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REAL-TIME MONITORING OF THE US INFLATION EXPECTATION PROCESS

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Real-time supervision of shifts in inflation expectations is an important issue for monetary policy makers, especially in the presence of economic uncertainty. In this paper, we elaborate tools for on-line monitoring of such shifts by extracting valuable information from noisy daily financial market data. For this purpose, first, we suggest a new risk adjustment for observable proxies of medium and long run inflation expectations assuming that the latter are well-anchored. Second, we propose an econometric methodology for sequential monitoring of level changes in the associated proxies at daily frequency. Our empirical evidence shows that the on-line surveillance of risk adjusted US forward breakeven inflation rates by means of the cumulative sum (CUSUM) detector appears to be helpful to extract timely signals on potential shifts. In particular, the obtained signals indicate important turning points in market-based measures of inflation expectations, which also tend to materialize in lower frequency experts' surveys.

Keywords: Breakeven Inflation, CUSUM, Early Warnings, Expected Inflation, Monetary Policy, On-Line Monitoring

1. INTRODUCTION

Well-anchored inflation expectations play a key role for monetary policy makers since they exert a stabilizing impact on the setting of wages and prices. Thereby, shifts in long-term inflation expectations may lead to undesirable second-round effects in wage and price-setting behavior, establishing a persistent regime shift toward increased inflation (or deflation), which is costly to reverse [Cecchetti and Moessner (2008)]. Given that monetary policy must be forward-looking and preemptive in order to be effective, the real-time monitoring of market participants' beliefs in long-run price stability is of great economic value.

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It is well known that policy makers pay close attention to real-time information inherent in asset prices in order to timely infer on economic conditions and expectations. Already Bernanke (2004) pointed at the importance of information derived from inflation-linked financial instruments to learn about market expectations of inflation. Being such an instrument, treasury inflation protected securities (TIPS) have steadily improved in terms of market depth and liquidity since their introduction in 1997. Nowadays, the associated inflation compensation rates are widely used as "quick and dirty" means to infer on the unobservable collective information and beliefs of economic agents about long run inflation and the central bank's commitment to the inflation target.[1] For instance, US policy makers frequently refer to the 5–10 year forward breakeven inflation (FBI) rate when commenting on the current state of long term expectations. As most other market-based indicators, however, these measures are subject to stochastic fluctuations, the magnitude of which depends on the current state of market volatility. Furthermore, they are biased due to both inflation and liquidity risk premia which are time varying and difficult to control for at the daily level.[2]

With respect to their stochastic (heteroskedastic) patterns as well as to the possibly imprecise accounting for risk premia, timely inference on unobserved systematic level shifts in market-based long-run inflation expectations by means of a simple (subjective) eyeball inspection (such as, e.g., flagging observations that exceed a threshold or correspond to local maxima/minima) appears nontrivial or even misleading. Frequently, economists struggle to interpret observed changes in these measures, in particular if no convincing arguments for changing beliefs or financial market dysfunction are available. In this respect, suitable formal (objective) statistical tools are required to condense the noisy and heteroskedastic market-based information to early but yet reliable warning signals on shifts in agents' attitudes. According to Bernanke (2004), research in econometrics to analyze this market-based information "has great potential to provide practical assistance to monetary policymakers" for the supervision of the current state of expectations and/or the anticipation of future developments. Up to now, however, no econometric instruments for this purpose have been suggested in the literature.

In this study, we close this gap and elaborate the use of statistical early warning instruments for the on-line monitoring of risk adjusted market-based proxies for inflation expectations (AFBI, hereafter) derived from FBI rates. For this purpose, we propose an econometric model in order to extract AFBI series and provide a tool for identifying shifting perceptions in real time. Our goal is to extract reliable signal information from these noisy market-based AFBI proxies, hinting at potential shifts in expectations. Of course, the latter shifts are unobservable and will be transitory in case that the central bank succeeds to reestablish the nominal anchor later on. To some extent, however, they should materialize in the daily price processes of associated financial instruments. On-line monitoring is suitable to obtain early warnings about such undesired shifts, which are of natural interest for policy makers and market analysts.

By implementing our approach, we first remove systematic biases in the conditional mean of the FBI process, which are present due to both inflation and liquidity risks. Thus, we make a proper level adjustment to obtain the AFBI series. Second, we provide a sparse but effective autoregressive generalized autoregressive conditional heteroskedasticity (AR-GARCH) time series specification for the AFBI series, which accounts both for autocorrelation and heteroskedasticity. This econometric approach is necessary in order to get residuals which follow a standard distribution under the null hypothesis "no mean change, no jumps/outliers" for our sequential monitoring purpose. Then, for the extracted model residuals, we apply control charts, which are the key tools of statistical process control for the real-time monitoring of structural alterations in a process of interest [cf. Stoumbos et al. (2000)]. Initially developed for engineering applications with a focus on quality control [cf. Montgomery (2013)], control charts have been recently used both in economic and financial applications [Schmid and Tzotchev (2004), Andersson et al. (2005), Gorr and Ord (2009), Golosnoy et al. (2012)]. A control chart is a sequential (period-by-period) decision rule that consists of a control statistic and critical boundaries. It provides signals if the control statistic, which is updated and re-evaluated at each new period (day), crosses the critical boundary. Optimally, a control chart should not provide a signal for a long time given that no shift has occurred yet while it should trigger a signal as soon as there is an actual shift. Any obtained signal leads to the rejection of the desired "in-control" scenario, indicating that a possible change may have occurred recently. As signals might falsely emerge under the absence of a factual change, each signal requires a careful further analysis of possible causes and consequences. Our approach facilitates a detection of factual level shifts as soon as possible in terms of detection delay.[3]

We apply the suitable cumulated sum (CUSUM) control chart for an on-line detection of level shifts in the process of risk adjusted AFBI rates as derived from the US index-linked and conventional treasury yields. Our methodology shows to be useful for a quick identification of deviations (turning points) in market expectations from the desired inflation target, which can be to some extent observed in alternative lower frequency survey based indicators later on. Given that judgements on real-time changes in expectations are often derived from subjective eyeball inspection of FBI series,[4] the approach at hand provides a formal statistical guidance to evaluate such fluctuations at the daily basis. Hence, we develop a novel formal (objective) decision tool for extracting relevant information concerning shifts in inflation expectations from high-frequency (noisy) data with a statistical control for the occurrence of false signals.

This study is organized as follows: In the subsequent section, we discuss the high frequency market-based instruments, from which we derive adjusted FBI measures of inflation expectations. For this purpose, we introduce a novel risk adjustment procedure that accounts for the time series properties of the FBI rates. Based on these properties, we setup a stylized econometric model to formalize the desired (in-control) situation for the inflation expectation process, the violation of which we are interested to detect. In Section 3, we provide the on-line monitoring methodology for an early detection of shifts in the unconditional mean of the aforementioned process. In Section 4, we present an empirical analysis by performing a realistic out-of-sample monitoring exercise with regard to the anchoring of US inflation expectations. Section 5 concludes the paper, whereas the supplemental materials could be found under www3.stat-econ.uni-kiel.de/de/mitarbeiterinnen-und-mitarbeiter/j.roestel internet address.

2. MEASURING MARKET INFLATION EXPECTATIONS

In the first part of this section, we discuss the daily US FBI rates, from which we extract proxy measures (adjusted FBI) for the corresponding market inflation expectations. As the FBIs are noisy and biased due to both inflation and liquidity risks [cf. Sack and Elsasser (2004)], a proper level adjustment is necessary. For this purpose, in the second part, we introduce a novel econometric procedure to adjust FBI rates for these risks, particularly taking the FBI time series properties into account. In the third part of this section, we discuss the desired (in-control) scenario defined via properties of the adjusted FBI series that should be present in case of a successful inflation targeting policy.

2.1. Forward Breakeven Inflation and its Pitfalls

The $n - m$ year FBIs are defined as the difference between the $n - m$ forward nominal rate[5] and the $n - m$ forward real rate on conventional (nominal) and inflation protected (real) government securities, respectively. By using forward rather than spot breakeven rates, we follow the related literature such as Beechey and Wright (2008) or Gürkaynak et al. (2010). FBIs allow to study average inflation rates that are expected to occur after prices have been subject to some adjustment during the initial n years with regard to the current state of the real economy. In other words, they help to quantify how monetary policy is expected to affect inflation at different horizons.

We consider measures both of medium and long term inflation expectations. In particular, for the long term horizon, we use 5–10 FBI quotes obtained directly from the data set of Gürkaynak et al. (2010), available on the homepage of the Fed. The latter measure is seen to provide information about the credibility of the central bank's commitment to price stability [Hördahl and Tristani (2010)]. Next, for the medium term horizon, we have constructed 2–5 year FBIs using the above-mentioned data set. The daily data is collected between January 1, 2005 and June 30, 2015 such that, for each FBI series, 2,738 time instances are available. Further information on data sources[6] are provided in Table 1.

