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Resumen

En este artículo comparamos las predicciones puntual y de densidad obtenidas a partir de la estimación de modelos AR y VAR usando datos desagregados de la inflación chilena de frecuencia trimestral. Esta comparación responde a nuestra creencia de que, en el contexto actual de inflación alta, el uso de la dinámica conjunta de la inflación de los componentes de la canasta básica de consumo produce mejores predicciones individuales de la inflación de estos componentes que aquellas obtenidas a partir de modelos univariados. Encontramos evidencia a favor de nuestra creencia solo para las predicciones puntuales.

Abstract

In this paper we compare point and density forecasts generated by estimating AR and VAR models using disaggregated quarterly data of Chilean inflation. We motivate this comparison by our belief that, in the recent high inflation context, the use of the joint dynamics of the price index inflation of the consumer basket's components renders multivariate model's forecasts more useful than the forecasts constructed based on univariate models. We find supportive evidence for our belief only for the case of point forecasts.

We thank comments received from the participants at an internal seminar at the Central Bank of Chile and from the participants at CEMLA's XIII Meeting of the Central Bank Researchers Network of the Americas (Mexico City, Mexico). The views and conclusions presented here are exclusively those of the authors and do not necessarily reflect the position of the Central Bank of Chile or of its Board members. E-mail: jdiaz@bcentral.cl; gleyva@bcentral.cl.

1 Introduction and Motivation

Currently, inflation is at the center of policymakers' concern. It is well known that shocks of different size and persistence like the increase of oil and grains prices have been the main drivers behind the recent upward trend in inflation rates observed in many emerging and developed countries.

Specially in this context, central banks committed to attain low, stable inflation rates need inflation forecasts at the relevant policy horizon in order to carry out in advance the necessary policy actions to bring inflation back to desired values. Thus, inflation forecasts are important tools not only because they are useful for guiding policy actions but also because expectations play a key role in the monetary policy transmission as central banks affect the real economy through real interest rates, whose values are determined ultimately by the inflation expected by private agents.

Accordingly, the construction of forecasting models has been at the core of technical improvements undertaken by many central banks in the last two decades. In practice, central banks' inflation forecasts rely on a combination of a battery of (semi-)structural and times series models and policy makers' judgements. Although recent improvements have been taken by many central banks for developing and understanding dynamic stochastic general equilibrium models (DSGE), the use of time series models seems to be more widespread.

Undoubtedly, the current scenario of high and persistent inflation rates, where the likelihood of having second-round effects in place is high,[1] is a challenge for people involved in making forecasts and developing models to do so because dealing with time series properties such as persistence is not an easy task and finding the best model or combination of a subset of models to forecast inflation has non trivial consequences on monetary policy, as pointed out above. Hence, one possible explanation—the persistence of food price inflation shocks (i.e, rice, wheat and maize) and the propagation of second-round effects are certainly complementary explanations—for still observing high inflation rates in many countries could emerge from an insufficient monetary policy reaction coming, in turn, from a biased reading—based on wrong projections—of the external scenario and its relationship with domestic conditions.

In this paper we use time series models to forecast the Chilean inflation rate. We believe that this unusual inflation scenario offers an opportunity to exploit the joint dynamics of *disaggregated* inflation data in a multivariate setting in order to improve forecasts performance at the univariate level. If this disaggregated information corresponds to the price index inflation of the consumer basket's components used to construct the aggregated price index (the Consumer

[1] Here, second-round effects stand for revisions made by private agents on their inflation expectations and adjustments in indexed prices as a result of big-magnitude inflationary shocks.

Price Index, CPI), our null hypotheses would be that, say, the food price inflation forecasts based on multivariate models—using the information of the rest of the components as well—is at least as accurate as than those constructed using univariate models. Our presumption on the superior predictive ability of multivariate models in high inflation environments would be consistent with the alternative hypothesis.[2]

For evaluating the forecast performance of multivariate models vis-à-vis univariate models we use recent point and density forecasts ability tests. Although discussions on inflation forecasts among policy makers are usually focused on point forecasts estimates, it is clear that the interest should change toward density forecasts as by nature inflation forecasts are statistical objects subject to uncertainty.

This paper is laid out as follows. In the next section we present briefly the forecasting models and discuss their modeling specification. We use traditional univariate and multivariate autoregressive models, which are known to be useful for making time series forecasts. Next, in section 3 we describe the data. In the fourth section we report the estimation and specification results. In section 5 we evaluate the relative performance of point and density forecasts using two samples, one of them capturing the recent upward trend in inflation rates. Finally, in section 6 we conclude.

2 Forecasting Models

In this section we discuss issues such as specification, stability conditions, and estimation related to VAR models. We can write a VAR(p) model as follows:

$$y_t = v + A_1 y_{t-1} + \ldots + A_p y_{t-p} + u_t \tag{1}$$

where y_t is a $(K \times 1)$ vector containing the stacked values in moment t of each variable. v and A_i, with $i = 1, \ldots, p$, are $(K \times 1)$ and $(K \times K)$ matrices of parameters, respectively. Finally, u_t is a $(K \times 1)$ vector of residuals with multivariate normal distribution.[3] Clearly, the AR model is a particular case of (1) when $K = 1$.

The search for the correct VAR specification[4] is a key task because estimation results are

[2]During the elaboration of this paper, we realized that this idea of non-linearities in the relative predictive ability of competitive models (in our case, which depends on the high or low inflation scenario) is currently undertaken formally in the literature; see Giacomini and Rossi (2008) and Rossi and Sekhposyan (2008). The conditional predictive ability test of Giacomini and White (2006) also allows for non-linearities in the explanation of the relative forecast performance.

[3]Although we do not estimate model (1) by Maximum Likelihood, it is well known that OLS is equivalent to Quasi-maximum Likelihood assuming normality for errors; see White (1982).

[4]This claim is pretentious as any estimation model, in essence, is misspecified.

sensitive to the lag order p chosen for the VAR system representation. Commonly, this parameter is chosen based on traditional information criteria (i.e., Akaike, Schwarz and Hannan-Quinn), which in the VAR context are expressed as follows:

$$\text{AIC} = -\frac{2}{T^*}\left(-\frac{T^*K}{2}\ln(2\pi)+\frac{T^*}{2}\ln\left(\det(\widehat{\Omega}^{-1})\right)-\frac{T^*K}{2}\right)+2\frac{P_\theta}{T^*} \quad (2)$$

$$\text{BIC} = -\frac{2}{T^*}\left(-\frac{T^*K}{2}\ln(2\pi)+\frac{T^*}{2}\ln\left(\det(\widehat{\Omega}^{-1})\right)-\frac{T^*K}{2}\right)+\frac{P_\theta}{T^*}\ln(T^*) \quad (3)$$

$$\text{HQN} = -\frac{2}{T^*}\left(-\frac{T^*K}{2}\ln(2\pi)+\frac{T^*}{2}\ln\left(\det(\widehat{\Omega}^{-1})\right)-\frac{T^*K}{2}\right)+2\frac{P_\theta}{T^*}\ln(\ln(T^*)) \quad (4)$$

where $T^* = T-p$ is the effective sample size after accounting for the use of initial conditions in the VAR estimation, $P_\theta = K(Kp+3)$ is the total number of estimated parameters, and $\hat{\Omega}$ is the estimated covariance matrix of residuals.

