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Estimating inflation-at-risk (IaR) using extreme value theory (EVT)*

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The Bangko Sentral ng Pilipinas (BSP) has the primary responsibility of maintaining stable prices conducive to a balanced and sustainable economic growth. The year 2008 posed a challenge to the BSP's monetary policy making as inflation hit an official 17-year high of 12.5 percent in August after ten months of continuous acceleration. The alarming double-digit inflation rate was attributed to rising fuel and food prices, particularly the price of rice. A high inflation rate has impact on poverty since inflation affects the poor more than the rich. From a macroeconomic perspective, a high level of inflation is not conducive to economic growth. This paper proposes a method of estimating inflation-at-risk (IaR) similar to the value-at-risk (VaR) used to estimate risk in the financial markets. The IaR represents the maximum inflation over a target horizon for a given low pre-specified probability. It can serve as an early warning system that the BSP can use to identify whether the level of inflation is extreme enough to be considered an imminent threat to its inflation objective. Extreme value theory (EVT), which deals with the frequency and magnitude of very low-probability events, is used as the

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basis for building a model in estimating the IaR. The estimates of the IaR using the peaks-over-threshold (POT) model suggest that while the inflation rate experienced in 2008 cannot be considered as an extreme value, it was very near the estimated 90 percent IaR.

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1. Introduction

The phenomena of fat tail distributions are commonly observed in data on financial returns. In assessing risks, the analysis focuses on low-probability events with high potential for devastating consequences when they do occur. The same can be said with episodes of high and volatile inflation rates, which are also manifestations of fat tails. The impact of these episodes in shaping the public's inflation expectations makes them time-critical events for the monetary policy decision-making process of an inflation-targeting central bank like the Bangko Sentral ng Pilipinas (BSP). As Woodford [2003] has aptly explained, "successful monetary policy is not so much a matter of effective control of overnight interest rates as it is of shaping expectations of the way in which interest rates, inflation and income are likely to evolve over the coming year and later". Ultimately, the relative strength of monetary policy rests on its efficacy in aggregate demand management and, hence, pricing.

History is replete with deleterious effects of high and volatile inflation. The period of stagflation in the 1970s is one concrete example. High and volatile inflation rates interfere with consumption and investment decisions of economic agents. With the unpredictability of real returns, investments and savings are curtailed, confidence in financial instruments undermined, and economic growth stalled. High and volatile inflation can potentially weaken the transmission channel of monetary policy, thereby making inflation management more difficult especially for an inflation-targeting central bank. They also erode purchasing power, with the strongest impact on the poor.

More important, high and volatile inflation rates make inflation forecasting and, by extension, inflation targeting very difficult. This has serious ramifications on central bank credibility, which largely depends on the congruence of the public's inflation expectations with the central bank target. The forward-looking nature of inflation dynamics would therefore hinge on the credibility of intentions about the future course of monetary policy. Establishing a credible commitment to price stability in the future reduces the cost of doing so in the present [Gali and Gertler 2003].

The paper is structured as follows: part 2 discusses current methods in analysing inflationary pressures; part 3 expounds on the various approaches in estimating value-at-risk (VaR) and, by extension, the proposed inflation-at-risk (IaR); part 4 details the empirical methodology used in the paper; part 5 presents the estimation results; and part 6 concludes.

2. Current practices in analysing inflation dynamics

For an informed and timely assessment of the turning points of inflation, it is best to analyse the growth of the relevant price index in the shortest horizon possible. However, inflation rate, when measured on a short horizon, exhibits leptokurtosis. This implies that there are many observations in the extremities of the tails that have disproportionate influence on the mean [Kearns 1998].

Measurement of inflation matters in setting the target. Unfortunately, measurement of inflation has inherent limitations. One is the *transitory or noise component*, which, theoretically, should not affect a policymaker's actions. Knowledge about the extent of this component is crucial because it affects the width of the target band. The other limitation is *bias* that may emanate from weighting schemes, sampling techniques, and quality adjustments in the estimation of price indices [Cecchetti 1996].

The consumer price index (CPI) is the most common reference price index used for setting the headline inflation target.[1] Its appeal is premised on the transparency of the index, information content, data consistency, computational effort, and cointegration between headline and core inflation rates. However, the general measure of the price index does not distinguish between demand-pull and cost-push inflation. It may also contain seasonal components and embed supply shocks over which monetary policy has no control and should therefore not be accommodated immediately. It is only when the supply shocks eventually induce demand pressures (second-round effects) that monetary policy action is warranted.