Although the original FBI rates contain valuable market information available on the daily basis, they, however, should not be used for monitoring market inflation expectations directly. Many studies underpin that the FBIs per se are both biased and rather unreliable proxies of market inflation expectations. E.g., in comparison to quarterly survey-based measures, their short-run patterns have

TABLE 1. Time series and data sources

Series	Source (code)
Forward breakeven inflation 5–10	http://www.federalreserve.gov
Zero coupon breakeven inflation 2y, 5y	http://www.federalreserve.gov
Quart. expected Inflation (5y, 10y)	Fed. Reserve Bank of Philadelphia
Quart. disagreement in exp. inflation (5y, 10y)	Fed. Reserve Bank of Philadelphia
VIX volatility index	Datastream (CBOEVIX)
US TIPS prim. dealer trad. vol. (detr.)	Datastream (USPDTVTIA)

shown to be far more volatile. According to Sack and Elsasser (2004), the most important FBI components are given by the compensation for future expected inflation rates, inflation risk, and eventual liquidity differences between the underlying nominal and inflation-protected securities. Thus, observed FBI fluctuations could be attributed to all of these sources, where especially the influence of liquidity risks might invalidate the inference on aspects of monetary policy. According to Friedman (1977) and Ball (1992) the expected inflation and the associated risk tend to be highly correlated. Therefore, an unbiased and precise measure of their aggregate compensation would still be informative for central bank credibility.

Gürkaynak et al. (2010) provide evidence that the liquidity risk premium moves rather sluggishly over time. They argue that, on a daily basis, it is primarily the premium raised on inflation risk which induces the excessive fluctuations that breakeven inflation measures exhibit on occasion. On the other hand, however, studies such as Hördahl and Tristani (2010), Chernow and Müller (2012), or Christensen et al. (2010) come to the conclusion that the impact of the inflation risk premium is rather small, stressing then the role of liquidity risk. Empirical evidence supports the conjecture that the unconditional level of US liquidity risk premia dropped substantially until 2005 [Gürkaynak et al. (2010), Herwartz and Roestel (2009)]. To minimize the influence of the permanent biases induced by a general lack of acceptance of TIPS as a new asset class, therefore, we only consider breakeven quotes after January 1, 2005 in our study. Since then, the market for inflation indexed debt is known to be rather liquid, at least in "normal" times. Nowadays, the United States has the world's largest inflation indexed securities market, with outstanding TIPS amounting to nearly one trillion USD and a daily turnover of more than 10 billion USD at the end of 2013 [Christensen and Gillan (2012)]. After 2005, severe biases according to liquidity risks have occurred rather transitorily during observable crisis scenarios such as the immediate post-Lehman period from September 2008 through the Spring of 2009.

2.2. A New Risk Adjustment Procedure for Daily FBI Series

Here, we introduce our econometric methodology for adjusting FBI series with respect to liquidity and inflation risks by accounting for their autocorrelation and heteroskedasticity properties. Let $\tilde{y}_t$ denote the observable FBI series, which are biased measures for the AFBI rates y_t. Let daily AFBI rates y_t be given by

$$y_t = \tilde{y}_t - \gamma' \mathrm{LR}_t - \lambda' \mathrm{I\!R}_t, \tag{1}$$

where LR_t and $\mathrm{I\!R}_t$ are the column vectors of nonnegative control (compensation) variables for liquidity and inflation risks, respectively. Candidate control variables are discussed in Section 4.1. As perceived inflation risks have a positive impact on nominal yields, while leaving inflation indexed (real) yields unaffected, we should expect positive signs for the elements in λ in order to get a meaningful inflation risk premium. In turn, liquidity risk premia raised on TIPS will ceteris paribus increase real TIPS yields in comparison with nominal yields, thus driving FBI rates down. Hence, one should expect negative signs for the elements in γ in order to reasonably quantify premia raised on (nonnegative) liquidity risks.

Now assume that, under the absence of structural changes in the inflation expectation process (i.e., under well-anchored inflation expectations), the dynamics of AFBI series y_t can be formalized by means of a stationary heteroskedastic AR(1) model (AR, autoregressive) such as

$$y_t = c + \phi y_{t-1} + u_t, \qquad u_t \sim (0, g_t), \qquad 0 < \phi < 1, \tag{2}$$

$$g_t = a_0 + a_1 u_{t-1}^2 + a_2 g_{t-1}, \qquad a_0 > 0,\ a_1, a_2 \geq 0, \tag{3}$$

where u_t reflects heteroskedastic noise summarizing unsystematic risk adjustment approximation errors and shocks to market inflation expectations.

Combining representations in (1) and (2) gives rise to the model

$$\begin{aligned}\tilde{y}_t &= c + \phi \tilde{y}_{t-1} + (1-\phi)(\gamma' LR_t + \lambda' IR_t) + \phi(\gamma'(LR_t - LR_{t-1}) \\ &\quad + \lambda'(IR_t - IR_{t-1})) + u_t,\end{aligned} \tag{4}$$

which can be estimated jointly with (3) via the quasi maximum likelihood procedure [cf. Francq and Zakoïan (2004)]. Notably, c and ϕ in (2) and (4) are fully equivalent. The obtained model estimators for the vectors γ and λ are used to extract the AFBI estimates, which are given as

$$\hat{y}_t = \tilde{y}_t - \hat{\gamma}' LR_t - \hat{\lambda}' IR_t. \tag{5}$$

These estimated AFBI series $\hat{y}_t$ are used in Section 4 for the sequential monitoring purpose.

2.3. The In-Control Specification

Now, we specify the desired state of "well-anchored inflation expectations" by linking characteristic time series patterns that AFBI rates should exhibit in this state to appropriate model parameter values in (2)–(3).

In particular, for inflation expectations to be well-anchored, first, the unconditional expectation $E(y_t) = c/(1-\phi) = \bar{y}$ should equal the inflation target.[7]

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Second, ϕ should not be too close to unity to guarantee that expectations are sufficiently tied to the announced inflation target, i.e., potential deviations are transitory and quickly mean-reverting. For a generally low or at least quickly resolving inflation uncertainty g_t, one would expect a small (compared to c, say) unconditional variance $a_0/(1 - a_1 - a_2) = E(g_t)$ and a limited persistence over time, i.e., $a_1 + a_2 < 1$.

Based on this model, the analyst observes standardized model errors on a daily basis

$$z_t = \frac{y_t - c - \phi y_{t-1}}{(g_t)^{1/2}}. \tag{6}$$

As long as realized dynamics of adjucted forward breakeven inflation (AFBI) levels are in line with our model implied state, these standardized errors should be zero in expectation, i.e., $E(z_t) = 0$. Likewise, if realized AFBI variance patterns conform with in-control generalized autoregressive conditional heteroskedasticity (GARCH) dynamics, we have $E(z_t^2) = 1$.

For a correctly specified model,[8] standardized innovations z_t follow a standard normal distribution under the null hypothesis "no change in the mean, no jumps/outliers," similarly to a very general stochastic process as, e.g., in Andersen et al. (2007). As the GARCH (1,1) specification in (3) appears to be generally suitable for modeling conditional volatility on financial markets,[9] we expect that the null hypothesis could be rejected either due of changes in the mean (shifts in inflation expectations) as described in Section 3.1, or due to outliers.

Put differently, violations of these error properties may indicate a deviation from the desired state of well-anchored inflation expectations. Our aim is to monitor on-line (period-by-period) whether the properties of these errors are in line with those expected in prevalence of the desired (in-control) state. The instruments for this monitoring are presented next in Section 3.

3. ON-LINE MONITORING FRAMEWORK

Residual-based online monitoring boils down to periodically reassuring that a predetermined econometric model that formalizes a normative (in-control) state still gives rise to properly behaved residuals [cf. Montgomery (2013)]. If the model begins to produce ill-behaved residuals at a certain point, a structural change is likely to have occurred. In the first part of this section, we introduce the statistical change point model, which establishes a formal link between currently observed residual behavior and shifts in the process parameters. In the second part, we present control charts as statistical on-line instruments to detect such shifts as early as possible after they occur. In this context, we discuss the popular CUSUM scheme that is suitable for the detection of unobserved changes in AFBI process means. Finally, we describe how to choose critical values for our monitoring procedure and discuss how to distinguish between true and false signals.

