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Aggregate Inflation Forecast with Bayesian Vector Autoregressive Models

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Abstract

We forecast 18 groups of individual components of the Consumer Price Index (CPI) using a large Bayesian vector autoregressive model (BVAR) and then aggregate those forecasts in order to obtain a headline inflation forecast (bottom-up approach). De Mol et al. (2006) and Banbura et al. (2010) show that BVAR's forecasts can be significantly improved by the appropriate selection of the shrinkage hyperparameter. We follow Banbura et al. (2010)'s strategy of "mixed priors," estimate the shrinkage parameter, and forecast inflation. Our findings suggest that this strategy for modeling outperform the benchmark random walk as well as other strategies for forecasting inflation.

Keywords: Inflation forecasting, aggregate forecast, Bayesian VAR.
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1 Introduction

The monetary policy in most central banks is designed for controlling inflation at low levels because inflation has clear welfare costs at high levels. According to Walsh (2010), inflation generates a welfare loss because money holdings yield utility and higher inflation reduces real money balances. In that regard, forecasts of different inflation measures are often used for the identification of underlying price pressures in the economy. This identification process usually requires a good understanding of both the aggregate inflation level and its components. It also requires to fine-tune methodologies that lead to better inflation forecasts.

Hubrich (2005) points out that the debate about aggregation versus disaggregation in economic modeling for variables such as GDP or inflation goes back to Theil (1954) and Grunfeld and Griliches (1960). Here the literature has focussed on the effect of contemporaneous aggregation on forecast accuracy.

The two main arguments for aggregating forecasts of disaggregated variables in order to improve predictions of the aggregate (instead of directly forecasting the aggregate variable) are: (i) the individual dynamic properties of disaggregated components are taking into account so each disaggregate variable can be predicted more accurately,[1] and (ii) forecast errors of disaggregated components might partially cancel each other.[2]

On the other hand, arguments against disaggregation for forecasting the aggregate are: (i) models for the disaggregate variables may not be correctly specified which might not improve the forecast accuracy for the aggregate,[3] (ii) a well specified model does not necessarily imply higher forecast accuracy, and (iii) unexpected shocks might affect the forecast errors of some of the disaggregate variables in the same direction (forecast errors do not cancel each other).

As suggested in Ibarra (2012), one possible way to improve the accuracy of inflation forecasts is to employ the information contained in the consumer price index (CPI) disaggregated data. In this regard, models such as vector autoregressions would require a large number of parameters to be estimated. As pointed out above, part of the previous literature about predictions of economic aggregates based on disaggregated information has focused on forecasting the component indices and aggregating such forecasts (bottom-up approach).

The existing literature present mixed results with respect to the bottom-up approach. Some studies we survey are:

[1] Modeling disaggregated variables may involve using a larger and more heterogenous information set, and specifications may vary across the disaggregate variables (see Barker and Pesaran, 1990). According to Duarte and Rua (2007) this strategy permits the capture of idiosyncratic characteristics of each variable by modelling each serie individually.

[2] See Clements and Hendry (2002) for a discussion on forecast combination and bias correction.

[3] This argument is valid in the presence of shocks that affect some of the disaggregate variables (see Grunfeld and Griliches, 1960).

- Hubrich (2005) examines whether aggregating inflation forecasts based on Harmonized Index of Consumer Prices (HICP) subindices for the euro area is better than forecasting aggregate HICP inflation directly and find that 12-month ahead forecasts are better by estimating directly HICP inflation.[4]

- For the case of forecasting inflation in Mexico using CPI disaggregated data we survey Capistrán et al. (2010) and Ibarra (2012). Capistrán et al. (2010) use models that deal with the stochastic properties of the trend and of the seasonal components of the series. These authors choose the best model for each of 16 series of inflation using a multi-horizon loss function, and then aggregate the resulting forecasts so that they satisfy the hierarchies among them. They conclude that forecasting the aggregates by disaggregates results in better forecasts than using the best individual models. Ibarra (2012) use a dynamic common factor model to forecast inflation in Mexico and evaluate weather the CPI disaggregated data improve forecasting performance by employing the information contained in a large number of economic series. His results suggest that the common component extracted from the CPI disaggregated data has a good predictive content, especially for the medium-term component of inflation. Factor models outperform the benchmark auto-regressive model (AR model) and perform as well as the surveys of experts.

- For the case of Portugal, Duarte and Rua (2007) evaluate weather considering different levels of data disaggregation improves inflation forecasting. The authors consider three CPI disaggregation levels: the aggregate price index (the lowest disaggregation level); five components; and almost sixty subcomponents. Their results suggest that for very short term inflation forecasting, it is better to pursue a bottom-up approach with a high disaggregation level while simpler models seem to perform better for longer horizons.

- Ögünç et al. (2013) find that the Bayesian VAR (BVAR) outperform other inflation forecast strategies in terms of lower forecast prediction error for the case of Turkey. It also beats the random walk in a two quarters ahead window.

Here we focus on the information content of different components of the CPI. We argue that the aggregation of different components into a smaller number of groups may have important forecasting properties in different periods of time, fact that is documented in previous literature. We estimate a large BVAR techniques for all groups. Then we aggregate each forecast and obtain a result for the aggregate level of inflation. Our results are promising for the case of Peru. We find that our strategy beats the random walk as well as other time series approaches.

The rest of the paper is organized as follows. Section 2 discusses the benefits of the BVAR approach. Section 3 describes the data used in this study as well as the aggregation

[4] Another interesting study is Ruth (2008) that evaluates forecast pooling for predicting actual macroeconomic variables in the euro area, including inflation. Ruth (2008) pools forecasts which are obtained from models for subgroups of countries rather than single countries, thereby formulating an intermediate case of disaggregation with regard to forecast combination.

process. Section 4 presents our forecasting results with a mixture of priors competing against other forms of forecasting. Finally, section 5 concludes.

2 Bayesian vector autoregressive approach

First proposed by Litterman (1980), Bayesian vector autoregressive (BVAR) models become an alternative to conventional VAR models because it deals with the loss of degrees of freedom due to overparametrization. This is known in the literature as dimensionality problem.

The dimensionality problem in VARs refers to the number of parameters to be estimated increases with the number of variables and with the number of lags included. Even more, when the number of parameters is large relative to the available number of observations, parameters estimated tend to be influenced by noise as opposed to signal and may loss statistical significance. Hence, VARs only with relatively small number of variables are feasible in practical applications.

On the other hand, VAR models are quite useful in forescasting economic variables because they allow for interaction of different related variables. However, it is possible that many different variables may be relevant in economic forecasting, probably more than a standard VAR can deal with.

The BVAR approach deals with the dimensionality problem by shrinking the parameters via the imposition of priors. Banbura et al. (2010) show that this approach can handle an unrestricted VAR with a large number of variables. Even more, Banbura et al. (2010) extend the data set in order to incorporate disaggregated sectoral or geographical indicators.

In our review we find that Ögünç et al. (2013) use BVAR estimates in order to forecast inflation in Turkey. This strategy outperform other inflation forecast strategies and beats the random walk in a two quarters ahead window. However there is not attemp in Ögünç et al. (2013) for forecasting individual components of inflation, rather, they focus in using the BVAR with variables that shares common behavior with inflation and sticks to the Minnesota prior.

We contribute to the existing literature of forecasting inflation by using the bottom-up approach and by the estimation of a BVAR. We estimate a BVAR for 18 groups that are components of the Headline inflation. We then aggregate the forecast for each group, obtain a forecast for the headline inflation for different time periods, and compare it with those of other forecast strategies.

3 The Data

We work with the different components of the CPI inflation (Headline inflation) for Peru. The National Institute of Statistics (INEI) reports every month the official numbers regarding movements in prices, specifically the CPI. Our data set consists of 174 CPI subcomponents for the period 1998 - 2013. The frequency of the data set is monthly and the base year of the CPI is 2009.

