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International Journal of Economics and Financial Issues ISSN: 2146-4138 available at http: www.econjournals.com International Journal of Economics and Financial Issues, 2018, 8(5), 96-102. International Journal of Economics and Financial Issues | Vol 8 • Issue 5 • 2018 96 Bayesian Approach for Indonesia Inflation Forecasting Zul Amry* Department of Mathematics, State University of Medan, Indonesia. *Email: zul.amry@gmail.com ABSTRACT This paper presents a Bayesian approach to find the Bayesian model for the point forecast of ARMA model under normal-gamma prior assumption with quadratic loss function in the form of mathematical expression.

The conditional posterior predictive density is obtained from the combination of the posterior under normal-gamma prior with the conditional predictive density. The marginal conditional posterior predictive density is obtained by integrating the conditional posterior predictive density, whereas the point forecast is derived from the marginal conditional posterior predictive density. Furthermore, the forecasting model is applied to inflation data and compare to traditional method.

The results show that the Bayesian forecasting is better than the traditional forecasting. Keywords: ARMA Model, Bayes Theorem, Inflation, Normal-gamma Prior JEL Classifications: C13, C15, C22 1. INTRODUCTION Bayes theorem calculates the posterior distribution as proportion to the product of a prior distribution and the likelihood function.

The prior distribution is a probability model describing the knowledge about the parameters before observing the currently by the available data. Main idea of Bayesian forecasting is the predictive distribution of the future given the fast data follows directly from the joint probabilistic model. The predictive distribution is derived from the sampling predictive density, weighted by the posterior distribution (Bijak, 2010).

This is to and (2015) the problem Bayesian for ARMA under prior. papers to research Amry Fan and Yao (2008), Kleibergen and Hoek (1996), and Uturbey (2006) also discussed the Bayesian analysis for ARMA model. This paper focuses to find the mathematical expression of the Bayes estimator prior with loss and compare traditional method. 2.

MATERIALS AND METHODS The materials in this paper are some theories in mathematics and integration, and the univariate student's t-distribution and inflation data. The method is study of literatures by applying the Bayesian analysis under normal-gamma prior assumption. ARMA (p, q) model (Liu, 1995) is defined by: yy ee ti ti jt j j q t i p =+ + -- = = ? ? ?? 1 1 (1) Where {et} i i d normal random variables with et ~ N(0,t -1), t>0 and unknown, f i and ? j are parameters.

The Bayes theorem (Ramachandran and Tsokos, 2009) stated as: p(y|x) a p(x|y) py (y) (2) Where p(y|x) is posterior distribution, p(x|y) is likelihood function and py(y) is prior distribution. A quantity, is to a distribution n degrees of freedom with mode µ and scale parameter t>0 if it has the probability density function (Pole et al.,

1994): pX n n n n x n n () () () = + ? ?? ? ?? ? ? ? ? ? ?? + - ? ? ? ? ? ? ? - + G G 1 2 2 1 2 2 2 1 2 pt µ t (3) International Journal of Economics and Financial Issues | Vol 8 • Issue 5 • 2018 97 The mean is E (X) µ and the variance is Va rX n n () = - ? 2 , if n >2 In the Bayesian approach the point forecast determined based the estimator.

to & (2006), is an of, a loss is real-valued function: ( ) 2 ˆˆ (4) For quadratic function, Bayes is mean of the posterior distribution (DeGroot, 2004). 3. RESULTS The k-step-ahead point forecast of yn+k, is defined by: ? yK Ey S nk n () (|) * = + (5) Where Sy yy nn k * (, ,,) = +- 12 1 ? ey ye tt it i i p it j j p =- - - = - = ?? ff 11 Based on the equation (1) can be obtained residuals: ey ye tt it ij tj j q i p =- - -- = = ? ? ?? 1 1 (6) By conditioning the first p observations and letting ep=ep-1=...= er = 0, where r = min(0, p+1-q), one may approximate by Box & Jenkins, the likelihood function for parameters ? = (? 1, ? 2 ,...,? p , ? 1 , ? 2 ,..., ? q) and t based is: LS yy e n nk p ti ti jt j j q i p (, |) ex p * () ?t at t ? ? -- ? ? ?? +- - -- = = ? ? 1 2 1 1 2 f ?? ? ?? ? ? ? ? ? ? ? ? ? ? ? ? ?? ? ? ? ?? ? ? =+ +- ? 2 1 1 tp nk (7) The equation (7) can be expressed as: LS yy BB n nk p t T tt T t tp n (, |) ex p * () ?t t t ?? ? -- + () +- - -- =+ + 1 2 2 11 2 1 2 2 kk tp nk tp nk - =+ +- =+ +- ? ? ? ? ? ? ? ? ? ? ? ? ?? ?? ? ?? ?? 1 1 1 1 1 (8) Where Bt = (yt, yt-1,...,yt +1- p,et, et-1,...,et +1- q) By letting U yy y yy y yy y ee e pp nk pp nk nk p pp nk = ++ - -+ - +- - ++ - 12 13 12 1 12 ... ... __ __ ... ... eee e ee e pp nk pq pq nk q -+ - +- +- +- - ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? 13 12 1 ... __ __ ... ?? ? ? ? ? ? ? ? ? ? = ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? + + +- , X y y y p p nk