3.1. The Change Point Model and the In-Control State

In cases when concerns about substantial deviations from the inflation target arise, the AFBI process, which is presented in (2) and (3), should exhibit a structural change. Hence, the desired (in-control) scenario specified in Section 2.3 will no longer apply. In order to formalize the undesired development where the process gets out of control assume that a nonzero shift in market inflation expectations $\bar{y}$ occurs at some unknown time point $\tau \geq 1$, $\tau \in \mathbb{N}$. Denoting the size of the latter shift as $\Delta \neq 0$, the statistical change point model for the standardized innovations z_t reads as

$$z_t \sim \begin{cases} i.i.d.\,(0,1) \text{ for } t < \tau, & \text{in-control state;} \\ i.i.d.\,(\Delta,1) \text{ for } t \geq \tau, & \text{out-of-control state.} \end{cases} \quad (7)$$

Hence, for standardized innovations in (6), the lack of adjustment in the unconditional mean of the underlying in-control specification implies a change in the mean of z_t for $t \geq \tau$. Note that due to $\bar{y} = c/(1-\phi)$, shifts either in c, or in ϕ, or in both may lead to a change in $\bar{y}$ and, hence, in $E[z_t]$. Such change in the mean of z_t is observationally equivalent to a (local) drift in AFBI rates pointing on gradual shifts in the inflation expectations as, e.g., also empirically documented by Baxa et al. (2014).

Such shifts in long-term expectations under an explicit inflation target mostly reflect lack of market participants' confidence in long term inflation targeting success. In this context, changing such a tendency of eroding reputation within a few days by conducting short-run interventions appears hardly possible (at justifiable economic cost).[10] As level shifts in (7) should be detected as soon as possible, they are intensively discussed in the Fed's monetary policy reports. Sequential detection of such shifts in the process mean is a primary task for the inspection of inflation targeting success. Apparently, the early detection of shifts requires a sequential evaluation of the observed residual behavior. The appropriate statistical instruments for this on-line monitoring procedure are introduced below.

3.2. The On-Line Monitoring Procedure

Control charts are the major tools of statistical process control for an early (on-line) detection of changes in a process of interest. They should provide alarm signals as soon as a change actually occurs but not earlier. A *one-sided* control chart consists of a control statistic S_t and a predetermined boundary $h > 0$, which is also called critical limit. A control chart is initiated at time $t = 1$ given the starting value $S_{t=0} = S_0$. In case that the control statistic exceeds the limit immediately such that $S_{t=1} > h$, a signal is given directly at $t = 1$. Otherwise, the monitoring continues, where the control statistic is repeatedly updated for $t = 2, 3, \ldots$ until it crosses the boundary for the first time at t^*, i.e., $S_{t^*} > h$. After a signal, the control statistic is usually reset to its initiation value $S_{t=t^*} = S_0$ and the chart is restarted at $t^* + 1$ in order to proceed monitoring. Hence, we get a repeatedly applied decision procedure, which is updated based on recent realizations of the process subject to monitoring. In each period, it is to decide whether the in-control scenario is rejected by the violation of the predetermined boundary.

The family of the cumulative sum charts (CUSUM) can be traced back to Page (1954) and originates from the sequential probability ratio test of Wald [for extensions see among others Hawkins (1992), MacEachern et al. (2007), Golosnoy et al. (2009)]. The appealing detection characteristics of the standard CUSUM chart for monitoring changes in the mean have been derived by Moustakides (1986, 2008). Properties of both univariate and multivariate CUSUM control charts for residuals extracted from models similar to our specification are investigated in detail by Ord et al. (2009) and Garthoff et al. (2013). Following Montgomery (2013), the one-sided CUSUM statistics for detecting upward shifts ($\Delta > 0$) is defined as a recursion

$$S_t^+ = \max\{0, S_{t-1}^+ + z_t - \delta/2\}, \qquad S_0^+ = 0, \tag{8}$$

where the reference value $\delta > 0$ is the control chart parameter. Usually, we choose δ for the mean charts such that it corresponds to the shift size Δ, which is mostly of interest to detect, i.e., $\delta \overset{!}{=} \Delta$. The role of parameter δ for the CUSUM chart performance is well-investigated in the literature, e.g., it is illustrated by Montgomery (2013) both formally, see equation (9.6), and by means of Monte Carlo simulations.

Similarly, the CUSUM scheme for detecting downward shifts is

$$S_t^- = \max\{0, S_{t-1}^- - z_t - \delta/2\}, \qquad S_0^- = 0. \tag{9}$$

A signal from the CUSUM scheme for detection of upward shifts in (8) would be given in t if $S_t^+ > h$, whereas for downward shifts in (9) if $S_t^- > h$.

The use of the recursive CUSUM scheme for our purposes is also guided by economic intuition. Arguably, a change in the long-run inflation climate is unlikely to be completely pronounced on one particular day if credibility is yet high. Initially, the market will only carefully adjust beliefs in the news arrival process until the change is recognized by more and more market participants. While reputation erodes, the evidence of a shift occurs to be much more pronounced and expectations might become self-energizing at a certain point. The CUSUM chart, which relies on local sums,[11] suits exactly for such a type of changes in monitored processes.

3.3. Choosing the Critical Value

Since control statistics are realizations of random variables, false alarm signals might emerge in prevalence of the in-control state, while factual change points might not be indicated. Hence, each sequential test decision is subject to a possible error. In the classical test framework, one would wish to derive the boundary h by fixing the type I error for a given number of test repetitions, i.e., for a given sample size. However, the number of monitoring periods that will pass until the first false signal occurs is unknown in advance, and thus, the number of sequential test decisions to make is not fixed as in the conventional test theory but random [cf. Woodall, (2000)]. For this reason, critical bounds of control charts are usually determined by not fixing the error probability but using other criteria based on the speed of change detection [Frisén, (2008)].

In order to introduce these criteria, define the run length $L \geq 1$ as the (random) number of time periods until the first alarm occurs:

$$L = \inf\{t \geq 1 | S_t > h\}.$$

The performance of control charts is usually evaluated using the concept of the average run length (ARL), which is defined as a conditional expectation of the run length L given the chart design $\mathcal{D}$, namely the control statistic and the chart parameters, and the presumed time point of a change τ:

$$\mathrm{ARL}_\tau = E(L|\mathcal{D}, \tau \geq 1).$$

The in-control $\mathrm{ARL}_{\tau=\infty}$ is defined as the average number of periods before the first *false* signal occurs, i.e., there is no change at all (and no outliers). In turn, the out-of-control $\mathrm{ARL}_{\tau=1}$ is the average detection delay for a change that occurs immediately at $\tau = 1$. Given that there is no actual shift in the process the in-control ARL should be chosen large in order to reduce the number of false signals. Thus, a good control chart with a given large in-control ARL, i.e., with rare false signals, should detect shifts with a possibly small time delay, i.e. its out-of-control ARL should be small. Of course, the out-of-control ARL should decrease with increase of the shift size.

The critical limit h is determined by setting the in-control $\mathrm{ARL}_{\tau=\infty}$ (no structural changes) equal to a desired large value ξ, which corresponds to the average number of periods until the first *false* signal occurs:

$$\mathrm{ARL}_{\tau=\infty}(h, \mathcal{D}) = \xi. \qquad \textbf{(10)}$$

The solution of equation (10) is the boundary h, which is a function of $\xi, \mathcal{D}$. The choice of in-control ARL ξ, of course, is guided by the desired degree of conservativeness.[12] Choosing a smaller value for the in-control ARL would lead to a quicker detection of actual shifts at cost of more frequent false alarms [cf. Montgomery (2013)], similarly to the choice of a significance level by conventional statistical tests. Under the use of daily economic data, typical choices for ξ are 120, 250, 370, or 500, depending on the application [cf. Golosnoy and Hogrefe (2013)].

The approximate analytical solutions of (10) for the one-sided CUSUM scheme under independent and identically distributed (i.i.d.) normality are provided in Siegmund (1985) and Rogerson (2006). Since one should consider both upward (indicating on inflation) and downward (pointing on deflation) shifts simultaneously, it is reasonable to define the ARL with regard to the simultaneous use of upward and downward CUSUM schemes. By symmetry, $\mathrm{ARL}_\tau^+ = \mathrm{ARL}_\tau^-$ such that the ARL for the joint scheme is given as

$$\mathrm{ARL}_\tau = 1/(1/\mathrm{ARL}_\tau^+ + 1/\mathrm{ARL}_\tau^-). \qquad \textbf{(11)}$$

The in-control ARL of this two-sided CUSUM scheme is related to the critical boundary h via equations (10) and (11).

3.4. Distinguishing True and False Signals

Any obtained signal can be either true—indicating a shift in inflation expectations—or false. We design our on-line monitoring scheme such that under the assumption that the model is true, i.e., there are no mean changes and no outliers, the first false signal occurs on average after a large number of days, which is called “the in-control ARL” and resembles to type I error of conventional statistical tests. In the monitoring philosophy false alarms—cased by an accident or outliers—are more desired than missing (or signaling with a considerable detection delay) an actual change, corresponding to type II error in conventional statistical tests. If the alarm is correct, the signal would be accompanied by a locally persistent shift in market expectations lasting over the time horizon that is necessary to re-establish credibility, where this will be rather a matter of quarters than a few days in our application.

Ex post, one can classify that signals were false by analyzing additional information, asking experts etc. A persistent shift in expectations would lead to repeated signals in the same direction. Thus, a good indicator for an actual change would be several signals in the same direction within a rather short period of time, as observed, e.g., in our study at the end of 2014 in Figure 4 (all signals downward). However, at the moment of the signal it is hardly possible to say whether we face a false alarm or not based solely on the historical information contained in the monitored time series. As we compare our results with the experts' opinion concerning inflation expectations, one can immediately ask them whether they would support or not the evidence from the monitoring scheme.

