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Starting Small: Building a Macroeconometric Model of the Philippine Economy

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Abstract

This study presents a small macroeconometric model of the Philippines. The model covers the basic parts of the economy—namely, private consumption and investment, international trade, employment, prices, and basic monetary sectors. Behavioral equations are estimated in error-correction form (using ARDL methodology) on quarterly data from 2002 to 2017. The model's validity is evaluated through various simulation exercises. It generates satisfactory in-sample and out-of-sample predictions for GDP growth, CPI inflation, and employment rate, but is less successful in tracking the movement of domestic interest rates. The model also shows plausible responses to exogenous shocks emanating from government consumption, world oil prices, and global GDP. Briefly, a government spending shock elicits increases in investment and imports, a shock to world oil prices generates faster inflation, while a global recession is transmitted to the domestic economy mainly through lower exports and investment. The next steps needed to extend the model beyond improving the existing blocks include developing the supply side, incorporating expectations, and adding fiscal and financial blocks.

Keywords: macroeconometric model, Philippine economy, forecast, simulation

Table of Contents

List of Tables

List of Figures

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1. Introduction

A scan of the literature reveals a dearth of macroeconometric models in the Philippines today. While new macroeconometric models were still being introduced in the country during the mid-2000s, activity in the area virtually died by the 2010s. This mirrored developments overseas, when major critiques of large-scale macroeconometric models beginning the late 1970s led to a shift towards systems that aimed to build on stronger microeconomic foundations, mainly towards a dynamic stochastic general equilibrium (DSGE) framework, which became the dominant approach by the turn of the century. However, failure of such models to anticipate the global financial crisis (GFC) and Great Recession in 2008/2009—or generate appropriate policies to address the crises—led to a similar disenchantment with the method.

After a re-examination of the macroeconomics field, there appears to be a consensus that different types of macroeconomic models are needed to meet different purposes (Vines and Willis, 2018). To analyze macroeconomic policy issues, Blanchard (2018) recommends approaches that are intended to study the impact of specific shocks and alternative policy scenarios, with such policy models allowed to be less stringent about microfoundations. Wren-Lewis (2018) likewise proposes continued development of models that are closer to the actual data to help improve policy advice, specifically for more traditional structural econometric models, which are arguably still better placed to monitor developments in the economy and note the emergence of important relationships (e.g., between the real economy and the financial sector) than DSGE models. Less restrictive models with greater data congruence are also the type to be successfully maintained over time, indicating an edge in quantitative economic analysis (see Hendry 2020).

In the Philippines, there is certainly room for broader frameworks that can be used for comprehensive policy analysis. There had been a few important macroeconometric models that helped aid government planning in the past, but virtually none seem to have been updated or maintained. DSGE models have also not been developed to take their place. A working structural macroeconometric model is especially needed at times when the country will need to enter unprecedented policy territory, such as during or after a crisis. A system that summarizes interrelationships in the economy, and thus deepens the understanding of these relationships, can provide better guidance than unsighted economic analysis.

In view of this important gap in macro policy research, we present a small macroeconometric model of the Philippine economy. This model will serve as the building block for a larger full-system model. The goal ultimately is to build a tractable and easy-to-maintain macroeconometric model that allows for quick yet sound policy analysis with some degree of forecasting power. Like the small models in recent literature, the macroeconometric model we created initially focuses on the demand side. It covers the basic parts of the economy—namely, private consumption and investment, international trade, employment, prices, and monetary

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sectors. Behavioral equations are estimated in error-correction form (using ARDL methodology) on quarterly data from 2002 to 2017, allowing economic theory and intuition to guide the long-run properties of the model.

The next section provides a brief review of the developments in macroeconomic modeling, from the Great Depression until after the GFC and the Great Recession of 2008/2009 in the US, as well as the concurrent progress in macroeconomic modeling in the Philippines. Section 3 introduces the small macroeconometric model of the Philippine economy constructed based on lessons from earlier experiences in building a working model for policy analysis and forecasting, explaining both model choice and model structure. Section 4 presents the in-sample and out-of-sample simulation results of the model, while Section 5 focuses on impact analysis, namely the effects of shocks to government consumption and world oil prices, and a global recession. Section 6 concludes the paper, outlining future tasks for developing the new Philippine macroeconometric model.

2. Literature review: developments in macroeconometric modeling[2]

2.1. A brief history of macroeconometric modeling

Approaches to macroeconometric modeling have generally followed theoretical developments through the years, with failure to predict important turning points typically leading to a reconsideration of the current dominant method. Hendry (2020) identifies four distinct phases in macro modeling history: (i) empirical demand modeling in the early 1900s; (ii) economic forecasting in the 1920s, which failed during the Great Depression; (iii) empirical macroeconomic system modeling that fell out of favor due to oil crises and stagflation in the 1970s; and (iv) dynamic stochastic general equilibrium (DSGE) modeling, which also faltered during the Great Recession.

The Great Depression could not be explained by the prevailing economic theory, leading Keynes (1936) to study the possibility of equilibrium unemployment and the mechanisms behind it. His ideas[3] were subsequently formalized by Meade (1937), through a complex 9-equation system; Hicks (1937), who extracted the 2-equation IS-LM model from this system; and Samuelson (1951 and 1955), who clarified the interpretation of Keynes' ideas and created a much simpler system in his "neoclassical synthesis" (Vines and Wills, 2018). These marked a shift in economic thinking that led to a golden age of macroeconomic policymaking and macroeconometric modeling.

2.1.1. Golden age of macroeconometric models in the 1950s and 1960s

Several other developments marked the era of large-scale macroeconometric systems during the 1950s and 1960s. One set of advancements had been the provision of macroeconomic data, particularly the computation of national income accounts and related measures. Another included breakthroughs in econometric theory and methods during the mid-1940s, especially

[2] See also Yap (2002), Reyes et al. (2017), and Reyes et al. (2018) for more detailed literature reviews of foreign and domestic trends in macroeconometric modeling.
[3] Keynes' ideas, as generally appreciated, included adding nominal rigidities (particularly in wages) to the macroeconomic analysis and introducing the consumption function, multiplier, and liquidity preference theory to explain a macroeconomic equilibrium with unemployment.

with the creation of the Cowles Commission after World War II.[4] Important papers were also published on stabilization policy, where it was argued that a well-designed fiscal program could be expected to generate good economic outcomes (e.g., Phillips, 1954 and 1957).

The strongest impetus came from the success of large-scale macroeconometric models in predicting the effects of a fiscal stimulus on the US economy in the early 1960s. These included the Brookings and Data Resources Inc. (DRI) models, followed by the FRB-MIT-PENN model, which evolved into the current FRB/US model, and the global macroeconometric models built under Project LINK.

Large macroeconometric models, however, eventually met systematic forecasting failures in the 1970s, amid global oil crises and stagflation. This period, which overlapped with the Great Inflation (1965 to 1982), saw a breakdown of the Phillips curve (which featured a negative relationship between price inflation and unemployment), striking a blow to the theoretical bases of the large empirical models (Hendry, 2020).

2.1.2. The Lucas Critique

Major criticisms of the existing large systems included the Lucas Critique, which noted that "any change in policy will systematically alter the structure of econometric models" (Lucas, 1976, p. 41). This highlighted the issue of structural instability, where estimated coefficients of a macroeconometric model may vary as private actors adjust their behavior in response to a policy change or even as their expectations about policies turn. Simply stated, since economic actors not only learned to adapt to policy changes, but also to anticipate them, models based on historical correlations could produce invalid results. Lucas therefore rejected using such models for policy analysis.

Different areas of macroeconomics and econometrics gained influence after this period, which revealed theoretical and empirical weaknesses of the existing systems. One had been monetarism, with Friedman and Schwartz (1963, 1982) arguing against Keynesian beliefs (and associated aggregate demand policies) and for the role of money (and the need for rules-based monetary policy to maintain macroeconomic stability). This led to the flourishing of monetarist macroeconometric models such as those found at the London Business School (Hendry, 2020). Another had been the use and development of vector autoregression (VAR), which made minimal use of theory, as an alternative technique to large-scale macroeconometric models following Sims' Critique. Sims (1980) proposed this method after noting the 'incredible' identification restrictions imposed, based on prevailing economic theory, on these large macroeconometric systems.[5]

A few other approaches emerged during the period, namely those associated with Hendry (1980) and Leamer (1983). The former, also known as the London School of Economics (LSE) methodology, recommended a "general-to-specific" approach to modeling where theory provided the explanatory variables, while the data revealed the nature of the relationship. This method featured cointegration analysis, thus avoiding spurious regressions when dealing with

[4] The Cowles Commission was a special team formed to develop a more scientific approach to economic modeling and involved prominent personalities such as Tjalling Koopmans, Kenneth Arrow, Trygve Haavelmo, T. W. Anderson, Lawrence Klein, G. Debreu, Leonid Hurwitz, Harry Markowitz, and Franco Modigliani (Valadkhani 2004). Other leading names in empirical macroeconomics during the time were Frisch, Goldberger, Stone, and especially Tinbergen, who built the first estimated macroeconometric system in 1930 (Hendry, 2020).

[5] A VAR model is the vector extension of an autoregressive (AR) model, where all included variables are treated as endogenous, and the reduced form kept unrestricted.

nonstationary macroeconomic data (also a criticism of the large-scale macroeconometric models), and typically involved a battery of diagnostic tests and forecast performance measures. The latter (Leamer) method supported a Bayesian technique, the main idea being that pure macroeconometric modeling could not replace judgment in policy formulation or even in macroeconomic assessment (Bodkin, Klein, and Marwah, 1991; from Valadkhani, 2004).

2.1.3. DSGE Dominance at the turn of the century

The Lucas Critique left an indelible impression on macroeconomic modeling, with theoretical modelers subsequently urged to adopt an optimizing framework with "rational" or "model-consistent" expectations. Lucas and Sargent (1979) stated that new models should incorporate expectations consistent with model-predicted outcomes and describe behavior derived from optimization by economic agents who held such beliefs or forecasts. They argued that only such models could precisely capture how the private sector would respond to external changes, including economic policy shifts, and make policy analysis acceptable. The goal correspondingly turned to investigating the "deep structural parameters" of microfounded models, such as those relating to tastes and technology.

The shift in thinking initially led to the construction of real business cycle (RBC) models characterized by competitive equilibrium with rational expectations (e.g., Kydland and Prescott, 1990). Economic cycles were attributed to productivity shocks in these models rather than to aggregate demand fluctuations, and money and stabilization policies were deemed irrelevant. Yet supposed ineffectiveness of Keynesian policies, which had been the main result of the early RBC models, could not be firmly supported, as further theoretical work (e.g., Fischer, 1977; Taylor, 1980; and Calvo 1983) showed that frictions in price setting, such as staggered changes in wages and prices, meant aggregate demand policies—both monetary and fiscal policy—could still influence output.