0 1 2 1 _ Where ey ye tp pn tt it ij tj j q i i p =- -= ++ -- = = ? ? _ _ _ … _ ff ? ,, ,, 12 1 1 et, et -1 ,…,et - q can be obtained via: ey B tt T t =- - ? ? 1 (9) Where _ __ … _ __ … _ ?? ?? = (, ,, ,,) ff f 12 12 pq From the likelihood function in equation (8) can be obtained: yB yB yB yB yy y tt pp pp nk nk tp nk pp p -+ ++ ++ - =+ +- +- =+ + = ? 11 21 2 1 1 11 ? (, ,, ,, ,, ,) (, ,, ,, ,, ?? ?? ye ee yy yy ee e pp pq pp pp pp 11 1 21 21 2 -+ - ++ ++ - + qq nk nk nk nk pn kn kq T yy yy ee UX) (, ,, ,, ,) ++ = ++ -+ -- -+ -+ -- ? ?? 21 21 0 ?? ?? T t tp nk T p T p T nk BB BB - =+ +- ++ - () = () + () ++ () ? 1 2 1 1 2 1 2 2 2 12 ? ?? ,, ? ?? ?? ?? ?? pq T pp pp pq yy ye ee ,, ,, ,, ,, ,, , 12 11 11 2 () () ? ? ? ? ? ? ? ? -- +- ++ () ++ ++ +- ?? ?? ?? 12 12 21 22 12 ,, ,, ,, ,, ,, ,, , ?? ?? pq T pp pp pq yy ye ee (() ? ? ? ? ? ? ? ? ++ () +- +- - 2 12 12 23 ? ?? ? ?? ?? ?? ,, ,, ,, ,, , pq T nk nk nk yy y --- +- +- +- - () ? ? ? ? ? ? ? ? = 12 31 2 pn kn kn kq TT ee e UU ,, ,, () ? ?? International Journal of Economics and Financial Issues | Vol 8 • Issue 5 • 2018 98 Such that the likelihood function in equation (8) can be expressed as: LS e yU XU U n nk p t TT TT tp nk ? ?? ? ,| ex p( )( ) * () ? ? () ? -- + +- - =+ + 1 2 2 0 1 2 2 - - ? ? ? ? ? ? ? ? ? ? ?? ? ? ? ? ?? ? ? 1 ?- -+ ? ? ? ? ? ? ? ? ? ?? ? ? ? ? ?? +- - =+ +- ? ey VW nk p t TT tp nk () ex p 1 2 2 1 1 2 2 ? ?? ? ?? ? (10) Where UT X 0 = V and UUT = W 3.1.

Posterior Distribution According to Broemeling and Shaarawy's suggestion (1988), the normal-gamma prior of parameters ? and t is: ?t ?t ?t t p t µµ (,)(|) .( ) ex p( )( ) ?? ?? = = ? ?? ? ? ? -- - ?? ? ? ??? 12 2 22 Q Q p T ???? () - () ? () -- - ?? ? ? - - +- x Q p T ß a tß t t t µµ ßt a a a G ?? 1 2 1 2 ex p ex p( )( ) ???? ? ? ? ?- -- + ?? ? ? ??? ??? ? + - + - t t µµ ß t a a p T p Q 2 2 1 2 2 1 2 2 ex p( )( ) ex ?? pp - --+ + ?? ? ? ?? ? ? ? ? t µµ µµ ß 2 2 ?? ?? TT TT QQ QQ (11) Where 1 ~ N -1,), 1 ~ GAM Q a definite matrix of the order (p + q), a and ß are parameters.