A false signal could occur by an accident (analogues to type I error events) or to be an outlier (jump) which is a single standing peak (trough) not in line with the data generating process either before or after it. For our heteroskedastic series, outliers violating the normality assumption usually occur at turbulent days where the conditional variance is underestimated. In our setting, however, assuming, e.g., a t-distribution for model errors would merely result in a broader nonreject region and loss of the procedure's detection power, which is equivalent to larger detection delay for actual changes. For these reasons, we rely on the normality assumption, while interpreting seldom outliers as false signals.

Thus, in this paper, we elaborate a formal (objective) decision approach with a statistical control for false signal probability. It is advantageous compared to ad hoc approaches such as “eyeballing” decisions. Without referring to a suitable formal model that accounts for the pronounced autocorrelation and heteroskedasticity, it is almost impossible to distinguish reliably between the in-control behavior and shifts in expectations.

4. IMPLEMENTATION AND EMPIRICAL RESULTS

Now, we illustrate our approach by pursuing a realistic monitoring analysis for market-based measures of US inflation expectations. First, we describe the stochastic properties of the original FBI series and extract the AFBI time series by drawing a special attention to the FBI level adjustment via accounting for inflation and liquidity risks. Then, we specify the design of our monitoring procedure for detecting shifts in the inflation expectations, which is based on AFBI model residuals obtained under the in-control AR-GARCH specification. Finally, we present the empirical evidence for the on-line monitoring of US inflation targeting success and analyze the obtained signals from the practitioner's perspective.

4.1. Constructing AFBI Series

The FBI time series are plotted along with medium- and long-run survey-based expectations in Figures 1 and 2 (the upper plots) for a visual inspection. The corresponding full sample descriptive statistics for the considered 2–5 and 5–10 year FBI rates are reported in the first block of Table 2. With regard to the FBI time series properties, one observes patterns with mean-reverting dynamics, where transitory deviations from any constant level appear to be quite substantial. Furthermore, there is also strong evidence for ARCH effects pointing on conditional heteroskedasticity. The turbulent fluctuations during the period of the acute financial disruption (beginning in September 2008) appear unlikely to fully reflect dynamics of inflation expectations. Instead, a considerable share of such temporary fluctuations in all FBI rates could be induced by a pronounced flight to liquidity [Gürkaynak et al. (2010)]. Nevertheless, the FBI rates exhibit rather quick mean-reverting behavior also in the postcrisis period. Inspecting Figure 1 suggests that most of the time the 2–5 FBI rate tends to be lower in comparison with associated survey based rates at similar (though not identical) horizons. In contrast, the 5–10 FBI rates in Figure 2 systematically exceed the respective 10 year inflation expectations. As expected, all FBI series exhibit higher volatility in comparison with survey-based expectations.

As discussed in Section 2.2, we need suitable control variables to adjust the levels of FBIs for the liquidity and inflation risks. The choice of these variables is guided by the requirement that they have to enter with the right sign and appear to be statistically significant. There is no consensus in the literature about what should be used as a proper liquidity risk measure. We consider the volatility index VIX[13] derived from the options on the S&P 500, which is often used to capture the short run variation in liquidity risks and inflation risk premia, see Söderlind (2011), Galati et al. (2011), Christensen and Gillan (2012), or Strohsal and

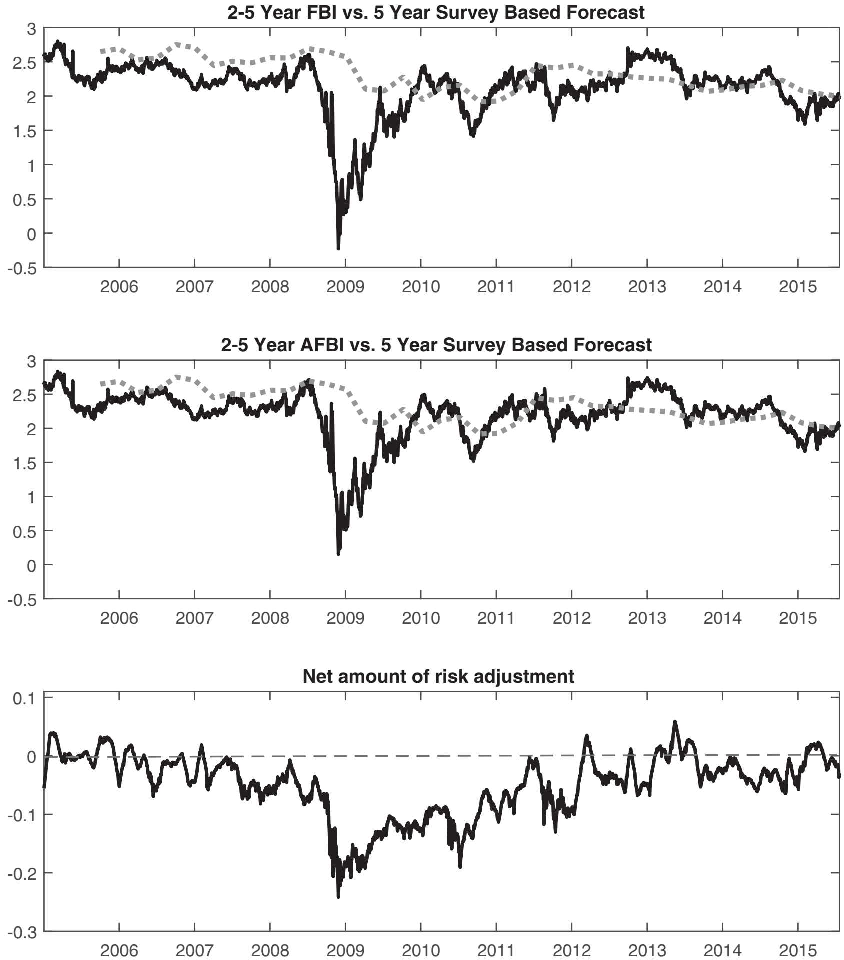

FIGURE 1. Unadjusted, adjusted, and net differences for 2–5 FBI rates. Time paths of unadjusted "FBI" (upper panel), adjusted "AFBI" (middle panel), and net differences (lower panel) for 2–5 forward breakeven inflation rates (solid) along with corresponding 5y survey-based expectations (dotted). The time paths of net adjustment given by $\hat{y}_t^{n-m} - \tilde{y}_t^{n-m} = \hat{\gamma}'\mathrm{LR}_t + \hat{\lambda}\mathbb{R}_t^m$ for the considered $n-m$ FBI rates.

Winkelmann (2015). Central bankers [cf. Salmon (2015)] also consider market volatility measured by the VIX as highly related to the liquidity risk issue. Alternatively, many authors recommend to use trading volume for this purpose [cf. Pastor and Stambaugh (2003)], some others discuss its eventual disadvantages due to its relation to idiosyncratic volatility [cf. Johnson (2008), Barinov (2014)]. For our purpose, we consider the detrended US TIPS primary dealer average daily trading volume, which is negatively correlated with the liquidity risk. Since both

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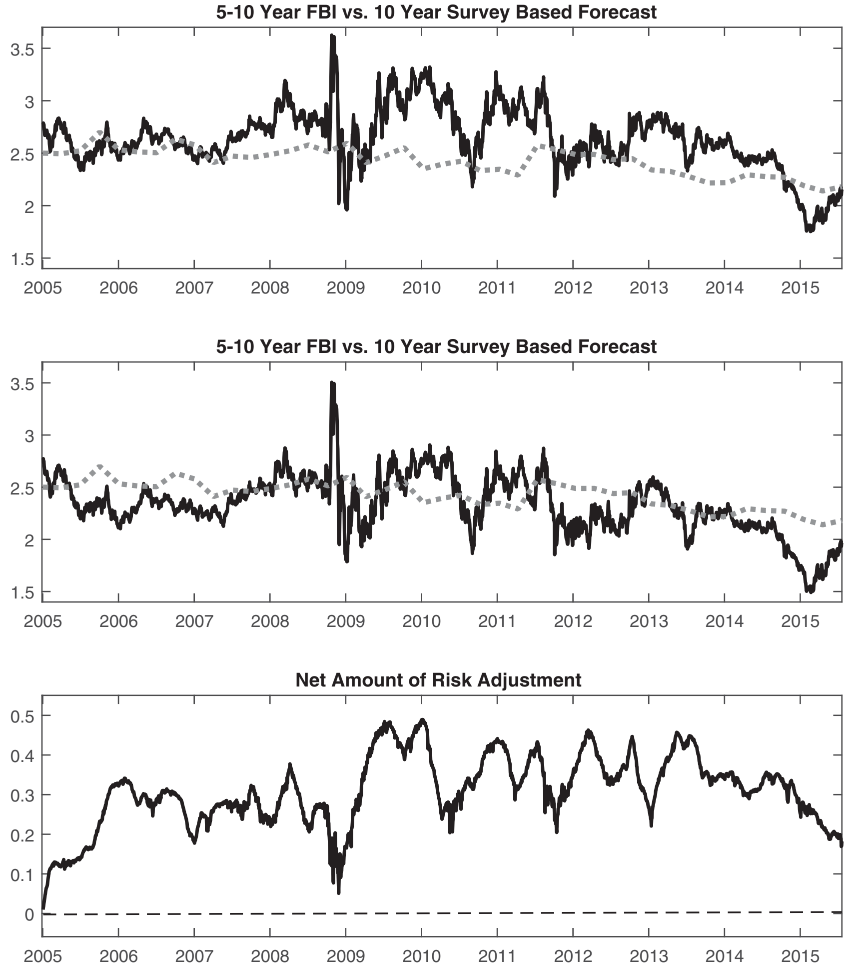

