The Usefulness of the Median CPI in Bayesian VARs Used for Macroeconomic Forecasting and Policy

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Abstract: In this paper we investigate the forecasting performance of the median Consumer Price Index (CPI) in a variety of Bayesian vector autoregressions (BVARs) that are often used for monetary policy. Until now, the use of trimmed-mean price statistics in forecasting inflation has often been relegated to simple univariate or Phillips curve approaches, thus limiting their usefulness in applications that require consistent forecasts of multiple macro variables. We find that inclusion of an extreme trimmed-mean measure—the median CPI—improves the forecasts of both core and headline inflation (CPI and personal consumption expenditures) across our set of monthly and quarterly BVARs. Although the inflation forecasting improvements are perhaps not surprising given the current literature on core inflation statistics, we also find that inclusion of the median CPI improves the forecasting accuracy of the central bank's primary instrument for monetary policy: the federal funds rate. We conclude with a few illustrative exercises that highlight the usefulness of using the median CPI.

JEL classification: C11, E31, E37, E52

Key words: inflation forecasting, trimmed-mean estimators, Bayesian vector autoregression, conditional forecasting

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1 Introduction

A key task for economic forecasters and monetary policymakers is to parse through the incoming data, separate signal from noise, and use these data to make judgments over the likely path of the economy heading forward. In forecasting inflation, for example, many studies in the core literature have shown trimmed-mean inflation statistics to be useful indicators. However, evaluating the usefulness of trimmed-means is almost universally performed in simple univariate and single-equation forecasting applications.

While it may be appropriate in some settings to separately forecast one or two variables of interest, a monetary policy setting requires consistent forecasts of multiple variables. The Federal Open Market Committee (FOMC), for example, requires each member to submit forecasts of real GDP growth, the unemployment rate, headline and core inflation, and the federal funds rate four times a year for publication in their Summary Economic Projections (SEP) materials.[1],[2]

In this paper, we evaluate the usefulness of trimmed-mean inflation statistics in a class of multivariate models often used for forecasting and policy analysis—Bayesian Vector Autoregressions (BVARs). We are particularly interested in whether using the median CPI as the underlying inflation measure in the BVAR system leads to any appreciable differences in forecast accuracy of important macro variables (real GDP, inflation, fed funds rate, and the unemployment rate). To the best of our knowledge, the performance of trimmed-mean inflation statistics and their influence on other macro variables has to be investigated in a BVAR setting.

[1] See http://www.federalreserve.gov/monetarypolicy/fomccalendars.htm for more details.
[2] We are aware that the FOMC has chosen to target PCE inflation. For purposes of this paper, we are making the switch back to the CPI. We leave the construction and evaluation of a median PCE for further research, but given that roughly ¾ of the initial PCE release is constructed directly from CPI component indexes, we doubt that the results will differ qualitatively.

Trimmed-mean inflation statistics were first investigated by Bryan and Pike (1991) and then more formally by Bryan, Cecchetti, et al (1994, 1997). These measures of underlying inflation uncover the inflation signal by stripping away the most volatile monthly relative price swings. These measures are much more systematic in the removal of relative price changes than exclusionary indexes like the ex food and energy "core" CPI. Exclusionary indexes, by design, implicitly assume that price changes in every component other than those they exclude are inflation signal. So, for example, if tobacco prices were to spike in a given month because of an excise tax increase, the core CPI would treat this as signal, whereas trimmed-mean inflation statistics would remove this relative price shock.

There is a fairly sizeable literature on the usefulness of trimmed-mean inflation statistics apart from Bryan and Cecchetti. Smith (2004), using both conditional and unconditional forecasting models, finds that the weighted median CPI outperforms the core CPI. Clark (2001) finds that the 16 percent trimmed-mean CPI and the CPI ex energy are better univariate forecasters than the core CPI or underlying inflation index that excludes the 8 most volatile CPI components. Meyer and Pasaogullari (2010) find the median and the 16% trimmed-mean CPI forecast year-ahead headline inflation about as well as inflation expectations do, and outperform simple forecasting models. Crone, Khettry, Mester, and Novak (2013) found that over longer-horizons (i.e. 24-months and longer), the median CPI yields a forecast significantly superior to that of the headline or ex food and energy CPI index.

Others, such Dolmas (2005) and Detmeister (2011) have investigated the use of trimmed-mean inflation statistics using Personal Consumption Expenditures Price Index (PCE) data. Dolmas (2005) finds that an optimally selected asymmetric trim tracked inflation much more closely than the ex food and energy ("core") PCE price index. And, Detmeister (2011) finds that trimmed-mean measures outperform exclusionary indexes (like the core PCE) in tracking the ex-post inflation trend and forecasting future inflation.

Stock and Watson (2008) engage in a comprehensive inflation forecasting exercise, performing a total of 192 forecasting procedures. The models they consider range from simple naïve (random-walk) forecasts, to an unobserved components-stochastic volatility (UC-SV) model, to various forms of the "Phillips-Curve." They do investigate median CPI and 16% trimmed-mean CPI, but find mixed results. However, the focus of that paper was just inflation, and not on other macro variables.

Two other inflation forecasting studies—Ball and Mazumder (2011) and Norman and Richards (2012)—investigate the use of trimmed-mean inflation statistics in Phillips Curve models, with mostly positive results. Ball and Mazumder are primarily focused on the Great Recession period and use the median CPI to partially solve a Phillips curve-based forecasting puzzle, where a standard estimated Phillips Curve predicted a dramatic deflation from 2008-2010 which did not materialize. Norman and Richards show that using a trimmed-mean inflation measure on Australian CPI data significantly improves the in-sample fit and forecasting power of standard New Keynesian Phillips Curves over those that are based on headline inflation.[3]

As to which trimmed-mean inflation statistic we should use in this exercise, we lean on the work of Meyer and Venkatu (2012), which shows that there is a wide-swath of statistically-

[3] In contrast, Giannone and Matheson (2007) using CPI data for New Zealand show that trimmed-mean estimators including the median CPI were unable to out-perform the method that utilized dynamic factor model and disaggregated CPI data in predicting future inflation. Specifically they were trying to predict the target inflation which they defined as the centered two-year moving average of the past and future inflation.

indistinguishably performing trims. They, then, suggest the use of the median CPI because of its advantages in communicating underlying inflation to the public.[4]

To preview our results: We find that inclusion of the median CPI in a macro policy BVAR consistently leads to an improvement in forecasting accuracy[5], not only for headline and core inflation, but also for the fed funds rate. In general, these improvements in accuracy are fairly modest, though statistically significant over multiple horizons. The usefulness of the median CPI tends to be greatest in monthly BVARs, as the median CPI can help separate signal from noise more quickly than using the ex food and energy CPI alone.

Another, perhaps equally interesting result, is that the median CPI helps to forecast PCE-based inflation in this suite of models. In fact, the gains in forecasting accuracy are on par with models using CPI-based inflation, if not better. This finding suggests that the median CPI is an appropriate measure of underlying inflation, as it highlights the monetary impulse of inflation through the pricing system and sloughs of relative price noise and idiosyncratic aspects related to the construction of the price indexes (i.e. formula, scope, and weighting differences between the CPI and PCE price indexes).

Finally, the structural analysis exercise suggests the model with median CPI produces credible impulse responses to an identified monetary policy shock and those responses are very similar to those from the model without median CPI.

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[4] We ran a few forecasting tests using the 16% trimmed-mean CPI and, consistent with Meyer and Venkatu (2012) found qualitatively similar results.

[5] In light of recent research (e.g. Gamber et al. (2015)) documenting an existence of a dynamic relationship between median CPI inflation and headline CPI inflation that is stable across monetary regimes we also ran model specifications that included information about the deviation of headline inflation from the median CPI (i.e. gap between the two) in addition to the median CPI. The results were quantitatively very similar. In the interest of brevity we do not report those results.

The paper is organized as follows. In Section 2 we describe the forecasting exercise and outline the various models we are employing. In Section 3 we detail the forecasting results and we highlight the usefulness of our approach with some practical forecasting exercises. Section 4 compares structural analysis across two models with and without median CPI. Section 5 concludes.

2.1 The data and the design of our forecasting exercise

Our primary objective is to evaluate the forecasting performance of the median CPI in a few common Bayesian VARs.

As a first step, let's define some notation for the VAR framework:

A VAR(p) model can be written as,

$$Y_t = \sum_{i=1}^{p} A_i Y_{t-1} + A_c + \varepsilon_t \qquad (1)$$

where $Y_t = (y_{1,t}, y_{2,t}, \ldots, y_{n,t})$ is a data vector of n random variables (n x 1 vector), $A_c = (c_1, c_2, \ldots\ldots c_n)$ is a vector of constants, $A_1, A_2, \ldots, A_p$ are n x n matrices of VAR coefficients, and $\varepsilon_t \sim N(0, \Sigma)$. The p indicates the number of lags, for the BVARs estimated with quarterly data we set p=4, and those estimated with monthly data we set p=13.

