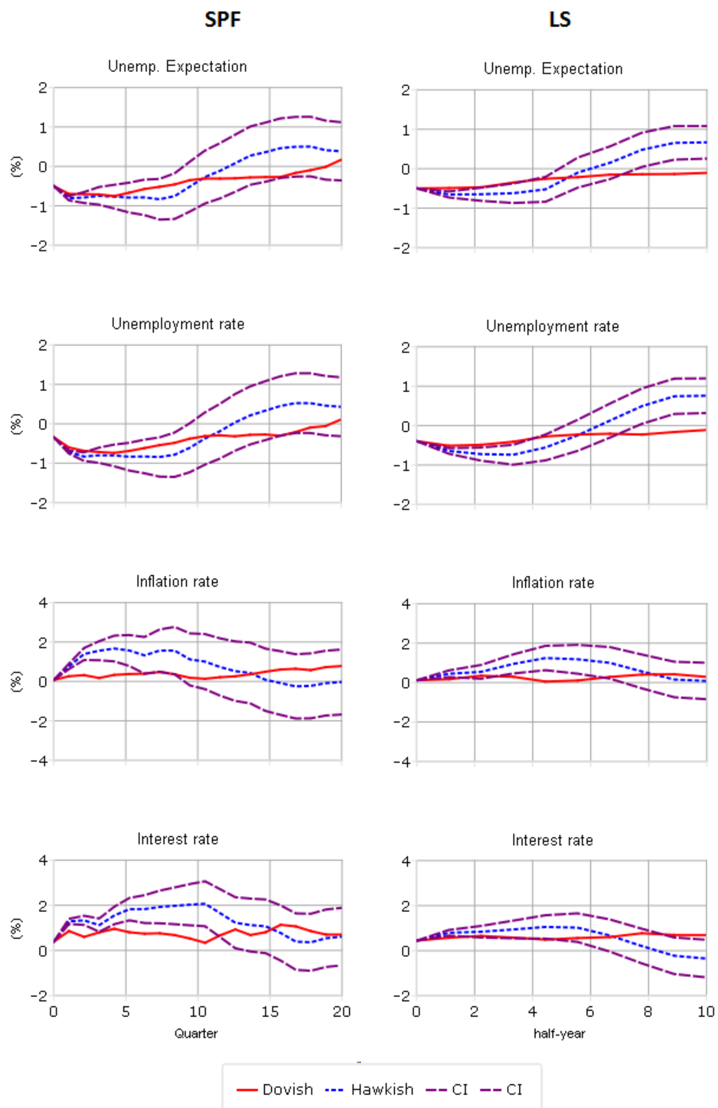

Figure 3.10
Impulse response functions from one standard deviation expectation shock using the unemployment rate as a threshold indicator. Threshold model using full sample that includes the Great Recession of 2008-09.

analysis, which is a popular tool from the traditional VAR analysis. We examine the variance decomposition analysis using local projections. We discuss it briefly to understand the overall procedure.[36]

[36]For theoretical detail, we refer the reader to Jordà (2005).

The mean squared error of the forecast error is given by

$$MSE_u(E(x_{t+s}|X_t)) = E(u^s_{t+s}u^{s'}_{t+s}) \qquad s = 0, 1, ..., h. \tag{3.8}$$

This can be estimated by using $\widehat{\Sigma}_{u^s} = \frac{1}{T}\sum_{t=1}^{T} \widehat{u}^s_{t+s}\widehat{u}^{s'}_{t+s}$ where $\widehat{u}^s_{t+s} = x_{t+s} - \widehat{\alpha}^s +_{i=1}^{p} \widehat{B}^{s+1}_i x_{t-i}$. The diagonal elements of this will be the variance of the s step ahead forecast errors for each of the elements in x_t. Next, defining the $n \times n$ experimental choice matrix D by the columns d_i from the mapping described above. Renormalizing MSE_u by the choice matrix D into

$$MSE(E(x_{t+s}|X_t)) = D^{-1}E(u^s_{t+s}u^{s'}_{t+s})D^{'-1} = D^{-1}\Sigma_{u^s}D^{'-1} \qquad s = 0, 1, ..., h. \tag{3.9}$$

From (3.9), we can calculate the traditional variance decompositions by directly plugging in the sample-based equivalents from the projections in (3.1). Extensions of this calculation to the threshold models can be done using a straightforward extension of the vector x_t by putting terms $I_{t-1}x_t$ in the upper half of the new vector and $(1 - I_{t-1})x_t$ in the lower half of the new vector.

Tables 3.1 and 3.2 report the results of two and five years ahead of forecast error variance decomposition. Table 3.1 shows the results both for linear and threshold models with inflation as a threshold indicator while Table 3.2 represents only the threshold model with unemployment as a threshold indicator. We only report the results of the percent of the total forecast error variance attributable to expectation innovations, which is of our main interest. The tables are organized into two vertical panels, with columns two through four showing the results when using SPF data and columns five through seven showing the results when using LS data. Each of the tables is also organized into two horizontal panels each of which corresponds to a different forecast horizon. Focusing on the top horizontal panel in Table 3.1, which summarizes the variance for the two year horizon, we see it is organized into three rows, with the first row showing the results for the linear model is given by (3.1) and the next two rows showing the results for hawkish and dovish regimes as found in the threshold model given by (3.3) with inflation as a threshold indicator.

To get a more concrete sense for the organization of the tables, let us focus on the first vertical panel of Table 3.1 at the two year forecast horizon. Conditional on the linear local projection, the expectation shocks take into account for an important share of the variance of unemployment (82.98%), inflation (15.48%) and the interest rate (51.22%). The threshold local projection shows an important distinction of the variance decomposition can be seen in hawkish and dovish inflation regimes over the forecast horizon. During the hawkish regimes expectation innovations account for 73.88% of the forecast error variance for unemployment, 26.29% of the forecast error variance for inflation rate and 61.92% of the forecast error variance for interest rate over two year forecast horizon, while during dovish regime expectation innovations account for 67.34% of the forecast error variance for unemployment, 10.96% of the forecast error variance for inflation rate and 41.64% of the forecast error variance for interest rate for the forecast horizon of two years. The remaining sub panels of the table have a similar organization.

Next moving down the Table 3.1, the differences of the variance decomposition between hawkish and dovish regimes are more prominent for the forecast horizon of five years. Conditional on the hawkish regime, the expectation shocks contribute 66.28% share of the variance of unemployment, 27.05% share of inflation rate and 40.42% share of interest rate. Quite differently, conditional on dovish regime, the share of unemployment takes into account 30.59% of the variance decomposition while the shares of the inflation rate and interest rate are 8.85% and 19.31% respectively. That is the forecast error variance of the variables in interests are almost are less than half than that of the hawkish regime.

Moving to the right panel of Table 3.1, we compare the findings of the variance decomposition using the LS data with the ones using the SPF data that we already discussed. The results are qualitatively similar using both the expectation measures. Though over two year forecast horizon the variances do not differ significantly, in which variance of unemployment is lower in hawkish regime than the dovish regime, as we move down the column, the difference is acuter over the horizon of five years. An important point to note is that over the two

Table 3.1: Percent of total FEV attributable to expectation innovations

(Using opportunistic monetary policy as threshold indicator)						
	SPF			LS		
States	Unemp.	Infl. rate	Int. rate	Unemp.	Inf. rate	Int. rate
			Forecast horizon of two-year ahead			
Linear	82.98	15.48	51.22	43.76	8.68	22.03
Hawkish	73.88	26.29	61.92	36.67	25.13	35.45
Dovish	67.34	10.96	41.64	45.64	23.58	29.15
			Forecast horizon of five-year ahead			
Linear	40.89	12.28	41.75	30.64	17.74	22.75
Hawkish	66.28	27.05	40.42	58.01	44.75	38.26
Dovish	30.59	8.85	19.31	36.26	14.74	31.87

year horizon there exists a somewhat wide range of variation of estimated contributions of expectations shocks to the forecast error variance of the unemployment rate, inflation rate, and the interest rate. A likely explanation of this variation in part the fact that observations on the expectations measures, and thus the sample periods, start at different dates.[37] But this variation in variance decomposition using both the SPF and LS data is somewhat comparable over five year forecast horizon.

Table 3.2: Percent of total FEV attributable to expectation innovations

(Using unemployment as threshold indicator)						
	SPF			LS		
States	Unemp.	Inf. rate	Int. rate	Unemp.	Inf. rate	In. rate
			Forecast horizon of two-year ahead			
High Unemp.	55.11	8.06	29.07	10.96	0.34	2.72
Low Unemp.	65.09	32.91	69.77	55.91	18.43	42.05
			Forecast horizon of five-year ahead			
High Unemp.	35.33	4.68	25.31	2.66	0.35	1.27
Low Unemp.	36.84	22.73	72.53	62.84	38.89	44.16

Table 3.2 reports the forecast error variance decomposition with unemployment as the threshold indicator. The organization of the table is similar to the Table 3.1 with some difference in the arrangement of horizontal panels, each of which has two rows now. The first

[37] See Leduc and Sill (2013).

row displays the results of the variance decomposition for the high unemployment regime; the second row shows the results for the low unemployment regime. Yet again, we find that the contribution of the expectation innovations to the share of variance decomposition of the variables in interests is significantly higher in low unemployment regime than the high unemployment regime. These findings are consistent with the ones above in a sense that the low unemployment rate is more often associated with the high inflation rate while the high unemployment rate is associated with the low inflation rate.