This evolution resulted in a broader class of models known as DSGE models, which were designed to have better microfoundations to escape the Lucas Critique. DSGE models started to dominate the field during the 1990s, as the profession switched away from large-scale macroeconometric systems (Cherrier, 2017; Boumans and Duarte, 2019). The New Keynesian DSGE model (essentially, the RBC model with nominal rigidities) became the benchmark framework by the 2000s, being widely taught in graduate schools worldwide.[6] It also became a fixture in many central banks.

DSGE models differed the most in terms of technique from the other models. Unlike traditional macroeconometric systems, which were estimated equation by equation across blocks (sets of equations) using basic least squares techniques then subsequently solved, they often required calibration for most parameters as well as some (Bayesian) estimation. This made them quite hard to statistically validate.[7] Despite great efforts to strengthen theoretical foundations, DSGE models failed to anticipate the Great Recession. Moreover, they were unable to provide the reasons for the crisis or the policies needed to address it. This prompted macroeconomists to embark on a reassessment of their field.

[6] The New Keynesian DSGE models of Smets and Wouters (2007) and Christiano, Eichenbaum, and Evans (2005) are said to form the basis of what can be viewed as the benchmark DSGE model (see Vines and Wills 2018).
[7] Under a calibration approach, parameters would have to be adjusted when the simulated model diverged from actual data.

2.1.4. Rebuilding macroeconomic models

As part of the Rebuilding Macroeconomic Theory Project conducted after the GFC and Great Recession, Blanchard (2018) highlighted the need for five types of macroeconomic models: (i) foundational models, to make a deep theoretical point with no intent to capture reality closely (e.g., Samuelson's consumption-loan model); (ii) DSGE models, to examine macroeconomic implications of distortions or sets of distortions, requiring them to be reasonably close to reality; (iii) policy models, to investigate the dynamic effects of specific shocks and explore the impact of alternative policies, where the aim Is to have a tight fit with the data (e.g., macroeconometric models); (iv) toy models meant to provide quick answers to urgent questions or to simplify a more complex model (e.g., IS-LM and Mundell-Fleming models); and (v) forecasting models, where the sole aim is forecast accuracy (e.g., atheoretical time series models).

Blanchard emphasized that policy models, which are the greater interest of this paper, should capture actual dynamics from the data while having enough theoretical structure to allow a user of the model to map out the effects of policies and shocks.[8] He added that such models should nonetheless be built on solid partial equilibrium foundations and empirical evidence.
In the same project, Hendry and Muellbauer (2018) argued that approximate consistency with relevant theory trumped closer consistency with highly stylized theory that bore little resemblance to reality. Stiglitz (2018) asserted that policymakers would have done far better in predicting the GFC and Great Recession and coping with the fallout if they had used alternative models (such as on housing and financial contagion) even though they were less fully articulated than the existing DSGE models.

Wren-Lewis (2018) meanwhile believed that macroeconomists may have responded better to the Great Recession if more traditional structural econometric models had been developed alongside microfounded ones, as real economy and financial sector linkages may have been more thoroughly explored. He proposed models that were closer to the data, and thus able to give better policy advice than DSGE models, the main value of which would be to improve the internal consistency of workhorse policy models.

In summing up the Rebuilding Macroeconomic Theory Project, Vines and Wills (2018) highlighted two important lessons. First, macroeconomists had to remove the bias for microfoundations in their models and allow greater room for the development and use of policy models. Second, in a related point, they needed to encourage more pluralism in the field.

2.2. Evolution of Philippine macroeconometric models[9]

Until the mid-2000s, macroeconomic modeling in the Philippines had for the most part kept pace with theoretical advances abroad (Yap, 2002). While macroeconometric models were built in the 1970s and 1980s,[10] it was in the 1990s and 2000s when larger full-system models emerged, especially with the later versions of the Philippine Institute for Development Studies-

[8] Blanchard (2018, p. 51) avers that having both a tight theoretical structure and tight fit with the data may be "a dangerous illusion" akin to "the marriage of a carp and a rabbit," adding that the goal of full integration has been proven counterproductive.
[9] Since this section focuses on macroeconometric and comparable modeling, we do not include advancements in computable general equilibrium (CGE) models, although there have also been numerous works in this area on the Philippines. For those interested, Yap (2002) provides a comprehensive review of the development of this class of models in the country until the mid-2000s.
[10] These include macroeconometric models by Encarnacion (1972), Villanueva (1977), Zialcita and Alfiler (1977), Zialcita (1983), and various PIDS-NEDA macroeconometric models (1985, 1987, 1989) (from Reyes and Buenafe, 2001). Velasco (1980) and Bautista (1988) provide comprehensive reviews of macroeconomic modeling in this era.

National Economic and Development Authority (PIDS-NEDA) Annual Macroeconometric Model and the development of the NEDA Quarterly Macroeconometric Model (NEDA-QMM).[11]

2.2.1. The PIDS and NEDA models

The PIDS-NEDA Annual Macroeconometric Model was created to provide a comprehensive framework for the medium-term development plan of the country. Later versions were essentially structuralist models, taking into account supply bottlenecks in some sectors and allowing the economy to settle at less than full employment (Reyes and Yap 1993, Yap 2000). They also had Keynesian elements, with spending specified according to the standard income-expenditure model.

The version presented in Yap (2000) contained four blocks: the real sector (including production, spending, employment, wages, and prices); the fiscal sector; the financial sector; and the external (trade) sector. It had 34 behavioral and 26 identity equations. Improvements over earlier versions include explicit treatment of unique features of the Philippine economy and stronger linkages among sectors.

Reyes and Buenafe (2001) later broadened the framework to include a social sector component to create the NEDA Annual Macro Social Model (AMSM). They also switched the estimation technique from ordinary least squares (OLS) to cointegration analysis through a 2-stage error correction model (ECM). In this method, the first stage determined the long-run relationship among variables, while the second stage captured short-run dynamics as variables adjusted to deviations from the long-run relationship.

The NEDA-QMM (1996 and 2000) was built by a team guided by Peter Pauly of the University of Toronto (Yap, 2002). The model, an intergovernmental agency effort, was of a larger scale than the previous Philippine models, with much greater information requirements. Its structure largely follows that of the PIDS-NEDA annual model but with private consumption disaggregated into food and nonfood components.

As an upgrade to previous models, it tried to capture inflation expectations by estimating an inflation function, then inserting this into the macroeconomic model (after adjusting the variables by one period). The system was estimated following an ECM approach, through an Engle-Granger 2-step procedure. Following the LSE tradition, the method adopted applied a battery of diagnostic tests (for non-normality, serial correlation, and heteroskedasticity) to help ensure the robustness of each equation.

The NEDA-QMM had been used to simulate fiscal policy scenarios for consideration by the interagency Development Budget Coordinating Committee (DBCC) as well as provide empirical support to policy recommendations made by NEDA to Congress. It was last revised and updated in the late 2000s. The last known version of the model (Bautista, Mariano, and Bawagan, 2009) dropped the cointegration methodology and estimated the model equations using simple OLS. While losing the advantages of an ECM approach in dealing with nonstationary macroeconomic data, the model tried to adhere to modern macroeconomic

[11] See Annex 1 for a summary of the features of the various macroeconometric models of the Philippine economy that were introduced during the period 1990-2021.

general equilibrium analysis and provide a stronger theoretical basis for the modeling of inflation expectations. [12] The revision/update had 48 behavioral equations and 56 identities.

2.2.2. Non-government macroeconometric models

In the academe, Rodriguez and Briones (2002) in the early 2000s built the quarterly Ateneo Macroeconomic and Forecasting Model (AMFM) based on the short-run version of the Murphy model of Australia (Murphy 1988). The model had Keynesian elements, capturing slow adjustment of prices and unemployment, and was designed for both forecasting and policy analysis. To this end, its modelers tried to meet several criteria in their specification search—first, estimated parameters were required to be consistent with economic theory; second, equations had to closely track actual data; and third, they also had to pass a series of statistical tests (for serial correlation, heteroskedasticity, and misspecification).

The AMFM had four major blocks (comprising real, government, financial, and external sectors) with 13 stochastic equations, 53 identities, and 3 supplementary equations. Unlike the NEDA models, output in the AMFM was determined from the demand side. Also, the model tried to account for forward-looking inflationary expectations through a fitted regression of an inflation function. Its estimation strategy was unique in that it combined OLS with an ECM-like approach specifically for the production sector, with parameters of the production function obtained through a mix of calibration and estimation techniques. [13]

In the mid-2000s, the Asian Development Bank (ADB), through a team led by Duo Qin of the University of London, developed macroeconometric models of select ADB member countries, also for forecasting and policy simulation. The model designed for the Philippines (Cagas et al., 2006; Ducanes et al., 2005) paid special attention to the government block of the model to enable fiscal simulations, as fiscal and debt burdens of the country were exceptionally high during that period. The estimation strategy highlighted a general-to-specific dynamic specification approach and use of the ECM form.

While the ADB's Philippine model was tagged as a small macroeconometric model, it was medium sized by current standards with eight blocks (private consumption, investment, government, trade, production, price, monetary, and employment sectors), 48 behavioral equations, and 25 identities. It tried to improve on previous models by minimizing the use of impulse dummy variables (which were restricted to seasonal dummies) and by ensuring that behavioral equations had economic meaning and that parameter estimates were robust and time invariant. There was no attempt though to deal with inflation expectations in the model.

2.2.3. Central bank models for inflation targeting

There had been, for the most part, a lull in macroeconometric modeling in the second half of the 2000s and the succeeding decade. In contrast, quantitative research at the *Bangko Sentral ng Pilipinas* (BSP) gained some momentum after the adoption of an inflation targeting framework for monetary policy in 2002. The shift naturally required leveraging all available

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[12] The core block of their model was based on a general equilibrium macroeconomic model with monopolistic competition following Blanchard and Kiyotaki (1989).

[13] In the 2-stage process adopted for the production sector, the first stage involved profit optimization of the representative firm to obtain the equilibrium values of key variables (gross output, exports, imports, domestic goods price, and labor), while the second stage characterized the adjustment of the actual values to their equilibrium values in the stochastic equations.

information to increase precision in inflation forecasting and help monetary authorities avoid a breach of official targets.

Under the new monetary framework, the BSP initially headed in a different direction (that is, away from structural macroeconometric models), making use of small models that focused on anticipating price pressures, especially those coming from known sources. The models used by monetary authorities for macroeconomic forecasting and policy simulation during the transition consisted of: (i) the Multi-Equation Model (MEM), a set of simultaneous equations estimated that aimed to capture the main channels of monetary transmission in the country; and (ii) the Single-Equation Model (SEM), equivalent to the inflation equation of the MEM. The two models were developed under the guidance of Roberto Mariano of the University of Pennsylvania in 1997 with an update in 2013.

