# Asymmetric effects of expectation shocks when monetary policy regimes shift: Evidence from survey data*

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August 30, 2019

**Abstract**

Using the Survey of Professional Forecasters and Livingston Survey data, this paper empirically investigates the effects of expectation shocks on macroeconomic activities when monetary policy shifts between policy regimes. Two policy switching structures, including an opportunistic monetary policy structure and a structure contingent on the unemployment rate, are investigated. Identifying an expectation shock by using the timing of information in the survey forecasts and the actual data releases, we show that the effects of expectation shocks on current and future macroeconomic activities are stronger in a hawkish monetary policy regime than in a dovish monetary policy regime. Our findings do not support the view of some central bank critics who argued that keeping monetary policy too easy for too long is responsible for fueling the booms. Instead, we find that a positive (negative) expectation about the future results in an anticipatory tightening (easing) of monetary policy.

*JEL Classification*: D84, E31, E32, E52
*Keywords*: Expectation shock, regime-switching, opportunistic monetary policy, local projection.

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*We thank Jesús Vázquez for helpful comments on an earlier draft of this paper.

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# 1 Introduction

Recent developments in the expectation driven business cycle literature provides evidence that expectations about the future have contributed to the boom-bust cycles of the post-war US economy.[1] The intuition connecting expectations to business cycles is that optimism about future growth prospects may help fuel booms and the subsequent revisions in expectations may help precipitate busts. This paper contributes to this literature by introducing a related business cycle literature in which monetary policy regimes can impact expectation formation and thus, as shown here, the degree to which expectations can impact the economy.[2]

This paper extends the work by Leduc and Sill (2013) who use unemployment survey data from the Livingston Survey and the Survey of Professional Forecasters as a proxy for expectations about future economic activity.[3] Using this survey data, along with the observed unemployment rate, one can extract expectation shocks that are independent of other data released at this same date and this timing allows one to properly order the variables in ones analysis.[4] Our extension adds a switching structure that reflects whether monetary policymakers are in either an "inflation-hawk" or "inflation-dove" regime.[5] One motivation for an asymmetric central bank reaction would interpret the expectation shocks as non-fundamental to expectations, and as such, they may trigger a self-fulfilling undesirable (inflationary or deflationary) outcome. Therefore, central bankers may react to these shocks to restore equilibrium

[1] Research in this area are both theoretical, such as Beaudry and Portier (2004, 2007) and Jaimovich and Rebelo (2009), and empirical, such as Carroll (2003), Beaudry and Portier (2006) and Leduc and Sill ( 2013). Beaudry and Portier (2014) provide a detailed survey of the expectation-driven business cycle literature. The idea of business cycles driven by expectations originally advanced by Pigou (1927).

[2] The idea that expectation-formation mechanisms are connected to the policy regime was noted near the dawn of the rational expectation revolution by Sims (1982, 1987). Later works by Ball and Croushore (2003) and by Liu et al. (2009) showed how monetary policy regimes are important to influence expectations and economic behavior.

[3] Other authors, such as Croushore (2010) and Faust and Wright (2013), have also noted that professional survey forecasts are a useful way to measure expectation.

[4] This fact is noted by Leduc et al. (2007) and Leduc and Sill (2013).

[5] Two switching structures are investigated. So to generically refer to results from either of these structures, we will often use the hawkish and dovish monetary policy terminology used by Liu et al. (2009), where a hawkish regime would be one where the Fed is more likely to be tightening its stimulus, and a dovish regime would be one where the Fed is more likely to be loosening.

determinacy and thus eliminate the possibility of self-fulfilling expectations. Interpreting the central bank reaction as asymmetric is reasonable since the dynamics that might lead to inflation or deflation are somewhat different.

We model these monetary policy regimes using two approaches. The first makes use of the opportunistic monetary policy switching structure described in Bunzel and Enders (2010), and the other simply reflects whether the unemployment rate is within an acceptable range. In the opportunistic monetary policy structure, falling inflation rates indicate that the central bank is inclined to take the opportunity to remain accommodative, while in the unemployment threshold structure models accommodative policy as occurring during high unemployment. The switching structure in Bunzel and Enders (2010) reflects a view 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.[6] Another reason for using the opportunistic strategy as a threshold indicator is that there exists a gap between people's beliefs about the Federal Reserve Bank's (Fed) policy announcements and the Fed's inertia to achieve the policy goals, suggesting that there is an asymmetric flow of information between the 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.[7] The unemployment rate formulation is motivated from several recent Fed policy statements which note that they consider policy changes near unemployment rates of 6.5 percent.

The effects of changes in expectations on economic variables are investigated by looking at impulse response functions and variance decompositions. Because of the switching structure in our model, we use the local projection method described in Jordà (2005) to compute these statistics under the different policy regimes. These

[6] "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).

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

methods are well suited to switching models and have advantages over traditional VAR methods, and have been applied in similar settings by Auerbach and Gorodnichenko (2012a, 2012b, 2016), Ramey and Zubairy (2018), Owyang et al. (2013), Ahmed and Cassou (2016), Ahmed et al. (2019).

Our main finding is that the effects of expectation shocks on macroeconomic activities are asymmetric between the different monetary policy regimes. During a hawkish monetary regime (rising inflation or low unemployment), a downward impulse in unemployment rate expectations leads to a relatively large rise in the inflation rate and consequently the interest rate. On the other hand, during a dovish monetary regime (low inflation or high unemployment) a downward impulse in unemployment rate expectations leads to a relatively small rise in the inflation rate and consequently the interest rate. Our results are robust across both survey measures of expectations and using each of the alternative regime-switching structures for monetary policy.

Several robustness exercises are also investigated. One investigates whether the results may be driven by uncertainty shocks that are not included in our baseline models, another considers a larger sample period, while another investigates the relative size of the effects from expectation shocks and monetary shocks. For the first, we augment our baseline regime-switching model by including an exogenous dummy variable that controls for major uncertain economic and political events. For the second, we adopt methods used by Bekaert et al. (2013) to generate a nominal interest rate series for the financial crises period and show that the results remain robust. For the third, we show that the expectation shocks are more important than monetary policy shocks in explaining economic fluctuations and that regime-switching models provide additional insights into this issue. The later finding that expectation shocks are relatively more important is consistent with Cochrane (1994) and Caggiano et al. (2014).[8]

These findings are also important within the context of certain monetary policy

[8] Cochrane (1994) shows that news about economic fundamentals are more important than other shocks like monetary policy shocks or technology shocks while Caggiano et al. (2014) show that expectation shocks are more important than monetary shocks.

debates. Some central bank critics have argued that keeping monetary policy too easy for too long is responsible for fueling recent booms.[9] Our findings do not support this view and are consistent with Bernanke and Gertler (2000) that a positive (negative) expectation about the future results in an anticipatory tightening (easing) of monetary policy. This tightening occurs in both hawkish and dovish monetary policy regimes. These findings differ from those in Leduc and Sill (2013), which did not consider the state of the economy. Our findings of the Fed's asymmetric responses across the state of the economy are similar to those in Bunzel and Enders (2010) but differ from theirs as our focus is on expectations about future fundamentals whereas their focus was on the Taylor rule. Also, our findings are consistent with Liu et al. (2009) who, using a DSGE framework, show that the effects of expectations on macroeconomic variables are stronger in hawkish regimes than dovish regimes. To the best of our knowledge, our paper is the first to empirically show that the effects of expectations on economic activities change across the state of the economy.

## 2 Empirical methodology

The empirical models use the same four variables used by Leduc and Sill (2013). These consist of data on expectations for future unemployment, observed values of unemployment, the inflation rate and interest rates which we generically denote using $u_t^e$, $u_t$, $\pi_t$ and $i_t$ respectively.[10] A more precise discussion of the sources for the data is given in the next section. For now we focus on the empirical models.

We consider two types of empirical models. The first is a simple linear model in which there is no threshold behavior. This model is analogous to the one used

[9] Taylor (2009) argues that the central bank adopted an overly accommodative stance starting in 2001 and maintained it for too long. The monetary excesses were the main cause of that boom and the resulting bust. Okina and Shiratsuka (2002) explain that too easy money supply fuels the Japanese stock market bubbles and subsequent busts. Similar arguments can be found in Obstfeld and Rogoff (2009).

[10] We use the expected and actual unemployment rates rather than expected and actual gross domestic product (GDP) because, as noted in Leduc and Sill (2013), GDP is subject to revisions which make sorting out the innovation in expected GDP challenging because the revised data may contain information that may be unavailable to forecasters at the time they prepare their forecasts. This problem is not an issue with unemployment data because it is subject to only a minor revision. A more detailed Appendix describing this issue is available from the authors upon request.

in Leduc and Sill (2013). Using this as a starting point is useful as it allows us to describe the local projection method for computing impulse response functions (IRF) suggested by Jordà (2005) in a simple setting.[11] Extending the local projection method for finding IRFs from the linear model into a threshold situation is fairly straight forward.

This local projection method generates IRFs by running a sequence of forecast equations given by

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

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. The parameters in the model are straight forward, with $\alpha^s$ denoting a $4 \times 1$ vector of constants and $B_i^{s+1}$ denoting $4 \times 4$ square matrices of parameters corresponding to the $i$th lag, $x_{t-i}$, in the $s$ step ahead forecasting model and $\varepsilon_{t+s}^s$ is a moving average of the forecast errors from time $t$ to time $t+s$. Although all the variables in the models are in percentage terms, it is useful to note that the local projection technique is robust to situations with nonstationary or cointegrated data.