Figure 2. Unadjusted, adjusted, and net differences for 5–10 FBI rates. Time paths of unadjusted “FBI” (upper panel), adjusted “AFBI” (middle panel), and net differences (lower panel) for 5–10 forward breakeven inflation rates (solid) along with corresponding 10y survey-based expectations (dotted). The time paths of net adjustment given by $\hat{y}_t^{n-m} - \tilde{y}_t^{n-m} = \hat{\gamma}'\mathrm{LR}_t + \hat{\lambda}\mathbb{IR}_t^m$ for the considered $n-m$ FBI rates.

VIX as well as FBI trading volume appear to be significant, we include both of them into our specification as proxies for the liquidity risk.

To capture longer term variation in inflation risks $\mathbb{IR}_t$, we refer to the dispersion among individual m year inflation expectations derived from survey data collected by the Federal Reserve Bank of Philadelphia (cf. Table 1). The diversity of survey participants’ views about the outlook for inflation is the standard indicator for inflation uncertainty in Fed policy reports. Since this measure is only raised at

TABLE 2. Full sample properties of FBI, AFBI, and model residuals

Series	Mean, %	Std.Dev., %	ADF	ARCH-LM	Inv. root			
FBI 2–5	2.12	0.41	−3.37	72.95	0.993			
			(0.01)	(0.00)				
FBI 5–10	2.64	0.29	−4.24	37.91	0.988			
			(0.00)	(0.00)				
Estimates	c	ϕ	γ_1	γ_2	λ	a_0	a_1	a_2
FBI 2–5	0.022	0.990	0.005	−0.005	0.062	$2.07e-05$	0.082	0.906
	(3.19)	(354.7)	(0.63)	(−10.71)	(0.212)	(2.64)	(4.79)	(51.69)
FBI 5–10	0.013	0.994	0.013	−0.004	0.793	$5.71e-06$	0.053	0.945
	(2.82)	(482.4)	(2.02)	(−12.16)	(2.56)	(3.81)	(12.18)	(225.38)
Series	Mean, %	Std.Dev., %	ADF	ARCH-LM	Inv. root			
AFBI 2–5	2.19	0.37	−3.57	73.88	0.992			
			(0.01)	(0.00)				
AFBI 5–10	2.33	0.27	−4.54	37.40	0.987			
			(0.00)	(0.00)				
Series	Mean	Std.Dev.	JB	LB-SC	LB-CH			
z_t 2–5	−0.00	1.00	541	11.80	15.60			
			(0.00)	(0.30)	(0.10)			
z_t 5–10	0.01	1.00	1541	9.533	7.5556			
			(0.00)	(0.48)	(0.67)			

Note: Descriptive statistics along with ADF test statistics, diagnostics for the ARCH-LM test, model specifications according to the SIC and inverted AR roots for FBI and IS rates. ADF test decisions are based on heteroskedasticity-robust p-values as introduced by Cavaliere and Taylor (2008), ADF regressions include an intercept term and lag selection is according to the SIC. ARCH-LM F-statistics refer to ARCH effects up to the tenth order in a simple AR(1) model. LB-SC (LB-CH) refer to Ljung-Box test statistics for serial correlation in the (squared) residuals up to the tenth order.

quarterly frequency, we interpolate it linearly to daily frequency. The interpolation scheme is conservative in the sense that the variable's quarterly value is assigned to the last day of the respective quarter at the daily perspective.

Thus, we have a two-dimensional parameter vector $\gamma = (\gamma_1, \gamma_2)'$ to quantify the impact of liquidity risk LR_t (as approximated by the VIX and the trading volume) and a scalar parameter λ attached to our inflation risk measure IR_t. Then, we estimate the AR-GARCH model given in (3) and (4) in order to obtain the AFBI series. We will subsequently discuss the full sample estimates, although we rely only on the in-sample estimates reported in Table 3 for the monitoring purpose later on. The second block of Table 2 provides full sample estimates of model (4), whereas the statistical properties of the full sample AFBI series are reported in the third block of Table 2. Further, Figures 1 and 2 (the second plots) provide the graphs of the AFBI series together with the corresponding medium- and long-run survey-based expectations.

Apparently, the risk adjustment has led to some convergence of FBI rates to quarterly survey-based inflation expectations, notably without using any level information from the latter. Time series properties of 2–5 and 5–10 FBI implied inflation expectation rates have changed visibly after the adjustment. In line with the Federal Reserve Bank of Philadelphia's quotes on 5 year inflation expectations, 2–5 AFBI rates are somewhat higher than their unadjusted FBI counterparts, as their unconditional mean increased from 2.12% to 2.19%. In turn, market-based 5–10 year ahead inflation expectations decrease when taking risk into account. Their unconditional mean dropped from 2.64% to 2.33%, being more in line with Philadelphia's survey data on 10 year expected inflation rates. Moreover, given that FBIs are based on the information derived from CPI inflation, the value of 2.3% is consistent with the Fed's implicit inflation target of 2% personal consumption expenditures (PCE) inflation because (as a rule of thumb) PCE inflation tends to be 0.3% points below CPI inflation.[14]

Both upward adjustments in 2–5 FBI rates and downward adjustments in 5–10 FBI's as explicitly sketched in Figures 1 and 2 are economically intuitive as they likely reflect the relative importance of liquidity and inflation risks at distinct maturities. For the 5–10 FBI's, inflation risks pushing FBI upward appear to be (relatively) more of concern than liquidity risks pushing FBI downward, as TIPS are known to be most liquid around the 10 year maturity. Accordingly, 10 year ahead inflation uncertainty enters with a highly significant positive coefficient estimate. Consequently, our risk adjustment procedure induces a drop of respective 5–10 forward rates. For the 2–5 FBIs, inflation risks should not be perceived as severe under a limited time horizon and sticky prices, while liquidity risk might be more of concern compared to 5–10 FBI rates. Hence, liquidity risk dominates TIPS risk premia such that the risk adjustment induces a level increase of the respective 2–5 AFBIs. The lower panels in Figures 1 and 2 suggest that the volatility of the net adjustment is much less in comparison with the FBI series. Thus, the achieved volatility reduction by AFBI construction is only of small to moderate scale. According to Figure 2, risk adjustment for 2–5 (5–10) AFBI rates varies between

TABLE 3. In-sample properties of FBI, AFBI, and model residuals

Series	Mean, %	Std.Dev., %	ADF	ARCH-LM	Inv. root			
FBI 2–5	2.08	0.53	−2.18	37.90	0.995			
			(0.21)	(0.00)				
FBI 5–10	2.70	0.24	−4.04	22.55	0.981			
			(0.00)	(0.00)				
Estimates	c	ϕ	γ_1	γ_2	λ	a_0	a_1	a_2
FBI 2–5	0.024	0.989	0.018	−0.003	0.121	$1.08e{-}05$	0.081	0.915
	(2.35)	(236.7)	(1.60)	(−3.91)	(0.759)	(1.86)	(3.66)	(44.68)
FBI 5–10	0.043	0.978	0.028	−0.002	1.521	$7.20e{-}06$	0.073	0.920
	(3.74)	(186.9)	(3.34)	(−4.04)	(5.64)	(2.59)	(8.09)	(91.09)
Series	Mean, %	Std.Dev., %	ADF	ARCH-LM	Inv. root	Median $(\tilde{g})^{1/2}$		
AFBI 2–5	2.14	0.48	−2.34	38.23	0.994	0.0333		
			(0.16)	(0.00)				
AFBI 5–10	2.05	0.22	−5.02	21.51	0.973	0.0292		
			(0.00)	(0.00)				
Series	Mean	Std.Dev.	JB	LB-SC	LB-CH			
$z^{(2-5)}$	−0.01	1.00	143	16.03	4.92			
			(0.00)	(0.092)	(0.90)			
$z^{(5-10)}$	0.00	1.00	263	16.62	4.44			
			(0.00)	(0.083)	(0.925)			

Note: Descriptive statistics along with ADF test statistics, diagnostics for the ARCH-LM test, model specifications according to the SIC and inverted AR roots for FBI and IS rates. ADF test decisions are based on heteroskedasticity-robust p-values as introduced by Cavaliere and Taylor (2008), ADF regressions include an intercept term and lag selection is according to the SIC. ARCH-LM F-statistics refer to ARCH effects up to the tenth order in a simple AR(1) model.