Both MEM and SEM remain as workhorse models in the BSP's suite of models. The MEM in its current form comprises equations for inflation, interest rates (relating to government securities of different maturities and bank lending), base money, and oil prices, all of which are estimated using an ECM approach. The monthly year-on-year inflation equation serves as the primary equation, with long-run prices following the quantity theory of money (QTM) but augmented by supply-side variables such as nominal wages and oil prices, and short-run prices explained by supply-side and demand-side variables and inflation expectations. Through additional (non-ECM) equations and identities, the MEM also models the links with GDP growth, the output gap, domestic liquidity, and exchange rates.

Apart from establishing nowcasting models, the BSP has been aiming to add a model with greater structure to its collection. It attempted to develop a small open economy DSGE model "for policy analysis and insight" to complement its workhorse models, with the initial specification and results presented in McNelis et al. (2009, p. 1). However, in 2012, the DSGE model was replaced by the Macroeconomic Model for the Philippines (MMPH), a small-scale semi-structural policy model outlined in Bautista, Glindro, and Cacnio (2013). In 2019/2020, the MMPH was in turn replaced by the Policy Analysis Model for the Philippines (PAMPH).

The PAMPH is based on the Forecasting and Policy Analysis System (FPAS) model blueprint developed by the International Monetary Fund (Alarcon et al., 2020). The BSP subscribes to the FPAS as the framework for analyses needed to support monetary policy formulation. The model basically extends the MMPH by incorporating Philippine-specific features such as a disaggregated consumer price index or CPI (into core, food, and energy components) and remittances from overseas Filipinos and business process outsourcing (BPO) firms.

BSP researchers describe the model as taking a spot between a statistical (time series) model, a VAR, and a DSGE. It is similar to a standard open economy New Keynesian DSGE in that it exhibits the structural, stochastic, and general equilibrium properties of that model; incorporates adaptive and rational expectations of agents; and makes use of calibrated (rather than estimated) parameters. However, it is not strictly microfounded because of the intent to fit the data more closely and to include the country's unique features.

The semi-structural PAMPH contains 15 equations relating to the output gap, Phillips curve, monetary policy rule, and uncovered interest parity (UIP) in addition to external and commodities blocks. The model is re-specified, and the parameters recalibrated as needed, under continuous review and assessment of the BSP.

2.2.4. Current and future advances in Philippine macroeconomic modeling

In general, a scan of the evolution of Philippine macroeconometric models shows only loose correlation with technical/theoretical advances at the turn of the century. The rise in DSGE modeling abroad during the period did not spill over locally except for pockets of activity at the central bank (the abovementioned small open economy DSGE for the BSP built in the late 2000s under the guidance of Paul McNelis of Fordham university), at PIDS (Majuca, 2011), and in academia (e.g., Majuca, 2014; Majuca and Dacuycuy, 2015; Pagaduan and Majuca, 2016).

In the meantime, interest in macroeconometric modeling in the country weakened considerably, mirroring developments overseas, notably as the bias for microfounded models deepened. As far as we know, none of the macroeconometric models of the Philippines that emerged in the 1990s and 2000s remain active today (see Reyes, 2018).

Several other reasons for failure to update and/or upgrade traditional macroeconometric models can be raised. Lindé (2018) notes the hefty requirements of building and maintaining large-scale models in terms of resources and capital. Even the medium-sized ones would require a research team to keep them up and running (e.g., trained staff to tweak the functional forms, handle the data, adjust specifications to fit the data, fix the frontend of the program, and make the model user-friendly for non-specialists, in addition to availability of various experts on important sectors of the economy).

In the Philippines, critical factors are also the retirement, resignation, or relocation of key researchers. There may be lack of continuity if complete program codes (including manuals and other vital documentation) are not turned over or if software become obsolete, requiring a rewriting of the codes for the macroeconometric model. Failure to train able successors may stall progress in model development, especially if glitches occur in the estimation or the system fails to solve with changes in specification or data updates, leading to eventual abandonment of the project.

Lindé (2018) argues that DSGE models, which tend to be smaller, are cheaper to maintain, especially for smaller policy institutions with limited funding, noting the opportunity to hire researchers from universities to work on model development or to consult with prominent academics on various issues regarding macroeconomic theory. This however has proven to be an insufficient condition for coming up with a suitable working model domestically.

The tepid reception for DSGE models among policymakers, even at the central bank, which had the financial resources to put together a research team that can develop such systems, may have been partly a matter of timing. As discussed earlier, there was disillusionment with the method after it failed to anticipate the GFC and Great Recession or offer explanations for the crises during the late 2000s, about the same time that such models were being built locally.

Writing on the use of DSGE models in monetary policy committees, Gerlach (2017) pointed out that such models, despite supposedly having deep structural parameters, failed to display stability when the distribution of shocks changed. Moreover, he said DSGE models in their current state relied on a rather limited number of economic indicators and transmission mechanisms, while policy discussions were often driven by broader research based on a richer set of empirical facts. Like Blanchard (2017, 2018), he remarked on the complex nature of DSGE models which, by not allowing a full narrative, made them ineffective communication devices.[14] Gürkaynak and Tille (2017) noted that many central banks continued to use large-scale macroeconometric models as well as statistical methods such as structural VARs for policy analysis and forecasting alongside DSGE models, in view of the latter's shortcomings.

As discussed previously, the BSP has moved towards establishing a small semi-structural policy model under the FPAS framework (see Laxton, Rose, and Scott, 2009) to complement the central bank's workhorse models, which also allows them to receive technical help from international experts. In mapping the ways forward for the Philippine central bank, Abenoja et al. (2022) report that the research department of the BSP intends to review and improve the PAMPH and eventually make the model its workhorse for monetary policy analysis.

The BSP has also started consultations with the Japan International Cooperation Agency (JICA), to collaborate on projects related to macroeconomic modeling and forecasting; and with the IMF's Institute for Capacity Development (ICD), to obtain technical assistance regarding the extension of the standard Quarterly Projection Model (QPM) for the Philippines (see Guo, Karam, and Vlcek, 2019; and Karam, Pranovich, and Vlcek, 2021). The extended model, which is also New Keynesian in design, incorporates credit cycle and macroprudential blocks to capture responses to shocks in the financial system (such as shocks to credit demand and bank profitability). The intent is to provide the BSP's research team with the capacity to further improve on the PAMPH by including features relevant to monetary policymaking such as credit aggregates and reserve requirements.

Quite recently, the BSP also collaborated with PIDS to create the PIDS-BSP Annual Macroeconometric Model for the Philippines (Reyes et al., 2020), indicating (perceived) usefulness of a more flexible model that can provide a clearer narrative. Additionally, as noted earlier, the PAMPH makes use of a calibration technique akin to that applied in DSGE modeling, a method that may not be as convincing as direct estimation (Blanchard, 2017 and 2018). The PIDS-BSP model closely followed the PIDS-NEDA Annual Macroeconometric Model in overall framework but allowed for greater disaggregation of household spending, wage, fiscal, and external trade sectors. It had four blocks like its predecessor but was much bigger in size with a total of 132 behavioral equations (65 for the real sector, 20 for the fiscal sector, 30 for the trade sector, and 17 for the monetary sector) estimated through an autoregressive distributed lag (ARDL)-ECM method.

3. A small macroeconometric model for the Philippines

3.1. Starting small: model selection considerations

While macroeconomic modelers at home had initially kept abreast of theoretical and empirical developments overseas, a visible break in activity occurred during the DSGE-dominated period. As the literature review has shown, hardly any of the Philippine macroeconometric models built in the 1990s and first half of the 2000s remain active, and yet no institution, whether in government or the academe, has maintained a functional DSGE model.

Despite the shift towards microfounded models in response to the Lucas Critique, many institutions continue to use more traditional macroeconometric models as their main analytic

[14] Other shortcomings of DSGE models stated by Blanchard (2018) include their unappealing/constraining assumptions; unconvincing/questionable estimation technique that relies on a-priori methods (mix of calibration and Bayesian estimation); and similarly unconvincing normative implications.

tool, such as the US Federal Reserve, which has retained the US-FRB model of the US economy. Other central banks have created non-DSGE models, including the Bank of Canada, the Norges Bank, the Reserve Bank of Australia (RBA), and the European Central Bank (Hendry, 2020).

Meanwhile, only a few policy institutions have been able to develop DSGE models in Asia. In a survey recently conducted by the Policy Research Institute of Japan's Ministry of Finance, only three in the region, apart from the BSP, were reported to have built a DSGE model (Yagihashi, 2020). These comprised the Hong Kong Monetary Authority, the Bank of Japan (which maintained the M-JEM model), and the Bank of Thailand.[15]

In building a policy simulation model for India, Mundle, Bhanumurthy, and Das (2011) underscored two reasons why traditional macroeconometric models remained attractive among policymakers despite the Lucas Critique. First, they noted that not all policy choices require selecting among alternative policy rules and that some choices simply fall within a given rule. Therefore, policy choices need not alter behavior or lead to structural changes in the economy.[16]

Second, they claimed that the information requirements of microfounded models are often exceedingly large and unavailable, especially in the case of developing economies. This being so, they argued that (Bayesian) DSGE models, while remaining an important field of research, may not yet be viable tools for studying alternative policy options.

For examining the effects of changes in policy, Blanchard (2018) recommended policy models that closely fit the data but are less stringent about microeconomic foundations, in contrast to DSGE models which are more closely tied to theory. Wren-Lewis (2018) similarly argues for models that are closer to the data—specifically, for more traditional structural econometric models that can help improve policy advice.

Lately, new types of models such as the RBA's Macroeconomic Relationships for Targeting Inflation (MARTIN) model have emerged, taking the place between a fully data-driven system and one guided solely by theory (Cusbert and Kendall, 2018). According to its developers (Ballantyne et al., 2019), the goal of MARTIN is to strike a balance between 'empirical realism' and 'theoretical rigor.' Its key feature is the flexibility in incorporating economic mechanisms that policymakers know to be important while also matching observable relationships in the data.[17]

Starting with the current paper, we move in a similar direction and embark on a research program to build a policy model that is guided by economic theory yet still able to fit the data reasonably well. Learning from local experience with building and sustaining macroeconometric models for policy analysis and prediction, we adopt a pragmatic approach and aim for usability, tractability, and ease of maintenance of the model, in addition to model validity and robustness.

[15] As mentioned earlier, the BSP's DSGE model (McNelis et al., 2009) was replaced by the MMPH in 2012 as complement to the monetary authority's workhorse models (the SEM and MEM). The MMPH, in turn, was replaced by the PAMPH.

[16] This is similar to the argument of Leeper and Zha (2003) who state that many policy options involve 'modest policy interventions' (i.e., minor shifts from standard policy settings). Such modest interventions, the authors stated, do not significantly change agents' beliefs about the policy regime nor induce changes in their behavior, in contrast to what had been emphasized by Lucas (1976) in his famous critique.