Jordà (2005) shows that IRFs generated by the local projections are equivalent to the ones that are calculated from VAR methods 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 local projection method. The IRFs are defined as

$$\widehat{IR}(t, s, d_i) = \widehat{B}_1^s d_i \qquad s = 0, 1, ..., h \tag{2}$$

where $B_1^0 = I$ and $d_i$ is an $n \times 1$ column vector that contains the mapping from the

[11] In discussing the IRF, we use the traditional interpretation that these represent how variables respond to one unit impulses in a structural shock. An alternative interpretation for the impulse response function under a Cholesky ordering is to note that it is the revision to the conditional forecast for a variable due to a one standard deviation impulse in one of the structural shocks. See Hamilton (1994) pages 318-23 for this approach. To avoid confusion, we stick with the traditional interpretation here.

structural shock for the $i$th element of $x_t$ to the experimental shocks.[12] 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 follow the intuition in Leduc and Sill (2013) in choosing the ordering. In particular, we ordered expected unemployment first, actual unemployment second followed by inflation and interest rates. Leduc and Sill (2013) noted that because of the timing for information potentially used by the survey respondents, and the release dates of the actual data, it is plausible that the expectation about future unemployment may have contemporaneous impacts on other variables, but since the current data does not become available to the forecasters when they make predictions, the other variables will not have contemporaneous impacts on expectations. Our ordering for the other variables is also reasonable. For example, it is more likely that unemployment will have contemporaneous effects on inflation, but the reverse may happen only with a lag. Furthermore, ordering the monetary policy variable last seems reasonable because impulses of any of the other variables may cause monetary policy to react, but it is unlikely that other variables would respond contemporaneously to a monetary policy impulse.

Next, using the 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 (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 $\sigma$ is a $n \times 1$ column

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

vector of ones.

Our extension of the baseline model is to incorporate threshold behavior to the impulse response structure that allows the possibility that the IRF may differ across the policy regimes. We define our extension to (1) by

$$x_{t+s} = I_{t-1}\left[\alpha^s_{dov} + \sum_{i=1}^{p} B^{s+1}_{i,dov} x_{t-i}\right] + (1-I_{t-1})\left[\alpha^s_{hawk} + \sum_{i=1}^{p} B^{s+1}_{i,hawk} x_{t-i}\right] + \varepsilon^s_{T,t+s} \qquad s = 0, 1, ..., h, \tag{3}$$

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 and hawkish monetary 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 $I_t$ and defined more completely below, indicates the distinction between hawkish (rising inflation or low unemployment) and dovish regimes (falling inflation or high unemployment).

By analogy to (2), we define the IRFs for the two states of the economy by

$$\widehat{IR}^{dov}(t, s, d_i) = \widehat{B}^s_{1,dov} d_i \qquad s = 0, 1, ..., h, \tag{4}$$

and

$$\widehat{IR}^{hawk}(t, s, d_i) = \widehat{B}^s_{1,hawk} d_i \qquad s = 0, 1, ..., h, \tag{5}$$

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.

We use monetary policy for the indicator variable because agents expectations about the future are tightly connected to monetary policy's actions.[13] We use two specifications for the monetary policy indicator variable. Our first formulation features an "opportunistic" monetary policy strategy by the Fed. An opportunistic

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

strategy aims to gradually ratchet down inflation by setting an intermediate target for the inflation rate based on recent inflation rates, but does virtually nothing to achieve the target, instead, waiting for a random event to achieve the target.[14] According to Rudebusch (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.[15]

We define our opportunistic threshold structure following Bunzel and Enders (2010).[16] Accordingly, we assume that the interim target of the Fed depends on the "inherited" or recent observed inflation rates. For our formulation, we assume the Fed uses an intermediate target which is a simple average of the inflation rate prevailing 1 and 2 years ago and is given by

$$I_t = \begin{cases} 1 & \text{for} \quad \pi_{t-1} < \pi^T = \frac{\pi_{t-5}+\pi_{t-9}}{2}, \\ 0 & \text{for} \quad \pi_{t-1} \geq \pi^T = \frac{\pi_{t-5}+\pi_{t-9}}{2}, \end{cases} \tag{6}$$

where $\pi^T$ is the interim target of inflation for period $t-1$. Equation (6) characterizes the essential feature of the opportunistic monetary policy. Since the Fed targets current inflation based on the 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 the inflation rate exceeds the average inflation rate over the past two years. Another statistical advantage of (6) is that the threshold variable $\pi_{t-1} - (\pi_{t-5} + \pi_{t-9})/2$ is

[14] 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...."

[15] 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 the public.

[16] See also Bomfim and Rudebusch (2000) for a theoretical motivation of the opportunistic monetary policy strategy.

clearly stationary. Conditioning the regimes on a stationary variable has better properties than conditioning the regime change on a nonstationary, or highly persistent, variable.[17]

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

$$I_t = \begin{cases} 1 & \text{for} \quad u_{t-1} \geq u^T, \\ 0 & \text{for} \quad u_{t-1} < u^T, \end{cases} \tag{7}$$

where $u^T$ is the threshold value. We choose 6.5% as the threshold value because it is often mentioned by the Fed as an unemployment rate at which they begin to consider a change in policy.[18] Because both the opportunistic threshold and the unemployment threshold indicators take values which generally exhibit tightening and loosening Fed behavior, we will often use the hawkish and dovish terminology introduced by Liu et al. (2009) to assist in showing similarities in the results across the two structures. In particular, we describe policy as hawkish if inflation is rising or the unemployment rate is below the threshold which generally would mean the Fed is likely to be tightening, and we describe policy as dovish if inflation is falling or the unemployment rate is above the threshold which generally would mean the Fed is likely to be loosening.[19]

[17] This feature characterizes the momentum threshold model introduced in Enders and Granger (1998).

[18] 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." Also, see Owyang et al. (2013), Ahmed and Cassou (2016), and Ramey and Zubairy (2018).

[19] A low (high) unemployment rate might not directly induce a hawkish (dovish) monetary policy action. However, as long as a low (high) unemployment rate somewhat anticipates high (low) inflation from a type of Phillips curve relationship, the hawkish-dovish terminology for monetary policy can be useful for describing a scenario in terms of observations on inflation or the unemployment rate. Moreover, the empirical evidence reported below confirm that a high (low) unemployment regime is associated with a hawkish (dovish) Fed policy reaction.

Finally, we conclude this section by looking at some of the primary advantage of the local projection method over the standard VAR approach is that each forecast horizon is computed separately from the others so that it can handle richer econometric specifications. 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 IFRs are generated at each horizon. Thus the IFRs at all horizons are directly connected to these VAR parameters. On the other hand, the local projection method computes the IFRs from a different forecast equation (here (1) or (3)), and thus the structure of the IRFs can vary over the horizon. This allows flexibility when the DGP is nonlinear. So for instance, if the DGP is given by the highly nonlinear structure in (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 methods proposed by Auerbach and Gorodnichenko (2012a).[20] In the STVAR approach suggested by Auerbach and Gorodnichenko (2012a), it is assumed that the economy stays in the current state over the horizon in which the impulse responses are calculated. Ramey and Zubairy (2018), for example, argue that this type of assumption is inconsistent with the fact that the average NBER recession period typically lasts 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.

# 3 Results

Our baseline empirical analysis uses the Survey of Professional Forecasters (SPF) data for the US economy from 1968:Q4-2008:Q4. We also use the half-yearly data from the Livingston Survey (LS) which has a sample period running from 1961:H2 to 2008:H2.

[20] See Ramey and Zubairy (2018) for details. Also see Auerbach and Gorodnichenko (2012b, 2016).

We eschew the post-Great Recession period data to avoid potential misspecification issues in expectations arising from hitting the zero lower bound on nominal interest rates. However, our results are also robust over the full sample which extends to 2016:Q3 and 2016:H2 for the SPF and the LS data, respectively.[21] Both the SPF and LS data for unemployment expectations 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) uses 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. These data are monthly series and had to be converted to quarterly series when using the SPF data or semiannual data when using the LS data. We followed Leduc and Sill (2013) in this calculation. In particular, the first quarter is redefined from February to April, the second quarter is from May to July, and so on. This alignment makes sure that actual data does not have any contemporaneous effects on the forecasted data. Based on this 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.

### 3.1 Linear model

Because our objective is to investigate the effects of expectation shocks, we only present the impulse responses for that type of shock. We first focus on the linear model given by (1) to gauge the economy's response to an unanticipated shock in expectations for future unemployment rates. This baseline linear model will be useful for comparison to the shifting monetary regime structure that is investigated next. One interpretation for the linear specification is that the current policy regime will last

[21] The opportunistic monetary policy results are presented in the robustness section below, while the unemployment threshold results can be obtained from the authors upon request.

indefinitely.[22] Later, in the monetary policy regime model, we show that differences arise when agents believe that the current regime will not last indefinitely.[23]

Figure 1 shows the impulse responses to a negative one standard deviation innovation in unemployment expectations in two vertical panels. The graphs in the left panel show the results when SPF data is used, while the graphs in the right panel show the results when the LS is used. The panels are placed side by side to facilitate comparison between the two surveys. Both models used two lags to generate the IRF as this lag length was found optimal according to the Akaike information criterion. The solid lines show the impulse responses, while the long dashed lines show one standard deviation error bands.

