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Extreme Value Theory (EVT)

by

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Estimating Inflation-at-Risk (IaR) using Extreme Value Theory (EVT)[1]

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ABSTRACT

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 10 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, high level of inflation is not conducive toeconomic 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 market. 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 can be used by the BSP to identify whether the level of inflation is extreme enough to be considered an imminent threat to its inflation objective. The extreme value theory (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. The estimates of the IaR using the peaks-over-threshold (POT) model suggest that the while the inflation rate experienced in 2008 can not be considered as an extreme value, it was very near the estimated 90 percent IaR.

Keywords: Inflation-at-Risk (IaR), Extreme Value Theory (EVT), Peaks-over-Threshold (POT)

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Estimating Inflation-at-Risk (IaR) using Extreme Value Theory (EVT)[2]

by Edward P. Santos,[3] Dennis S. Mapa,[4] and Eloisa T. Glindro[5]

1. Introduction

The phenomenon of fat tail distribution is commonly observed in financial returns data. In assessing risks, the focus of analysis is on low probability events with high potential for devastating consequences when they occur. The same can be said with episodes of high and volatile inflation rate, which are manifestations of fat tails as well. 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, investment 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 the purchasing power, with most impact on the poor.

More importantly, 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 analyzing 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

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empirical methodology used in the paper. Part 5 presents the estimation results and Part 6 concludes.

2 Current practices in analyzing inflation dynamics

For an informed and timely assessment onthe turning points of inflation, it is best to analyze 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 policy maker's action. 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 (Cechetti, 1996; Moreno, 2009).

The consumer price index (CPI) is the most common reference price index used for setting the headline inflation target.[6] Its appeal is premised on the transparency of the index, information content, data consistency, computational effort, and cointegration between headline and core inflation rates (Moreno, 2010). 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 that monetary policy has no control over 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.

One gauge by which the central bank analyzes 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 change as well. Thus, there may be components remaining in the trend that still exhibit high volatility but are not properly accounted for. [7]

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[6] More complete discussion can be found in the work of Diwa G. Guinigundo (2009) entitled 'Measurement of Inflation and its Implications on the Philippine Monetary Policy Framework' (BIS Papers No. 49).

[7] In the Philippines, the headline inflation rate is the official rate used in the Bangko Sentral ng Pilipinas' inflation targeting framework. The National Statistical Coordination Board (NSCB) defines headline inflation as the rate of change in the consumer price index (CPI), 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

Another common measure is the trimmed mean. This measure involves removing a certain proportion of the tails of the distribution thenthe 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 the 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 will systematically be lower that 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, eliminate the undesirable effects of temporarily high or low prices in certain goods and is therefore, believed to represent a better measure of the core inflation.

This paper 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 that can be used by the BSP to identify ifthe level of inflation is extreme enough to be considered a threat to its inflation objective. The IaR approach can be used to complement the analysis 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 challenge to monetary policy.

3 Estimating Value-at-Risk (IaR)

Inflation rate (year-on-year basis) in the Philippines rose to a17-year high of 12.5% in August 2008 after 10 months of continuous acceleration. The double-digit inflation rate was way above the 5.5% 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 (Inflation Report, Q3 2008).

various consumer items as determined by the nationwide Family Income and Expenditure Survey (FIES) conducted every three years by the National Statistics Office (NSO).

Figure 1. Year-on-Year Inflation Rate

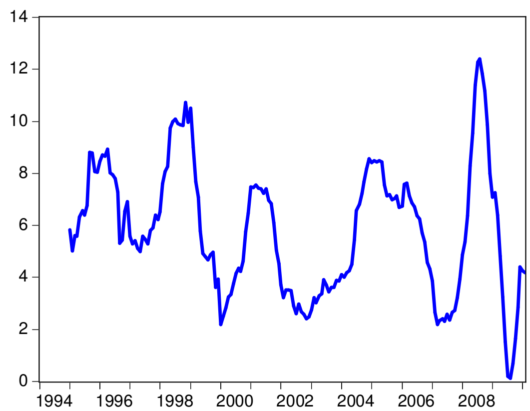
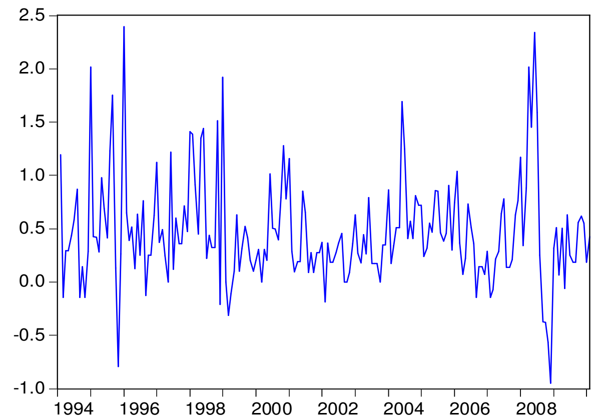
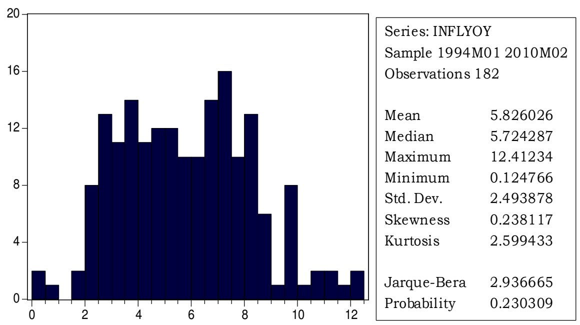
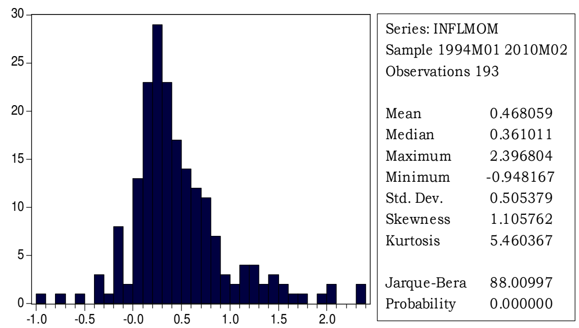