[17] Introducing features specific to a country, for instance, may be difficult to do in a model derived from a single theoretical framework as in a DSGE model. The downside of course is that causal mechanisms in such a model are less clear than in a DSGE model making it hard to interpret the drivers of some relationships.

As earlier discussed, developing and maintaining a macroeconometric model, even a medium-sized one, would require a substantial amount of resources and capital, both financial and human. In view of the constraints, we start with a small model of the Philippine economy consisting of 5 blocks containing 10 behavioral equations, 5 identities, and 23 variables, 16 of which are endogenous variables. It covers the basic parts of the economy—namely, private demand, international trade, employment, prices, and in rudimentary form, financial and monetary sectors.

As in some macroeconometric models of comparative size in contemporary literature (e.g., Kasimati and Dawson, 2009; Hammersland and Traee, 2014), our model focuses initially on the demand side. However, it is meant to be a building block for a larger system down the road, as more sectors and linkages deemed important for policy analysis—and variables that policymakers typically monitor given their known influence on economic activity—are incorporated and developed. It is geared mainly towards policy analysis, though it aims for some degree of forecasting power.[18]

Following most macroeconometric models in recent literature, including MARTIN, we use the ECM form for most behavioral equations.[19] This not only helps us solve econometric issues associated with nonstationary macroeconomic data but also allows us to impose a theoretically coherent structure on the model's long-run properties while retaining flexibility to capture short-run dynamics from the data (Ballantyne et al., 2019). More concretely, the ECM framework allows us to incorporate economic theory and intuition through our choice of variables in the equations defining long-run equilibrium relationships as well as to account for short-term empirical relationships observed in the data.

3.2. Data and estimation method

The data used in the model consists of quarterly series from 2002 to 2017, though some series begin at a later date for various reasons.[20] The sample coincides with the BSP's adoption of inflation targeting as the country's monetary framework beginning 2002 and includes the GFC of 2008/2009. Though the data are readily available, we exclude the COVID-19 pandemic years of 2020 and 2021 because of the atypical economic behavior and business settings during the period. We also set aside data from 2018 to 2019 for use in model evaluation, particularly for assessing out-of-sample forecast performance.

Table 1 summarizes the basic features of the data used in constructing the model. Data series were seasonally adjusted using the X-13 routine in EViews. Augmented Dickey-Fuller tests were applied to determine the order of integration of the variables. Appendix A displays the results of the unit root tests, with most reported to be of order $I(1)$, except for three that were stationary in levels.

[18] Thus, model building in this paper was especially guided by the following selection criteria: consistency with economic theory or intuition (parameters with correct signs or estimates that were in line with expectations, ideally statistically significant); correct specification of each behavioral equation; parameter constancy/stability; and close fit with the empirical data. This is apart from meeting standard diagnostic tests for linear regressions.

[19] This paper uses an ARDL-ECM method, which allows for estimation of long-run (cointegrating) relationships among variables of different orders of integration. Further details of the empirical method applied are discussed in Section 3.2.

[20] The employment rate series starts in the second quarter of 2005 due to an important break in the definition of labor force participation, while the series on the retail price of rice begins in the fourth quarter of 2004.

Behavioral equations were estimated using the ARDL method in ECM form. Lag lengths were optimally selected using the Akaike Information Criterion restricted to a maximum of 2 lags. Cointegration between level variables was tested using the bounds test approach developed by Pesaran, Shin, and Smith (2001). We chose specifications such that estimated coefficients of variables that enter the long-run equation display signs that are consistent with theory; variables with parameters that failed to conform with expectations based on either theory or intuition were relegated to the short-run equation or omitted altogether. In cases where the bounds test indicated the absence of cointegration, behavioral relationships were modeled as a short-run equation in first differences. Residual diagnostic checks testing for homoskedasticity, serial correlation, and normality were performed to ensure model adequacy.

We used EViews to solve the model, combining estimated behavioral equations and identities to obtain the dynamic numerical solution for simulation.[21] Various simulation exercises were subsequently conducted to validate the model.

Table 1. Data summary

Variable	Obs.	Mean	Std. dev.	Min	Max
Gross Domestic Product (GDP)*†	64	14.83	0.25	14.42	15.29
Consumption*	64	14.55	0.23	14.16	14.97
Investment*	64	13.17	0.39	12.61	13.93
Government consumption*	64	12.60	0.29	12.18	13.13
Imports*	64	13.66	0.30	13.29	14.38
Exports*	64	13.48	0.27	12.99	14.06
Domestic demand*	64	14.89	0.26	14.50	15.39
Tax revenues*	64	12.75	0.29	12.22	13.34
Global GDP*	61	14.09	0.07	13.95	14.22
Employment rate (%)	48	93.09	0.75	91.91	94.73
Consumer Price Index (CPI)*	64	4.31	0.19	3.99	4.57
Inflation rate (%)	64	3.66	1.96	-0.04	9.82
World oil price (USD per barrel) *	64	4.08	0.49	3.05	4.77
Retail price of rice (USD per ton) *	53	6.46	0.26	5.88	6.81
Bank lending rate (%)	64	7.68	1.84	5.43	10.83
Real bank lending rate (%)	64	4.02	1.82	-0.95	7.71
91-day Treasury rate (%)	63	3.48	2.18	0.00	7.83
Real 91-day Treasury rate (%)	63	-0.11	2.08	-4.12	4.15
Central bank policy rate (%)	64	5.08	1.61	3.00	7.50
Nominal PHP-USD exchange rate*	64	3.87	0.09	3.71	4.03
Inflation target (%)	64	4.13	0.72	3.00	5.50

Notes: GDP, consumption, investment, government consumption, imports, exports, domestic, demand, and tax revenues were in millions of pesos in 2018 prices. Global GDP is the trade-weighted aggregation of the real GDPs (2014 prices in million USD) of the Philippines' major export partners in (see footnote 42).

* Log-transformed variables.

† GDP is equal to sum of aggregate demand components, omitting statistical discrepancy.

Source: Authors' calculation.

3.3. Model structure

Figure 1 illustrates the model's structure and linkages, while Table 2 enumerates the model's variables and equations in simplified form. We initially adopt a stylized framework with output determined from the aggregate demand side in the spirit of earlier Keynes-based models and

[21] The model was solved using the Broyden solution algorithm. For a description, see IHS Markit (2020, pp. 1044, 1324).

some small macroeconometric models in recent literature. The model consists of a domestic demand block (consumption and investment), a trade block, an employment block, a monetary block, and a price block. Exogenous variables influencing the system include government spending, world income, the real effective exchange rate, the peso-dollar exchange rate, and world oil and domestic rice prices. We provide a description of each block below, with estimation results summarized in Appendix B.[22]

3.3.1. Domestic demand block[23]

The long-run equation for consumption is formulated as a function of disposable income, defined as the difference between GDP and tax revenues (in turn determined by GDP); the employment rate; the real bank lending rate; and inflation.[24] As in Kasimati and Dawson (2009), the latter is included to capture wealth effects in the absence of an appropriate indicator. Meanwhile, short-run consumption growth is mainly a function of its own lag. In line with accelerator theory, long-run investment is cast as a function of GDP. Investment growth, however, is additionally influenced by changes in the real bank lending rate in the short run, though the impact is statistically insignificant.[25]

3.3.2. Trade block

The trade block consists of behavioral functions for exports and imports. The long-run equation for exports is specified as a function of world income (constructed from a trade-weighted aggregation of the GDP indicators of the Philippines' major export partners)[26], imports, and the real effective exchange rate. Short-run export growth is mainly influenced by import growth, reflecting the country's intermediate role in global production. Imports, on the other hand, are driven by private investment and exports in the long run. We omit the real effective exchange rate as an explanatory variable from the levels equation of imports because the estimated coefficient takes the wrong sign (positive instead of negative). The same set of variables in first differences is shown to be influential for import growth in the short run.

3.3.3. Employment block

The employment block consists solely of the specification for the domestic employment rate. We adopt a version of Okun's Law and model aggregate employment as a function of GDP. The country's employment rate is cast as a function of GDP in the long run, while changes in the employment rate depend solely on changes in its own lag in the short run. We do not formulate employment and labor force participation as separate behavioral functions, since such treatment is not required by the model in its current form, given limited aggregate supply dimensions.

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[22] Appendix B shows the estimated equations as well as the results of the bounds and residual diagnostic tests.

[23] Domestic demand is computed as the sum of private consumption, investment, and exogenous government consumption, while GDP is the sum of domestic demand and net exports.

[24] We also estimated long-run specifications that included remittances, given their presumed strong role in driving economic activity, but estimated coefficients took the wrong (negative) sign, and the variable was eventually dropped.

[25] This representation is taken as the estimated coefficient of the real bank lending rate in levels takes the wrong sign (should be negative, based on theory).

[26] The countries included in the trade-weighted aggregate world GDP are Singapore, Malaysia, and Thailand from Southeast Asia; Japan, Hong Kong, and South Korea from East Asia; the United States and Mexico from North America; and Netherlands, Germany, France, and the United Kingdom from Europe. On average, these economies comprise 74.88 percent of the market for Philippine exports from 2002 to 2019. The quarterly series used for each country is real GDP in 2014 prices converted to US dollars. The following major export partners were omitted: China (accounting for an average of 10.4 percent of exports during the period) and Taiwan (4.22 percent) due to the absence of comparable quarterly GDP data; and Vietnam (1.05 percent) and Indonesia (1.10 percent) due to their GDP series being short (starting only in 2010).

3.3.4. Monetary block

Given the shift to an inflation targeting framework, monetary policy is represented by the central bank's policy rate (the overnight reverse repurchase rate or RRP rate). In the absence of long-run cointegration among variables, the policy rate is modeled as a short-run equation, where the monetary authority responds to the difference between the inflation rate and the inflation target.[27] The policy rate in turn influences the long-run path of the 91-day Treasury bill rate, which then drives the bank lending rate in the short and long run. Movements in monetary policy are thus transmitted to the real economy through the (real) bank lending rate, which affects both consumption and investment.

3.3.5. Price block

We model the consumer price index (CPI), which is the country's most closely monitored index, as a short run equation driven by domestic demand, supply-side factors (the exogenous world price of oil and retail price of rice), and the (nominal) peso-dollar exchange rate.[28] This specification has similar elements as the BSP's SEM and MEM, which are the Philippine monetary authority's most commonly used models in making policy decisions. The inflation rate is computed as the year-on-year change in the CPI.

[27] Specifications of the policy rate equation incorporating a variable that represented economic activity, as in a standard Taylor Rule, were not used because of wrong signs on the estimated coefficients (negative instead of positive). Both output gap and GDP growth rate were considered in the estimation.

[28] The CPI was initially modeled as an ECM with money supply (M3 as a percentage of GDP) as the long run determinant following the quantity theory of money. However, bounds tests showing the lack of evidence for cointegration between the two variables led us to specify the CPI equation as a short-run model.