0.01 and 0.49 (-0.24 and 0.06) percentage points. For a proper accounting for conditional volatility in the AFBI series, we apply a GARCH(1,1) specification as in (3).

Our analysis is based on the presumption that although the AFBI measures appear to exaggerate local fluctuations in expectations compared to alternative (survey based) *measures* of unobserved market expectations,[15] they contain valuable timing information available on the daily basis. This information has great advantages compared to expert surveys, which are collected over time intervals of considerable length and represent personal opinions but not investment decisions. Before responding to the survey, participants have plenty of time to gather information and talk to other experts. When reacting to daily news, market participants are in a less comfortable situation; moreover, incorrect assumptions on future inflation will imply immediate cost. In this sense, it is not a surprise that daily market-based measures react more sensitive to news and are more volatile than survey-based expectations. Note that building moving averages (rolling windows) for AFBI's would provide smoother series, which are more similar to those from expert surveys. However, such smoothing would lead to a loss of information actuality. Instead, we account for the time varying volatility and potential local exaggerations of these market-based measures by means of suitable statistical models. This allows to infer in real time on alterations of the AFBI series from their in-control behavior under well-anchored inflation expectations.

Thus, by arguing that market-based FBI measures of medium- and long-run ex ante inflation should exhibit a stationary heteroskedastic AR process under well-anchored inflation expectations (in-control state) and taking above-mentioned risks into account, we arrive at AFBI levels which, on average, appear consistent with both survey-based expectations and the Fed's communication strategy. Our modeling strategy receives further support by the residual diagnostics provided in the fourth block of Tables 2 and 3. However, as there could be temporary deviations from the desired state, we proceed with our sequential analysis.

4.2. Design of the Monitoring Procedure

The implementation of an on-line monitoring procedure requires a specific parametrization of the desired in-control scenario, the control chart design and the critical boundaries. We subsequently describe the parameter settings used for our purposes, acknowledging that a realistic out-of-sample (on-line) monitoring requires all parameters to be known ex ante.

To formalize the desired state of monetary policy, we use the in-sample (i.e., pre-monitoring sample) estimates for the in-control scenario by using the parsimonious model specification in (3) to (4). More precisely, we refer to estimates obtained from a sampling period from the 1st January 2005 to the 31 December 2009, which is characterized by both calm and turbulent market conditions particularly during the subprime crisis. Though at first sight it might appear counterintuitive to use this period as a reference for the in-control scenario, it is reasonable with regard to our

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monitoring objectives. First, this period is characterized by sufficient variation in transitory crisis-induced liquidity risks that can be captured by the VIX. Second, the reports of the Fed reserve board suggest that long-run expectations were quite stable during this period, while perceived inflation risks were not, as one could also conclude from analyzing the considered $\mathbb{R}_t$ series. The descriptive statistics and estimation results for the presample are summarized in Table 3, while the corresponding full sample diagnostics are given in Table 2.

According to the residual diagnostics in Table 3, the model setting as specified above appears to match the empirical AFBI dynamics during the in-control period quite well. The Ljung-Box Q-statistics indicate the absence of autocorrelation up to the tenth lag order both in standardized and squared standardized AFBI residuals.

Having specified the in-control process parameters for the AFBI series, we need to complete the design $\mathcal{D}$ of our CUSUM monitoring procedure by selecting the reference value δ and the critical boundary h. Arguably, an economically significant change in $\bar{y}$ would require a reaction of monetary policy. During 2010, for instance, the Fed staff members started to worry about deflation scenarios when inflation was very low, about half of the Fed's implicit target. Based on this observation and a mean value of about $\bar{y} \in [2.0\%, 2.3\%]$ as a proxy for the desired ex ante inflation [Ireland (2007), Hördahl and Tristani (2010)], we consider a change of about 1% in inflation expectations as economically significant. We emphasize that our aim is not to detect changes in the observed noisy market based AFBI rates but in the unconditional mean of the process. Heuristic ad hoc decision rules (say, "AFBI rates exceed 3.5%") are often misleading because one disregards autoregressive and heteroskedastic nature of AFBI time series.

In order to relate the shift of 1% affecting $\bar{y}$ to the corresponding change Δ defined via (6) and (7), we have to specify the in-control value of the conditional variance g_t. For this purpose, we use the robust median measure denoted by $\tilde{g}$. For 5–10 AFBI quotes, for instance, its square root in "normal" times is roughly $(\tilde{g})^{1/2} \approx 0.0292$. Then, using numerical values for ϕ, $\bar{y}$, and c from the in-control 5–10 AFBI model, we specify the change magnitude in the mean of 5–10 AFBI residuals we want to detect. Referring to in-control estimates in Table 3, the value of Δ_{5-10} as defined in (7) amounts to

$$\Delta_{5-10} = \frac{(\bar{y} + 1\%)(1 - \phi) - c}{(\tilde{g})^{1/2}} = \frac{(2.05 + 1) \cdot (1 - 0.978) - 0.043}{0.0292} \approx 0.825. \tag{12}$$

The change magnitude of interest in the means of 2–5 AFBI residuals can be obtained in full analogy. The corresponding critical values h for different in-control ARLs obtained from solving (10) are provided in Table 4 where we summarize the information about the control chart parameters.

Keeping the in-control parameters fixed, we perform out of sample monitoring for the period from the 1st January, 2010 till the 30th June 2015. For this purpose,

TABLE 4. Design parameters for the control charts

	In-control parameters					Critical value h for
Series	$\hat{c}$	$\hat{\phi}$	$\bar{y}$	$(\tilde{g})^{1/2}$	Δ	ARL$\in$ {200, 300, 400, 500}
2–5	0.024	0.989	2.14	0.0333	0.326	{6.99, 8.013, 8.768, 9.368}
5–10	0.043	0.978	2.05	0.0292	0.825	{4.065, 4.514, 4.837, 5.089}

we apply two-sided CUSUM control charts for monitoring medium- and long-run AFBI rates.

4.3. On-Line Monitoring: The Empirical Evidence

Subsequently, we present and evaluate alarms from monitoring the daily AFBI series. In this respect, judgment has to be made on whether the obtained signals provide significant assistance for an analyst to identify shifts in the inflation climate in real time. Of course, the true shifts are not directly unobservable. To some extent, however, shifts of a meaningful magnitude (in economic terms) should instantaneously materialize in market based AFBI rates and, with some delay, in survey based indicators.

In this sense, at least two different ways appear reasonable to evaluate the economic significance of the obtained signals. First, one might ask to what extent the signals give quick indications on substantial alterations concerning the path of the AFBI series itself. Signals should emerge in case that AFBI rates start to deviate “strongly” (with regard to the current state of market turbulence) and/or permanently from the presumed inflation target.

Second, one might evaluate the signals by studying their ability to forestall or at least mimic movements in alternative lower frequency indicators such as survey-based inflation expectations [cf. Branch (2004)].[16] Normally, correct upward (downward) signals should be followed by respective movements in lower frequency survey-based indicators.[17] Likewise, if survey-based indicators persistently exceed (fall below) the in-control inflation target in a meaningful manner, one would expect repeated upward (downward) AFBI-based alarms for the case of the unchanged in-control specification.

The CUSUM control charts, in particular control statistics, critical limits, and the obtained signals for the medium- and long-run AFBI rates are visualized in Figures 3 and 4 for the in-control ARL = 400, which corresponds (on average) to about three false signals during the monitoring period of 1,435 daily observations. The first and second panels of Figures 3 and 4 show the CUSUM charts for positive and negative changes in observed proxies of inflation expectations. Furthermore, the respective AFBI time paths and the quarterly survey-based expectations converted to daily frequency by a linear interpolation are sketched in the third and fourth panels, respectively. Moreover, Table 5 provides a complete list of dates for the observed alarms for several settings with different in-control ARLs.