During the past years the INEI has made some changes in the CPI composition. The increase in the number of items, as well as the change in the weight of each item, are the result of a careful evaluation of the representative bundle of goods and services that characterizes the living expenses in Peru. In Table 1 we show the main changes as well as the dates for those changes.

Table 1: CPI and base years

Sample period	Base year	Items
Jan-1998 to Dec-2001	1994	150
Jan-2002 to Dec-2009	2001	156
Jan-2010 to Jul-2014	2009	174

Note: Number of items considered in each base year, during each sample period.

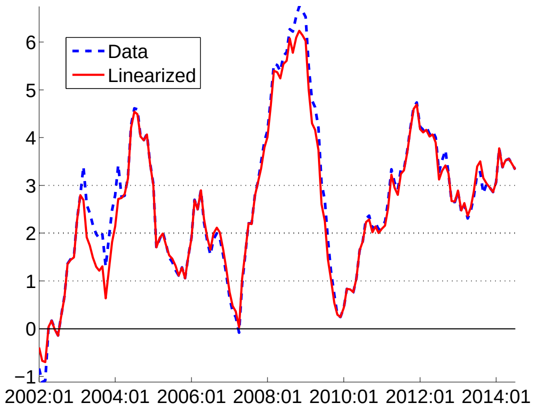
We set our sample from 1998 because the Peruvian economy experienced a hyperinflation process during the late 80's and early 90's and the inflation rate stabilized at the end of the 90's (see Armas et al., 2001). In that regard, we argue that the dynamics of inflation in Peru previous to 1998 correspond to different regimes (high inflation and transition from high to low inflation).

The main focus in our paper is forecasting the headline inflation, however we also present results corresponding to core and non-core inflation.[5] Figure 1 plots the headline, core, and non-core inflation from 2002 to 2014. The 2008 financial crisis is associated with high levels of headline inflation (see Figure 1a). One core inflation index includes the least volatile components of the CPI which usually has a lagged response to macroeconomic variables such as interest rates, exchange rates, and wages (see Figure 1b). In contrast, the non-core index contains the most volatile components, such as agricultural goods, gasoline, electricity, and local transportation and mainly responds to external variables, such as international prices and other domestic non-market forces (see Figure 1d). Another core index usually estimated in Peru is the one which excludes food and energy (see Figure 1c) and, by complement, the non-core index build by adding only food and energy components (see Figure 1e).

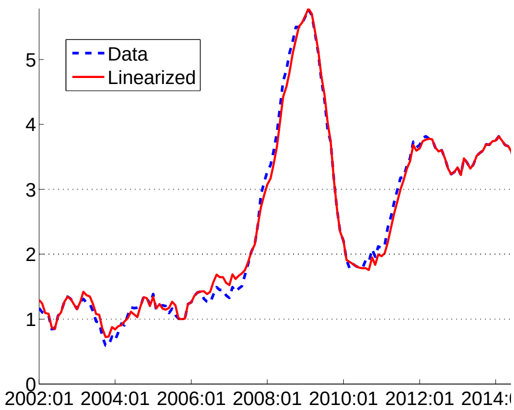
[5] Core inflation is most often calculated by taking the CPI and excluding certain items from the index, usually energy and food products. Other methods include the outliers method, which removes the products that have had the largest price changes. Core inflation is though as an indicator of underlying long-term inflation.

Figure 1: Inflation rates (percentage change over 12 months)

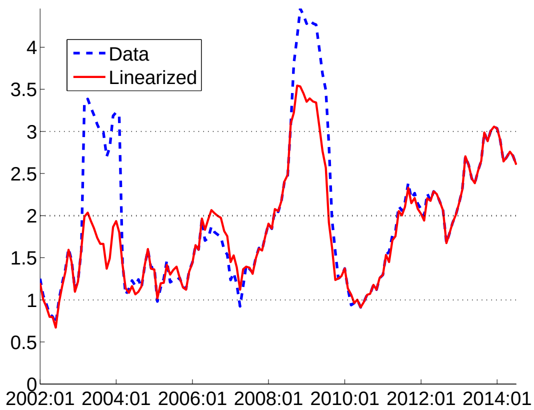
(a) Headline inflation



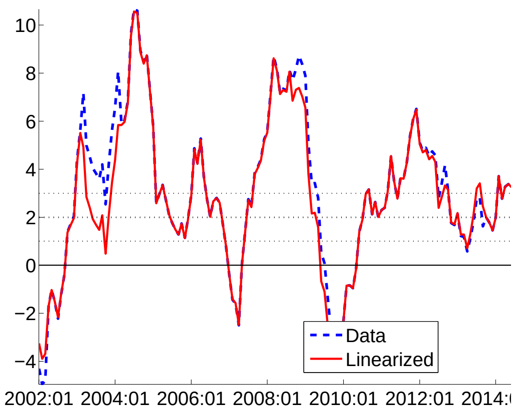
(b) Less volatile components



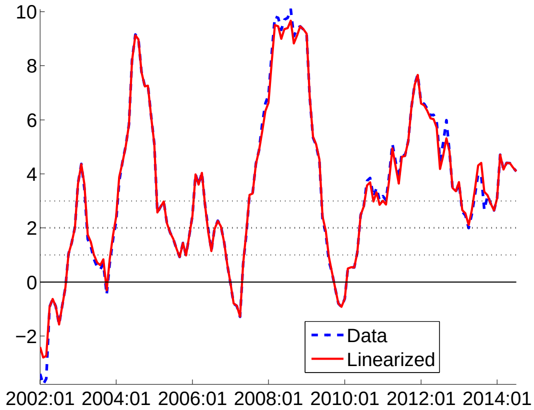
(c) Excluding food and energy



(d) More volatile components



(e) Food and energy



Note: Realized data and linearized model (Tramo - Seats) for identification of outliers in the data.

3.1 Bottom up components

We aggregate the 174 subcomponents of the CPI into only 18 groups (see Table 2). We select those components in such a way that it is easy to recover the two measures of core inflation previously described. In Table 2, one measure of core inflation in Peru is the weighted average from Group 1 to Group 14. Another measure of core inflation typically used is estimated by excluding energy and food products i.e. exclude Groups 1, 2, 3, 8, 14, 15, and 16.[6]

Table 2: CPI components aggregated in groups

Groups	Description	Weight	Groups	Description	Weight
G_1	Agricultural food	0.92	G_{10}	Rents	2.41
G_2	Processed foods	7.67	G_{11}	Health	1.08
G_3	Beverages	2.65	G_{12}	Other personal services	3.33
G_4	Textiles	4.13	G_{13}	Other services	4.58
G_5	Footwear	1.38	G_{14}	Food	14.83
G_6	Appliances	1.29	G_{15}	Other non-core food	5.58
G_7	Rest of industrial	14.86	G_{16}	Energy	5.74
G_8	Meals outside home	11.74	G_{17}	Transportation	8.87
G_9	Education	9.12	G_{18}	Utilities	5.47

Note: Each group includes a number of the 174 subcomponents of the CPI.
Weight correspond to the 2009 base year.

3.2 Seasonallity in Large BVARs

For each group we consider monthly data of growth rates with respect to the corresponding month of the previous year.[7] This measure is robust to seasonal effects. However, the presence of breaking points is not ruled out. The three changes in the base year reported in Table 1 may produce significant changes in the dynamics of each group under analysis. Those changes may lead to the identification of structural breaks in the data.

