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FORECASTING EXTREME ECONOMIC MISERY INDICES

by

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ABSTRACT

A methodology for forecasting extreme economic misery is proposed. The economic misery index is defined as the sum of the inflation rate, unemployment rate, and underemployment rate. The methodology involves the following steps. First, a univariate autoregressive integrated moving average (ARIMA) model is fit for each of the components of the economic misery and the index itself. Second, we estimate the appropriate adjustments to the forecasts of the components and the whole through an optimal forecast reconciliation methodology. Third, we produce bootstrap samples of the forecasts by residual-based bootstrapping based on the ARIMA model of the first step and repeating the second step. Fourth, we estimate the extreme level of economic misery, called the Misery-at-Risk (MaR) based on the bootstrap distribution of the forecasts. We demonstrate the methodology on the Philippine context and unlock new insights in economic historical analysis. The methodology opens up research in early-warning systems for economic statistics beyond GDP and inflation alone.

1. Introduction

Economic misery is described by the combination of misery due to the inflation of prices and the misery of joblessness as measured by the unemployment rate. The idea of the link between the problems of inflation and unemployment is discussed in Okun (1971), in which the experience of the people within an economy is impacted by the problem in these two aspects and is not totally covered by macroeconomic measures, such as gross domestic product. Inflation monitoring is a key aspect in macroeconomic policy-making of the Bangko Sentral ng Pilipinas [BSP], through inflation targeting (BSP Department of Economic Research 2019). Misery of joblessness has been augmented in recent years with underemployment, thus the combined measure is called the job misery index, in which econometric analyses has been jointly conducted with respect to its ability to explain the behavior of net satisfaction ratings of presidents in the Philippines (Mapa, et al. 2013), inflation rate, self-rated poverty, and self-rated hunger to create a Philippine misery index (Beja 2014); or with rice price and self-rated hunger (Mapa, Castillo, & Francisco 2015).

The idea of monitoring economic misery in the Philippine context is broken to individual components. The executive branch of the national government conducts labor policies to facilitate the improvement of employment while the central bank devises and executes monetary policies which influences consumer price movements, among others. Limited coordination between government institutions involved is evident, especially when the national government is involved with taxation which ultimately affects price movements. An example of the situation was the implementation of the Tax Reform for Acceleration and Inclusion Law (RA 10963), which produced a short-run increase in inflation (BSP Department of Economic Research 2019) which went beyond inflation targets. A gap in insights for scenarios of extreme economic misery also exists, especially that effects of extreme economic scenarios tend to have impacts that can persists long after the occurrence of the extreme event.

In lieu, the research proposes a methodology of monitoring and forecasting the extreme values of the misery index and its components using financial risk management statistics. The proposed methodologies are based on the Value-at-Risk [VaR] approach but are estimated using parametric and semiparametric statistics.

The research aims to augment macroeconomic policy-making by providing relevant early-warning systems for economic monitoring and economic targeting. This also facilitates economic historical analysis with respect to indicating periods of extreme economic misery in terms of labor underutilization and inflation.

With these aims, the objectives of the research are: (1) to propose a methodology of estimating extreme levels of economic misery through the VaR approach, the extreme level being called Misery-at-Risk [MaR]; and (2) to evaluate the utility of the methodology through hold-out analysis, in which more recent data are held out from estimation as checks on the approach and analyze recent economic events.

The paper is summarized accordingly; the first section details in the introduction and some initial background, with highlights on the aims and the specific objectives of the research. The review section discusses the misery indices and the alternative index used in the paper. It also covers the background information on the concept of VaR from financial risk management. The statistical techniques of the Box-Jenkins methodology, the bootstrapping approach, and the optimal forecast reconciliation approaches are also discussed. The methodology section discusses the definition of the MaR and its application to real data from the Philippines. The fourth section of the paper outlines the discussion of results, with insights from the descriptive analysis of the index time series data, on the forecast accuracy of the procedure with respect to expected misery, and the MaR overall and on individual components. Conclusions and some summary remarks are in the fifth section. References follow next.

2. Review of Literature

a. Misery Indices

The first idea of the misery index was in Okun (1971), in which worsening inflation and high unemployment indicates poor state of welfare for people in an economy. The misery index M, using the year-on-year inflation rate π, as measured by the year-on-year growth rate of the consumer price index, and the unemployment rate u_1, was defined as:

$$M = \pi + u_1.$$

However, the labor situation and job quality of an economy cannot just be fully described by unemployment rate alone. Thus, a common measure is the sum of unemployment rate u_1 and the underemployment rate u_2 which is defined as the job misery index m_j (Mapa, et al. 2013; Beja 2014; Mapa, Castillo, & Francisco 2015):

$$m_{job} = u_1 + u_2.$$

Note that the underemployment rate defined by the Philippine Statistics Authority, then the National Statistical Coordination Board (2007) as the ratio of underemployed individuals $u_{2,unadj}$ over employed individuals, which is different from the base of the unemployment rate, which is the labor force participation population. To rebase the underemployment rate to the labor force participation population and when the unemployment rate is already in percentage units, the adjustment is (Beja 2014):

$$u_2 = u_{2,unadj}\left(1 - \frac{u_1}{100}\right).$$

By this idea, the modified misery index M_p is defined as the sum of inflation and job misery:

$$M_{prop} = \pi + m_{job} = \pi + u_1 + u_2.$$

This is the index that the paper will be using for generation of the forecasted extreme economic misery index. To estimate extreme misery, the paper borrows from the field of financial risk management the concept of VaR.