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[1] A more complete discussion can be found in Guinigundo [2009].

One gauge by which the central bank analyses second-round effects of supply shocks is the core inflation, which measures the change in average consumer prices excluding certain items in the CPI with volatile price movements. It is interpreted as a measure of underlying long-term inflation. There are different methods used to uncover the underlying trend and transitory movements of the CPI. The more popular measure is the exclusion method, i.e., volatile components of the CPI, like food and energy prices, are removed and the remaining components are re-weighted. The problem with this approach is that it does not capture changing weights. Moreover, even the composition of volatile items changes as well. Thus, there may be components remaining in the trend that still exhibit high volatility but are not properly accounted for.[2] Another common measure is the trimmed mean, which involves removing a certain proportion of the tails of the distribution before the average price change of the weighted center of the distribution is estimated. As the degree of excess kurtosis increases, implying that there are more price changes that are unrepresentative of the core rate, it may be desirable to remove a larger proportion of the tails in calculating the trimmed mean. If the distribution is, on average, positively skewed, observations in the right-hand tail would be higher than the mean inflation. Hence, if the trim is symmetric, then the trimmed mean would systematically be lower than the sample mean. If the distribution is negatively skewed, the trimmed mean would then be systematically higher. There is also the weighted-median CPI or the 100 percent trimmed centered at the midpoint of the distribution. The median addresses the problem of relative price changes. Temporary inflation spikes in certain goods would show up in the mean inflation rate. The median, however, sometimes eliminates the undesirable effects of temporarily high or low prices in certain goods.

The present study attempts to go beyond the measurement of underlying price pressures. We propose a complementary measure of maximum inflation over a target horizon for a given low pre-specified probability or what we call the inflation at risk (IaR). It can serve as an early warning system

[2] In the Philippines, the headline inflation rate is the official rate used in the BSP's inflation targeting framework. The National Statistical Coordination Board (NSCB) defines headline inflation as the rate of change in the consumer price index, which is a measure of the average price of a standard "basket" of goods and services consumed by a typical family. In the Philippines, this CPI is composed of various consumer items as determined by the nationwide Family Income and Expenditure Survey (FIES) conducted every three years by the National Statistics Office (NSO).

that the BSP can use to determine whether the level of inflation is extreme enough to be considered a threat to its inflation objective. The IaR approach can be used to complement the analyses and forecasts generated from the BSP in-house models during periods characterized by high and volatile inflation, which are normally accompanied by economic slowdown. The combination of economic contraction and inflationary pressures imposes extra challenges to monetary policy.

3. Estimating value-at-risk

Inflation rate (year-on-year basis) in the Philippines rose to a 17-year high of 12.5 percent in August 2008 after ten months of continuous acceleration. The double-digit inflation rate was way above the 5.5 percent mean inflation rate for the period 2002-2009. The marked increase in inflation reading was driven by momentum in global commodity prices such as rising fuel and food prices, particularly that of rice, which is largely imported [BSP Inflation Report, Q3 2008].

Unlike many statistical methods that cull the underlying trend of the prices to gauge appropriate monetary policy stance, the present study proposes a complementary method of estimating IaR, which is an extension of the VaR methodology used to estimate risk in the financial markets.[3]

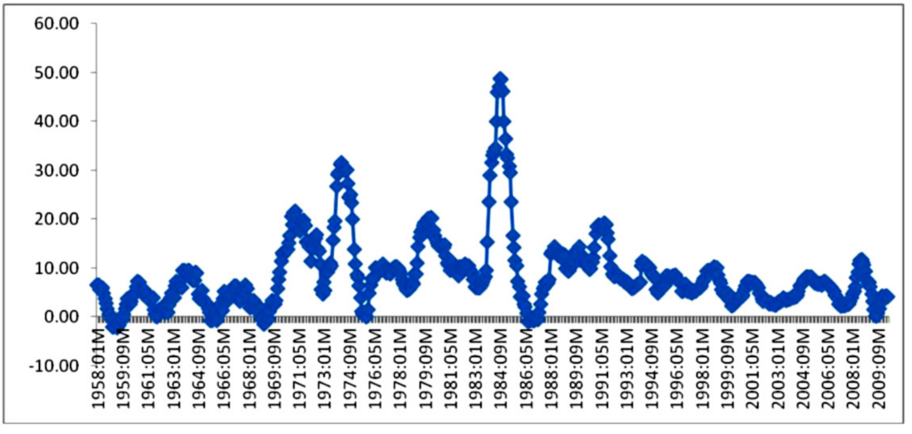

Figure 1. Headline inflation rate in the Philippines (year-on-year) January 1958 to May 2010

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[3] Suaiso and Mapa [2009] and Beronilla and Mapa [2008] provide a good discussion of the applications of VaR in the Philippine financial market setting.