Both the left and right panels show similarities between the impulse response patterns. Focusing on the impulse response functions presented in the left panel using the SPF data, we see the following results. On impact, a negative one standard deviation innovation in unemployment expectations lowers the expected unemployment by about 0.5 percentage point. This results in a contemporaneous decline in the realized unemployment rate by a similar magnitude. Furthermore, these declines continue for the next two quarters before both expected unemployment and unemployment reverse and start to move back upward. Inflation does not have any contemporaneous effect from the expected unemployment impulse, but it does start to rise in the first quarter afterward, and this rise continues until the fourth quarter before topping and starting a decline back to the long-run level. In addition, the expected unemployment decline does produce a contemporaneous rise in interest rates of half a percentage point, which could be interpreted as indicating concern on the part of the monetary authorities who preemptively take action before the inflation increases take hold. The rise in interest rates continues for the next two quarters before topping around a 1.5 percentage point gain and then reversing back toward long-run levels. The impulse

[22] This point is elaborated in Clarida et al. (2000) and Lubik and Schorfheide (2004). According to these papers, when monetary policy enters a particular regime, rational agents naively believe that the regime will prevail indefinitely.

[23] A rational agent's expectation formation mechanism changes when the policy regime changes. See Sims (1982, 1987) and Sargent (1984) for details.

responses using the LS data are qualitatively the same, although they do not show the same continuation type effects over the first few periods. In particular, the initial decline in expected unemployment bottoms out more or less on impact and the other variables show more modest continuing effects over the first few periods than the SPF data. This may be because the LS data is collected only twice a year, so there is greater time for the effects to dissipate between survey periods.

Overall, these findings are consistent with the expectation driven business cycle literature. In particular, an optimistic expectation (decline in unemployment expectations) about the future causes a boom in current economic activities with the unemployment rate falling and the inflation rate rising. Furthermore, the interest rate responses are consistent with the conventional view that the monetary authority's reaction is aggressive in the wake of rising inflation. These local projection findings are similar to Leduc and Sill (2013), which is based on the assumption that the policy regime remains the same over the forecast horizon. We now turn to the macroeconomic effects of expectation shocks when policy regimes shift and show that differences from these linear model results arise.

### 3.2 Threshold local projection model

Figures 2 and 3 show the impulse response plots for the threshold model (3) with Figure 2 presenting the results when the threshold is given by the opportunistic structure in (6) and Figure 3 presenting the results from the unemployment threshold given in (7). Like Figure 1, 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 line types as in Figure 1, there are a few differences in the plotting notations relative to the plots in Figure 1. In particular, we now plot both policy regimes. To avoid having too many lines, we have plotted the rising inflation (hawkish) regime IRFs along with their one standard deviation bands using blue, while for the falling inflation (dovish) regime we only plotted the IRF using red.[24]

[24] Results are still robust when we plot confidence bands around the IRFs in the dovish regime. A more detailed Appendix with these figures is available from the authors upon request.

Figures 2 and 3 show that the economy responds in significantly asymmetric ways to expectation shocks across the policy regimes. To get a deeper insight of this, let us first consider Figure 2, where impulse responses are plotted based on the assumption that the opportunistic Fed is more aggressive in the rising inflation regime than the falling inflation regime. In other words, the Fed would not be aggressive to lower unemployment expectations unless the current inflation rate exceeds the average inflation rate of the recent past.

In the left panel, a one standard deviation negative innovation in unemployment expectations lowers the expected unemployment by about half a percentage point on impact. Accordingly, the realized unemployment rate declines by a similar magnitude in both regimes. After one quarter, the unemployment rate starts creeping back up. For the first ten or so quarters, the two regimes track each other pretty closely, but after ten quarters, differences start to surface. After ten quarters, the unemployment rate increased significantly higher during the rising inflation regime than during the falling inflation regime. The reason for the asymmetric responses of the unemployment rate can be understood by considering the impulse responses of the inflation rate and the interest rate. The positive unemployment expectation shock produces a larger increase over time in the inflation rate during the rising inflation regime. Consequently, the interest rate increases to a greater extent over time, and this is what produces the relatively higher long term increase in the unemployment rate. On the other hand, during the dovish falling inflation regime, the expectation shock does not lead to as large an increase in long term inflation and thus a more modest policy action and consequently milder effects on long term unemployment.

Next focusing on the right panel that uses the LS data, an unanticipated expectation shock tells a similar qualitative story. Again, we see that the inflation rate does not rise as much during the falling inflation regime and this leads to a more muted rise in interest rates. This smaller rise in interest rates implies that the long-run effect on the unemployment rate is less than the long-run effect in the rising inflation regime where policymakers take stronger action which leads to somewhat higher long-run unemployment rates.

Finally, turning to Figure 3, which uses the unemployment rate as the threshold variable, we see very similar qualitative results. Here the high unemployment (dovish) regime shows that a favorable unemployment rate shock has a smaller effect on the inflation rate and consequently, a smaller rise in interest rates. This lower rise in interest rates implies that in the long-run, the unemployment rate does not rise to the extent that is seen in the low unemployment (hawkish) regime.

## 4 Variance decomposition results

Another interesting way to illustrate the differences between the regimes is to compare the forecast error variance decompositions (FEVDs). We begin with a short description of how to compute the FEVD for the various models in this paper.[25]

The mean squared error of the forecast error in (1) is given by

$$MSE_u(E(x_{t+s}|X_t)) = E(u^s_{t+s}u^{s'}_{t+s}) \qquad s = 0, 1, ..., h. \tag{8}$$

This can be estimated by using $\widehat{\Sigma}_{u^s} = \frac{1}{T}\sum_{t=1}^{T}\widehat{u}^s_{t+s}\widehat{u}^{s\prime}_{t+s}$ where $\widehat{u}^s_{t+s} = x_{t+s} - \widehat{\alpha}^s - \sum_{i=1}^{p}\widehat{B}^{s+1}_i x_{t-i}$. 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, define 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 $D$ gives

$$MSE(E(x_{t+s}|X_t)) = D^{-1}E(u^s_{t+s}u^{s'}_{t+s})D^{'-1} = D^{-1}\Sigma_{u^s}D^{'-1} \qquad s = 0, 1, ..., h. \tag{9}$$

From (9), we can calculate the traditional variance decompositions by directly plugging in the sample-based equivalents from the projections in (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.

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

Table 1 reports the results of the two and five year ahead FEVDs for the linear model and the two threshold models. The table only reports the results of the percent of the total forecast error variance attributable to expectation innovations because this is our main interest. The table is 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. The table is also organized into two horizontal panels, each of which corresponds to a different forecast horizon. Both the top horizontal panel which summarizes the FEVDs for the two year horizon and the bottom horizontal panel which summarizes the FEVDs for the five year horizon are organized into five rows, with the first row showing the results for the linear model given by (1), the next two rows showing the results for the opportunistic monetary policy threshold model given by (3) and (6), and the last two showing the results for the unemployment threshold model given by (3) and (7). For each of the threshold models, the first row reports the FEVD under the hawkish monetary policy regime (rising inflation and low unemployment) while the second row reports the FEVD under the dovish monetary policy regime (falling inflation and high unemployment).

To get a more concrete understanding for the organization of the table, let us focus on the first vertical panel at the two year forecast horizon. The linear model in the first row shows that innovations in unemployment expectations account for 84.21% of the variance of unemployment, 16.52% of the variance in inflation and 51.94% of the variance in the interest rate at the two year ahead horizon. Both threshold models show an important difference. Both show that there is a relatively higher amount of the forecast variance during the hawkish regime and a relatively lower amount of the forecast variance during the dovish regime. For instance, under the opportunistic monetary policy threshold model, during the rising inflation regime, unemployment expectation shocks account for 75.58% of the variance of unemployment, 28.54% of the variance in inflation and 63.76% of the variance in the interest rate, while during the falling inflation regime, unemployment expectation shocks account for only 66.34% of the variance of unemployment, 11.12% of the variance in inflation and 40.51% of the variance in the interest rate at the two year ahead horizon. With only a single exception, this pattern of higher percentage forecast error variances during the hawkish regime (rising inflation or low unemployment) also holds for the Livingston Survey data results reported in the second vertical panel at the two year horizon as well as for both data sources at the five year horizon reported in the second horizontal panel at the bottom of the table.[26] Furthermore, these differences in the size of the percentage of the forecast error variance accounted for by unemployment expectation innovations are particularly large under the unemployment threshold model.

# 5 Robustness

Robustness of the baseline results was investigated in several ways. We report three here, while several others are included in an appendix that is available from the authors upon request. The first exercise reported here controls for exogenous uncertainty shocks that may play a role in the system's dynamic behavior while the second exercise extends the data set to include the financial crises years. The third exercise compares the FEVD results for a shock to unemployment expectations with the FEVD results for a monetary policy shock. These results confirm our general finding that a threshold model provides insights about economic behavior that can be missed by a simple linear model.

## 5.1 Controlling for economic uncertainty

A number of recent papers, including the seminal contribution by Bloom (2009), show that heightened economic uncertainty due to uncertain economic and political shocks have a significant impact on economic activities. One concern with the previous results is whether the policy regimes simply reflect exogenous uncertainty. In this robustness exercise, we control for exogenous uncertainty shocks that may play

[26] The single exception is the two-year ahead forecast error variance for unemployment under the opportunistic monetary policy threshold model when using the LS data.

a significant role in our system's dynamic behavior to see if the previous results continue to hold.

We construct a volatility index by following the construction methods in Bloom (2009) which use the observed and implied stock market volatility to identify uncertainty shocks.[27] In particular, we use data on the implied volatility of the VXO index, which is available from June 1986 to the present, but for the pre-1986 period, we use the observed volatility from the daily S&P 500 stock index.[28] Figure 4 plots this index. The figure shows that there were nineteen major political and economic events in which there were sudden jumps in stock market volatility.[29] Most of these major events signaled significant downturns in economic activities. In our model, to control for this exogenous uncertainty, we augment our regime-switching model in equation (3) by adding a dummy variable that takes a value of 1 for each of the uncertain events and 0 otherwise. Fourteen of the nineteen events lie within our baseline samples that use the SPF data while seventeen events lie within the baseline sample that uses the LS data.[30] For comparison, note that Leduc and Sill (2013) control for exogenous oil and fiscal shocks by identifying five 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 dummy variable takes into account all of these events.