b. Value-at-Risk

In the field of quantitative risk management, the activities of buying and selling financial instruments carries risks in the viability and value of these instruments. Fluctuations in the holding of financial instruments are called returns. If $\{P_t\}_{t=1}^{T}$ is the price of a non-dividend paying financial instrument, the returns is defined as:

$$r_t = \frac{P_t - P_{t-1}}{P_{t-1}}.$$

The risk of extreme downward fluctuations in the value of and the returns of holding a financial instrument is called market risk. Value-at-risk VaR_α is a measure of market risk defined as the loss that can occur given a coverage probability α that the loss will not be exceeded (Jorion 2007). In statistical terms, it is the $(1-\alpha)$ quantile of the return distribution; that is:

$$P(r_t < VaR_\alpha) = 1 - \alpha.$$

If a distribution function F_{r_t} of the returns is well-defined, the VaR is the inverse function at $1-\alpha$:

$$VaR_\alpha = F_{r_t}^{-1}(1-\alpha).$$

The concept of value-at-risk is utilized in the paper to measure and forecast extreme economic misery. However, this requires full description of the forecast distribution of economic misery, which is facilitated by modeling through the Box-Jenkins methodology and the bootstrapping algorithm.

c. Box-Jenkins Methodology

As the economic misery indices are time series data, the paper uses the Box-Jenkins methodology, also known as autoregressive integrated moving average [ARIMA] models (Box, Jenkins, & Reinsel 2008). The model fit to the indices is the seasonal ARIMA model, which is capable to express the seasonal and nonseasonal properties of the time series data. For time series $\{y_t\}_{t=1}^{T}$ with s seasons in a year, the family of models is denoted as $y_t \sim SARIMA(p,d,q) \times (P,D,Q)_s$ described below:

$$\Phi_{\mathrm{P}}(B^s)\phi_p(B)(1-B^s)^D(1-B)^d y_t = \delta + \Theta_{\mathrm{Q}}(B^s)\theta_q(B)\epsilon_t, \qquad \epsilon_t \sim WN(0,\sigma^2).$$

In the model equation, the individual components are as follows. First, the term B is known as the backshift operator. It expresses a time series variable to its lagged form. As an example, for some positive integer i:

$$B^i y_t = y_{t-i}.$$

The backshift operator simplifies the notation of different parts in the ARIMA model, in which Φ_P, ϕ_p, Θ_{Q}, and θ_q are polynomial functions of the backshift called lag polynomials.

An intercept in the ARIMA model is denoted by δ. This parameter may be set to zero in some instances when it is not significant based on statistical testing. When a model has $d + D = 1$, it is often called the drift parameter.

The term ϵ_t is a random process with zero mean and constant variance and covariance between the variables in the process is zero, which is also known as a white-noise process. This process is important because it means that the ARIMA model should explain much of the behavior of the time series y_t in such that nothing should remain. The white noise process is often modeled as a Gaussian or normal distribution for the purpose of specifying a likelihood function for estimating ARIMA parameters. The density function f_Z of the normal distribution is:

$$f_Z(z;\ \mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left\{-\frac{1}{2\sigma^2}(z-\mu)^2\right\}, \qquad z \in \mathbb{R}.$$

Simple differencing of order d is described by $(1-B)^d$, which is also called integrated model of order d, or $I(d)$. Seasonal differencing of order D for s seasons in time series is described by $(1-B^s)^D$, or a seasonally integrated model of order D and season s and is denoted as $SI(D)_s$. Differencing aims to transform the time series data y_t to a mean-reverting or stationary process, in which the transformed time series would consistently and quickly fluctuate around a mean value.
The polynomial $\phi_p(B)$ is the autoregressive [AR] model of order p, or $AR(p)$, which implies that there would be p polynomial terms of B, each having a parameter describing autoregression order:

$$\phi_p(B) = 1 - \sum_{i=1}^{p} \phi_i B^i$$

On its own in modeling, it produces:

$$\phi_p(B) y_t = \epsilon_t \ \Rightarrow \left(1 - \sum_{i=1}^{p} \phi_i B^i\right) y_t = \epsilon_t \ \Rightarrow \ y_t - \sum_{i=1}^{p} \phi_i y_{t-i} = \epsilon_t \Rightarrow y_t = \sum_{i=1}^{p} \phi_i y_{t-i} + \epsilon_t.$$

This implies that y_t is regressed with its past values, thus an autoregressive model.

Seasonal AR models of order P with s seasons have the notation $SAR(P)_s$ and are summarized in the $\Phi_P(B^s)$ polynomial:

$$\Phi_P(B^s) = 1 - \sum_{i=1}^{P} \Phi_i B^{s\times i}.$$

The polynomial describes the case when y_t is regressed with past values of the same season:

$$y_t = \sum_{i=1}^{P} \Phi_i y_{t-s\times i} + \epsilon_t.$$

Nonseasonal moving average models are denoted by $MA(q)$ and are expressed through the $\theta_q(B)$ polynomial which is expanded below:

$$\theta_q(B) = 1 + \sum_{i=1}^{q} \theta_i B^i.$$

The model equation that the $MA(q)$ specification implies is:

$$y_t = \sum_{i=1}^{q} \theta_i \epsilon_{t-i} + \epsilon_t.$$

Lagged model errors are used as terms in modeling and forecasting the direction of y_t, which can be thought as adjusting forecasts by some scaled of past errors.