In order to control for structural changes, we use TRAMO-SEAT tools. We focus on the TRAMO component given our interest in identifying and filtering structural breaks and outliers (see Gómez and Maravall, 1996; and Gómez and Maravall, 1998).[8] As a result, we use filtered data in which any identified structural change is removed.[9]

[6] For more details on the aggregation process of each group by components, see Apendix A.
[7] These rates are denoted by $\Delta_{12} x_t$ and is defined by $100 \times [(x_t - x_{t-12})/x_{t-12}]$.
[8] TRAMO stands for Time series Regression with ARIMA noise, Missing values, and Outliers.
[9] See Appendix B for Figures B.1, B.2, and B.3 in which some structural breaks are identified.

4 Forecasting framework and priors structures

For improving the forecasting performance of VAR models, the BVAR literature has proposed to combine the likelihood function with some informative prior distributions. These priors have been successful because they reduce the estimation error and generates small biases in the estimates of the parameters. There are three predominant priors structures in the BVAR literature: (i) the Minnesota prior, (ii) the sum of coefficients prior, and, (iii) the initial dummy observation prior. Here we present some of the most important characteristics for assuming any of these structures:[10]

- **The Minnesota prior** was initially proposed by Litterman (1980) and modified by Kadiyala and Karlsson (1997). This prior assumes that the mean of the BVAR coefficients are random walks so that the variance of the coefficients decay as lags increases. The Hyper-parameter λ is a constant proportion that multiply all prior variances. Consequently, if $\lambda \to 0$ the variance of the BVAR coefficients would collapse to 0 and the prior mean (random walk) predominate in the forecast.

- **The sum of coefficients prior** was proposed by Doan et al. (1983) and asumes that all mean coefficients matrices in the BVAR model add up to the identity matrix. The Minnesota prior has the inconvenience of excluding any correlation between variables, since all of them are assumed to be random walks. Nonetheless, as it is reported by Robertson and Tallman (1999), including these correlations in the beliefs can increase the estimation average accuracy and one way to do so is by summing all of those coefficients priors.[11] Similar to the Minnesota prior, the coefficients variances are modulated by τ, i. e. if $\tau \to 0$ the variance of the BVAR's coefficients would collapse to 0 and variables are estimated mainly as a joint system of random walks.

- **Initial dummy observation prior** is discussed by Sims (1993). Sims argues that these prior is preferible to the previous prior structures because it includes the belief that the system goes to a constant value in the long run. Variances are regulated by τ. If $\tau \to 0$ the variance of the BVAR coefficients would collapse to 0 implying that either all variables are stationary and converge to the mean or there might be some stochastic trends in the underlying process of the series.

We follow the approach suggested in Sims and Zha (1998) in which the prior is directly introduced in the BVAR reduced form by extending the data with some dummy observations which reproduce any moment of the three previous mentioned priors. Then, we use the extended data in order to compute the posterior distribution by implementing a non-informative Jeffrey's prior.[12]

[10] For a more detailed exposition regarding these three prior beliefs see Karlsson (2012).

[11] In the VECM representation of a VAR, the matrix of coefficients associated to the vector of levels is always the identity minus the sum of coefficients; therefore, with this prior it is assumed that this is a null matrix. As a result, the sum of coefficients prior is the belief that the BVAR is ruled by as many stochastic trends as variables in the system without ruling out correlations between trends. Notice that this prior include the Minnesota prior.

[12] For more details on non-informative Jeffrey's Prior, see Jeffreys (1961).

4.1 Forecasting design and model

Using 12-months inflation rates, we estimate a BVAR model that include a mix of prior distributions for the 18 Groups. For the Minnesota prior, the hyper-parameter is denoted by λ. Following Banbura et al. (2010), we consider the hyper-parameters $\tau = 5 \times \lambda$ for the sum of coefficients prior and for the initial dummy observation prior, respectively.[13] As a result, the determination of the prior collapses to the measure of only one hyper-parameter, which is λ.

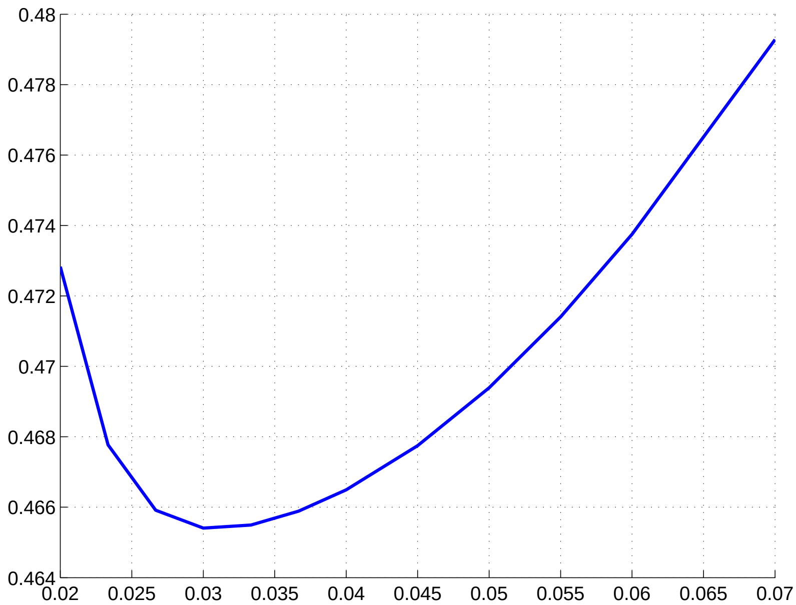
We design a grid search for the value of λ that minimizes the following loss function:

$$LF(\lambda) = mean\left(\left\{\varepsilon^{x}_{Aug2011:Jul2014}(h)\right\}^{h\in\{1,\ldots,12\}}_{x\in\left\{\Delta_{12}P_t,\Delta_{12}P^{c}_{t},\Delta_{12}P^{nef}_{t}\right\}}\right),$$

where $\varepsilon^{x}_{Aug2011:Jul2014}(h)$ is the Root Squared of the Mean Forecast Error (RSMFE) for the variable x with a forecast horizon of h in the sample between August 2011 and July 2014.[14] Therefore, this loss function is the average of the forecast error for the first 12 forecasts when forecasting inflation.

In Figure 2 we plot the loss function and find a value of λ of 0.03 that minimizes this function. This small value of λ is consistent with the dimensionality of the BVAR model. A classical VAR that includes 18 variables and 12 lags would require the estimation of 4041 parameters. In a BVAR with this dimension, the tightness parameter needs to be close to cero.

Figure 2: Loss function - Hiper-parameter determination



[13] The hyper-parameters determines the tightness of the prior. Also, Banbura et al. (2010) approach considers a τ that is a loose multiple of λ.

[14] See the Appendix C for a detailed discussion of RSMFE.

4.2 Forecast evaluation

We evaluate the forecast of our BVAR by competing with other forms of forecasting by comparing the RSMFE. In line with Robertson and Tallman (1999), the natural first challenge correspond to a BVAR with only a Minnesota prior. Then, we consider a frequentist approach in which the forecast of best time-series models competes with our BVAR forecast.

Finally, a naive random walk is used as our last benchmark because it usually performs better in terms of forecasting compared to other time series models. Although some of the time series models in the literature either improve on, or are roughly on a par with a naive random walk, most models rarely neither beat it across all forecasting horizons nor have a smaller RSMFE of all horizons.

We also perform some additional exercises over two different levels of aggregation over core inflation measures. In addition to forecasting the headline inflation ($\Delta_{12}P_t$), we evaluate: (i) core inflation index that includes the less volatile components of the CPI ($\Delta_{12}P_t^{lv}$), (ii) core inflation index that excludes food and energy ($\Delta_{12}P_t^{efe}$), (iii) inflation index that includes the more volatile components ($\Delta_{12}P_t^{mv}$), and (iv) inflation index for food and energy ($\Delta_{12}P_t^{fe}$).