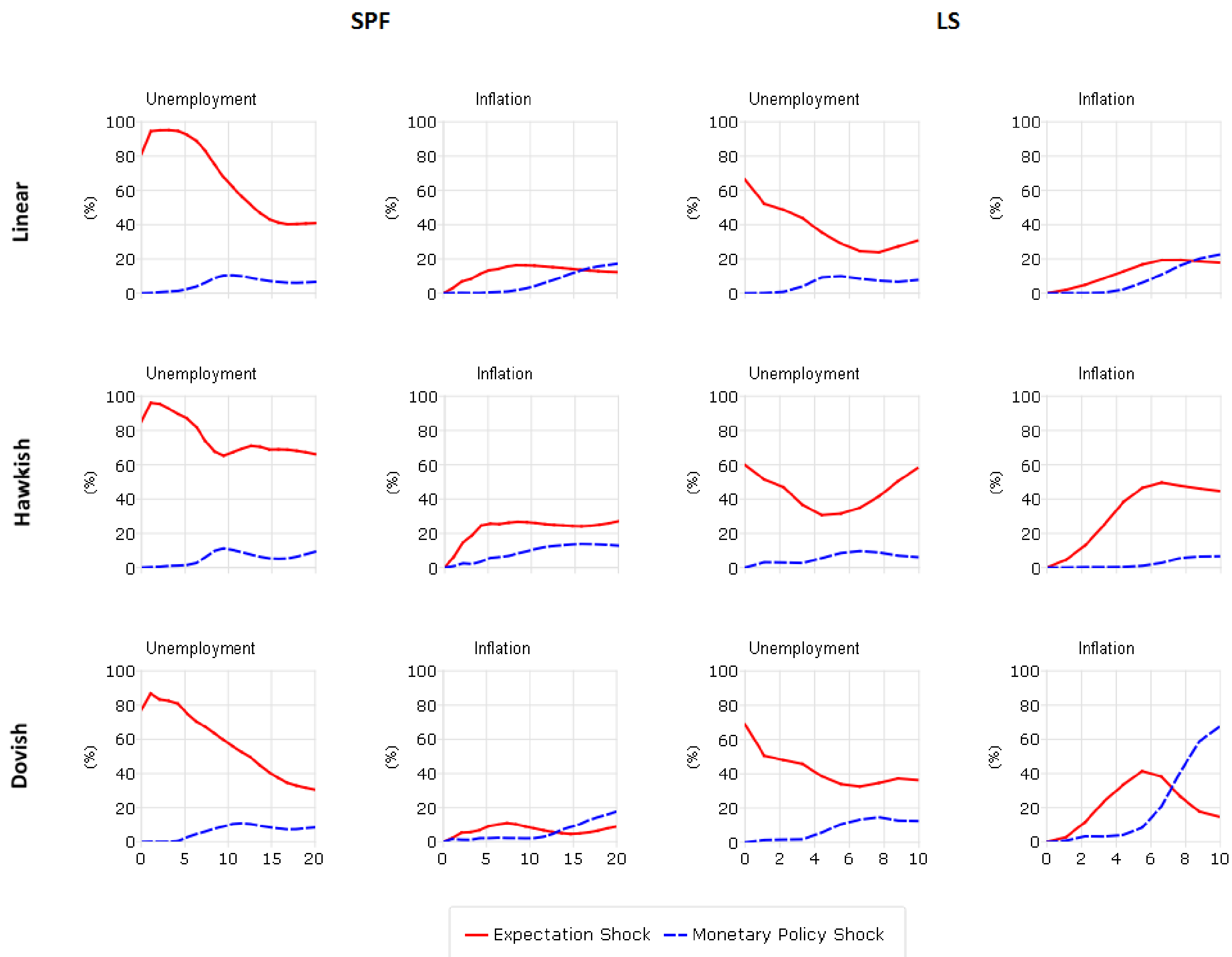

Figure 3.11
Comparison of FEVD between expectation shocks and monetary policy shocks. First horizontal panel plot the FEVD for linear model while second and third horizontal panels show the results of threshold model using opportunistic monetary policy strategy as a threshold indicator.

3.6.1 How important the expectation shocks are?

To understand the importance of expectation shocks on economic activities, we compare them with the estimated contribution of monetary policy shocks, which we identify with the same Cholesky ordering.[38]

Figure 3.11 reports a comparative analysis of the forecast error variance of expectation and monetary policy shocks on economic activities over the five-year horizon. The figure is organized with two vertical panels and three horizontal panels. Two vertical panels reflect the plots of the variance decomposition using the SPF and LS data respectively. The first horizontal panel displays the plots of the forecast error variance using the linear model. The second and third panels provide the plots of the forecast error variance in hawkish and dovish regimes using the threshold model with the opportunistic monetary policy as a threshold indicator. We only report the forecast error variance of the unemployment rate and inflation rate. Each plot has two lines. The solid lines correspond to the forecast error variance of expectation shock while the dashed lines are the ones with monetary policy shock. First, focus on the vertical panel with the SPF data. The contribution of expectation shock on unemployment is larger than that of the monetary policy shock over the five-year forecast horizon. The difference in the estimated contribution of the two shocks on the unemployment rate is significantly larger in the hawkish regime than the dovish regime. Now we focus on the inflation rate, though the importance of monetary policy shocks look more important towards the end of the five-year horizon in both linear model and the dovish regime, the contribution of the expectation shock on the inflation rate, on the other hand, is significantly higher in the case of the hawkish regime throughout the forecast horizon. Our findings using the LS data are qualitatively similar as shown in the left panel.[39] Our findings support Caggiano et al. (2014) who find that uncertainty shocks are more important than monetary policy shocks to explain the economic fluctuations.

[38]This kind of exercise can be motivated from Cochrane (1994) who argued that news about economic fundamentals likely to be more important than monetary policy or technology shocks to understand the economic fluctuations.

[39]We also conduct a similar kind of exercise using the unemployment rate as a threshold indicator. The results are consistent with the above.

We can draw some lessons from the variance decomposition analysis. First, the threshold models can better describe the effects of expectation shocks than the linear models. Second, expectation shocks importantly contribute to the dynamics of economic activities in the boom periods than the lean periods. Thus a linear model analysis could under or overestimate the contribution of expectation shocks on macroeconomic variables. Third, uncertainty shocks turn out to be more important than monetary policy shocks in explaining the dynamics of economic activities.

3.7 Conclusion

This chapter investigates the effects of expectation shocks on macroeconomic activities. We find that the effects of expectation shocks on macroeconomic activities transmit asymmetrically across the policy regimes. In particular, in a hawkish regime, the results of impulse responses and forecast error variance analysis show that an anticipation of a good time ahead leads to a boom in current economic activities like falling unemployment and rising future inflation. However, the effects of the shocks are transient in the dovish regime as they fade away quickly. We also find that the Fed's reactions to a positive innovation of expectation are asymmetric across the policy regimes. The Fed reacts more aggressively in the hawkish regime than the dovish regime with a more than proportionate increase in the interest rate. Our results are robust using both SPF and LS survey data on unemployment expectations, using different samples that also include the period of the Great Recession, and alternative regime switching structures. Controlling the major uncertain economic and political events, we also conducted a robustness analysis that supports our baseline results.

These findings have important implications for recent policy debates as critics opined that keeping monetary policy too easy for too long is responsible for fueling the recent booms. Our findings do not support this view. Instead, our findings are consistent with Bernanke and Gertler (2000) who claim that a positive (negative) expectation about the future coincides with an anticipatory tightening (easing) monetary policy as the Fed always tends to stabilize the economy.

Our findings on the effects of economic activities to expectation shocks and its interaction with the monetary policy are also consistent with a number of recent studies that investigate the Fed's asymmetric behavior to macroeconomic activities.[40] We further provide a comparative analysis by computing the forecast error variance decomposition of expectation shocks and monetary policy shocks on economic activities using the linear and the regime switching models. We find that expectation shocks are more important than the monetary policy shocks in explaining the fluctuations of economic activities. Our results also provide a new empirical benchmark for theoretical investigations.

[40] For example, see Surico (2007) and Cassou et al. (2012) among others.

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Appendix A

Appendix for Chapter 1

This appendix provides additional results for Chapter 1. We conducted robustness checks using capacity utilization of the manufacturing units. To investigate cointegration we now estimate our baseline regression equation (1) in Section 1.1 of Chapter 1 for the capacity utilization series of manufacturing sector recover the residuals for unit root analysis and later error correction estimation. For the purpose of comparison, we also provide estimates of the baseline analysis that uses total capacity utilization. The estimated long-run relationships between inflation and capacity utilization are given by

$$c_{M,t} = \underset{(0.0049)}{4.35} + \underset{(0.0009)}{0.0041}\pi_t + \widehat{\mu}_{M,t} \tag{A.1}$$

and

$$c_{T,t} = \underset{(0.0049)}{4.37} + \underset{(0.0009)}{0.0046}\pi_t + \widehat{\mu}_{T,t} \tag{A.2}$$

where $c_{M,t}$ and $c_{T,t}$ indicate the manufacturing and total capacity utilization variables respectively, $\widehat{\mu}_{M,t}$ and $\widehat{\mu}_{T,t}$ are the residuals from each equation and a mnemonic convention of denoting the manufacturing capacity utilization variables with initial subscripts of M and total capacity utilization variables with initial subscripts of T has been used. The standard errors for the estimated coefficients are presented directly below the parameter estimates in parenthesis. These regression results show highly significant parameter estimates in both equations as well as very comparable values between the two equations. The estimated slope coefficients show the elasticity of capacity utilization with respect to inflation and indicate that if the inflation rate goes up by 1% then MCU will go up by 0.0041%, and TCU will go up by 0.0046%.