But this *modus operandi* only suggests parsimony degrees for the model and tell us nothing with regard to the correct specification of VAR processes—with regard to the generation of white noise residuals. As in univariate models the researcher usually performs autocorrelation tests for the residuals (e.g., Box and Pierce (1970), Ljung and Box (1978)), this requirement should also be accomplished in a multivariate setting. Lütkepohl (2007) proposes a test of zero serial autocorrelation in a vectorial sense (i.e., among errors of different VAR equations).

To optimize the selection strategy of the best VAR process it is advisable, first, to use information criteria to prioritize parsimony—Schwarz (BIC) and Hannan-Quinn (HQN) criteria penalize the inclusion of parameters more than what the Akaike criterion does—and then, to prove if the residuals of the chosen VAR specification—associated to an order p^*—are white noise in the vectorial sense. If that p^* produces white noise residuals, that order should suggest the final VAR specification. Otherwise, researcher should look for another p for which the null hypothesis of zero serial autocorrelation is not rejected.

The Lütkepohl (2007)'s test is useful theoretically but not in practice if relying in asymptotic results. This test's asymptotic distribution for the null hypothesis follows *approximately* a chi-squared distribution $\left(\chi^2\right)$ with $K^2(h-p)$ degrees of freedom, and only follows it exactly when assuming that h, the maximum order of autocorrelation to be tested, grows with T.[5] As we do not know the true distribution of the test when assuming h fixed, or the autocorrelation order value the test requires given the sample size when h is large, we calculate the associated p-values by bootstrap—using 2000 replications—and report the test statistic for several values of h.

Finally, after selecting the best VAR representation, the researcher should verify if that

[5] Technically speaking, it is required that $h \to \infty$ as $T \to \infty$. As usual, a sample biased-corrected test is available in the literature; see Lütkepohl (2007), Ch. 4.

model satisfies the stability condition. This condition in the VAR context applies if:

$$\det(I_K - A_1 z - A_2 z^2 - \ldots - A_p z^p) \neq 0 \quad \text{for} \quad |z_i| \leq 1 \quad \text{with} \quad i = 1, \ldots, p \tag{5}$$

Next, we describe briefly the parametric bootstrap algorithm used for generating artificial series of the VAR model's variables.

2.1 Bootstrap Algorithm For Generating Artificial Data

Before describing the algorithm, it is convenient to rewrite the VAR model (1) in a compact manner:[6]

$$Y = BZ + U$$

where

$$\begin{aligned}
Y_{(K\times T)} &= \big(y_1, \ldots, y_T\big) \\
B_{(K\times(Kp+1))} &= \big(v, A_1, \ldots, A_p\big) \\
Z_t &= \begin{bmatrix} 1 \\ y_t \\ \vdots \\ y_{t-p+1} \end{bmatrix} \\
Z_{((Kp+1)\times T)} &= \big(Z_0, \ldots, Z_{T-1}\big) \\
U_{(K\times T)} &= \big(u_1, \ldots, u_T\big)
\end{aligned}$$

The bootstrap algorithm is composed of the following steps:

1. Obtain the VAR model's estimated parameters, $\hat{v}$ and $\hat{A}_i$, with $i = 1, \ldots, p$—by OLS or Maximum Likelihood.

2. Generate the estimated matrix of residuals $\widehat{U}_{(K\times T)}$. Given that the covariance matrix of residuals is any squared matrix but diagonal by construction—there is cross-section correlation among the VAR equations' residuals—resampling should be done by K-tuples in each period t.

[6] In this notation we follow closely Lütkepohl (2007).

Consider the following matrix of estimated residuals:

$$\widehat{U}_t = \begin{pmatrix} \widehat{u}_{11} & \widehat{u}_{12} & \widehat{u}_{13} & \ldots & \widehat{u}_{1T-2} & \widehat{u}_{1T-1} & \widehat{u}_{1T} \\ \widehat{u}_{21} & \widehat{u}_{22} & \widehat{u}_{23} & \ldots & \widehat{u}_{2T-2} & \widehat{u}_{2T-1} & \widehat{u}_{2T} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \widehat{u}_{K1} & \widehat{u}_{K2} & \widehat{u}_{K3} & \ldots & \widehat{u}_{KT-2} & \widehat{u}_{KT-1} & \widehat{u}_{KT} \end{pmatrix}$$

An artificial (bootstrapped) matrix of residuals would be:

$$\widetilde{U}_t = \begin{pmatrix} \widetilde{u}_{15} & \widetilde{u}_{1T-3} & \widetilde{u}_{12} & \ldots & \widetilde{u}_{1T-1} & \widetilde{u}_{15} & \widetilde{u}_{12} \\ \widetilde{u}_{25} & \widetilde{u}_{2T-3} & \widetilde{u}_{22} & \ldots & \widetilde{u}_{2T-1} & \widetilde{u}_{25} & \widetilde{u}_{22} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \widetilde{u}_{K5} & \widetilde{u}_{KT-3} & \widetilde{u}_{K2} & \ldots & \widetilde{u}_{KT-1} & \widetilde{u}_{K5} & \widetilde{u}_{K2} \end{pmatrix}$$

3. Compute artificial time series of the variables by simulating recursively the VAR system, using the parameters estimated in step 1, the pseudo-estimated residuals, and assuming some initial conditions. For each variable, the initial condition could be its unconditional mean.

4. Repeat steps 2-3 B times, where B is large—e.g., 1000, 2000.

3 The Data

Our sample consists of monthly Chilean CPI information at the first level of disaggregation. Since December 1998, the aggregate price index components are the following (with their respective weight in the CPI):[7] food (27.25%), housing (20.15%), housing equipments (8.11%), clothes (7.9%), transportation (12.18%), health (9.39%), education (11.12%), and others[8] (3.9%). The data source is the National Institute of Statistics (INE)' website and the time sample covers the period December 1998–August 2008.