4.2.1 Minnesota and mixed priors

In Table 3 we present the RSMFE for BVARs with both Minnesota and mixed priors. The Minnesota hiperparameter is estimated under the same methodology used for the estimation of the mixed-prior hyperparameter.[15]

In general, a BVAR with a mixed prior does a better job than the BVAR with a Minnesota prior. It is clearly superior in forecasting the headline inflation for all periods, up to a year. However, a BVAR with Minnesota prior has better forecasting properties in the case of core inflation that excludes food and energy from 1 to 6 months ahead. In all remaining cases, mixed prior is the superior strategy.

[15] The Minnesota hiperparameter estimated is $\lambda^M = 0.01$. See appendix D for a detailed forecast performance.

Table 3: RSMFE for BVARs

Variable	Minnesota prior				Mixed prior			
	h=1	h=3	h=6	h=12	h=1	h=3	h=6	h=12
$\Delta_{12}P_t$	0.33	0.61	0.94	1.33	0.31	0.50	0.67	1.06
$\Delta_{12}P_t^{lv}$	0.11	0.26	0.56	0.86	0.10	0.20	0.43	0.71
$\Delta_{12}P_t^{efe}$	0.16	0.32	0.49	0.60	0.17	0.34	0.50	0.59
$\Delta_{12}P_t^{mv}$	0.78	1.34	1.84	2.33	0.74	1.14	1.33	1.76
$\Delta_{12}P_t^{fe}$	0.73	1.30	1.85	2.46	0.70	1.17	1.47	1.98

Note: RSMFE is the Root Squared of the Mean Forecast Error, h stands for the horizon of forecasting, $\Delta_{12}P_t$ is the headline inflation, $\Delta_{12}P_t^{lv}$ is the inflation of the less volatile components, $\Delta_{12}P_t^{efe}$ is the inflation excluding food and energy, $\Delta_{12}P_t^{mv}$ is the inflation of the more volatile components, and, $\Delta_{12}P_t^{fe}$ is the inflation from food and energy.

4.2.2 BVAR versus frequentist approaches

From this point forward, we evaluate the quality of the forecasts by the relative RSMFE. This measure is the ratio of the RSMSE of all those alternative models for forecasting inflation to the RSMFE of our BVAR model. A relative RMSE above one means that the alternative approach performs worse than our proposed model. On the contrary, a measure lower than one implies better forecasting performance.

First, we estimate the best univariate model with a Tramo-Seats procedure for the headline inflation. In general, performances of this model is not promising. Table 4 shows that it delivers relatively high forecast errors compared to our BVAR with mixed priors. The only time horizont for which this model has better forecasting properties is one month ahead. Regarding the other indexes, again, only for one month ahead and only for non-core measures of inflation.

Table 4: RSMFE relative to BVAR with a mixed prior

Variable	Best univariate			
	h=1	h=3	h=6	h=12
$\Delta_{12}P_t$	0.93	1.28	1.54	1.97
$\Delta_{12}P_t^{lv}$	2.02	2.19	1.83	2.74
$\Delta_{12}P_t^{efe}$	1.12	1.34	1.70	2.41
$\Delta_{12}P_t^{mv}$	0.82	1.04	1.27	1.67
$\Delta_{12}P_t^{fe}$	0.78	1.13	1.21	1.55

Note: RSMFE is the Root Squared of the Mean Forecast Error, h stands for the horizon of forecasting, $\Delta_{12}P_t$ is the headline inflation, $\Delta_{12}P_t^{lv}$ is the inflation of the less volatile components, $\Delta_{12}P_t^{efe}$ is the inflation excluding food and energy, $\Delta_{12}P_t^{mv}$ is the inflation of the more volatile components, and, $\Delta_{12}P_t^{fe}$ is the inflation from food and energy.

Our second round of exercises considers the forecast under the bottom-up approach with the best frequentist VARs for two levels of disaggregation:[16]

- 18 components: This VAR parallels the same number of variables that our BVAR.
- Two main components: core and non-core components.

In the case of two main components, we consider two possible estimations: (i) less and more volatile components, and (ii) just food and energy and then excluding food and energy. The RSMFE for the estimation (ii) was lower, and it is the one reported.[17]

Results are reported in Table 5. Our approach reports by far lower RSMFE than the two alternatives under consideration.

Table 5: RSMFE relative to BVAR with a mixed prior

Variable	18 components				Two main components			
	h=1	h=3	h=6	h=12	h=1	h=3	h=6	h=12
$\Delta_{12}P_t$	1.19	1.42	1.47	1.31	1.10	1.13	1.12	1.12
$\Delta_{12}P_t^{lv}$	1.68	2.32	2.28	1.76	-	-	-	-
$\Delta_{12}P_t^{efe}$	1.22	1.14	1.15	1.18	1.09	1.21	1.33	1.35
$\Delta_{12}P_t^{mv}$	1.12	1.14	1.02	1.24	-	-	-	-
$\Delta_{12}P_t^{fe}$	1.13	1.21	1.17	1.20	1.06	1.15	1.25	1.31

Note: RSMFE is the Root Squared of the Mean Forecast Error, h stands for the horizon of forecasting, $\Delta_{12}P_t$ is the headline inflation, $\Delta_{12}P_t^{lv}$ is the inflation of the less volatile components, $\Delta_{12}P_t^{efe}$ is the inflation excluding food and energy, $\Delta_{12}P_t^{mv}$ is the inflation of the more volatile components, and, $\Delta_{12}P_t^{fe}$ is the inflation from food and energy.

[16] In each case, we use the Schwartz criteria for the optimal number of lags.
[17] Results for the estimation (i) can be obtained under request.

4.2.3 BVAR versus a random walk

We argue that the random walk is also a convenient model to compare the forecasting performances of our BVAR specification. more complicated models. Our results are promising. We find that our forecast beats the naive random walk across all forecasting horizons (up to 12 months) in terms of a smaller RMSE (see Table 6).[18]

In terms of the core and non-core inflation indexes, results favor our approach. BVAR forecasts beats almost all horizonts for different measures of inflation. Same as the exercise with the Minnesota prior, the only case in which the random walk beats our BVAR forecast is for inflation that excludes food and energy, and for horizonts up to 6 months.

Table 6: RSMFE relative to BVAR with a mixed prior

Variable	Random walk			
	h=1	h=3	h=6	h=12
$\Delta_{12}P_t$	1.03	1.11	1.22	1.26
$\Delta_{12}P_t^{lv}$	1.02	1.08	1.02	1.14
$\Delta_{12}P_t^{efe}$	0.96	0.89	0.84	1.11
$\Delta_{12}P_t^{mv}$	1.04	1.11	1.25	1.40
$\Delta_{12}P_t^{fe}$	1.03	1.06	1.18	1.30

Note: RSMFE is the Root Squared of the Mean Forecast Error, h stands for the horizon of forecasting, $\Delta_{12}P_t$ is the headline inflation, $\Delta_{12}P_t^{lv}$ is the inflation of the less volatile components, $\Delta_{12}P_t^{efe}$ is the inflation excluding food and energy, $\Delta_{12}P_t^{mv}$ is the inflation of the more volatile components, and, $\Delta_{12}P_t^{fe}$ is the inflation from food and energy.

5 Conclusion

In time series econometrics, the history of any series has important information about its future evolution. In that regard, the forecasting ability of time series models has been widely accepted in most fields in economics. Most time series models have been empowered with Bayesian techniques, in particular VAR models.

In this paper we have used a large Bayesian VAR (BVAR) to forecast inflation in Peru. The approach that we consider is to bottom-up disaggregated components of the CPI into 18 groups. We estimate a shrinkage hyperparameter for the BVAR that is built for those 18 groups using a multi-horizon loss function (in terms of out-of-sample RSMFE), forecast each group, and then aggregate the resulting forecasts so that they satisfy the hierarchies among them. The best forecasts are obtained by combining the forecast for each group so as to make better use of the individual dynamics contained in all of them while satisfying the hierarchies. Hence, in this case forecasting the aggregates by disaggregates in groups results in better inflation forecasts (up to one year ahead)

[18] See appendix D for the detailed forecast performance.

than using traditional VARs, univariates models, or even a random walk.