Table A.1: Unit root tests

Inflation			MCU			TCU		
Trend	Cons	None	Trend	Cons	None	Trend	Cons	None
Augmented Dickey-Fuller - H_0: Nonstationarity								
	Lags = 13			Lags = 4			Lags =4	
-3.16	-1.89	-1.24	-3.87**	-3.53**	-0.22	-4.39**	-3.78**	-0.23
(-3.41)	(-2.86)	(-1.95)	(-3.41)	(-2.86)	(-1.95)	(-3.41)	(-2.86)	(-1.95)
				(-3.71)			(-3.83)	
Phillips-Perron Test - H_0: Nonstationarity								
-3.25	-2.02		-2.62	-2.40		-3.03	-2.85	
(-3.42)	(-2.87)		(-3.42)	(-2.87)		(-3.42)	(-2.87)	
				(-3.46)			(-3.71)	
KPSS Test -H_0: Stationarity								
0.21**	2.35***		0.43***	2.19***		0.36***	3.07***	
(0.15)	(0.46)		(0.15)	(0.46)		(0.15)	(0.46)	

Notes: Values in parenthesis are 5% critical values. For Tables A.1- A.3, ***, ** and * denote the significance at the 1%, 5% and 10% level respectively. ADF tests significance are based on conventional (nonbounded series adjusted) critical values.

Table A.2: Testing for threshold cointegration between inflation and capacity utilization

	M CU					T CU				
	E-G	TAR	TAR	M-TAR	M-TAR	E-G	TAR	TAR	M-TAR	M-TAR
Threshold		$\tau = 0$	$\tau = -0.0029$	$\tau = 0$	$\tau = -0.0029$		$\tau = 0$	$\tau = -0.0414$	$\tau = 0$	$\tau = -0.0053$
ρ_1	-0.021***	-0.016	-0.013	-0.023***	-0.030***	-0.024***	-0.020**	-0.017***	-0.024***	-0.031***
	(0.006)	(0.0086)	(0.008)	(0.008)	(0.007)	(0.006)	(0.009)	(0.008)	(0.008)	(0.007)
ρ_2		-0.024***	-0.030***	-0.019***	-0.001		-0.027***	-0.032***	-0.025***	-0.001
		(0.007)	(0.008)	(0.008)	(0.001)		(0.008)	(0.008)	(0.008)	(0.012)
γ_1	0.256***	0.255***	0.252***	0.255***	0.246***	0.256***	0.255***	0.254***	0.256***	0.238***
	(0.044)	(0.044)	(0.044)	(0.045)	(0.04)	(0.042)	(0.042)	(0.042)	(0.042)	(0.043)
γ_2	0.242***	0.242***	0.243***	0.239***	0.224***	0.149***	0.149***	0.151***	0.149***	0.141***
	(0.046)	(0.046)	(0.045)	(0.046)	(0.046)	(0.044)	(0.044)	(0.0435)	(0.044)	(0.045)
γ_3	0.136***	0.137***	0.143***	0.133***	0.127	0.153***	0.153***	0.156***	0.153***	0.142***
	(0.045)	(0.046)	(0.046)	(0.046)	(0.046)	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)
γ_4	0.027	0.029	0.036	0.026	0.019	0.113**	0.115***	0.117***	0.114***	0.110**
	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)
γ_5						-0.025	-0.023	-0.019	-0.025	-0.034
						(0.043)	(0.043)	(0.043)	(0.043)	(0.043)
AIC	-1810.49	-1808.92	-1810.88	-1808.61	-1814.25	-2030.20	-2028.62	-2029.98	-2028.21	-2033.32
H_0: $\rho = 0$	-3.79**					-4.16**				
Φ		7.39**	8.38**	7.23**	10.11**		8.86**	9.55**	8.64**	11.26***
$t - Max$		-1.95**	-1.64*	-2.28**	-0.16		-2.27**	-2.01**	-2.92***	-0.06
H_0: $\rho_1 = \rho_2$		0.43	2.37*	0.13	5.73**		0.41	1.76	0.01	5.08**

Table A.3: Estimated results of the threshold VECM

	MCU		TCU	
Variables	Δc_t	$\Delta \pi_t$	Δc_t	$\Delta \pi_t$
$I_t \widehat{\mu}_{t-1}$	-0.015**	0.541**	-0.015**	0.651***
	(0.007)	(0.213)	(0.007)	(0.234)
$(1 - I_t)\widehat{\mu}_{t-1}$	0.003	1.033***	0.004	1.518***
	(0.010)	(0.290)	(0.012)	(0.384)
Δc_{t-1}	0.260***	-1.922	0.272***	-1.608
	(0.044)	(1.313)	(0.043)	(1.415)
Δc_{t-2}	0.276***	2.17*	0.194***	1.279
	(0.044)	(1.298)	(0.043)	(1.421)
$\Delta \pi_{t-1}$	-0.001	0.250***	-0.001	0.244***
	(0.001)	(0.044)	(0.001)	(0.042)
$\Delta \pi_{t-2}$	-0.004***	0.215***	-0.003***	0.193***
	(0.001)	(0.044)	(0.001)	(0.042)
$\overline{R}^2$	0.25	0.24	0.19	0.22
F-statistic	5.28**	1.86	3.77**	0.83

Notes: Constant terms are not reported.

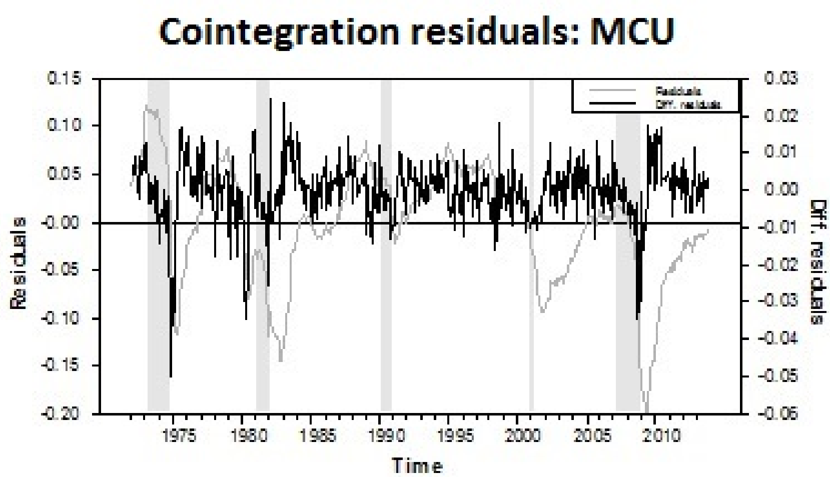

Figure A.1: Cointegration residuals: MCU

Appendix B

Appendix for Chapter 2

This appendix presents rigorous robustness exercises to validate our baseline findings. In particular, we provide impulse response function results for some alternative specifications to the empirical model investigated in the study in order to demonstrate that our baseline results are robust. Each section describes the structure for the alternative investigation. Because the main purpose of these exercises is to show that alternative specifications result in qualitatively similar graphs to those in Figures 2.4 and 2.5 in Section 2.3.2 of Chapter 2, we do not discuss the graphs individually at length. The reader should simply compare the alternative graphs from each exercise with Figures 2.4 and 2.5.[1]

Alternative measures of consumer confidence

First, consider alternative measurements for consumer confidence. In the baseline estimation, we use the confidence index, commonly known as ICS, which is the most commonly reported measure of consumer confidence by both the press and the academic literature. The Michigan Survey also provides consumers' sentiment based on expectations about economic conditions over a five year horizon and a twelve month horizon. We denote them as C5Y and C12M, respectively.[2] In addition, we use another measure of consumer confidence that

[1]Impulse responses for the linear models are similar to the baseline Figures 2.2 and 2.3. We do not report them, but they are available upon request.

[2]The confidence measure denoted by C5Y is based on the question: "Looking ahead, which would you say is more likely – that in the country as a whole we'll have continuous good times during the next 5

is based on whether or not it is currently a good time to buy "large households items." We denote this measure as CDUR. We use this measure only to generate impulse responses for the durable goods model.

The Figures B.1 - B.5 below show impulse response results using one of these alternative definitions for x_t where $x_t = [AltConf_t \quad c_t \quad y_t \quad f_t]'$, and $AltConf_t$ denotes a vector using either $C5Y_t$, $C12M_t$ or $CDUR_t$.

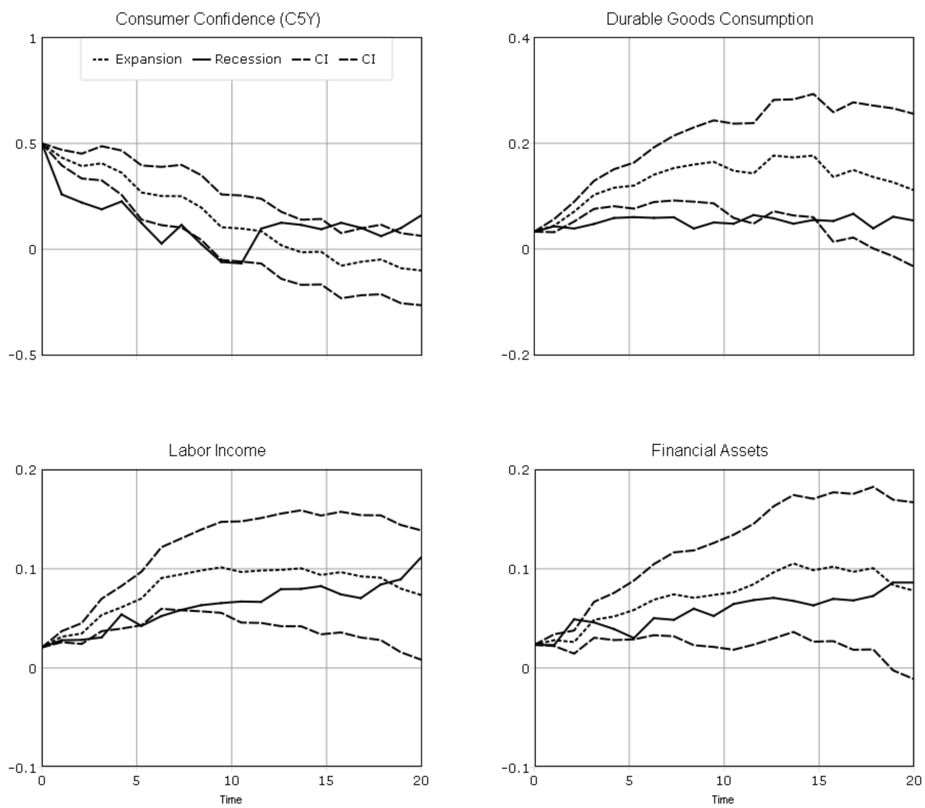

Figure B.1
Impulse responses from one standard deviation confidence shock in a model with durable goods using C5Y as a measure of confidence

Sub-components of durable goods

The baseline analysis used real per capita spending on total durable goods. Here two

years, or that we'll have periods of widespread unemployment or depression, or what?" while the confidence measure denoted by C12M is based on the question question: "Now turning to business conditions in the country as a whole – do you think that during the next 12 months we'll have good times financially or bad times or what?"