Figures 5 shows the impulse response functions for our baseline opportunistic monetary policy switching model that are modified to incorporate the dummy variable to control for the uncertainty shocks.[31] This model uses the same recursive ordering

[27] The implied volatility of the stock market is a popular proxy for uncertainty. See, for example, Leahy et al. (1996), Bloom et al. (2007), Bloom (2009) and Jones and Enders (2016), among others.

[28] Essentially, we took the uncertainty data from Bloom (2009) and updated it from July 2008 using the CBOE's VXO index.

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

[30] The reason all nineteen events are not in our baseline data periods is that our baselines exclude data after the Great Recession of 2008. All nineteen events are considered for the full sample estimation. IRFs that control all nineteen events for the full sample estimation are included in an appendix that is available upon requests from the authors.

[31] The plot for the unemployment switching regime is similar and can be obtained from the authors

and uses the same plotting conventions used earlier.

Comparing this with Figure 2, we find that controlling for uncertainty shocks results in only minor qualitative differences. In particular, an unanticipated decrease in the expected unemployment rate has stronger effects in the hawkish regime than the dovish regime. Consequently, monetary policy's reaction is more aggressive in the various hawkish regimes than the dovish regimes, and this produces different long-run effects on the economy.

### 5.2 Full sample results

In our primary analysis, we focused on data that did not include the financial crises, because shortly after the onset of the crises the Fed set the federal funds target to be the range from 0 to 0.25, which has become known as the zero lower bound. It was felt that including data from this period may arouse suspicions that our results were driven by the unusual interest rate data from this period. Here we show that including all available data does not change the results.

We begin by first generating an implicit nominal interest rate series following methods used by Bekaert et al. (2013). This approach uses the Taylor rule (TR) to approximate the nominal interest rate for the financial crises period.[32] In particular, using Taylor's (1993) values for the Taylor rule, an implicit nominal interest rate can be computed using

$$i_t^{TR} = \pi_t + i_t^* + 0.5(\pi_t - \overline{\pi}) + 0.5y_t^*, \tag{10}$$

where we use $i_t^{TR}$ to denote the implicit nominal interest rate using the Taylor rule, $\pi_t$ is the annual inflation rate, $i_t^*$ is the full-employment real interest rate which is assumed to be 2%, $\overline{\pi}$ is the target inflation rate which is also assumed to be 2% , and $y_t^*$ is the output gap which is the percentage deviation of real GDP from potential GDP. For the output gap, we use the series (GDPC1_GDPPOT) from the FRED database. For our interest rate series for the period from January 2009 to December

upon request.

[32] Rudebusch (2009) also suggested using the TR rate to generate a proxy for the "true" federal funds rate post-2008.

2015, we used the minimum value of the interest rate generated using this method and 0.125, which is the midpoint of the Fed's declared policy range of 0 to 0.25.

Next, we re-estimated the baseline regime-switching models over 1968:Q4-2016:Q3 for the SPF and 1961:H2-2016:H2 for LS data. Figure 6 shows the results for the full sample using opportunistic monetary policy as the threshold structure. This figure shows that our baseline results still hold when we consider the Great Recession periods. Comparing to Figure 2, the asymmetric effects of expectation shocks on the inflation rate, and the interest rate are even stronger when we consider the full sample. That is, the responses of inflation and interest rates are stronger in a hawkish regime than in the dovish regime. These stronger results are not surprising because the financial crisis indeed has weighed down agents' expectation during the dovish regimes.[33]

### 5.3 How important are expectation shocks?

Cochrane (1994) explains the role of news about economic fundamentals to understand economic fluctuations. He argued that news and sentiment shocks are more important than technology and monetary policy shocks. Recently, Caggiano et al. (2014) show that uncertainty shocks are more important than monetary shocks for economic fluctuations. Here we investigate this issue with an eye toward whether a threshold model structure provides any new insights into this question.

Our approach here is to study the FEVDs for unemployment and inflation over twenty quarters for each of these two types of shocks. We compare these using the same Cholesky ordering as described above. Figure 7 shows results of this exercise for the linear model given by (1) and the threshold model with an opportunistic monetary policy given by (3) and (6). The figure is organized with three rows of plots, with the first row showing the FEVDs for the linear model, the second row showing the FEVDs for the rising inflation (hawkish) regime of the opportunistic monetary policy threshold model and the third row showing the FEVD for the falling inflation (dovish)

[33] The IRFs using unemployment as an alternative threshold structure and the forecast error variance for the full sample are provided in the appendix.

regime of the opportunistic monetary policy threshold model. Each row shows four subplots, with the first two corresponding to the unemployment and inflation FEVD using the SPF data and the second two corresponding to the unemployment and inflation FEVD using the LS data. Each of the subplots shows the FEVD for different horizons, beginning with a one quarter horizon and extending out to a twenty quarter horizon. All the subplots use the same line types, with the red line showing the percentage of the forecast error variance accounted for by the expectation shock and the blue line showing the percentage of the forecast error variance accounted for by the monetary policy shock.

The subplots have standard interpretations. So, for instance, the subplot in the top left shows the FEVD for the two types of shocks in the linear model for unemployment using the SPF data. The solid line shows that expectation shocks initially explain roughly 80% of the variation in the unemployment rate, that the amount of variation explained by the expectation shocks rises to around 95% for quarters two to five and then the variation drops modestly to around 40% by the end of the twenty quarter horizon. Similarly, this same subplot shows that monetary shocks explain close to 0% of the FEVD for the first few quarters. The variation explained rises slowly to roughly around 10% by the tenth quarter where it begins to decline very modestly until the twenty quarter horizon.

These plots show several results. First, they show that for both types of data, expectation shocks explain most of the variation in unemployment for the linear model and both states of the threshold model. This confirms the findings in Caggiano et al. (2014). The strongest difference can be seen in the inflation plots where the threshold model shows that during the hawkish, rising inflation, regime, expectation shocks explain more of the variation in inflation over the entire twenty period horizon, while during the dovish, falling inflation, regime, expectation shocks, and monetary shocks show similar FEVDs. A somewhat weaker difference can be seen in the SPF data for unemployment. Here, the hawkish regime shows a more persistent portion of the forecast error explained by expectation shocks, staying above 60% over the entire twenty period horizon. In contrast, the dovish regime shows a less persistent portion of the forecast error explained by expectation shocks, descending to around 30% of the variation by the end of the twenty period horizon. However, it should be noted that the LS data does not show such strong differences between the two regimes for the unemployment FEVDs.

## 6 Conclusion

This paper investigates the effects of expectation shocks on macroeconomic activities using threshold models. Two threshold structures were investigated, each with a connection to monetary policy. In addition, two data sources were used to compute expectation shocks. The primary finding is that the effects of expectation shocks on macroeconomic activities are asymmetric for both policy models and both data sets. In particular, during hawkish (rising inflation or low unemployment) regimes, the results of impulse responses and forecast error variance analysis show that an anticipation of good times ahead leads to a boom in current economic activities like falling unemployment and rising future inflation, and this explains much of the variation in observed unemployment and inflation up to horizons of twenty quarters. However, the effects of the expectation shocks are smaller and less persistent in the dovish (falling inflation or high unemployment) regimes, and they explain less of the variation in unemployment and inflation than they do during hawkish regimes. We also find that the Fed's reactions to a positive innovation in expectations are asymmetric across the policy regimes. As expected, the Fed reacts more aggressively in the hawkish regimes than the dovish regimes with a more than proportionate increase in the interest rate. Controlling for major uncertain economic and political events, we also conducted a robustness analysis, and this 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 results in an anticipatory tightening (easing) monetary policy as the Fed always tends to stabilize the economy. Our findings on the effects of expectation shocks on economic activities and their interaction with the monetary policy are also consistent with a number of recent studies that investigate the Fed's asymmetric behavior to macroeconomic activities.[34] 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 about the asymmetric effects of expectation shocks across the monetary policy regimes.

