The Anchoring of Inflation Expectations: A Bayesian Approach.

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Job Market Paper

Abstract

An important indicator for policy makers is whether long-term inflation expectations (IEs) are anchored. In this paper, I employ Bayesian time-varying news regressions to assess whether medium- and long-term IEs are anchored. First, I show that the sensitivity of long-term IEs to most macroeconomic and monetary policy news either stayed constant or gradually decreased in the aftermath of the recent crisis, resulting in more anchored IEs. Second, I show that the clear decrease in the sensitivity of long-term IEs to some news is not only due to the introduction of an explicit inflation target by the Fed in 2012, but also to other macroeconomic variables. Third, I document time variation in the response of market-based inflation expectations to price, real side and monetary policy news.

Keywords: inflation expectations, anchoring, news, time-varying parameters, Bayesian analysis, TIPS break-even rates, structural breaks

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1 Introduction

Price stability is one of the important mandates of all central banks across the world. Having inflation expectations anchored reflects the credibility of a central bank and in turn helps keep inflation in check, as the New Keynesian Philips curve predicts. Recently, many central banks adopted the anchoring of IEs as an important indicator in deciding whether to lift policy rates off the zero lower bound.

The extent of (de)anchoring is commonly measured as the magnitude of the response of changes in long-term market-based IEs to macroeconomic news see – Gurkaynak, Sack and Swanson (2005).[1] If IEs do not respond to these news, they are anchored. If their response is sizable, they are not anchored. Given that the private sector constantly updates its beliefs about the macroeconomy, it is plausible that it will react to the same news in a time-varying fashion, that is, in a slower or a faster way, depending on the type of announcement and the state of the economy (see - Faust et al. (2007)).

In this paper, I employ a Bayesian analysis to quantify the time-varying response of US market-based IEs to different macroeconomic and monetary policy news. The reasons behind applying a Bayesian econometric framework can be summarized as follows: First, it is intuitive to assume that financial market participants learn in a Bayesian manner and quantify their beliefs econometrically. Thus, they start with some beliefs on the true sensitivity of IEs to news and update these beliefs as news arrive through Bayes rule, see – Baxter (1985) and Rossi and Rebucci (2004) who use a similar reasoning but in a different context. Second, Kuroda (2015) in his speech at the Economic Club of Minnesota, highlights the importance of using Bayesian updating when analyzing how inflation expectations are formed and revised. Third, Cogley and Sargent (2002) and Primiceri (2005) stress the importance of using Bayesian techniques when the coefficients are modeled as random variables and data comes from economies in which agents are learning.

[1]There are other criteria to assess the anchoring of IEs. For example, Strohsal and Winkelmann (2015) study the anchoring of IEs by analyzing their level and persistence. In addition to employing news regressions, Beechey, Johannsen and Levin (2011) study the volatility of IEs. Moreover, Jochmann, Koop and Potter (2010) and Gefang, Koop and Potter (2012) focus on inflation pass through, i.e., how changes in short term IEs affect long term IEs. Bomfim and Rudebusch (2000) and Demertzis, Marcellino and Viegi (2012) characterize the anchoring of IEs by the absence of a significant impact of lagged inflation on long-run IEs.

I employ both medium-term and long-term market-based measures of IEs. I show that in the aftermath of the recent crisis (2009-2011), long-term IEs became more anchored since their sensitivity to most news is non-increasing; suggesting that the credibility of the Federal Reserve Bank surged in recent years.

To my knowledge, this is the first paper that analyzes time-variation in US IEs' anchoring in a Bayesian context. The most common approach so far is to estimate constant news-regressions - see Gurkaynak, Sack and Swanson (2005), Gurkaynak, Levin and Swanson (2010), and Beechey and Jonathan (2009). Gurkaynak, Sack and Swanson (2005) find that US long-run IEs are not perfectly anchored and highlight a potential drawback in current macroeconomic models which assume that long-run level of inflation is constant and perfectly known by all agents. In a similar fashion, Gurkaynak, Levin and Swanson (2010) show that Inflation targeting helps anchor IEs and Beechey and Jonathan (2009) find that IEs are more firmly anchored in the Euro Area than in the United States. More recent papers by Galati, Poelhekke and Zhou (2011) and Nautz and Strohsal (2015) allow for time-variation by means of structural breaks. They confirm the de-anchoring of IEs by finding a break around 2008-2009. However, Nautz and Strohsal (2015) find no significant break in the aftermath of the crisis, hinting that re-anchoring did not occur yet.

In contrast to the previous studies, we allow for time-variation in the response to news in the spirit of Cooley and Prescott (1976) and Lucas (1976), where the coefficients are modelled as driftless random walks. Using the latter more flexible specification estimated by Bayesian techniques, we find gradual decrease in the sensitivity of far ahead forward break-even inflation (BEI) rates to CPI (consumer price index), PPI (producer price index), RS (retail sales), ISM manufacturing index, Capacity Utilization, Industrial Production and Monetary policy news, in the aftermath of the crisis. Closer to our work, Scharnagl and Stapf (2015) examine whether IEs were de-anchored during the European sovereign debt crisis. They estimate time-varying news regressions, however by Flexible least squares, to find that the response of inflation expectations to monetary policy news exhibits some time variation. Moreover, Strohsal, Melnick and Nautz (2015) propose a time-varying parameter model, estimated by Maximum Likelihood, to explore whether lagged inflation and short-term IEs affect long term IEs. They conclude that US IEs were partially de-anchored during the financial crisis but got re-anchored since then, which is in line with our findings but using a different anchoring criterion.

Additionally, by regressing responses on macro determinants, I show that this credibility surge is not only due to the Fed inflation target announcement in 2012 but also to the state of the labor market (Unemployment rate), the stock market volatility (VIX), the federal funds rate and the exchange value of the dollar.

The remainder of the paper is structured as follows. In section 2 we lay out the constant parameter and time-varying news regressions. In section 3, we discuss the data used to obtain IEs and news. In section 4, we discuss the Bayesian inference used to estimate the time-varying news regressions. In section 5 and 6, we examine the results from constant parameter and time-varying news regressions. In section 7, we provide results of news regressions with structural breaks. In section 8, we uncover the determinants of time-variation and we carry out some robustness checks in section 9. In the last section we conclude and an appendix contains supplementary material.

2 News Regressions

2.1 Constant Parameter News Regressions

The effect of macroeconomic announcements on IEs is studied in the following news regression, or event study, as in Balduzzi, Elton and Green (2001):

$$\Delta\pi^e_{t,i} = \beta_{0i} + \beta_{1i}S_{it} + \sum_{k=1}^{K} \beta_{k+1,i}S_{i_k t} + \epsilon_{it} \tag{1}$$

where $\Delta\pi^e_{t,i}$ corresponds to the daily[2] change, in basis points, of long and medium term IEs after announcement i at time t, β_{1i} is the basis point change in IEs to a one standard error change in announcement i, controlling for concurrent announcements, K denotes the total number of concurrent announcements (with announcement i), $\beta_{k+1,i}$ is the sensitivity of IEs to the kth announcement concurrent with i, $S_{i_k t}$ is the standardized surprise in the kth announcement concurrent with announcement i, ϵ_{it} is a residual representing the influence of other news and factors on IEs that day.

S_{it} and $S_{i_k t}$ consist of the unforecastable component of data releases and are calculated as the difference between the actual economic release, A_{it}, and

[2] We stick to a daily window instead of an intra daily window and that is because forward BEI rates take some time to adjust to incoming news – see D. Bauer (2015).

the consensus expectations of the release, E_{it}, and then normalized by their standard errors to facilitate comparison across different news types, as follows: $S_{it} = \frac{A_{it}-E_{it}}{\sigma(A_{it}-E_{it})}$.

Since we use the unexpected component of macro releases, S_{it} can be regarded as strictly exogenous and thus we can rule out any reverse causality stemming from interest rates (in our cases yields and forward rates) feeding back to the economy, under the assumption that survey expectations incorporate all relevant information as of the day before the release.[3]

It is important to note that there are two ways to assess the effect of news on IEs. The first approach pursued by Balduzzi, Elton and Green (2001) and Faust et al. (2007), which we also adopt throughout the paper and is summarized by equation (1), studies the response of a particular surprise on IEs taking into account the concurrent announcements. This specification allows the differential impact of the announcement under study given the concurrent announcements. Thus, the number of observations and the frequency used in regressions like (1) are solely determined by the frequency of the announcement under consideration (i.e., quarterly, monthly, or weekly). Thus, they are not daily regressions, however, each observation of the dependent variable is the one-day change in BEI rates around the announcement date.[4]

The second approach, see Beechey, Johannsen and Levin (2011) and Gurkaynak, Sack and Swanson (2005), includes in a single regression surprises in all economic announcements (concurrent and nonconcurrent), and the sample contains only announcement days across all surprises. Since macro economic announcements have different frequencies, the one-regression approach entails putting a lot of zeros for macro announcements which are announced less frequently (i.e., GDP), to make the regression balanced. This leads to the introduction of false time-variation, which biases the estimates and inflates their standard errors. For this reason, we stick to the first approach. Conceptually, putting zeros for low frequent variables on days when they are not announced is incorrect because it means that we equate 'no announcement' to having zero forecast errors.

[3]Rigobon and Sack (2008) argue that data surprises commonly used are noisy measures of the true surprises. One reason is that MMS survey expectations are taken the Friday before the announcement and this might violate the assumption that they incorporate all information until the release day and in turn underestimate the response to news.

[4]Implicitly, this approach entails that announcements taking place at different days are orthogonal or independent. This assumption is plausible given that financial markets react to surprises very fast, typically within hours or minutes.

2.2 Time-Varying News-Regression in State Space Representation

How does the sensitivity of IEs to incoming news evolve over time and by how much? The answer to this question requires allowing for gradual changes in the response to news, rather than assuming, ex-ante, that sensitivity exhibits discrete and sudden breaks. Gradual movements in the sensitivity of IEs is economically more plausible if market participants are learning and updating their expectations over time – see Cogley and Sargent (2002) and Goldberg and Grisse (2013). Moreover, as highlighted in Boivin (2006) and Stock and Watson (2002) the estimates of multiple break dates can be quite uncertain in macroeconomic applications. Furthermore, Strohsal, Melnick and Nautz (2015) argue that using structural breaks when investigating the anchorage of IEs can be particulary misleading because they tend to either underestimate the de-anchoring period when it is very short or overestimate it as we will see in Section 7. Thus as in equation (3) below, we model time variation as a driftless random walk following Cooley and Prescott (1976), Cogley and Sargent (2002), Cogley and Sargent (2005) and Boivin (2006).[5]

The observation equation is as in (1) above:

$$\Delta\pi^e_{t,i} = \beta_{0i} + \beta_{1i,t}S_{it} + \sum_{k=1}^{K}\beta_{k+1,i}S_{i_k t} + \epsilon_{it}, \qquad \epsilon_{it} \sim IIN(0,R) \tag{2}$$

The latent state variable follows a driftless random walk:

$$\beta_{1i,t} = \beta_{1i,t-1} + \nu_t, \qquad \nu_t \sim IIN(0,Q) \tag{3}$$

The covariance matrix of all innovations in our model is:

$$V = Var\begin{pmatrix}\epsilon_t \\ \nu_t\end{pmatrix} = \begin{pmatrix} R & 0 \\ 0 & Q\end{pmatrix} \tag{4}$$

where the off diagonal elements are set to zero.
The assumption regarding the IID error terms in equation (2) is in line with Cogley and Sargent (2002). This assumption could be relaxed to account for stochastic volatility.[6] We follow the literature in assuming that ϵ_t and ν_t are

[5]The driftless random walk assumption has also been widely used in forecasting applications see – Stock and Watson (1996) and for an application in finance see – Dangl and Halling (2012).

[6]Cogley and Sargent (2005) allow for both time-varying coefficients and stochastic volatility in the error terms. They find that allowing for stochastic volatility does not remove time variation in the coefficients.

uncorrelated - see Primiceri (2005). In this way, the errors can be structurally interpreted. Following the Bayesian literature, β_t are called "parameters" and R and Q are "hyperparameters". Hyperparameter refers to the parameter of a prior distribution or can be thought of as a nuisance parameter similar to the innovation variance in classical econometrics.

