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Interpolating poverty statistics in the Philippines for non-FIES years using DFM

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Abstract. The establishment of the Sustainable Development Goals in 2015 entails generating relevant and timely statistics for monitoring and policymaking. The Philippine Statistics Authority (PSA) generates poverty statistics using the Family Income and Expenditure Survey (FIES). However, due to certain limitations, the FIES collection and calculation of official poverty statistics is done only every three years. In this regard, this paper presents a method of filling in the gaps by interpolating annual poverty statistics, particularly the poverty incidence, using macroeconomic indicators and demographic and employment information from the Labor Force Survey (LFS). These explanatory variables were related to the poverty incidence using the Dynamic Factor Model (DFM) in the state-space form to produce estimates for years when poverty statistics are not available. Relatively high forecast accuracy was observed for the predicted values of poverty incidence.

Keywords: Dynamic Factor Model (DFM), factor analysis, poverty statistics, poverty incidence, state-space form, forecasting, poverty interpolation

1. Introduction

The Family Income and Expenditure Survey (FIES) is a nationwide survey conducted by the Philippine Statistics Authority (PSA) that provides information on the complete range of household income, expenditures, and other characteristics. The survey is vital for policy analysis and decision making as it is used in calculating the poverty incidence. It also contributes to the estimation of the Gross Domestic Product (GDP) and is used in a wide variety of academic research. The survey is conducted every three years, resulting in a triennial report of official poverty statistics in the Philippines.

During non-FIES years, the Annual Poverty Indicators Survey (APIS) provides statistics that can be used to assess and monitor poverty. APIS is a nationwide survey that collects data on the socio-economic profile and living conditions of Filipino families. It provides non-income indicators of poverty which are inputs in developing the country's integrated poverty indicator and monitoring system. While FIES and APIS are both designed to provide indicators related to poverty, experts suggest that results from both surveys are not comparable. This is due to certain variations in the survey domain and questionnaire items [1–3]. The FIES contains more detailed questions on income and expenditure, whereas APIS has a summarized version of questions on income and expenditure and includes modules on non-monetary indicators of poverty [4]. The sample size of the APIS is also smaller than the sample size of the FIES. Essentially, APIS is based on non-income measures of poverty and only gives a general picture of the country's poverty situation. Due to these inconsistencies between the two sampled surveys, non-income-based poverty measures from APIS cannot supplement official indicators from FIES. Hence, an alternative methodology is needed to estimate comparable poverty statistics for years when FIES data is not available.

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This study explored the use of a statistical model in interpolating poverty indicators during non-FIES years. Since poverty is influenced by the country's macroeconomic situation as well as the labor and demographic characteristics of the population, such variables were used to build a model that could estimate poverty statistics in the absence of FIES data.

Several studies have recommended macroeconomic indicators for estimating poverty during non-FIES years. These factors include demographic variables [5–7], open-economy variables [8], geographic characteristics [9], regional development and urbanization [10], governance quality [11], among others. Nonetheless, these studies are cross-country analyses focused on looking for poverty determinants rather than estimation or prediction.

Another set of studies attempted to estimate poverty rates. One study proposed a methodology that utilizes the Italian Labor Force Survey focusing on labor income, to produce timely indicators for inequality and poverty despite lags in data from standard household income surveys [12]. Another study reviewed several existing alternative imputation methods employed to generate poverty estimates despite unavailable household consumption data [13]. In another paper, a methodology for estimating poverty rates for non-survey years using a cross-survey imputation method was proposed. Data from the Household Expenditure Surveys and Labor Force Surveys in Morocco were utilized [14].

1.1. *Objectives of the study*

This paper builds upon the main objective of proposing a methodology to estimate an annual national poverty series for the Philippines using selected macroeconomic welfare indicators, demographic information, and employment data. A dynamic factor model (DFM) in state-space form is proposed to estimate missing poverty statistics during non-FIES years. Specific objectives are listed as follows:

a) Determine macroeconomic indicators and Labor Force Survey (LFS) employment indicators that can predict poverty based on literature review;
b) Create an annual time series of selected macroeconomic indicators and LFS from 1988 to 2018;
c) Construct a dynamic model to estimate poverty statistics on non-FIES years using selected macroeconomic indicators and labor force information; and
d) Validate model used in estimating poverty statistics on non-FIES years by comparing actual and predicted poverty statistics during FIES years.

2. Review of related literature

This chapter presents the related literature and studies on poverty estimation. The literature reviewed included topics on the methodology for poverty calculation and macroeconomic indicators of poverty. It also particularly highlights techniques for poverty estimation during non-survey years.

2.1. *Discussion of poverty estimation*

2.1.1. *Official methodology for poverty calculation in the Philippines*

To estimate poverty, one must first define who the poor are. Section 3 of Republic Act 8425 of 1997 defines the poor as individuals and families whose income fall below the poverty threshold, as defined by the National Economic and Development Authority (NEDA), and or cannot afford in a sustained manner to provide their minimum basic needs of food, health, education, housing, and other essential amenities of life.

Official poverty statistics are computed based on the final results of the FIES, a nationwide survey conducted every three years by the PSA. The poverty statistics are income-based and use a low-cost, nutritionally adequate one-day menu that is used in estimating the food threshold and is determined by the Food and Nutrition Research Institute. To provide the equivalent cost of menus, price data are obtained from the Bureau of Agricultural Statistics and the PSA; the former for agricultural commodities and the latter for non-agricultural commodities. Based on this one-day menu, the monthly food threshold or the food poverty line of an average-sized Filipino family is derived.

Using income and expenditure data from FIES, the poverty threshold is computed. The ratio of food expenditure to the total expenditure of families with income within the tenth percentile of the food poverty line is used as the denominator of the latter, thereby producing indirect estimates of the total poverty threshold. The poverty threshold for the region is computed as the weighted average of urban and rural poverty thresholds, while the national poverty threshold is computed as the weighted average of all the regional poverty thresholds. In the Philippines, regions pertain to administrative divisions made up of different provinces and cities established to effectively coordinate and organize planning and implementation of national government services across multiple local government units (provinces, cities/municipalities, and barangays). The Philippines has a total of 17 regions: 16 administrative regions and one autonomous region. These regions are also used as a basis for statistical disaggregation in the country.

Estimates of annual per capita income and the number of poor families are also computed from the FIES data. The number of families with annual per capita income falling below the food poverty line is considered as the number of subsistence poor families. The number of poor families is computed by counting the number of families with annual income falling below the total poverty line. National-level statistics are calculated by adding all counts obtained in the regions.