Figure 2. Month on Month Inflation Rate







Unlike many statistical methods that cull the underlying trend of the prices to gauge appropriate monetary policy stance, this paper proposes a complementary method of estimating Inflation-at-Risk (IaR), which is an extension of the Value-at-Risk (VaR) methodology used to estimate risk in the financial market.

3.1 Approaches in Estimating Value-at-Risk (VaR)

There are four known approaches in estimatingVaR of portfolios (or prices, as propounded in this paper): These are GARCH modeling, Riskmetrics approach, historical simulation approach, and the traditional Extreme Value Theory (EVT) by blocks.

3.1.1 VaR using GARCH models: The mean series of the return is modeled using an econometric model.

$$r_t = \mu_t + a_t,$$

$$\mu_t = \phi_0 + \sum_{i=1}^{p} \phi_i r_{t-1} - \sum_{i=1}^{q} \theta_i a_{t-1}$$

The VaR of the asset return is computed as: $VaR = \mu_t + Q_p \sigma_t$,

3.1.2 VaR using Riskmetrics: The assumption is that the return or change series follows an IGARCH(1,1) process

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

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 (EVT)

The extreme value theory (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 Inflation-at-Risk (IaR). The EVT 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, AJ, Frey R, Embrechts P (2005). Given normalized return series, the asymptotic distribution function of the minimum (analogously after a transformation, the maximum) is

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

where k is the shape parameter that governs the tail index of the distribution ,[8]

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

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

[8] *r* is used as a generic representation of series of extreme values

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

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

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 events, α_n), location (the average position of extremes in the distribution, β_n) and the shape of the tail (the density of extreme observations, κ_n). These parameters are estimated using the maximum likelihood method, which assumes that the extremes are drawn exactly from the limit 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:

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

4 Empirical Methodology: Peaks-Over-Threshold Approach

The VaR paradigm fits well into the estimation of the inflation-at-risk (IaR) 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 (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 by using price changes greater than a chosen high threshold η(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:

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

$$\textit{where}\lambda\textit{=g/D; and}\quad g(z;k,\alpha,\beta)=\begin{cases}\dfrac{1}{\alpha}\left[1-\dfrac{k(z-\beta)}{\alpha}\right]^{1/(k-1)} & if\,k\neq 0\\[2ex] \dfrac{1}{\alpha}\exp\left[\dfrac{-(z-\beta)}{\alpha}\right] & if\,k=0\end{cases}$$

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.

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

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

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 (POT) or the threshold-exceedances methodology, which models the inflation values *(r)* higher than the threshold *(η).*

4.1.1 Alternative parameterization for the peaks-over-threshold (POT) approach:

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

$$F_*(r)=\exp\left[-\left(1-\frac{k(r-\beta)}{\alpha}\right)^{1/k}\right] \quad \text{and} \quad \Pr(r\leq\langle x+\eta\,|\,r>\eta\rangle\approx 1-\left(1-\frac{kx}{\psi(\eta)}\right)^{1/k}$$

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

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

The VaR is then computed as: $VaR_p = \eta + \frac{\psi(\eta)}{k}\left\{1 - \left[\frac{T}{N_\eta}(1-q)\right]^k\right\}$.

4.1.2 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 over-estimates or under-estimates of the true loss incurred. A validation method involves backtesting of the extreme value estimates or VaR. There are three backtesting methods commonly used, namely, the unconditional coverage, independence, and conditional coverage (Kuester, et al, 2006)

- **Unconditional Coverage (UC)** is the test-check for the true value of the failure rate in VaR estimation, i.e., that the percentage of VaR violations or non-coverage are at their theoretical set value. The test statistic is (chi-square, 1df).

- **Independence (Ind)** is the test-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 a short time interval. The test statistic is (chi-square, 1df).