3 Data

3.1 Market-based measures of inflation expectations

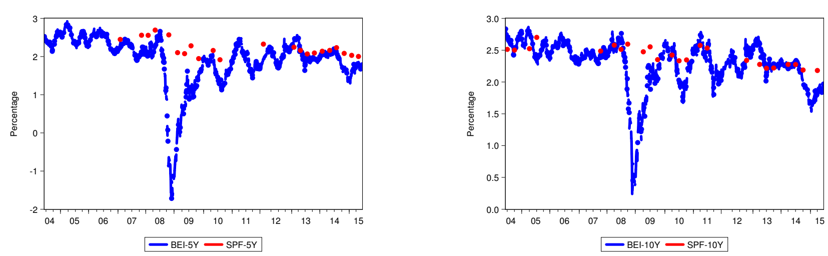
IEs are not observed and not easy to measure. There are two main measures of IEs: survey-based and market-based measures. One major drawback of survey-based expectations is their low frequency which renders them not suitable to identify changes in expectations in a short horizon while market-based measures are available at high frequencies (daily or even intra-daily). Several studies have used yields and forward rates[7] of index-linked and nominal bonds with equal maturity to derive BEI rates or synonymously Inflation Compensation (IC), see for example (Gurkaynak, Sack and Wright (2010), Gurkaynak, Levin and Swanson (2010), Beechey, Johannsen and Levin (2011) and and many others). The data is available from the Board of Governor's website.

We focus on one-year forward rate from 9 to 10 years ahead (1F9) as in Gurkaynak, Levin and Swanson (2010) and Galati, Poelhekke and Zhou (2011)– see Figure 2 for a plot of the data. In contrast to yields, forward rates are not influenced by short-term developments and thus can be seen as a better proxy for IEs. As Gurkaynak, Levin and Swanson (2010) argue, the one-year forward rate ending in 10 years is far enough in the future for macro models to go back to their steady state, so any significant response of IEs at these horizons can be alarming. We also report results for BEI yields at 5-years maturity – see Figure 1 below. The data is daily except that for the weekends and on days where the yields are not present.

BEI rates are not a pure measure of IEs because they also comprise of liquidity risk premium and inflation risk premium. A generalized Fisher equation helps see this: $\pi^e_{t,i} = i^{NB}_t - r^{TIPS}_t - \rho^\pi_t + \rho^{LRP}_t = BEI_t - \rho^\pi_t + \rho^{LRP}_t$ where i^{NB}_t is the yield or forward rate on a nominal bond, r^{TIPS}_t is the yield or forward rate on a TIPS (Treasury Inflation-Protected Securities) bond, ρ^π_t is inflation risk premium of nominal bonds and ρ^{LRP}_t is liquidity risk premium of TIPS relative to nominal bonds. Figure 1 below shows BEI

[7]The spot rate is the current yield for a given term. The forward rate is the interest rate for a certain term that begins in the future and ends later.

yields plotted against the forecasts of CPI from the Survey of Professional Forecasters (SPF)[8] at maturities 5 and 10 years. Throughout our sample, the BEI yields are typically below the survey expectations, especially during the financial crisis episode and more recently during 2014 onwards. This implies that liquidity premium dominates inflation risk premium, as the generalized Fisher equation predicts, and thus BEI yields should be corrected for liquidity premium because they underestimate true BEI rates. On the other hand, forward rates are typically above the SPF forecasts, except for year 2015, hinting that inflation risk premium dominates liquidity premium – see Figure 2. We purge liquidity risk premium from BEI yields following the regression-based method in Strohsal and Winkelmann (2015) and Pflueger and Viceira (2011) – see Appendix A. We consider inflation risk premium as part of the one-year forward rate ending in 10 years, following Strohsal and Winkelmann (2015) who argue that a central bank should not only aim at anchoring inflation expectations but also minimizing uncertainty about future inflation. Additionally, D. Bauer (2015) argues that risk premia move slowly, typically at business cycle frequencies, and thus they wont matter since our dependent variable is the daily change in BEI rates.[9] In summary, far forward BEI rates were not purged from neither inflation risk nor liquidity premium but as I highlighted above liquidity premium was not an issue until mid 2014.



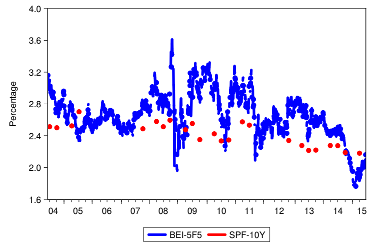
(a) 5 years maturity

(b) 10 years maturity

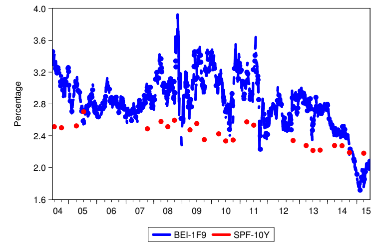
Figure 1: Unadjusted break-even inflation yields and survey forecasts (5 and 10 years maturity)

[8]The SPF quarterly data was obtained from the Federal Reserve Bank of Philadelphia.

[9]Gurkaynak, Sack and Wright (2010) use the Kalman filter to remove the estimate of the inflation risk premium from inflation compensation using professional forecasters survey data. But survey expectations are overly stable and the resulting IEs underestimate the amount of variance in true IEs.



(a) 5F5



(b) 1F9

Figure 2: Unadjusted break-even inflation forward rates and survey forecasts (5 and 10 years maturity)

3.2 Economic News

The data on macroeconomic releases and the corresponding median forecast is obtained from the Money Market Services (MMS)[10] conducted by Action Economics - following Beechey, Johannsen and Levin (2011) and Gurkaynak, Sack and Swanson (2005). Our sample period starts in June 2004, since it is only until then that a relatively big number of inflation indexed bonds have been traded in the US secondary market, and ends in the first quarter of 2015. We consider a bigger set of economic releases than is used in current studies. Besides the 14 releases considered in Beechey and Jonathan (2009) or Gurkaynak, Sack and Swanson (2005), we study the sensitivity of IP (Industrial Production) and PCE (Personal Consumption Expenditures) since IP is concurrently announced with Capacity utilization and PCE has recently become the reference price index, especially that the numerical inflation target of 2% is based on it – see Table 1. Moreover, we verified that the forecast errors that we employ, pass the standard tests of forecast rationality i.e., they are close to zero, mostly uncorrelated and dont reject the null of normality.

Each macroeconomic surprise, except for the monetary policy surprise, is computed as the difference between the actual release and median expectation and then standardized by its standard error, as highlighted in Section 2.1. As for the Monetary policy surprise, it is calculated as the one-day percentage change in the 3-month U.S. Treasury Bill (obtained from the FRED

[10]The Money Market Survey (MMS) survey is conducted the Friday before each data release and one would expect that their forecasts incorporates almost all relevant information just few days before the actual announcement. Additionally, the quality of the MMS data in the sense that it passes forecast rationality tests has been verified by Balduzzi, Elton and Green (2001) and Andersen et al. (2003).

Table 1: US macroeconomic Announcements

Data Release	Frequency	Standard Error	First Release	Last Release	Units	Obs
Capacity Utilization	Monthly	0.4	15/07/2004	15/06/2015	Percent	132
Consumer Confidence	Monthly	5.21	29/06/2004	26/05/2015	Index	131
Core CPI	Monthly	0.1	16/07/2004	18/06/2015	Percent change mom	133
Employment Cost Index	Quarterly	0.18	29/07/2004	30/04/2015	Percent change qoq	44
GDP (advance)	Quarterly	0.67	30/07/2004	29/04/2015	Percent change qoq	44
Initial Claims	Weekly	18.64	10/6/2004	18/06/2015	Thousands	576
Leading Indicators	Monthly	0.21	17/06/2004	18/06/2015	Percent	134
NAPM	Monthly	1.99	1/7/2014	1/5/2015	Index	131
New Home sales	Monthly	58.5	24/06/2004	23/06/2015	Thousands	132
Non-farm payrolls	Monthly	67.71	2/7/2004	5/6/2015	Thousands	132
Core PPI	Monthly	0.25	15/07/2004	12/6/2015	Percent change mom	132
Retail Sales	Monthly	0.5	14/06/2004	11/6/2015	Percent change mom	133
Unemployment rate	Monthly	0.15	2/7/2004	5/6/2015	Percent	132
Monetary policy surprises	8 per year	3.93	30/06/2004	17/06/2015	Percent	89
Industrial Production	Monthly	0.4	16/06/2004	15/06/2015	Percent	133
Personal Consumption Expenditures	Monthly	0.168	28/06/2004	01/06/2015	Percent	132

Notes: Standard Errors pertain to the Macro/Monetary surprise and correspond to the sample June 2004-June 2015.

website) around each monetary policy announcement and then standardized by its standard error-as in Nautz and Strohsal (2015). But that only applies for the period between June 2004 till October 2008 (i.e., before the zero lower bound was effective). Hence, since December 2008, monetary policy surprises are measured as the one-day change in a 10-year off-the-run nominal bond around the FOMC meetings – see Wright (2012).

4 Bayesian Inference

In this section, we discuss the simulation method, the priors used and the details of the simulation. Let $Y^T = [\Delta\pi_1^e, ..., \Delta\pi_T^e]$ and $\beta^T = [\beta_0', \beta_1', ..., \beta_T']$. The superscript, T, denotes the entire sample that runs from time period 1 to T, whereas the subscript, T, denotes the last time period in the sample.

4.1 Priors

The prior distributions used below are chosen in line with much research in this area – see Primiceri (2005), Cogley and Sargent (2002), Cogley and Sargent (2005) and many others. In particular, the prior of the initial state of the time-varying parameters is $p(\beta_0) = N(\bar{\beta}, \bar{P})$ and that of the hyperparameters is $p(V) = IW(\bar{V}^{-1}, T_0)$ where IW(S, df) represents the inverse-Wishart distribution with scale matrix S and degrees of freedom, df. T_0 is the prior degrees of freedom.

Assuming an inverse-Wishart prior for the hyperparameters is convenient because when combined with gaussian likelihood yields an inverse-Wishart posterior. The joint prior for β_0 and V, given that they are assumed to be independent of each other, takes the following form: $p(\beta_0, V) = N(\bar{\beta}, \bar{P})IW(\bar{V}^{-1}, T_0)$.

The latter prior is conjugate and, in turn, the posterior distribution, $p(\beta^T, V)$, is also inverse-Wishart.

4.2 Posterior density and Simulation method

Our goal is to summarize the posterior density for the object of interest, $p(\beta^T, V)$. Conditional on prior beliefs and the data until date T, the joint posterior distribution for the time-varying coefficients and hyperparameters is given by: $p(\beta^T, V|Y^T)$. The Gibbs sampler is used to simulate draws from the joint posterior density of interest. It accomplishes that by first drawing a history of the states (i.e., the time-varying coefficients) from $p(\beta^T|Y^T, V)$, conditional on the data and hyperparameters. Then conditional on the data and states, the hyperparameters are drawn from $p(V|Y^T, \beta^T)$. Eventually, the sequence of draws converges to a draw from the ergodic equilbrium joint distribution, $p(\beta^T, V|Y^T)$.[11]

4.3 Calibration of priors and details of simulation

We calibrate the priors following Reusens and Croux (2015) and Primiceri (2005). Twenty percent of the sample size of each macro announcement is used as a training sample to calibrate the prior. The mean of the prior for β_0, $\bar{\beta}$, is the OLS estimate for β obtained in the training sample. The variance of the prior of β, $\bar{V}$, is 4 times the standard error of $\hat{\beta}$ obtained also from the training sample. It is worth noting that these estimates are obtained from running constant parameter news regressions as explained in Section 2 above. Finally, degrees of freedom and scale matrices are needed for the inverse-Wishart prior distributions of the hyperparameters (R and Q).
We follow Reusens and Croux (2015) in setting the degrees of freedom and the scale matrix of Q. They show via Monte Carlo simulations that the prior for Q used in Primiceri (2005) underestimates the amount of time variation. Thus, the degrees of freedom for Q are set to be equal to the number of time-varying parameters (k)[12] minus 1+0.1, which is the minimal degrees of freedom to ensure finiteness of first moments. The degrees of freedom of R is set to the dimension of R plus 1, which makes 2 in our case. The scale matrix of Q is a constant fraction of the variance of the corresponding OLS estimate on the training sample. As for the scale matrix of R, it is set to the

[11]For details on the Gibbs Sampler, Kalman filter and smoother check appendix B below.