2.1.2. *Methodologies for poverty calculation among various national statistical offices*

A myriad of poverty measurement approaches exists among national statistical offices of different countries. In 2014, the United Nations Economic Commission for Europe (UNECE) surveyed how poverty is measured across different national statistical offices, noting the practices, standards, and techniques adopted in measuring poverty. Various types of poverty and poverty indicators were also observed. Some countries account for absolute poverty or relative poverty only, whereas others measure both types. The poverty indicator varies from consumption expenditure, disposable income, subjective assessment of living standards, material deprivation, and at-risk-of-poverty or social exclusion. The poverty threshold likewise differs across countries, while the unit of analysis is either household, person, or economic family. The periodicity of indicators published is primarily annual, with some instances of countries also publishing poverty indicators quarterly, every two years, or every five years. The most common data source is a sample survey, but administrative records and census were also utilized by some countries [15].

2.1.3. *Poverty measurement by international organizations*

To provide guidance on applying the various approaches of poverty measurement and improve comparability of poverty statistics across countries, the UNECE published a guide on poverty measurement in 2017. Different household-based surveys and the corresponding disadvantages associated with each survey were reviewed [15].

In 2005, the United Nations Statistics Division (UNSD) presented alternative ways to collect and measure poverty indicators through its Handbook on Poverty Measurement. These methods include collecting non-monetary data from other surveys or correcting for the incomparability between household surveys [16].

The Elbers, Lanjouw, and Lanjouw method, also known as the World Bank's official method in estimating poverty, combines both survey and census data for poverty estimation. This method involves estimating household income and consumption data from survey results and using these estimates to create corresponding forecasts for census observations [17].

The methodological and conceptual approach used by the Organisation for Economic Co-operation and Development (OECD) in measuring and comparing household income poverty across member countries was described and discussed by a study [18], focusing on the household income poverty indicators collected and analyzed by the OECD as part of its Income Distribution Database. A review of the challenges and possible changes regarding the timeliness, coverage of middle-income and emerging countries, sub-national indicators, and alternative indicators of household economic resources and non-monetary poverty was also conducted.

2.2. *Macroeconomic variables related to poverty*

Prior research showed evidence that economic growth relates to poverty; the higher the growth in the economy, the lower the poverty in the country. These findings were confirmed by a study [19] that employed a formal error-correction model in the analysis. The authors found that for all families, increasing economic growth significantly reduces the poverty rate. Moreover, other explanatory variables such as transfer payments and the number of female-headed households were also statistically significant. Findings showed that the male unemployment rate changes on poverty are relatively small when the equation is controlled for GDP. When GDP is omitted, the male unemployment rate becomes significant, indicating that this variable is heavily reliant on the changes in the GDP.

The estimation of the poverty rate will include statistical errors. Studies have applied adjustments to improve prediction accuracy. One study focused on the effect of imputed welfare estimates in regression analysis, particularly the use of imputed data such as highly disaggregated welfare indicators, which serve two purposes: as an explanatory variable and as the phenomenon to explain. To reflect the error brought by using imputed indicators instead of actual indicators, the authors adjusted the standard errors of the regression equation coefficients. Data from Ecuador were utilized, and results showed that using an imputed variable as the phenomenon to explain results to the same aggregate relationship as that of using actual variables [20].

Another study developed a methodology using various econometric techniques to estimate poverty without comparable consumption data. Using a series of Demographic Health Surveys and secondary rainfall data in Kenya, poverty estimates were calculated. The actual data and estimates indicated a decline in poverty in Nairobi, although the change reflected in the estimates was not significant. Although the produced economic asset index proved to be promising in tracking poverty, caution on the selection of assets and time-variable forecast must be exercised as this would affect the empirical precision of the model. To reduce the model error in predicting poverty, the inclusion of critical time-varying variables and careful pre-selection of assets based on their predictive power must be considered [21].

A study [22] analyzed various poverty prediction models based on small area estimation techniques. Using an adapted version of the small area estimates technique described in the other related studies [23,24], the performance of models in predicting changes in poverty was scrutinized with actual data. Consumption prediction models using consumption subcomponents and combinations of non-consumption assets were tested, drawing data from two surveys with highly comparable expenditure data and two case study applications. Results showed that the critical determinant of success in predicting reliable poverty estimates lies in the explanatory power of the primary consumption mode. Non-staple food and non-food expenditures and full assets models performed well. Poverty can be tracked in the absence of comparable consumption data by tracking poverty predictors, although further validation of parameter stability assumption in shorter or longer periods and rapid poverty deterioration settings must be considered.

Using time-series data from 1972 to 2010, a study [5] analyzed the relationship between poverty and various economic indicators such as consumer price index (CPI), literacy rate, and population growth in Pakistan. Poverty was measured using the headcount rate. A unit root Augmented Dickey-Fuller test was conducted to check the stationary data. Likewise, Johansen's cointegration test was conducted to check for the long-run relationship between poverty and economic indicators. Results showed a correlation between poverty and the economic variables, thereby indicating that CPI, literacy rate, and population growth are pertinent factors in poverty measurement.

Corresponding to a study that conducted cross-country regressions examining the link between macroeconomic and structural variables and poverty, higher per capita income, higher real exchange rates, a higher degree of commercial openness, and better health conditions were found to lower poverty, whereas inflation rate, higher income inequality, and macroeconomic volatility increase poverty. The negative growth rate was found to have a significant relationship to poverty as well [8].

A study on the relationship between poverty, economic growth, agricultural and industrial employment, and dependency ratio used cross-country data from 41 countries in Asia, Latin America, and Sub-Saharan Africa. An analysis using the ordinary least squares method and correlation and econometric tools showed that the age dependency ratio and economic growth have a significant relationship with poverty. On the contrary, agricultural and industrial employment is insignificant [7].

A cross-national study consisting of data from 97 developing countries examined the relationship of various variables to poverty [9]. Using a ridge regression modeling, poverty incidence and income deficit between the poor and non-poor populations were analyzed. The study's outcome revealed that factors such as the country's income level, landlockedness, population growth, and opportunity for secondary schooling significantly impact poverty reduction. Although other variables such as political factors such as democracy, military spending, and war and government social spending are correlated with poverty, they have very little association and are only weak predictors. The association of economic openness to poverty was not proven in the study.

A study on the association of macro determinants such as road density, employment rate, dependency ratio, urbanization rate, people to hospital ratio, and the number of factories to two dimensions of poverty (Basic Needs Index and Asset Index) showed that road density, number of factories, and employment rates are the only variables that significantly impact poverty. Economic analysis indicates that infrastructure development, especially roads, is one of the most significant contributors to poverty reduction. Likewise, the number of factories is also highly correlated with poverty; a higher number of factories will benefit the people through employment generation and will, in turn, enhance the income of households. The employment rate is also associated with poverty, as higher employment will result in greater business activity and a greater ability to acquire assets that will enhance living conditions [10].