Seasonal moving average models are denoted by $SMA(Q)_s$ with order Q and s seasons. The polynomial is expressed as:

$$\Theta_Q(B^s) = 1 + \sum_{i=1}^{q} \Theta_i B^{s\times i}.$$

When modeling with the SMA, the equation will be:

$$y_t = \sum_{i=1}^{Q} \Theta_i \epsilon_{t-s\times i} + \epsilon_t.$$

To fit a SARIMA model, maximum likelihood estimation is used. The likelihood is specified in terms of $z_t = (1-B^s)^D(1-B)^d y_t$, the appropriately differenced and stationary time series, and μ_{ARMA} is the specification of the ARMA components into equation form with z_t left behind on the left side of the equal sign. The expression of the likelihood is given below:

$$L\big(\delta, \phi_1, \dots, \phi_p, \theta_1, \dots, \theta_q, \Phi_1, \dots, \Phi_P, \Theta_1, \dots \Theta_Q \big| z_1, \dots, z_T\big) = \prod_{i=1}^{T} f_Z(z_t; \mu = \mu_{ARMA}, \sigma^2).$$

To facilitate modeling with the SARIMA family of specifications, a search algorithm was devised by Hyndman and Khandakar (2008) and is encoded in the auto.arima() function of the forecast package in R. The automatic ARIMA feature in the package minimizes the Akaike information criterion [AIC] (Akaike 1974), adapted to the SARIMA specification:

$$AIC = \begin{cases} -2\log(L_{\max}) + 2(p+q+P+Q+1) & if\ \delta \neq 0 \\ -2\log(L_{\max}) + 2(p+q+P+Q) & if\ \delta = 0 \end{cases}.$$

The $L_{\max}$ is the maximized value of the likelihood after estimating the unknown parameters.

With respect to the differencing for the auto.arima() function, seasonal differencing is determined first by whether $D = 0$ or $D = 1$ by the Canova-Hansen test (Canova & Hansen 1995). Then, nonseasonal differencing order d is determined by repeated use of the KPSS test (Kwiatkowski, et al. 1992) until the first instance of stationarity. If $d + D \leq 1$, then $\delta \neq 0$, while for all other cases, $\delta = 0$. Afterwards, the proper SARMA orders are automatically selected by which minimizes the AIC and where, by default settings, $0 \leq p + q \leq 5$ and $0 \leq P + Q \leq 2$, the models are appropriate stationary and invertible, and no other problems in the estimation process are encountered.

The process above is used to describe the patterns of the misery indices. It is one of our first steps in generating a forecast distribution in estimating extreme economic misery. The second step would be bootstrapping, in which the methodology has been adjusted to accommodate time series data.

d. Bootstrapping

Efron & Tibshirani (1993) devised the bootstrap approach for nonparametric estimation of the sampling distribution of sample statistics. This is achieved by repeated resampling via simple random sampling with replacement from the collected random sample, in which the target statistic is computed for each resample. The empirical distribution of the computed statistics from all resamples constitutes as the estimated sampling distribution of the target statistic. From this approach, one can derive robust standard errors, confidence intervals, and hypothesis tests about the unknown quantity.

However, this approach does not work well with time series data, as data points are not necessarily independent and identically distributed. Buhlmann (1997) devised the sieve bootstrap which adjusts the bootstrap approach by first fitting an ARMA-type model to generate residuals which act similar to white noise processes, and then apply the bootstrap on the residuals. The process is expounded below; suppose that $W = W(z_1, \dots, z_T)$ is a target statistic computed from a time series dataset $\{z_t\}_{t=1}^{T}$ and let n_B is number of performed resamples.

Step 1: Fit an $AR(\infty)$ model, of which a SARIMA model is a restricted form, on $\{z_t\}_{t=1}^{T}$ and extract the residuals $\{\hat{\epsilon}_t\}_{t=1}^{T}$ and fitted values $\{\hat{z}_t\}_{t=1}^{T}$.

Step 2: Resampling Procedure; for each i^{th} instance, $i = 1,2, \dots, n_B$,

Sub-step 1: Generate a random sample $\left\{\hat{\epsilon}_t^{(i)}\right\}_{t=1}^{T}$ from $\{\hat{\epsilon}_t\}_{t=1}^{T}$

Sub-step 2: Evaluate $\left\{z_t^{(i)} = \hat{z}_t + \hat{\epsilon}_t^{(i)}\right\}_{t=1}^{T}$

Sub-step 3: Evaluate $W^{(i)} = W\left(z_1^{(i)}, \dots, z_T^{(i)}\right)$

Step 3: Let $I(A) = 1$ if statement A is true, and $I(A) = 0$ otherwise. The estimator for the sampling distribution F_W of the target statistic is

$$\hat{F}_W(w) = \frac{1}{n_B}\sum_{i=1}^{n_B} I\left(W^{(i)} \leq w\right).$$

For the paper, the target statistic to be bootstrapped would be the forecasted values of the indices. The forecast distribution will be generated by sieve bootstrap and the $100(1-\alpha)^{th}$ percentile of the distribution will be the estimated extreme economic misery index. However, as the methodology aims to provide both for the forecasted economic misery on the overall and the individual components, a means of reconciling forecasts from both levels needs to be executed, which will be done through the optimal forecast reconciliation approach.

e. Optimal Forecast Reconciliation

Since the proposed methodology involves generating forecasts for individual components of the economic misery and their aggregate, forecasts between these levels should be reconciled for consistency such that the sum of level forecasts on the individual components equal to the level forecast of the aggregate economic misery index.

Hyndman, et al. (2011) proposed an optimal forecast reconciliation approach in combining forecasts. To simplify the discussion, let us suppose the current set-up on the misery indices. Let $\hat{Y}_t = \left[\widehat{M}_{prop,t}, \widehat{m}_{job,t}, \hat{p}_t, \hat{u}_{1,t}, \hat{u}_{2,t}\right]'$ be the unreconciled forecasts for overall misery, job misery, and the individual components at time t, respectively; and $\hat{Y}_t^* = \left[\hat{p}_t^*, \hat{u}_{1,t}^*, \hat{u}_{2,t}^*\right]'$ are the target but unknown reconciled individual time series forecasts that generates the forecasts for the aggregates. The link between the unreconciled and reconciled forecasts would be the summing matrix S:

$$S = \begin{bmatrix} 1 & 1 & 1 \\ 0 & 1 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}.$$

The three parts $\hat{Y}_t$, S, and $\hat{Y}_t^*$ are linked in a regression equation below with $e_t = \left[e_{1,t}, e_{2,t}, e_{3,t}, e_{4,t}, e_{5,t}\right]' \sim N_5(0, \Sigma_t)$, where Σ_t is the covariance matrix of the unreconciled forecasts:

$$\hat{Y}_t = S\hat{Y}_t^* + e_t.$$

By ordinary least squares approach, which assumes that Σ_t is a diagonal matrix of similar values, the methodology produces the estimated reconciled forecasts $\tilde{Y}_t^*$ for each time t as:

$$\tilde{Y}_t^* = (S'S)^{-1}S'\hat{Y}_t.$$

As all methodologies to be used in the paper to create the proposed measure have been discussed, the procedures for estimating misery-at-risk are now discussed.