[12]Since we study the effect of a particular surprise on IEs, the number of time-varying parameters is either 1 or 2 in the case of Unemployment and Nonfarm Payrolls and Industrial Production and Capacity Utilization which are announced together.

identity matrix. In this way, the priors are not flat, but diffuse and weakly informative. The simulations are based on 100000 iterations of the Gibbs sampler, discarding the first 50000 as a burn in and then taking every tenth draw to reduce autocorrelation between draws. Thus the structural analysis is based on the remaining 5000 draws. In more details, the priors used are:

$$\beta_0 \sim N(\hat{\beta}_{OLS}, 4 \cdot V(\hat{\beta}_{OLS}))$$
$$R \sim IW(I_k, 2)$$
$$Q \sim IW(k_Q^2 \cdot (k-1+0.1) \cdot V(\hat{\beta}_{OLS}), k-1+0.1), k_Q = 0.01$$

In section 8, we also experiment with a non-informative prior for Q where the degrees of freedom are set to k-1+0.00001 and the scale matrix to $0.00001 I_k$, where (I) is the identity matrix.

5 Results for News regressions with constant parameters

This section presents the estimates of the constant parameter news regressions in Section 2.1. Table 2 shows the Announcement Releases which are concurrent with the announcement under study- see Table 3 for the regression estimates.

Table 2: Contemporaneous Announcement Releases

	GDP	Unemp	CPI	CU	CC	Claims	ISM	Nonfarm	NH	PPI	RS	ECI	LI	MP	IP	PCE
GDP	44	0	0	0	0	9	0	0	0	0	0	23	0	10	0	0
Unemp	0	132	0	0	0	3	9	132	0	0	0	0	0	0	0	6
CPI	0	0	133	47	0	29	0	0	1	0	0	0	12	7	47	0
CU	0	0	47	133	0	16	0	0	0	25	7	0	0	1	133	0
CC	0	0	0	0	133	3	0	0	16	0	1	0	0	3	0	0
Claims	9	3	23	16	3	577	18	3	32	26	30	7	102	5	16	30
ISM	0	9	0	0	0	18	131	9	0	0	0	0	0	2	0	29
Nonfarm	0	132	0	0	0	3	9	132	0	0	0	0	0	0	0	6
NH	0	0	1	0	16	32	0	0	133	0	0	0	1	6	0	12
PPI	0	0	0	25	0	26	0	0	0	133	34	0	2	6	25	0
RS	0	0	0	7	1	30	0	0	0	34	133	0	0	4	7	0
ECI	23	0	0	0	0	7	0	0	0	0	0	44	0	7	0	13
LI	0	0	12	0	0	102	0	0	1	2	0	0	134	0	1	1
mp	10	0	7	1	3	5	2	0	6	6	4	7	0	89	0	2
IP	0	0	47	133	0	16	0	0	0	25	7	0	1	0	133	0
PCE	0	6	0	0	0	30	29	6	12	0	0	13	1	2	0	133

Notes: The table reports the number of times each economic announcement is released concurrently with other announcements for the 16 economic announcements that I consider. The sample period covers June 10, 2004-June 25, 2015. Since I am studying the response of daily IEs, it is irrelevant whether the announcements are released at 8:30 am, 9:15 am or later in the day.

For pro-cyclical indicators: like GDP, CPI, Capacity Utilization, ISM manufacturing, and Retail Sales, a positive surprise represents stronger than expected growth or higher than expected inflation (in consumer and producer prices). Thus, we expect the coefficients on the surprise component of pro-cyclical indicators to be zero or positive, as news of overheating would arguably imply higher inflation expectations. Indeed, Table 3 shows that all of these responses are positive albeit some are not statistically different from zero. For counter-cyclical indicators, like unemployment and Initial claims, a positive surprise represents lower than expected growth, so we would expect a negative coefficient. The results in Table 3 confirm that for forward rates, however, for 5-year BEI yields the sign of the coefficient on Unemployment surprises is positive though statistically insignificant. Additionally, a positive monetary policy surprise, means that monetary policy is tighter than expected. It is worth noting that the estimates in Table 3 represent the average response of IEs to news over our sample. The unexpected sign of some coefficients might be due to the stable coefficients' specification which disguises the variation in the response over time, as will be outlined in Section 6.

For price news, the constant news regression seem to suggest that IEs (derived from yields and forward rates) do not react significantly to all other prices but the core PPI. [13]

As for real side news, and in line with D. Bauer (2015), far ahead forward rates react significantly to real side news – see coefficients on Claims, Retail Sales, GDP and Industrial Production. In contrast to what Beechy and Wright (2009) find[14], the sensitivity of IEs, derived from yields or forward rates, to nonfarm payroll surprises is not statistically significant at the 5% level. This discrepancy is most probably due to our longer sample or might hint that the intrinsic value of Nonfarm Payrolls on IEs is decreasing, in the spirit of Gilbert et al. (2015).

A surprise tightening of policy should in principal decrease BEI yields and forward rates. Intuitively speaking, policy tightening leads investors to revise down their inflation expectations and what they command for bearing inflation risk, thus, decreasing inflation compensation. Our results confirm this hunch only for 5-year BEI yields. On the other hand, we obtain a positive statistically significant coefficient for far ahead forward rates. We shed more light on this phenomenon after we explore the time variation in this effect.

[13] Using a sample that only extends to 2008, D. Bauer (2015) and Beechy and Wright (2009) find that CPI surprises are also statistically significant.

[14] Their sample extends only to 2008.

Table 3: Separate Regressions of daily US BEI yields and forward rates on macroeconomic and monetary policy surprises

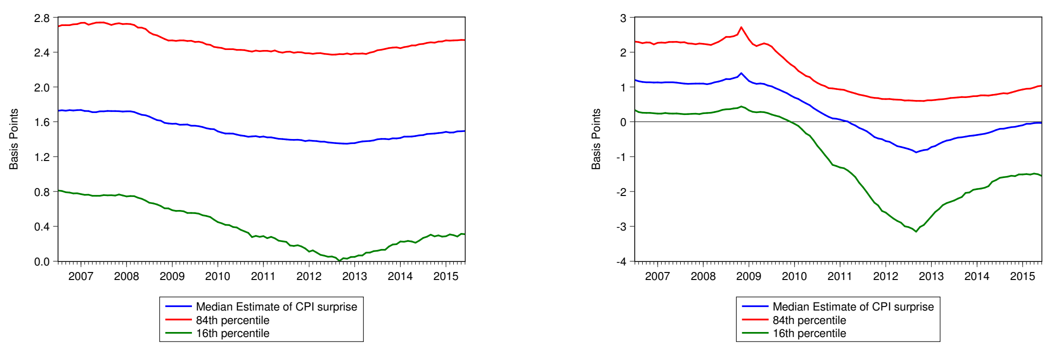
	Δ Adj-BEI-Five-year yield		Δ1F9		# of Obs
	Surprise Coefficient ($\hat{\beta}_{1i}$)	R^2	Surprise Coefficient ($\hat{\beta}_{1i}$)	R^2	
Core CPI	2.03 (1.41)	0.02	0.8 (0.66)	0.12	133
Core PPI	1.04** (0.37)	0.17	1.25** (0.43)	0.15	130
Initial Claims	-0.71** (0.29)	0.006	-0.73** (0.35)	0.015	575
MP	-4.01 (2.70)	0.11	1.32* (0.7)	0.15	65
Nonfarm Payrolls	2.60** (0.44)	0.19	0.45 (0.44)	0.008	132
Unemployment	0.50 (0.55)	0.19	-0.07 (0.42)	0.008	132
GDP	1.10 (1.37)	0.16	1.22* (0.62)	0.097	44
ISM	0.58 (0.65)	0.036	0.68 (0.63)	0.021	131
PCE	0.02 (0.52)	0.03	0.51 (0.49)	0.046	131
Retail Sales	1.21 (0.76)	0.04	1.67** (0.52)	0.155	132
Consumer Confidence	0.47 (0.70)	0.008	0.09 (0.51)	0.026	131
Capacity Utilization	0.88 (1.21)	0.015	0.93 (0.58)	0.094	132
Industrial Production	-0.56 (1.44)	0.015	-1.72** (0.76)	0.094	132
New Homes	0.64 (0.46)	0.007	0.69** (0.30)	0.028	132

Notes: The coefficients in this table pertain to OLS estimates of regressions (1). The independent variables, in the first column of this table, are the surprise components of the respective releases. The dependent variable is the daily change, in basis points, of adjusted 5-year BEI yields (second column) and 1 year forward rate 9 years ahead (third column). We include a concurrent announcement if there is at least 10% overlap with the announcement under consideration. The intercepts are insignificant and thus not included. ** denotes significance at 5% level and * at 10% level. We omitted the announcement of PPI on this day 11-Jun-2014 because there was no corresponding yield value. Similarly, we omitted the following announcement for Initial Claims:10-jun-2004. We also omitted the announcement on the 29th of March 2013 for PCE for the same reasons. We also omitted 6/14/2004 for retails sales for the same reasons. For consumer confidence, the following announcements were omitted: 25-March-2008 and 30-Oct-2012. White heteroskedasticity standard errors are used.

6 Time Varying Parameter Estimates

6.1 Price news

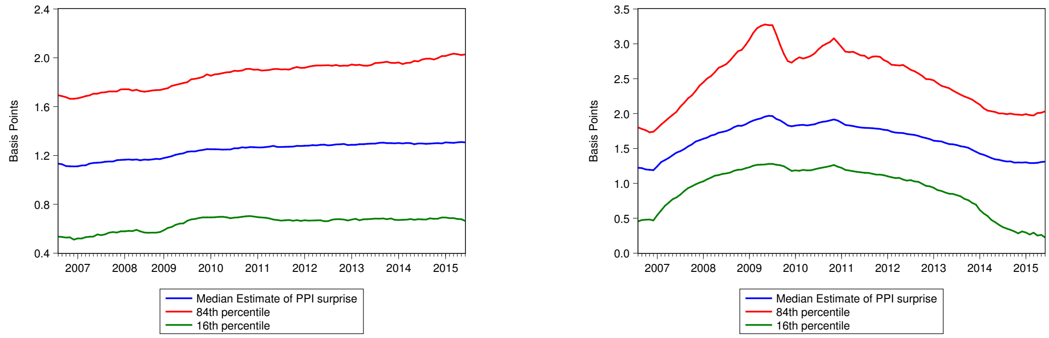
Looking at Figure 3[15], it seems that time variation is not pronounced in the response of 5-year BEI yields, though there is a discernable decrease in the wake of the financial crisis followed by a slight increase starting in mid 2012. For far ahead forward rates, there is a significant and gradual decrease in the response from 1.1 bps in 2009 to zero bps in 2011. The sensitivity becomes negative after 2011 and from mid 2012 we see a pick up towards zero or positive sensitivity. The negative response to CPI surprises is probably due to disinflation or deflation scares during this period. Moreover before 2010, the sensitivity of long-term IEs to CPI news was significantly different from zero, since zero did not pass in the credible band. However, after 2010 it is not anymore. In turn, this implies that financial market participants do not alter their IEs to transitory shocks in CPI. In section 8 below, I relate time variation in CPI news to changes in communication policy of the Fed, the federal funds rate and the VIX index.



(a) CPI Surprise(Adj-BEI-5Y) (b) CPI Surprise(BEI-1F9)

Figure 3: Time varying estimates of Core CPI surprise

[15] The 16th and 84th percentile correspond to a 68% confidence interval, under normality, as in Primiceri (2005). Additionally, all plots in this section are generated by k_Q=0.01. To assess the mixing of the chain, autocorrelation function of the draws is below 0.2 with some exceptions–check figure 26. Moreover, to assess the convergence of the chain, inefficiency factors are estimated using the Bartlett kernel and they are generally around or below 20 as highlighted in Primiceri (2005)–check figure 27. All the results are available upon request.