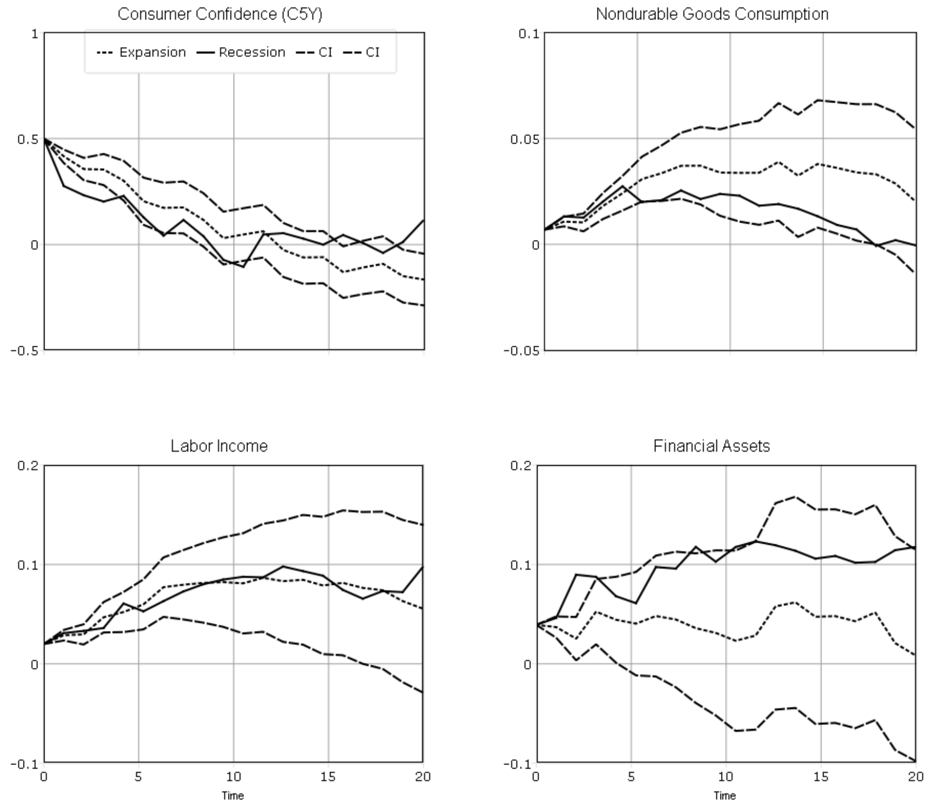

Figure B.2
Impulse responses from one standard deviation confidence shock in a model with nondurable goods using C5Y as a measure of confidence

subcomponents, motor vehicles and other durable goods, are used. Because motor vehicles are not reported in per capita terms, there are some differences in obtaining a series suitable for our analysis. To obtain real per capita spending on motor vehicles we adjust the FRED nominal series (DMOTRC1Q027SBEA) using the CPI and the population series. For the real per capita spending on other durable goods we subtract the real per capita spending on motor vehicles from total spending on durable goods.[3] Figures B.6 and B.7 show the IRFs of motor vehicles and other durable goods, respectively.[4]

Using sub-sample (1960:Q1-2007:Q3)

[3]Here we used the nominal series for total durable goods given by PCDG in the FRED data base in order to eliminate the impact of different price deflators on the calculation. The PCDG was converted to per capita nominal terms by using the CPI and population series described in the paper for some of the series.

[4]From here on, the robustness exercises use the ICS series unless otherwise mentioned.

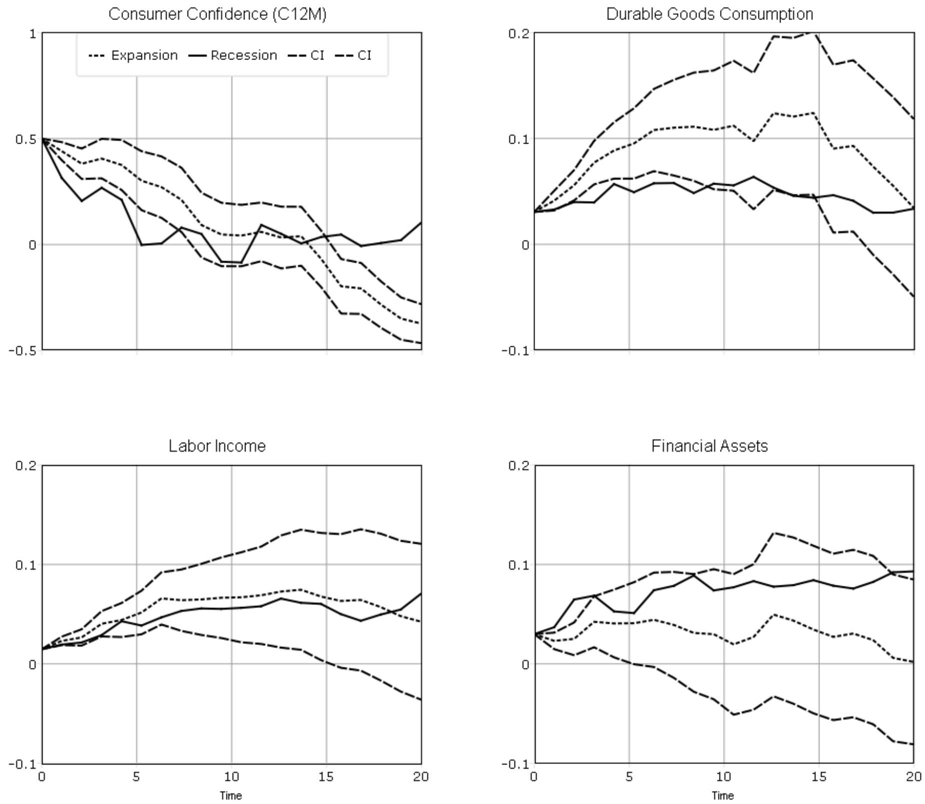

Figure B.3
Impulse responses from one standard deviation confidence shock in a model with durable goods using C12M as a measure of confidence

Next to investigate whether the upheaval during and after the 2008-09 financial crisis might impact the results, a subsample which excludes the financial crises and its recovery is considered. These are presented in Figures B.8 and B.9. These figures show that the general conclusion found in the paper are considerably stronger.

Alternative Cholesky ordering

In the baseline investigation, we followed the Cholesky decomposition with confidence ordered first. This was motivated by the view that exogenous news shocks cause the innovations in consumer confidence. However, this assumption is questionable as consumer sentiment may vary in accordance with personal labor income as well as holdings of financial assets. To check the extent to which this ordering affect our results, we reorder the variables in the system to $x_t = [c_t \quad y_t \quad f_t \quad cc_t]'$. Here confidence is orthogonalized with respect to

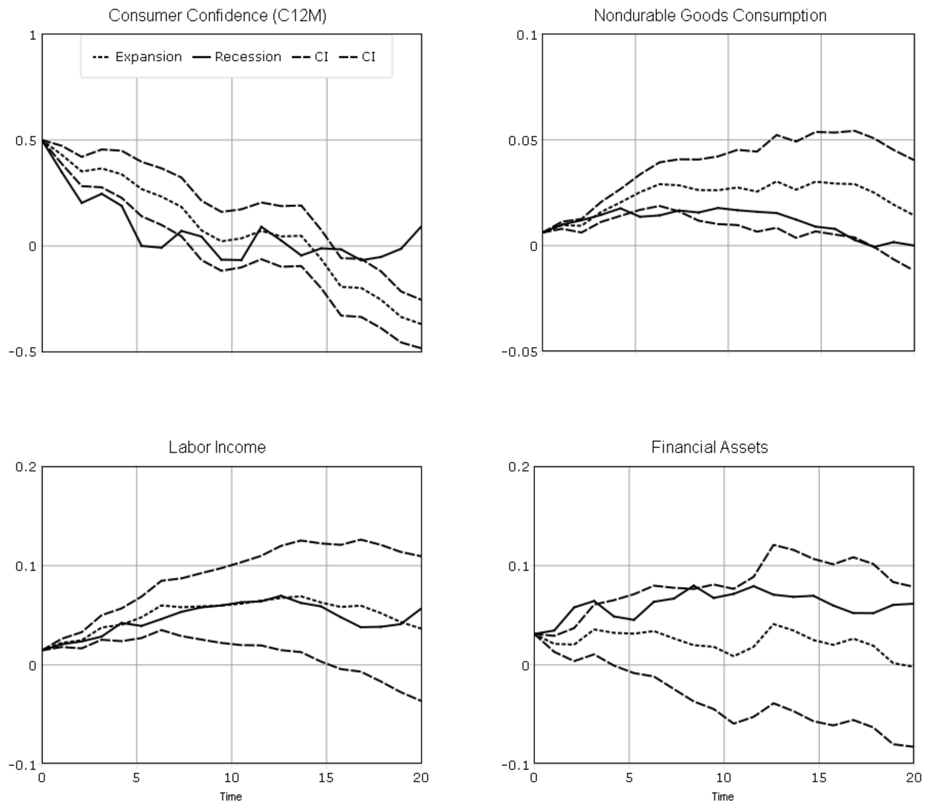

Figure B.4
Impulse responses from one standard deviation confidence shock in a model with nondurable goods using C12M as a measure of confidence

financial assets, consumption goods spending and labor income. We focus on the durable goods diagrams and consider two different measures of confidence. The results are displayed in Figures B.10 and B.11 and show the result that there are differences in durable goods consumption behavior across the different states is robust and that the difference is more acute for the C5Y measure of confidence.