3. Proposed Measure

a. Misery-at-Risk

Misery-at-risk MaR_α is a measure defined as the economic misery that can occur given a risk probability α that the misery will not be exceeded. For example, a 90% misery-at-risk is denoted as $MaR_{0.90}$ and it means that there is 90% probability that misery will be less than or equal to such value. As the paper proposes to estimate for both overall and individual components, distinction on what type of MaR is presented. The overall, job MaR, inflation, unemployment, and underemployment MaRs with forecast horizon h are denoted as $MaR_{\alpha,T+h}^{M}$, $MaR_{\alpha,T+h}^{JM}$, $MaR_{\alpha,T+h}^{P}$, $MaR_{\alpha,T+h}^{U_1}$, and $MaR_{\alpha,T+h}^{U_2}$, respectively. Inflation MaR is also known as inflation-at-risk (IaR) which was devised by Santos, Mapa, & Glindro (2010), though the proposed methodology will not use extreme value theory approaches to generate the IaR.

The procedure for generating the MaR is discussed below:

Step 1: Misery Calculation. Solve for the job misery and overall misery indices as described in Section II.a. For the paper, the misery is solved per quarter, as unemployment and underemployment are quarterly indices. To solve for headline inflation, the monthly consumer price index [CPI] is first averaged per quarter and year-on-year growth rates are solved from the converted quarterly CPI.

Step 2: SARIMA Modeling. Using auto.arima(), Fit SARIMA models on overall misery $\{M_t\}_{t=1}^T$, job misery $\{m_{job,t}\}_{t=1}^T$, inflation $\{\pi_t\}_{t=1}^T$, unemployment $\{u_{1,t}\}_{t=1}^T$, and adjusted underemployment $\{u_{2,t}\}_{t=1}^T$. Extract the residuals $\{\hat{\epsilon}_{M,t}\}_{t=1}^T$, $\{\hat{\epsilon}_{JM,t}\}_{t=1}^T$, $\{\hat{\epsilon}_{\pi,t}\}_{t=1}^T$, $\{\hat{\epsilon}_{u_1,t}\}_{t=1}^T$, and $\{\hat{\epsilon}_{u_2,t}\}_{t=1}^T$; and fitted values $\{\hat{z}_{M,t}\}_{t=1}^T$, $\{\hat{z}_{JM,t}\}_{t=1}^T$, $\{\hat{z}_{\pi,t}\}_{t=1}^T$, $\{\hat{z}_{u_1,t}\}_{t=1}^T$ and $\{\hat{z}_{u_2,t}\}_{t=1}^T$.

Step 3: Bootstrapping and Forecast Reconciliation. For each i^{th} instance, $i = 1,2,\dots,n_B$:

Sub-step 1: Resampling. Generate a random sample $\left\{\hat{\epsilon}_{K,t}^{(i)}\right\}_{t=1}^T$ from $\{\hat{\epsilon}_{K,t}\}_{t=1}^T$ for each $K \in \{M, JM, \pi, u_1, u_2\}$.

Sub-step 2: Reproduction. Evaluate $\left\{z_{K,t}^{(i)} = \hat{z}_{K,t} + \hat{\epsilon}_{K,t}^{(i)}\right\}_{t=1}^T$ for each index K.

Sub-step 3: Forecasting. Evaluate the forecast function $\hat{Y}_{K,T+h}^{(i)} = \hat{Y}\left(z_{K,1}^{(i)}, \dots, z_{K,T}^{(i)}\right)$ as forecasts based on the SARIMA model estimated in Step 2 with forecast horizon h for each index K.

Sub-step 4: Reconciliation. Define $\hat{Y}_{T+h}^{(i)} = \left[\hat{Y}_{M,T+h}^{(i)}, \hat{Y}_{JM,T+h}^{(i)}, \hat{Y}_{\pi,T+h}^{(i)}, \hat{Y}_{u_1,T+h}^{(i)}, \hat{Y}_{u_2,T+h}^{(i)}\right]'$ as a vector of unreconciled forecasts for each component. Using the optimal forecast reconciliation approach, with the summing matrix S defined as example in Section II.e., the reconciled forecasts $\tilde{Y}_{T+h}^{(i)} = \left[\tilde{Y}_{\pi,T+h}^{(i)}, \tilde{Y}_{u_1,T+h}^{(i)}, \tilde{Y}_{u_2,T+h}^{(i)}\right]'$, $\tilde{Y}_{JM,T+h}^{(i)}$, $\tilde{Y}_{M,T+h}^{(i)}$ and are solved by:

$$\tilde{Y}_{T+h}^{(i)} = (S'S)^{-1}S'\hat{Y}_{T+h}^{(i)};\ \tilde{Y}_{JM,T+h}^{(i)} = \tilde{Y}_{u_1,T+h}^{(i)} + \tilde{Y}_{u_2,T+h}^{(i)};\ \tilde{Y}_{M,T+h}^{(i)} = \tilde{Y}_{\pi,T+h}^{(i)} + \tilde{Y}_{JM,T+h}^{(i)}.$$