Table 1. Descriptive statistics for the headline inflation rate in the Philippines (year-on-year) January 1958 to May 2010

Statistic	Value
Mean	8.59
Median	6.90
Mode	4.65
Standard deviation	7.61
Sample variance	57.86
Kurtosis	6.59
Skewness	2.16
Range	50.90

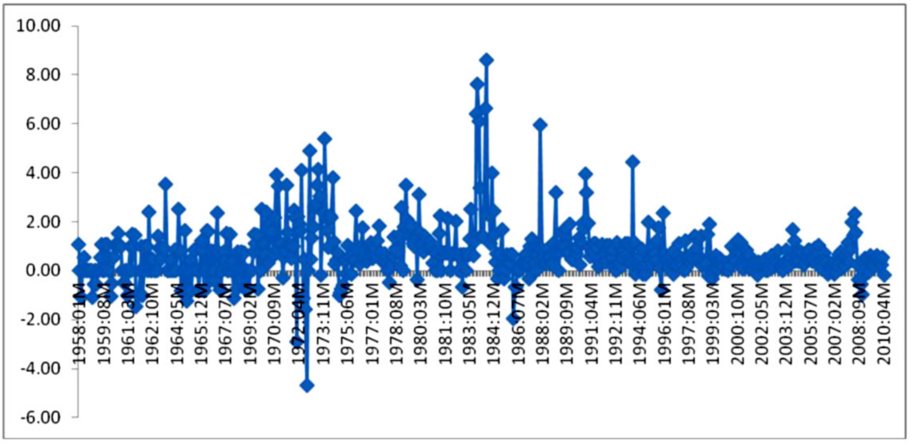

Figure 2. Headline inflation rate in the Philippines (month-on-month), January 1958 to May 2010

Table 2. Descriptive statistics for the headline inflation rate in the Philippines (month-on-month) January 1958 to May 2010

Statistic	Value
Mean	0.71
Median	0.53
Mode	0.00
Standard deviation	1.13
Sample variance	1.27
Kurtosis	10.71
Skewness	2.06
Range	13.27

3.1. Approaches in estimating value-at-risk

There are four common approaches in estimating the VaR of portfolios, or prices (P_t), as propounded in the present study: GARCH modeling, the RiskMetrics approach, the historical simulation approach, and the traditional extreme value theory (EVT) by blocks.

3.1.1. VaR using GARCH models

In this approach, the mean series of the return is modeled using an econometric model (ARMA-GARCH class) as follows:

$$r_t = \mu_t + a_t, \tag{1}$$

$$\mu_t = \varphi_0 + \sum_{i=1}^{p} \varphi_i r_{t-1} - \sum_{i=1}^{q} \theta_i a_{t-1} \tag{2}$$

where $r_t = \ln(P_t) - \ln(P_{t-1})$ and a_t is a white noise process with mean 0 and non-constant variance, σ_t^2.

The VaR of the asset return at time t is computed as

$$VaR_t = \mu_t - Q_p \sigma_t \tag{3}$$

where Q_p is the p^{th} quantile of a given distribution.

3.1.2. VaR using Riskmetrics

This technique is based on the assumption that the return or change series follows an IGARCH(1,1) process:

$$\sigma_t^2 = \alpha \sigma_{t-1}^2 + (1-\alpha) r_{t-1}^2 \tag{4}$$

The VaR is computed as $VaR = Q_p \sigma_t$.

3.1.3. VaR using historical simulations

The estimate of the VaR corresponds to the quantile in the empirical distribution of the previous returns. There is, however, an implicit assumption that shocks are at most as large as historical values of losses/gains.