By applying the Bayes theorem to equation (10) and (11), the posterior distribution of ? and t -n is: pt t t ? ?? ? ,| ex p * - +- - () =+ +- () ? -- + ? ? ? ? 1 1 2 1 2 1 1 2 2 S yV W n nk p t TT tp nk ?? ? ? ? ? ? ?? ? ? ? ?? ? ? t t µµ µµ ß a p TT TT QQ QQ + - - --+ + ?? ? ? ?? ? ? ? ? 2 2 1 2 2 ex p ?? ?? ? - -+ +- -+ + +- -+ + - t t µµ µµ a nk pp t TT T TT T yV WQ QQ Q 12 2 1 2 2 2 2 ex p ?? ?? ? ?? ßß tp nk =+ +- ? ? ? ? ? ? ? ? ? ? ?? ? ? ? ?? ? ? 1 1 ? +- -+ + - - +- -- -+ + t a t µ µµ µ nk pp WQ VQ VQ yQ TT T TT t T 12 2 1 2 2 ex p () ?? ?? ?? + + ? ? ? ? ? ? ? ? ? ? ? ? ? ? ?? ? ? ? ? ? ?? ? ? ? =+ +- ? 2 1 1 ß tp nk ? - +- +- -+ + +- -+ + - t t µ µµ a nk pp TT TT t T WQ VQ VQ y 12 2 1 2 2 ex p () () () ?? ? ?? QQ tp nk µß + ? ? ? ? ? ? ? ? ? ? ? ? ? ? ?? ? ? ? ? ? ?? ? ? ? =+ +- ? 2 1 1 ? - +- +- ++ + +- -+ + - t t µ µµ µ a nk pp TT T t T WQ VQ VQ yQ 12 2 1 2 2 ex p () () () ?? ? ?+ + ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ?? ? ? ? ? ? ?? ? ? ? =+ +- ? 2 1 1 ß tp nk ? () ? -- +- + - +- -+ + - p? tt t µµ a ,| ex p( )( ) * 1 12 2 1 2 S PV QV Q n nk pp TT T ?? ?? ++ ?? ? ? ? ? ?? ? ? ? K (12) Where WQ P and yQ K t T tp nk += ++ = =+ +- ? 2 1 1 2 µµ ß 3.2.

Conditional Posterior Predictive Density Based on ey ye tt it ij tj j q i p =- - -- = = ? ? ?? 1