Figure 1. Model structure

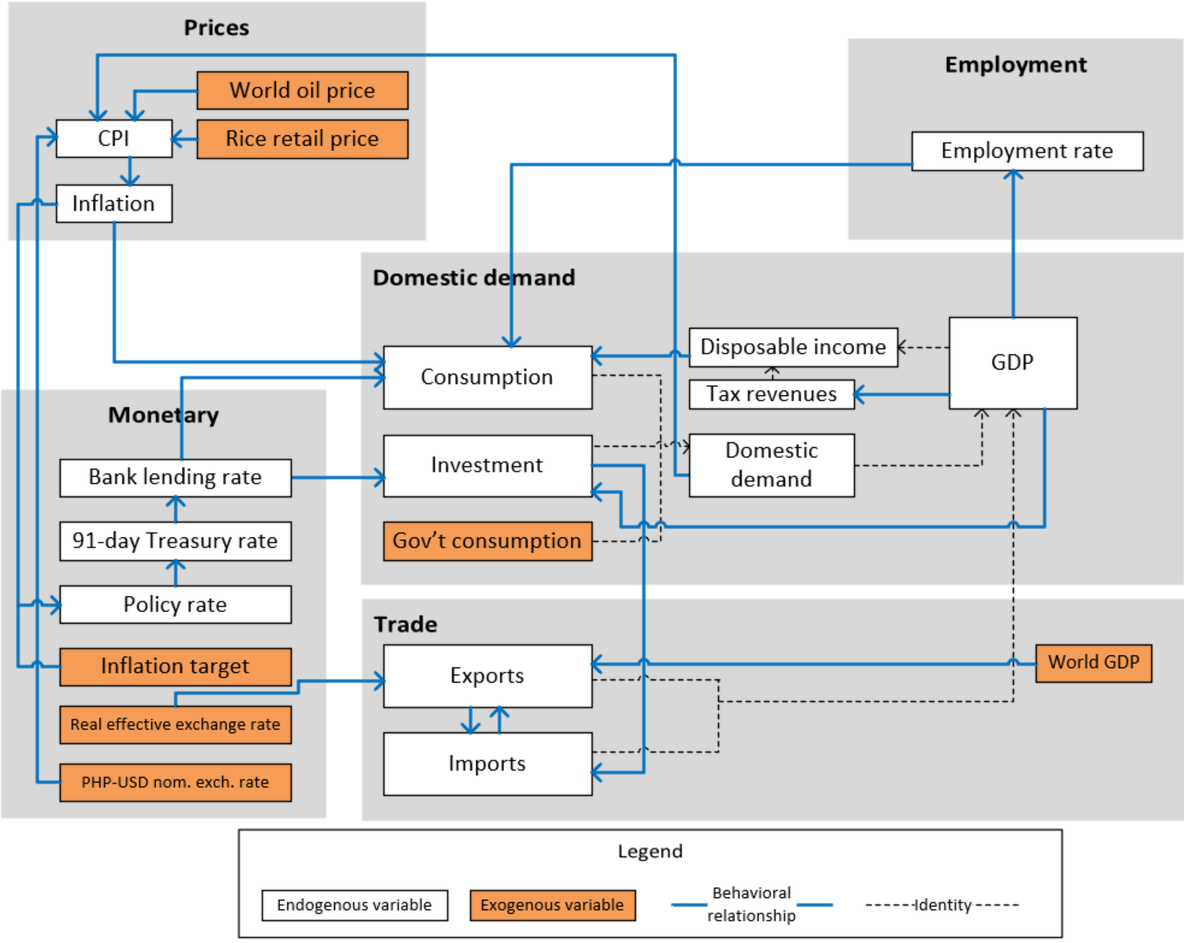

Table 2. Model equations and variables

Equations	Variables
Aggregate demand block	
$\log(C_t) = f(\log(YD_t), \widetilde{r_t}, \pi_t, emp_t)$	*C* = private consumption*
$\log(I_t) = f(\log(Y_t), \Delta\widetilde{r_t})$	*I* = investment*
$\log(TX_t) = f(Y_t)$	*G* = government consumption
$Y_t \equiv C_t + I_t + G_t + X_t - M_t$	*TX* = tax revenues*
$DD_t \equiv C_t + I_t + G_t$	*Y* = GDP*
$YD_t \equiv Y_t - TX_t$	*DD* = domestic demand*
	YD = disposable income*
Trade block	
$\log(X_t) = f\left(\log(Y_t^{World}), \log(M_t), \log(reer_t)\right)$	*X* = exports*
$\log(M_t) = f(\log(I_t), \log(X_t))$	*M* = imports*
	Y^{World} = major trading partners' GDP
	reer = real effective exchange rate
Employment block	
$emp_t = f(Y_t)$	*emp* = employment rate*
Monetary block	
$tr_t = f(rrp_t)$	*tr* = 91-day Treasury rate*
$r_t = f(tr_t)$	*r* = bank lending rate*
$\Delta rrp_t = f(\Delta(\pi_t - \pi_t^T))$	*rrp* = BSP policy rate*
$\widetilde{tr_t} \equiv tr_t - \pi_t$	$\widetilde{tr}$ = real 91-day Treasury rate *
$\widetilde{r_t} \equiv r_t - \pi_t$	$\tilde{r}$ = real bank lending rate*
	π^T = BSP inflation target
Price block	
$\Delta\log(CPI_t) = f(\Delta\log(oil_t), \Delta\log(rice_t), \Delta\log(DD_t), \Delta\log(er_t))$	*CPI* = Consumer Price Index*
$\pi_t = \log(CPI_t) - \log(CPI_{t-4})$	π = inflation*
	oil = world price of oil
	rice = retail price of rice
	er = PHP-USD nominal exchange rate

Note: * Endogenous variable.

4. Model evaluation

In this section, we assess the ability of the model, simulated as a complete system, to generate forecasts that are close to the actual data. Both in-sample and out-of-sample model evaluations are presented.

For in-sample evaluation, we generated forecasts for the period 2012Q1 to 2017Q4 through static and dynamic simulations in a deterministic setting, where model inputs are held fixed at their known values and endogenous variables follow a single path over the forecast period.

Static simulation produces a series of one-period ahead forecasts using actual (historical) values for lagged endogenous variables, while dynamic simulation uses values for lagged endogenous variables that are predicted (solved) based on previous periods.

For out-of-sample evaluation, we generated forecasts for the period 2018Q1 to 2019Q4, which are beyond the estimation period, through dynamic stochastic simulations, incorporating uncertainty in the projections. Five thousand simulations using bootstrapped innovations were performed, yielding a distribution of forecast paths for endogenous variables. The innovations were randomly drawn from the estimation residuals of each behavioral equation and then added to these equations.

We compute several measures to formally gauge forecast accuracy. For real GDP and its components, where forecast deviations are more easily interpreted in percentage terms, we use the mean absolute percentage error (MAPE). For variables already expressed in percentage form (e.g., rates of change), where errors are better measured in percentage-point deviations, we use the mean absolute error (MAE) to assess their forecasts.

For comparability across variable types, we use the normalized root mean square error (NRMSE) with the sample standard deviation as the normalizing parameter to assess forecast performance. This measure is interpreted as the ratio of the overall forecast deviation with the overall variation of the data around its mean. NRMSEs that are close to zero are considered good forecasts, while those above 1 are considered poor.

The formulas of the three measures are as follows:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right|$$

$$MAE = \sum_{t=1}^{n}\frac{|A_t - F_t|}{n}$$

$$NRMSE = \frac{\sqrt{\sum_{t=1}^{n}\frac{(A_t - F_t)^2}{n}}}{\widehat{\sigma_A}}$$

where n is the number of observations, A_t are the actual values, F_t are the forecast values, and $\widehat{\sigma_A}$ is the sample standard deviation of A_t.

4.1. In-sample forecast performance

Figure 2 illustrates the in-sample forecasts alongside the historical data, while Table 3 presents predictive accuracy statistics. Next-quarter forecasts of real GDP and its components track actual data quite well in both static and dynamic simulations, while those of next-quarter (annual) GDP growth are able to capture many important turning points in the data (Figure 2).

GDP and its largest component, consumption, have the smallest prediction errors among real variable forecasts, with absolute percentage deviations of less than 1 and 2 percent on average, respectively, for static and dynamic simulations (Table 3).[29] Investment forecasts, on the other hand, have the largest deviations from historical values, followed by exports and imports, with

[29] Static predictions are naturally more precise than dynamic predictions, as forecast errors do not cumulate across periods.

MAPEs of above 2 percent in all simulations. However, NRSMEs are generally low for real variables, at far below 1 for both static and dynamic forecasts.

As GDP is modeled as an identity (sum of aggregate demand components), growth predictions may lose accuracy as they absorb the forecast errors of the components. Yet mean absolute errors of 0.67 and 0.87 of a percentage point, respectively, for static and dynamic quarter-ahead GDP growth projections, appear to be within an acceptable range.

Figure 2 shows simulations produce accurate representations of quarter-ahead inflation until 2015, after which dynamic forecasts diverge from historical data. Forecast errors are nonetheless still relatively low for both static and dynamic simulations of inflation. Employment rate projections also deviate minimally from actual values but are unable to capture the swings in the data.

Static forecasts of the policy rate mimic historical movements of the series, while dynamic forecasts seem to capture just the general trend. Similarly, while projections of the 91-day Treasury bill rate and bank lending rate from static simulations can replicate the path of actual data, projections from dynamic simulations are unable to do so. Static and dynamic predictions of real interest rates generally do a better job of mirroring the swings in the data than their nominal counterparts, largely because of the model's mostly good performance in predicting inflation.

Forecast errors are generally small for interest rate variables in static simulations, except for the bank lending rate. They tend to be much higher in dynamic simulations, particularly as measured by NRMSEs, which are above 1 for forecasts of the policy rate (1.20) and the 3-month Treasury bill rate (1.76) and exceed 5 for forecasts of the bank lending rate in nominal terms, reflecting well-known difficulties of reproducing the long-run behavior of such variables.

4.2. Out-of-sample evaluation

Figure 3 illustrates the dynamic stochastic out-of-sample forecasts, with the red broken lines depicting the average forecast path and outer orange lines representing 95-percent confidence bounds. Table 4 provides the corresponding accuracy statistics based on deviations of the mean forecast with actual data.[30]

Simulations show that out-of-sample quarter-ahead projections of GDP, mainly because of consumption performance, continue to compare reasonably well with actual outcomes (Figure 3). Absolute percentage errors of both forecasts are substantially less than 2 percent on average, while NRMSEs lie comfortably below 1 (Table 4). As had been the case with in-sample forecasts, the model's out-of-sample predictions for investment, exports, and imports are less precise than those for consumption, with MAPEs of between 2 to 5 and NRSMEs close to or above 1. The wider confidence bands of the three demand components (especially, investment) also reflect a high degree of uncertainty.