3.1.4. VaR using extreme value theory

The EVT, which deals with the frequency and magnitude of very low-probability events, is used as the basis for building a model in estimating the IaR. Extreme value theory is a branch of statistics that attempts to make use of information about the extremes of the distributions. It encompasses the asymptotic behavior of extreme observations of a random variable and provides the fundamentals for the statistical modeling of rare events, and is used to compute tail risk measures.

The following discussion is culled mainly from McNeil, Frey, and Embrechts [2005] and Tsay [2005]. Given normalized return series, the asymptotic distribution function of the minimum (analogously after a transformation, the maximum) is

$$F_*(r) = \begin{cases} 1 - \exp[-(1+kr)^{1/k}] & \text{if } k \neq 0 \\ 1 - \exp[-\exp(r)] & \text{if } k = 0 \end{cases} \tag{5}$$

where k is the shape parameter that governs the tail index of the distribution.[4]

The cdf F simplifies to the Gumbel, Frechet, and Weibull families depending on the range of r. The corresponding derived density function is

$$f_*(r) = \begin{cases} (1+kr)^{1/k-1} \exp[-1(1+kr)^{1/k}] & \text{if } k \neq 0 \\ \exp[r - \exp(r)] & \text{if } k = 0 \end{cases} \tag{6}$$

where the range of r changes according to the value of k.

Changing the parameterization to a more general, non-normalized form that includes a location and scale parameter and adopting the notation r to represent the extreme of the distribution yields

$$f(r_{n,}i) = \begin{cases} \frac{1}{\alpha_n}\left(1 + \frac{k_n(r_{n,i} - \beta_n)}{\alpha_n}\right)^{1/(k_n - 1)} \exp\left[-\left(1 + \frac{k_n(r_{n,i} - \beta_n)}{\alpha_n}\right)^{1/k_n}\right] & \text{if } k_n \neq 0 \\ \frac{1}{\alpha_n}\exp\left[\frac{(r_{n,i} - \beta_n)}{\alpha_n} - \exp\frac{(r_{n,i} - \beta_n)}{\alpha_n}\right] & \text{if } k_n = 0 \end{cases} \tag{7}$$

The behavior of extremes in the tails ($r_{n,i}$) could be determined by estimating the three parameters: namely, the scale (the dispersion of extreme

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[4] r is used as a generic representation of series of extreme values.

events, a_n), the location (the average position of extremes in the distribution, b_n), and the shape of the tail (the density of extreme observations, k_n). These parameters are estimated using the maximum likelihood method, which assumes that the extremes are drawn exactly from the limiting distribution known as the generalized Pareto distribution [LeBaron and Samanta 2004].

VaR in EVT is deduced as the quantile, governed by p, of the limiting extreme value distribution F. Given the location, scale, and shape parameters, VaR is computed as follows:

$$VaR = \begin{cases} \beta_\eta - \dfrac{\alpha_\eta}{k_n}\left\{1 - [-\eta \ln(1-\rho)]^{k_\eta}\right\} & \text{if } k_n \neq 0 \\ \beta_\eta - \alpha_\eta \ln[-\eta \ln(1-\rho)] & \text{if } k_n = 0 \end{cases} \tag{8}$$

4. Empirical methodology: peaks-over-threshold approach

The VaR paradigm fits well into the estimation of the inflation-at-risk due to its inherent nature of utilizing large values in the inflation series.

The block maxima method is the conventional EVT approach. It subdivides the sample into several blocks, from which a maximum can be drawn from each block. The distribution of the block maxima is determined by fitting the generalized extreme value distribution (GEV) to the set of block maxima. One caveat in this approach is the choice of block size.

The more flexible approach to VaR-IaR estimation is that of using price changes greater than a chosen high threshold *ç* (for exceedances), known as the peak-over-threshold (POT) approach. The focus of the extreme value density would be the right tail of the distribution. Inflation entries that are higher than the specified threshold are used to model the likelihood of the Pareto distribution.