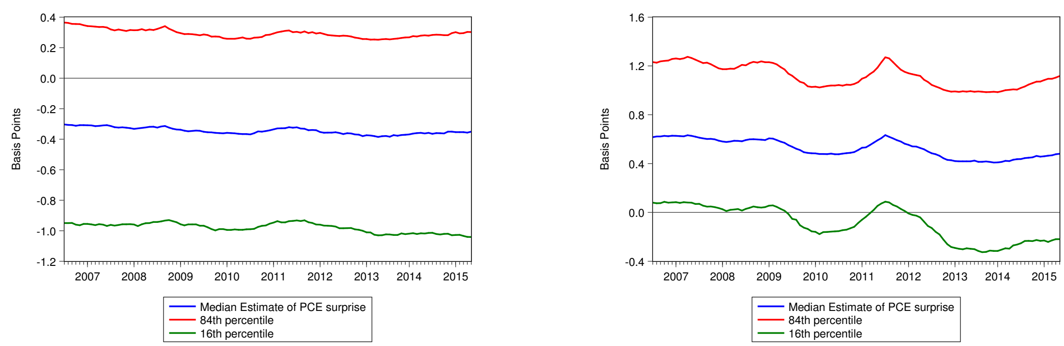


(a) PPI Surprise (Adj-BEI-5Y)

(b) PPI Surprise(BEI-1F9)

Figure 4: Time varying estimates of Core PPI surprise

As for the response of 5-year BEI yields to PPI surprises, we notice a rather stable response except for a slight increase starting from the financial crisis, as the left panel of Figure 4 shows. Since the anchoring of IEs is defined in terms of forward rates, a slight increase in the sensitivity of 5-year BEI yields does not hint towards de-anchoring. The right plot of Figure 4 shows that the sensitivity of far ahead forward rates to PPI surprises is building up pre the financial crisis to reach 1.8 bps in 2009, to decrease in the aftermath of the crisis and go back to its pre-crisis level.



(a) PCE surprise (Adj-BEI-5Y)

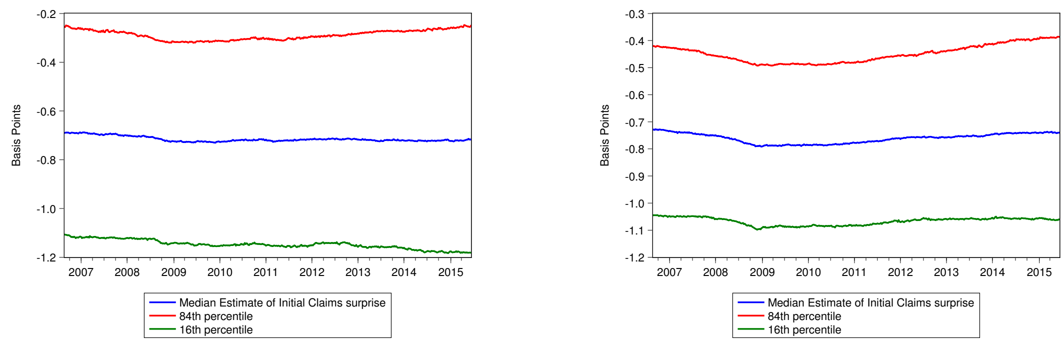
(b) PCE surprise (BEI-1F9)

Figure 5: Time varying estimates of PCE Surprise

In a similar fashion, the right panel of Figure 5 shows that the sensitivity of far ahead forward rates to PCE news was only statistically different from zero until 2009 because afterwards the credible band includes zero. In summary, IEs captured by far ahead forward BEI rates, became less sensitive to unexpected shocks in CPI, PPI, and PCE. In turn, this entails that IEs became more anchored in the aftermath of the financial crisis. In other words, IEs of financial market participants react less to transitory inflation shocks and that reflects the surge in credibility of the Fed policies.

6.2 Real Side News

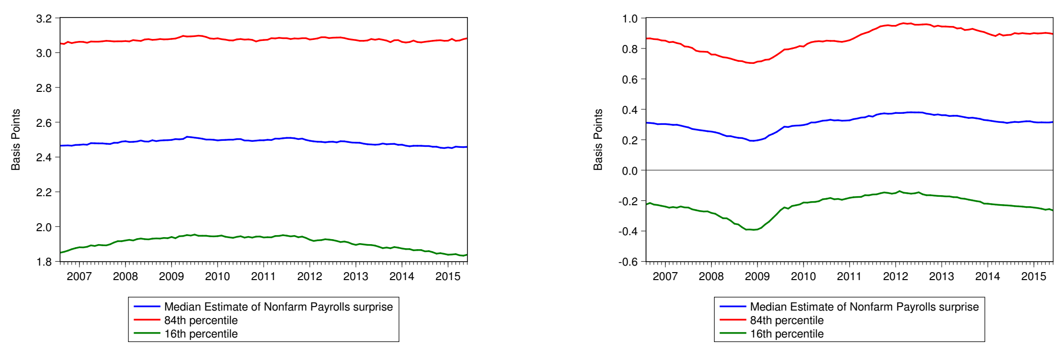
The response of 5-year BEI yields and forward rates to surprises in Initial Claims does not exhibit significant time variation as Figure 6 shows.



(a) Initial claims (Adj-BEI-5Y)

(b) Initial claims (BEI-1F9)

Figure 6: Time varying estimates of Initial Claims surprise

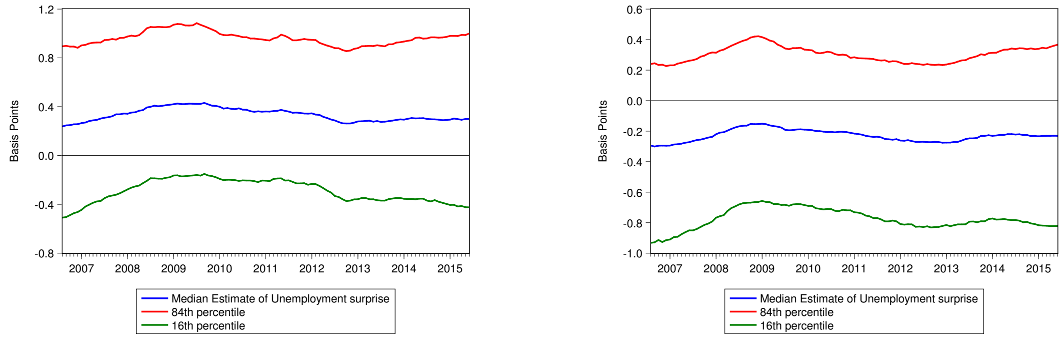


(a) Nonfarm Payrolls surprise (Adj-BEI-5Y)

(b) Nonfarm Payrolls surprise (BEI-1F9)

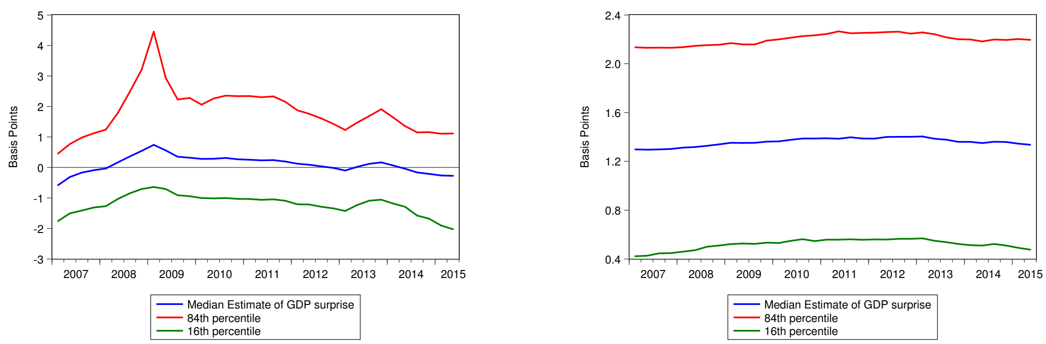
Figure 7: Time varying estimates of Nonfarm Payrolls surprise

Figures 7 and 8 show that the response of IEs to Unemployment and



(a) Unemployment surprise (Adj-BEI-5Y) (b) Unemployment surprise (BEI-1F9)

Figure 8: Time varying estimates of Unemployment Surprise



(a) GDP surprise (Adj-BEI-5Y) (b) GDP surprise (BEI-1F9)

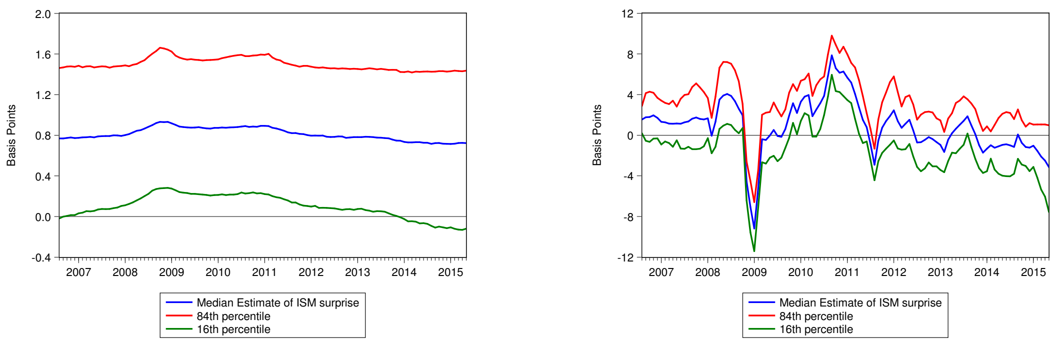
Figure 9: Time varying estimates of GDP Surprise

Nonfarm Payrolls surprises is not changing significantly over time, for both 5-year BEI yields and far ahead forward rates. Additionally, only the sensitivity of 5-year BEI yields to Nonfarm payrolls surprises is statistically significant since the credible band does not contain zero.

With respect to the effect of GDP surprises on IEs, Figure 9 shows that the sensitivity of 5-year BEI yields does not exhibit time variation and is not statistically significant different from zero since zero passes in the credible band. As for the response of forward rates to news, we see a slight increase during the crisis but the sensitivity goes back to its pre-crisis level in the aftermath of the crisis.[16]

[16] Although 20% of the sample size is used to obtain the prior, to generate the results in Figure 9, 25% of the sample size was used and the Initial Claims announcements which

Regarding forward looking economic indicators like the ISM index, Figure 10 shows that the response of IEs, derived from 5-year BEI yields is rather stable throughout the sample though there is a slight decrease in the aftermath of the crisis. As for far ahead forward rates, there is very pronounced time variation especially during the financial crisis and the period extending from mid 2010 till mid 2011. There is also a clear downward trend in the sensitivity of forward rates in comparison to its pre-crisis level though zero passes through the credible band throughout most of the sample.



(a) ISM surprise (Adj-BEI-5Y)

(b) ISM surprise (BEI-1F9)

Figure 10: Time varying estimates of ISM Surprise

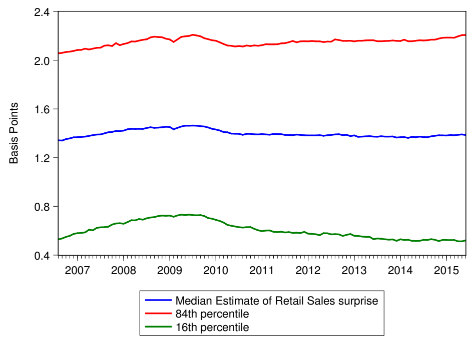
Figure 11 shows that the sensitivity of forward BEI rates to Retail Sales surprises is more time-varying than that of 5-year BEI yields. Additionally, there is a clear decrease in the response of both forward rates and BEI yields post the financial crisis.

The response of BEI yields and forward rates to Consumer confidence surprise was rather stable throughout the sample, as Figure 12 shows. Moreover, since zero passes in the credible band, we can not reject the null hypothesis that the sensitivity is zero.