The forecasts obtained can be employed as a good starting point in the recurrent process of fine-tuning the forecasting inflation process. There are several ways to improve the forecasts presented here. For instance, let this bottom up approach compete with that based on extracting common factors for each group. Another interesting avenue for future research involves allowing another level of aggregation, for instance, just aggregate core and no-core components and estimate an BVAR with those two time series.

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A Aggregation by components of the CPI

Table A.1: Groups 1, 2, 3, and 4 (weight for base year 2009, in %)

Code	Description	Weight	Code	Description	Weight
$\mathbf{G_1}$	**Agricultural food**	**0.93**	$\mathbf{G_2}$	**Processed foods**	**7.67**
P_1	Other trifles	0.29	P_8	Beef	1.20
P_2	Other legumes	0.22	P_9	Canned milk	1.65
P_3	Other poultry	0.12	P_{10}	Spices and seasonings	0.55
P_4	Pork	0.14	P_{11}	Cheeses	0.48
P_5	Mutton	0.06	P_{12}	Other meat preparations	0.45
P_6	Wheat	0.04	P_{13}	Margarine	0.16
P_7	Other cereals slightly processed	0.05	P_{14}	Coffee	0.17
			P_{15}	Cakes	0.38
$\mathbf{G_3}$	**Beverages**	**2.65**	P_{16}	Fresh milk	0.15
P_{36}	Beer	0.79	P_{17}	Canned fish	0.22
P_{37}	Drinks	1.30	P_{18}	Avena	0.15
P_{38}	Low-alcohol drinks	0.11	P_{19}	Sugary products	0.21
P_{39}	Beverages of high alcoholic content	0.06	P_{20}	Cookies	0.36
P_{40}	Juices and nectars packed fruit	0.17	P_{21}	Prepared food stuffs	0.10
P_{41}	Refreshments fluids	0.22	P_{22}	Miscellaneous food products	0.27
			P_{23}	Farina	0.08
$\mathbf{G_4}$	**Textiles**	**4.13**	P_{24}	Other dairy products	0.41
P_{42}	Clothing for men over 12 years	1.52	P_{25}	Tea	0.03
P_{43}	Clothing for women over 12 years	1.46	P_{26}	Cacao	0.09
P_{44}	Clothing for children	0.12	P_{27}	Butter	0.05
P_{45}	Fabrics	0.03	P_{28}	Flour and other derivatives	0.03
P_{46}	Other accessories	0.13	P_{29}	Sal	0.03
P_{47}	Sheets	0.06	P_{30}	Dried Fruits	0.02
P_{48}	Towels	0.04	P_{31}	Other herbal infusion	0.03
P_{49}	Bedspread and comforters	0.07	P_{32}	Fruit preserves	0.02
P_{50}	Sewing products	0.06	P_{33}	Processed grains	0.06
P_{51}	Blankets	0.02	P_{34}	Prepared foods	0.05
P_{52}	Curtains	0.03	P_{35}	Ice cream and edible ice	0.28
P_{53}	Children's Apparel	0.34			
P_{54}	Clothing for girls	0.28			

Table A.2: Groups 5, 6, 7, 8, 9 and 10 (weight for base year 2009, in %)

Code	Description	Weight	Code	Description	Weight
$\mathbf{G_{5,t}}$	**Footwear**	**1.38**	$\mathbf{G_{7,t}}$	**Rest of industrial**	**14.86**
$P_{55,t}$	Shoes for men over 12 years	0.55	$P_{67,t}$	Personal care items	4.93
$P_{56,t}$	Shoes for women over 12 years	0.5	$P_{68,t}$	Cleaning supplies	0.92
$P_{57,t}$	Shoes for children	0.03	$P_{69,t}$	Medicinal products	2.08
$P_{58,t}$	Shoes for kids	0.16	$P_{70,t}$	Textbooks and school supplies	0.74
$P_{59,t}$	Shoes for girls	0.14	$P_{71,t}$	Newspapers	0.25
			$P_{72,t}$	Other miscellaneous expenses	0.34
$\mathbf{G_{6,t}}$	**Appliances**	**1.29**	$P_{73,t}$	Recreation equipment	0.75
$P_{60,t}$	Television	0.49	$P_{74,t}$	Purchase of vehicles	1.62
$P_{61,t}$	Radios	0.19	$P_{75,t}$	Other household items	0.62
$P_{62,t}$	Refrigerator	0.17	$P_{76,t}$	Furnishings	0.29
$P_{63,t}$	Kitchen appliances	0.23	$P_{77,t}$	Articles of jewelery	0.11
$P_{64,t}$	Blenders and extractor	0.05	$P_{78,t}$	Cigarettes	0.13
$P_{65,t}$	Washers	0.15	$P_{79,t}$	No textbooks	0.03
$P_{66,t}$	Iron	0.02	$P_{80,t}$	Other household items	0.07
			$P_{81,t}$	Magazines and related	0.06
$\mathbf{G_{8,t}}$	**Meals outside home**	**11.74**	$P_{82,t}$	Spare parts and vehicle washing and	0.21
$P_{94,t}$	Meals outside the home	8.4	$P_{83,t}$	Therapeutic devices	0.16
$P_{95,t}$	Other food away from home	2.29	$P_{84,t}$	Other furniture and accessories	0.03
$P_{96,t}$	Non-alcoholic beverages	0.69	$P_{85,t}$	Mattress	0.14
$P_{97,t}$	Alcoholic Drinks	0.37	$P_{86,t}$	Beds	0.1
			$P_{87,t}$	Apparatus for recreation and culture	0.88
$\mathbf{G_{9,t}}$	**Education**	**9.12**	$P_{88,t}$	Dinnerware	0.03
$P_{98,t}$	Tuition and board of education	8.83	$P_{89,t}$	Pump light	0.18
$P_{99,t}$	Teaching in various areas	0.29	$P_{90,t}$	Glassware	0.02
			$P_{091,t}$	Storage cupboards	0.12
$\mathbf{G_{10,t}}$	**Rents**	**2.41**	$P_{92,t}$	Natural products manufactured	0.08
$P_{100,t}$	Rental housing	2.41	$P_{93,t}$	Contraceptive devices	0.01

Table A.3: Groups 11, 12, 13, and 15 (weight for base year 2009, in %)