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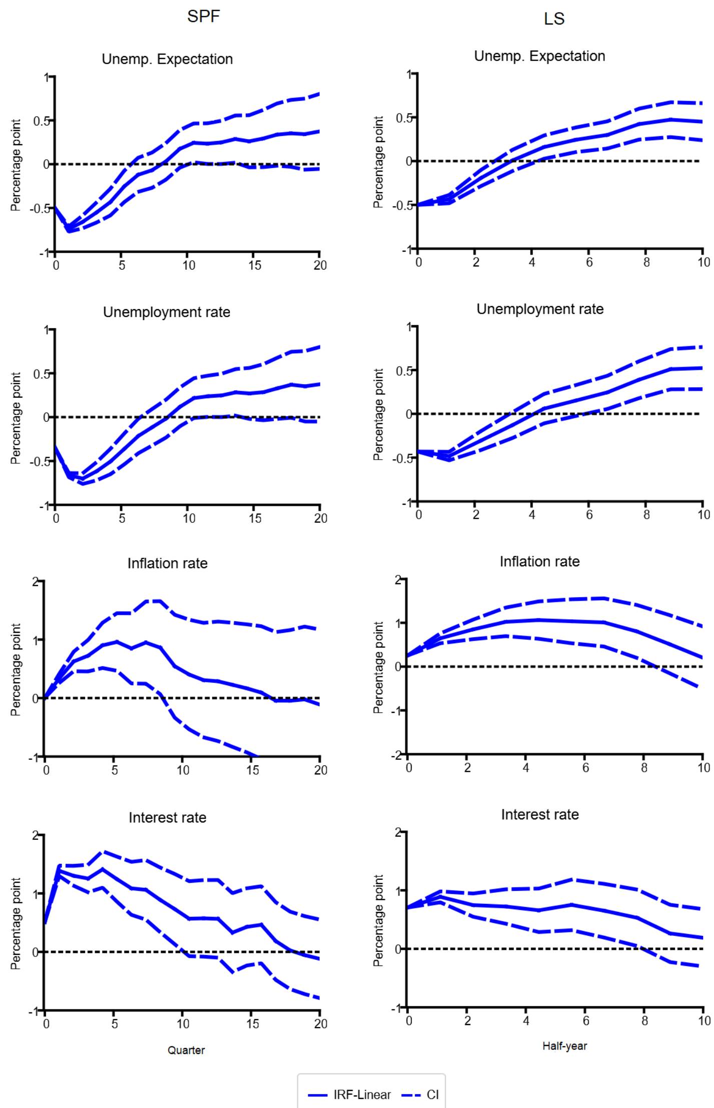


Figure 1: Impulse response functions using linear model.

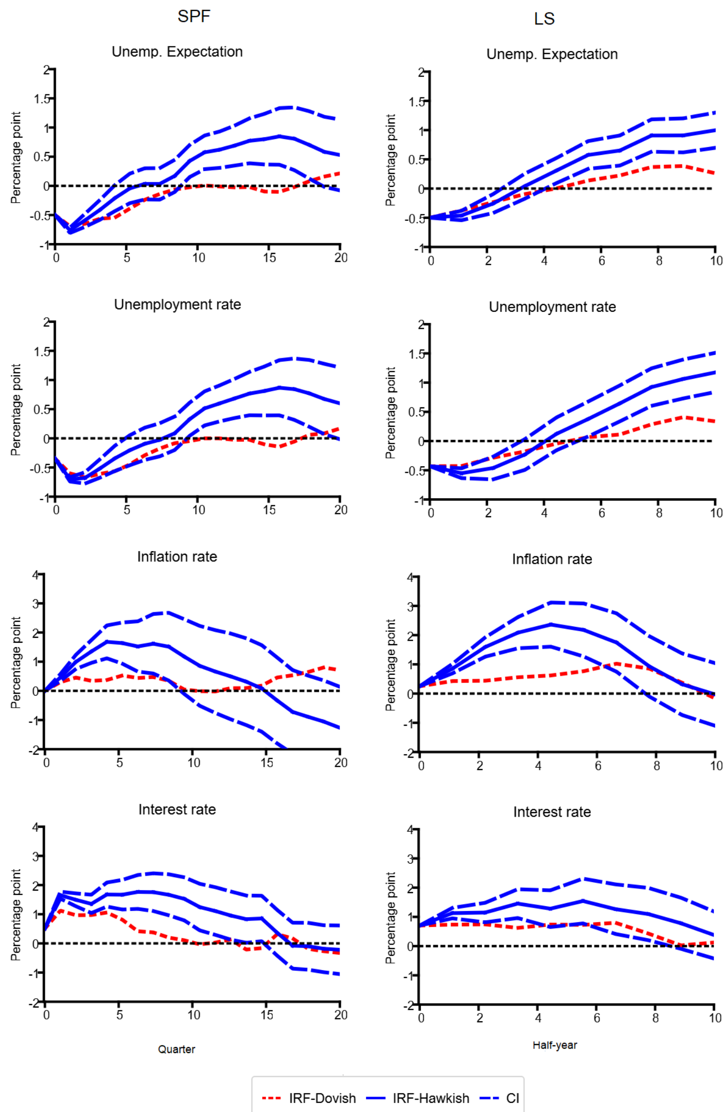


Figure 2: Impulse response functions from one standard deviation expectation shock using opportunistic monetary policy strategy as the threshold indicator.

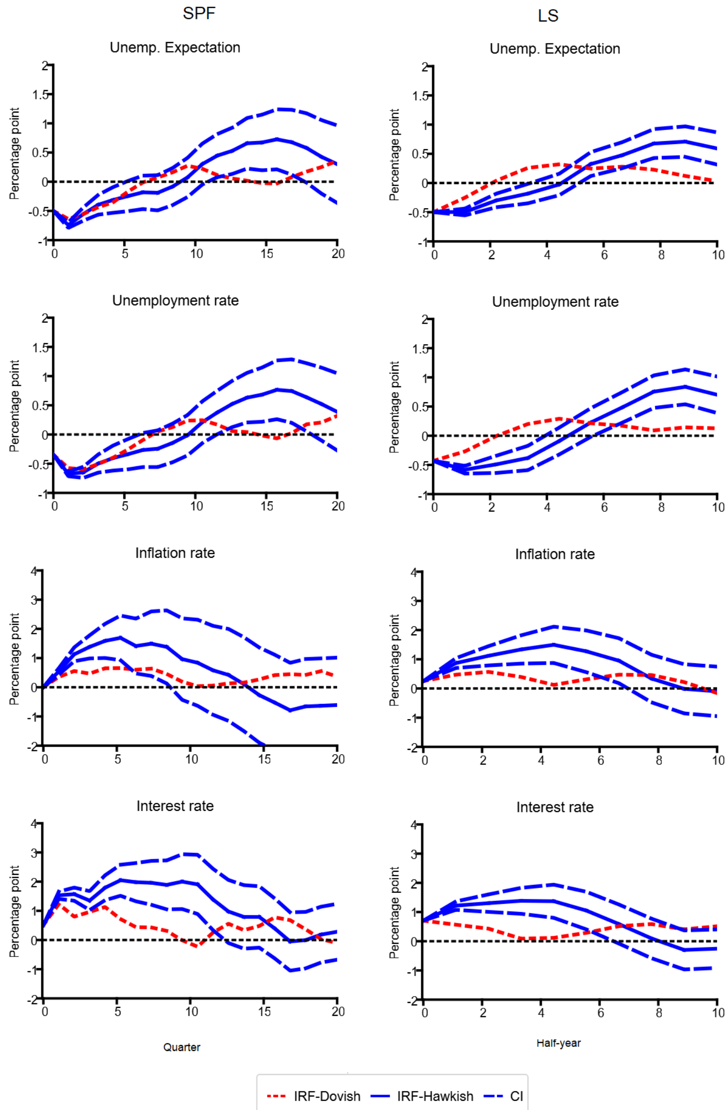


Figure 3: Impulse response functions from one standard deviation expectation shock using unemployment rate as the threshold indicator.

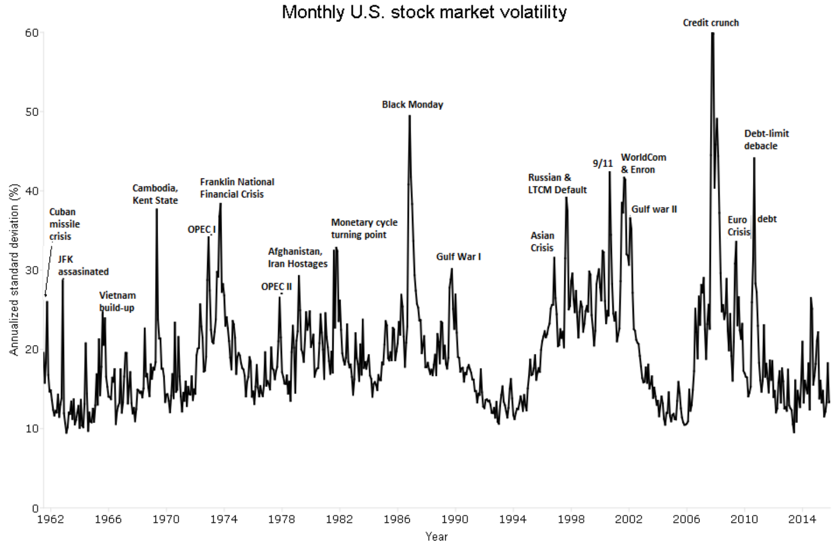


Figure 4: Measuring uncertainty shocks from the realized and implied volatility of the U.S. stock market.