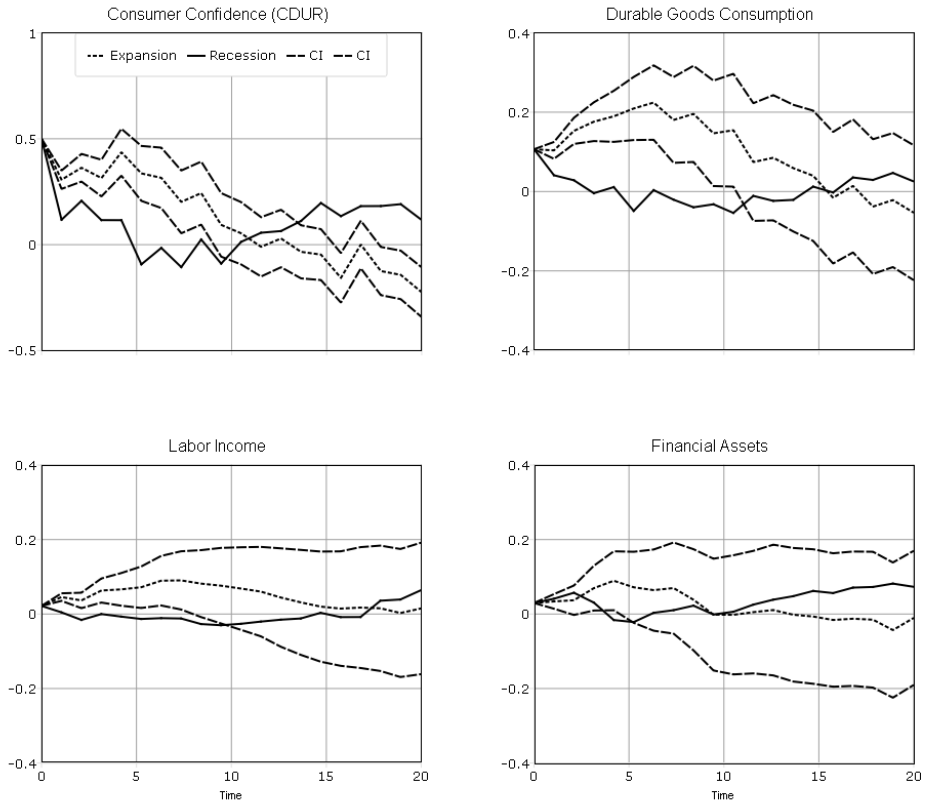

Figure B.5
Impulse responses from one standard deviation confidence shock in a model with durable goods using CDUR as a measure of confidence

A one lag model

Next a one lag model, which is optimal using the Schwarz Bayesian Information Criterion (BIC), was used to generate the impulse responses. Only the durable goods plot is provided.

Using total assets

In the baseline formulation of the empirical model, we chose only financial assets. Here both financial and non-financial assets are included to get total assets. Results for durable goods are provided in Figure B.13.

Unemployment as the threshold variable

Finally, the unemployment rate, denoted by w_t, was considered as an alternative thresh-

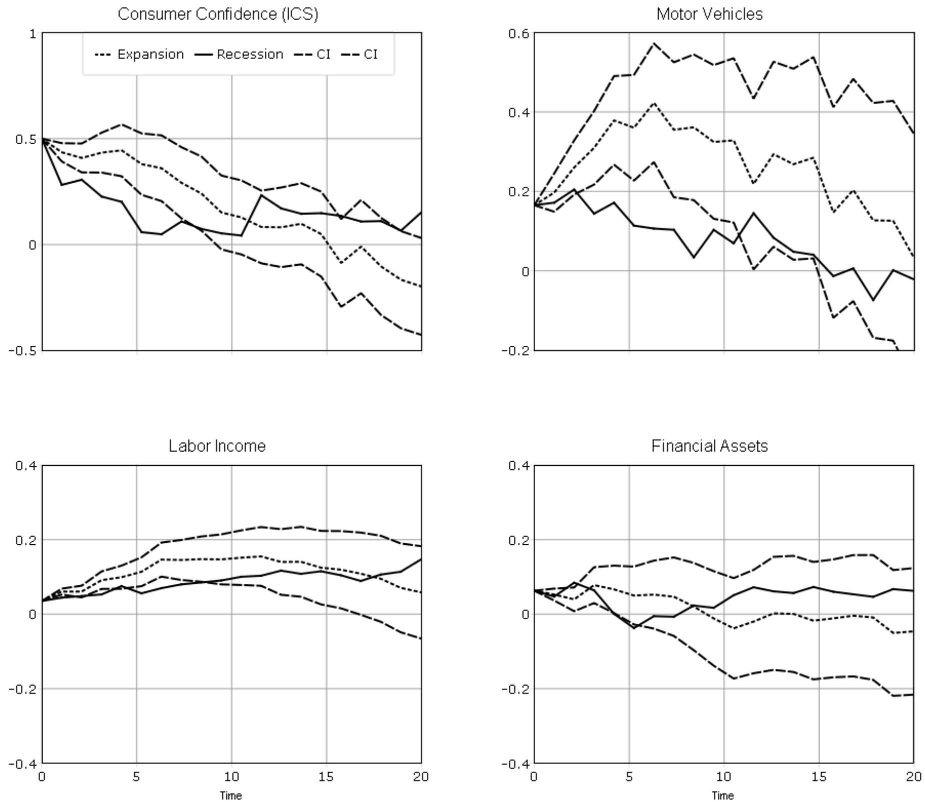

Figure B.6
Impulse responses from one standard deviation confidence shock substituting motor vehicles for all durable goods

old variable for defining the two states of the economy.[5] Here, the threshold dummy variable is defined by

$$I_t = \begin{cases} 1 & \text{for} \quad w_{t-1} \geq w^T, \\ 0 & \text{for} \quad w_{t-1} < w^T, \end{cases}$$

where w^T is the threshold value. Two formulations for determining w^T were investigated. One uses an a priori threshold value of 6.5% and the other uses an endogenously estimated threshold using methods described in Chan (1993).[6] The endogenous threshold occurs at a

[5]We take the quarterly unemployment rate (UNRATE) which comes from the FRED database.

[6]The 6.5% threshold is because it is often mentioned by the Federal Reserve Bank of the United States as an unemployment rate in which they begin to consider policy changes. See for instance, the Federal Open Market Committee minutes from December 2012 which states, "In addition, all but one member agreed to replace the date-based guidance with economic thresholds indicating that the exceptionally low range for

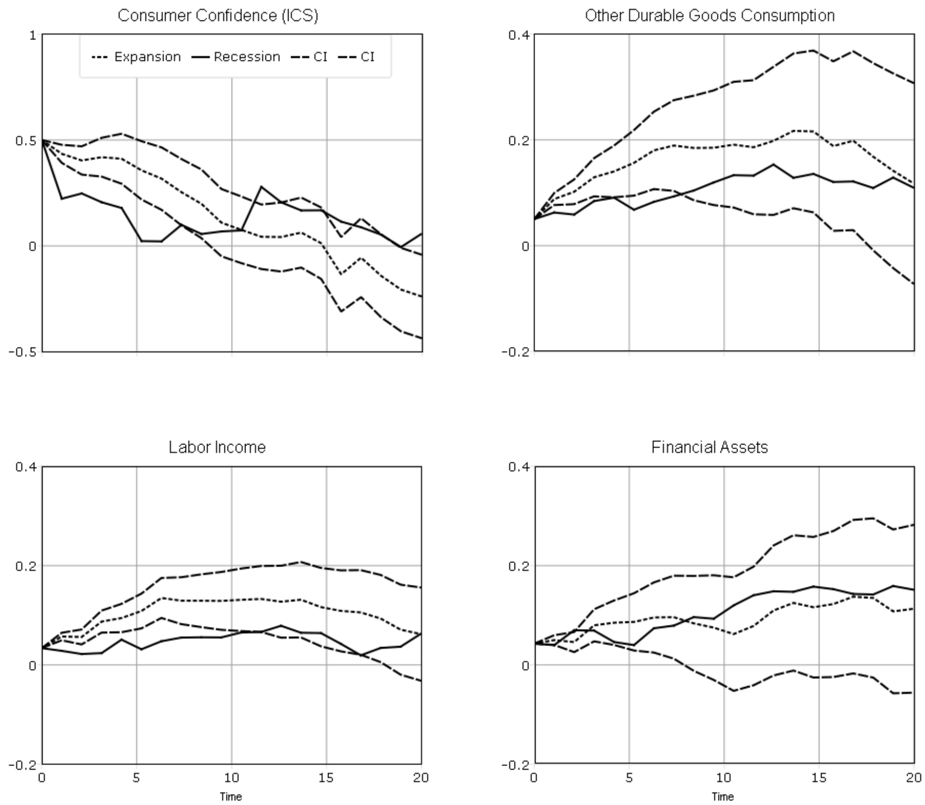

Figure B.7
Impulse responses from one standard deviation confidence shock substituting other durable goods for all durable goods

6.7% unemployment rate. In the figures, we use the term "bad time" when w_{t-1} is greater than or equal to the threshold and the term "good time" for the otherwise case.

the federal funds rate would remain appropriate at least as long as the unemployment rate remains above $6\frac{1}{2}$ percent, inflation between one and two years ahead is projected to be no more than a half percentage point above the Committee's longer-run goal, and longer-term inflation expectations continue to be well anchored."