In another study, a new methodology in measuring the effect of price changes on poverty relative to its price elasticity in Brazil was derived. The authors obtained an empirically operational index to check whether the price changes are pro-poor or anti-poor and a new price index for the poor. Results showed that price changes in Brazil for the period 1999 to 2006 had been anti-poor. However, price changes have affected the poor less than the non-poor during the last 2 to 3 years [25].

Using time-series data from 1980 to 2003, a study [26] examined the correlation between poverty and four (4) macroeconomic indicators, namely GDP, government spending, employment, and the ratio of Foreign Direct Investment to GDP (FDRI). Findings revealed that GDP, government spending, and FDRI are the only statistically significant determinants of poverty reduction in Kenya. GDP has a significant negative relationship with poverty; as the economy progresses, poverty tends to fall. Likewise, aggregate government spending has a negative relationship with poverty; the higher the government spending, the lower poor population. In contrast, FDRI is positively related to poverty reduction. Increasing FDRI results in an increase in the number of people living below the poverty threshold due to limited potential employment and labor displacement.

Using annual time series data from 1981 to 2010 applied in multiple regression techniques, a study [6] focused on the correlation between various macroeconomic variables (i.e., inflation, GDP growth, population growth, major crops, minor crops, livestock, and per capita income) and poverty in Pakistan. The empirical and econometric analyses showed an inverse relationship between poverty and macroeconomic variables such as GDP growth, per capita income, and major and minor crops. As these variables increase, poverty in Pakistan reduces. Contrary to this, inflation and population growth are positively related to poverty; the higher these two (2) variables are, the higher the poverty level.

A study [11] conducted an empirical study of the macroeconomic fundamentals of poverty and deprivation in developed countries. Data from 24 countries in the European Union over the period 2005 to 2010 were analyzed using two (2) models; one with poverty or deprivation, which is the Index of Multiple Deprivation for Developed Countries (IMD_D) as the dependent variable and one with people at-risk-of-poverty rate or social inclusion (AROPE) as the dependent variable. *Ceteris paribus*, increasing public investment as a percentage of GDP, per capita GDP growth rate, and governance quality reduces IMD_D and AROPE. Likewise, per capita GDP and employment rate are also significant determinants of poverty reduction; the higher the values, the lower the poverty and deprivation levels. Gini coefficient is insignificant in explaining IMD_D but is positively related to AROPE.

The association between macroeconomy and poverty was the subject of a study analyzing the macroeconomic performance and poverty rate in developing and transition economies with 47 episodes of growth and 52 episodes of downturn [27]. Econometric estimations of the relationship between growth and poverty showed that an average of 1% growth in the macroeconomy results in a 1.38% reduction in the poverty rate. Moreover, a higher Gini coefficient results in a lesser impact of economic growth in poverty reduction.

In the Philippines, various studies have tackled macroeconomic determinants of poverty. One study focused on the profile and determinants of poverty in the Philippines. Parameter estimates for the regression model were used and yielded the following results: an increase in the total number of children reduces the per capita income, every increase in the number of household members employed increases per capita income as a ratio of the poverty line, accessibility to water source leads to improvements in household welfare, housing characteristics such as roofs and walls materials and access to sanitary toilets, water, and electricity are related to poverty, age and marital status of the household head affects poverty, and education of the household head influences the level of household welfare [28].

Another study examined the impact of demographic transition variables, namely average population growth and average workers' population growth rates, on economic growth and poverty [29]. Results of the econometric analysis showed that total population growth negatively affects economic growth while workers' population growth has a positive effect. Findings also showed that the growth in the population indirectly influences the economy through the illiteracy rate, which is considered human capital. At a fixed level of illiteracy rate, any increase in population growth negatively influences economic growth.

In a study [30] of the robust determinants of income growth in the Philippines using data from 74 provinces from 1985 to 2003 and applying it to simulation techniques, the effect of population dynamics on the income inequality among provinces was quantified. Explanatory variables used were also examined to determine the corresponding relationship to income growth. Results showed that population is highly related to growth and can explain the growth differentials among the provinces.

An econometric analysis of the panel data for the Philippines for the period 1980s to 1990s which reflected an evolution of poverty across provinces in the country was also conducted [31]. The growth elasticity of poverty was calculated at just above 0.5, which supports the conclusion that income growth does not proportionately benefit the poor. Other factors such as education, infrastructure, terms of trade, agrarian reform, governance, and geographic attributes were also found to influence the welfare of the poor via an indirect effect on economic growth.

2.3. Techniques for poverty estimation during non-survey years

A study showed how to compare incomparable statistics due to changes in data collection methodology using an inverse probability weighting procedure [32]. This method requires a set of auxiliary variables that are not affected by the different survey designs, which has a stable relationship with the primary variable across surveys. As pointed out by the author, one particular application of this methodology is the welfare estimation for small areas since national household surveys do not have enough observations to allow precise poverty estimation. A census may be used as the target population, while household surveys may be the auxiliary data.

Given that household consumption data is vital in poverty estimation, a study was able to identify alternative methods to produce poverty estimates depending on the missing data typology [33]. Three broad categories were identified: entirely missing data, partially missing data, and available cross-section but missing panel data. For entirely missing data, wherein the typical situations are non-consumption surveys and small-scale surveys, wealth index from household assets and physical characteristics of the house is the most commonly used imputation method. On the other hand, imputation techniques such as Survey-to-Survey imputation and Survey-to-Census imputation are deemed applicable to partially missing consumption data. Such cases include consumption information not available in the main survey but accessible through other related surveys. For available cross-sections but missing panel data, typical among surveys in developing countries, the imputation method may be the construction of synthetic panel data from the available cross-sectional data.

Another study conducted an estimation of missing observations [34]. A nonlinear time series model was formulated, which can be used to estimate missing data in exceptional cases of time series data study using two methods: prediction and fixed-point smoothing algorithms and optimal estimating equation theory. In this study, the authors applied estimation equation theory to generate estimates for the missing observations in the time-series data.

2.4. Forecasting estimates using alternative models

A study presented a dynamic factor analysis or a "single index" model, which implicitly defines a variable that can represent the overall state of the economy [35]. Using data from 1959 to 1987, the unobserved variable was estimated and was found to be highly correlated with the official U.S. Commerce Department's series. This result solidifies and rationalizes the use of the traditional methodology to develop the Coincident Index. Further, it indicates that traditional leading variables can be used in forecasting short-run growth for the series.