As the selected VAR order could be large given the size of the estimation sample, the use of these 8 price index components in the estimations is cumbersome. For that reason, we regroup those components in 4 items without losing the informational linkages at disaggregated data that motivate this paper. Thus, in the empirical exercises we merge the groups housing and housing equipments in only one item which we call *housing*, whose weight is 28.25%. We

[7] See table 1.

[8] The items that compose this group are professional services, cigarettes, and various expenditures.

follow the same approach with items such as clothes, health, education, and others, calling the resulting item *others*, with 32.31% of importance in the CPI. Thus, we work with a sample of 4 groups of disaggregation—i.e., food, housing, transportation, and others.

For the estimations, we use the seasonally adjusted quarterly inflation rate. This is an important issue—which must be considered by researchers in future works—since the stability of the VAR representation is sensitive to the frequency basis in which inflation is measured—annual, quarterly, or monthly inflation rates. For instance, if we use annual inflation rates, the estimation, simulation, and forecast exercises of the variables involved in the VAR model show patterns associated to the system's instability—the condition stated in equation 5 is violated—which is a typical outcome when dealing with highly persistent time series. With quarterly inflation data, however, we do not face with this problem, and this is the reason why we use this inflation variable.

As mentioned before, our key hypothesis is that the predictive ability of VAR models improves in high inflation environments where, as a result of the activation of indexation mechanisms and revision of inflation expectations, the relationship among the consumer price index components becomes more important. For assessing this hypothesis empirically, we use two samples. The first one, which we call *sample I*, ends in February 2006, and the second one, which we call *sample II*, ends in August 2007. We choose intentionally these samples for working with a period of stable inflation rates (sample I) and a period of high and volatile inflation rates (sample II).

To warrant the choice of these samples, and motivate at the same time our paper we propose the natural logarithm of the determinant of the covariance matrix of the 4 price index inflation's components as a measure of their whole variation. To see how this measure has changed over time, we compute rolling estimates of 24 monthly observations since February 2004 to August 2008.[9] This measure is displayed in figure 1. We see that this measure starts to growth rapidly since the middle of 2007.

From this figure, however, we cannot know if this recent increase in our measure of whole variation is due mainly to the specific contribution of variance or covariance components. Certainly, our interest rests on the specific contribution of covariances. For this purpose, we decompose the variance of the sum of the 4 price index inflation's components into the variance and covariance components. The product of the decomposition are obviously rough measures because of the following reasons. First, as we estimate the variance of the sum of the 4 inflations we assume that the weight is the same for all the components. Second, even if we use the proper weights, the calculation of the aggregate inflation is not based on the application of weights on rates

[9]For instance, in figure 1 the rolling estimate reported for period t is estimated using the last 24 observations, including the observation in t.

but on price index levels. Third, as we sum the inflation rates we implicitly assume that the logarithm approximation works well. But quarterly inflation data exhibit in general low values, implying that this latter assumption should be uncritical.

The result of this exercise is shown in figure 2 suggesting the following. First, interestingly, the behavior of both series is similar in the whole sample. Both series exhibit an u-shaped curve with high values during the periods 2002-2003 and 2003-2004, at the beginning, and during the period 2007-August 2008 at the end of the sample. Second, the period in which the series of the left panel show negative values coincides with the low inflation period (annual inflation rates below 2%, which is the inferior limit of the inflation target) registered between the middle of 2003 and 2004. Third, chiefly, we notice that at the end of the sample both series share an increasing tendency toward values never registered before (right panel), or similar to those registered in the past (left panel).

As a conclusion, in recent times, both the variance and covariance components are important to explain the increase on the whole variance of the aggregate inflation.

4 Estimation Results

We report the specification and estimation results for samples I and II in the set of tables 2-6 and 7-11, respectively.[10] We remark the following key findings. First, as we argued above the traditional information criteria do not necessarily suggest VAR representations that produce white noise residuals. Nevertheless, focusing on the BIC statistic, which is the more parsimonious criterion, we see that the suggested VAR order coincides with the lag order for which we are able to not reject the null hypothesis of zero serial autocorrelation in 3 cases of 5 for each sample.

Second, interestingly, a cross comparison among the set of tables 2-6 and 7-11 reveals that the lag order needed to generate white noise estimated residuals increases when using the sample II, which is the sample that incorporates the most recent information, characterized, in turn, by more persistent inflation data.

Third, the p-values associated to the Lütkepohl (2007)'s test calculated by bootstrap show that in general that test has low power against many alternative hypothesis[11]—recall the null is a joint hypothesis—as the asymptotic p-value does not reject the null hypothesis while its bootstrap counterpart rejects it.

[10] The selected (V)AR lag order in each table are remarked in bold numbers.

[11] Indeed, this finding is consistent with Monte Carlo experiments; see Lütkepohl (2007).

5 Forecast Results: Forecast Performance Comparison

Before presenting the point and density ability tests and their results we describe briefly the forecasting exercise parameters. We perform two exercises that correspond to each estimation sample. The predictive window (P), which is the out-of-sample period for making forecasts comparisons, is 12 months of quarterly inflation data in both cases. For sample I the predictive window covers the period March 2006-February 2007 while for sample II the predictive window covers the period September 2007-August 2008. Moreover, for distinguishing forecasts results by their horizon—short and long-term forecasts—we consider prediction horizons of 1, 3, and 6 months; that is, we construct 1, 3 and 6 step-ahead forecasts.

The estimation of the parameters are based, again in both exercises, on the rolling scheme—thus, taking into account the uncertainty due to parameters' estimation—and estimation windows (R) of 60 months.

5.1 Point Forecasts

Today, it is well known that for assessing the relative predictive ability of competitive forecasts it is not sufficient to rely on traditional forecast performance indicators, such as the mean squared error (MSE) or the mean absolute error (MAE). From the perspective of point forecasts, what really matters is if a competitive method or model is statistically more accurate in average than the alternative in producing forecasts. Diebold and Mariano (1995) initiate the literature on comparing predictive accuracy. This literature has evolved noticeably over the years. Recently, Giacomini and White (2006) propose a conditional test of predictive ability among forecasting methods—instead of forecasting models, thus, allowing for the comparison among nested models. This test works in such a setup because it is constructed taking into account the uncertainty due to the parameters' estimation by proposing rolling or fixed schemes for this purpose. The Giacomini and White (2006)'s unconditional test in a particular case of their conditional test, by imposing the conditional information to be the trivial σ-algebra.