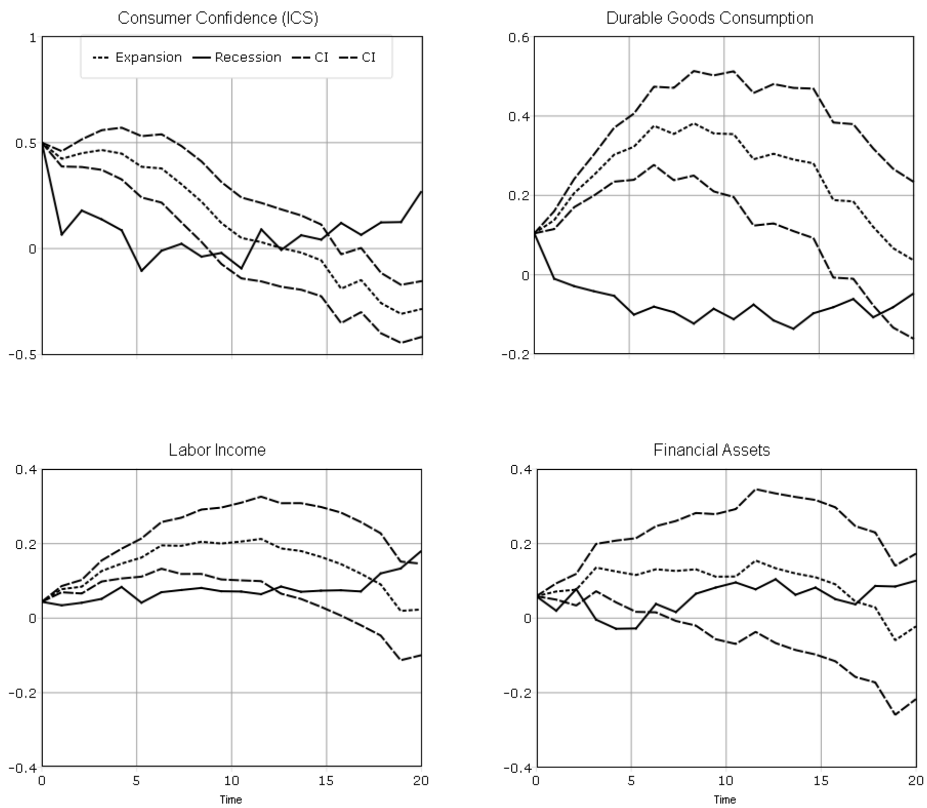

Figure B.8
Impulse responses from one standard deviation confidence shock in a model with durable goods using sample of 1960:Q1 to 2007:Q3

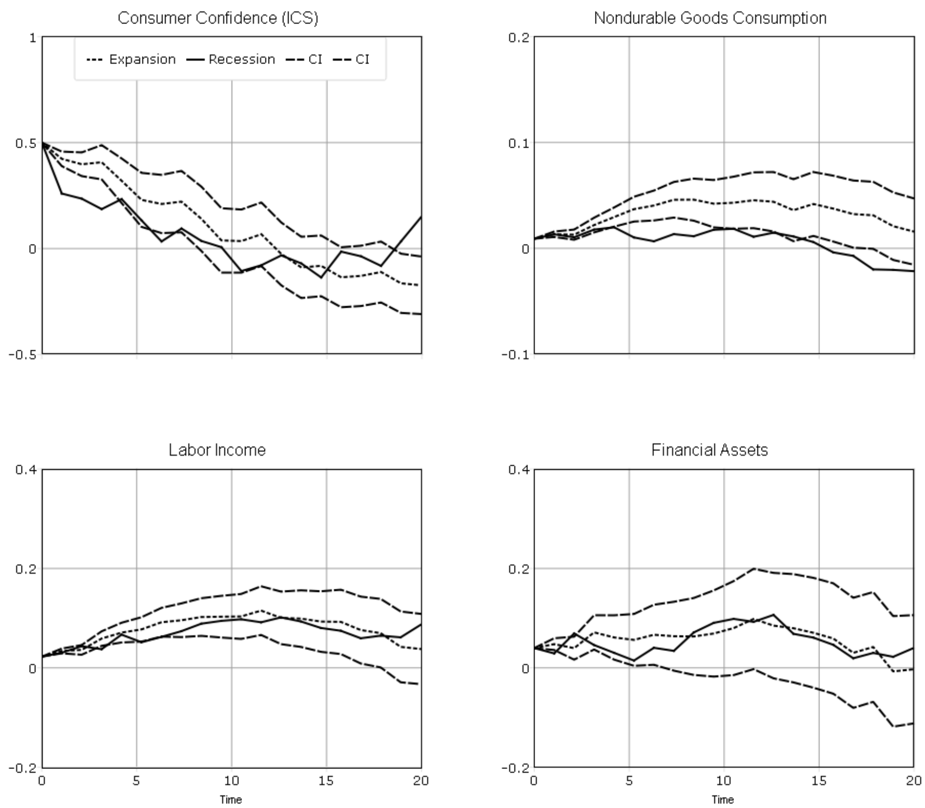

Figure B.9
Impulse responses from onestandard deviation confidence shock in a model with nondurable goods using a sample of 1960:Q1 to 2007:Q3

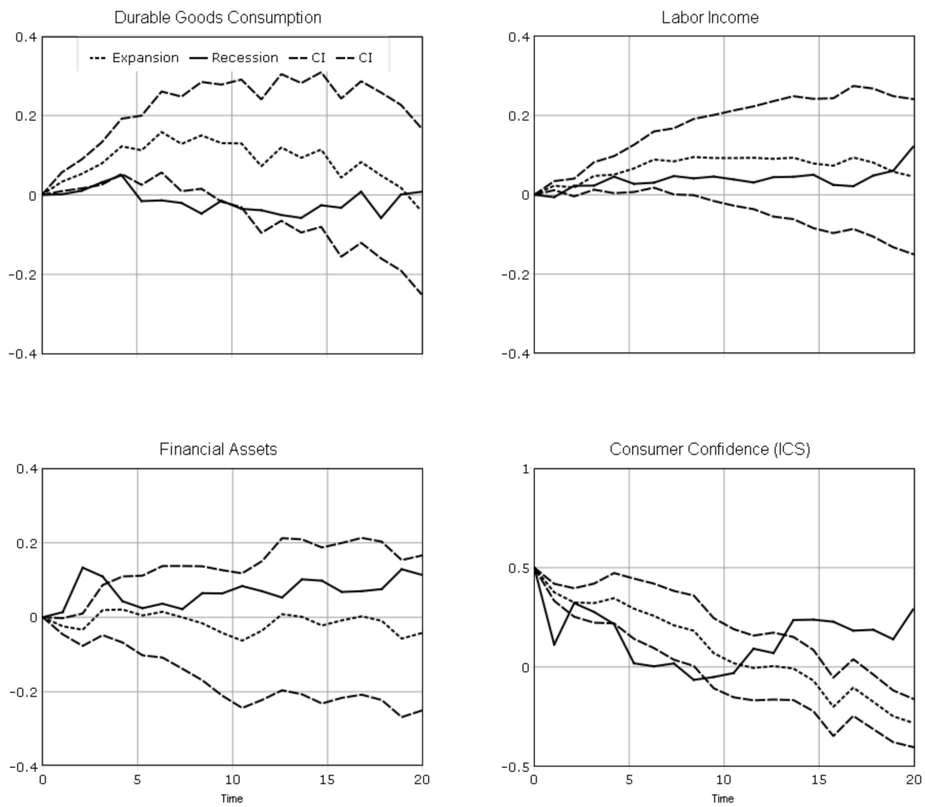

Figure B.10
Impulse responses from one standard deviation confidence shock in a model with durable goods with consumer confidence (ICS) ordered last