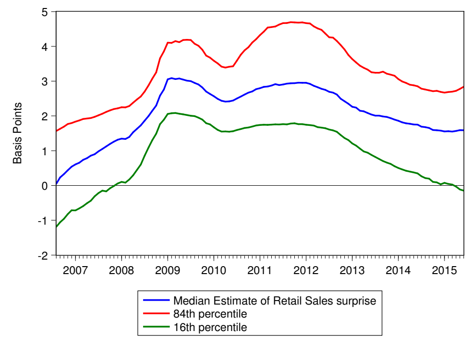
Regarding the reaction to Capacity Utilization and Industrial Production surprises, Figures 13 and 14[17] show significant time variation for BEI yields and forward rates across our sample. There are two notable dips in the

overlap with GDP announcements were removed because they didnt contain a nonzero surprise in the 25% proportion and the OLS estimates were not identified due to singularity of the matrix.

[17]To obtain the time varying estimates of the sensitivity of 5-year BEI yields, 200000 iterations of the Gibbs sampler were used to ensure the convergence to the equilibrium distribution.

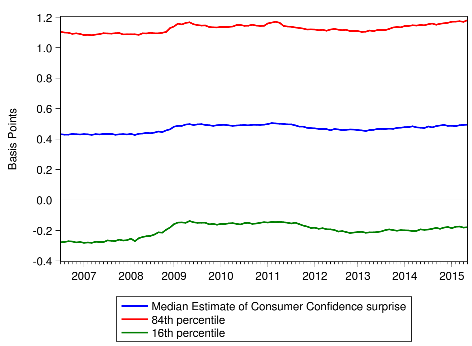


(a) Retail Sales surprise (Adj-BEI-5Y)

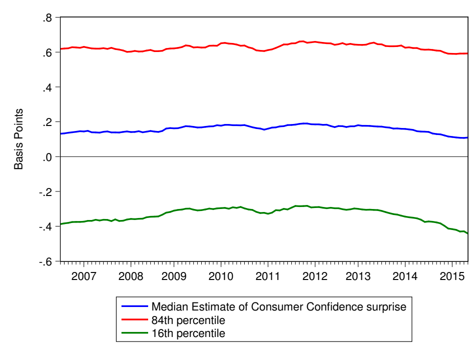


(b) Retail Sales surprise (BEI-1F9)

Figure 11: Time varying estimates of Retail Sales Surprise

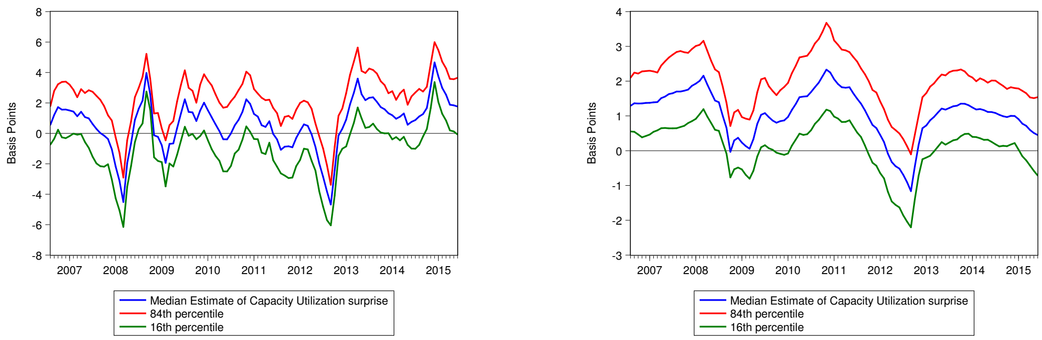


(a) CC surprise (Adj-BEI-5Y)



(b) CC surprise (BEI-1F9)

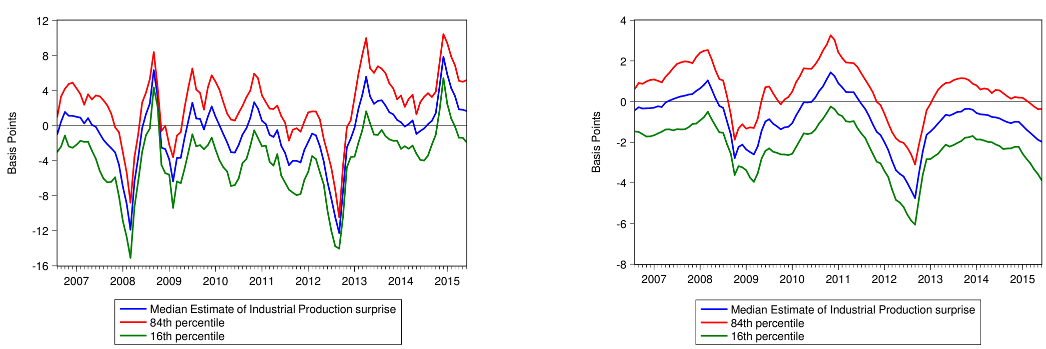
Figure 12: Time varying estimates of Consumer Confidence Surprise



(a) CU surprise (Adj-BEI-5Y)

(b) CU surprise (BEI-1F9)

Figure 13: Time varying estimates of Consumer Utilization Surprise

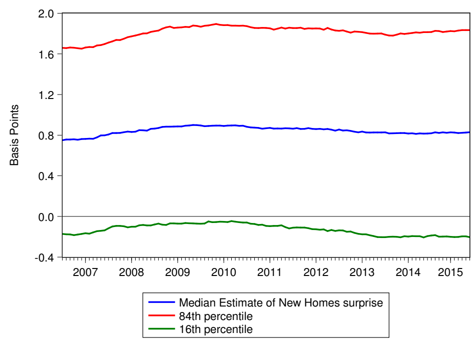


(a) IP surprise (Adj-BEI-5Y)

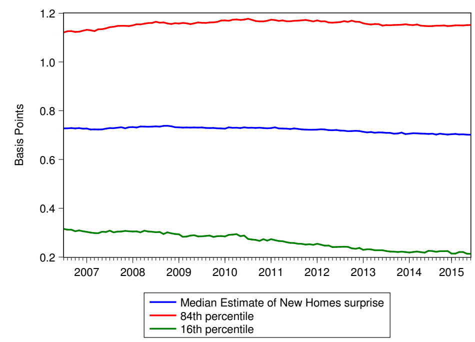
(b) IP surprise (BEI-1F9)

Figure 14: Time varying estimates of Industrial Production Surprise

sensitivity of yields and forward rates to both types of surprises: the first during the 2008-2009 financial crisis and the second in the mid of 2012. The reaction of forward rates shows some cyclical behavior in which the reaction becomes more negative during crisis periods and less negative during normal periods. Additionally, there is an overall downward trend in the sensitivity of forward rates compared to the beginning of the sample, alluding to the anchoring of long term inflation expectations.



(a) NH surprise (Adj-BEI-5Y)



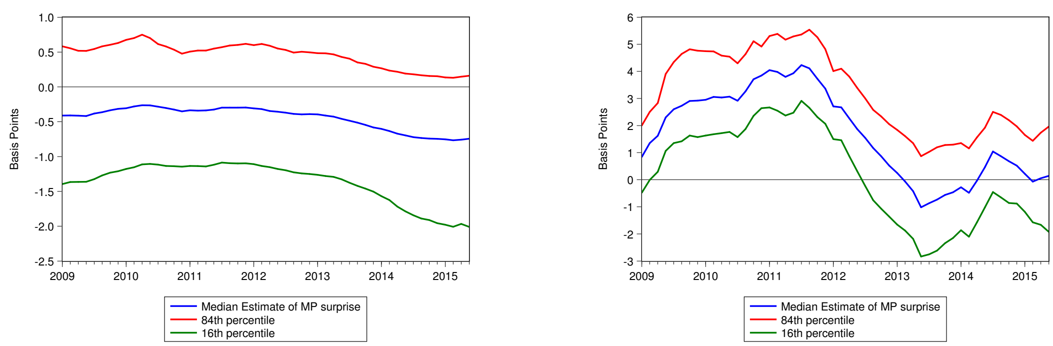
(b) NH surprise (BEI-1F9)

Figure 15: Time varying estimates of Index of New Homes Surprise

It is clear that the response to New Homes news does not exhibit any time variation, as Figure 15 shows, though there is a discernable decrease in the effect of NH surprises on forward rates.

6.3 Monetary Policy News

The response of far-ahead forward rates to Monetary policy news exhibits significant time variation, as shown in the right plot of Figure 16.[18] The response started increasing in 2009 to reach its peak of 4 bps in 2011, to decrease back to 0 bp in 2013 and fluctuate around that level thereafter, given that the credible band includes zero from mid 2012 onwards. In other words, investors revised up their long term IEs due to surprise tightening in the period extending from 2009 till 2011. This result can be explained by the fact that during this high period of uncertainty investors started losing their confidence in the central bank's ability to combat inflation and thus they marked up their expectations. In late 2011, the effect of monetary policy news on IEs started to decrease. On the other hand, the response of BEI yields to monetary policy news is not statistically different from zero throughout the entire sample, since the credible band contains zero. It also seems that the effect of monetary policy news on BEI yields is decreasing in absolute terms post the financial crisis. This means that investors do not downgrade their medium term inflation expectations, due to a surprise policy tightening, as much as they did before the crisis. In general, the effect of MP news on yields and forward rates, decreased after the financial crisis and the ensuing deep recession, and that is further evidence that long term inflation expectations indeed became more anchored.



(a) Monetary policy surprise (Adj-BEI-5Y)

(b) Monetary policy surprise (BEI-1F9)

Figure 16: Time varying estimates of MP surprise

[18] 22% of the sample is used to calibrate the prior. Additionally, the prior is calibrated on the sample before the Zero Lower bound binds (i.e., using the change in 3-month U.S.treaury bill around monetary policy announcements). Time variation is explored duirng the period where the Zero Lower bound binds.

7 Results for News regressions with Structural Breaks

In this section we test for Structural breaks in the coefficients, β_{1i}, of equation 1 in Section 2.1, using Bai and Perron (1998) multiple break tests. We study the instability of the response of far ahead forward BEI rates to economic news since they exhibit more pronounced time variation compared to BEI rates derived from yields as we saw in Section 6.

Table 4 below reports the pre- and post break estimates when 1 or no breaks are detected. A structural break in July 2010 is detected in the response to CPI surprises and a break in November 2011 is detected for ISM surprises but no breaks are detected in the other macroeconomic surprises. Table 5 reports two structural breaks in the response to Monetary Policy and Retail Sales surprises: one during the financial crisis and the second in either 2012 or 2014. Figure 17 plots the time-varying response to surprises in CPI and ISM versus the response subject to a structural break. First, it seems that structural breaks exaggerate or dampen the magnitude of the response. For example, the response to CPI surprise before and after the crisis is larger, in absolute terms, compared to the time-varying response. On the other hand, the response to ISM surprise, subject to a structural break, is smaller in magnitude compared to the time-varying estimate. Furthermore, figure 18 shows that structural breaks might underestimate or overestimate the magnitude of the response to news even if they capture the regimes correctly. Generally speaking, structural breaks in the response to news fail to capture smooth transitions or gradual changes which are at the heart of the learning process undertaken by financial market participants.

Table 4: News regressions with at most one Structural Break

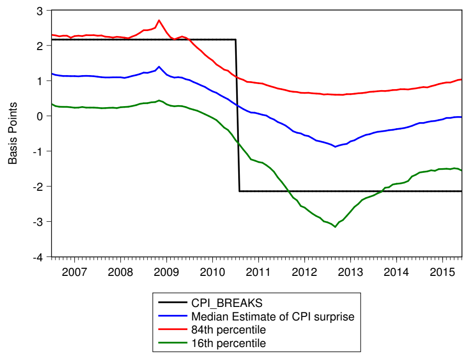
	Before Break	After Break	Break Date
	Δ1F9		
Core CPI	2.17**	-2.14**	2010M07
	(0.83)	(0.71)	
Core PPI	1.25**	1.25**	-
	(0.43)	(0.43)	
Initial Claims	-0.73**	-0.73**	-
	(0.35)	(0.35)	
Nonfarm Payrolls	0.45	0.45	-
	(0.44)	(0.44)	
Unemployment	-0.07	-0.07	-
	(0.42)	(0.42)	
PCE	0.51	0.51	-
	(0.49)	(0.49)	
ISM	1.13	-0.35	2008M11
	(1.28)	(0.88)	
CU	0.93	0.93	-
	(0.58)	(0.58)	
IP	-1.72**	-1.72**	-
	(0.76)	(0.76)	

Notes: The estimates in this table are obtained from regression (1) estimated by OLS and using White heteroskedasticity standard errors. The dependent variable is the daily change, in basis points, of 1 year forward rate 9 years ahead. The independent variables are the surprise components of the Macroeconomic variables in the first column of this table. ** denotes significance at 5% level and * at 10% level. M denotes month. Sample: June, 2004 to June, 2015.