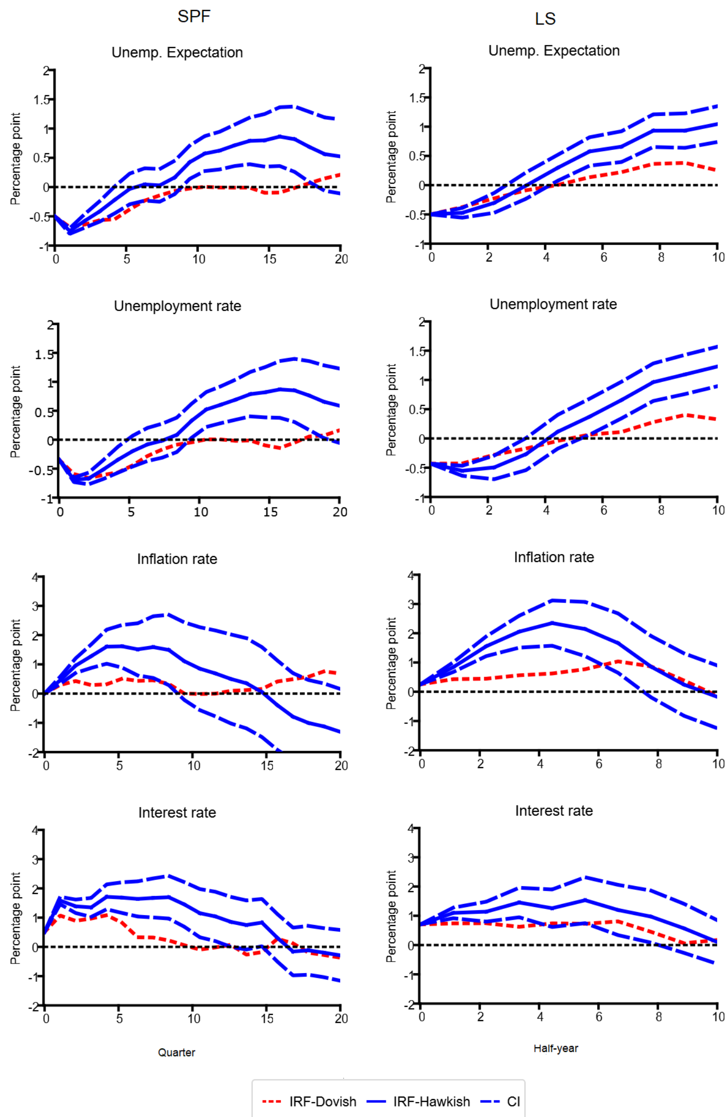


Figure 5: Impulse response functions from one standard deviation expectation shock using the opportunistic monetary policy strategy as a threshold indicator. Controlling for uncertain economic and political events.

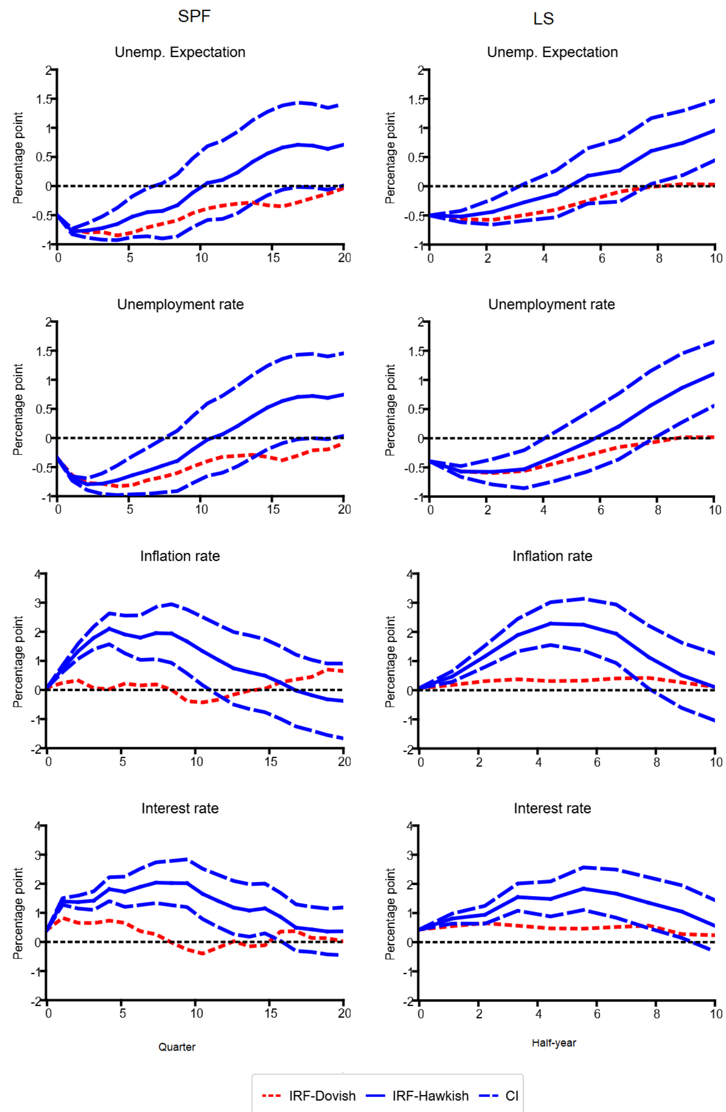


Figure 6: Impulse response functions from one standard deviation expectation shock using opportunistic monetary policy strategy as the threshold indicator. Full sample results.

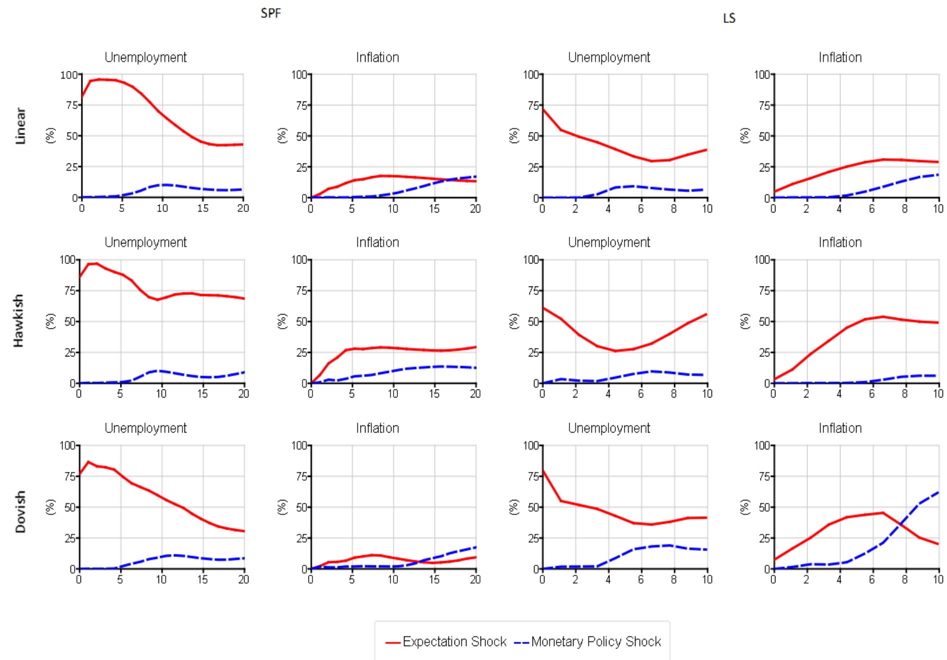


Figure 7: Comparison of FEVD for expectation shocks and monetary policy shocks.

Table 1: FEVD attributable to expectation innovations

| | SPF | | | LS | | |
|---|---|---|---|---|---|---|
| States | Unemp | Infl rate | Int rate | Unemp | Infl rate | Int rate |
| | | | Forecast horizon of two-year ahead | | | |
| | | | Linear model | | | |
| | 84.21 | 16.52 | 51.94 | 44.87 | 20.84 | 27.31 |
| | | | Opportunistic monetary policy threshold model | | | |
| Rising Infl (Hawkish) | 75.58 | 28.54 | 63.76 | 30.07 | 34.34 | 34.28 |
| Falling Infl (Dovish) | 66.34 | 11.12 | 40.51 | 48.59 | 35.83 | 31.06 |
| | | | Unemployment threshold model | | | |
| Low Unemp (Hawkish) | 48.28 | 33.03 | 49.67 | 51.79 | 33.41 | 49.89 |
| High Unemp (Dovish) | 60.18 | 22.68 | 31.84 | 10.32 | 2.07 | 2.78 |
| | | | Forecast horizon of five-year ahead | | | |
| | | | Linear model | | | |
| | 42.94 | 13.35 | 42.52 | 38.62 | 28.93 | 29.25 |
| | | | Opportunistic monetary policy threshold model | | | |
| Rising Infl (Hawkish) | 68.65 | 29.24 | 42.73 | 55.71 | 49.13 | 39.59 |
| Falling Infl (Dovish) | 30.54 | 9.29 | 18.45 | 41.44 | 20.30 | 30.94 |
| | | | Unemployment threshold model | | | |
| Low Unemp (Hawkish) | 38.29 | 20.80 | 59.06 | 66.38 | 45.82 | 51.13 |
| High Unemp (Dovish) | 36.66 | 12.46 | 25.24 | 2.66 | 0.71 | 2.15 |

# 7 Appendix (not intended for publication):

In this Appendix, we further explain the measure and identification of expectation shocks and provide some further analysis mentioned in the robustness section.

## 7.1 Timing of information

We elaborate on the timing of information coming from the expectations surveys and the observed data to get a better understanding of why the expectation shocks are exogenous and not contemporaneously affected by the observed data. We follow the strategy used in Leduc and Sill (2013).

The survey forecasts of the unemployment rate are our proxy for expectations about future economic activity. This, along with the observed unemployment rate, help us to extract expectation shocks. We use the unemployment rate data because it is subject to only minor revisions. Data, such as GDP, which is revised is problematic because the revised data may contain information that may have been unavailable to forecasters at the time when they prepared their forecasts, which would likely make it difficult to extract the true expectation shocks.

For our baseline specification, we use the expected unemployment rate from both 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 in 1968.[35] 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.[36] The Federal Reserve Bank of Philadelphia conducts the SPF four times a year. For the purpose of illustration, a time-line of the SPF survey is constructed in

[35] 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.

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

Figure A1.[37] 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.[38] 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.[39] 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.[40] The SPF survey reports always come out before the release of BEA's first revision of GDP and its components for the last quarter.

[37] The information is taken from http://phil.frb.org. One can construct a similar timeline for the LS.

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

[39] 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.