We apply this predictive ability test in the prediction horizons associated to samples I and II, showing the results in tables 12 and 13, respectively. The following results arise. First, as we said before, the forecasts comparison based on traditional forecast performance indicators is poorly informative as it is silent with regard to the *statistical* relative predictability among competitive models.[12] This is more noticeable in table 12. Consider the results corresponding to the item called housing. In horizons of 1 month the AR(2) produces more accurate forecasts, in

[12]The measure proposed by Peña and Sánchez (2007) for comparing VAR and AR point forecasts fits in this class of indicators.

average, than the VAR(4)—the benchmark model—as shown by the MSE statistic (in italics), but in horizons of 3 and 6 months, the opposite results holds. Statistically speaking, however, despite of the predictive horizons considered we find that VAR's forecasts are at least as accurate as than those constructed using the AR model, as revealed by the associated p-values. As a conclusion, relying in traditional forecasts performance measures is naive.

Second, using the sample I we are not able to reject the null hypothesis at conventional levels of significance in any predictive horizon and for any price index component; see table 12. When we carry out the forecasting exercise using the sample II, however, we reject generally at 5% or 10% of significance the null in horizons of 3 and 6 months. We find exceptions in the items transportation, in which there is no evidence for rejecting the null in any case, and in the item others, where we only find evidence in favor of VAR's forecast superiority in horizons of 6 months.

5.2 Density Forecasts

This section discusses the comparison of predictive density of AR and VAR models. We devote some space to discuss this test in detail because it is less common in the empirical literature.

Corradi and Swanson (2005) and Corradi and Swanson (2006) introduce and discuss a test of distributional accuracy for comparing multiple misspecified models. Their approach can be interpreted as a distributional generalization of the mean square error.

Let's suppose that $F_1\big(\cdot|X, \theta_1^*\big)$ is the predictive density obtained from the benchmark model. Our goal is to compare this benchmark with others models $(F_2(\cdot|X, \theta_2^*), \ldots, F_m(\cdot|X, \theta_m^*))$ in terms of their predictive densities accuracy. The latter comparison is always relative to the true model, whose density forecast is denoted by $F_0\big(\cdot|X, \theta_0\big)$.

It is direct to define the mean square error (MSE) associated to model i $(i = 1, \ldots, m)$ calculated over a zone of interest. If U is our region of interest, then the MSE in terms of the average over U is the following expression:

$$MSE = E\left[(F_i(u|X, \theta_i^*) - F_0(u|X, \theta_0))^2\right]$$

with $u \in U$.

If our interest is to compare, for example, model 1 and model 2, we have that model 1 is more accurate than model 2 if:

$$\int_U E\left[(F_1(u|X, \theta_1^*) - F_0(u|X, \theta_0))^2 - (F_2(u|X, \theta_2^*) - F_0(u|X, \theta_0))^2\right]\phi(u)du < 0$$

where $\int_U \phi(u)du = 1$ and $\phi(u) \geq 0$, for all $u \in U$.

As said before, the main goal is to compare the benchmark (model 1 in our case) with others models in terms of density forecast accuracy. Then, by generalizing the latter expression, the null and the alternative hypotheses are defined as:

$$H_0 : \max_{k=2,\ldots,m} \int_U E\left[(F_1(u|X,\theta_1^*) - F_0(u|X,\theta_0))^2 - (F_k(u|X,\theta_k^*) - F_0(u|X,\theta_0))^2\right]\phi(u)du \leq 0$$

$$H_1 : \max_{k=2,\ldots,m} \int_U E\left[(F_1(u|X,\theta_1^*) - F_0(u|X,\theta_0))^2 - (F_k(u|X,\theta_k^*) - F_0(u|X,\theta_0))^2\right]\phi(u)du > 0$$

Basically, if we cannot reject H_0 we have that, in terms of density forecast ability, model 1 is at least as accurate as than the others models. Moreover, however we do not know the true model —and therefore, the true density $F_0(\cdot|X,\theta_0)$)—we can disregard our knowledge about $F_0(\cdot|X,\theta_0)$ because of the following equality:

$$\begin{aligned} & E\left[(F_1(u|X,\theta_1^*) - F_0(u|X,\theta_0))^2 - (F_2(u|X,\theta_2^*) - F_0(u|X,\theta_0))^2\right] \\ = \; & E\left[(\mathbf{1}(y_{t+1} \leq u) - F_1(u|X,\theta_1^*))^2\right] - E\left[(\mathbf{1}(y_{t+1} \leq u) - F_k(u|X,\theta_k^*))^2\right] \end{aligned}$$

where $\mathbf{1}(\cdot)$ is the indicator function which is set equal to 1 if the argument is true and 0 otherwise. In this context, the statistic of interest is the following:

$$Z_P = \max_{k=2,\ldots,m} \int_U Z_{P,u}(1,k)\phi(u)du \leq 0$$

The statistic defined above can be constructed with rolling and recursive estimation schemes. In addition, $Z_{P,u}(1,k)$ is defined as follows:

$$Z_{P,u}(1,k) = \frac{1}{\sqrt{P}} \sum_{t=R}^{T-1} \left[(\mathbf{1}(y_{t+1} \leq u) - F_1(u|X,\hat{\theta}_1^*))^2\right] - E\left[(\mathbf{1}(y_{t+1} \leq u) - F_k(u|X,\hat{\theta}_k^*))^2\right]$$

where P is the prediction's window. Unfortunately, this statistic follows an unknown distribution. Therefore, for inference purposes the latter statistic is compared with critical values obtained by bootstrap techniques. Later, we discuss this procedure with more detail.

Other important issue is the choice of $\phi(u)$ and the set U over which the MSE counterpart in the forecast density literature is calculated. Depending on the problem (or simply, for the sake of robustness), the researcher can assume a particular distribution for u—i.e., normal, uniform—choosing the set U accordingly.

Next, we discuss the approach we follow for generating density forecasts. We use a bootstrap-based parametric method to generate artificial forecasts realizations relying in the parametric structure of VAR or AR models according to the model of interest.[13] The bootstrap algorithm builds on the algorithm described in section 2.1. After passing step 4, when all the artificial time series have been generated, we estimate (V)AR models for each pseudo-sample and store the estimated parameters ($\widetilde{v}$, $\widetilde{A}_i$). As our models are autoregressive structures, we compute the artificial forecasts by using the last p observations of the original data and the parameters estimated using the artificial data,[14] which is generated following the algorithm outlined in section 2.1.[15]

Once we have the artificial forecasts we use the Gaussian kernel function to estimate the density associated to them. It is well known in the density estimation literature that the choice of the kernel function is not as crucial as it is the choice of the bandwidth or smoothing parameter. We use the Silverman (1986)'s bandwidth parameter as this is proper when using the Gaussian kernel.[16]

In the exercises we discuss below we let $\phi(u)$ to be the uniform, the normal and a normal-based mixture distribution. We choose these distribution functions in order to investigate if the relative density predictive ability of VAR and AR models varies with the local importance given to the range of values over which the out-of-sample forecasts distribute. If $\phi(u)$ is the uniform distribution, we assign the same probability of occurrence to all the values while if $\phi(u)$ is normal distribution, we assign the major probability to the values locally distributed around the mean. We generate a left-biased mixture distribution in order to investigate if that relative predictive accuracy changes when weighting more high inflation values.