Another study took note of the limitations of popular monthly coincident indices of business cycles such as the composite index and the Stock-Watson coincident index [36]. Two shortcomings were noted: ignoring information contained in quarterly indicators such as real GDP and lack of economic interpretation, thus, the presence of peaks and depths in graphs depending on the index used. With this information, the authors performed a maximum likelihood analysis of mixed-frequency economic measures by deriving the state-space form of the DFM model. Kalman filter was then utilized to produce estimates of a monthly series with missing observations. An extended Stock-Watson index was produced and was found to be related to the latent monthly real GDP.

3. Methodology

3.1. Data collection and management

The paper used two sets of economic variables as explanatory information in estimating poverty incidence: (1) selected macroeconomic indicators in the country, and (2) selected variables from the LFS.

3.1.1. Scope of poverty indicator used

The PSA calculates official poverty estimates from the triennial FIES. A time-series dataset of official poverty indicators from 1988 to 2018 with a total of 11 observations, was initially constructed using published estimates from the PSA. For this study, the indicator

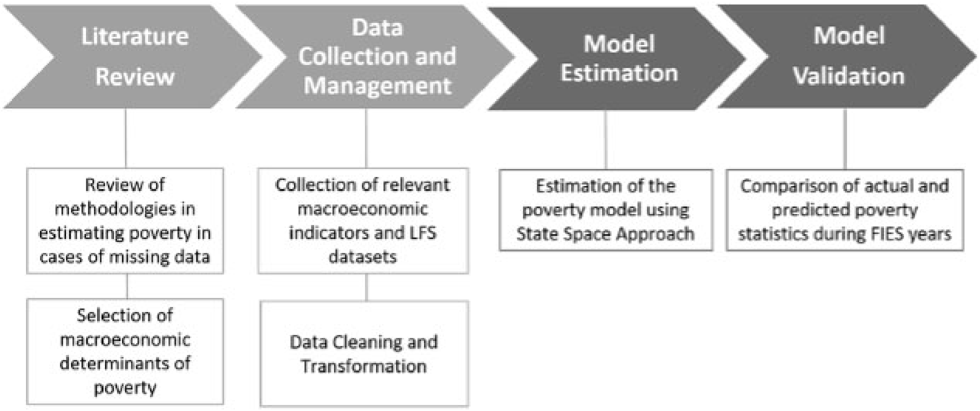

Fig. 1. Methodology for the study.

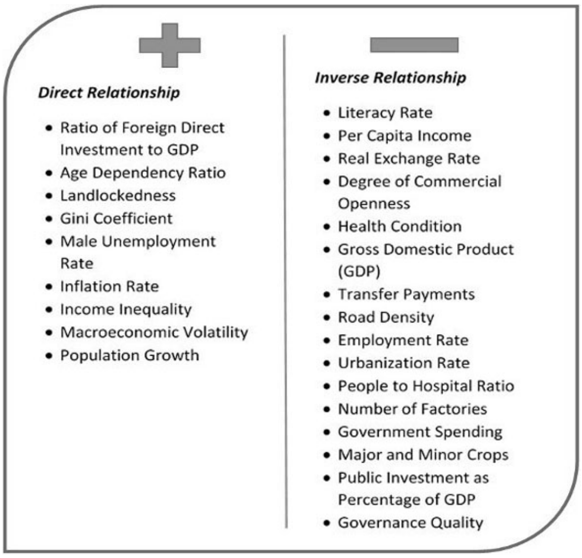

Fig. 2. Relationship of significant macroeconomic indicators to poverty.

Poverty Incidence among Families was used to represent the poverty situation in the country. *Poverty Incidence among Families* is defined as "the proportion of families with per capita income/expenditure less than the per capita poverty threshold to the total number of families."

3.1.2. Selected macroeconomic indicators in the Philippines

The first pool of data collected consists of selected macroeconomic indicators. A myriad of existing studies related to the relationship between macroeconomic indicators and poverty was expounded in the review of the related literature section of this paper. Figure 2 lists the relationship between the different macroeconomic indicators and poverty.

The initial list of macroeconomic indicators was further refined to suit the methodology and case of this study. From the initial list of variables, the dataset was constructed using select macroeconomic indicators grouped into six categories, namely: (1) price statistics, (2) labor and employment, (3) external accounts, (4) national income accounts, (5) poverty statistics, and (6) other select variables.

Table 1 provides the list of macroeconomic variables, including their definitions and data sources. Per capita indicators were generated by multiplying the total component (ex. Total GDP in the industry) by a million pesos and dividing the product by the total population projection.

3.1.3. Selected LFS variables

The second pool of data collected consists of select LFS variables sourced from the PSA, also presented in Table 1. A total of 124 quarterly observations from 1988 to 2018 for each variable was used for the study.

The LFS data has undergone various changes in definitions. Changes in definitions were noted especially starting April 2016 round. The LFS adopted the 2013 Master Sample Design, with a sample size of approximately 44,000 households, and utilized the 2012 Philippine Standard Occupational Classification (PSOC). Before this, the 1992 PSOC was previously used. Population projections based on the 2010 Census of Population and Housing have also been adopted to generate the labor force statistics. Changes were also observed in October 2016. The 2008 Philippine Standard Classification of Education, previously used in the 2015 Population Census, was adopted. The categories for highest

Table 1
Final variables included in the model with variable definitions and data sources

Variable	Definition	Source
Macroeconomic indicators		
Poverty incidence among families (%)	The proportion of families with per capita income/expenditure less than the per capita poverty threshold to the total number of families	Philippine Statistics Authority (PSA)
Inflation rate	The annual rate of change or the year-on-year change in the Consumer Price Index.	
Labor force participation rate (%)	Percentage of the total number of persons in the labor force to the total population 15 years old and over	
Underemploy-ment rate (%)	Percentage of the total number of underemployed persons to the total number of employed persons	
Unemployment rate (%)	Percentage of the total number of unemployed persons to the total number of persons in the labor force.	
Per capita GDP growth	Growth rate of GDP per capita	Computed Variables from Philippine Statistics Authority (PSA)
Per capita GDP growth in agriculture	Growth rate of GDP per capita in the agriculture sector	
Per capita GDP growth in industry	Growth rate of GDP per capita in the industry sector	
Per capita GDP growth in services	Growth rate of GDP per capita in the services sector	
Peso per USD growth	Growth rate of exchange rate of philippine peso per US dollar	Bangko Sentral ng Pilipinas (BSP)
OFW remittances (in thousand US dollars)	Remittances from Overseas Filipino Workers (OFW). OFWs include OCWs who were presently and temporarily out of the country during the reference period to fulfill an overseas contract for a specific length of time, or who were presently at home on vacation during the reference period but still had an existing contract to work abroad.	
Self-rated poverty (%)	Percentage of families who rated themselves as poor, based on the survey conducted by the Social Weather Station (SWS)	Social Weather Station (SWS)
Demographics and employment information		
Education: High school graduate and higher	Percentage of individuals with high school or higher as highest grade completed	Labor Force Survey (LFS)
PSOC: Non-Professionals	Percentage of individuals with occupation classified as Non-Professionals including Clerical Support, Service and Sales Workers, Skilled Agricultural, Forestry and Fishery Workers, Craft and Related Trades Workers, Plant and Machine Operators, and Assemblers, and Elementary Occupations	
Nature of employment: Short term/seasonal/casual	Percentage of individuals with nature of work is Short Term/Seasonal/Casual	
Nature of employment: Worked daily or on weekly basis	Percentage of individuals with nature of work is worked daily or on weekly basis	
Class of worker: Private household	Percentage of individuals who worked for a private household	
Class of worker: Private establishment	Percentage of individuals who worked for a private establishment	
Class of worker: Government	Percentage of individuals who worked for a government entity	
Class of worker: Others (Owned Business)	Percentage of individuals who worked for their own business	