Step 4: Forecast Distribution Estimation. The estimated forecast distribution is for misery index I and horizon h is $\hat{F}_{\tilde{Y}_{K,T+h}}$ and is solved by

$$\hat{F}_{\tilde{Y}_{K,T+h}}(w) = \frac{1}{n_B}\sum_{i=1}^{n_B} I\left(\tilde{Y}_{K,T+h}^{(i)} \le w\right).$$

Step 5: Misery-at-Risk Estimation. Evaluate $MaR_{\alpha,T+h}^K$ for each K by:

$$MaR_{\alpha,T+h}^K = \hat{F}_{\tilde{Y}_{K,T+h}}^{-1}(1-\alpha) = \tilde{Y}_{K,T+h}^{[(1-\alpha)n_B]}.$$

The notation $\tilde{Y}_{K,T+h}^{[(1-\alpha)n_B]}$ means that the $(1-\alpha)n_B$-th smallest value from the forecast distribution will be used, with $(1-\alpha)n_B$ truncated to the nearest integer.

With misery-at-risk defined, real data was applied to the proposed methodology using Philippine inflation and labor force time series which will be discussed in the next section.

b. Real Data Application

The proposed measure will be applied to the Philippine inflation, unemployment, and underemployment data from Q1 1995 to Q2 2019 as made available by the Philippine Statistics Authority. Inflation is the headline inflation computed as the year-on-year change in the CPI:

$$\pi_t = \frac{CPI_t - CPI_{t-4}}{CPI_{t-4}} \times 100\%$$

Since CPI is reported monthly, a quarterly average is solved to derive the quarterly CPI values. As the CPI changed base years in 2018 from 2006=100 to 2012=100, the transform for data points on or before 2011 are shown below, in compliance with symmetric time and circularity properties of price indices (Diewert 1993):

$$CPI_t^{(2006=100 \Rightarrow 2012=100)} = \frac{CPI_t^{(2006=100)}}{\frac{1}{4}\sum_{t=Q1\ 2012}^{Q4\ 2012} CPI_t^{(2006=100)}} \times 100.$$

The underemployment rate was transformed to have the labor force participation population as its base through the unemployment rate as discussed in Section II.a.

The MaR is derived with two coverage probabilities: 80% and 90%. MaR at 80% can be used as an early warning to preempt worsening misery while the exceedance of the 90% MaR would be indicative of severe misery.

In the next section, the discussion of results is shown that will tackle some descriptive analyses of the indices, performance of mean forecasts, and hold-out analysis of misery-at-risk estimates.

4. Results and Discussion

a. Descriptive Analyses of Indices

The Philippine misery indices and their components are plotted into a line graph for descriptive analysis.

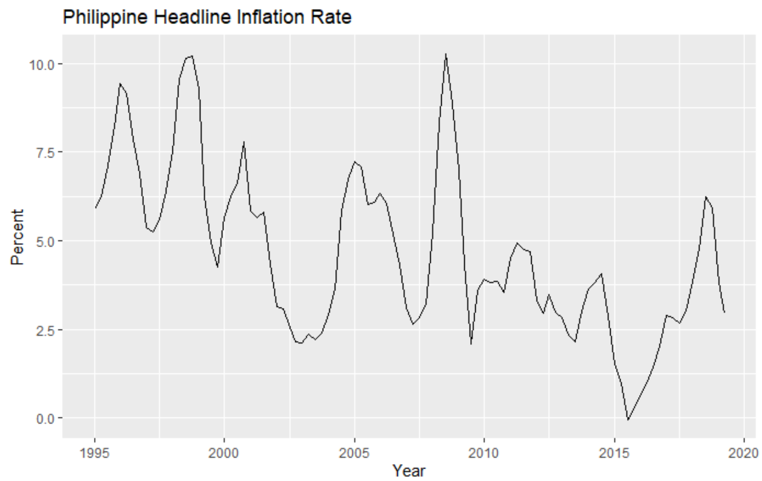

Fig. 1: Philippine Headline Inflation Rate, Q1 1995 to Q2 2019

First, the inflation data is plotted. Generally, there is a weak downtrend in the inflation data with a strong cyclical component. By crude estimation through the duration between peaks or between troughs, the typical length of a cycle is about 3 to 5 years. Since seasonal differencing was performed in estimation of the inflation rate, the data did not exhibit any seasonal behavior.

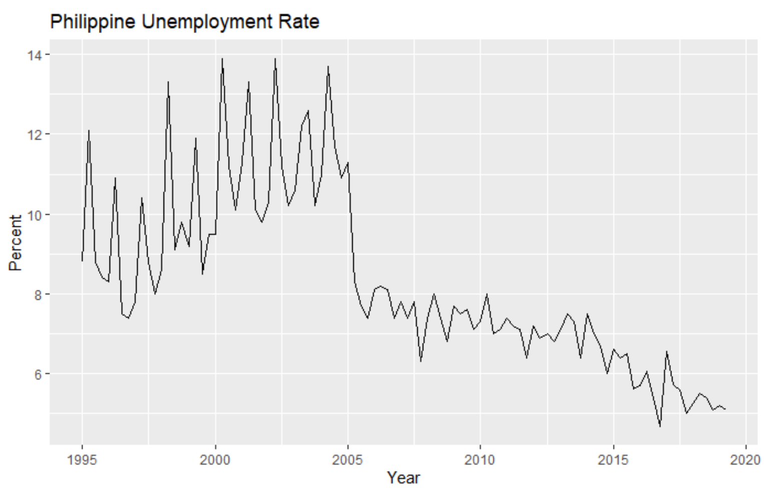

Fig. 2: Philippine Unemployment Rate, Q1 1995 to Q2 2019

The change in level in the unemployment rate starting 2005 was due to a change in the technical definition used for unemployed individuals (National Statistical Coordination Board 2004). Before 2005, there was strong seasonality for unemployment with a peaks at Q2 due to inflows to the workforce from college graduates. After 2005, the seasonal behavior has diminished. After 2005, there is an observed downward trend in unemployment.