We estimate the VARs using Bayesian shrinkage (hence the term BVARs). This implies that we use an objective statistical approach to estimation that combines modeler's prior beliefs with the available data. We achieve this by imposing prior restrictions on the parameter estimates. Specifically, we shrink the coefficients of the VAR towards the univariate random walk model with a drift or white noise process depending whether the variable is characterized as highly persistent (i.e. trending) or characterized by mean reversion (i.e. non-trending). Doing this gives us an a priori system consisting of random walk and white noise processes. The overall degree of shrinkage is controlled by hyperparameter λ. As $\lambda \rightarrow 0$, shrinkage increases and prior dominates making data less influential in determining the posterior coefficient estimates (with a $\lambda = 0$ prior equals posterior), whereas $\lambda \rightarrow \infty$, data dominates the prior and influences the posterior estimates to a greater extent (with $\lambda = \infty$ we obtain OLS estimates). The value assigned to the hyperparameter λ for each of the BVAR under study is discussed later with the description of the specific BVARs. The BVARs we consider in this paper implement the Normal-inverted Wishart prior proposed by Kadiyala and Karlson (1997) and Sims and Zha (1998), which is basically a version of the Minnesota prior introduced by Litterman (1986). More specifically, the prior beliefs on the coefficient's first and second moments are as follows:

For a prior corresponding to random walk with drift process:

$$E\left[(A_k)_{ij}\right] = \begin{cases} \delta_i = 1, & if\ i = j, k = 1 \\ 0, & otherwise \end{cases}, \quad Var\left[(A_k)_{ij}\right] = \lambda^2 \frac{\sigma_i^2}{\sigma_j^2} \frac{1}{l^2}, \qquad l = 1, \dots, p$$

For a prior corresponding to white noise process:

$$E\left[(A_k)_{ij}\right] = \begin{cases} \delta_i = 0, & if\ i = j, k = 1 \\ 0, & otherwise \end{cases}, \quad Var\left[(A_k)_{ij}\right] = \lambda^2 \frac{\sigma_i^2}{\sigma_j^2} \frac{1}{l^2}, \qquad l = 1, \dots, p$$

In addition to the Minnesota prior, all of the BVARs we employ are equipped with the sum of coefficients prior (proposed Sims (1992), Sims and Zha (1998)) that allows for the inexact differencing of the variables of the system. This means that the VAR coefficients on a variable's own lags sum to one. The hyperparameter μ governs the degree of the tightness of this prior. Lower the value of μ, greater its influence on the posterior estimates. As μ goes to zero, we reach the case of exact differences, and as μ goes to infinity we reach the case of no shrinkage.

One of the BVARs we use is equipped with the co-integration prior, or what is often referred to as a "dummy initial observation" prior. This prior is motivated by the belief that most of the macroeconomic data is characterized by a high degree of co-integration. To account or adjust for that co-movement, the co-integration prior is imposed. The hyperparameter τ controls the degree of cointegration. As $\tau \to 0$ a system tends to the form in which all the variables are stationary.

All these three set of priors are implemented in the usual way, that is, by augmenting the datasets with the corresponding dummy observations.

Given that our focus is point forecasting and the models under consideration are homoscedastic BVARs with natural conjugate prior (i.e. Normal-Inverted Wishart prior and each equation treated symmetrically) posterior parameter estimates can be solved analytically. Hence we avoid simulating the forecast distributions to obtain the forecast as the posterior mean of the associated distributions. Carriero, Clark, and Marcellino (2015) have documented that, for the models they considered, in the case of point forecasts, what you obtain without simulation is effectively the same that will be obtained with simulation (their benchmark model is one of the models we evaluate). And so following in the footsteps of the studies describing our models of interest, we estimate the posterior estimates analytically.

Next let's briefly discuss the methodology used to compute the 1 to H steps ahead forecast for the variables of interest.

At each forecast horizon, using the estimated posterior mean of the coefficients in equation (1), we compute one-step ahead forecast as,

$$\hat{Y}_{t+1} = \overline{A_c} + \overline{A_1}Y_t + \overline{A_2}Y_{t-1} + \cdots + \overline{A_p}Y_{t-p+1}$$

By iterating forward and employing recursive substitution, the remaining h=1,..H-1 step-ahead forecasts can be computed. More generally,

$$\hat{Y}_{t+h} = \overline{A_c} + \overline{A_1}\hat{Y}_{t+h-1} + \overline{A_2}\hat{Y}_{t+h-2} + \cdots + \overline{A_p}\hat{Y}_{t+h-p}$$

where $\hat{Y}_{t+h} = Y_{t+h} - p \ \ for\ h \leq p$

We report the forecasting accuracy in terms of relative mean-squared forecasting error (RMSFE) for real GDP (or payroll employment growth for monthly models), the unemployment rate, the federal funds rate, and headline and "core" inflation—as these are the variables of interest for most central banks.

More specifically, the out-of-sample forecast accuracy in terms of mean squared forecast error (MSFE) for each forecast variable $i \in \{real\ GDP\ (or\ payroll),$ $unemployment\ rate, federal\ funds\ rate, core\ inflation, headline\ inflation\}$ and forecast horizon h=1,… H is defined as,

$$MSFE_{i,h} = \frac{\sum_{t=T_0}^{T_1-h} \left(\mathrm{Y}_{i,t+h} - \hat{\mathrm{Y}}_{i,t+h}\right)^2}{T_1 - h - T_0 + 1}$$

where T_0 = 1986:Q4 (or in the case of monthly model 1986:M12), T_1 = 2016:Q2 (or 2016:M8), H=8 in the case of quarterly model (and H=24 in the case of monthly model).

And the correspondingly, the MSFE relative to the benchmark (RMSFE) is defined as,

$$RMSFE_{i,h} = \frac{{MSFE_{i,h}}^{BVAR\ with\ Median\ CPI}}{{MSFE_{i,h}}^{Benchmark\ BVAR}}$$

We investigate both monthly and quarterly models, with data starting in 1967Q1 (January 1967 for the monthly data) and running through 2016Q2 (August 2016). We estimate the model recursively, starting with a block of the first 20 years (80 quarters or 240 months) and iterate forward by adding 1 additional quarter (month) to the estimation period at each step. After each estimation step, we forecast over the next 2 years (8 quarters or 24 months), with our first set of 8 quarters from 1987Q1 through 1989Q1 (24 months from January 1987 to January 1989). We gather up these recursive forecast errors and calculate mean squared forecasting errors (MSFEs) for each quarter (month) over the next two years. In each model exercise, we report the RMSFEs, comparing a baseline BVAR that does not include the median CPI to one that does. We report the RMSFEs for all quarters up to 2 years out (h= 1 to 8), or for monthly applications we report the MSFEs at h=1-,6-,9-,12-,15-,18-,21-, and 24-months ahead.

The design of the forecast evaluation is "dynamic" in nature, meaning that our h-step-ahead evaluation period runs through the end of our data sample. For example, with data running through 2016Q2, we can evaluate the 1 step-ahead RMSFEs models estimated through 2016Q1, but for the 8 quarter-ahead forecasts, the estimation period stops at 2015Q2.

Also included in the appendix are the forecast evaluation results corresponding to the pre-crisis sample, i.e. 1987-2007Q3[6]. We include those to illustrate that our findings are robust across sub-samples and more importantly they are not sensitive to unusual developments since the 2007 financial crisis.

[6] For these we report forecast evaluation results that are 'static' in nature. That is our last estimation run stops in 2005:Q3 giving us same number of one-step to eight-step forecast errors over the forecast evaluation window.

To roughly gauge the difference in forecasting performance we use an equality of prediction test set forth by Diebold and Mariano (1995) to test for equal mean square forecast error.[7] Our forecasting exercise entails the use of nested models over a finite sample. While Clark and McCracken (2013a,b) show that the Diebold Mariano test is a bit too conservative under these conditions, we are unaware of the existence of a more appropriate equality of prediction test for this setting. Nevertheless, the Diebold and Mariano test should give us a rough gauge of how significant the differences in forecasting accuracy are.

To test the robustness of inclusion of the median CPI, we perform our forecasting exercise over a variety of **B**VARs: a medium scale BVAR put forth by Beauchemin and Zaman (2011), 3 classes of monthly BVARs used in Banbura, Giannone, and Reichlin (2010), and the BVAR set forth Carriero, Clark, and Marcellino (2015).[8] In each setting, we perform two exercises. The first exercise is to add the median CPI into each model. The second is to replace the core CPI with the median CPI as the underlying inflation measure.

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[7] We make an adjustment to correct the standard errors for heteroskedasticity and autocorrelation using the *Newey-West estimator. Using* pre-whitened quadratic spectral kernel introduced by Andrews and Monahan (1992) gives very similar results.

[8] We also perform this forecasting exercise in a classical VAR framework (or a BVAR with very diffuse priors). The results are qualitatively similar to those we report.