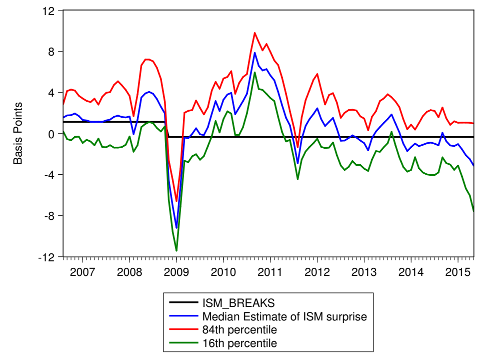
Table 5: News regressions with two Structural Breaks

	Before Break 1	Before Break 2	After Break 2	Break Date
	Δ1F9			
MP	4.14**	-2.17**	0.23	2012M09
	(0.62)	(1.19)	(0.57)	2014M04
RS	-0.24	3.61**	0.27	2008M11
	(0.64)	(0.61)	(0.49)	2012M10

Notes: Same notes as in Table 4. MP is short for Monetary policy and RS for Retail Sales.

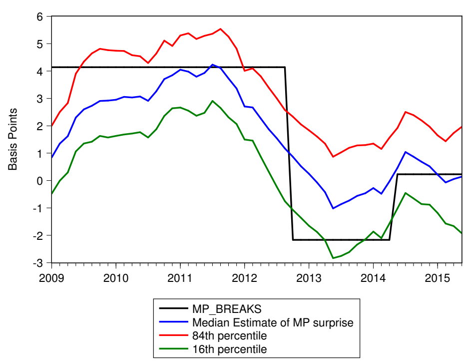


(a) CPI surprise

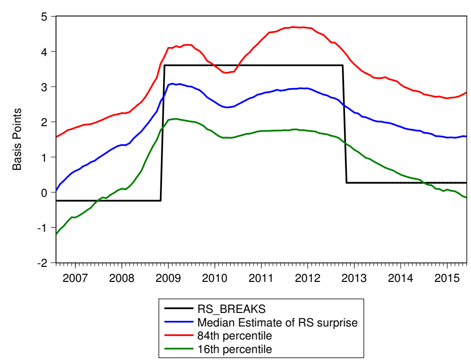


(b) ISM surprise

Figure 17: TV estimates vs Breaks for CPI and ISM surprises



(a) MP surprise



(b) RS surprise

Figure 18: TV estimates vs Breaks for Monetary Policy and Retail Sales surprises

8 Macro Determinants of Time Variation

In the previous sections we have shown that the response of market-based long-term IEs to price, real-side and monetary policy news is indeed time-varying. In this section, we uncover the macroeconomic determinants behind the reduced sensitivity of IEs to news.

Bernanke (2007), among others, stressed the importance of unearthing the factors that determine IEs as this is crucial to carry out sound policy analysis and better forecast inflation.

More recently, Fischer (2015) discussed US inflation developments in his speech in Jackson Hole. He highlighted that the ongoing economic slack, the rise in the US dollar, and the drop in oil prices are putting downward pressure on (core) inflation. We suspect that some of these factors might also be determinants of the sensitivity of IEs to news. Following Drager and Lamla (2013), we also use a dummy variable that takes value 1 after the first month of 2012 to capture the effect of the explicit inflation target on IEs. Moreover, Drager, Lamla and Pfajfar (2015) control for the following macroeconomic variables (Inflation, Oil price, Unemployment gap) when evaluating the effects of communication on the consistency of consumers.

8.1 Data

The macro determinants that we employ are: the Federal Funds Rate (FFR), a dummy variable for the explicit inflation target announced by the Fed in 2012 (FedTarget), VIX Index, Broad Exchange value of the dollar, Core Personal Consumption Expenditures (PCE) as a measure of inflation, Civilian Unemployment rate as a proxy for economic slack and Crude Oil price. All variables are monthly and enter the regression in first differences since most unit root tests suggested that they are not stationary, except for VIX and FedTarget. Additionally, Unemployment, Inflation, FFR, Crude Oil price and Exchange Value of the dollar are included with one lag to circumvent the fact that those macro variables are potentially endogenous and to account for a publication lag. The Federal Funds Rate, VIX Index, Core PCE, Unemployment and Crude Oil price are obtained from FRED. The Broad exchange value of the dollar is obtained from the Federal Reserve Board. Appendix C contains plots of the data used.

8.2 Results

To study the drivers of the time variation in the response of long-term IEs to economic news, we estimate the regression in equation (5) below. Let MD_{jt}

be short for macro determinant, where j denotes the jth macro determinant and J the total number of macro determinants. And $\hat{\beta}_{1i,t}$ corresponds to an estimate of the time-varying response of IEs to an announcemnt i as in Equation (1) above.

$$\Delta\hat{\beta}_{1i,t} = \beta_{0i} + \sum_{j=1}^{J} \delta_{1ij} MD_{jt} + \nu_{it} \tag{5}$$

Moreover, to account for the use of generated regressors as a dependent variable, we use the 5000 draws that we based our analysis on in section 6. For each of these draws we run the regressions in Table 6. As a result of that, we obtain a distribution for each coefficient. The mean of each of these distributions is reported in Table 6, in addition to the 95% quantile.

We study the causes behind the time variation in response to CPI, PPI, Retail Sales, Monetary Policy and ISM index surprises. These responses, among others, exhibited the most pronounced time variation as we saw in Section 6.

Table 6 portrays interesting results. With respect to the determinants of time variation to price news–CPI and PPI–, two variables play a significant role: the FedTarget and the federal funds rate. An explicit inflation target increases the sensitivity of long run IEs to CPI news. Taking this result at face value, makes it counterintuitive because one would expect the opposite sign. But given that the sensitivity to CPI news is nonpositive for a considerable part of our sample (Figure 3 above), an explicit numerical target most probably helped raise the sensitivity from negative values back to nonegative territory. In other words, the explicit inflation target helped anchor IEs at a positive value (2%) during a period where inflation was very low and there were worries that long run IEs are anchored at the wrong value. On the other hand, an explicit numerical target decreases the sensitivity to PPI news and this makes sense given that the sensitivity to PPI news is positive and decreasing in the aftermath of the crisis, as Figure 4 above shows. Additionally, an increase in FFR and VIX decreases the sensitivity of IEs to CPI surprises.

Regarding the response to Real side news, we find that different macro variables have a significant effect on the sensitivity of IEs except for one common denominator: the FedTarget decreases the sensitivity to both Retail Sales and ISM news. For example, Inflation, the FedTarget, and FFR decrease the sensitivity of IEs to Retail Sales news while an increase in the exchange value of the dollar and Unemployment rate increases it. On the other hand, we find that inflation, FFR and the price of oil increase the sensitivity of IEs to ISM news.

As for monetary policy news, we find that the exchange value of the dollar decrease the sensitivity of IEs whereas the FFR rate increases it.

Taken together, the results in Table 6 allude to five important drivers of time-variation in far ahead forward BEI rates to news, namely: The Explicit inflation target in 2012, the Federal Funds Rate, Unemployment rate, VIX index and Exchange Value of the dollar.

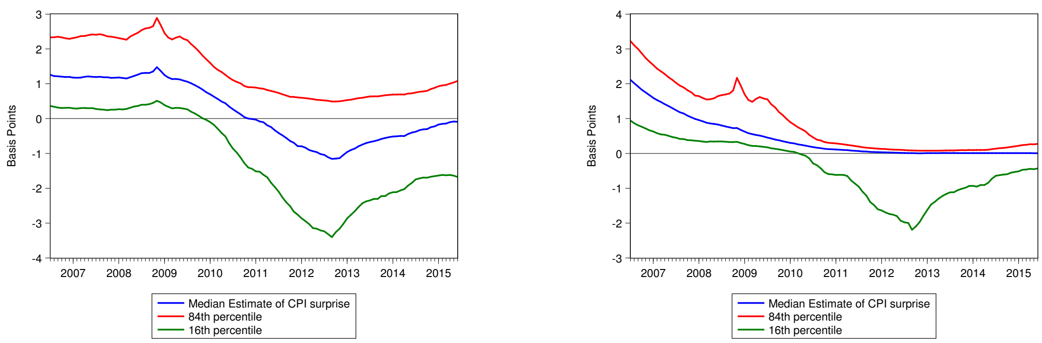
Table 6: Macro Determinants of Time Variation

	$\Delta\hat{\beta}_{1t,CPI}$	$\Delta\hat{\beta}_{1t,PPI}$	$\Delta\hat{\beta}_{1t,RS}$	$\Delta\hat{\beta}_{1t,MP}$	$\Delta\hat{\beta}_{1t,ISM}$
$\Delta Exchangerate_{t-1}$	0.009	0.001	0.0078**	-0.088**	0.076
	[-0.006,0.002]	[-0.001, 0.0069]	[0.003, 0.019]	[-0.18, -0.064]	[-0.046, 0.21]
$\Delta Inflation_{t-1}$	-0.009	-0.039	-0.133**	-0.21	1.074**
	[-0.042,0.020]	[-0.152,0.0007]	[-0.186, -0.095]	[-0.772, 0.008]	[1.015, 1.16]
$FedTarget_t$	0.048**	-0.023**	-0.091**	-0.09	-0.12**
	[0.023,0.116]	[-0.069,-0.0122]	[-0.125, -0.078]	[-0.21, 0.16]	[-0.17, -0.09]
ΔFFR_{t-1}	-0.123**	-0.017	-0.156**	1.93**	2.47**
	[-0.243,-0.087]	[-0.03,0.014]	[-0.175, -0.133]	[1.37, 3.85]	[1.28,3.38]
VIX_t	-0.001**	-0.0001	-0.001	0.004	0.015
	[-0.003,-0.001]	[-0.0009,0.0008]	[-0.001, 0.00028]	[-0.002, 0.028]	[-0.005,0.028]
ΔOil_{t-1}	0.001	7.37E-05	-0.0016	-0.0023	0.054**
	[-0.0006,0.0025]	[-0.0007,0.0007]	[-0.0023,-0.0006]	[-0.007, 0.0009]	[0.03, 0.072]
$\Delta Unemployment_{t-1}$	0.057**	0.024	0.0496**	0.288	0.35
	[0.020, 0.125]	[-0.008, 0.069]	[0.025, 0.082]	[-0.06, 0.404]	[-0.09, 1.076]
Observations	107	106	107	51	105
R^2	0.40	0.30	0.50	0.20	0.20
H0: β=0(joint test: p value)	0.000	0.000	0.000	0.000	0.000

Notes: The dependent variable is in basis points and enters in first differences because it is generated by a unit root process. Additionally, the time varying estimates used are generated using the noninformative prior mentioned in section 4.3. Inflation and Unemployment enter the regression in Percentage points. The intercepts are omitted because they were not significant. Exchange rate is the Exchange Value of the dollar. FFR is short for federal funds rate. FedTarget is a dummy variable that takes value 1 after the introduction of the numerical inflation target in 2012. Regression is estimated by OLS. ** denotes statistical significance (when zero is not included in the confidence interval) . RS for Retail Sales, MP for Monetary Policy, ISM for the manufacturing Index by the Institute of Supply Management, PPI for producer price index and CPI for consumer price index.