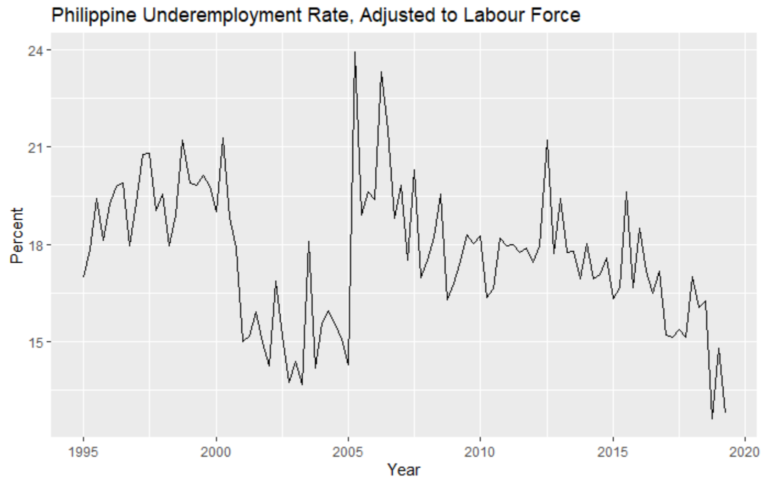

Fig. 3: Philippine Underemployment Rate, Adjusted to Labor Force, Q1 1995 to Q2 2019

There is a period in 2001 to Q4 2004 in which there was a low underemployment compared to adjacent period. The underemployment rate was also affected by the change in definition in 2005 for the labor statistics (National Statistical Coordination Board 2004), suddenly peaking at 24%. However, from that point there is a downtrend in underemployment.

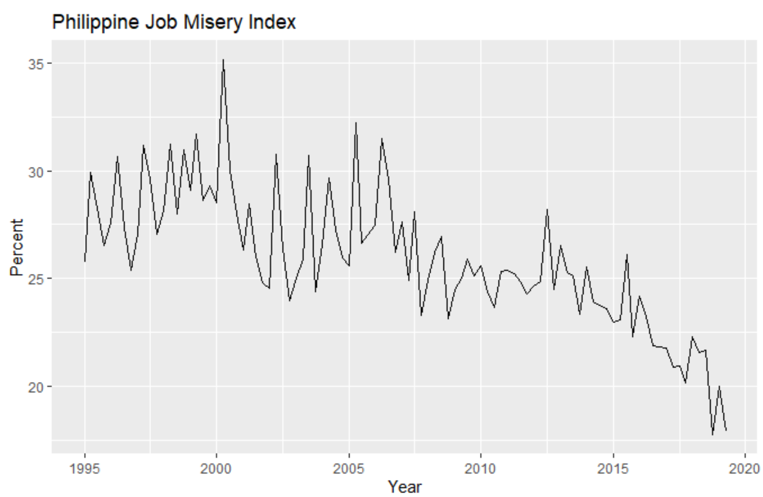

Fig. 4: Philippine Job Misery Index, Q1 1995 to Q2 2019

An interesting case occurred with the job misery index as there is no trace of the changes in labor statistics from NSCB Resolution No. 15 (2004). There seems to be a realignment between underemployed and unemployed individuals based on the resolution. There seems to be a downtrend since 2000. Seasonal behavior may be inconsistent or may be confounded by large variation especially before 2007. The job misery index has a trough in the general trend in the from 2000 to 2005.

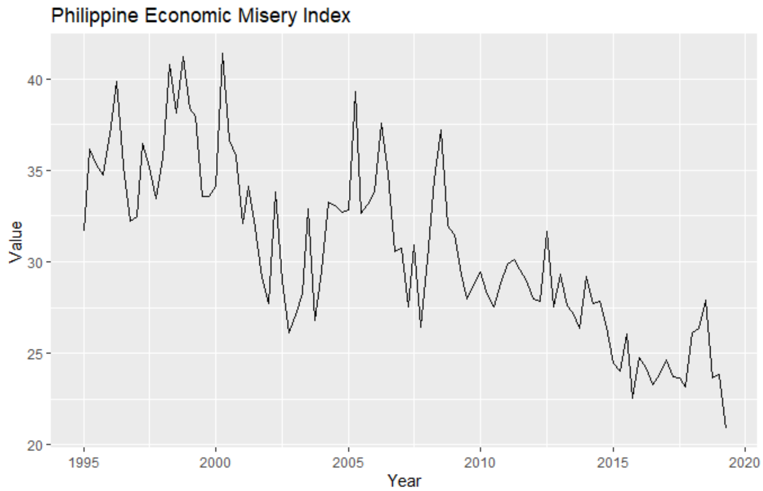

Fig. 4: Philippine Economic Misery Index, Q1 1995 to Q2 2019

There is a general downtrend in the economic misery in the Philippines since 2000. A trough on economic misery from 2000 to 2005, which coincided with the cyclical trough of inflation and the trough on job misery.

b. Out-of-Sample Performance of Mean Forecasts

Out-of-sample forecast performance with respect to expected misery is assessed. Q1 1995 to Q4 2016 are used as training data periods while the rest is used as test data for forecast performance assessment. The forecasts are evaluated from an estimated SARIMA model on the training dataset through the auto.arima() function and followed by optimal forecast reconciliation.