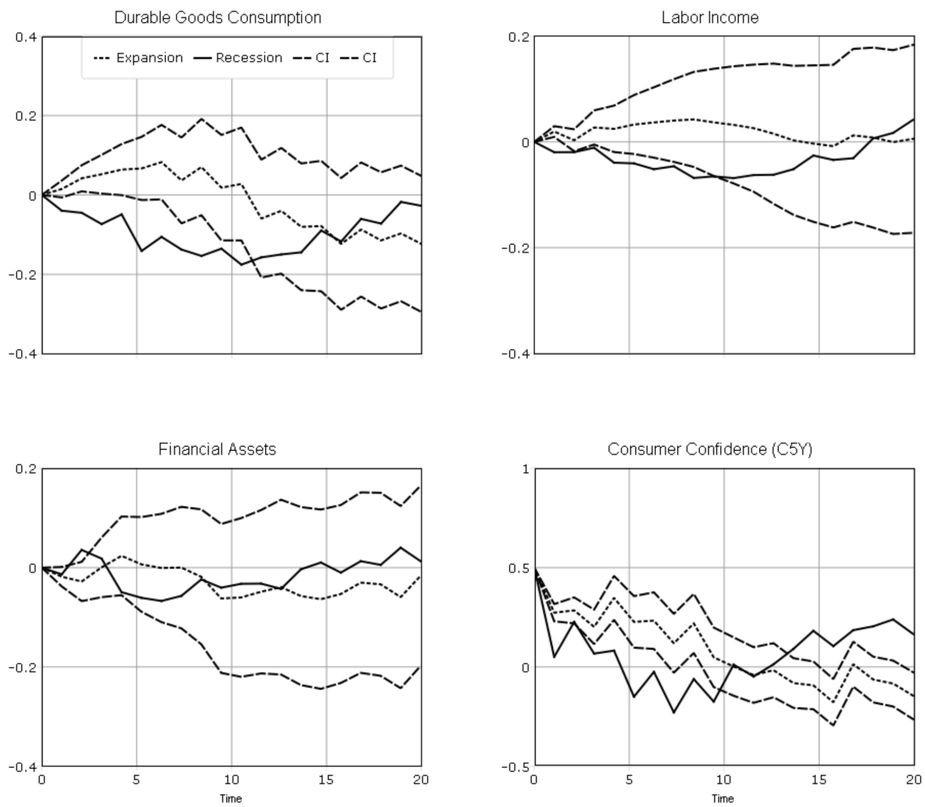

Figure B.11
Impulse responses from one standard deviation confidence shock in a model with durable goods with consumer confidence (C5Y) ordered last

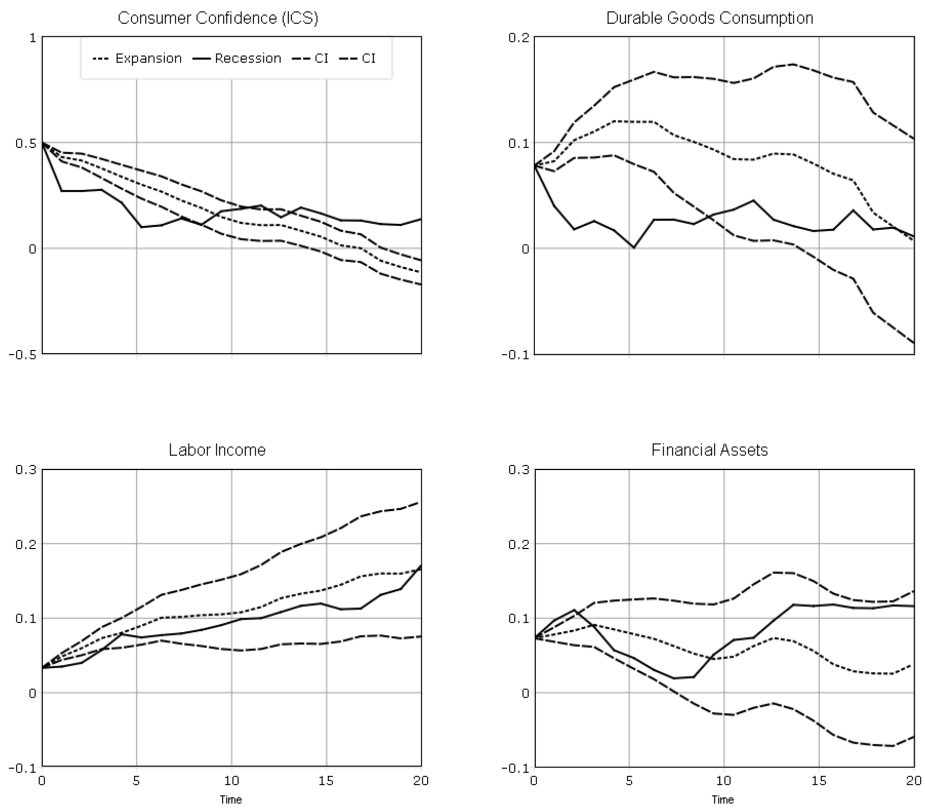

Figure B.12
Impulse responses from one standard deviation confidence shock in a model with durable goods in a one lag model

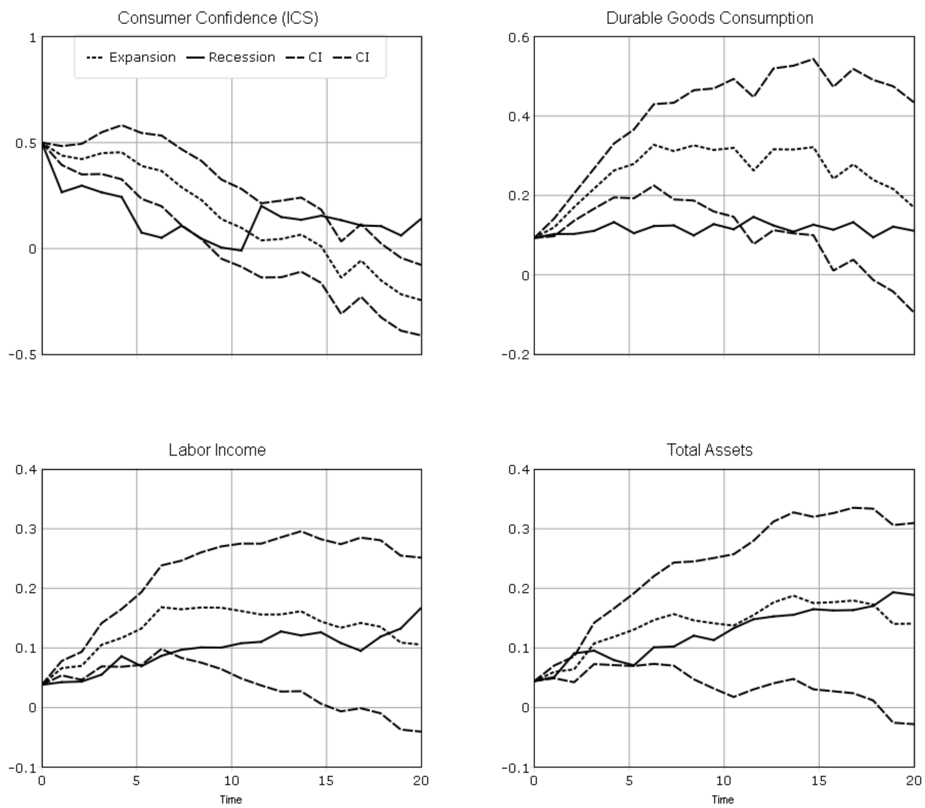

Figure B.13
Impulse responses from one standard deviation confidence shock in a model with durable goods substituting total assets for financial assets

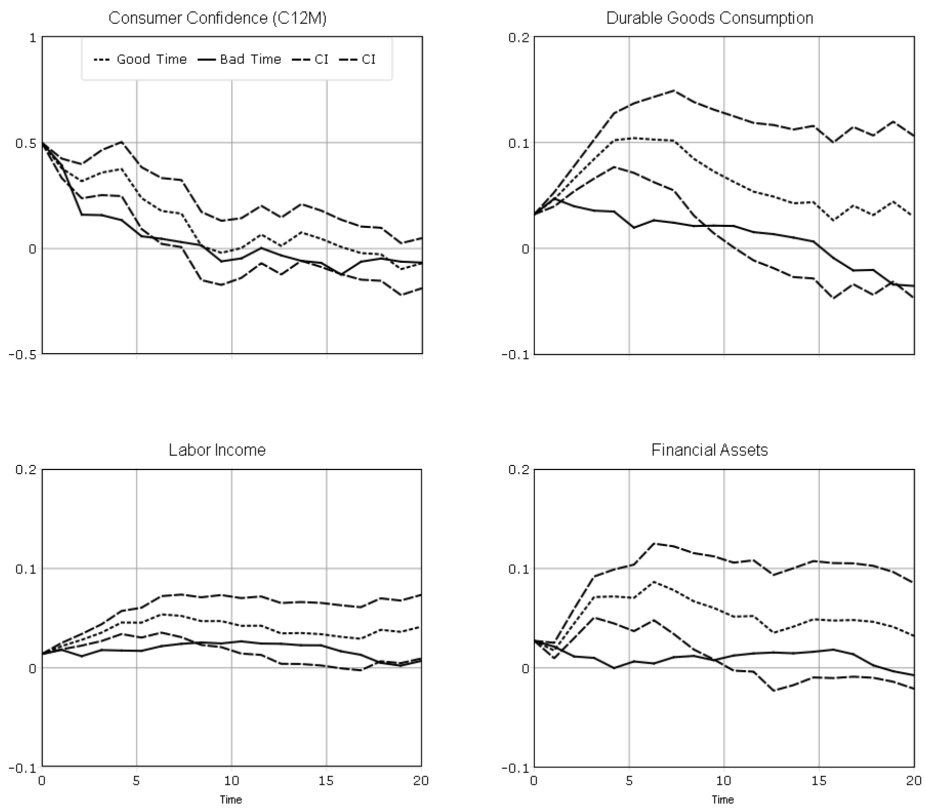

Figure B.14
Impulse responses from one standard deviation confidence shock in a model with durable goods with unemployment as exogenous threshold