9 Sensitivity to priors, robustness to alternative specifications and convergence diagnostics

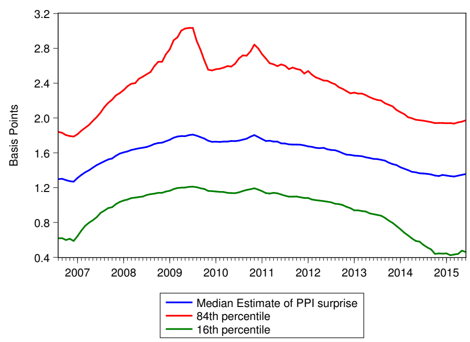
In this section I examine whether the sensitivity of long term IEs to news is robust to using a non-informative prior for Q, as explained in section 4.3 above, and an autoregressive process with an autoregressive parameter equal to 0.95 instead of a driftless random walk. I will only investigate the degree of time variation for the news variables that exhibited considerable time variation in Section 6. The plots in the left panel below correspond to using a non-informative prior for Q and the ones in the right panel correspond to employing an autoregressive process along with a weakly informative prior as illustrated in Section 4.3 above.



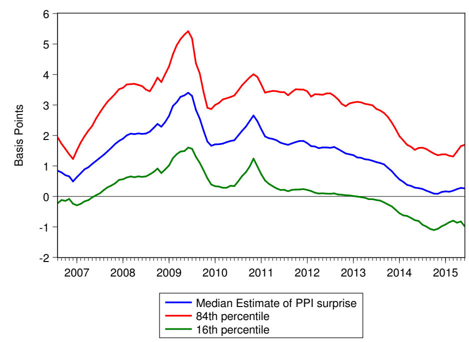
(a) CPI surprise (Noninformative prior) (BEI-1F9)

(b) CPI surprise (Autoregressive process) (BEI-1F9)

Figure 19: Time varying estimates of Core CPI surprise

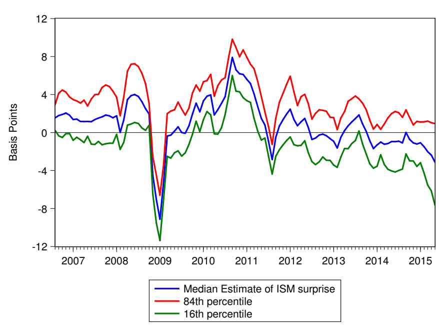


(a) PPI surprise (Noninformative prior) (BEI-1F9)

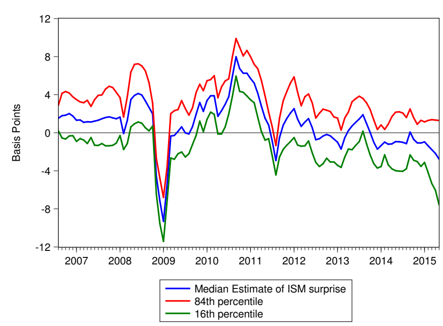


(b) PPI surprise (Autoregressive process) (BEI-1F9)

Figure 20: Time varying estimates of Core PPI surprise

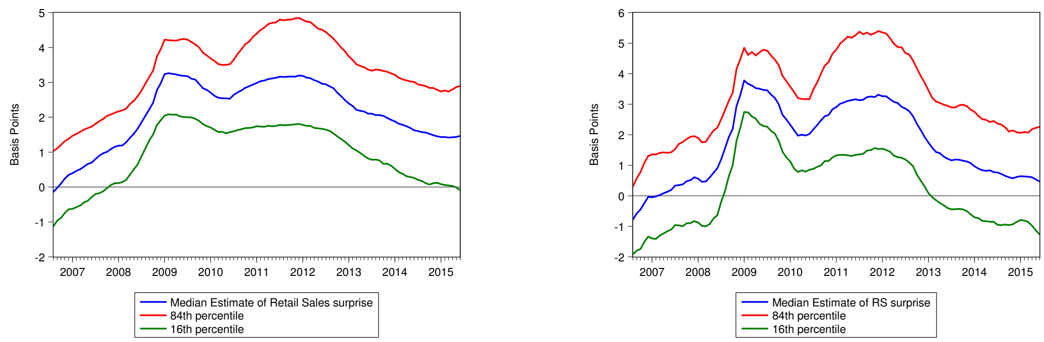


(a) ISM surprise (Noninformative prior) (BEI-1F9)



(b) ISM surprise (Autoregressive process) (BEI-1F9)

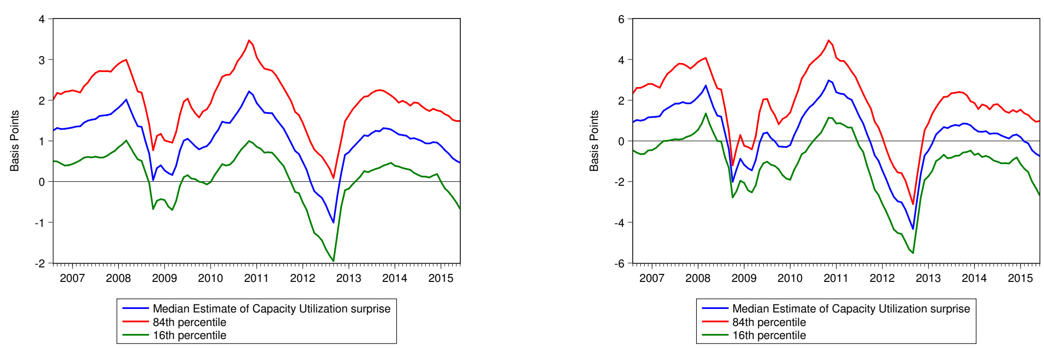
Figure 21: Time varying estimates of ISM surprise



(a) RS surprise (Noninformative prior) (BEI-1F9)

(b) RS surprise (Autoregressive process) (BEI-1F9)

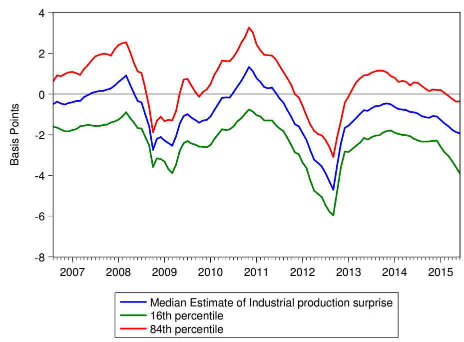
Figure 22: Time varying estimates of Retail Sales surprise



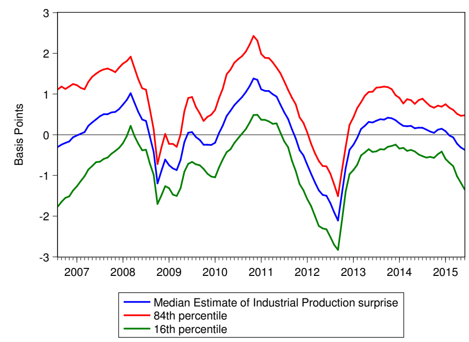
(a) CU surprise (Noninformative prior) (BEI-1F9)

(b) CU surprise (Autoregressive process) (BEI-1F9)

Figure 23: Time varying estimates of Capacity Utilization surprise

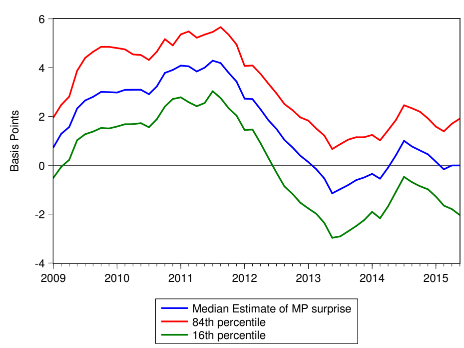


(a) IP surprise (Noninformative prior) (BEI-1F9)

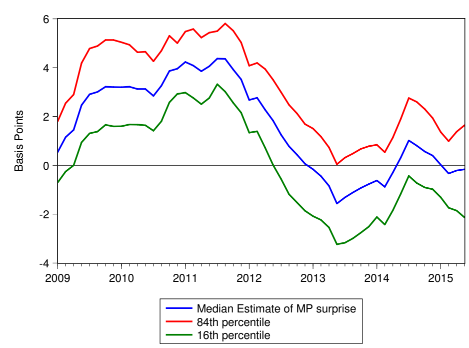


(b) IP surprise (Autoregressive process) (BEI-1F9)

Figure 24: Time varying estimates of Industrial Production surprise



(a) MP surprise (Noninformative prior) (BEI-1F9)



(b) MP surprise (Autoregressive process) (BEI-1F9)

Figure 25: Time varying estimates of Monetary Policy surprise

Analyzing the plots above, we conclude that the general pattern of less sensitivity to news is preserved regardless which prior is used and specification of the evolution of the state variable.

Figure 26: 20th order sample autocorrelation of the draws

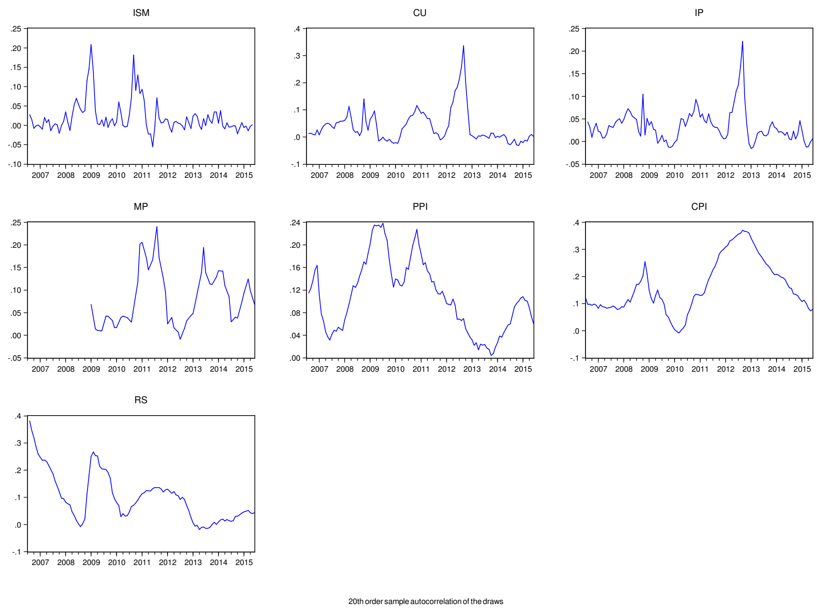
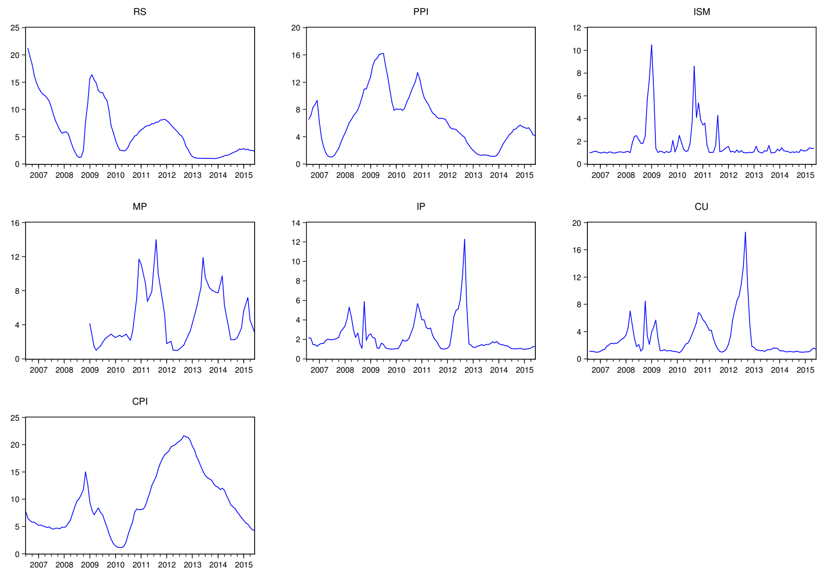


Figure 27: Inefficiency Factors



10 Conclusion

This paper addresses two questions. First, whether long-term US IEs got re-anchored in the aftermath of the crisis. Second, it uncovers the Macro determinants that caused time variation in the response of IEs to news. Using Time Varying news regressions estimated with Bayesian techniques from 2004 till 2015, we find that the response of far ahead forward BEI rates to the majority of the Macro news considered dwindled in the aftermath of the crisis. The financial crisis can be seen as a turning point for the sensitivity of IEs to unexpected components of announcements. Our results allude that US IEs indeed became more firmly anchored and in turn implies that the credibility of the Federal Reserve system surged in the aftermath of the crisis. Regarding the drivers of time variation in response to news, we find that the introduction of an explicit inflation target in 2012 reduces the response to price and real side news. Additionally, our results highlight that the Unemployment rate, Federal Funds rate and the VIX index are important determinants of time variation.