1 with e t ~ N -(be obtained fe Se tn t (| ,,)e xp * ? tp t t -- - = () - () ?? ? ? ? ? 11 1 2 2 2 2 If expressed in yt: fy S yy e tn ti ti jt j j q i p (| ,,) ex p * ? tp t t ?? -- - -- = = = () -- - ? ? 11 1 2 1 1 2 2 ?? ? ? ? ? ? ? ? ? ? ?? ? ? ? ?? ? ? 2 (13) predictive density of Yn+k: fy S yy e nk n nk in ki jn kj j (| ,,) ex p * + -- - ++ -+ - = = () -- - ? tp t t ?? 11 1 2 2 2 11 1 2 q i p ? ? = ? ? ? ? ? ? ? ? ? ?? ? ? ? ?? ? ? International Journal of Economics and Financial Issues | Vol 8 • Issue 5 • 2018 99 ?- -- ? ? ? ? ? ? ? ? ? ?? ? ? ? ? ++ -+ - = = ? ? t t ?? 1 2 1 1 2 2 ex p yy e nk in ki jn kj j q i p ?? ? ? ?- -+ ? ? ?? ? ? ?? ? ? ? ? ? ? ? ? ++ -+ - = = ? ? t t ?? 1 2 1 1 2 ex p yy e nk in ki jn kj j q i p 22 ? ?? ? ? ? ?? ? ? ?- -+ () ? ?? ? ?? ?? ? ? ? ? ++ -+ +- ? ? 1 2 2 11 2 2 2 ex p yB yB nk T nk nk T nk ?? ? ?- +- ?? ? ? ??? ??? ++ -+ ? ? 1 2 2 1 2 2 ex p yR By nk TT nk nk ?? ? (14) Where Bn + k-1 yn + k-1, yn + k-2,...,yn + k-p, en + k-1,...,en + k-2,...,en + k -q RB B nk nk T =? +- +- 11 Based on the equation (12) and (14) can be obtained the conditional posterior predictive density of Yn+k: fy SS fy S pn kn nn kn nk p (| ,,), |(|, ,) ** * + -- + - +- -+ ? () ? ?? ? tp tt t 11 1 1 22 2 1 2 a t µ µ () + - - -+ - ++ ? ? ? ? ? ? ? ? ? ?? ?? ? ?? ?? p TT T PV Q VQ K ex p () () ?? ? ? tt t a 1 2 2 1 12 2 2 ex p -+ - ?? ? ? ??? ??? ? ++ -+ +- -+ () yR By nk TT nk nk nk p ?? ? ++ - - -+ - ++ ? ? ? ? ? ? ? ? ? ?? ?? ? ?? ?? p TT T PV Q VQ K 2 1 1 2 2 ex p () () e t µ µ t ?? ? ? xxp - +- - ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ?? + +- ++ -+ t 2 2 11 yR By By nk TT nk nk nk T nk ?? ? ? ??? ? - -+ -+ ++ +- -+ () ++ - + t t µ µ a nk pp TT T n PV Q VQ Ky 12 1 2 1 2 ex p () () ?? ? ? kk T T nk nk nk T nk R ByBy 2 11 + -- ? ? ? ? ? ? ? ? ? ? ? ? ? ? ?? ? ? ? ? ? ? ?? ? +- ++ -+ ?? ?? ?? ? ? - -+ - ++ + +- -+ () ++ - + t t µ µ a nk pp TT T n PV Q VQ Ky 12 1 2 1 2 ex p () () ?? ? ? kk T T nk nk nk T nk R ByBy 2 11 + -- ? ? ? ? ? ? ? ? ? ? ? ? ? ? ?? ? ? ? ? ? ? ?? ? +- ++ -+ ?? ?? ?? ? The conditional posterior predictive density of Yn+k using norma gamma prior is: ? () ? - -+ + - +- -+ () ++ - fy S GV Q pn kn nk pp TT |, , ex p (* ` ? ?? ? tt t a 1 12 1 2 1 2 µµ µ +- ++ ++ ? ? ? ? ? ? ? ? ? ? ?? ?? +- + +- ++ By VQ By yK nk nk T nk T nk nk 1 1 2) (( )) ? ?? ?? ?? (15) Where G = P + R 3.3.

Marginal Conditional Posterior Predictive The marginal conditional posterior predictive density of Yn+k can be obtained by integrating the conditional posterior predictive density in equation (15): density in equation (15): fy Sf yS dd pn kn pn kn nk pp ++ - -8 8 8 +- -+ () + () = ? ? ? |(|, ,) ** ?? tt t a 1 0 12 ++ - -8 8 8 +- + +- ? ? - -+ +- ++ 1 2 1 0 1 2 ex p () (( ) t µ µ ?? ? TT nk nk T nk GV QB y VQ B 1 1 2 12 1 2 T nk nk nk pp yy K dd ++ +- -+ () ++ ++ ? ? ? ? ? ? ? ? ? ? ?? ?? ? ?? ?? ?) ? ? t t a -- -8 8 8 ? ? 1 0 ex p () () - +- ++ () ++ () ? ? ++ -+ - +- + t µ µ 2 2 1 1 1 yK VQ By GV QB y nk nk nk T nk nk ?? ? ? ? ? ? ? ? ?? ?? ? ?? ?? - -+ + () () - - +- + - ex p () (t µ 2 1 1 1 ? ? GV QB y GZ V nk nk T +++ () () ? ? ? ? ? ? ? ? ? ? ? ? ?? ?? ? ?? ?? ? ? ? ? ?? ? ? ? ? ?? ? ? ? ? ? ? ?? ? +- + QB y nk nk µ) 1 ?? ? ?? dd ? t ? - +- ++ () +- -+ () + - 8 ++ -+ ? t t µ a nk pp nk nk nk T yK VQ By G 12 1 2 1 0 2 1 2 ex p () -- +- + - ++ () ? ? ? ? ? ? ? ? ? ? ?? ?? ? ?? ?? - -+ + 1 1 1 2 () ex p () VQ By GV Q nk nk µ t µ ? BBy GG VQ By nk nk T nk nk +- + - +- + () () -+ + () () ? ? ? ? ? ? ? ? ? ? ? ? ?? ?? 1 1 1 ? () µ ?? ?? ?? ? ? ? ? ? ? ? ? ? ? ? -8 8 ? dd ? t ? - +- ++ () +- -+ () ++ - ++ -+ - t t µ a nk pp nk nk nk T yK VQ By G 12 1 2 1 2 1 1 2 ex p () (() VQ By d nk nk ++ () ? ? ? ? ? ? ?