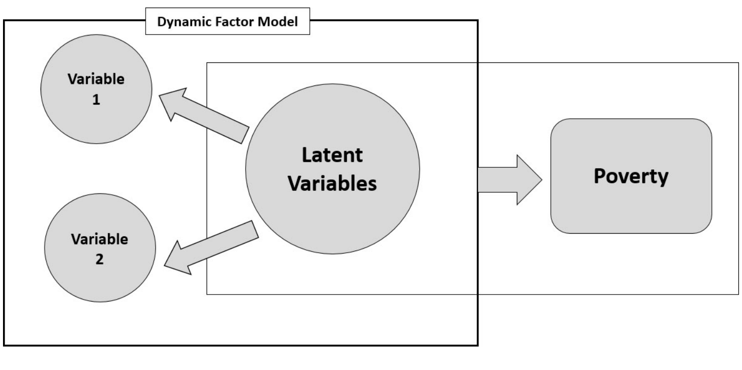

Fig. 3. Diagram for model estimation.

Table 2
Final variables included in the model with the corresponding transformation

Variables	Transformation
Macroeconomic indicators	
Inflation rate	–
Labor force participation rate	First difference
Underemployment rate	First difference
Unemployment rate	First difference
Per capita GDP growth rate	–
Per capita GDP growth rate in agriculture	–
Per capita GDP growth rate in industry	–
Per capita GDP growth rate in services	–
Peso per USD growth rate	–
OFW remittances growth rate	–
Self-Rated poverty	First difference
Demographics and employment information	
Education: High school graduate and higher	First difference
PSOC: Non-professionals	First difference
Nature of employment: Short term/seasonal/casual	First difference
Nature of employment: Worked daily or on weekly basis	First difference
Class of worker: Private household	First difference
Class of worker: Private establishment	First difference
Class of worker: Government	First difference
Class of worker: Others (Owned Business)	First difference

grade completed were also revised considering the new K to 12 programs in the education system.

The changes in the number of categorical variables in the LFS dataset were addressed during data management to ensure consistency of categorical variables throughout the data. Additionally, the DFM will address changes in the LFS master list and adjustments to the variable definition.

3.1.4. Merged poverty, macroeconomic, and employment dataset

The datasets for macroeconomic and LFS employment indicators were combined to create a merged dataset containing all the explanatory variables to be used in constructing the model. Table 2 shows the final variables, and the transformation applied. No transformations were performed for inflation rate, OFW remittances growth rate, and per capita GDP growth rates, and the original values were used in the model. Subsequently, the variables were standardized to have a historical mean of 0 and historical variance unit. The process will reduce the number of DFM parameters to be estimated.

The quarterly macroeconomic and employment dataset was merged with the poverty incidence. The quarterly observations were aggregated annually, resulting in 31-time points, with 11 poverty incidence values observed every three years from 1988 to 2018.

3.2. DFM model and estimation

The interpolation of poverty statistics during non-FIES years was treated as a missing observation problem. The assumption was that the poverty rates during FIES years are manifestations of a dynamic system based on the economy. The macroeconomic fundamentals were assumed to be linked to and affect the poverty rates over time. The general idea was to estimate this dynamic system using the known values of the poverty rates and time-series data from different macro and household demographic variables. Figure 3 shows the conceptual diagram for the model estimation. In this paper, we cast a DFM in a state-space form and apply the Kalman filter for estimation and prediction, an approach that had already been adopted by many studies [36–39].

The state-space model, following Durbin and Koopman's [40], with minor modifications, is given by:

$$\boldsymbol{y}_t = \boldsymbol{Z}_t\boldsymbol{\alpha}_t + \boldsymbol{X}_t\boldsymbol{\delta} + \boldsymbol{\epsilon}_t,\ \boldsymbol{\epsilon}_t \sim N(\boldsymbol{0}, \boldsymbol{H}) \tag{1.1}$$

$$\begin{aligned}\boldsymbol{\alpha}_t &= \boldsymbol{T_{t-1}}\boldsymbol{\alpha_{t-1}} + \boldsymbol{W}_t\gamma + \boldsymbol{c}_t + \boldsymbol{\eta}_t,\\ &\quad \boldsymbol{\eta}_t \sim N(\boldsymbol{0}, \boldsymbol{Q}_t)\end{aligned} \tag{1.2}$$

where $\boldsymbol{y}_t$ is the q-dimensional response vector, $\boldsymbol{Z}_t$ is a qxm-dimensional matrix of state effect, $\boldsymbol{\alpha}_t$ is the vector of state sequence following a Markovian structure, $\boldsymbol{X}_t$ is a qxk-dimensional matrix of exogenous variables with regression effects $\boldsymbol{\delta}$, $\boldsymbol{\epsilon}_t$ is the Gaussian random disturbance of Eq. (1.1) with zero mean and diagonal covariance matrix $\boldsymbol{H}$, $\boldsymbol{T}_t$ is the m-dimensional state transition matrix, $\boldsymbol{W}_t$ is an mxg-dimensional matrix of fully known elements with effects γ, $\boldsymbol{c}_t$ is an m-dimensional state-input vector, and $\boldsymbol{\eta}_t$ is the Gaussian random disturbance of Eq. (1.2) with zero mean and covariance matrix $\boldsymbol{Q}_t$. It is assumed that $E(\boldsymbol{\epsilon}_t\boldsymbol{\eta}_t') = \boldsymbol{0}$. In the literature, Eq. (1.1) is known as the observation or measurement equation, and Eq. (1.2) is called the state or transition equation.