2.2 The models we employ[9]

Beauchemin and Zaman

Beauchemin and Zaman (2011) set forth a medium scale (16 variable) BVAR designed to be used in a monetary policy setting. They implement a natural-conjugate version of the Minnesota prior and a "sum-of-coefficients" prior (see Sims 1992). They select hyperparameters that govern the shrinkage for Minnesota and sum-of-coefficients priors by grid search that maximizes the marginal likelihood of the data. The variables they include are: real GDP, the unemployment rate, headline inflation, ex food and energy inflation, the effective fed funds rate, nonfarm business compensation and productivity, real personal consumption expenditures, real personal disposable income, nonfarm payrolls, the KR-CRB spot commodity price index for all commodities, the 10-treasury note yield at constant maturity, Moody's Aaa corporate bond yield, the S&P 500 composite stock price index, the S&P 500 composite dividend yield, and the nominal trade-weighted exchange rate vs. major currencies. They set the hyperparameters λ and μ through a grid search that maximizes the marginal likelihood at forecast iteration.

Banbura, Giannone, and Reichlin

The BVARs have been around since mid-80s (Litterman, 1986) and have been used for forecasting but it is only recently that their popularity have gained mainly due to an important work by Banbura, Giannone, and Reichlin (2010), henceforth BGR, who show that it is possible to estimate a VAR with more than hundred variables as along as the forecaster accordingly adjusts the degree of Bayesian shrinkage. They illustrate the forecasting performance of host of variables belonging

[9] Detailed tables for each model appear in the Appendix. Section A1

to a set of differently-sized monthly VARs that may potentially be used in monetary policy. They find that the use of shrinkage to reduce over-parameterization and circumvent omitted-variable bias leads to better performance in terms of forecast accuracy and (what they call) "credible" impulse responses to a monetary policy shock. The models they consider are:

1) A small VAR that includes employment, inflation, and the fed funds rate. They set the hyperparameters $\lambda = \infty$ and $\mu = \infty$
2) The monetary policy VAR from Christiano, Eichenbaum, and Evans (1999) that includes the variables in the small VAR and adds a measure of commodity prices, non-borrowed reserves, total reserves, and a measure of the money stock (M2). For this specification they set the hyperparameters $\lambda = 0.262$ and $\mu = 10*0.262$
3) A Medium-scale (20 variable) model that adds to CEE: Personal income, real consumption, industrial production, capacity utilization, housing starts, producer prices, real personal consumption expenditures, average hourly earnings, M1, S&P 500, the 10 year t-bond yield, and the effective exchange rate. They set hyperparameters $\lambda = 0.108$ and $\mu =10* 0.108$
4) A large-scale VAR that uses the 131 variable dataset from Stock and Watson (2005).

Interestingly, BGR finds that the forecasting performance of the largest model, while outperforming the smallest models, is roughly on par with the medium-scale (20-variable) model. Given this finding, we use the first 3 monthly BVARs (small, CEE, and medium) in our analysis of the median CPI.

Carriero, Clark, Marcellino

The model we implement in our investigation is the medium-scale "simple" BVAR (benchmark) advocated by Carriero, Clark, and Marcellino (2015). They embark on an investigation of different BVAR modeling choices and investigate the payoff associated with using more computationally expensive methods (such as priors that require Monte Carlo Markov Chain simulations) for estimation. Interestingly, they find evidence for the Keep-It-Simple method, advocating for the use of BVAR with the variables transformed to be stationary (e.g., employment or GDP specified in growth rates as opposed to levels), longer included lag lengths (they recommend 12 for monthly data), and a Normal Inverse-Wishart prior. Their baseline model, and the one we implement, is monthly and includes 18 variables: the unemployment rate, headline and core inflation, nonfarm payrolls, weekly hours worked, initial claims for unemployment insurance, nominal retail sales, an index of consumer confidence (we use UM Sentiment), single-family housing starts, industrial production, capacity utilization, two forward-looking sub-indexes (new orders and supplier delivery times) from the Institute for Supply Management's Manufacturing Purchasing Managers' Index (PMI), the spot price of West Texas Intermediate oil, S&P 500, the 10-year Treasury bond yield, the fed funds rate, and the real exchange rate.[10] In their baseline setup, they use the following values for the hyperparameters: $\lambda = 0.2$, $\mu = 1$ and $\tau = 1$.

2.3 Conditional forecasting through the Crisis Period and ZLB

The onset of the financial crisis in the fall of 2008 was accompanied by a severe decline in the real output and a spike in the unemployment rate. As a result monetary policy makers responded by sharply lowering the federal funds rate to zero. Since then, the Federal Reserve has kept the fed funds rate close to zero, and through the use of forward guidance, has communicated to keep them

[10] Due to data availability, our sample starts in January 1971.

low for foreseeable future. Not surprisingly, feeding a severe contraction into this class of forecasting models leads to projection of a negative federal funds rate path, which is unattainable given the current language of the Federal Reserve Act. Given that, in practice, the funds rate is bounded by zero, we need a set up to address this issue.

The federal funds rate equation in a BVAR can be characterized as a monetary policy reaction function, as it is responding to a large set of variables. That being said, the most important drivers of the federal funds rate in a macro policy BVAR are real output and unemployment rate. At a forecast origin in 2008, as the model encounters a large decline in real GDP and a subsequent sharp rise in the unemployment rate it drives the fed funds rate forecast to a negative territory. A detailed exercise of this outcome using a Bayesian VAR is illustrated in Tallman and Zaman (2012). The federal funds rate is a nominal interest rate and so it cannot go below zero[11], a constraint known as Zero Lower Bound (ZLB).

To deal with these constraints, we employ conditional forecasting of the sort discussed and documented in Doan, Litterman and Sims (1984) and Waggoner and Zha (1999). Specifically, we condition the forecast of all the variables in the model on a given path of the federal funds rate once we reach our forecast origin at the beginning of 2008. That constrained path of the federal funds rate is the actual fed funds rate observed from 2008 onwards (quarterly average for the case of quarterly models and monthly average for the case of monthly models), and is essentially a fed funds rate level of less than 50 basis points. This approach is commonly used to handle incomplete data matrices in BVAR models, and for performing policy analysis by assuming future paths for variables of the model as known data and then evaluating the conditional outcomes of the

[11] At least so far this is the case in the USA

unconstrained variables. In short, this approach in our application entails adjusting the unconditional forecast of all the variables (with the exception of fed funds rate) in light of the future constrained path of the fed funds rate path. The adjustment to each variable's forecast would depend on its historically observed correlation with the fed funds rate. For example, if we condition on a federal funds rate path that is lower than implied by the unconditional path (i.e. unconditional forecast of the fed funds rate) than due to high positive correlation between real GDP and fed funds rate (found in data with which the model is estimated with), the real GDP forecast path will be adjusted downwards (i.e. conditional forecast of real GDP) to reflect the historical correlation between the two. In statistical terms, a conditional forecast of variable of interest at time t, is an expected value of that variable at time t given all the available data up to time t, and future data of the conditioning variable (in our case federal funds rate). Compare that to an unconditional forecast which is essentially an expected value of a variable at time t given all the available data at time t.

Since fed funds rate is constrained to follow the actual path in all models starting in 2008, so in the case of the federal funds rate, mean square errors and corresponding statistical significance are evaluated from the forecast origin starting in 1986:Q4 (or 1986:M12) and ending in 2005:Q3 (or 2005:M09). That is, the eight step ahead forecasts generated at the forecast origin 2005:Q3 (or 24-steps ahead at the forecast origin 2005:M09) are the last entries for evaluating the federal funds rate forecast performance.[12]

[12] The eight step-ahead forecast generated at the forecast origin 2005:Q3 corresponds to forecast date of 2007:Q3. The forecast evaluation results one-step to eight-step ahead reported for fed funds rate are static in nature. That is the same number of one-step to eight-step ahead forecasts errors are used in computing the squared errors. We have also performed the forecast evaluation using the unconditional forecasting throughout the recursive sample (i.e. without conditional forecasting). The results are qualitatively similar for all variables except the fed funds rate, in which the forecasts from models that include the median CPI dramatically improve upon models without the median CPI, but are still, in an absolute sense, very poor. These unconditional results are available on request.

3.1 The Results

Tables 1 through 3 report the recursive pseudo-out-of-sample RMSFEs for the BVARs we use to examine the forecasting performance of the median CPI. Each table corresponds to a different model and contains two panels. The first panel in each table reports the forecasting results of baseline model to the results with the median CPI added to the model. In the second panel, the median CPI replaces the core CPI as the measure of underlying inflation. An RMSFE less than one indicate a lower forecast error for alternative model (i.e. the one that includes the median CPI).

In general, our results indicate that inclusion of the median CPI yields a modest improvement over using the core CPI as the measure of underlying inflation. The RMSFEs are lower than one in nearly every time horizon across all the models we test. However, the improvements tend to be a little too modest for our equality of prediction test in most settings. Even though the Diebold-Mariano test is biased against finding significance, we still find that inclusion of the median CPI in the larger monthly BVAR models we consider yields a statistically significant improvement at the year-ahead horizon.