Out-of-sample forecasts of next-quarter GDP growth deviate by 1.33 percentage points on average from actual values, which does not pale in comparison with the record of established

[30] Mean forecast paths of endogenous variables and their corresponding accuracy statistics vary slightly with each stochastic simulation.

forecasters with a large amount of resources and using a wide array of techniques.[31] The stochastic predictions for inflation also perform well, with the mean dynamic forecast replicating the historical path quite closely and with relatively small errors—mean absolute error at 0.56 of a percentage point and NRMSE of just 0.34. [32]

As observed under in-sample simulations, out-of-sample employment rate projections continue to exhibit low absolute percentage errors (MAE of half a percentage point) but fail to track actual data. Mean forecasts of the interest rate variables are less satisfactory, with larger absolute errors (higher than 1 percentage point on average) and NRMSEs greater than 1. Deviations are largest for short-term interest rates, as reflected by the policy rate and especially the 91-day Treasury bill rate, with mean absolute errors of 1.26 and 2.85 percentage points, respectively, and NRSMEs that are above 2.

Figure 3 shows how stochastic predictions of the central bank policy rate are unable to capture the monetary policy tightening observed in 2018, with the flat trajectory mirrored in the forecasts of the 91-day Treasury rate and bank lending rate. Meanwhile, actual values of the 91-day Treasury bill rate during the forecast period lie outside of the model's 95-percent confidence band, indicating a failure to adequately forecast the series.

[31] As an indication, the mean absolute error of current-year forecasts of GDP growth published by the Asian Development Bank (ADB) in its Asian Development Outlook Update (ADOU, regularly released in September) for the years from 2008 to 2011, which included crisis years, was 0.96 of a percentage point; the comparative figure computed by the IMF and published in the World Economic Outlook Update (WEOU, regularly released in October) was 1.94 percentage points (Ferrarini, 2014). For the period from 2000 to 2006, the comparative figure for the ADOU was 0.93 of a percentage point (ADB, 2007). The MAEs are clearly not directly comparable, as the forecasts referred to by the mentioned study are of full-year GDP growth, but one can argue that the information content is similar, with actual performance of the first half of the year already known prior to estimation. On the other hand, the values for the exogenous variables used in our model forecasts are simply assumed to be at close to historical values.

[32] The model's performance in inflation forecasting (specifically, MAE of 0.55 percentage point) compares well with that of the ADOU and WEOU for the years 2008 to 2011—with MAEs of current-year full-year inflation projections calculated to be equal to 0.52 and 1.44 percentage points, respectively (Ferrarini, 2014). The comparative figure for the ADOU was 0.89 of a percentage point for the years from 2000 to 2006 (ADB, 2007). Similar qualifications apply as in the case of GDP growth forecast comparisons (see previous footnote).

Figure 2. In-sample simulations

Source: Authors' calculations

Table 3. In-sample forecast accuracy, 2012Q1 – 2017Q4

	Static		**Dynamic**	
I. Real variables	**MAPE (%)**	**NRMSE**	**MAPE (%)**	**NRMSE**
GDP	0.67	0.08	1.80	0.18
Consumption	0.29	0.03	1.79	0.22
Investment	3.41	0.17	6.16	0.34
Exports	2.00	0.14	2.69	0.21
Imports	2.98	0.14	5.05	0.31
II. Rate variables	**MAE**	**NRMSE**	**MAE**	**NRMSE**
GDP growth rate	0.67	0.85	0.87	1.08
Employment rate	0.29	0.51	0.33	0.59
CPI inflation rate	0.28	0.30	0.77	0.89
Policy rate	0.15	0.64	0.42	1.20
91-day Treasury rate	0.32	0.66	0.98	1.76
Real 91-day Treasury rate	0.44	4.00	1.15	1.00
Bank lending rate	0.16	1.49	0.78	5.76
Real bank lending rate	0.36	0.39	1.08	1.20

Note: MAPE = mean absolute percentage error, MAE = mean absolute error, NRMSE = normalized root mean squared error.
Source: Authors' calculation.

Table 4. Out-of-sample accuracy of mean dynamic stochastic forecast, 2018Q1 – 2019Q4

I. Real variables	MAPE	NRMSE
GDP	1.75	0.67
Consumption	1.01	0.37
Investment	5.12	1.58
Exports	2.13	1.03
Imports	3.10	0.99
II. Rate variables	MAE	NRMSE
GDP growth rate	1.33	3.63
Employment rate	0.48	1.11
Inflation rate	0.56	0.34
Policy rate	1.26	2.23
91-day Treasury rate	2.85	2.72
Real 91-day Treasury rate	2.80	1.67
Bank lending rate	1.00	1.88
Real bank lending rate	1.26	0.70

Source: Authors' calculation.

Figure 3. Out-of-sample dynamic simulations

Source: Authors' calculation.

5. Impact analysis (analytic shocks)

To further test the model, we introduce impulse (temporary) shocks to the exogenous variables and examine the reaction of the endogenous variables relative to their baseline paths from the deterministic dynamic simulation. We consider three shocks: (i) a positive shock to government consumption, (ii) a positive shock to world oil prices, and (iii) a recession in the country's major export partners. The succeeding figures illustrate the simulation results, with the green lines representing the baseline path of the variables and the red broken lines depicting the shocked paths.

5.1. Government consumption shock

In this simulation experiment, we raise government consumption by 10 percent relative to its baseline path for all quarters of 2013. The results are illustrated in Figure 4.

During the shock period, investment and imports rise considerably relative to the baseline (by an annual average of 6.32 percent and 2.71 percent, respectively).[33] GDP growth in turn rises by an average of 1.82 percentage points above the baseline rate in 2013. The increase in GDP is short-lived, disappearing almost entirely by the first quarter of 2014. The cumulative government spending multiplier during all four quarters of the shock is 1.62,[34] which is higher than the short-term fiscal multipliers computed for the Philippines in the empirical literature.[35]

Higher domestic demand causes the inflation rate to inch up to above its baseline path, by about 0.41 percentage points by the fourth quarter of 2013, before starting to reverse thereafter. However, the response of the monetary policy rate to higher inflation is quite small. Treasury bill and bank lending rates nonetheless follow the policy rate and rise incrementally. Overall, there is slight evidence of a "crowding-out" effect as private investment dips below its baseline path after the public spending shock due partly to higher Treasury bill and bank lending rates.

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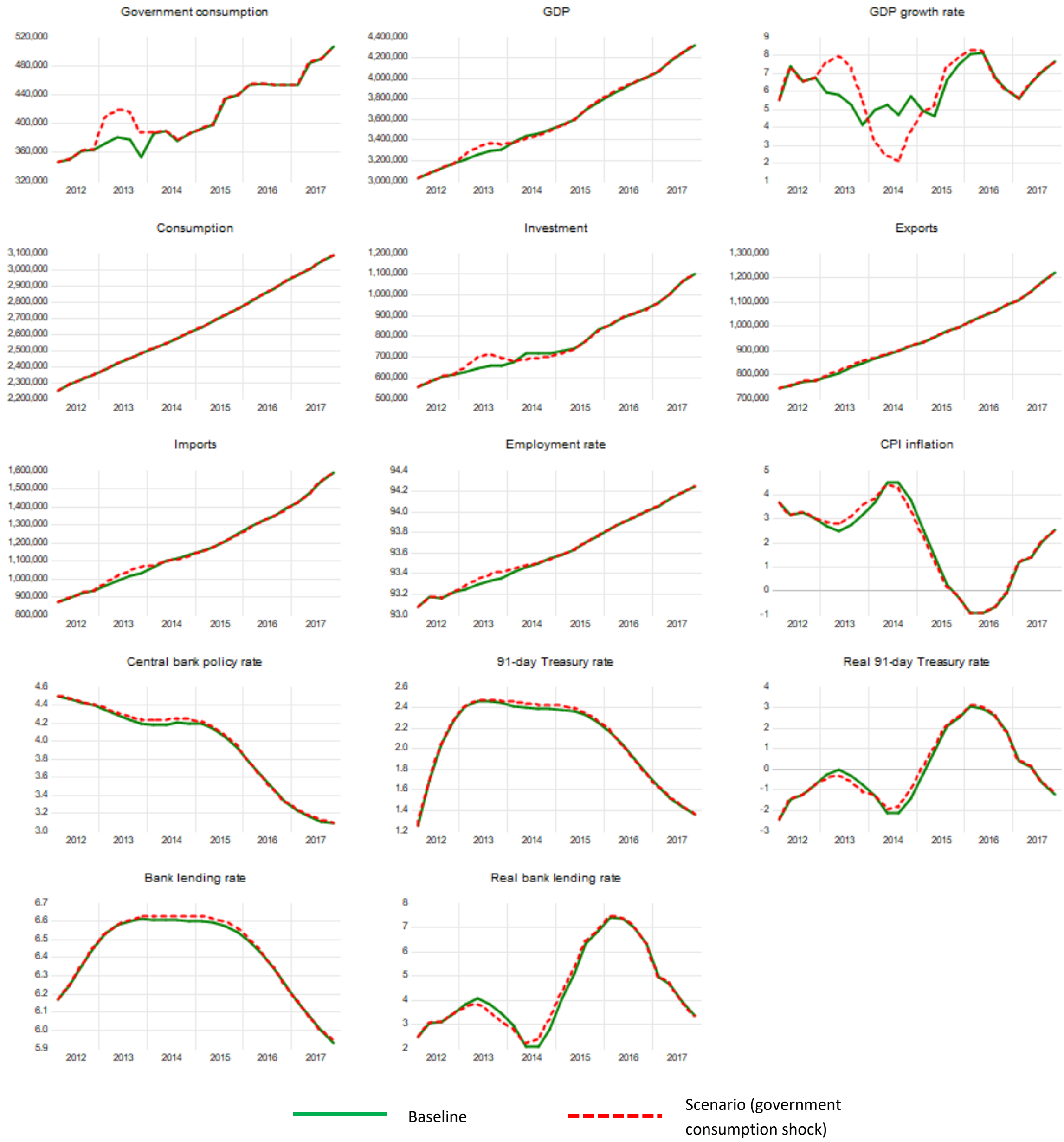
[33] Consumption and the employment rate also rise, but the increases are not substantial.

[34] The cumulative multiplier is computed as the ratio between the cumulative change in output and the cumulative change in government spending during the shock period, $\sum_{t=2013Q1}^{2013Q4} \Delta Y_t / \sum_{t=2013Q1}^{2013Q4} \Delta G_t$, where ΔY_t is the difference between the shocked and baseline value of GDP at time *t*, and ΔG_t is the difference between the shocked and baseline value of government consumption at time *t*.

[35] The average for public spending (impact) multipliers is about 0.3. However, regional multipliers are computed to be around 1.2 (Debuque-Gonzales, 2021).