[40] 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

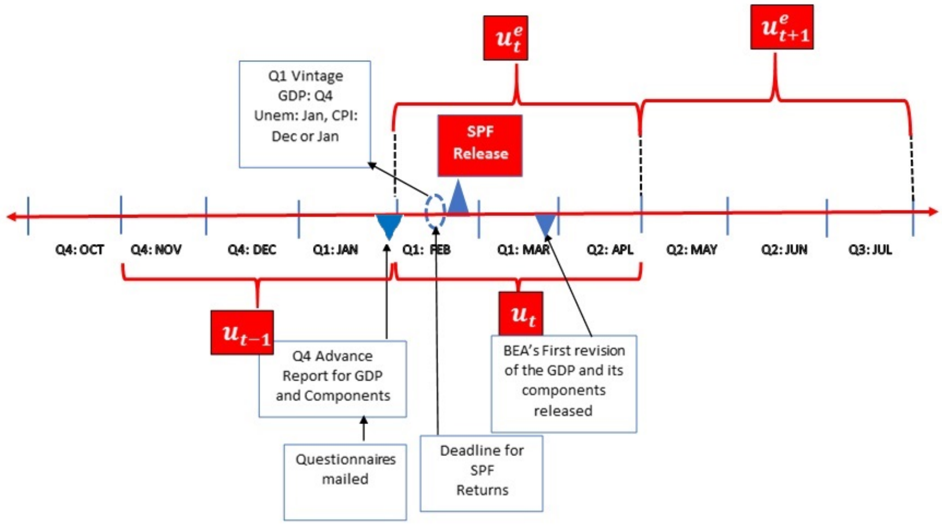


Figure A1: Timing information of survey and actual data releases

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 alignment makes sure that actual data does not have any contemporaneous effects on the forecasted data. Based on the timing and data re-alignment, 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.

## 7.2 Additional robustness exercises

Figures A.2 and A.3 plot IRFs that use both the opportunistic monetary policy strategy and the unemployment rate as threshold indicators, respectively. An important difference from the baseline estimation results, as shown in Figures 2 and 3 is that here we plot the confidence bands around the IRFs in the dovish regime.

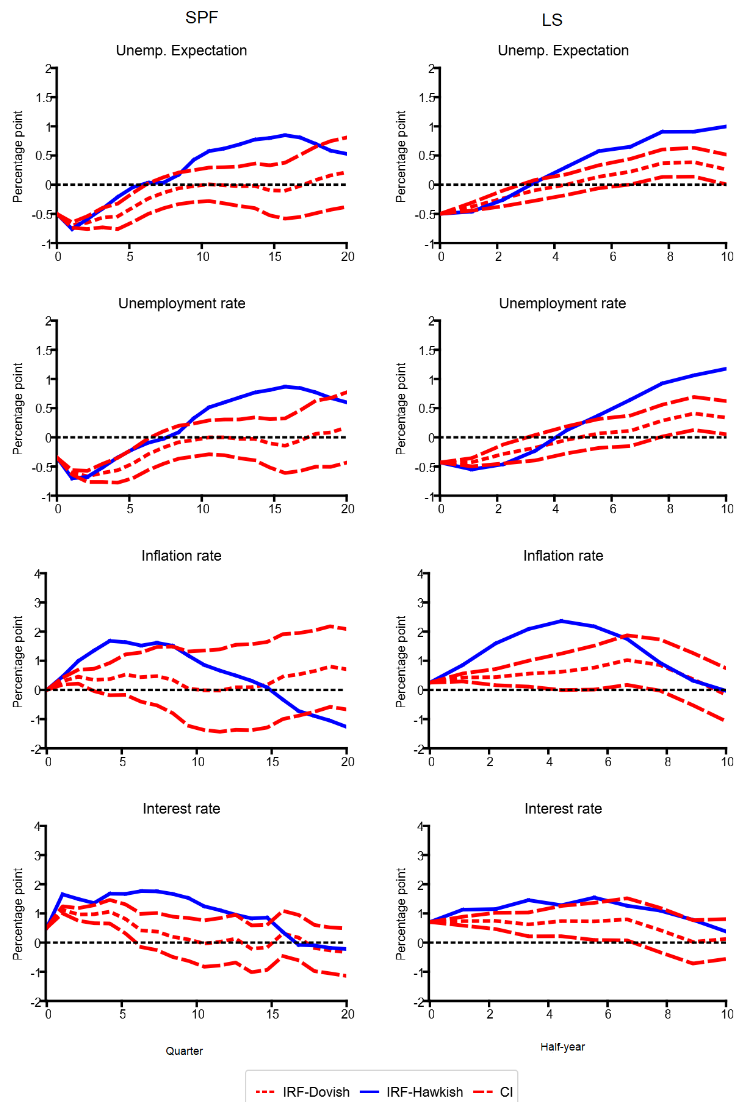


Figure A2: Impulse response functions from one standard deviation expectation shock using opportunistic monetary policy strategy as the threshold indicator. The cofidence bands are plotted around the IRFs in the dovish regime.

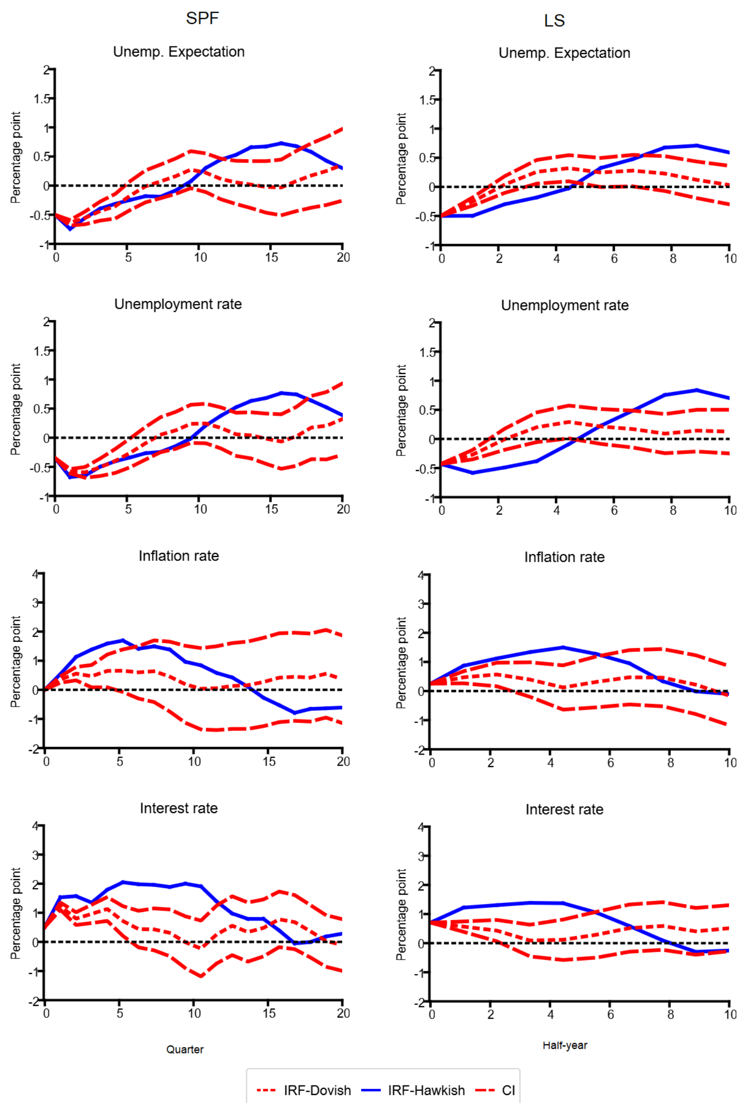


Figure A3: Impulse response functions from one standard deviation expectation shock using the unemployment rate as the threshold indicator. Confidence bnds are plotted around the IRFs in the dovish regime.

Figure A.4 plots impulse response functions after controlling for uncertainty shock in the unemployment switch model. This is the analogue to Figure 5 in the text. It was not included in the text because it is similar to the opportunistic monetary policy case.

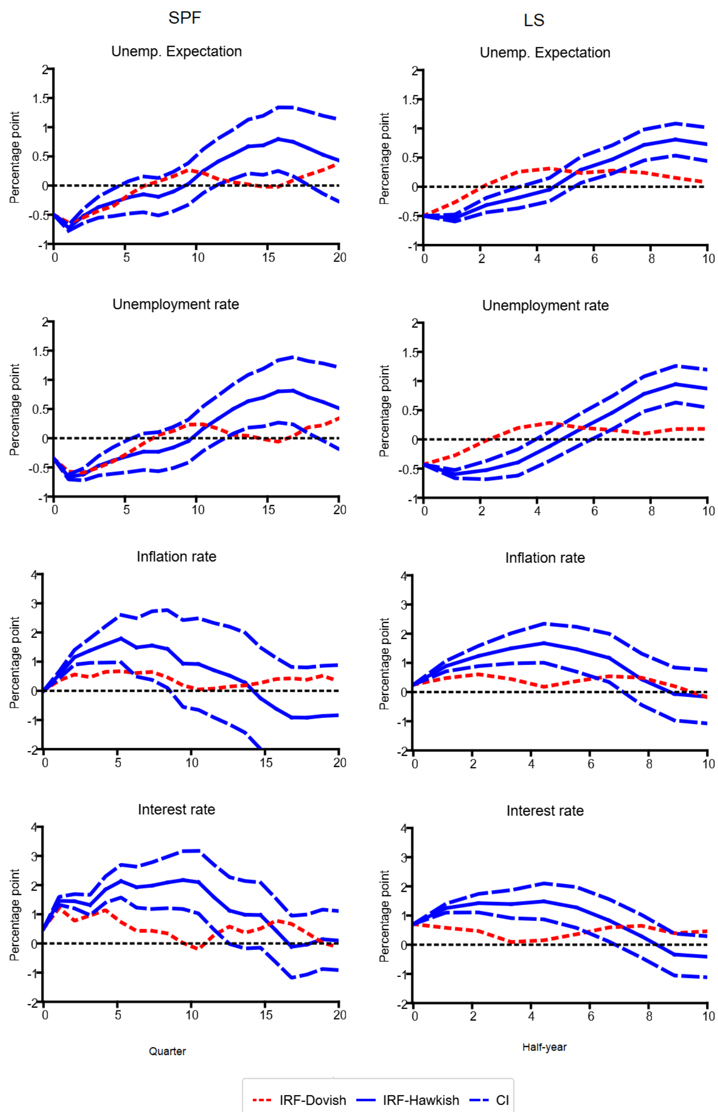


Figure A.4: Impulse response functions from one standard deviation expectation shock using the unemployment rate as the threshold indicator. Controlling for uncertain economic and political events.