? ? ?? ? ? ? ?? ? ? +- + µ t 1 International Journal of Economics and Financial Issues | Vol 8 • Issue 5 • 2018 100 ? - +- ++ () +- -+ () ++ - 8 ++ -+ ? t t µ a nk pp nk nk nk T yK VQ By G 12 1 2 1 0 2 1 ex p () - - +- + ++ () ?? ? ? ? ? ? ? ? ? ?? ? ? ? ? 1 1 2 () VQ By d nk nk µ tt (16) By applying the formula of Gamma distribution from the equation (16) can be obtained: fy S yK VQ By GV QB pn kn nk nk nk T n + + +- + - + () ? +- + + ? ?? ? ?? ++ | () () * 2 1 1 µ µ kkn k nk p p y -+ - +- - ++ + () ? 1 12 21 2 2 a ? +- ++ () ++ () ? ? ? ? ? ? ? ? ++ -+ - +- + Ky VQ By GV QB y nk nk nk T nk nk 2 1 1 1 () () µ µ ?? - +- -+ + () nk p 12 1 2 a ?+ -- () + () ? ? ? ? ? ? ? ? ? ? ? ++ - - +- - +- - 1 1 1 1 1 1 1 1 yB GB BG VQ nk nk T nk nk T () ? TT nk T nk nk nk T nk nk T BG B yB GB BG 1 1 1 1 1 1 1 1 1 1 1 - () -- () +- - +- ++ - - +- - +- - 1 1 0 () () () VQ KV QG VQ T + () ? ? ? ? ? ? ? ? ? ? ? -+ + ? ? ? ? ? ? ? ? ? ? ? ? ?? ? ? ? ? ? ? ? ? ? ? ?? ?? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ?? ?? - +- -+ + ( ) nk _ 1 _1 _ a Fig u re 1: Plot of data Fig u re 2: Ta b l e 1 : Va l u e o f p a r a m e t e r s a n d A I C MODEL EQ EQ EQ AIC ARMA (0,1) - - 0.4058 335.00 ARMA (1,0) 0.3544 - - 340.84 ARMA (1,1) 0.0686 - 0.3528 331.79 ARMA (2,0) 0.4317 -0.2129 - 333.46 ARMA (2,1) 0.5883 -0.2712 -0.1625 334.96 Table 2: Comparison of point forecast between Bayesian with traditional forecasting k Factual data Result of forecasting: EQ Bayesian Traditional 1 0.51 0.443232000 0.42096670 2 -0.09 0.006368232 0.02118361 3 0.19 0.262402900 0.02374863 4 -0.45 0.538752700 -0.02603840 5 0.24 0.175542000 0.01485990 6 0.66 0.369192000 0.20172880 7 0.69 0.455384000 0.20085360 8 -0.02 0.027196330 0.04167132 9 0.22 0.235994600 0.27691080 10 0.14 0.123299330 0.08616260 11 0.47 0.365324000 0.27197930 12 0.42 0.469548070 0.39836110 Fig ure 4: Plot of factual data (red), Bayesian (green) and traditional (blue) Fig ure 3: Plot of PACF International Journal of Economics and Financial Issues | Vol 8 • Issue 5 • 2018 101 ?+ -- ++ - - ? ? ? ? ? ? ? + + +- - +- - +- - () (nk p y B GB BG V nk nk T nk nk T 12 1 1 1 1 1 1 1 a QQ KV QG VQ nk p T µ µµ a) () () ? ?? ? ?? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? -+ + +- -+ () - 2 0 12 1 BBG B nk T nk +- - +- () ? ? ? ? ? ? ? ? ?? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ?? ? ? ? ? ? ? ? ? ? ? ? ? ? ? 1 1 1 ?? - +- -+ + ( ) nk p 1 21 2 a Where GG BG BG RG nk T nk 0 1 1 1 1 1 1 1 1 =+ - () () - +- - +- - -- T h e m a rg i n a l c o n d i t i o n a l p o s t e r i o r p r e d i c t i v e d e n s i t y o f Yn+k is a univariate student's t-distribution on (n + k -(p +2a) degrees of freedom with mode ?? =- () + () +- - +- - +- - 1 1 1 1 1 1 1 BG BB GV Q nk T nk nk T () 3 . 4 .