Code	Description	Weight	Code	Description	Weight
$\mathbf{G_{11,t}}$	**Health**	**1.08**	$\mathbf{G_{15,t}}$	**Other non-core food**	**5.58**
$P_{101,t}$	Surgeries	0.33	$P_{136,t}$	Fresh and frozen fish	0.68
$P_{102,t}$	Hospitalization	0.37	$P_{137,t}$	Eggs	0.58
$P_{103,t}$	Other medical services	0.13	$P_{138,t}$	Citrus	0.52
$P_{104,t}$	Dental Service	0.25	$P_{139,t}$	Other vegetables	0.38
			$P_{140,t}$	Onion	0.4
$\mathbf{G_{12,t}}$	**Other personal services**	**3.33**	$P_{141,t}$	Fresh Vegetables	0.23
$P_{105,t}$	House Cleaning	2.06	$P_{142,t}$	Other fresh fruit	0.4
$P_{106,t}$	Personal Care Service	0.57	$P_{143,t}$	Banana	0.29
$P_{107,t}$	Vehicle Repair	0.2	$P_{144,t}$	Apple	0.22
$P_{108,t}$	Housekeeping	0.19	$P_{145,t}$	Tomato	0.2
$P_{109,t}$	Miscellaneous repairs	0.09	$P_{146,t}$	Fréjol	0.14
$P_{110,t}$	Preparation of various items	0.05	$P_{147,t}$	Corn	0.14
$P_{111,t}$	TV and Radio Repair	0.03	$P_{148,t}$	Papaya	0.17
$P_{112,t}$	Repair and maintenance of housing	0.06	$P_{149,t}$	Pumpkin	0.08
$P_{113,t}$	Composure Furniture	0.02	$P_{150,t}$	Varrot	0.13
$P_{114,t}$	Repair of various items	0.07	$P_{151,t}$	Chicken giblets and other	0.14
			$P_{152,t}$	Garlic	0.07
$\mathbf{G_{13,t}}$	**Other services**	**4.58**	$P_{153,t}$	Palta	0.12
$P_{115,t}$	Show tickets	1.7	$P_{154,t}$	Uva	0.12
$P_{116,t}$	Airfare	0.41	$P_{155,t}$	Seafood	0.03
$P_{117,t}$	municipal taxes	0.15	$P_{156,t}$	Olluco and similar	0.08
$P_{118,t}$	Repair and maintenance of housing	0.18	$P_{157,t}$	Celery	0.04
$P_{119,t}$	Miscellaneous insurance	0.28	$P_{158,t}$	Yuca	0.05
$P_{120,t}$	Court expenses	0.38	$P_{159,t}$	Peaches	0.08
$P_{121,t}$	Expenses in hotels and similar	0.13	$P_{160,t}$	Olive	0.09
$P_{122,t}$	Repair and Parts	0.03	$P_{161,t}$	Sweet Potato	0.06
$P_{123,t}$	Baptism and marriage expenses	0.07	$P_{162,t}$	Corn	0.06
$P_{124,t}$	Tour Desk	0.04	$P_{163,t}$	Chili	0.06
$P_{125,t}$	Other vehicle expenses	0.09			
$P_{126,t}$	Expenditure sport classes, music and dance	0.22			
$P_{127,t}$	Pet services and products	0.48			

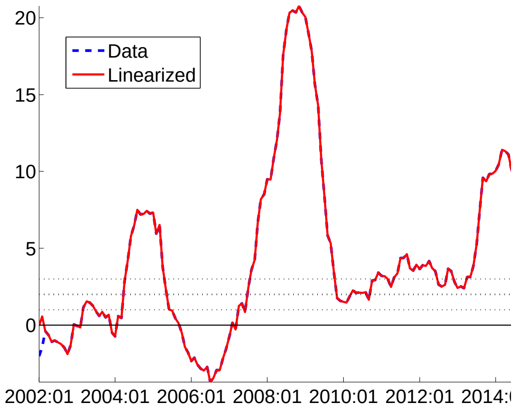
Table A.4: Groups 14, 16, 17, and 18 (weight for base year 2009, in %)

Code	Description	Weight	Code	Description	Weight
$\mathbf{G_{14,t}}$	**Food**	**14.83**	$\mathbf{G_{16,t}}$	**Energy**	**5.74**
$P_{129,t}$	Chicken meat	2.96	$P_{164,t}$	Electricity	2.95
$P_{130,t}$	Bread	1.92	$P_{165,t}$	Fuel and lubricants	1.3
$P_{131,t}$	rice	1.91	$P_{166,t}$	Gas	1.4
$P_{132,t}$	Pope	0.89	$P_{167,t}$	Kerosene	0.09
$P_{133,t}$	Sugar	0.53	$P_{168,t}$	Natural gas consumption for housing	0.01
$P_{134,t}$	Noodles	0.54			
$P_{135,t}$	Oils	0.52	$\mathbf{G_{18,t}}$	**Utilities**	**5.41**
			$P_{171,t}$	Phones	2.92
$\mathbf{G_{17,t}}$	**Transportation**	**8.87**	$P_{172,t}$	Water consumption	1.64
$P_{169,t}$	Urban landscape	8.54	$P_{173,t}$	Post	0.02
$P_{170,t}$	National transportation	0.33	$P_{174,t}$	Internet and other	0.83

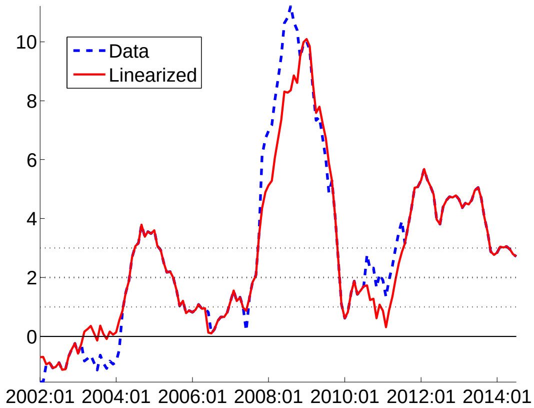
B Inflation for Groups

Figure B.1: Inflation rates for groups (percentage change over 12 months)