The overall gains in accuracy and significance are larger with monthly models compared to quarterly models. The most likely reason for this finding is because in quarterly models time series averaging helps reduce noise in headline inflation. In monthly models, which are characterized by higher degree of noise in headline inflation, inclusion of the median CPI more quickly separates signal from noise.

In panel (a) of tables 1 and 3 we can see that including the median CPI alongside the current model improves on the forecasts of the core CPI. For the Carriero et al. BVAR (BVAR 5) in table 3, the gains in forecast accuracy range from 6 to 11 percent, and are statistically significant in 5 of the 8 horizons. If forecasters are using the ex food and energy CPI measure as a gauge of underlying inflation, these results suggest that the median CPI is a more appropriate measure (at least in the sense that it forecasts “core” inflation more accurately). That said, given the existing “core” inflation literature, it is probably not a surprise that using the median CPI leads to lower RMSFEs for headline and ex food and energy inflation over most models and time horizons.

Perhaps a more interesting result is that use of the median CPI consistently leads to lower RMSFEs for the fed funds rate. The intuition behind this result is that embedded in each of these macro policy models is an implicit Taylor Rule, or monetary policy reaction function, that among other variables responds to the evolution of the real side growth and of inflation. Since inclusion (or sole use) of the median CPI as the underlying inflation measure improves the forecast accuracy of inflation, feeding a more accurate forecast for inflation into the implicit rule yields an improved fed funds forecast. On the other hand, there are only a handful of significant improvements in forecasting the fed funds rate. As we will see in section 3.2, this is likely a combination of an equality of prediction test that is a little too conservative and that the FOMC targets PCE-based inflation.

Only in a few specifications does use of the median CPI yield significant forecasting improvement to output growth (or employment growth for monthly models). That said, the inclusion of the median CPI generally doesn’t usually yield material deteriorations in forecasting accuracy on the real side.

3.2 What about forecasting PCE-based inflation?

This next section answers a simple question: If the median CPI is an appropriate underlying inflation measure, even though it is calculated using CPI components, would it be useful in a policy forecasting model that uses PCE-based inflation? There are differences in measurement, scope, and construction between the two price indexes. However, if the median CPI is systematically removing sources of noise and uncovering the inflation signal appropriately, these small differences between the two indexes should not matter. Tables 4 and 5 take the monthly BVAR from Carriero, Clark, and Marcellino (2015) and the quarterly BVAR from Beauchemin and Zaman (2011), and perform this experiment in much the same way as the previous tests, where the median CPI is first added alongside the current inflation measure in the BVAR system, and then replaces the core inflation measure.

As was the case with CPI-based inflation forecasts, inclusion of the median CPI improves the inflation forecasts. Interestingly, the gains in the Carriero, Clark, and Marcellino (2015) monthly BVAR are more impressive when forecasting PCE-based inflation. For example, in comparing tables 3a and 4a, the relative MSFE for core CPI inflation at the 24-months ahead horizon is 0.926 (and not significant), while the relative MSFE for core PCE over that horizon is 0.888 and significant at the 5% level. A similar pattern holds true for headline inflation in tables 3b and 4b though both are statistically not significant. Many of the components that enter into the PCE are directly taken from the CPI report (roughly 70 percent of the overall index by expenditure weight). So, it may be that inclusion of non-market-based (imputed) items in the PCE (such as imputed financial services) is the culprit. This would indicate that the absence of a market pricing mechanism in these components or the lack of accurate data is clouding the inflation signal. We leave this for further study.

The modest improvements to PCE-based inflation forecasting accuracy suggest that the median CPI is an appropriate measure of underlying inflation, as it removes noise not only associated with volatile relative price fluctuations, but also overcomes idiosyncratic noise due to the differences in construction between the CPI and PCE (i.e., weight, scope, and formula effects). This is an important result, as it implies that forecasters and policymakers might be better served by using the median CPI (or trimmed-mean estimators in general) as their measure of underlying inflation.[13]

It is also worth noting that, in models with PCE-based inflation—adding the median CPI (or replacing the core inflation measure with the median CPI) significantly improves the model's accuracy in forecasting the fed funds rate. This is over and above the improvements seen in BVARs with CPI-based inflation. We interpret this result as consistent with the fact that the FOMC targets PCE-based inflation, combined with the increased gains in PCE-based inflation forecasting accuracy.

3.3 What if an "ex food and energy" inflation forecast is required?

The above exercises have shown a moderate advantage in replacing the ex food and energy ("core") CPI with the median CPI as the underlying measure of inflation in a variety of BVARs. This presents a potential problem for forecasters, such as FOMC participants, that are required to provide a core CPI or core PCE forecast. In this case, we suggest just using the forecasts of the median CPI *as* the core inflation forecast. We think it is a reasonable thing to do since core CPI is supposed to be the underlying trend, so why not forecast that underlying trend with an underlying trend obtained from the median CPI.

Tables 6 and 7 present the results of using the forecasts of the median CPI *as* the core CPI forecasts in both the Beauchemin and Zaman (2011) quarterly BVAR and the Carriero, Clark, and

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[13] Some policymakers may balk at this suggestion, stating that communicating the change to the public would be difficult. However, in the early 2000s, despite widespread awareness of the CPI, the Committee switched to implicitly targeting PCE-based inflation. Moreover, in times when food and energy prices are spiking (such as mid-2008 or 2011), public outbursts arise decrying the central bank's ignoring of these price changes. (see http://online.wsj.com/article/SB10001424052748704893604576199113452719274.html for an example).

Marcellino (2015) monthly BVAR models. The results suggest that using the forecasted values of median CPI in lieu of the core CPI generally leads to an improvement in accuracy. And in the case of the Carriero, Clark, and Marcellino (2015) monthly BVAR model, yields a statistically significant improvement in the 9-month, and 24-month ahead forecasting horizons.

4 Structural Analysis

Finally, we perform a structural analysis exercise that examines the credibility of the response of variables to a monetary policy shock in a model without median CPI and compare it to the model with median CPI[14]. For the sake of brevity will illustrate the analysis using the quarterly BVAR model as in Beauchemin and Zaman (2011), and a monthly BVAR model as in Carriero et al. (2015). The design of the exercise is similar to that in Beauchemin and Zaman (2011) and Banbura, et al. (2010). Specifically, the monetary policy shock is identified through a recursive ordering of the variables of the model. With the exception of the federal funds rate, all other variables are divided into two groups: "fast moving" and "slow moving" (a notation that is commonly used in literature dealing with identification of monetary policy shock in VARs). The variables labelled slow moving are assumed to respond to a monetary policy shock with a lag and so are ordered before the federal funds rate (i.e. monetary policy variable) whereas the variables labelled as fast moving are assumed to respond contemporaneously to the policy shock and therefore are ordered after the federal funds rate. Broadly financial variables fit the designation of the fast moving with the rest of the variables of our model falling under the slow moving. For the identification of the monetary policy shock, the order of the variables within the block does not matter[15].

[14] We thank Domenico Giannone for suggesting this exercise.
[15] For econometric details of the identification of the monetary policy shocks please refer to Beauchemin and Zaman (2011) or Banbura et al (2010).

Figure 1 shows the responses of the variables of the two models to a monetary policy shock, i.e. increasing the federal funds rate by roughly 70 basis points. For ease of comparison, the responses of each of the variable from the two models are plotted side-by-side. By visual inspection few observations are worth pointing out. First the responses of each of the variable to a monetary policy shock are as expected[16]. Second, price variables continue to exhibit "price puzzle". That is adding median CPI does not help in solving the price puzzle. Third, responses of real variables across the two models are identical but there are minor differences in the response of nominal variables. For example, two to three years out the median response of core PCE and headline PCE inflation is couple tenths lower in the model with median CPI compared to the model without it.

Figure 2 shows the impulse responses for the same two model specifications (i.e. with and without median CPI) to a roughly 65 basis point increase in the federal funds rate but now the estimations ends in 2005:Q3 (i.e. pre-crisis). Again, the responses of the variables to a monetary policy shock are quite identical across the two model specifications with minor differences in responses of the price variables but importantly there is a pretty weak evidence of price puzzle. That is quite interesting. It does suggest that monetary policy shock is appropriately identified in our exercise when estimating with pre-crisis sample.

Figures 3 and 4 correspond to outcomes of similar exercise as in figure 1 and 2 but this time it corresponds to the monthly BVAR as in Carriero et al. (2015) and the size of the contractionary monetary policy shock is roughly 40 basis points. Just like in the case of quarterly BVAR, the responses of the variables are as expected and the model with median CPI continues to give

[16] A contractionary monetary policy shock leads to increase in prices which are contrary to intuition but this result is expected because significant body of research (dealing with monetary VARs) has documented this behavior and accordingly dubbed it the "price puzzle".

credible impulse responses. Generally speaking the outcomes of the structural exercise using the monthly BVAR are consistent with the outcomes we observed in the quarterly BVAR, for example weak evidence of price puzzle when estimated with pre-crisis data but not so when estimated with full sample.