Model Parameters	Economic Misery	Inflation	Job Misery	Unemployment	Underemployment
d	1	1	1	0	0
D	0	0	0	1	0
$\hat{\delta}$ $se(\hat{\delta})$	-- --	-0.0610 0.0306	-- --	-- --	17.8858 0.5490
Nonseasonal Terms					
$\hat{\phi}_1$ $se(\hat{\phi}_1)$	0.6391 0.1014	-- --	-- --	0.8266 0.0825	0.8163 0.0990
$\hat{\theta}_1$ $se(\hat{\theta}_1)$	-0.9554 0.0376	0.4530 0.0918	-0.7101 0.0815	-0.2786 0.1285	-0.4841 0.1404
Seasonal Terms					
$\hat{\Phi}_1$ $se(\hat{\Phi}_1)$	0.9492 0.0486	-- --	0.9454 0.0457	-0.5454 0.0900	-0.3702 0.2001
$\hat{\Theta}_1$ $se(\hat{\Theta}_1)$	-0.7664 0.0952	-0.7681 0.0770	-0.7431 0.0972	-- --	0.6889 0.1494
AIC	412.96	198.87	357.57	231.28	340.60

Table 1: SARIMA Model Estimates for the Misery Index and Components

The table below shows the SARIMA model fit for each component before optimal reconciliation. Generally, the orders of the AR, MA, SAR, and SMA terms did not deviate from 1. Only underemployment has been assessed to be stationary. Seasonal nonstationarity is assessed on the unemployment time series. All series have seasonal AR and/or MA terms. Once the estimates are computed, the forecasts for all five indices are generated and the optimal forecast reconciliation is applied. These reconciled forecasts are compared with the realized values of the five indices and forecast performance statistics are computed.

	Economic Misery	Inflation	Job Misery	Unemployment	Underemployment
ME	-0.1175	1.8969	-2.0143	0.4343	-2.4487
RMSE	1.7996	2.4076	2.3912	0.5993	2.7855
MAE	1.4762	1.8969	2.0143	0.4351	2.4487
MAPE (in %)	6.0653	42.0931	10.3769	7.7276	17.2429
MPE (in %)	-1.0301	42.0931	-10.3769	7.7137	-17.2429

Table 2: Out-of-Sample Performance Statistics of Mean Forecasts for Misery Indices

One apparent result is the inflation forecast performance as assessed by the MAPE and MPE. Both being at 42% indicates a large underestimation of inflation from 2017 to Q2 2019, of which this is due to the effects of the TRAIN law (Republic Act 10963). The effect of the law on inflation is not anticipated by the reconciled SARIMA forecasts as they only modeled up to 2016 Q4. Some biases in out-of-sample forecasts are also observed in the labor misery indices, with overestimations in job misery and underemployment and an underestimation in unemployment.

c. Hold-Out Analysis of Misery-at-Risk

Miseries-at-risk for the indices at 80% and 90% are computed for the test periods 2017 to 2020. The realized index values from 2017 to 2019 Q2 and MaRs are plotted in a line graph.

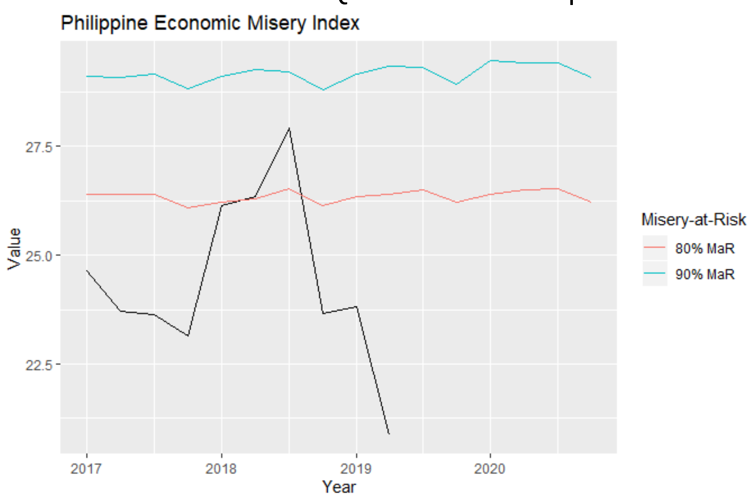

Fig. 5: Philippine Economic Misery Index MaR, 2017 to 2020

With the overall economic MaR, the realized economic misery index has exceeded the 80% MaR, estimated at around 26.25, in the Q2 and Q3 of 2018, which would serve as an early warning before misery worsens. This is due to the TRAIN law in which it increased the sales tax of some goods and services. It is observed that economic misery was addressed which facilitated misery not reaching the 90% MaR, estimated at around 28.

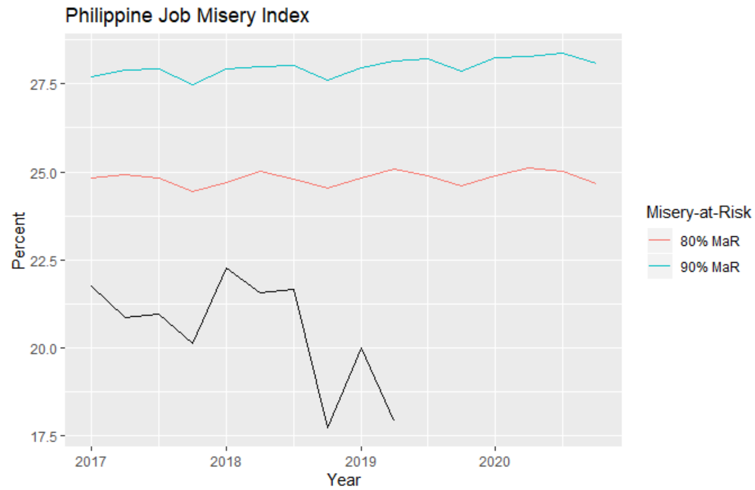

Fig. 6: Philippine Job Misery Index MaR, 2017 to 2020

Job misery is generally in a decline, though it slightly pulled up in 2018 Q1 but has dropped largely by 2018 Q4. The estimated 80% MaR was at around 25% while 90% MaR was above 27.5%.