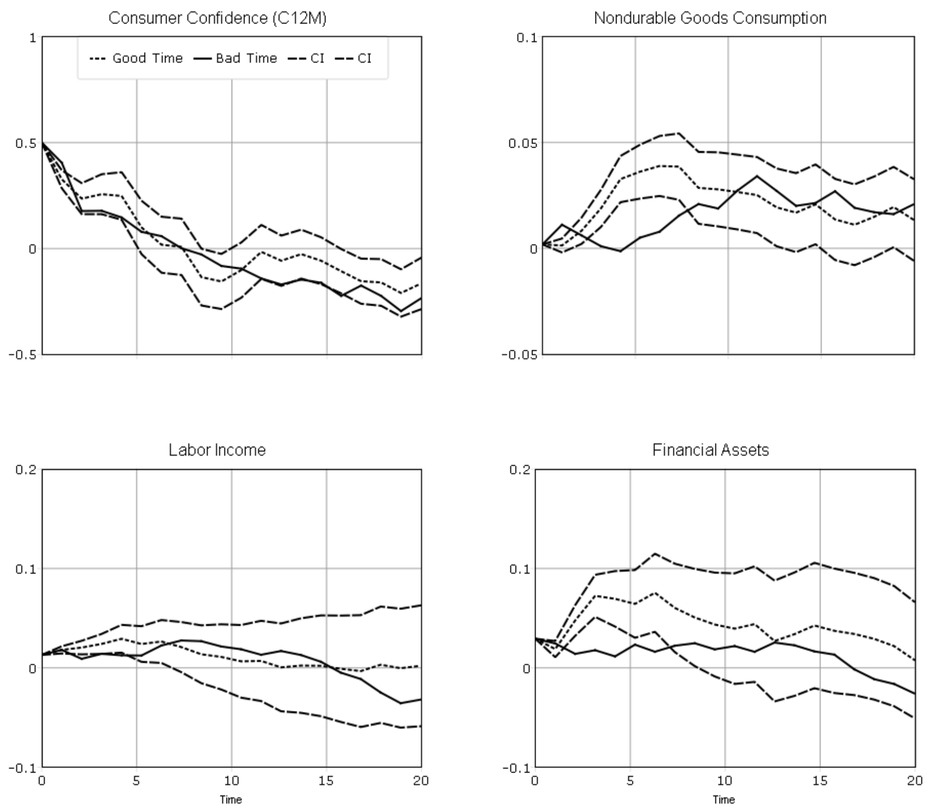

Figure B.15
Impulse responses from one standard deviation confidence shock in a model with nondurable goods with unemployment as exogenous threshold

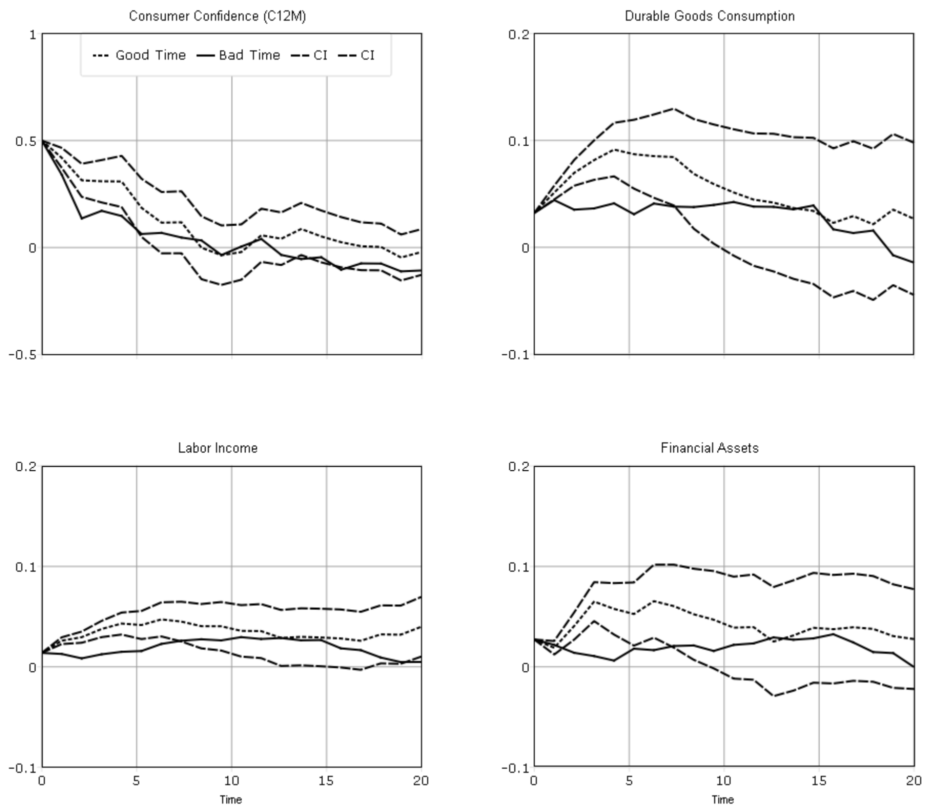

Figure B.16
Impulse responses from one standard deviation confidence shock in a model with durable goods with unemployment as endogenous threshold

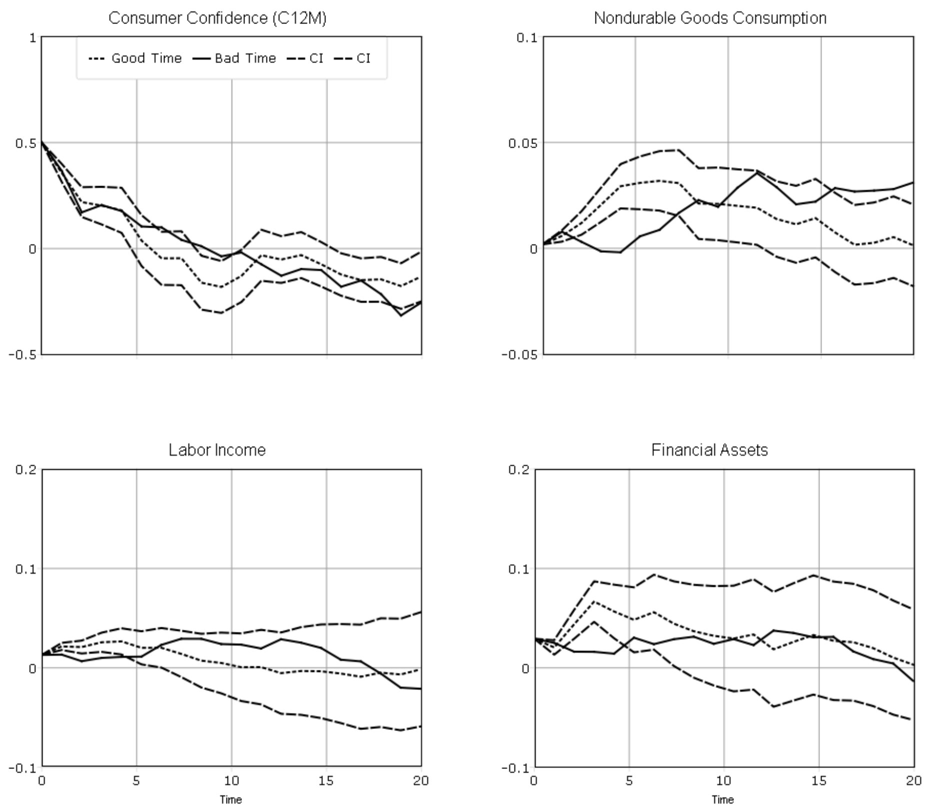

Figure B.17
Impulse responses from one standard deviation confidence shock in a model with nondurable goods with unemployment as endogenous threshold

Appendix C

Appendix for Chapter 3

Tables 3.1 and 3.2 provide further detail information of the forecast error variance decomposition as reported in Section 3.6 of Chapter 3.

Table C.1: Percent of total forecast error variance attributable to expectation innovations (full table)

(Using opportunistic monetary policy as a threshold indicator)						
	SPF			LS		
States	Unemployment	Inflation rate	Interest rate	Unemployment	Inflation rate	Interest rate
Forecast horizon of one-year ahead						
Linear	95.05	8.20	52.02	52.16	1.96	29.30
Hawkish	92.79	18.85	65.79	51.44	4.61	38.96
Dovish	82.43	5.62	38.52	50.51	2.70	24.71
Forecast horizon of two-year ahead						
Linear	82.98	15.48	51.22	43.76	8.68	22.03
Hawkish	73.88	26.29	61.92	36.67	25.13	35.45
Dovish	67.34	10.96	41.64	45.64	23.58	29.15
Forecast horizon of three-year ahead						
Linear	56.20	15.51	47.98	28.98	16.67	23.15
Hawkish	69.38	25.40	49.81	31.53	46.63	35.94
Dovish	52.55	6.70	33.98	33.94	41.34	39.08
Forecast horizon of five-year ahead						
Linear	40.89	12.28	41.75	30.64	17.74	22.75
Hawkish	66.28	27.05	40.42	58.01	44.75	38.26
Dovish	30.59	8.85	19.31	36.26	14.74	31.87

Table C.2: Percent of total forecast error variance attributable to expectation innovations (full table)

(Using unemployment as a threshold indicator)						
	SPF			LS		
States	Unemployment	Inflation rate	Interest rate	Unemployment	Inflation rate	Interest rate
Forecast horizon of one-year ahead						
Linear	95.05	8.20	52.02	52.16	1.96	29.30
High Unemp	78.58	5.86	36.14	13.19	0.27	5.13
Low Unemp	94.38	16.53	59.41	61.32	5.13	43.85
Forecast horizon of two-year ahead						
Linear	82.98	15.48	51.22	43.76	8.68	22.03
High Unemp	55.11	8.06	29.07	10.96	0.34	2.72
Low Unemp	65.09	32.91	69.77	55.91	18.43	42.05
Forecast horizon of three-year ahead						
Linear	56.20	15.51	47.98	28.98	16.67	23.15
High Unemp	47.31	5.55	24.05	8.92	0.48	1.78
Low Unemp	42.40	33.47	75.86	43.75	39.70	45.32
Forecast horizon of five-year ahead						
Linear	40.89	12.28	41.75	30.64	17.74	22.75
High Unemp	35.33	4.68	25.31	2.66	0.35	1.27
Low Unemp	36.84	22.73	72.53	62.84	38.89	44.16