Therefore adding median CPI to a BVAR (be it a monthly or quarterly) does not seem to hurt as structural analysis performed using a model that includes it continues to give credible impulse responses which are broadly identical to a model without it.

5 Conclusion

This paper assesses the forecasting performance of trimmed-mean inflation statistics—the median CPI to be precise—in a variety of BVARs that are often used in monetary policy settings. We are primarily concerned with whether inclusion of the median CPI leads to significant changes in forecasting accuracy for not only inflation, but other policy-relevant macro variables (real GDP, unemployment, and the federal funds rate).

Perhaps unsurprisingly, we find that inclusion of the median CPI improves the inflation forecasting accuracy of both monthly and quarterly models over many horizons at times the gains are statistically significant. A more interesting finding is that the federal funds rate predictions almost always improve (many times significantly) with inclusion of the median CPI. We interpret this result in a "garbage-in, garbage-out" framework. Feeding into the implicit monetary policy reaction function a more accurate inflation forecast (a better input) yields a more accurate prediction of the funds rate (a better output).

We also find that even though our trimmed-mean inflation measure is CPI-based, its inclusion into the BVAR significantly improves the forecasting accuracy of PCE-based inflation variables. In addition, if a core inflation forecast is required, just providing the median CPI forecasts in lieu of a core CPI forecast is as good (if not better) in terms of forecasting accuracy.

Throughout the paper we switch between adding the median CPI to the model and replacing the core CPI with the median CPI. Our results do not clearly distinguish which approach is best. However, for the sake of parsimony, it appears that just using the median CPI as the underlying inflation measure in a macro policy BVAR is at least as good as (and often times much better than) adding it alongside the current model.

Furthermore, adding median CPI does not seem to affect the credibility of the variables' responses to an identified monetary policy shock as the responses are generally similar across the models with and without median CPI.

Overall, our results suggest that the median CPI is a more accurate measure of underlying inflation than ex food and energy ("core") inflation, and is a useful addition to a variety of BVARs used for forecasting, especially in a monetary policy setting.

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Table 1: Forecast Comparison of BVAR in Beauchemin and Zaman (2011)

Relative Mean Squared Error (RMSE) --- relative to BVAR1								
1a: BVAR1 vs. BVAR1 with median CPI inclusion								
	h=1Q	h=2Q	h=3Q	h=4Q	h=5Q	h=6Q	h=7Q	h=8Q
Real GDP growth	1.002	**0.998**	1.004	1.004	1.000	1.006	1.003	**0.997**
Core CPI inflation	**0.933**	**0.922**	**0.916**	**0.918***	**0.932***	**0.939**	**0.953**	**0.966**
Headline CPI inflation	**0.983**	**0.970**	**0.976**	**0.978**	**0.978**	**0.980**	**0.989**	**0.998**
Unemployment Rate	1.007	1.007	1.010	1.011	1.012	1.013	1.013	1.011
Fed Funds Rate	**0.999**	**0.985**	**0.975**	**0.967**	**0.962**	**0.960***	**0.956***	**0.958**
1b: BVAR1 vs. BVAR1 with median CPI replacing the core CPI								
	h=1Q	h=2Q	h=3Q	h=4Q	h=5Q	h=6Q	h=7Q	h=8Q
Real GDP growth	**0.996**	**0.996**	1.002	1.006	**0.999**	1.011	1.005	**0.994**
Core CPI inflation	-----	-----	-----	-----	-----	-----	-----	-----
Headline CPI inflation	**0.984**	**0.966**	**0.973**	**0.972**	**0.969**	**0.977**	**0.989**	1.002
Unemployment Rate	**0.978**	**0.974**	**0.986**	**0.992**	**0.996**	**0.998**	1.000	1.001
Fed Funds Rate	**0.986**	**0.978**	**0.974**	**0.966**	**0.958**	**0.955**	**0.947***	**0.946***

Notes for the table: The table 1a lists the mean squared forecast error (MSFE) of the modified Bayesian VAR with Median CPI added to it relative to the mean squared forecast error of the modified BVAR1. The table 1b lists the mean squared forecast error (MSFE) of the modified BVAR1 in which core CPI is replaced with Median CPI relative to the mean squared forecast error of the modified BVAR1. The reported RMSFEs are for the real GDP growth (quarterly at annual rate), core CPI inflation (quarterly at annual rate), headline CPI inflation (quarterly at annual rate), the unemployment rate, and the federal funds rate for h=1,2,…8 step head forecasts (i.e. 2 years out) for the evaluation period 1987Q1 – 2016Q2. Numbers in the bold indicate that the MSFE of the modified BVAR1 with Median CPI is less than the MSFE from the modified BVAR1.

*denotes significance at 5% level
**denotes significance at 10% level

Table 2: Forecast Comparison of BVARs in Banbura et al. 2010

Relative Mean Squared Error --- relative to BVARs in Banbura at al 2010								
SMALL BVAR (BVAR2) in Banbura et al. 2010								
2a: BVAR2 vs. BVAR2 with median CPI inclusion								
	h=1M	h=6M	h=9M	h=12M	h=15M	h=18M	h=21M	h=24M
Payroll growth	1.043	1.024	1.035	**0.998**	**0.997**	1.031	1.044	1.065
Headline CPI inflation	**0.996**	1.003	**0.977**	**0.966**	1.006	**0.972**	**0.973**	**0.974**
Fed Funds Rate	**0.961**	1.043	1.068	1.074	**0.997**	**0.884**	**0.819**	**0.793**
2b: BVAR2 with Core CPI vs. BVAR2 with median CPI								
	h=1M	h=6M	h=9M	h=12M	h=15M	h=18M	h=21M	h=24M
Payroll growth	1.020	1.096	1.043	**0.945**	**0.880***	**0.829***	**0.807***	**0.819**
Headline CPI inflation	**0.986**	**0.949**	**0.942**	**0.932**	**0.960**	**0.933**	**0.970**	**0.971**
Fed Funds Rate	**0.922**	**0.836**	**0.898**	1.039	1.049	1.018	**0.974**	**0.947**
CEE BVAR (BVAR3) in Banbura et al. 2010								
2c: BVAR3 vs. BVAR3 with median CPI inclusion								
	h=1M	h=6M	h=9M	h=12M	h=15M	h=18M	h=21M	h=24M
Payroll growth	**0.948***	**0.964**	**0.999**	1.002	1.010	1.014	1.017	1.024
Headline CPI inflation	**0.994**	**0.981**	**0.987**	**0.951***	**0.997**	**0.989**	**0.997**	1.006
Fed Funds Rate	**0.940**	**0.994**	1.017	**0.990**	**0.972**	**0.954**	**0.922**	**0.901**
2d: BVAR3 with Core CPI vs. BVAR3 with median CPI								
	h=1M	h=6M	h=9M	h=12M	h=15M	h=18M	h=21M	h=24M
Payroll growth	1.010	1.043	1.034	1.022	1.016	1.014	1.022	1.020
Headline CPI inflation	**0.999**	**0.985**	**0.986**	**0.954***	1.002	**0.994**	**0.999**	1.005
Fed Funds Rate	**0.977**	1.037	1.053	1.058	1.042	1.022	**0.985**	**0.957**

Medium BVAR (BVAR4) in Banbura et al. 2010								
2e: BVAR4 vs. BVAR4 with median CPI inclusion								
	h=1M	h=6M	h=9M	h=12M	h=15M	h=18M	h=21M	h=24M
Payroll growth	**0.992**	**0.989**	**0.997**	**0.998**	1.000	**0.997**	**0.997**	1.000
Headline CPI inflation	**0.983**	**0.978***	**0.986**	**0.967*****	**0.990**	**0.985**	**0.992**	1.002
UR	1.000	**0.984**	**0.989**	**0.995**	**0.999**	1.001	1.002	1.001
Fed Funds Rate	**0.960**	**0.952***	**0.970**	**0.968**	**0.967**	**0.962**	**0.947**	**0.933***
2f: BVAR4 with Core CPI vs. BVAR4 with median CPI								
	h=1M	h=6M	h=9M	h=12M	h=15M	h=18M	h=21M	h=24M
Payroll growth	**0.995**	**0.991**	**0.999**	1.004	1.006	1.006	1.018	1.014
Headline CPI inflation	**0.999**	**0.983****	**0.986**	**0.965*****	**0.989**	**0.986**	**0.990**	1.001
UR	1.005	**0.992**	1.001	1.005	1.007	1.007	1.006	1.005
Fed Funds Rate	1.006	**0.994**	**0.988**	**0.981**	**0.975**	**0.969**	**0.951**	**0.933**

Notes for the table: The tables 2a-2f lists the mean squared forecast error (MSFE) of the BVAR with Median CPI added to it relative to the mean squared forecast error of the BVAR without it. The reported RMSFEs are for the payroll growth (monthly at annual rate), core CPI inflation (monthly at annual rate), headline CPI inflation (monthly at annual rate), the unemployment rate, and the federal funds rate for h=1,2,…24 step head forecasts (i.e. 2 years out) for the evaluation period 1987M1 – 2016M8. Numbers in the bold indicate that the MSFE of the BVAR with Median CPI is less than the MSFE from the BVAR without Median CPI.