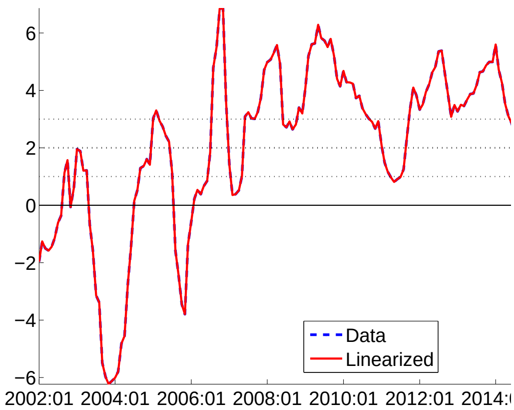
(f) Agricultural food



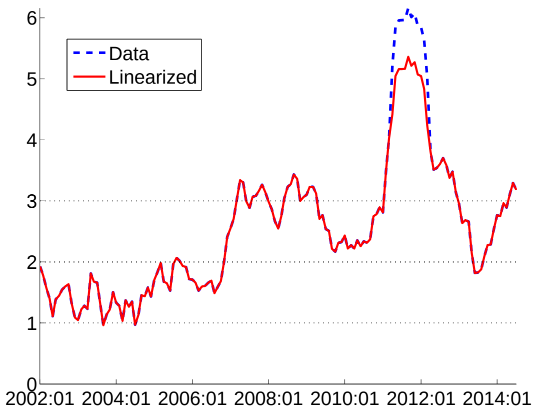
(g) Processed foods



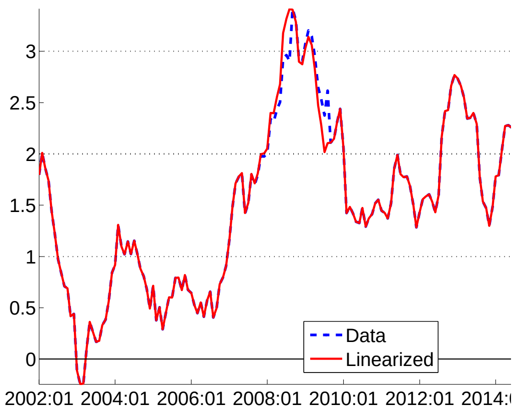
(h) Beverages



(i) Textiles



(j) Footwear



(k) Appliances

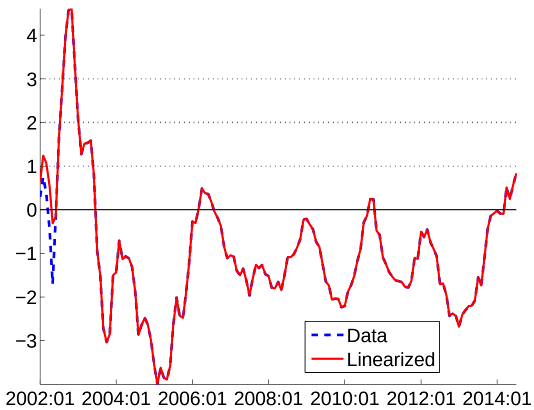
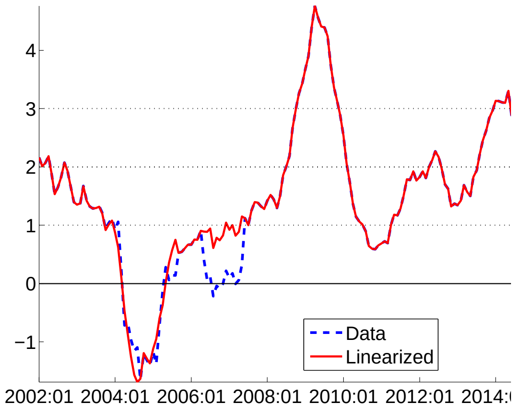
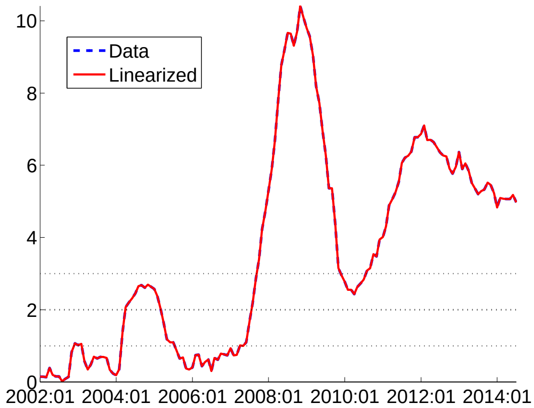


Figure B.2: Inflation rates for groups (percentage change over 12 months)

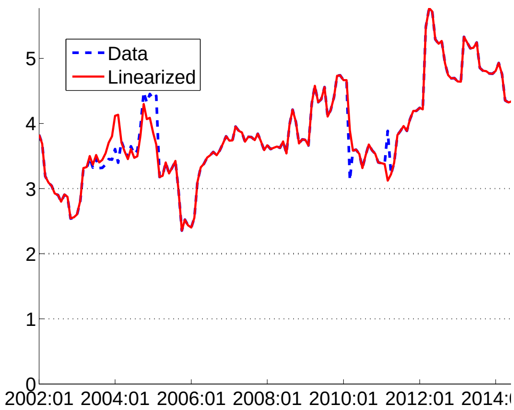
(a) Rest of industrial



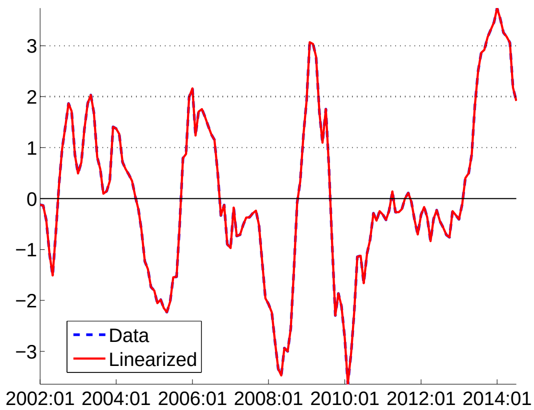
(b) Meals outside home



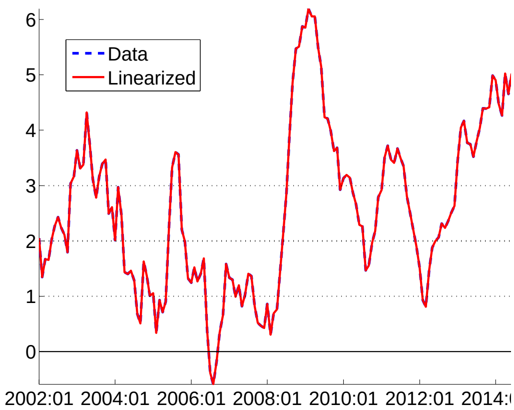
(c) Education



(d) Rents



(e) Health



(f) Other personal services

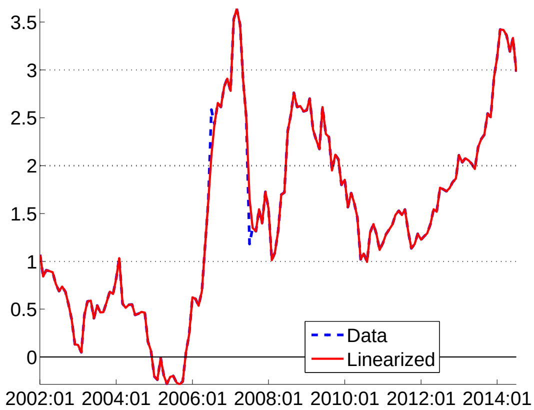
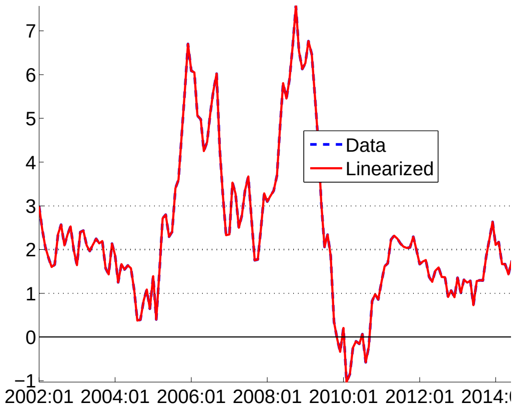
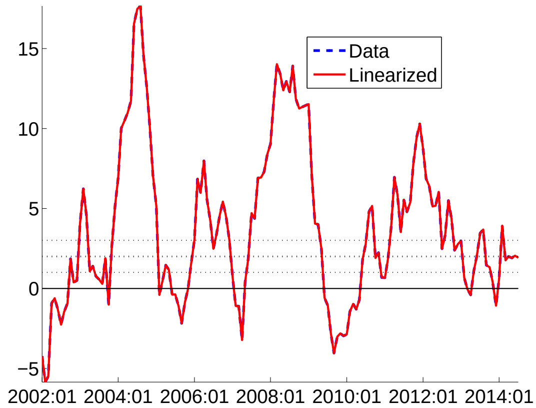


Figure B.3: Inflation rates for groups (percentage change over 12 months)