Figure 4. Impact of government consumption shock



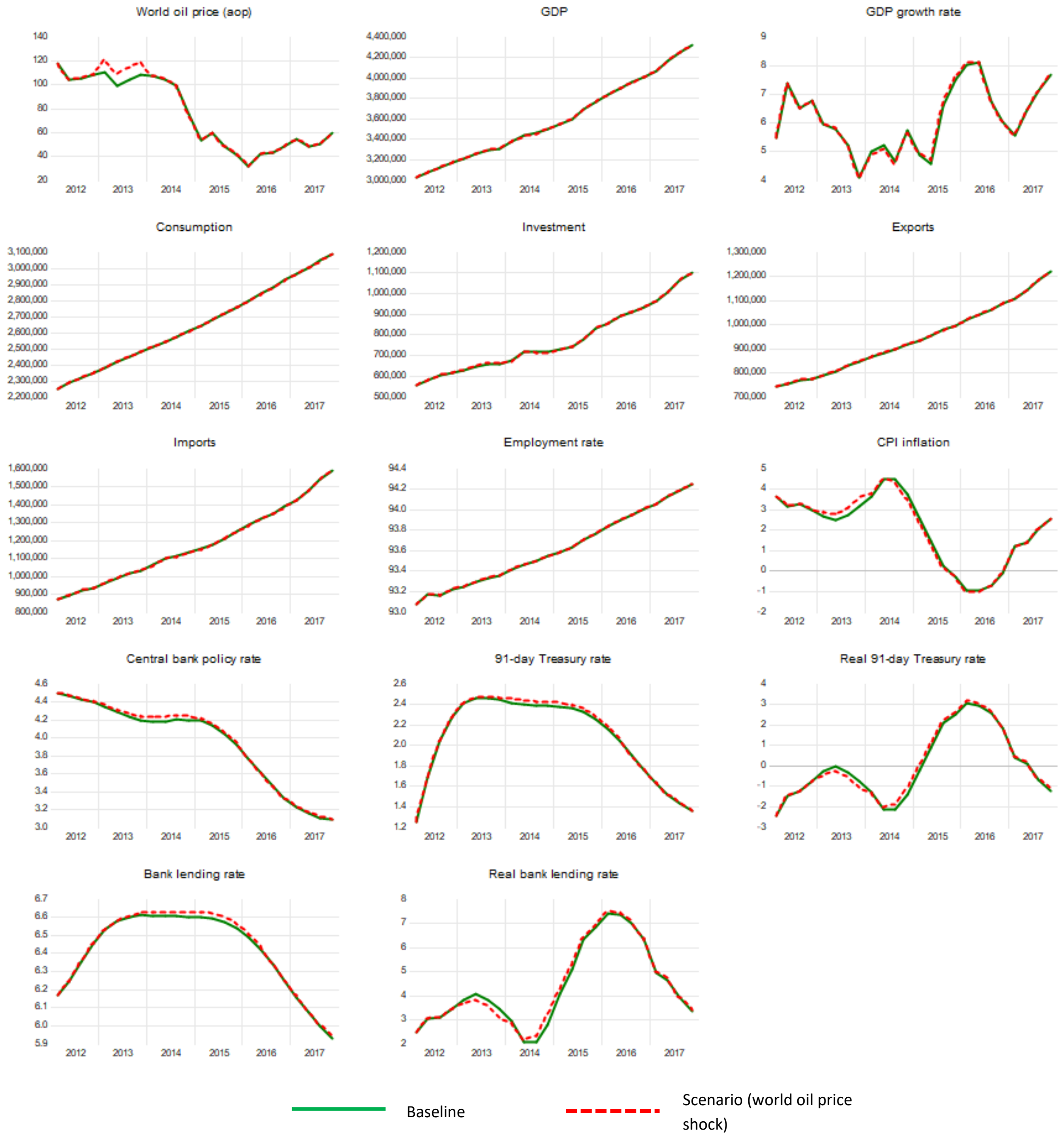
Source: Authors' calculation.

5.2. World oil price shock

In this scenario, the world price of oil is raised by 10 percent above its baseline path in 2013. The shock translates to the price of oil rising from an average of 105.42/barrel to an average of \$115.96/barrel during the period considered. Figure 5 depicts the simulation results.

The higher price of oil causes inflation to accelerate though not substantially, with the headline rate rising by only 0.30 percentage points on average relative to the baseline in 2013. Moreover, the effect starts to diminish by the first quarter of 2014. The rise in inflation leads to only a small adjustment of the policy rate and, in turn, of other interest rates. The increase in the policy rate relative to the baseline cumulates to just 5 basis points (0.05 percentage points) by the middle of the succeeding year and gradually peters out soon after. The slightly faster inflation produces only a small, negative effect on the real economy, with the simulation experiment reflecting an imperceptible decline in consumption and GDP.

Figure 5. Impact of world oil price shock



Source: Authors' calculation.

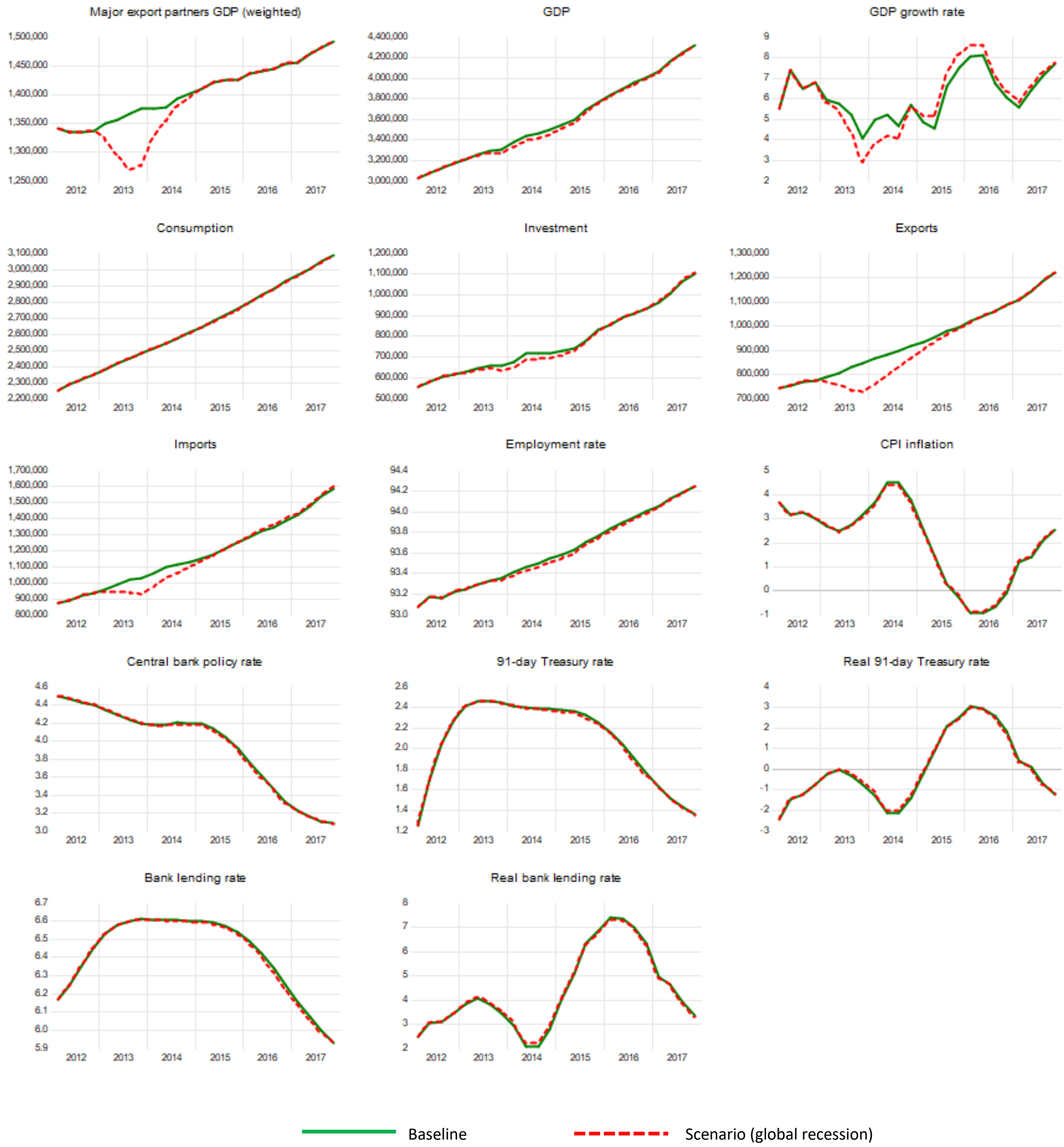
5.3. Global recession

As a final experiment, we examine the domestic impact of a global recession on the Philippine economy. We construct a quarter-on-quarter contraction in the trade-weighted aggregate GDP of the Philippines' major export partners from 2013Q1 to 2013Q4 that mirrors the path observed in the same synthetic GDP measure from 2008Q3 to 2009Q1 during the Global Financial Crisis (GFC) of 2008-2009. In year-on-year terms, the artificial recession translates to GDP growth declines of 1.43 percent in 2013Q1, 3.0 percent in 2013Q2, 4.94 percent in 2013Q3, and 4.55 percent in 2013Q4.[36] The simulation results are shown in Figure 6.

The global recession is transmitted to the Philippine economy through exports, which slips below its baseline path by an annual average of 8.61 percent in 2013. The shock in total demand meanwhile causes investment to fall below baseline by an average of 1.89 percent in the same period, but consumption and employment prove to be largely stable. The drop in exports and weaker domestic demand combine to pull down imports by an average of 6.32 percent in the same period. GDP growth remains positive but slows by an average of 0.61 percentage points from 2013Q1 to 2013Q4. Mirroring the direction of global GDP, the country's exports, investment, and output remain below their baseline paths in 2014 but start to move towards recovery.

[36] While the GFC had lasting effects on the global economy in that world GDP never returned to its pre-crisis path, this experiment assumes the shock to be temporary. After bottoming out in 2013Q4, we let our measure of world GDP quickly rise and return to its baseline path by 2015Q1.

Figure 6. Impact of global recession



Source: Authors' calculation.

6. Conclusion

This paper presents a new macroeconometric model of the Philippine economy. In view of past difficulties in maintaining larger macroeconometric models, we aim for a more compact system that is tractable, easy to communicate, and relatively inexpensive to update and maintain. Following modern-day central bank models and models in the empirical literature, we adopt a pragmatic approach that incorporates economic theory (and intuition) through long-run equilibrium relationships of the ECM, while having the flexibility to capture immediate data dynamics through short-run equations.

The small macroeconometric model we show in this paper is just the first step towards building a more robust and structurally sound full-system model for policy analysis with enough forecasting power to make quick predictions. So far, the model we have constructed has been validated through various simulation exercises. It has been able to track historical turning points of GDP growth and CPI inflation quite well and produce relatively low in-sample prediction errors for employment. Moreover, it has been rather successful in generating out-of-sample forecasts of these three closely watched macro variables.