We show the associated results for sample I and II in tables 14 and 15, respectively. By comparing both tables, we see that in sample I, which is the sample that disregard the recent high inflation period, the evidence is strong at not rejecting the null hypothesis for any distribution assumed for $\phi(u)$. Table 15 reveals, however, interesting patterns, some of them consistent with findings reported in the preceding section and despite of the high p-values that make difficult

[13] Manzan and Zerom (2008) discuss a recent bootstrap-based non-parametric method.

[14] This approach is similar to that one discussed in Alonso et al. (2003).

[15] Two notes at this respect. First, unlike Corradi and Swanson (2006) we do not face with the location bias problem attributed to the use of the block bootstrap when using rolling estimation schemes because we use a parametric-based bootstrap method that relies on the recursive simulation of the entire series. Second, in each bootstrap replication, VAR and AR series are simulated separately in order to not introduce a bias in the generation of the series.

[16] We use 500 and 100 bootstrap replications for the generation of the time series and the construction of the estimated density forecasts, respectively.

to not reject the null at conventional levels in all cases but one.

First, for the items food and others we see that the p-value decreases when increasing the predictive horizon. Although in the items housing and transportation we do not observe that monotonic relationship, the p-values corresponding to horizons of 3 months are noticeably lower than those shown for horizons of 1 month. In this table, the only case in which we are able to reject the null hypothesis at 10% of significance corresponds to the forecasts of housing price inflation in horizons of 3 months and for the uniform distribution case.

Second, interestingly, we see that when using the normal distribution in the construction of the statistic, we do not reject the null with more strength than when using the alternative distribution function. That is, the evidence against the VAR's forecasts superiority is weaker when assuming the uniform distribution.

6 Conclusions

In this paper we have compared point and density forecasts generated by estimating VAR and AR models using disaggregated Chilean inflation data. We have motivated this comparison by our belief that in the recent high inflation context the use of the joint dynamics of the price index inflation of the consumer basket's components renders multivariate model's forecasts more profitable than the forecasts constructed based on univariate models.

These paper's results confirm our belief only for point inflation forecasts and for some price index components as revealed by the comparison of the relative predictive ability of our times series models in two samples, one of them capturing the high inflation scenario.

We think that more conclusive results could be reached if using more data of the recent high inflation period. In this sense, our results are promising because we were able to find gains in producing forecasts based on multivariate models despite of working with the starting phase of the recent upward trend in inflation rates.

Finally, the idea of using VAR models in high inflation scenarios fits in the recent literature on non-linearities in the relative forecasts performance as was pointed out in the introduction. This fact should prone policy makers to use forecasting models based on their specific abilities and conditions that make them profitable in terms of forecast performance.

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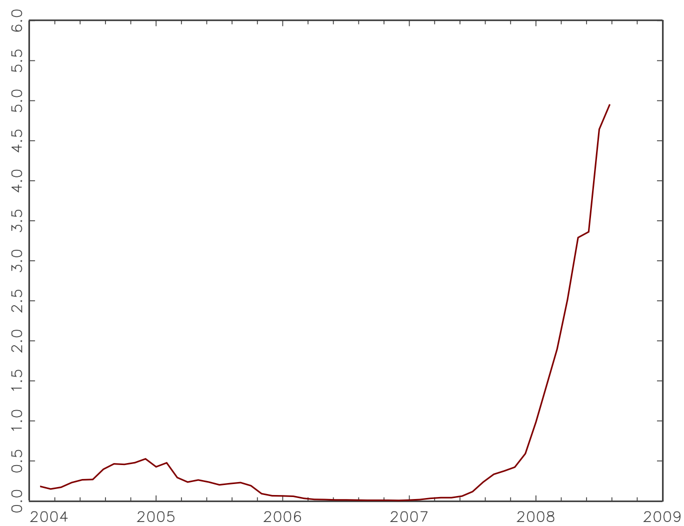
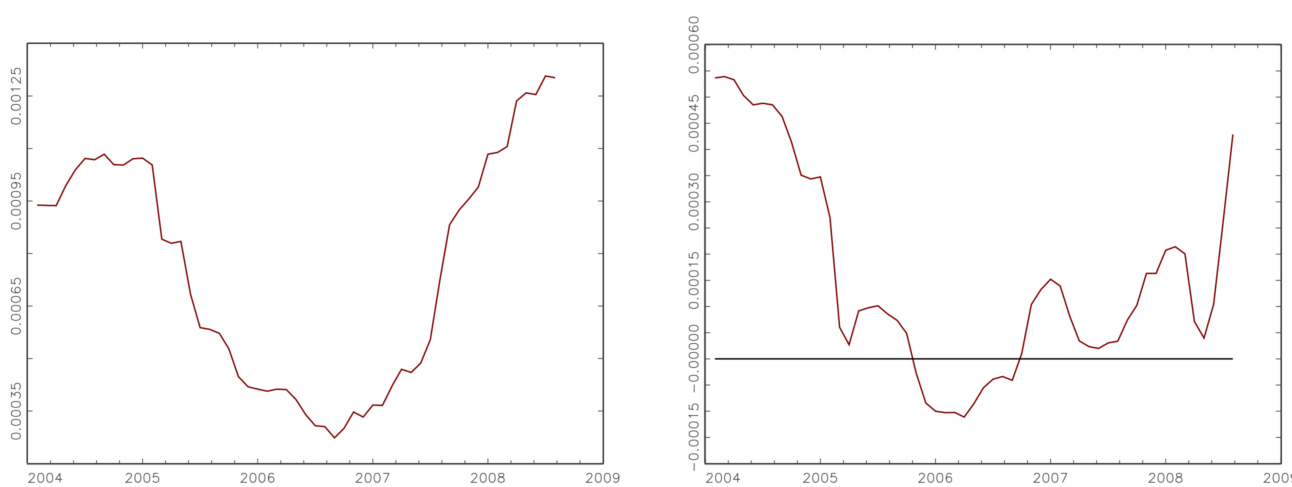
7 Appendix