*denotes significance at 5% level
**denotes significance at 10% level
(based on modified Diebold-Mariano test)

Table 3: Forecast Comparison of Benchmark BVAR in Carriero et al. 2015 (BVAR5)

Relative Mean Squared Error --- relative to modified BVAR5

3a: BVAR5 vs. BVAR5 with median CPI inclusion

	h=1M	h=6M	h=9M	h=12M	h=15M	h=18M	h=21M	h=24M
Payroll growth	**0.986**	**0.975**	1.007	1.015	1.018	1.010	1.002	**0.999**
Core CPI	**0.937*****	**0.948**	**0.891*****	**0.902*****	**0.927***	**0.919***	**0.930**	**0.926**
Headline CPI	**0.986**	**0.983**	**0.982**	**0.955****	**0.994**	**0.991**	1.013	1.020
UR	**0.995**	**0.984**	**0.990**	**0.997**	1.001	1.007	1.010	1.010
Fed Funds Rate	1.026	**0.935**	**0.940**	**0.924**	**0.908**	**0.898**	**0.892**	**0.878**

3b: BVAR5 vs. BVAR5 with median CPI replacing core CPI

	h=1M	h=6M	h=9M	h=12M	h=15M	h=18M	h=21M	h=24M
Payroll growth	1.001	1.006	1.013	**0.999**	**0.993**	**0.997**	1.001	**0.991**
Core CPI	-----	-----	-----	-----	-----	-----	-----	-----
Headline CPI	**0.978**	**0.979**	**0.971**	**0.940*****	**0.989**	**0.976**	**0.998**	1.001
UR	1.000	**0.987**	1.006	1.005	**0.994**	**0.991**	**0.991**	**0.992**
Fed Funds Rate	1.068	**0.946**	**0.967**	**0.957**	**0.927**	**0.918**	**0.912**	**0.900**

Notes for the table: The tables 3a-3b lists the mean squared forecast error (MSFE) of the BVAR with Median CPI added to it relative to the mean squared forecast error of the BVAR without it. The reported RMSFEs are for the payroll growth (monthly at annual rate), core CPI inflation (monthly at annual rate), headline CPI inflation (monthly at annual rate), the unemployment rate, and the federal funds rate for h=1,2,…24 step head forecasts (i.e. 2 years out) for the evaluation period 1987M1 – 2016M8. Numbers in the bold indicate that the MSFE of the BVAR with Median CPI is less than the MSFE from the BVAR without Median CPI.

*denotes significance at 5% level
**denotes significance at 10% level
(based on modified Diebold-Mariano test)

Table 4: Exercise using the median CPI to forecast PCE-based inflation using Carriero et al. (2015) Monthly BVAR

Relative Mean Squared Error --- relative to BVAR6								
4a: BVAR6 vs. BVAR6 with median CPI inclusion								
	h=1M	h=6M	h=9M	h=12M	h=15M	h=18M	h=21M	h=24M
Payroll growth	**0.999**	1.007	1.035	1.021	1.006	1.008	1.022	1.027
Core PCE inflation	**0.958****	**0.963****	**0.948****	**0.945***	**0.924****	**0.906*****	**0.898*****	**0.888****
Headline PCE inflation	**0.964****	**0.975**	**0.984**	**0.960***	**0.973**	**0.958***	**0.968**	**0.971**
UR	1.004	**0.998**	1.012	1.018	1.016	1.015	1.018	1.022
Fed Funds Rate	1.010	**0.918****	**0.970**	**0.960**	**0.927**	**0.904**	**0.885**	**0.862***
4b: BVAR6 vs. BVAR6 with median CPI replacing core PCE								
	h=1M	h=6M	h=9M	h=12M	h=15M	h=18M	h=21M	h=24M
Payroll growth	**0.977**	**0.997**	1.038	1.025	1.013	1.023	1.031	1.023
Core PCE inflation	-----	-----	-----	-----	-----	-----	-----	-----
Headline PCE inflation	**0.975**	**0.981**	**0.979**	**0.949****	**0.964***	**0.949****	**0.961**	**0.970**
UR	1.001	**0.966**	**0.992**	1.006	1.007	1.011	1.019	1.027
Fed Funds Rate	1.007	**0.902***	**0.953**	**0.933**	**0.889**	**0.867**	**0.851***	**0.832***

Notes for the table: The tables 4a-4b lists the mean squared forecast error (MSFE) of the BVAR with Median CPI added to it relative to the mean squared forecast error of the BVAR without it. The reported RMSFEs are for the payroll growth (monthly at annual rate), core PCE inflation (monthly at annual rate), headline PCE inflation (monthly at annual rate), the unemployment rate, and the federal funds rate for h=1,2,…24 step head forecasts (i.e. 2 years out) for the evaluation period 1987M1 – 2016M8. Numbers in the bold indicate that the MSFE of the BVAR with Median CPI is less than the MSFE from the BVAR without Median CPI.

*denotes significance at 5% level
**denotes significance at 10% level (based on modified Diebold-Mariano test)

Table 5: Exercise using the median CPI to forecast PCE-based inflation using Beauchemin and Zaman (2011) Quarterly BVAR

Relative Mean Squared Error (RMSE) --- relative to BVAR7								
5a: BVAR7 vs. BVAR7 with median CPI inclusion								
	h=1Q	h=2Q	h=3Q	h=4Q	h=5Q	h=6Q	h=7Q	h=8Q
Real GDP growth	1.007	1.005	1.013	1.007	1.005	1.009	1.009	1.004
Core PCE inflation	**0.945****	**0.934***	**0.941***	**0.937****	**0.932*****	**0.942****	**0.949**	**0.961**
Headline PCE inflation	**0.977**	**0.967**	**0.979**	**0.976**	**0.976**	**0.982**	**0.984**	**0.992**
Unemployment Rate	1.010	1.016	1.021	1.026	1.027	1.028	1.030	1.032
Fed Funds Rate	1.007	**0.994**	**0.996**	**0.995**	**0.987**	**0.980**	**0.972***	**0.970***
5b: BVAR7 vs. BVAR7 with median CPI replace core PCE								
	h=1Q	h=2Q	h=3Q	h=4Q	h=5Q	h=6Q	h=7Q	h=8Q
Real GDP growth	1.004	1.006	1.012	1.007	1.005	1.007	1.003	**0.998**
Core PCE inflation	-----	-----	-----	-----	-----	-----	-----	-----
Headline PCE inflation	**0.982**	**0.972**	**0.983**	**0.978**	**0.980**	**0.991**	**0.993**	1.005
Unemployment Rate	1.002	1.009	1.017	1.022	1.023	1.025	1.027	1.029
Fed Funds Rate	**0.998**	**0.974**	**0.971**	**0.966**	**0.960****	**0.959***	**0.956***	**0.958**

Notes for the table: The tables 5a-5b lists the mean squared forecast error (MSFE) of the BVAR with Median CPI added to it relative to the mean squared forecast error of the BVAR without it. The reported RMSFEs are for the real GDP growth (quarterly at annual rate), core PCE inflation (quarterly at annual rate), headline PCE inflation (quarterly at annual rate), the unemployment rate, and the federal funds rate for h=1,2,…8 step head forecasts (i.e. 2 years out) for the evaluation period 1987Q1 – 2016Q2. Numbers in the bold indicate that the MSFE of the BVAR with Median CPI is less than the MSFE from the BVAR without Median CPI.

*denotes significance at 5% level
**denotes significance at 10% level
(based on modified Diebold-Mariano test)

Table 6: Exercise using the forecasted values of the median CPI *as* the forecast for core CPI with Beauchemin and Zaman (2011) Quarterly BVAR

Relative Mean Squared Error (RMSE) --- relative to BVAR1								
6a: BVAR1 vs. BVAR1 in which we use Median CPI to predict Core CPI								
	h=1Q	h=2Q	h=3Q	h=4Q	h=5Q	h=6Q	h=7Q	h=8Q
Real GDP growth	**0.996**	**0.996**	1.001	1.006	**0.999**	1.011	1.005	**0.994**
Core CPI inflation	1.164	1.131	1.031	**0.983**	**0.987**	**0.980**	**0.993**	**0.992**
Headline CPI inflation	**0.984**	**0.966**	**0.973**	**0.972**	**0.969**	**0.977**	**0.989**	1.002
Unemployment Rate	**0.978**	**0.974**	**0.986**	**0.992**	**0.996**	**0.998**	1.000	1.001
Fed Funds Rate	**0.986**	**0.978**	**0.974**	**0.966**	**0.958**	**0.955**	**0.947***	**0.946***

Notes for the table: The table 6a lists the mean squared forecast error (MSFE) of the BVAR (which is estimated using Median CPI and uses the forecasts of the Median CPI to predict core CPI) relative to the mean squared forecast error of the BVAR without Median CPI. The reported RMSFEs are for the real GDP growth (quarterly at annual rate), core CPI inflation (quarterly at annual rate), headline CPI inflation (quarterly at annual rate), the unemployment rate, and the federal funds rate for h=1,2,…8 step head forecasts (i.e. 2 years out) for the evaluation period 1987Q1 – 2016Q2. Numbers in the bold indicate that the MSFE of the BVAR with Median CPI is less than the MSFE from the BVAR without Median CPI.