The DFM used in this study is a special case of the state-space model, wherein the state variable includes the common component, a latent or hidden variable that drives the macroeconomic movement, of the observed variables $\boldsymbol{y}_t$. Therefore, $\boldsymbol{y}_t$ is assumed to be determined by the common component and its idiosyncratic movement. The procedure will estimate the model coefficients and, in effect, estimate the missing values in $\boldsymbol{y}_t$. Several approaches with varying complexities and computational rigor could be utilized to operationalize the estimation procedure.

Closely following Mariano and Murasawa [36], the modeling process starts by specifying the DFM and defining its corresponding state-space model.

- P_t^* is the annual poverty incidence, which is observable only every three years;
- P_t is the observed poverty incidence available only every three years;
- $\boldsymbol{x}_t$ is the vector of n time series macroeconomic and demographic variables assumed to be part of the dynamic system, standardized across the available time horizon; and
- t is from $1, 2, \ldots, T$.

Due to the assumed stochastic trend of poverty incidence, we define the differenced series of the variables as follows:

$$\begin{aligned} p_t^* &= P_t^* - P_{t-1}^* \\ p_t &= P_t - P_{t-1} \\ \Delta_3 P_t &= P_t - P_{t-3} \end{aligned}$$

If the latent variable p_t^* is observed, the DFM would be:

$$\begin{bmatrix} p_t^* \\ \boldsymbol{x}_t \end{bmatrix}_{n+1} = \boldsymbol{\mu} + \boldsymbol{\beta} f_t + \boldsymbol{u}_t \tag{2}$$

where the dynamic factor f_t and the components of $\boldsymbol{u}_t$, a vector of order $n+1$, follow an autoregressive structure of order 1 or AR(1). The model assumes that there is only a single factor driving the economy.

We can express $\boldsymbol{\mu}$, $\boldsymbol{\beta}$, and $\boldsymbol{u}_t$ as partitioned matrices following conformability, which yields a system of equations:

$$\begin{cases} p_t^* = \mu_1 + \beta_1 \boldsymbol{f}_t + u_{1t} \\ \boldsymbol{x}_t = \boldsymbol{\mu}_2 + \boldsymbol{\beta}_2 \boldsymbol{f}_t + \boldsymbol{u_{2t}} \end{cases} \tag{3}$$

However, Eq. (3) cannot be estimated since the data for poverty incidence is available only every three years. Thus, we can get the observable $\Delta_3 P_t$ to be on the left-hand side of the first equation.

From the definition of $\Delta_3 P_t$, we have:

$$\begin{aligned} \Delta_3 P_t = P_t - P_{t-3} &= (P_t - P_{t-1}) + \\ &(P_{t-1} - P_{t-2}) + (P_{t-2} - P_{t-3}) \\ \longrightarrow \Delta_3 P_t &= p_t + p_{t-1} + p_{t-3} \end{aligned} \tag{4}$$

Since p_t is an observed series of p_t^*, p_t follows the same structure as p_t^*. Therefore, we now have the reparametrized DFM as follows:

$$\begin{bmatrix} \Delta_3 P \\ \boldsymbol{x}_t \end{bmatrix}_{n+1} = \begin{pmatrix} 3\mu_1 \\ \boldsymbol{\mu}_2 \end{pmatrix} + \begin{pmatrix} \beta_1 \\ \boldsymbol{\beta}_2 \end{pmatrix} \odot \begin{pmatrix} f_t + f_{t-1} + f_{t-2} \\ f_t \boldsymbol{I} \end{pmatrix} + \begin{pmatrix} u_{1t} + u_{1t-1} + u_{1t-2} \\ \boldsymbol{u_{2t}} \end{pmatrix} \tag{5}$$

where $\odot$ is the Hadamard product, $\boldsymbol{I}$ is the identity matrix of dimension $n \times n$, and f_t, u_{1t} and the n components of $\boldsymbol{u_{2t}}$ each follows an AR(1) process.

Rewriting Eq. (5) into a state-space form, the measurement equation is given by:

$$\begin{bmatrix} \Delta_3 P_t \\ \boldsymbol{x}_t \end{bmatrix}_{n+1} = \begin{bmatrix} 3\mu_1 \\ \boldsymbol{\mu}_2 \end{bmatrix} + \begin{bmatrix} \beta_1 & \beta_1 & \beta_1 & 1 & 1 & 1 & \boldsymbol{0} \\ \boldsymbol{\beta}_2 & 0 & 0 & 0 & 0 & 0 & \boldsymbol{I} \end{bmatrix} \boldsymbol{s}_t \tag{6}$$

where $\boldsymbol{s}_t$ is the state vector that follows the following Markovian movement:

$$\boldsymbol{s}_t = \begin{bmatrix} f_t \\ f_{t-1} \\ f_{t-2} \\ u_{1t} \\ u_{1t-1} \\ u_{1t-2} \\ \boldsymbol{u}_{2t} \end{bmatrix} = \begin{bmatrix} \phi & 0 & 0 & 0 & 0 & 0 & \boldsymbol{0} \\ 1 & 0 & 0 & 0 & 0 & 0 & \boldsymbol{0} \\ 0 & 1 & 0 & 0 & 0 & 0 & \boldsymbol{0} \\ 0 & 0 & 0 & \theta & 0 & 0 & \boldsymbol{0} \\ 0 & 0 & 0 & 1 & 0 & 0 & \boldsymbol{0} \\ 0 & 0 & 0 & 0 & 1 & 0 & \boldsymbol{0} \\ 0 & 0 & 0 & 0 & 0 & 0 & \boldsymbol{\Gamma} \end{bmatrix} \boldsymbol{s}_{t-1} + \boldsymbol{e}_t \tag{7}$$

where

- ϕ and θ are the AR coefficients of f_t and u_{1t}, respectively.
- $\boldsymbol{\Gamma} = \mathrm{diag}\{\gamma_1, \gamma_2, \ldots, \gamma_n\}$ is an nxn diagonal matrix with diagonal elements equal to the AR coefficients of the elements of $\boldsymbol{u}_{2t}$,
- $\boldsymbol{e}_t \sim N(\boldsymbol{0}, \mathrm{diag}\{\sigma_1^2, 0, 0, \sigma_2^2, 0, 0, \boldsymbol{\Sigma}\}$; $\boldsymbol{\Sigma}$ is an nxn diagonal matrix containing the variances of the components of $\boldsymbol{u}_{2t}$.