Figure 1: **Measure of whole variance**



Rolling estimations of $\ln(\det(\hat{\Omega}))$ (scaled by a factor of 10^{-16})

Figure 2: **Decomposition of total variance into individual variance and covariance components**



Rolling estimations of the sum of individual variance components $\sum_{i=1}^{4} V(\pi_{i,t})$

Rolling estimations of the sum of covariance components $2\sum_{i=1}^{4}\sum_{j\neq i}^{4} Cov(\pi_{i,t},\pi_{j,t})$

Table 1: **Annual end-of-year Inflation Rate by Price Index Components (%)**

Group Name	Number of items	Weight (%)	Dec-03	Dec-04	Dec-05	Dec-06	Dec-07
Food	58	27.25	-0.83	0.18	5.25	1.28	15.16
Housing	12	20.15	3.03	3.53	3.96	3.35	12.05
Housing Equipments	25	8.11	-2.40	-0.78	-0.51	-1.51	-0.10
Clothes	26	7.90	-4.56	-1.78	-0.16	-1.21	-0.84
Transporting	11	12.18	0.35	9.12	4.73	6.10	3.16
Health	9	9.39	4.81	1.03	2.51	1.30	1.94
Education	12	11.12	3.90	2.63	3.19	3.74	3.97
Others	3	3.90	2.05	-1.71	4.03	2.74	6.80
Aggregated Inflation	-	-	1.1	2.4	3.7	2.6	7.8

Source: INE and own elaboration.

Table 2: **Vectorial White Noise Test: Food, Housing, Transportation and Others Prices Inflation (Sample I)**

VAR order (p)	Information criteria	Maximum autocorrelation order (h) 3	6	9	12	24
1	BIC	78.36	141.37	213.32	282.20	527.18
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
		[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
2	FPE,AIC,HQN	37.89	96.69	161.23	223.53	429.98
		(0.0016)	(0.0052)	(0.0016)	(0.0007)	(0.0028)
		[0.0145]	[0.0025]	[0.0005]	[0.0000]	[0.0000]
3		-	76.10	128.82	174.57	366.22
		-	(0.0060)	(0.0143)	(0.0421)	(0.1234)
		-	[0.0190]	[0.0055]	[0.0105]	[0.0000]
4		-	58.40	99.28	144.54	324.02
		-	(0.0030)	(0.0710)	(0.1507)	(0.4268)
		-	[0.1350]	[0.2060]	[0.1350]	[0.0105]
5	LR	-	46.33	82.33	130.08	299.37
		-	(0.0001)	(0.0612)	(0.1165)	(0.5642)
		-	[0.6065]	[0.6980]	[0.4135]	[0.0695]
6		-	-	78.29	122.02	291.14
		-	-	(0.0037)	(0.0377)	(0.4372)
		-	-	[0.8190]	[0.6530]	[0.1170]

The test requires that $h > p$, see Lütkepohl (2007). Numbers in the table correspond to test statistic values. $(\cdot)$ denotes asymptotic p-value, $[\cdot]$ denotes p-value calculated by *bootstrap*. For this latter computation we use 2000 *bootstrap* replications. AIC: Akaike criterion, BIC: Schwarz criterion, HQN: Hannan-Quinn criterion, FPE: final prediction error, LR: likelihood ratio test (at 5% level).

Table 3: **Vectorial White Noise Test: Food Price Inflation (Sample I)**

AR order (p)	Information criteria	Maximum autocorrelation order (h)				
		3	6	9	12	24
1		15.44	16.78	21.09	27.00	35.83
		(0.0004)	(0.0049)	(0.0069)	(0.0046)	(0.0429)
		[0.0000]	[0.0030]	[0.0095]	[0.0020]	[0.0140]
2	BIC,HQN	6.08	7.94	11.08	14.23	21.23
		(0.0137)	(0.0938)	(0.1351)	(0.1627)	(0.5065)
		[0.0155]	[0.0790]	[0.0850]	[0.0850]	[0.2135]
3		-	8.21	11.47	15.20	22.99
		-	(0.0419)	(0.0750)	(0.0855)	(0.3447)
		-	[0.0260]	[0.0495]	[0.0390]	[0.1120]
4	LR,FPE,AIC	-	3.74	7.86	10.45	17.81
		-	(0.1542)	(0.1639)	(0.2346)	(0.5997)
		-	[0.1370]	[0.1100]	[0.1310]	[0.2590]
5		-	3.17	5.67	7.54	15.13
		-	(0.0748)	(0.2250)	(0.3746)	(0.7143)
		-	[0.1365]	[0.1945]	[0.2660]	[0.3570]
6		-	-	5.06	6.91	15.77
		-	-	(0.1672)	(0.3294)	(0.6087)
		-	-	[0.1450]	[0.2400]	[0.2350]

See footnote in table 2.

Table 4: **Vectorial White Noise Test: Housing Price Inflation (Sample I)**

AR order (p)	Information criteria	Maximum autocorrelation order (h)				
		3	6	9	12	24
1		10.42	14.60	15.97	18.23	49.28
		(0.0055)	(0.0122)	(0.0428)	(0.0765)	(0.0011)
		[0.0020]	[0.0085]	[0.0275]	[0.0430]	[0.0020]
2	BIC	6.41	12.66	13.92	17.94	43.94
		(0.0113)	(0.0131)	(0.0525)	(0.0560)	(0.0036)
		[0.0125]	[0.0085]	[0.0330]	[0.0215]	[0.0005]
3		-	11.15	12.74	15.33	42.11
		-	(0.0110)	(0.0473)	(0.0822)	(0.0041)
		-	[0.0075]	[0.0250]	[0.0385]	[0.0000]
4		-	12.41	13.60	16.72	42.93
		-	(0.0020)	(0.0184)	(0.0331)	(0.0021)
		-	[0.0000]	[0.0070]	[0.0095]	[0.0005]
5		-	14.99	16.97	22.53	50.07
		-	(0.0001)	(0.0020)	(0.0021)	(0.0001)
		-	[0.0000]	[0.0010]	[0.0005]	[0.0000]
6	LR,FPE,AIC,HQN	-	-	9.62	11.78	35.73
		-	-	(0.0221)	(0.0671)	(0.0076)
		-	-	[0.0085]	[0.0305]	[0.0005]

See footnote in table 2.