P o i n t F o re c a s t For quadratic loss function, the point forecast of Yn+k is the posterior mean of the marginal conditional posterior predictive, that is: EY SB GB BG VQ nk nn k T nk nk T ++ - - +- - +- - () =- () + () | () * 1 1 1 1 1 1 1 ? (17) 4. APPLICATION The results of point forecast are applied to a set of time series data that been by ARMA using based on data from 1 to 192. 4.1.

Data, Stationarity, Identification, and Model Selection Data 204 y, monthly in from January 2000 to December 2016 is displayed in Fig ure 1. Plot of ACF in Figure 2 in the form of damped sine wave, indicates that the time series data is stationary. Plot ACF in Figure 2 is disconnected after lag plot PACF Figure 3 is disconnected after second lag, these indicate that the appropriate model for data ARMA(2,1).

The the of and value is presented as Table 1. The smallest AIC value in Table 1 is 331.79 on ARMA(1,1) model, it means the suitable model for the data is ARMA(1,1) model. In Yt, its model is written: Yt = 8530606=0.3335 Yt -1 + et (18) 4.2. Comparison to Traditional Method The comparison of point forecast between Bayesian forecasting in equation equation (17) with traditional forecasting in equation (18) is presented in the Table 2. Columns 2 through 4 containing the factual data, result of Bayesian forecasting, and result of traditional forecasting.

The comparison of forecast accuracy between Bayesian method and traditional method is presented in the Table 3. Rows 2 through 5 containing the RMSE, MAE, MAPE and U-Statistics. The results show that the forecast accuracy value of the Bayesian method is smaller than the traditional method, so in this case it is concluded that the forecast accuracy for the Bayesian forecasting is better than the traditional forecasting.

The comparison of descriptive statistics between the Bayesian method and the traditional method is presented in the Table 4. Columns 2 through mean, third quartile (Q3), maximum (Max), and standard deviation for factual 192 data the of forecasting for the 12 steps ahead, and 192 factual data and the result of traditional forecasting for the 12 steps ahead.

Plot of factual data, Bayesian and traditional forecasting for the 12 steps ahead is displayed in Figure 4, shows that the plot of factual data is more varied to the plot of Bayesian than the traditional forecasting. 5. CONCLUSION of the point forecast for Bayesian forecasting under normal- gamma prior. The conditional posterior predictive density Table 3: Comparison of forecast accuracy Forecast accuracy Bayesian Traditional RMSE 0.12476883 0.2545024 MAE 0.09569079 0.1962556 MAPE 47.6807038 81.4006722 U-statistics 0.16897685 0.4092601 Table 4: Comparison of descriptive statistics Data Min.

Q1 Median Mean Q3 Max SD Factual 1–204 140 1.14 0.5 0.55 0.9 3.3 0.589 Factual 1–192, Bayesian 193–204 140 1.13 0.5 0.55 0.9 3.3 0.590 Factual 1–192 Trad. 193–204 140 1.12 0.4 0.54 0.9 3.3 0.588 is obtained by multiplying the normal-gamma prior with the conditional predictive density.

The marginal conditional posterior predictive density is obtained by integrating the conditional posterior predictive density to paramaters, whereas the point forecast is derived based on the mean of marginal conditional posterior predictive density that has the univariate The computational results show that the forecast accuracy value of Bayesian forecasting is smaller than the traditional forecasting, while the values of descriptive statistics show that the Bayesian forecasting is closer to the factual data than the traditional forecasting, it indicates that the Bayesian forecasting is better than the traditional forecasting. REFERENCES Amry, Z.

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4202204&asf_in=null&asf_rpp=null&asf_iv=null&asf_sp=null&asf_pn=2