This state-space model was estimated using the Kalman filter through the Multivariate Autoregressive State-Space Modeling (MARSS) package in R. The MARSS package provides maximum-likelihood parameter estimation for linear multivariate autoregressive state-space models fit for multivariate time-series data. Estimability was ensured by setting the first element of $\boldsymbol{\beta}$ to one and standardizing the stationary version of the variables in $\boldsymbol{x}_t$. Moreover, an exogenous dummy variable for 2003 was added in the model to account for the change in the definition of the official poverty statistics.

The number of observations is relatively lower than higher frequency datasets [41,42]. The Philippines only started conducting the FIES in 1985. However, using a higher frequency dataset for this study, such as quar-

Table 3
Computed AIC and AICc of the constructed DFMs

	AIC	AICc
One-factor DFM	1503.68	1505.27
Two-factor DFM	1543.68	1550.13
Three-factor DFM	1583.68	1598.65
Four-factor DFM	1562.01	1589.64

terly or monthly series, may dilute the relationship between the dynamic factor and poverty and extract general macroeconomic movements from the variables instead. We view this as a limitation of the study because the model assumes a fixed effect of the factor on poverty through time. Since poverty is observed every three years, quarterly or monthly data will extend the time when the poverty movement has no observed input to the DFM estimation.

After the model estimation, four DFM models were constructed, with model 1 having one latent factor. Models 2 to 4 are extensions of the DFM model above, with two to four latent factors, respectively. The extension of the DFM model is detailed by [36].

3.3. Model selection and validation

The model selection was based on the Akaike Information Criterion (AIC) and the small-sample corrected AIC (AICc). The DFM with the lowest AICc was then selected as the final model for poverty interpolation.

To measure the accuracy of the generated estimates, the Mean Absolute Error (MAE) was computed for actual and predicted poverty estimates, as well as the determinants of poverty using the formula:

$$\text{Mean Absolute Error} = \frac{\sum_{t=1}^{\mathrm{T}} |y_t - \hat{y}_i|}{T}$$

where: T is the number of observations. y_t is the actual observed values. $\hat{y}_i$ is the predicted values.

To estimate the in-sample MAE of the poverty incidence, the one-step-ahead forecasts were used, denoted by $\hat{P}_{t|t-1} = E(\hat{P}_t|t-1)$, where the expectation is computed using the information set until time $t-1$. Getting expectations:

$$E(P_t|t-1) = E(\Delta_3 P_t|t-1) + P_{t-3}$$

Due to the limited number of observations, all 31 observations are in the estimation of the model. Dividing the data into in-sample and out-of-sample datasets will reduce the number of observations and further affect the estimates.

3.4. Poverty interpolation

The smoothed series was used to produce estimates of the poverty incidence. The filtered series is the expectation given all observations in the information set; for the case of P_t, the filtered series is $\hat{P}_{t|T} = E(\hat{P}_t|T)$. Initial values for the non-FIES years assume that the annualized $\Delta_3 P_t$ from 1988 to 1991 are equal across these two years. $\hat{P}_t$ and P_t were then compared graphically and through distance measures to see how well the model provided poverty incidence estimates between FIES years.

Table 4
MAE of predicted values

Variables	MAE
Poverty incidence among families	2.0
Self-Rated poverty	0.8
Labor force participation rate	0.7
Underemployment rate	0.7
Unemployment rate	0.6
Per capita GDP growth	0.6
Per capita GDP growth in agriculture	0.7
Per capita GDP growth in industry	0.6
Per capita GDP growth in services	0.7
Peso per USD growth	0.7
OFW remittances growth	0.7
Inflation rate	0.6
Education: High school graduate and higher	0.7
PSOC: Non-professionals	0.6
Nature of employment: Short term/seasonal/casual	0.8
Nature of employment: Worked daily or on weekly basis	0.8
Class of worker: Private household	0.8
Class of worker: Private establishment	0.7
Class of worker: Government	0.8
Class of worker: Others (Owned Business)	0.7

4. Discussion of results

4.1. Model selection and validation

As shown in Table 3, one-factor DFM posted the lowest AIC and AICc at 1503.68 and 1505.27, respectively. This indicates that the one-factor DFM exhibits the best model fit for the given data. Table 4 shows the forecast accuracies for all the time series data used in the model. To compute for the MAE, one-step-ahead forecasts of poverty incidence during FIES years were generated to compare observed and predicted values produced by the model.

The predicted values of poverty incidence among families exhibit a relatively low MAE, with only two percentage points. This means that, on average, the predicted values of poverty incidence differ by only two percentage points compared to its actual value. MAEs for the explanatory variables used in the model were also generated to test the model's prediction accuracy further. Low errors, which are interpreted in standard

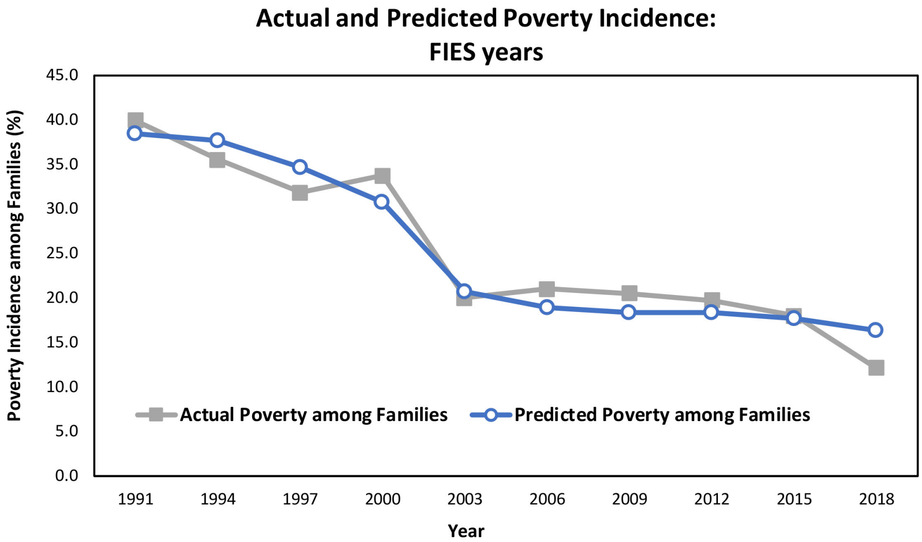

Fig. 4. Comparison of actual and predicted poverty incidence among families during FIES years: 1988 to 2018.