Table 5: **Vectorial White Noise Test: Transportation Price Inflation (Sample I)**

AR order (p)	Information criteria	Maximum autocorrelation order (h) 3	6	9	12	24
1		28.54	35.44	38.35	44.57	67.80
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
		[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
2		3.42	13.77	16.54	19.06	32.01
		(0.0644)	(0.0081)	(0.0206)	(0.0396)	(0.0772)
		[0.0770]	[0.0045]	[0.0110]	[0.0225]	[0.0290]
3		-	8.91	11.41	12.36	24.62
		-	(0.0305)	(0.0766)	(0.1937)	(0.2641)
		-	[0.0235]	[0.0435]	[0.1115]	[0.0735]
4	LR,BIC,HQN	-	3.02	4.41	5.56	16.15
		-	(0.2214)	(0.4926)	(0.6959)	(0.7072)
		-	[0.2505]	[0.4340]	[0.6265]	[0.3830]
5	FPE,AIC	-	2.29	4.02	4.84	15.76
		-	(0.1303)	(0.4031)	(0.6789)	(0.6735)
		-	[0.2540]	[0.4195]	[0.6060]	[0.3510]
6		-	-	2.56	3.27	13.50
		-	-	(0.4647)	(0.7739)	(0.7613)
		-	-	[0.5655]	[0.7750]	[0.4285]

See footnote in table 2.

Table 6: **Vectorial White Noise Test: Others Price Inflation (Sample I)**

AR order (p)	Information criteria	Maximum autocorrelation order (h) 3	6	9	12	24
1		20.76	25.62	35.65	46.66	62.94
		(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)
		[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
2	BIC	4.37	8.91	18.60	25.26	31.32
		(0.0366)	(0.0633)	(0.0095)	(0.0049)	(0.0897)
		[0.0365]	[0.0415]	[0.0045]	[0.0015]	[0.0245]
3		-	7.39	15.18	22.18	28.26
		-	(0.0603)	(0.0189)	(0.0083)	(0.1330)
		-	[0.0395]	[0.0115]	[0.0015]	[0.0280]
4	LR,FPE,AIC,HQN	-	7.61	14.19	20.62	26.06
		-	(0.0223)	(0.0145)	(0.0082)	(0.1637)
		-	[0.0150]	[0.0060]	[0.0010]	[0.0235]
5		-	7.37	13.69	20.02	25.39
		-	(0.0066)	(0.0084)	(0.0055)	(0.1480)
		-	[0.0050]	[0.0060]	[0.0000]	[0.0215]
6		-	-	13.25	22.23	30.65
		-	-	(0.0041)	(0.0011)	(0.0316)
		-	-	[0.0040]	[0.0010]	[0.0030]

See footnote in table 2.

Table 7: **Vectorial White Noise Test: Food, Housing, Transportation and Others Prices Inflation (Sample II)**

VAR order (p)	Information criteria	Maximum autocorrelation order (h)				
		3	6	9	12	24
1	BIC	98.95	170.02	236.20	307.46	570.68
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
		[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
2	HQN	54.18	114.50	176.66	237.41	434.53
		(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0017)
		[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
3		-	86.85	142.03	185.81	359.55
		-	(0.0005)	(0.0016)	(0.0108)	(0.1805)
		-	[0.0010]	[0.0015]	[0.0055]	[0.0030]
4		-	61.30	103.95	137.20	317.02
		-	(0.0014)	(0.0373)	(0.2733)	(0.5365)
		-	[0.0970]	[0.1655]	[0.3975]	[0.0850]
5	LR,FPE	-	49.54	90.85	123.44	296.04
		-	(0.0000)	(0.0153)	(0.2165)	(0.6174)
		-	[0.3375]	[0.3455]	[0.6255]	[0.2315]
6	AIC	-	-	89.60	118.05	289.95
		-	-	(0.0003)	(0.0629)	(0.4566)
		-	-	[0.2865]	[0.6735]	[0.2290]

See footnote in table 2.

Table 8: **Vectorial White Noise Test: Food Price Inflation (Sample II)**

AR order (p)	Information criteria	Maximum autocorrelation order (h)				
		3	6	9	12	24
1		14.27	15.50	20.80	25.31	30.49
		(0.0008)	(0.0084)	(0.0077)	(0.0082)	(0.1360)
		[0.0030]	[0.0170]	[0.0130]	[0.0155]	[0.0920]
2	BIC	7.27	9.09	14.75	16.82	25.14
		(0.0070)	(0.0589)	(0.0394)	(0.0785)	(0.2903)
		[0.0135]	[0.0600]	[0.0295]	[0.0475]	[0.1225]
3		-	9.01	14.52	16.76	24.92
		-	(0.0291)	(0.0244)	(0.0525)	(0.2508)
		-	[0.0305]	[0.0150]	[0.0265]	[0.0975]
4	LR,FPE,AIC,HQN	-	4.13	9.93	12.18	22.54
		-	(0.1270)	(0.0773)	(0.1434)	(0.3121)
		-	[0.2445]	[0.1045]	[0.1425]	[0.1510]
5		-	3.60	9.07	10.98	21.37
		-	(0.0577)	(0.0594)	(0.1396)	(0.3168)
		-	[0.1785]	[0.0695]	[0.1265]	[0.1325]
6		-	-	8.48	9.86	19.34
		-	-	(0.0371)	(0.1308)	(0.3713)
		-	-	[0.0475]	[0.1080]	[0.1360]

See footnote in table 2.

Table 9: **Vectorial White Noise Test: Housing Price Inflation (Sample II)**

AR order (p)	Information criteria	Maximum autocorrelation order (h) 3	6	9	12	24
1		23.08	26.26	28.53	32.74	56.19
		(0.0000)	(0.0001)	(0.0004)	(0.0006)	(0.0001)
		[0.0000]	[0.0005]	[0.0010]	[0.0005]	[0.0005]
2		8.95	14.81	17.12	22.90	48.41
		(0.0028)	(0.0051)	(0.0166)	(0.0111)	(0.0010)
		[0.0025]	[0.0050]	[0.0120]	[0.0090]	[0.0010]
3		-	13.01	16.25	20.21	43.95
		-	(0.0046)	(0.0125)	(0.0166)	(0.0024)
		-	[0.0060]	[0.0055]	[0.0095]	[0.0005]
4		-	13.76	15.31	19.93	43.12
		-	(0.0010)	(0.0091)	(0.0106)	(0.0020)
		-	[0.0000]	[0.0060]	[0.0050]	[0.0005]
5		-	17.83	20.38	27.86	55.34
		-	(0.0000)	(0.0004)	(0.0002)	(0.0000)
		-	[0.0000]	[0.0000]	[0.0000]	[0.0000]
6	LR,FPE,AIC,BIC,HQN	-	-	9.02	11.09	29.93
		-	-	(0.0290)	(0.0857)	(0.0381)
		-	-	[0.0310]	[0.0525]	[0.0085]

See footnote in table 2.