Figure A5 shows the impulse response functions using the full sample that includes the Great Recession of 2008-09. Here again, we use the unemployment rate as an alternative threshold indicator.

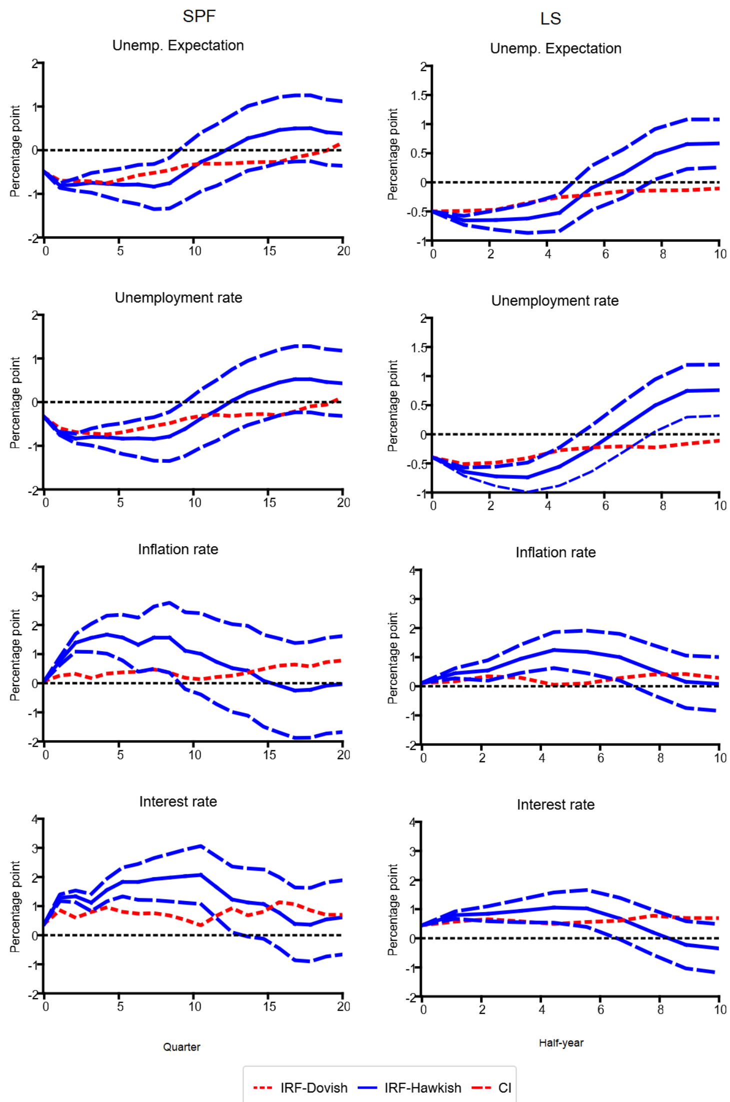


Figure A5: Impulse response functions from one standard deviation expectation shock using unemployment rate as the threshold indicator. Full sample results.

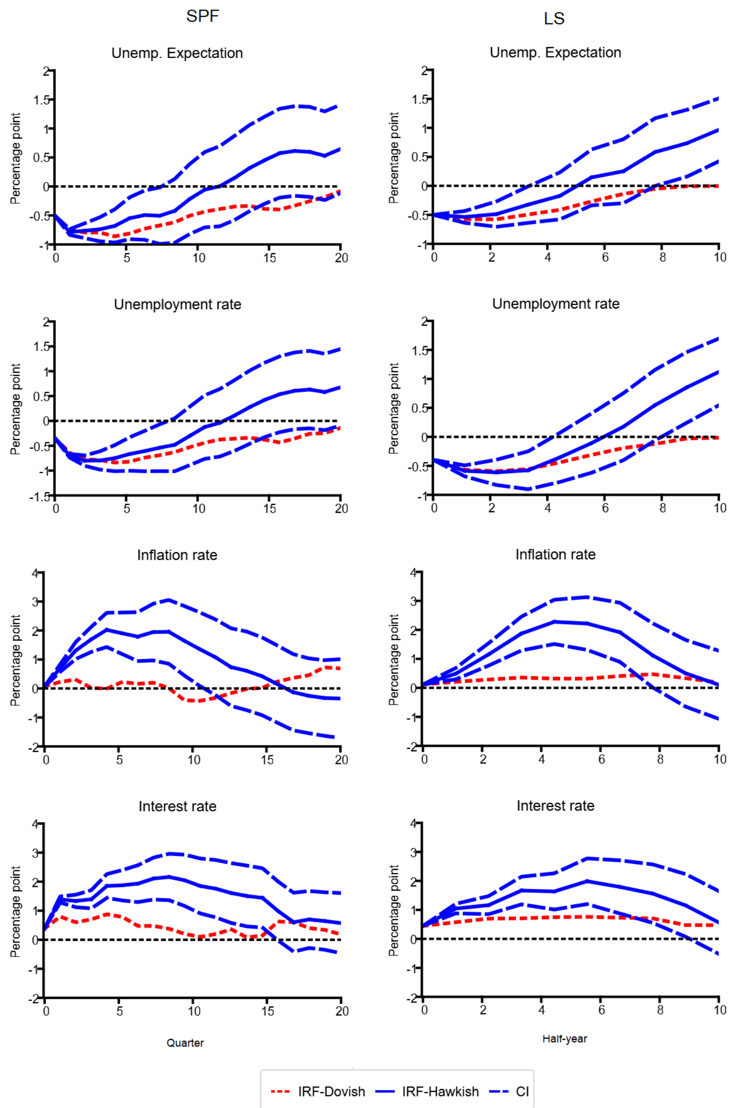


Figure A6: Impulse response functions from one standard deviation expectation shock using opportunistic monetary policy as the threshold indicator. Full sample results with controlling for uncertain economic and political events.

## 7.3 Additional FEVD (Extended version of Table 1)

Table A.1 displays FEVD using the full sample.

Table A.1: FEVD attributable to expectation innovations

| | SPF | | | LS | | |
|---|---|---|---|---|---|---|
| States | Unemp | Infl rate | Int rate | Unemp | Infl rate | Int rate |
| | Forecast horizon of one-year ahead | | | | | |
| | Linear model | | | | | |
| | 95.42 | 8.80 | 52.75 | 54.84 | 11.03 | 32.51 |
| | Opportunistic monetary policy threshold model | | | | | |
| Rising Infl (Hawkish) | 92.96 | 20.80 | 67.29 | 52.25 | 11.21 | 37.24 |
| Falling Infl (Dovish) | 82.28 | 5.63 | 37.58 | 55.01 | 16.52 | 29.17 |
| | Unemployment threshold model | | | | | |
| Low Unemp (Hawkish) | 83.16 | 21.48 | 45.94 | 65.23 | 17.95 | 50.04 |
| High Unemp (Dovish) | 79.26 | 12.46 | 31.88 | 14.27 | 2.02 | 4.99 |
| | Forecast horizon of three-year ahead | | | | | |
| | Linear model | | | | | |
| | 58.77 | 16.85 | 48.20 | 33.48 | 28.70 | 29.35 |
| | Opportunistic monetary policy threshold model | | | | | |
| Rising Infl (Hawkish) | 71.84 | 27.75 | 51.40 | 30.07 | 51.81 | 36.62 |
| Falling Infl (Dovish) | 52.46 | 7.06 | 31.94 | 48.59 | 43.81 | 38.03 |
| | Unemployment threshold model | | | | | |
| Low Unemp (Hawkish) | 30.04 | 32.14 | 59.69 | 46.58 | 48.21 | 52.55 |
| High Unemp (Dovish) | 53.86 | 15.98 | 25.79 | 8.18 | 0.94 | 1.87 |
| | Forecast horizon of five-year ahead | | | | | |
| | Linear model | | | | | |
| | 42.94 | 13.35 | 42.52 | 38.62 | 28.93 | 29.25 |
| | Opportunistic monetary policy threshold model | | | | | |
| Rising Infl (Hawkish) | 68.65 | 29.24 | 42.73 | 55.71 | 49.13 | 39.59 |
| Falling Infl (Dovish) | 30.54 | 9.29 | 18.45 | 41.44 | 20.30 | 30.94 |
| | Unemployment threshold model | | | | | |
| Low Unemp (Hawkish) | 38.29 | 20.80 | 59.03 | 66.38 | 45.81 | 51.13 |
| High Unemp (Dovish) | 36.66 | 12.46 | 25.24 | 2.66 | 0.71 | 2.15 |