*denotes significance at 5% level
**denotes significance at 10% level
(based on modified Diebold-Mariano test)

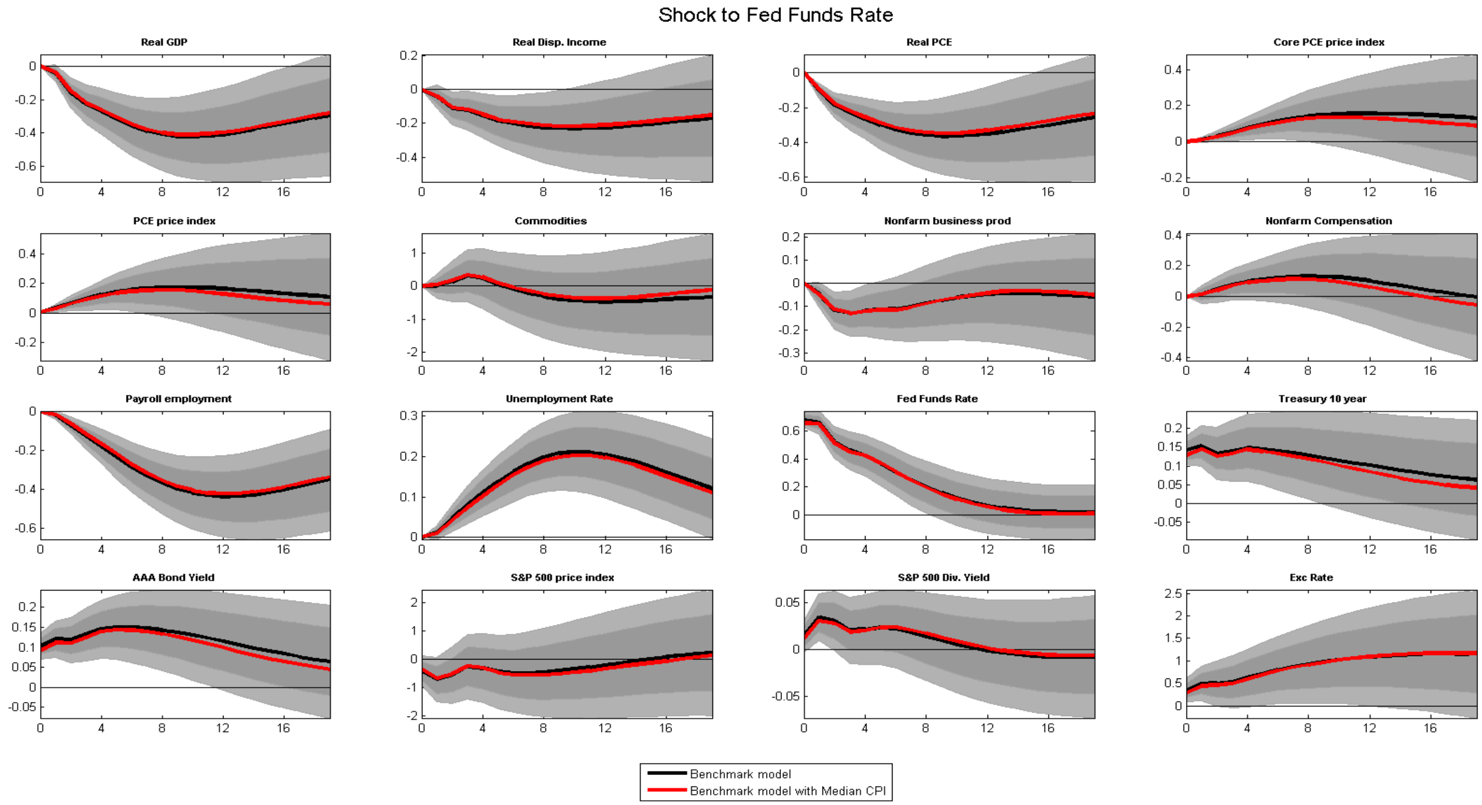
Table 7: Exercise using the forecasted values of the median CPI *as* the forecast for core CPI with Carriero et al. (2015) Monthly BVAR

Relative Mean Squared Error --- relative to BVAR5								
7a: BVAR5 vs. BVAR5 in which Median CPI is used to predict core CPI								
	h=1M	h=6M	h=9M	h=12M	h=15M	h=18M	h=21M	h=24M
Payroll growth	**0.965***	1.005	1.010	**0.995**	**0.990**	**0.995**	**0.998**	**0.990**
Core CPI	**0.906**	**0.925**	**0.843****	**0.917**	**0.956**	**0.910**	**0.863**	**0.813****
Headline CPI	**0.988**	**0.977**	**0.974**	**0.946****	**0.987**	**0.974**	**0.997**	1.005
UR	**0.993**	**0.983**	1.002	1.001	**0.991**	**0.989**	**0.989**	**0.990**
Fed Funds Rate	1.052	**0.945**	**0.966**	**0.955**	**0.927**	**0.920**	**0.915**	**0.903**

Notes for the table: The table 7a lists the mean squared forecast error (MSFE) of the BVAR (which is estimated using Median CPI and uses the forecasts of the Median CPI to predict core CPI) relative to the mean squared forecast error of the BVAR without Median CPI. The reported RMSFEs are for the payroll growth (monthly at annual rate), core CPI inflation (monthly at annual rate), headline CPI inflation (monthly at annual rate), the unemployment rate, and the federal funds rate for h=1,2,…24 step head forecasts (i.e. 2 years out) for the evaluation period 1987M1 – 2016M8. Numbers in the bold indicate that the MSFE of the BVAR with Median CPI is less than the MSFE from the BVAR without Median CPI.

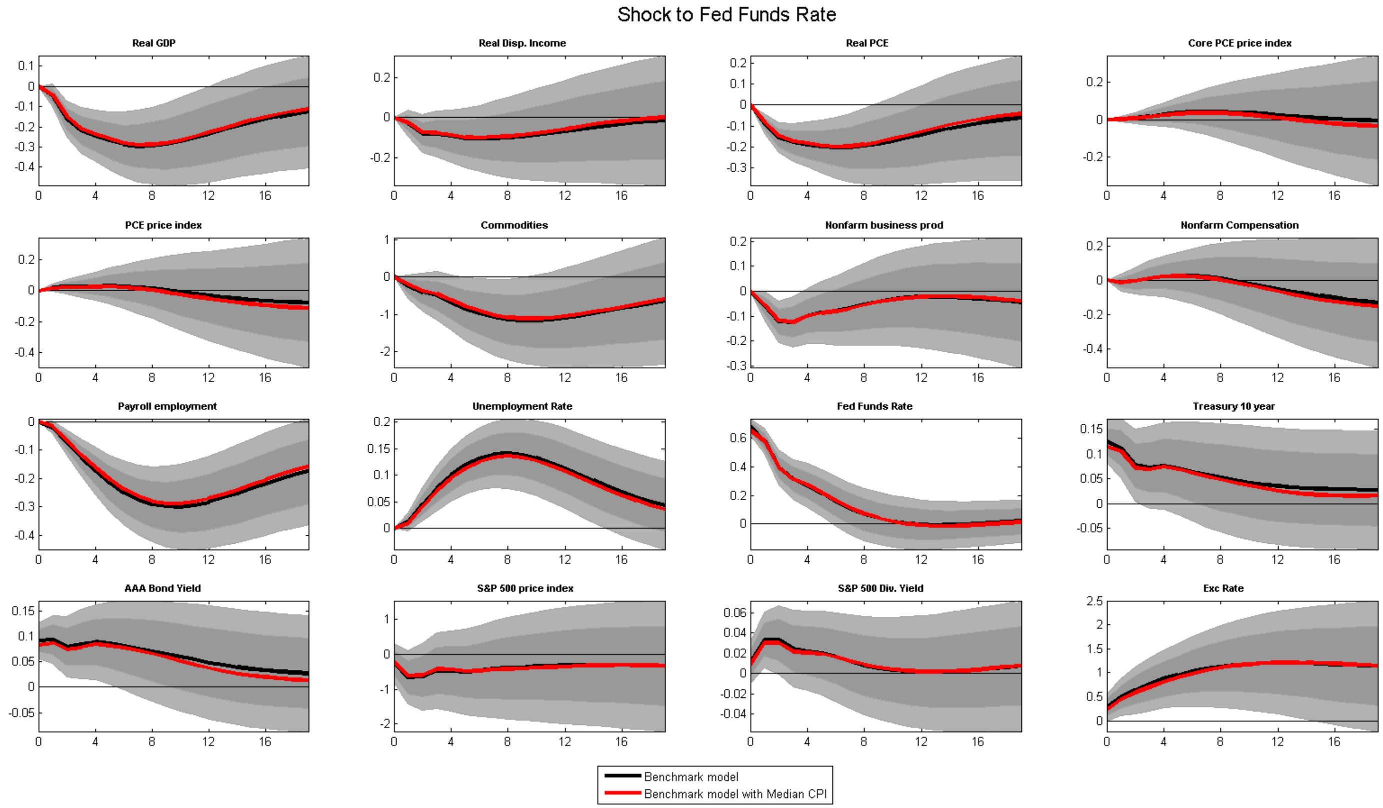
*denotes significance at 5% level
**denotes significance at 10% level
(based on modified Diebold-Mariano test