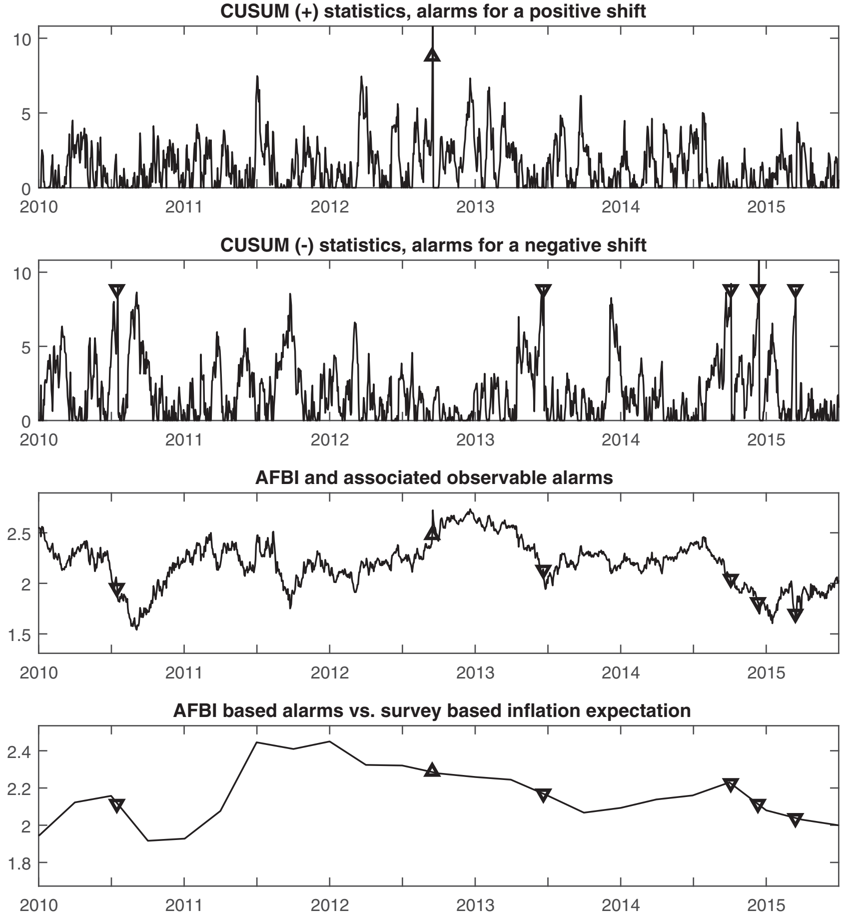

FIGURE 3. Observable high frequency alarms from 2 to 5 year AFBI rates, ARL=400. AFBI CUSUM charts (solid) and associated alarms based on the critical limit $h = 8.768$ (given in triangles) for both positive shifts (upper panel) and negative shifts (second panel). In the third panel, the aforementioned signals are plotted along with the AFBI series and, in the lower panel, along with lower frequency expert survey-based 5 year expected inflation rates.

We will subsequently refer to results based upon the in-control ARL= 400. The evidence for other ARLs is rather similar (see Table 5), which points on the robustness of our detection procedure. First, we discuss monitoring results for the medium term 2–5 AFBI series provided in Figure 3. In the third panel of Figure 3, there are six signals of deviations from the in-control target of 2.14%, five pointing downward and one upward. The marked temporary downshift in 2–5 AFBI rates in mid-2010 is early indicated on 16/7/2010. Next, the downward signal at 20/6/2013 heralds a local minimum of AFBI rates. Last, the AFBI

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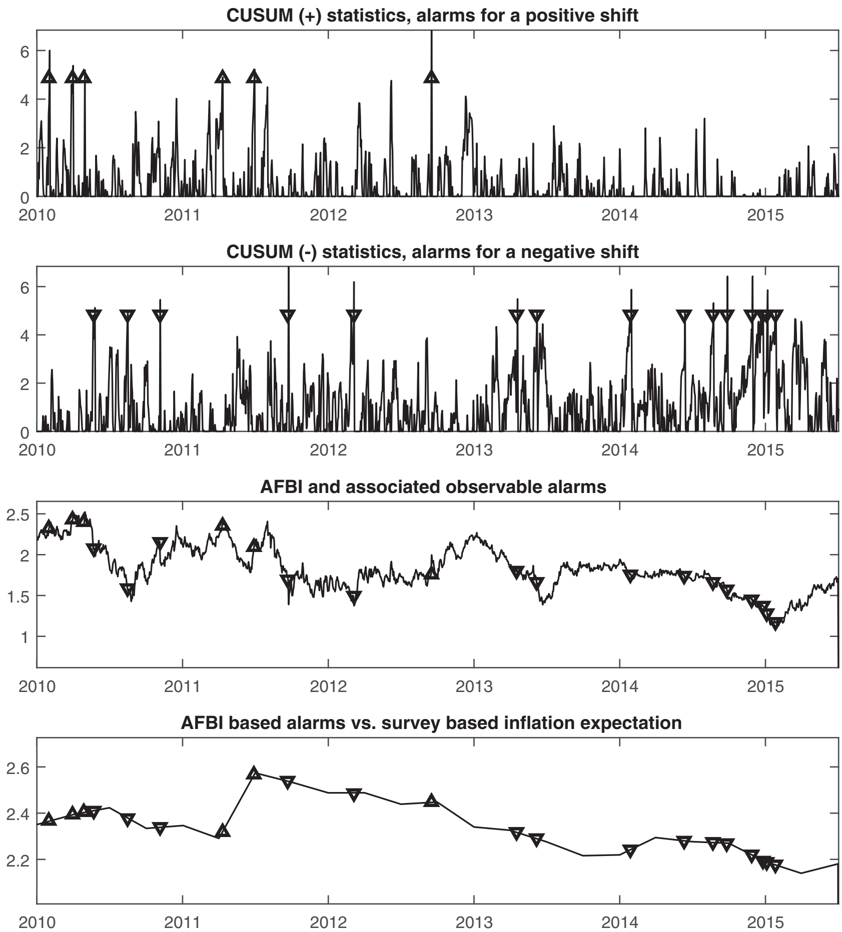

FIGURE 4. Observable high frequency alarms from 5 to 10 year AFBI rates, ARL = 400. AFBI CUSUM charts (solid) and associated alarms based on the critical limit $h = 4.837$ (given in triangles) for both positive shifts (upper panel) and negative shifts (second panel). In the third panel, the aforementioned signals are plotted along with the FBI series and, in the lower panel, along with lower frequency expert survey-based 10 year expected inflation rates.

downshift between the end of 2014 and the beginning of 2015 is indicated three times, namely on 3/10/2014, 12/12/2014, and 16/3/2015. Apparently, most signals appear to provide a reasonable timing with regard to important developments either by announcing temporary shifts or by indicating current deviations of AFBI rates from the target. Regarding the only upward signal on 14 September 2012, one might dispute if it reflects an early indication, or an outlier in AFBI rates, given that the corresponding hike fully reverses within a few days.

TABLE 5. Dates of signals for the CUSUM charts

Series	ARL	2010	2011	2012
2–5	200	6/7▼ 12/8▼	1/7▲ 19/9▼	20/3▲ 14/9▲ 18/12▲
	300	16/7▼ 1/9▼	22/9▼	14/9▲
	400	16/7▼		14/9▲
	500	19/7▼		14/9▲
5–10	200	1/2▲ 26/3▲ 29/4▲ 20/5▼ 13/8▼ 4/11▼	8/4▲ 28/6▲ 1/8▲ 22/9▼	27/2▼ 5/6▲ 14/9▲ 10/12▲
	300	1/2▲ 26/3▲ 29/4▲ 20/5▼ 16/8▼ 4/11▼	8/4▲ 29/6▲ 1/8▲ 22/9▼	27/2▼ 6/6▲ 14/9▲
	400	1/2▲ 31/3▲ 29/4▲ 25/5▼ 16/8▼ 4/11▼	11/4▲ 29/6▲ 22/9▼	5/3▼ 14/9▲
	500	1/2▲ 31/3▲ 29/4▲ 25/5▼ 18/8▼ 4/11▼	12/4▲ 29/6▲ 22/9▼	5/3▼ 14/9▲
Series	**ARL**	**2013**	**2014**	**2015**
2–5	200	13/6▼ 4/12▼	19/9▼ 28/11▼ 12/12▼	11/3▼
	300	14/6▼ 6/12▼	22/9▼ 8/12▼	15/1▼ 16/3▼
	400	20/6▼	3/10▼ 12/12▼	16/3▼
	500	21/6▼	7/10▼ 12/12▼	
5–10	200	25/2▼ 18/4▼ 6/6▼ 13/6▼	23/1▼ 12/6▼ 20/8▼ 26/9▼ 26/11▼ 8/12▼ 30/12▼	7/1▼ 27/1▼ 16/3▼ 31/3▼
	300	18/4▼ 6/6▲	24/1▼ 12/6▼ 22/8▼ 26/9▼ 28/11▼ 12/12▼	5/1▼ 12/1▼ 16/3▼
	400	18/4▼ 6/6▼	29/1▼ 12/6▼ 22/8▼ 26/9▼ 28/11▼ 24/12▼	6/1▼ 27/1▼
	500	18/4▼ 10/6▲	29/1▼ 13/6▼ 22/8▼ 26/9▼ 28/11▼ 26/12▼	6/1▼ 28/1▼

Note: ▲ and ▼ denote the upward and downward signals, respectively.