The time of the peaks (t) and the associated inflation rate (z) are modeled using a two-dimensional Poisson process with intensity measure given by

$$\Lambda\left[(D_2 D_1) \times (r, \propto)\right] = \int_{D_1}^{D_2} \int_{r_1}^{\propto} \lambda(t, z; k, \alpha, \beta) dt dz \tag{9}$$

where $\lambda = g/D$ and

$$g(z; k, \alpha, \beta) = \begin{cases} \dfrac{1}{\alpha}\left[1 - \dfrac{k(z-\beta)}{\alpha}\right]^{1/(k-1)} & \text{if } k \neq 0 \\ \dfrac{1}{\alpha}\exp\left[\dfrac{-(z-\beta)}{\alpha}\right] & \text{if } k = 0 \end{cases} \tag{10}$$

Conditional probabilities over the time interval [0,*D*] give the survival function of the limiting extreme value distribution previously illustrated.The properties of the Poisson process enable the construction of the likelihood function for the periods of exceedances and the associated inflation rate.

$$L(k,\alpha,\beta)=\left(\prod_{i=1}^{N_\eta}\frac{1}{D}g(r_{ti};k,\alpha,\beta)\right)x\exp\left[-\frac{T}{D}S(\eta;k,\alpha,\beta)\right] \quad (11)$$

where $S(r;k,\alpha,\beta)=\left[1-\frac{k(r-\beta)}{\alpha}\right]^{1/k}$.

The parameters k, α, and β can be estimated then by maximizing the log-likelihood function for the Extreme Value distribution.The generation of the maximal loss in EVT is commonly called peaks-over-threshold or the threshold-exceedances methodology, which models the inflation values (r) higher than the threshold (η).

4.1. Alternative parameterization for the peaks-over-threshold approach

Computing the conditional distribution of $r \leq x+\eta$ given $r>\eta$ under the non-normalized Extreme Value distribution yields,

$$F_*(r)=\exp\left[-\left(1-\frac{k(r-\beta)}{\alpha}\right)^{1/k}\right] \quad (12)$$

and $$\Pr(r \leq \langle x+\eta \,|\, r>\eta\rangle \approx 1-\left(1-\frac{kx}{\psi(\eta)}\right)^{1/k} \quad (13)$$

where $\psi(\eta) = \alpha - k(\eta-\beta)$.

The resulting probability is of the class of generalized Pareto distributions (GPD) with the generic cdf of $G(x)=1-\left(1-\frac{kx}{\psi(\eta)}\right)^{1/k}$.

The VaR is then computed as

$$VaR_p=\eta+\frac{\psi(\eta)}{k}\left\{1-\left[\frac{T}{N_\eta}(1-q)\right]^k\right\}. \quad (14)$$

4.2. Stress testing and backtesting of VaR estimates

It is important to determine if the VaR estimates do not fluctuate with a trend, and are not consistent overestimates or underestimates of the true loss incurred. A validation method involves backtesting or checking of the extreme value estimates or VaR. An IaR forecasting model will ideally capture and envelope extreme inflation values every time (thus avoiding a "violation") while maintaining realistic and practical sizes. Three backtesting methods are commonly used: the unconditional coverage, independence, and conditional coverage tests [Kuester, Mittnik, and Paolella 2006]:

1. *Unconditional coverage* (*UC*). The unconditional coverage test is the check for the true value of the failure rate in VaR estimation, i.e., that the percentage of VaR violations or noncoverage is at the theoretical set value, the given low pre-specified probability. The test statistic is chi-square with one degree of freedom.
2. *Independence* (*Ind*). The independence test is a check for the grouping of the VaR violations or misses in the time series of price changes. Independence testing explores the possibility that the misses are clustered around short time intervals. The test statistic is chi-square also with one degree of freedom.
3. *Conditional coverage* (*CC*). The conditional coverage test is the simultaneous check for the independence of the VaR violations and the true failure rate of the VaR estimates. It jointly combines the UC and Ind likelihoods for its test statistic, which is chi-square with two degrees of freedom.

The likelihood ratio tests (LRTs) constructed for examining the VaR estimates assume the existence of a long series of price changes and require a handful number of violations and consecutive VaR violations for validation. To circumvent this dilemma, simulated *p-values* of the backtesting LRTs using Monte Carlo sampling of the violation series and obtaining the percentage of high likelihood values are used to confirm the soundness of the IaR values.

5. Discussion of results

The headline inflation data from January 1958 to May 2010 (compiled for all goods and services) are used to estimate inflation-at-risk.The estimation of the IaR used a rolling window of 250 months.[5] The coverage probabilities considered are 90 percent, 95 percent, and 99 percent. Forecasting of the IaR ranged from November 1978 to May 2010 (379 months).