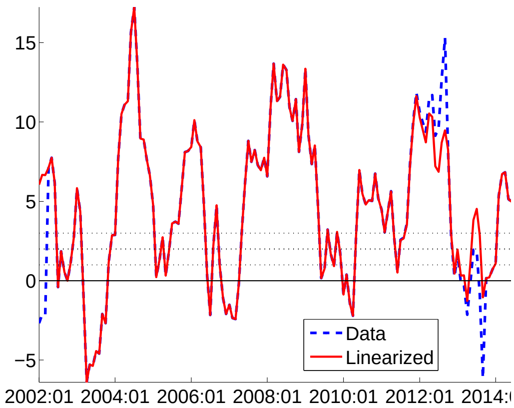
(a) Other services



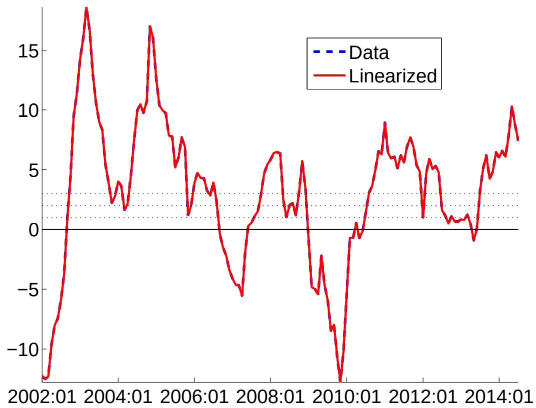
(b) Food



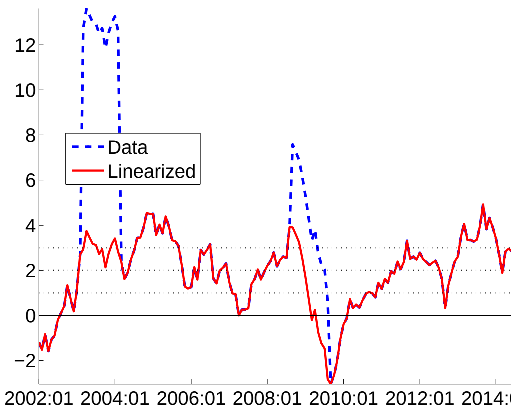
(c) Other non-core food



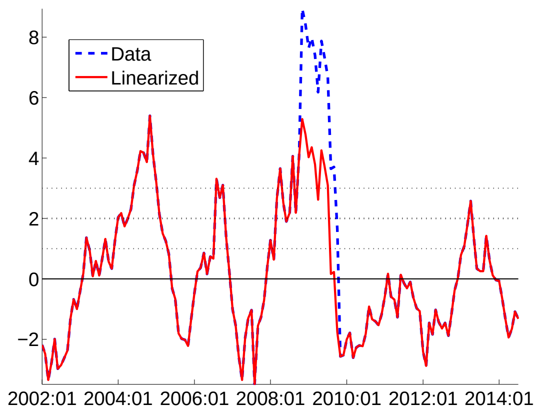
(d) Energy



(e) Transportation



(f) Utilities



C Root Squared of the Mean Forecast Error (RSMFE)

RSMFE is a measure that estimates the average forecast error, holding constant a forecast horizon. We denote this measure by $\varepsilon^{x}_{t_0:T}(h)$ and refers to the average forecast error for the variable x, for the sample that starts in t_0 and ends in T. Here, h is the forecast horizon. We compute this measure by:

i. Consider $t \in \{1, ..., T\}$ as the time identifier for T observations of x.

ii. Perform a forecast for x at the moment $t \leq T$ with information until $t = t_0 - h < T$. Let us denote it $x^{f}_{t_0|t_0-h}$ so that the squared forecast error can be computed

$$\varepsilon^2_{t_0|t_0-h} = \left(x_{t_0} - x^{f}_{t_0|t_0-h}\right)^2.$$

iii. Repeat this process for every $t \in \{t_0, ..., T\}$ and build a sequence of $T - t_0 + 1$ squared errors

$$\left\{\varepsilon^2_{t_0|t_0-h},\ \varepsilon^2_{t_0+1|t_0+1-h},\ ...,\ \varepsilon^2_{T|T-h}\right\}$$

iv. Calculate the root squared for the average of sequence of errors estimated in (iii) and interpret this result as an average error when a prediction of the variable x is made with h periods in advance

$$\varepsilon^{x}_{t_0:T}(h) = \sqrt{\frac{\varepsilon^2_{t_0|t_0-h} + \varepsilon^2_{t_0+1|t_0+1-h} + ... + \varepsilon^2_{T|T-h}}{T - t_0 + 1}}$$

D Forecast perform per group

Table D.1: RSMFE for Minnesota and mixed priors by groups

Variable	Minnesota prior				Mixed prior			
	h=1	h=3	h=6	h=12	h=1	h=3	h=6	h=12
$\Delta_{12}G_{1,t}$	0.77	1.95	3.25	4.52	0.83	2.08	3.52	5.21
$\Delta_{12}G_{2,t}$	0.39	0.85	1.23	1.58	0.40	0.88	1.33	1.67
$\Delta_{12}G_{3,t}$	0.48	1.14	1.58	1.76	0.48	1.12	1.55	1.84
$\Delta_{12}G_{4,t}$	0.23	0.54	0.99	1.76	0.21	0.48	0.89	1.55
$\Delta_{12}G_{5,t}$	0.19	0.43	0.63	0.53	0.18	0.38	0.54	0.72
$\Delta_{12}G_{6,t}$	0.35	0.77	1.26	1.64	0.34	0.72	1.18	1.37
$\Delta_{12}G_{7,t}$	0.17	0.33	0.59	0.93	0.18	0.39	0.71	0.95
$\Delta_{12}G_{8,t}$	0.21	0.35	0.73	1.37	0.22	0.44	0.90	1.60
$\Delta_{12}G_{9,t}$	0.28	0.47	0.68	1.01	0.29	0.54	0.87	1.37
$\Delta_{12}G_{10,t}$	0.34	0.78	1.29	1.79	0.37	0.84	1.36	1.95
$\Delta_{12}G_{11,t}$	0.39	0.88	1.39	1.87	0.37	0.79	1.16	1.49
$\Delta_{12}G_{12,t}$	0.17	0.37	0.58	0.68	0.17	0.36	0.54	0.60
$\Delta_{12}G_{13,t}$	0.32	0.58	0.95	1.47	0.33	0.61	1.04	1.74
$\Delta_{12}G_{14,t}$	1.45	2.29	2.47	3.21	1.49	2.46	2.86	3.64
$\Delta_{12}G_{15,t}$	2.63	4.64	5.55	6.06	2.67	4.79	6.26	7.94
$\Delta_{12}G_{16,t}$	1.60	2.78	3.59	4.60	1.63	2.94	3.97	5.45
$\Delta_{12}G_{17,t}$	0.59	0.99	1.25	1.30	0.58	0.92	1.18	1.22
$\Delta_{12}G_{18,t}$	0.68	1.31	1.82	2.08	0.66	1.23	1.63	1.76

Table D.2: Others (RSMFE relative to BVAR with mixed priors)

Variable	Desaggregated VAR				Random walk			
	h=1	h=3	h=6	h=12	h=1	h=3	h=6	h=12
$\Delta_{12}G_{1,t}$	1.13	1.19	1.24	1.17	0.98	0.89	0.83	0.92
$\Delta_{12}G_{2,t}$	1.42	1.69	1.80	1.42	0.96	0.93	1.00	1.16
$\Delta_{12}G_{3,t}$	1.45	1.56	1.48	1.32	1.02	1.00	1.02	1.06
$\Delta_{12}G_{4,t}$	1.08	1.09	1.35	1.06	0.99	0.97	0.94	0.94
$\Delta_{12}G_{5,t}$	1.20	1.08	1.09	1.59	1.02	0.99	1.04	1.39
$\Delta_{12}G_{6,t}$	2.56	2.50	2.11	1.30	0.90	0.83	0.86	0.98
$\Delta_{12}G_{7,t}$	1.48	1.93	2.07	1.25	1.07	1.18	1.12	1.10
$\Delta_{12}G_{8,t}$	1.29	1.91	2.32	2.08	1.02	1.18	1.01	1.14
$\Delta_{12}G_{9,t}$	1.15	1.35	1.75	2.04	1.03	1.14	1.11	0.94
$\Delta_{12}G_{10,t}$	2.11	1.90	1.64	1.23	1.03	0.98	0.98	1.11
$\Delta_{12}G_{11,t}$	1.32	1.13	0.79	0.57	0.93	0.86	0.80	0.91
$\Delta_{12}G_{12,t}$	1.74	1.84	1.52	1.09	0.90	0.83	0.84	1.03
$\Delta_{12}G_{13,t}$	1.68	2.14	2.06	1.82	0.94	0.81	0.62	0.66
$\Delta_{12}G_{14,t}$	1.22	1.47	1.47	1.13	1.03	1.07	1.19	1.34
$\Delta_{12}G_{15,t}$	1.09	1.10	1.04	0.99	1.02	1.05	1.17	1.37
$\Delta_{12}G_{16,t}$	1.06	1.03	1.02	1.01	0.97	0.93	0.85	1.07
$\Delta_{12}G_{17,t}$	1.07	1.03	1.11	0.97	0.99	0.97	1.00	1.19
$\Delta_{12}G_{18,t}$	1.06	1.13	1.05	0.72	0.96	0.91	0.89	1.02