Figure 1: Estimated Impulse response functions from **Beauchemin and Zaman (2011)** model using **Full Sample**



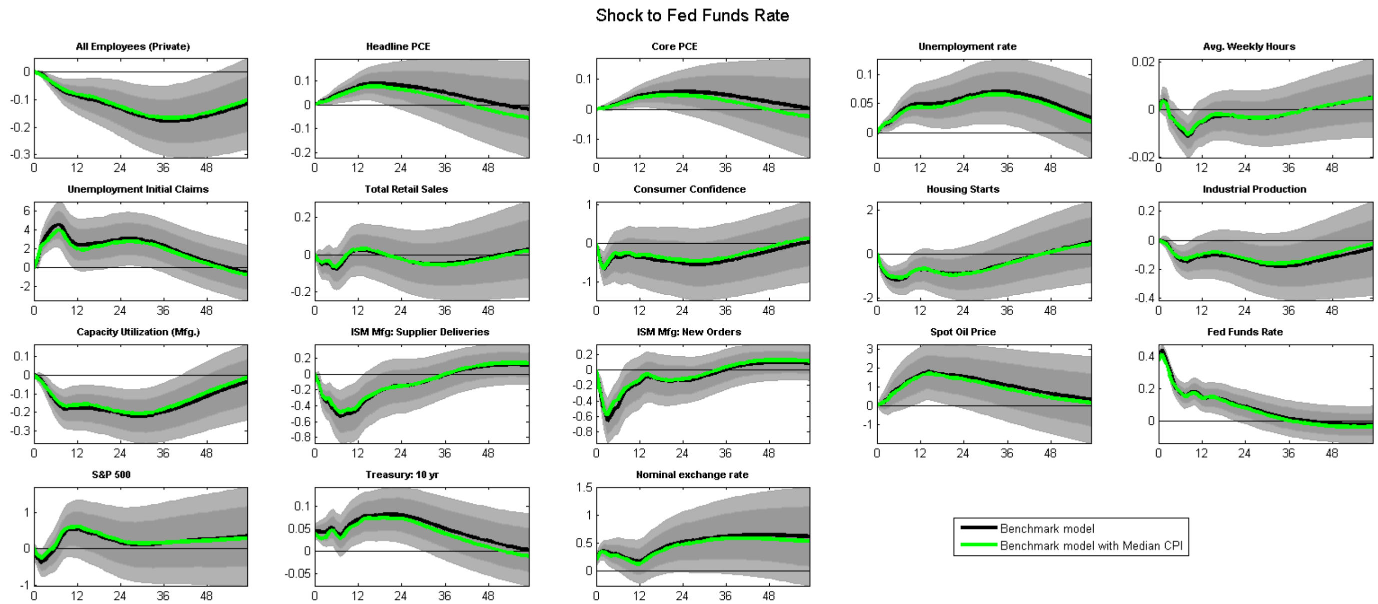
Notes: The figure presents the estimated impulse response functions of the Beauchemin and Zaman (2011) model with and without median CPI to a contractionary monetary policy shock of 70 basis points. The solid black lines represent the median response corresponding to the model specification that does not include median CPI; the solid red lines represent the median response corresponding to the model with median CPI. The shaded dark grey and light grey represent the posterior coverage intervals at 0.68 and 0.90 level corresponding to the model that does not include median CPI. The y-axis corresponds to quarters from the shock. The zero quarter corresponds to the quarter the shock is hit. The model is estimated beginning 1967:Q1 through 2016:Q2.

Figure 2: Estimated Impulse response functions from **Beauchemin and Zaman (2011)** model using **Pre-Crisis Sample**



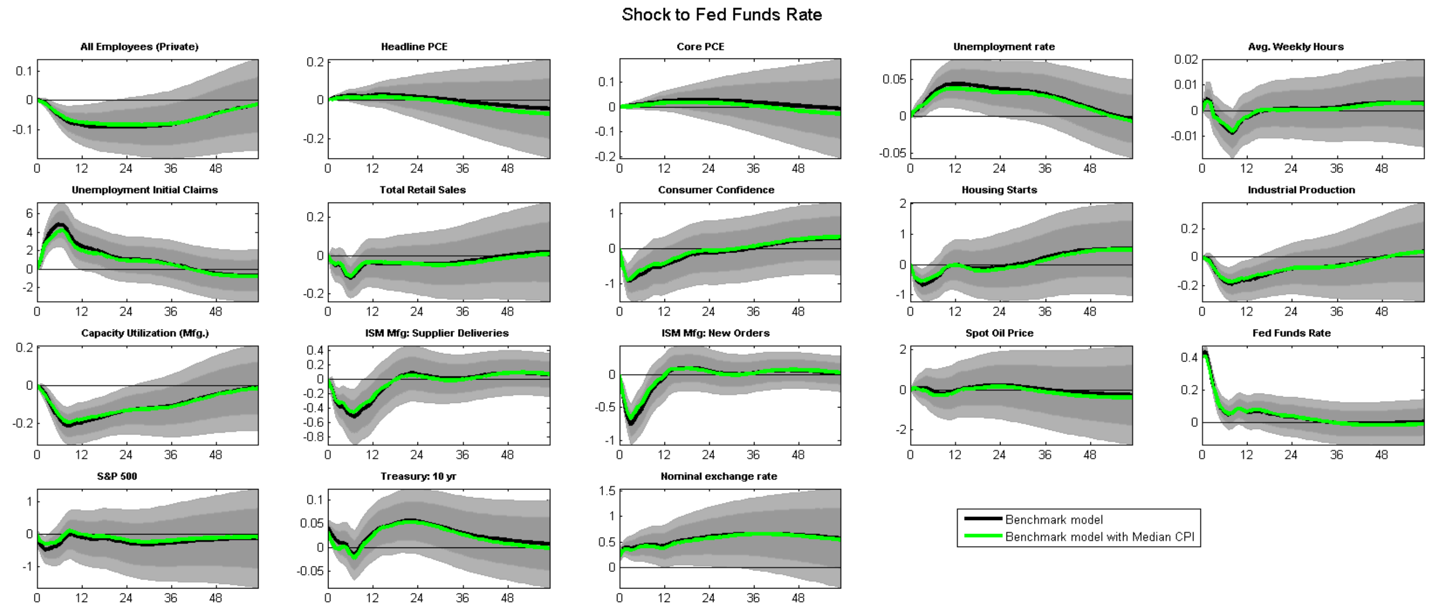
Notes: The figure presents the estimated impulse response functions from the Beauchemin and Zaman (2011) model with and without median CPI to a contractionary monetary policy shock of 65 basis points. The solid black lines represent the median response corresponding to the model specification that does not include median CPI; the solid red lines represent the median response corresponding to the model with median CPI. The shaded dark grey and light grey represent the posterior coverage intervals at 0.68 and 0.90 level corresponding to the model that does not include median CPI. The y-axis corresponds to quarters from the shock. The zero quarter corresponds to the quarter the shock is hit. The model is estimated beginning 1967:Q1 through 2005:Q3.

Figure 3: Estimated Impulse response functions from **Carriero et al. (2015)** model using **Full Sample**



Notes: The figure presents the estimated impulse response functions from the Carriero et al. (2015) model with and without median CPI to a contractionary monetary policy shock of 40 basis points. The solid black lines represent the median response corresponding to the model specification that does not include median CPI; the solid green lines represent the median response corresponding to the model with median CPI. The shaded dark grey and light grey represent the posterior coverage intervals at 0.68 and 0.90 level corresponding to the model that does not include median CPI. The y-axis corresponds to months from the shock. The zero month corresponds to the month the shock is hit. The model is estimated beginning 1967:M1 through 2016:M8.

Figure 4: Estimated Impulse response functions from **Carriero et al. (2015)** model using **Pre-Crisis Sample**



Notes: The figure presents the estimated impulse response functions from the Carriero et al. (2015) model with and without median CPI to a contractionary monetary policy shock of 40 basis points. The solid black lines represent the median response corresponding to the model specification that does not include median CPI; the solid green lines represent the median response corresponding to the model with median CPI. The shaded dark grey and light grey represent the posterior coverage intervals at 0.68 and 0.90 level corresponding to the model that does not include median CPI. The y-axis corresponds to months from the shock. The zero month corresponds to the month the shock is hit. The model is estimated beginning 1967:M1 through 2005:M9.