Whereas the choice of block size is the main problem with the block maxima method, the choice of threshold is the root of attention for the POT approach. Nonetheless, several simulations using different thresholds are conducted. Nineteen thresholds ranging from 1 percent to 10 percent at intervals of 0.5 percent are considered for ç in the Pareto model: 1 percent, 1.5 percent, 2 percent, 2 .5 percent, 3 percent, 3.5 percent, 4 percent, 4.5 percent, 5 percent, 5.5 percent, 6 percent, 6.5 percent, 7 percent, 7.5 percent, 8 percent, 8.5 percent, 9 percent, 9.5 percent, and 10 percent.

The IaR using the POT approach to EVT is obtained using maximum likelihood estimation. The IaR risk figures are then backtested using the likelihood ratio tests previously discussed with the Monte Carlo equivalent p-values also provided for completeness.

5.1. The 90 percent IaR coverage level

As shown in the violation percentage column of Table 3, the variability in the empirical failure rate ranges from 6 percent to 7 percent for the 90 percent coverage level. This corresponds to the percentage of the entire stress testing sample of size 250. The violations correspond to IaR exceedances that range from 25 to 27 for all chosen model thresholds. The IaR thresholds that have the relatively lower violations are the smaller thresholds (1-2 percent) and the largest threshold (10 percent). The mid-level thresholds (specifically 5.5 percent) have the relatively higher empirical failure.

Almost all the threshold-POT models fail to reject the hypothesis that the true coverage probability is 0.9. In general, though, for the values of η, this can be eluded if the significance level is 1 percent. As a good choice, a threshold of 5.5 percent provides IaR estimates that satisfy their theoretical

[5] The choice of 250 for the rolling window is based on the traditional approach in VaR analysis of risk returns.

Table 3. Summary of inflation-at-risk (IaR) model violations at 10% coverage

Threshold	IaR exceedances	Violation percentage
1.0%	25	6.60%
1.5%	25	6.60%
2.0%	25	6.60%
2.5%	26	6.86%
3.0%	26	6.86%
3.5%	26	6.86%
4.0%	26	6.86%
4.5%	26	6.86%
5.0%	26	6.86%
5.5%	27	7.12%
6.0%	26	6.86%
6.5%	26	6.86%
7.0%	26	6.86%
7.5%	26	6.86%
8.0%	26	6.86%
8.5%	26	6.86%
9.0%	27	7.12%
9.5%	27	7.12%
10.0%	25	6.60%

Based on 379 points from November 1978 to May 2010.

failure rate at a 0.05 level of significance (p-values are a little over 0.05 for the asymptotic chi-square and the Monte Carlo counterpart), showing its efficacy for use as a threshold for mildly large values in the Philippine inflation series (Appendix 1).

5.2. The 95 percent IaR coverage level

The empirical failure rates to bound the inflation series are consistently at the 4 percent level for all thresholds from 1 percent to 10 percent (Table 4).[6] Similarly, all sets of IaR estimates for all thresholds pass the test of

[6] A complementary and similar measure, the excess shortfall (ES) risk value, is always larger than its VaR (equivalently, IaR) counterpart. The average value of violation rates of the ES for both 90 percent and 95 percent coverage for inflation risk is from 3 percent to 3.5 percent in the estimation. As anticipated, the average of the ES failure rate is even smaller at 99 percent coverage (1.3 percent). The ES can be used as the conservative expected inflation warning value if the IaR is ever exceeded.

Table 4. Summary of inflation-at-risk (IaR) model violations at 5% coverage

Threshold	IaR exceedances	Violation percentage
1.0%	15	3.96%
1.5%	15	3.96%
2.0%	15	3.96%
2.5%	15	3.96%
3.0%	15	3.96%
3.5%	15	3.96%
4.0%	15	3.96%
4.5%	16	4.22%
5.0%	16	4.22%
5.5%	16	4.22%
6.0%	16	4.22%
6.5%	16	4.22%
7.0%	16	4.22%
7.5%	16	4.22%
8.0%	16	4.22%
8.5%	16	4.22%
9.0%	16	4.22%
9.5%	16	4.22%
10.0%	16	4.22%

Based on 379 points from November 1978 to May 2010.

unconditional coverage, implying that the IaR estimates produced capture extreme inflation risks appropriately 95 percent of the time (Appendix 2).

It is important to note that the accuracy of the asymptotic test can be scrutinized due to differences from their Monte Carlo counterparts (approximately 5 basis points for the given thresholds). None of the POT models pass the independence and conditional coverage tests.This can be attributed to the small number of consecutive IaR violations.