11 Appendix A. Liquidity adjustment of BEI yields

We use the GARCH standard deviation of daily increments of the BEI yields and the AAA-spread as proxies for liquidity premium as in Strohsal and Winkelmann (2015). The AAA-spread is the difference between AAA-rated US corporate bond yields and nominal government bond yields of the same maturity. The former are considered less liquid than the latter and thus the spread is a good proxy for liquidity premium. The AAA corporate bond yields are obtained from Datastream. We regress BEI rates (5 years maturities) on these two proxies. See Table 7 for the results and Figure 26 for the US liquidity proxies. The coefficient on (GARCH standard deviation) in Table 7 is significant at the 5% level while that for AAA-spread is significant at the 10% level and both have the expected sign. An increase in the AAA-spread and/or BEI volatility decreases break even inflation rates, as it increases the TIPS liquidity premium and, in turn, its yield. The estimated liquidity premium is obtained using the fitted values of the regressions in Table 7 (see Pflueger and Viceira (2011) for details). Figure 27 shows the estimated liquidity premium for 5-year BEI yields.

The Liquidity-adjusted BEI yields are larger than the unadjusted break even inflation yields as shown in Figure 28. The Liquidity-adjusted BEI yields, along with the forwards rates are used as dependent variables in the news regressions.

Table 7: Liquidity Premium Regressions

BEI-yields-5Y	
	US
AAA-spread	-0.22*
	(0.13)
BEI-volatility	-23.50**
	(2.07)
R^2	0.66

Notes: Least Squares estimation of BEI_t= c + β_1 $AAA - spread_t$+β_2 BEI-volatility $+u_t$. The sample period is June 2004-June 2015. Daily data is used for independent and dependent variables. ** represent statistical significance at the 5% level and * statistical significance at 5% level. BEI is short for Break-even inflation rate. Newey-West HAC standard errors are used.

Figure 28: US liquidity proxies (5 years maturity)

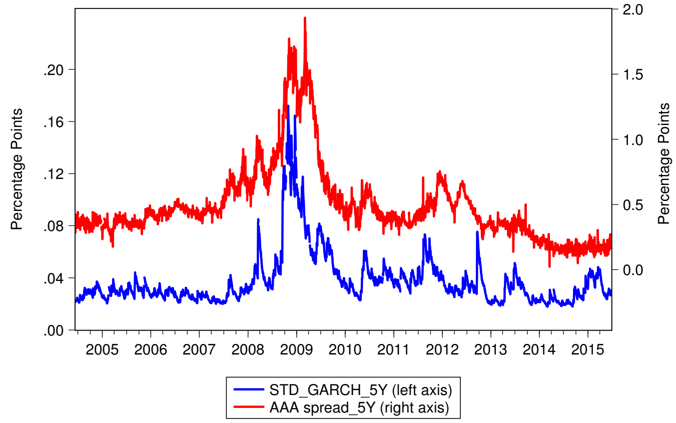


Figure 29: Estimated Liquidity Premium(5 years maturity)

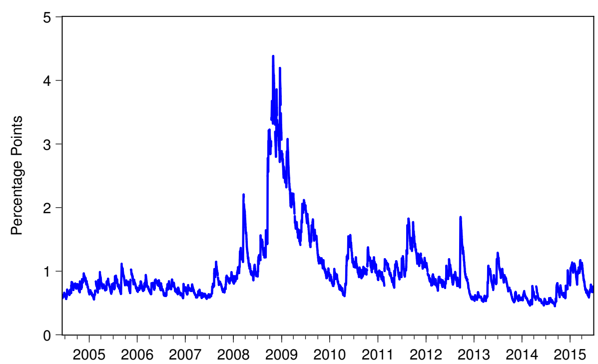
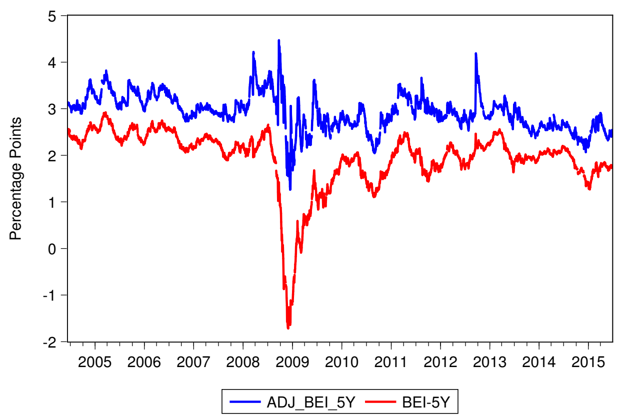


Figure 30: Adjusted BEI yields (5 years maturity)



12 Appendix B. Gibbs Sampler, Kalman Filter and Smoother

12.1 Gibbs Sampler

Gibbs Step 1: Using the rules of conditional probability and the random walk driftless assumption in (3), we obtain the following:

$$p(\beta^T|Y^T,V) = \underbrace{p(\beta_T|Y^T,V)}_{\mathrm{I}} \underbrace{\prod_{t=1}^{T-1} p(\beta_t|\beta_{t+1},Y^T,V)}_{\mathrm{II}} . \tag{6}$$

Conditional on the data and hyperparameters, the state space form given by (2) and (3) is linear and Gaussian. Thus, all the conditional densities on the right hand side of (5) are Gaussian and thus to draw from $p(\beta^T|Y^T,V)$ we only need to update the conditional means and variances of the conditional densities on the right hand side of (5).
To obtain the conditional mean and variance of the conditional density (I), we use the Kalman filter to go forward in time, until we reach the terminal state, T. Therefore, the conditional density of the terminal state, $p(\beta_T|Y^T,V)$, is $N(\beta_{T|T}, P_{T|T})$ where $\beta_{T|T} = E(\beta_T|Y^T,V)$ and $P_{T|T} = Var(\beta_T|Y^T,V)$. This enables us to draw β_T from that density.
Accordingly, we obtain the conditional mean and variance of (II) using the Kalman smoother to work backward through the sample. Thus, (II) has the following distribution: $N(\beta_{t|t+1}, P_{t|t+1})$ where $\beta_{t|t+1} = E(\beta_t|\beta_{t+1},Y^t,V)$ and $P_{t|t+1} = Var(\beta_t|\beta_{t+1},Y^t,V)$. For the first step of the backward recursion, the draw of β_T and the output of the Kalman filter (i.e., $\beta_{T-1|T-1}$, $P_{T-1|T-1}$ and $P_{T|T-1}$) are used to determine $\beta_{T-1|T}$ and $P_{T-1|T}$ which are in turn used to make a draw of β_{T-1}. The backward recursion continues until the first period.
Gibbs Step 2: Given Y^T and β^T, we can obtain the prediction error for the states and data (i.e., $\hat{\nu}_t$ and $\hat{\epsilon}_t$). Given that their conditional likelihood is Gaussian, combined with an inverse-Wishart prior, yields an inverse-Wishart posterior. Thus, $P(V|Y^T,\beta^T) = IW(V_1^{-1}, T_1)$ where $V_1 = \bar{V} + \bar{V}_T$. $\bar{V}$ is the prior scale matrix that we are going to assign a value for it in the next section and $\bar{V}_T = \sum_{t=1}^T \begin{pmatrix} \hat{\epsilon}_t \\ \hat{\nu}_t \end{pmatrix} \begin{pmatrix} \hat{\epsilon}_t \\ \hat{\nu}_t \end{pmatrix}^{\intercal}$ is like a sum of squared residuals.

12.2 Kalman Filter

We introduce the following notation:

$$\beta_{t|t} = E(\beta_t|Y^t,V)$$

$$P_{t|t-1} = Var(\beta_t|Y^{t-1}, V)$$
$$P_{t|t} = Var(\beta_t|Y^t, V)$$

Given $\beta_{0|0}$, V, Y^T, and $P_{0|0}$, we iterate on the following equations, for a generic time t, to obtain $\beta_{T|T}$ and $P_{T|T}$.

$$P_{t|t-1} = P_{t-1|t-1} + Q$$
$$K_t = P_{t|t-1}X_t(X_t'P_{t|t-1}X_t + R)^{-1}$$
$$\beta_{t|t} = \beta_{t-1|t-1} + K_t(y_t - X_t'\beta_{t-1|t-1})$$
$$P_{t|t} = P_{t|t-1} - K_tX_t'P_{t|t-1}$$

where K_t is the Kalman gain.

12.3 Kalman Smoother

We introduce the following notation:

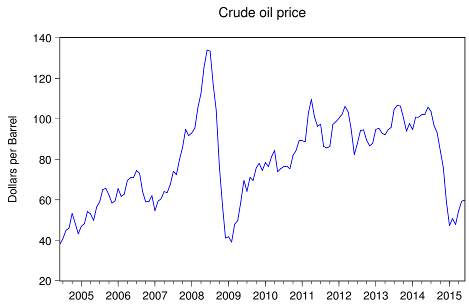
$$\beta_{t|t+1} = E(\beta_t|\beta_{t+1}, Y^t, V)$$
$$P_{t|t+1} = Var(\beta_t|\beta_{t+1}, Y^t, V)$$

Because the states (i.e., time-varying parameters) are conditionally normal, the mean and variance take the following expressions.

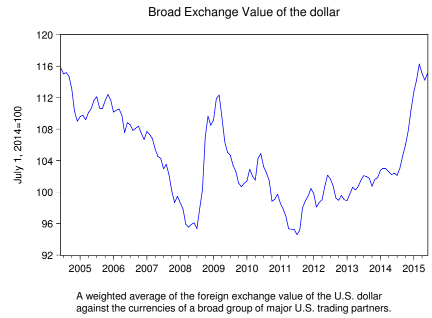
$$\beta_{t|t+1} = \beta_{t|t} + P_{t|t}P_{t+1|t}^{-1}(\beta_{t+1} - \beta_{t|t})$$
$$P_{t|t+1} = P_{t|t} - P_{t|t}P_{t+1|t}^{-1}P_{t|t}$$

13 Appendix C

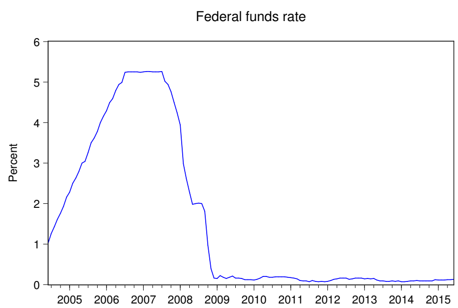
Plots of the Macro determinants used in Section 8.



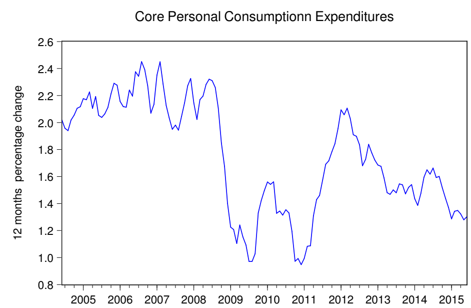
(a) Crude Oil Price



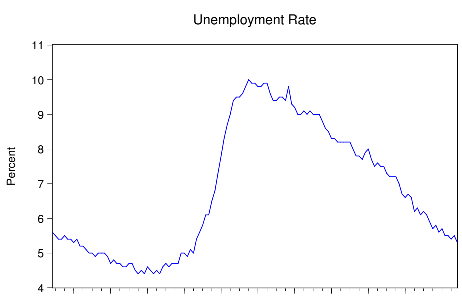
(b) Broad Exchange Value of the Dollar



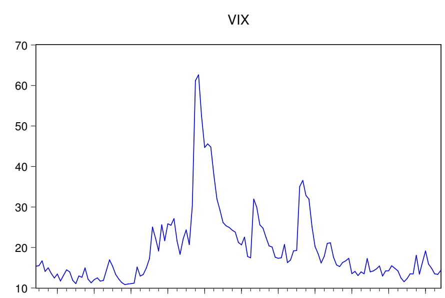
(c) Federal Funds Rate



(d) Core PCE



(e) Civilian Unemployment Rate



(f) VIX index

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