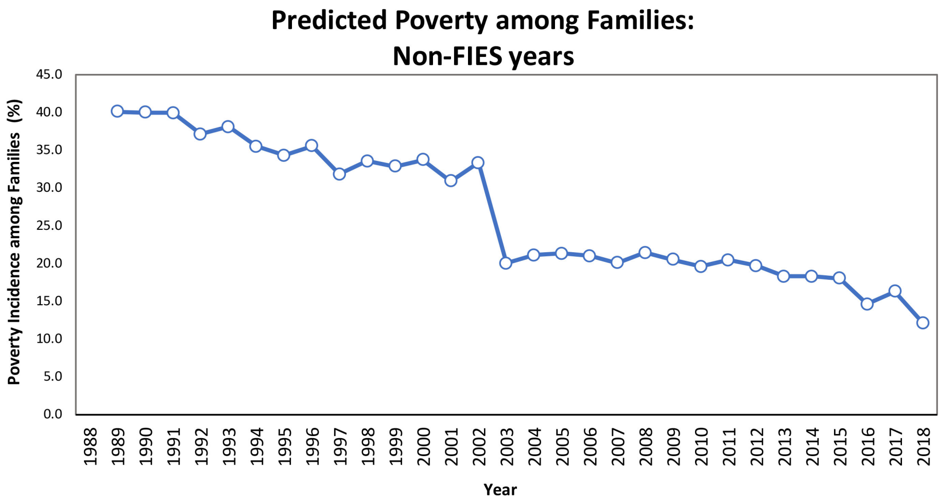

Fig. 5. Historical estimates of poverty incidence among families on Non-FIES years: 1988 to 2018.

deviations, were observed across the standardized explanatory variables used in the DFM.

To better visualize the model's performance, Fig. 4 shows the graph of actual, P_t, and predicted values of Poverty Incidence, $\hat{P}_t$. The predicted values generally move in the same direction as the actual observed values, except for the year 2000, where the predicted poverty incidence declined while the actual rate increased.

4.2. Interpolated poverty statistics on non-FIES years

The factor loadings of the identified variables are presented in Table 5. Noting that higher factor loadings denote strong correlation with the dynamic factor, variables with the highest positive factor loadings are Per Capita GDP Growth Rate, Per Capita GDP Growth Rate in Services, Per Capita GDP Growth Rate in Industry, Class of Worker: Private Establishment, Per Capita GDP Growth Rate in Agriculture, Nature of Employment: Worked daily or on a weekly basis, and Class of Worker: Government. These variables are mainly related to the country's productivity and employment.

Applying the estimation procedure specified in the methodology, annual estimates of Poverty Incidence among Families were generated. In Table 6, $\Delta_3 P_t$ represents the differenced poverty incidence during FIES years, while the $\hat{p}_t$ denote the predicted annual first dif-

Table 5
Factor loadings of determinants of poverty incidence among families

Variables	Factor loadings
Per capita GDP growth rate	56.47
Per capita GDP growth rate in services	53.66
Per capita GDP growth rate in industry	49.24
Class of worker: Private establishment	28.58
Per capita GDP growth rate in agriculture	20.90
Nature of employment: Worked daily or on weekly basis	16.16
Class of worker: Government	16.11
Underemployment rate	5.14
Nature of employment: Short term/seasonal/casual	4.32
Education: High school graduate and higher	3.54
Class of worker: Private household	−8.32
Self-rated poverty	−10.76
Labor force participation rate	−13.60
PSOC: Non-professionals	−15.82
Unemployment rate	−17.96
Inflation rate	−21.52
OFW remittances growth rate	−22.12
Class of worker: Others (owned business)	−29.60
Peso per USD growth rate	−30.05

Table 6
Estimates of poverty incidence among families during non-FIES years

Year	$\Delta_3 P_t$	$\hat{p}_t$	Standard error	P_t	$\hat{P}_{t\|T}$
1988		−2.0345	2.0832	40.2	
1989		−1.2093	1.6631		40.1
1990		−2.1732	2.0826		40.0
1991	−0.3	−0.3000	0.0000	39.9	39.9
1992		−3.0031	2.0065		37.1
1993		−1.8911	1.9883		38.1
1994	−4.4	−4.4000	0.0000	35.5	35.5
1995		−2.8217	1.9883		34.3
1996		−2.5546	1.9883		35.6
1997	−3.7	−3.7000	0.0000	31.8	31.8
1998		−0.7485	1.9883		33.5
1999		−2.6983	1.9883		32.9
2000	1.9	1.9000	0.0000	33.7	33.7
2001		−2.6416	1.9883		30.9
2002		0.4677	1.9883		33.3
2003	−13.7	−13.7000	0.0000	20.0	20.0
2004		0.2300	1.9883		21.1
2005		−1.9936	1.9883		21.3
2006	1	1.0000	0.0000	21.0	21.0
2007		−1.0643	1.9883		20.1
2008		0.0787	1.9883		21.4
2009	−0.5	−0.5000	0.0000	20.5	20.5
2010		−0.4671	1.9883		19.6
2011		−0.9474	1.9883		20.5
2012	−0.8	−0.8000	0.0000	19.7	19.7
2013		−1.3178	1.9883		18.3
2014		−2.1588	1.9883		18.3
2015	−1.7	−1.7000	0.0000	18.0	18.0
2016		−3.6657	1.9884		14.6
2017		−2.0028	2.0545		16.3
2018	−5.9	−5.9000	0.0000	12.1	12.1

ferences of poverty incidence, including those of non-FIES years. Using the estimated annual first differences $\hat{p}_t$ and the actual values of poverty incidence P_t the predicted annual values, $\hat{P}_t$, are then computed given the official poverty statistics as initial values. Note that during FIES years, $P_t = \hat{P}_t$ since $\hat{P}_t$ in this table is the smoothed series as mentioned in the methodology, i.e., $\hat{P}_t = \hat{P}_{t|T}$.

From a value of 40.2 in 1988, predicted poverty estimates are declining, which is consistent with the movement of the actual observed values. Figure 5 demonstrates the movement of predicted poverty estimates from 1988 to 2018. Following the general trend of the actual values, the predicted poverty estimates demonstrate a downward trend, most apparent with the sharp decline in 2003.

5. Conclusion

This study is an attempt to fill data gaps in the official poverty statistics of the Philippines. Because poverty statistics in the Philippines are reported every three years with the conduct of the FIES, this study applied the DFM to interpolate poverty incidence during non-FIES years. The results provide an idea of how poverty changes with developments in the macroeconomy and labor market.

The methodology in the paper can be extended and utilized to produce timely poverty statistics, which is known in the literature as nowcasting. It is recommended to update the model as new information becomes available to improve the interpolation results further and apply the necessary sensitivity analysis to assess the consistency of the interpolation results. Moreover, variable selection methods, such as LASSO regression, partial least squares, and machine learning methods are recommended as more explanatory variables are introduced in the factor model.

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