5.3. The 99 percent IaR coverage level

There is a consistent level for noncoverage at this required accuracy level of the IaR (Table 5). Seventeen of the 19 POT models have ten violations, equivalent to 2.64 percent of the forecasting set. Using thresholds of 9 percent and 9.5 percent deviates from this trend, with the empirical failure rates at 1.32 percent and 2.11 percent (or five and eight violations, respectively) Note that choosing a high coverage rate would commonly decrease the number of violations in a natural manner. There is a bigger disparity in the simulated and asymptotic p-values for the backtesting

Table 5. Summary of inflation-at-risk (IaR) model violations at 1% coverage

Threshold	IaR exceedances	Violation percentage
1.0%	10	2.64%
1.5%	10	2.64%
2.0%	10	2.64%
2.5%	10	2.64%
3.0%	10	2.64%
3.5%	10	2.64%
4.0%	10	2.64%
4.5%	10	2.64%
5.0%	10	2.64%
5.5%	10	2.64%
6.0%	10	2.64%
6.5%	10	2.64%
7.0%	10	2.64%
7.5%	10	2.64%
8.0%	10	2.64%
8.5%	10	2.64%
9.0%	5	1.32%
9.5%	8	2.11%
10.0%	10	2.64%

Based on 379 points from November 1978 to May 2010.

procedure compared to the lower coverage rates showing risks involved in the assessment of the IaR at high levels of accuracy, even with this relatively available sample size (Appendix 3).

Only a threshold limit of 9 percent provides a relatively large and somewhat acceptable p-value for the test of the true coverage rate. Note that again due to the limited count of violations and limited consecutive noncoverage, assessing the independence (and CC as well) of IaR exceedances becomes arduous.

5.4. Assessing the inflationary situation in 2008 using the IaR estimates

Continuous price increases for an extended six-month period in 2008 led to a double-digit inflation rate in June 2008 (11.39 percent), which peaked in August 2008 (12.41 percent).[7] This was the highest increase in prices in 200 months (17-year maximum) since December 1991.

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[7] A double-digit inflation was last recorded in January 1999.

The August 2008 inflation rate belongs to the upper 20 percent of the highest recorded inflation rates in the country. It is very close to the IaR values at the 90 percent coverage level. This is a very rare situation in which the actual price hike approaches the estimated IaR. Due to its nature, values-at-risk are constructed to be larger than the actual rates used for any period.

Specifically, at a threshold of 2.5 percent, the IaR value for August 2008 is at 15.38 percent, the largest among the Pareto estimates. The biggest signal that the August 2008 inflation rate is an extreme event is an IaR value of 13.29 percent at a threshold of 6.5 percent.

6. Conclusion

The IaR model was able to capture the most prominent episode of high inflation during the inflation-targeting period, i.e., the August 2008 inflation rate. This finding is supported by the more stringent expected shortfall method and unconditional back test results. While the IaR model cannot determine the appropriate magnitude of policy rate adjustment, the results, nonetheless, lend credence to the policy move by the BSP for the period June-August 2008, in which it raised policy rates by a cumulative 100 basis points.

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Appendix 1. Backtesting P-values of model IaR estimates at 10% coverage

Threshold	U.C.*		Ind.*		C.C.*	
1.0%	0.0193	0.0195	0.0000	0.0000	0.0000	0.0000
1.5%	0.0193	0.0160	0.0000	0.0000	0.0000	0.0000
2.0%	0.0193	0.0163	0.0000	0.0000	0.0000	0.0000
2.5%	0.0317	0.0248	0.0000	0.0000	0.0000	0.0000
3.0%	0.0317	0.0285	0.0000	0.0000	0.0000	0.0000
3.5%	0.0317	0.0228	0.0000	0.0000	0.0000	0.0000
4.0%	0.0317	0.0231	0.0000	0.0000	0.0000	0.0000
4.5%	0.0317	0.0257	0.0000	0.0000	0.0000	0.0000
5.0%	0.0317	0.0256	0.0000	0.0000	0.0000	0.0000
5.5%	0.0503	0.0536	0.0000	0.0000	0.0000	0.0000
6.0%	0.0317	0.0253	0.0000	0.0000	0.0000	0.0000
6.5%	0.0317	0.0269	0.0000	0.0000	0.0000	0.0000
7.0%	0.0317	0.0269	0.0000	0.0000	0.0000	0.0000
7.5%	0.0317	0.0240	0.0000	0.0000	0.0000	0.0000
8.0%	0.0317	0.0264	0.0000	0.0000	0.0000	0.0000
8.5%	0.0317	0.0259	0.0000	0.0000	0.0000	0.0000
9.0%	0.0503	0.0476	0.0000	0.0000	0.0000	0.0000
9.5%	0.0503	0.0481	0.0000	0.0000	0.0000	0.0000
10.0%	0.0193	0.0160	0.0000	0.0000	0.0000	0.0000

*Figures in right panel are Monte Carlo equivalents.