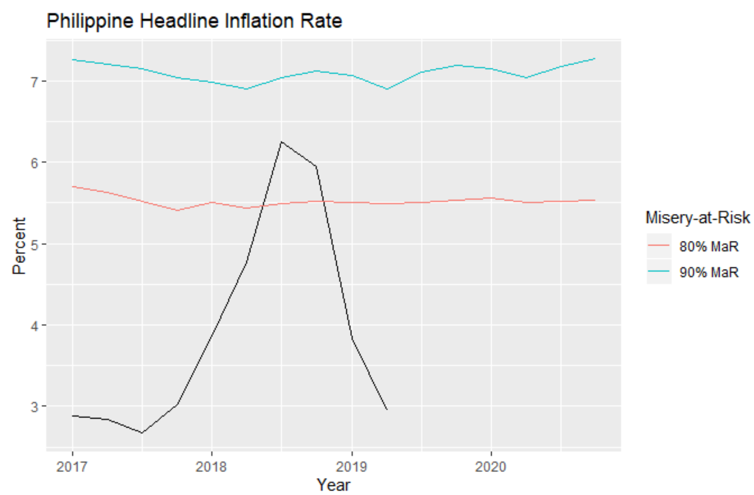

Fig. 7: Philippine Inflation Misery Index MaR, 2017 to 2020

Inflation was in warning territory in Q3 and Q4 of 2018 from exceeding the 80% MaR estimated at about 5.5%. A drop in inflation occurred in 2019 which removed the inflation misery from warning territory. The 90% MaR was estimated around 7%.

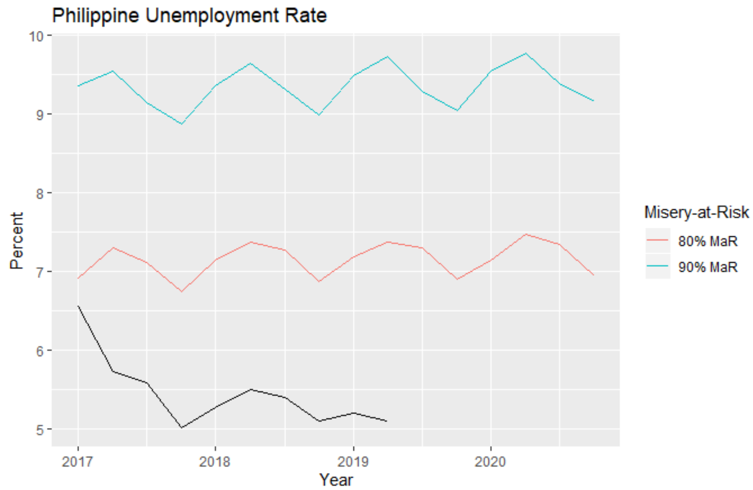

Fig. 8: Philippine Unemployment Misery Index MaR, 2017 to 2020

The unemployment rate does not exceeded the estimated 80% MaR of around 6.8% at the lowest or 7.3% at the highest. Unemployment rate was generally keeping to its decreasing trend with low variation. The 90% MaR fluctuates from about 9% to as high as 9.8%.

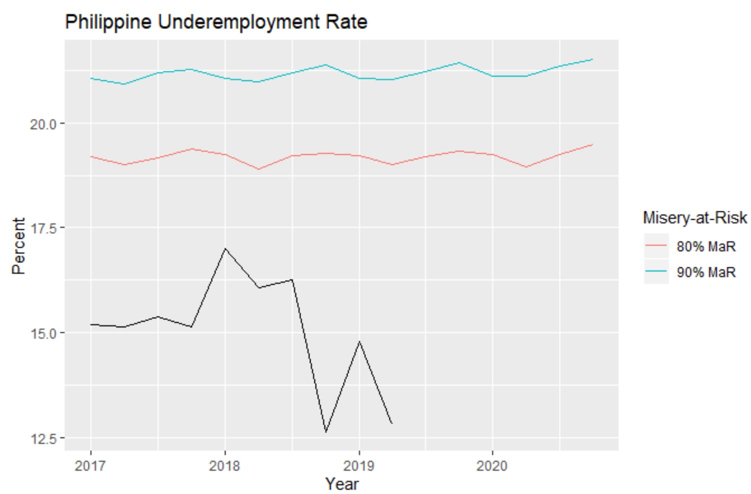

Fig. 9: Philippine Underemployment Misery Index MaR, 2017 to 2020

Underemployment has different behavior from unemployment in the short run, as it was at a higher level from Q1 to Q3 2018 to until the drop in Q4 2018. It seems that the underemployment rate is quicker to move from changing economic conditions than the unemployment rate. Even so, it did not reach the 80% MaR of about 17.8%. The 90% MaR was at around 21.25%.

Overall, the economic misery reached warning levels at the second and Q3s of 2018 but was reduced starting the Q4 of the year. Note that inflation misery was at warning in Q3 and Q4, of which the Q3 would be the intersection of the overall and inflation miseries. The increased level of job misery, which was dominated by the increased level of underemployment and occurred from first to Q3 of 2018, would have added to the overall misery, even though both components did not have warning levels. The sudden reduction in job misery by Q4 2018 has reduced overall misery in the same quarter, even though price inflation misery was at warning.

5. Summary and Conclusion

In this paper, the aim was to propose a methodology that will aid in the monitoring of the economic situation of the country through the index of misery as measured by inflation and job quality and availability. The misery-at-risk was devised with this aim in mind, and used principles of modern developments in time series and data science for its inception. The method was applied in real data and it offered insights into the dynamics of the components of misery. This research seeks to open more opportunities in devising economic monitoring approaches by adopting methods from other fields such as finance and data science.

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