Comparing 2–5 AFBI-based signal information to patterns of lower frequency survey-based medium run expected inflation in the lower panel of Figure 3 reveals that, apart from the (ambiguous) upward signal on 14 September 2012, all important downward deviations of survey-based expectations from the in-control target receive an early indication, namely this holds for the downward shifts after 2010Q2, 2013Q2, and 2014Q3.

Second, we consider monitoring results for the 5–10 AFBI series, which (in the unadjusted form) is the standard market-based monetary policy indicator for long-term market inflation expectations. For this series, we observe 6 upward and 15 downward shifts. It appears that 19 out of 21 signals either come along with substantial AFBI turning points or coincide with local AFBI maxima/minima. As given in the third panel of Figure 4, in particular 5 of 6 observed upward signals at 1/2/2010, 31/3/2010, 29/4/2010, 11/4/2011, 29/6/2011, as well as the majority of downward shifts at 25/5/2010 16/8/2010, 22/9/2011, 5/3/2012, 6/6/2013, 29/1/2014, 22/8/2014, 26/9/2014, 28/11/2014, 24/12/2014, 6/1/2015 and 27/1/2015 announce or point at local extrema in AFBI rates. Again, all persistent level shifts in inflation expectations are indicated at an early stage. The large number of signals for the 5–10 AFBI series compared to the 2–5 AFBI series is due to its relatively low unconditional variance (see Table 3) so that changes in the 5–10 expectations can be identified more easily. In addition, the 5–10 AFBI series exhibits a lower persistence (in comparison to the 2–5 series), which also facilitates the identification of such level shifts. Inspecting the fourth panel of Figure 4 suggests that almost all AFBI-based alarms tend to anticipate or mimic longer term movements in the survey-based expectations. For instance, the "large" upswing of survey-based expectations after 2011Q1 is accompanied by a signal on 11/4/2011, indicating an upshifting unconditional expectation. The decline in expectations at the beginning of 2011Q3 is indicated early at 22/9/2011, as well the observed downward shifts after 2013Q2 and 2014Q3 are indicated at 16/6/2013 and 22/8/2014, respectively. Notably, only 2 out of 21 signals are clearly at odds with survey-based expectations, namely the presumed outlier at 14/9/2012 and the signal at 21/1/2014, which is, however, supported by further developments of the AFBI series.

Several signal dates are of particular interest as they occur for all considered inflation horizons and most ARLs, namely the downward signals in August 2010, September 2011, June 2013, September 2014, December 2014, and March 2015, as well as the pronounced upward signal at 14/9/2012. The former six downward shifts can be explained by information available from both financial markets and by statements of the Fed. In August 2010, the Fed reported that "measures of underlying inflation have trended lower in recent quarters and, with substantial resource slack continuing to restrain cost pressures and longer-term inflation expectations stable, inflation is likely to be subdued for some time." The downward signals on 22 September 2011 correspond to the sharp drop of stock markets in the mid of September 2011 initiated by the Standard & Poor's downgrade of the US credit rating from AAA to AA+ on 6th August 2011. In June 2013, the

Fed recognized that "inflation persistently below its 2 percent objective could pose risks to economic performance, but it anticipates that inflation will move back toward its objective over the medium term." On the contrary, the outlier at 14/9/2012 seems to be related to the local peak in volatility of energy prices at that day, which caused a steep but temporary increase in all considered AFBI series. The clustering of downward signals in late-2014 and early-2015 is also supported by statements of the Fed.[18] According to the Fed, "A steep drop in crude oil prices since the middle of last year has put downward pressure on overall inflation." The Fed further noted that "As of December 2014, the price index for personal consumption expenditures was only 3/4 percent higher than a year earlier, a rate of increase that is well below the FOMC's longer-run goal of 2 percent."

Subsuming, our evidence suggests that a formal sequential analysis reveals additional information that cannot be just "seen" by a simple ex ante eyeball inspection of the AFBI series. Hence, our procedure appears to be helpful for the on-line detection of shifts in the inflation climate. Frequently, AFBI signals either come along with substantial AFBI turning points or coincide with local AFBI maxima/minima. It is noteworthy that, despite the fact that AFBI rates and survey based expectations are correlated rather weakly, AFBI based signals tend to anticipate or mimic important deviations from the presumed in-control inflation target in the survey based indicators. Hence, applying our on-line surveillance techniques to noisy and heteroskedastic financial market-based monetary policy indicators helps to extract reliable timely information from them. Furthermore, signals appear to be meaningful throughout the period 1/1/2010–20/6/2015, although the model is estimated for data collected between 1/1/2005–31/12/2009. This might reflect that both the in-control period and the model specification were chosen reasonably.

5. CONCLUSION

Policy makers pay close attention to real-time information inherent in asset prices in order to infer on economic conditions and expectations in a timely manner. Real-time monitoring of market participants' inflation expectations at distinct horizons is of particular concern under the presence of potential inflation/deflation threats and economic uncertainty. Monitoring such market based expectations, however, is notoriously difficult as respective indicators such as FBI rates tend to be biased, noisy, and heteroskedastic.

In this paper, we propose a novel econometric specification to adjust FBI rates for risks, and then suggest an on-line monitoring procedure for an early detection of possible level (mean) shifts in AFBI series. By condensing the noisy information from daily AFBIs into early warning signals, the CUSUM control chart appears to facilitate the detection of shifting inflation perceptions in real time. We apply our methods for US data from 2005 till 2015. Our signals either come along with substantial AFBI turning points or coincide with local AFBI maxima/minima. Moreover, the changes we detect frequently materialize (usually with a small delay) in the most important movements of survey (expert-based) indicators, which are available on a quarterly basis.

NOTES

1. Initial acceptance problems of inflation indexed debt gave rise to temporary liquidity risk premia pushing breakeven inflation below factual expectations. Since 2005, the influence of liquidity risk on daily movements appears small, except in situations of massive financial market dysfunction such as the immediate post-Lehman period [Gürkaynak et al. (2010)].

2. Survey-based control variables are often available only at the quarterly frequency.

3. This art of monitoring is different from procedures as in Chu et al. (1996), Zeileis et al. (2005), or Breitung and Homm (2012) that are conservative in the sense that they are designed to fix the test size (type I error probability).

4. Notably, particularly for the AFBI process, inferences by means of "naive eyeballing" would be rather misleading as their time series patterns exhibit a pronounced persistence and heteroskedasticity. Thus, our approach should be favored over heuristic "naive eyeballing" procedures, as the latter are subjective in the sense that different heuristic rules may provide very different signals.

5. The $n - m$ year nominal rate in t refers to the nominal interest rate that market participants currently expect to prevail between year n and m.

6. The exact links are www.federalreserve.gov/pubs/feds/2006/200628/200628abs.html; www.philadelphiafed.org.../research-and-data/real-time-center/survey-of-professional-forecasters/historical-data/mean-forecasts.../research-and-data/real-time-center/survey-of-professional-forecasters/historical-data/dispersion-forecasts.

7. Of course, the inflation risk premium should also be rather low. In this study, however, we concentrate on the level of inflation expectations.

8. Note that an analyst could formalize a normative state by selecting particular parameter values within a suitable econometric framework.

9. A closely related stochastic volatility approach is applied by Rafiq (2014), Henzel and Wieland (2017).

10. In general, changing public perceptions on central bank credibility is a long-term issue. However, such shifts would be transitory in case that the central bank succeeds to re-establish (in some time) credibility tightening around the target.

11. If $S_t^+ < 0$ then it is set to zero for further calculation of the CUSUM recursion. Thus, the CUSUM scheme cumulates observations locally, i.e., from the last restart.

12. One should reconsider the term "conservativeness" in the framework of on-line monitoring. Obtaining false signals is not crucial as the cost of analyzing the economic circumstances for an observed signal are small in relation to the cost of missing a factual level shift. In this respect, our approach differs from the monitoring procedures in spirit of Chu et al. (1996), which are designed to control probability of type I error.

13. We also tried Merryl Lynch's MOVE 6 month bond volatility index; however, its liquidity risk premia estimate appears to be of the wrong sign.

14. We thank Jonathan Wright for this remark.

15. In general, no reason exists to consider survey quotes as being "true" or clearly superior to more volatile market-based proxies in reflecting the markets' expectations. We thank Kajal Lahiri for emphasizing this point.

16. Such comparisons are standard in the literature on extracting long-term expectations from (forward) breakeven inflation rates (see Gürkanak et al. 2010, for instance). With regard to such comparison, however, one has to keep in mind that (i) most of the corresponding survey-based data is only available at quarterly frequency and (ii) it is not based on real economic decisions. Moreover, survey sheets are collected over substantial time horizons, which implies some form of averaging in comparison to daily quotes on market expectations. In general, one should be cautions to uncritically

consider survey quotes as "true" or clearly superior to market-based proxies in reflecting the markets' expectation [Grothe and Meyler (2015), Trehan (2015)].

17. This might be not the case if overreactions on news put themselves into perspective before the collection of surveys sheets has finished.

18. See http://www.federalreserve.gov/monetarypolicy/mpr_20150224_summary.htm

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