Table 10: **Vectorial White Noise Test: Transportation Price Inflation (Sample II)**

AR order (p)	Information criteria	Maximum autocorrelation order (h)				
		3	6	9	12	24
1		30.74	43.47	49.61	58.03	99.76
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
		[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
2		4.50	19.31	25.92	28.73	50.32
		(0.0339)	(0.0007)	(0.0005)	(0.0014)	(0.0005)
		[0.0350]	[0.0005]	[0.0020]	[0.0020]	[0.0010]
3		-	15.96	23.40	24.26	42.79
		-	(0.0012)	(0.0007)	(0.0039)	(0.0033)
		-	[0.0010]	[0.0010]	[0.0025]	[0.0015]
4	LR,BIC,HQN	-	5.49	8.95	9.88	23.87
		-	(0.0643)	(0.1109)	(0.2736)	(0.2480)
		-	[0.0710]	[0.0750]	[0.2050]	[0.0895]
5		-	5.70	9.49	10.27	24.44
		-	(0.0170)	(0.0499)	(0.1737)	(0.1799)
		-	[0.0225]	[0.0370]	[0.1165]	[0.0390]
6	FPE,AIC	-	-	5.12	5.66	17.85
		-	-	(0.1635)	(0.4627)	(0.4654)
		-	-	[0.1675]	[0.4195]	[0.2005]

See footnote in table 2.

Table 11: **Vectorial White Noise Test: Others Price Inflation (Sample II)**

AR order (p)	Information criteria	Maximum autocorrelation order (h) 3	6	9	12	24
1		21.22	24.68	34.17	45.95	62.79
		(0.0000)	(0.0002)	(0.0000)	(0.0000)	(0.0000)
		[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0005]
2		9.42	12.23	20.25	28.32	33.47
		(0.0021)	(0.0157)	(0.0051)	(0.0016)	(0.0555)
		[0.0015]	[0.0080]	[0.0030]	[0.0000]	[0.0200]
3		-	7.92	13.15	20.70	25.40
		-	(0.0476)	(0.0408)	(0.0140)	(0.2302)
		-	[0.0330]	[0.0190]	[0.0035]	[0.0865]
4	LR,FPE,AIC,BIC,HQN	-	7.34	12.66	19.42	23.42
		-	(0.0255)	(0.0267)	(0.0128)	(0.2686)
		-	[0.0160]	[0.0165]	[0.0075]	[0.0855]
5		-	6.41	12.36	18.94	23.25
		-	(0.0113)	(0.0149)	(0.0084)	(0.2263)
		-	[0.0150]	[0.0060]	[0.0045]	[0.0545]
6		-	-	13.45	22.67	29.20
		-	-	(0.0038)	(0.0009)	(0.0460)
		-	-	[0.0025]	[0.0000]	[0.0075]

See footnote in table 2.

Table 12: **Point Forecast Performance Results: Sample I**

Price Index Component	Benchmark Model	Competitive Model	Prediction Horizon 1	3	6
Food	AR(2)	VAR(4)	0.96	1.00	0.94
			0.65	*0.49*	*0.65*
Housing	AR(2)	VAR(4)	0.84	0.11	0.29
			0.80	*1.16*	*1.08*
Transportation	AR(3)	VAR(4)	0.20	0.76	0.92
			1.18	*0.92*	*0.80*
Others	AR(2)	VAR(4)	0.61	0.71	0.55
			0.87	*0.86*	*0.94*

Reported number in the first row for each price index component are p-values. Numbers in italics (in the second row) are the ratio of the MSE of the AR model to the MSE of the VAR model.

Table 13: **Point Forecast Performance Results: Sample II**

Price Index Component	Benchmark Model	Competitive Model	Prediction Horizon 1	3	6
Food	AR(2)	VAR(4)	0.31	0.00	0.06
			1.22	*1.65*	*1.42*
Housing	AR(6)	VAR(4)	0.35	0.00	0.02
			1.14	*3.19*	*1.77*
Transportation	AR(4)	VAR(4)	0.79	0.79	0.48
			0.68	*0.78*	*1.02*
Others	AR(3)	VAR(4)	0.84	0.66	0.01
			0.74	*0.90*	*1.48*

See footnote in table 12.

Table 14: **Density Forecast Performance Results: Sample I**

Price Index Component	Benchmark Model	Competitive Model	Prediction Horizon 1	3	6
$\phi(u)$ is the uniform distribution					
Food	AR(2)	VAR(4)	0.98	0.74	0.86
Housing	AR(2)	VAR(4)	0.97	1.00	0.58
Transportation	AR(3)	VAR(4)	0.91	1.00	0.75
Others	AR(2)	VAR(4)	0.98	0.71	0.99
$\phi(u)$ is the normal distribution					
Food	AR(2)	VAR(4)	0.97	0.89	0.78
Housing	AR(2)	VAR(4)	0.99	1.00	0.69
Transportation	AR(3)	VAR(4)	0.97	1.00	0.68
Others	AR(2)	VAR(4)	0.97	0.38	0.86
$\phi(u)$ is the normal-based mixture distribution					
Food	AR(2)	VAR(4)	0.97	0.74	0.65
Housing	AR(2)	VAR(4)	0.96	1.00	0.67
Transportation	AR(3)	VAR(4)	0.90	1.00	0.71
Others	AR(2)	VAR(4)	0.93	0.48	0.84

Reported numbers are p-values.

Table 15: **Density Forecast Performance Results: Sample II**

Price Index	Benchmark	Competitive	Prediction Horizon		
Component	Model	Model	1	3	6
$\phi(u)$ is the uniform distribution					
Food	AR(2)	VAR(4)	0.99	0.74	0.10
Housing	AR(6)	VAR(4)	0.87	0.07	0.19
Transportation	AR(4)	VAR(4)	0.97	0.61	1.00
Others	AR(3)	VAR(4)	0.86	0.29	0.17
$\phi(u)$ is the normal distribution					
Food	AR(2)	VAR(4)	1.00	0.81	0.39
Housing	AR(6)	VAR(4)	0.89	0.14	0.49
Transportation	AR(4)	VAR(4)	1.00	0.66	1.00
Others	AR(3)	VAR(4)	0.88	0.27	0.21
$\phi(u)$ is the normal-based mixture distribution					
Food	AR(2)	VAR(4)	0.99	0.94	0.71
Housing	AR(6)	VAR(4)	0.97	0.50	0.95
Transportation	AR(4)	VAR(4)	0.97	0.54	1.00
Others	AR(3)	VAR(4)	0.95	0.58	0.48

See footnote in table 14.

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