- **Conditional Coverage (CC)** is the simultaneous test-check for the independence of the VaR misses and the true failure rate of the VaR estimates. It jointly combines the UC and Ind likelihoods for its test statistic (chi-square, 2df).

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, consecutive VaR misses, among others, for validation. One can construct the simulated *p-values* of these LRT's using Monte Carlo replicates of the violation series and obtaining the percentage of high likelihood values.

5 Discussion of Results

Actual headline inflation data from January 1957 to May 2010 (compiled for all goods and services) is used to estimate inflation-at-risk (IaR). The estimation of the IaR used a rolling window of 250 months.[9] The coverage probabilities considered are 90%, 95%, and 99%. Forecasting of the IaR ranged from November 1978 to May 2010 (379 months).

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[9] The choice of 250 rolling windows is based on the standard approach in VaR analysis of risk returns.

Whereas the choice ofblock size is the main problem with block maxima method, it is the choice of threshold for the POT approach. Nonetheless, several simulations using different thresholds may be conducted. Nineteen thresholds ranging from 1% to 10% with 0.5% interval are considered for ηin the Pareto model: 1%, 1.5%, 2%, 2 .5%, 3%, 3.5%, 4%, 4.5%, 5%, 5.5%, 6%, 6.5%, 7%, 7.5%, 8%, 8.5%, 9%, 9.5%, and 10%.

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

5.1 Ninety percent (90%) IaR Coverage Level

As shown in the violation percentage column of Table 1, the variability in the empirical failure rate range from 6% to 7% for 90% coverage level. This corresponds to the percentage of the entire stress testing sample of 250. The violations correspond to IaRexceedances 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% to 2%) and the largest threshold (10%). The mid-level thresholds (specifically 5.5%) has the relatively higher empirical failure or violations.

Almost all of the POT models with the thresholds fail to reject the hypothesis that the true coverage probability is 0.9. This, however, can be augmented if the significance level is at 1%.

A threshold of 5.5% provides IaR estimates that satisfy their theoretical failure rate at a 0.05 level of significance (p-value is approximately 0.05 for the asymptotic chi-square and the Monte Carlo counterpart), showing added validity for the use of this threshold in the Philippine inflation series (Appendix 1).

Table 1. Summary of Inflation-at-Risk (IaR) Model Violations at 10% Coverage

Threshold	IaRExceedances	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.

5.2 Ninety five percent (95%) IaR Coverage Level

The empirical failure rates to bound the inflation series are consistently at the 4% level for all thresholds from 1% to 10% (Table 2).[10] In like manner also, all sets of IaR estimates for all thresholds pass the test of unconditional coverage, implying that the IaR estimates produced capture inflation risks appropriately 95% of the time (Appendix 2).

It is important to note that the accuracy of the asymptotic test can be placed under scrutiny 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.

[10]The corresponding excess shortfall (ES) risk values are always larger than their original IaR counterparts. The average values of miss rates of the ES for both 90% and 95% coverage for inflation risk is from 3% to 3.5%. As anticipated, the average of the ES failure rate is even smaller at 90% coverage (1.3%). The ES can be used as the conservative expected inflation warning value if the IaR is ever exceeded.

Table 2. Summary of Inflation-at-Risk (IaR) Model Violations at 5% Coverage

Threshold	IaRExceedances	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.

5.3 Ninety nine percent (99%) IaR Coverage Level

There is a consistent level for non-coverage at this required accuracy level of the IaR (Table 3). 17 of the 19 POT models have 10 violations, equivalent to 2.64% of the forecasting set. Using thresholds of 9% and 9.5% deviates from this trend, with the empirical failure rates at 1.32% and 2.11% respectively (5 and 8 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 procedure compared to the lower coverage rates showing risks involved in the assessment of the IaR at high levels of accuracy (Appendix 3).

Only a threshold limit of 9% provides a relatively large p-value for the test for true coverage rate. Note that again due to the limited number or specific violations, assessing the independence of IaRexceedances would be difficult.

Table 3. Summary of Inflation-at-Risk (IaR) Model Violations at 1% Coverage

Threshold	IaRExceedances	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

5.4 Assessing the inflationary situation in 2008 using the IaR estimates

Continuous price increases for an extended six-month period in 2008led to a double-digitinflation rate in June 2008 (11.39%) which peaked in August 2008 (12.41%).[11] This is the highest increase in prices in 200 months (17 year maximum) since December 1991.

The August 2008 inflation rate belongs to the upper 20% of the highest recorded inflation rates in the country. It is very close to the IaR values at the 90% coverage level. It is a very rare situation in which the actual price changes 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 the threshold of 2.5%, the IaR value for August 2008 is at 15.38%, 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% at a threshold of 6.5%.

6. Conclusion

The IaR model was able to capture the most prominent episode of high inflation during the inflation targeting period, i.e., August 2008 inflation rate. Thisfinding 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 the Bank raised policy rates by a cumulative 100 basis points.

[11]The last time a double-digit inflation was recorded was in January 1999.

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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