The small model has also shown strong potential for use in policy simulation, as it illustrates the probable impact of exogenous shocks reasonably well. A government spending shock, for example, elicits strong increases in investment and imports as well as GDP growth on impact, based on the model, while a shock to world oil prices shows greater resiliency of the Philippine economy than might have been anticipated. A global recession, meanwhile, is largely transmitted to the domestic economy mainly though exports and a subsequent decline in investment.

Logical extensions to improve policy simulations entail developing the supply side of the model (especially as it relates to productivity), disaggregating important sectors, providing greater detail on determinants of key variables, strengthening linkages across sectors, and modeling and incorporating the role of expectations. To optimize use of the model, it would be necessary to add a fiscal/government block, further develop the monetary block, and ultimately introduce a detailed financial block. Failure of the model in its current form to closely trace historical movements in the domestic interest rates are fairly indicative of these shortcomings.

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Appendix A. Results of Augmented Dickey-Fuller tests on model variables

	diff=0	diff=1	diff=2
log(GDP)	0.99	0.00	0.00
GDP growth rate	0.01	0.00	0.00
log(consumption)	1.00	0.00	0.00
log(government consumption)	0.95	0.00	0.00
log(investment)	0.99	0.00	0.00
log(imports)	1.00	0.00	0.00
log(exports)	0.95	0.00	0.00
log(disposable income)	0.99	0.00	0.00
log(tax revenues)	0.99	0.00	0.00
log(domestic demand)	1.00	0.00	0.00
log(employment rate)	0.94	0.00	0.00
Policy rate (reverse repurchase rate)	0.72	0.00	0.00
91-day Treasury rate	0.09	0.00	0.00
Real 91-day Treasury rate	0.02	0.00	0.00
Bank lending rate	0.07	0.00	0.00
Real bank lending rate	0.00	0.00	0.00
log(nominal PHP-USD exchange rate)	0.54	0.00	0.00
log(real effective exchange rate)	0.75	0.00	0.00
log(Consumer Price Index)	0.58	0.00	0.00
log(world price of oil)	0.16	0.00	0.00
log(retail price of rice)	0.13	0.00	0.00
log(world GDP)	0.80	0.00	0.00
Inflation	0.00	0.00	0.00
Inflation target	0.57	0.00	0.00
Inflation deviation from target	0.03	0.00	0.00

Note: Figures are *p*-values from the Augmented Dickey-Fuller tests, with the null hypothesis being the presence of a unit root. The first, second, and third column shows result of the test in levels, first difference, and second difference, respectively.

Appendix B. Estimated behavioral equations

Notes: (1) In estimated equations, subscripted figures enclosed in square brackets are t-statistics; (2) Figures enclosed in parentheses in residual diagnostic tests are p-values; (3) Asterisks after F-Bounds test statistic are significance levels (*** 1 percent, ** 5 percent, * 10 percent).

1. Consumption

Estimation sample: 2005Q2 – 2017Q4

a. Long-run equation

$$\log(C_t) = 1.44_{[0.29]} + 0.34\log(YD_t)_{[0.26]} + 0.10emp_{t[0.50]} - 0.08\tilde{r}_{t[-0.43]} - 0.10\pi_{t[-0.44]} + ec_t$$

b. ECM form

$$\Delta\log(C_t) = -0.36\Delta\log(C_{t-1})_{[-2.82]} - 0.03ec_{t-1[-9.57]} + \varepsilon_t$$

Adjusted R-squared (ARDL)	0.998
Adjusted R-squared (ECM)	0.32
Residual diagnostics	
Residual normality (Jarque-Bera)	2.55 (0.28)
Homoskedasticity (Breusch-Pagan-Godfrey) F(5,42)	1.67 (0.16)
No serial correlation (Breusch-Godfrey) F(2,40)	1.65 (0.22)
F-Bounds test	13.70***

2. Investment

Estimation sample: 2002Q1 – 2017Q4

a. Long-run equation

$$\log(I_t) = -10.83_{[7.84]} + 1.60\log(Y_t)_{[7.84]} + ec_t$$

b. ECM form

$$\Delta\log(I_t) = -0.29\Delta\log(I_{t-1})_{[-2.58]} + 2.40\Delta\log(Y_t)_{[3.37]} + 2.46\Delta\log(Y_{t-1})_{[3.23]} - 0.01\Delta\tilde{r}_{t[-1.10]} - 0.16ec_{t-1[-3.44]} + \varepsilon_t$$

Adjusted R-squared (ARDL)	0.97
Adjusted R-squared (ECM)	0.32
Residual diagnostics	
Residual normality (Jarque-Bera)	0.75 (0.68)
Homoskedasticity (Breusch-Pagan-Godfrey) $\chi^2(6)$	16.81 (0.01)**
No serial correlation (Breusch-Godfrey) $\chi^2(2)$	0.19 (0.91)
F-Bounds test	3.81*

3. Exports

Estimation sample: 2002Q4 – 2017Q4

a. Long-run equation

$$\log(X_t) = -21.86_{[-3.89]} + 2.14\log(Y_t^{World})_{[4.12]} - 0.19\log(reer_t)_{[-0.88]} + 0.44\log(M_t)_{[4.21]} + ec_t$$

b. ECM form

$$\Delta\log(X_t) = -0.19\Delta\log(X_{t-1})_{[-2.13]} + 0.39\Delta\log(M_t)_{[4.21]} - 0.42ec_{t-1_{[-5.16]}} + \varepsilon_t$$

Adjusted R-squared (ARDL)	0.98
Adjusted R-squared (ECM)	0.47
Residual diagnostics	
Residual normality (Jarque-Bera)	11.68 (0.002)***
Homoskedasticity (Breusch-Pagan-Godfrey) $\chi^2(6)$	4.31 (0.63)
No serial correlation (Breusch-Godfrey) $\chi^2(4)$	4.76 (0.31)
F-Bounds test	4.96**

4. Imports

Estimation sample: 2002Q1 – 2017Q4

a. Long-run equation

$$\log(M_t) = -1.20_{[1.78]} + 0.65\log(I_t)_{[6.94]} + 0.29\log(X_t)_{[2.93]} + ec_t$$

b. ECM form

$$\Delta\log(M_t) = -0.37\Delta\log(M_{t-1})_{[-5.06]} + 0.32\Delta\log(I_t)_{[9.01]} + 0.69\Delta\log(X_t)_{[10.81]} + 0.69\Delta\log(X_{t-1})_{[4.06]} - 0.21ec_{t-1_{[-4.22]}} + \varepsilon_t$$

Adjusted R-squared	0.99
Adjusted R-squared	0.75
Residual diagnostics	
Residual normality (Jarque-Bera)	0.66 (0.72)
Homoskedasticity (Breusch-Pagan-Godfrey) $\chi^2(7)$	10.06 (0.19)
No serial correlation (Breusch-Godfrey) $\chi^2(4)$	5.52 (0.24)
F-Bounds test	4.22**

5. Employment rate

Estimation sample: 2005Q4 – 2017Q4

a. Long-run equation

$$emp_t = 40.83_{[6.13]} + 3.50\log(Y_t)_{[7.82]} + ec_t$$

b. ECM form

$$\Delta emp_t = -0.31\Delta emp_{t-1_{[-2.40]}} - 0.54ec_{t-1_{[-3.54]}} + \varepsilon_t$$

Adjusted R-squared (ARDL)	0.79
Adjusted R-squared (ECM)	0.46
Residual diagnostics	
Residual normality (Jarque-Bera)	0.71 (0.70)
Homoskedasticity (Breusch-Pagan-Godfrey) $\chi^2(3)$	2.31 (0.51)
No serial correlation (Breusch-Godfrey) $\chi^2(2)$	4.08 (0.13)
F-Bounds test	3.99*

6. Policy rate

Estimation sample: 2002Q3 – 2017Q4

$$\Delta rrp_t = 0.30\Delta rrp_{t-1[2.44]} + 0.03(\pi_t - \pi_t^T)_{[1.24]} + \varepsilon_t$$

Adjusted R-squared	0.08
Residual diagnostics	
Residual normality (Jarque-Bera)	186.41 (0.00)***
Homoskedasticity (Breusch-Pagan-Godfrey) $\chi^2(3)$	1.82 (0.61)
No serial correlation (Breusch-Godfrey) $\chi^2(2)$	2.20 (0.33)

7. Treasury rate

Estimation sample: 2002Q1 – 2017Q4

a. Long-run equation

$$tr_t = -1.82_{[-1.59]} + 1.00rrp_{t[4.00]} + ec_t$$

b. ECM form

$$\Delta \mathrm{tr}_t = 0.27\Delta\pi_{t[2.44]} - 0.26ec_{t-1[-4.16]} + \varepsilon_t$$

Adjusted R-squared (ARDL)	0.90
Adjusted R-squared (ECM)	0.23
Residual diagnostics	
Residual normality (Jarque-Bera)	3.38 (0.83)
Homoskedasticity (Breusch-Pagan-Godfrey) $\chi^2(3)$	9.74 (0.02)**
No serial correlation (Breusch-Godfrey) $\chi^2(4)$	4.46 (0.11)
F-Bounds test	5.59**

8. Bank lending rate

Estimation sample: 2002Q1 – 2017Q4

a. Long-run equation

$$r_t = 4.75_{[13.33]} + 0.78tr_{t[7.88]} + ec_t$$

b. ECM form

$$\Delta r_t = 0.43\Delta tr_{t[7.47]} - 0.26ec_{t-1[-4.09]} + \varepsilon_t$$

Adjusted R-squared (ARDL)	0.96
Adjusted R-squared (ECM)	0.23
Residual diagnostics	
Residual normality (Jarque-Bera)	0.31 (0.86)
Homoskedasticity (Breusch-Pagan-Godfrey) $\chi^2(3)$	11.15 (0.01)**
No serial correlation (Breusch-Godfrey) $\chi^2(4)$	4.93 (0.29)
F-Bounds test	5.39**

9. Consumer price index

Estimation sample: 2005Q1 – 2017Q4

$$\Delta\log(CPI_t) = 0.49\Delta\log(CPI_{t-1})_{[5.50]} + 0.23\Delta\log(CPI_{t-2})_{[2.82]} + 0.02\Delta\log(oil_t)_{[4.37]} \\ + 0.06\Delta\log(rice_t)_{[8.40]} + 0.08\Delta\log(DD_t)_{[2.97]} + 0.05\Delta\log(er_t)_{[3.44]} + u_t$$

Adjusted R-squared	0.72
Residual diagnostics	
Residual normality (Jarque-Bera)	0.91 (0.63)
Homoskedasticity (Breusch-Pagan-Godfrey) $\chi^2(6)$	3.84 (0.70)
No serial correlation (Breusch-Godfrey) $\chi^2(4)$	7.44 (0.11)