Appendix 2. Backtesting P-values of model IaR estimates at 5% coverage

Threshold	U.C.*		Ind.*		C.C.*	
1.0%	0.3347	0.2873	0.0000	0.0000	0.0000	0.0000
1.5%	0.3347	0.2939	0.0000	0.0000	0.0000	0.0000
2.0%	0.3347	0.2856	0.0000	0.0000	0.0000	0.0000
2.5%	0.3347	0.2963	0.0000	0.0000	0.0000	0.0000
3.0%	0.3347	0.2889	0.0000	0.0000	0.0000	0.0000
3.5%	0.3347	0.2960	0.0000	0.0000	0.0000	0.0000
4.0%	0.3347	0.2898	0.0000	0.0000	0.0000	0.0000
4.5%	0.4755	0.4172	0.0000	0.0000	0.0000	0.0000
5.0%	0.4755	0.4057	0.0000	0.0000	0.0000	0.0000
5.5%	0.4755	0.4143	0.0000	0.0000	0.0000	0.0000
6.0%	0.4755	0.4147	0.0000	0.0000	0.0000	0.0000
6.5%	0.4755	0.4186	0.0000	0.0000	0.0000	0.0000
7.0%	0.4755	0.4164	0.0000	0.0000	0.0000	0.0000
7.5%	0.4755	0.4031	0.0000	0.0000	0.0000	0.0000
8.0%	0.4755	0.4155	0.0000	0.0000	0.0000	0.0000
8.5%	0.4755	0.4116	0.0000	0.0000	0.0000	0.0000
9.0%	0.4755	0.4136	0.0000	0.0000	0.0000	0.0000
9.5%	0.4755	0.4202	0.0000	0.0000	0.0000	0.0000
10.0%	0.4755	0.4045	0.0000	0.0000	0.0000	0.0000

*Figures in right panel are Monte Carlo equivalents.

Appendix 3. Backtesting P-values of model IaR estimates at 1% coverage

Threshold	U.C.*		Ind.*		C.C.*	
1.0%	0.0078	0.0222	0.0000	0.0000	0.0000	0.0000
1.5%	0.0078	0.0240	0.0000	0.0000	0.0000	0.0000
2.0%	0.0078	0.0231	0.0000	0.0000	0.0000	0.0000
2.5%	0.0078	0.0264	0.0000	0.0000	0.0000	0.0000
3.0%	0.0078	0.0262	0.0000	0.0000	0.0000	0.0000
3.5%	0.0078	0.0251	0.0000	0.0000	0.0000	0.0000
4.0%	0.0078	0.0241	0.0000	0.0000	0.0000	0.0000
4.5%	0.0078	0.0253	0.0000	0.0000	0.0000	0.0000
5.0%	0.0078	0.0249	0.0000	0.0000	0.0000	0.0000
5.5%	0.0078	0.0244	0.0000	0.0000	0.0000	0.0000
6.0%	0.0078	0.0228	0.0000	0.0000	0.0000	0.0000
6.5%	0.0078	0.0252	0.0000	0.0000	0.0000	0.0000
7.0%	0.0078	0.0220	0.0000	0.0000	0.0000	0.0000
7.5%	0.0078	0.0261	0.0000	0.0000	0.0000	0.0000
8.0%	0.0078	0.0234	0.0000	0.0000	0.0000	0.0000
8.5%	0.0078	0.0260	0.0000	0.0000	0.0000	0.0000
9.0%	0.5515	0.4457	0.0000	0.0000	0.0000	0.0000
9.5%	0.0585	0.0358	0.0000	0.0000	0.0000	0.0000
10.0%	0.0078	0.0240	0.0000	0.0000	0.0000	0.0000

*Figures in right panel are Monte Carlo equivalents.