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Forecasting developing Asian economies during normal times and large external shocks: Approaches and challenges

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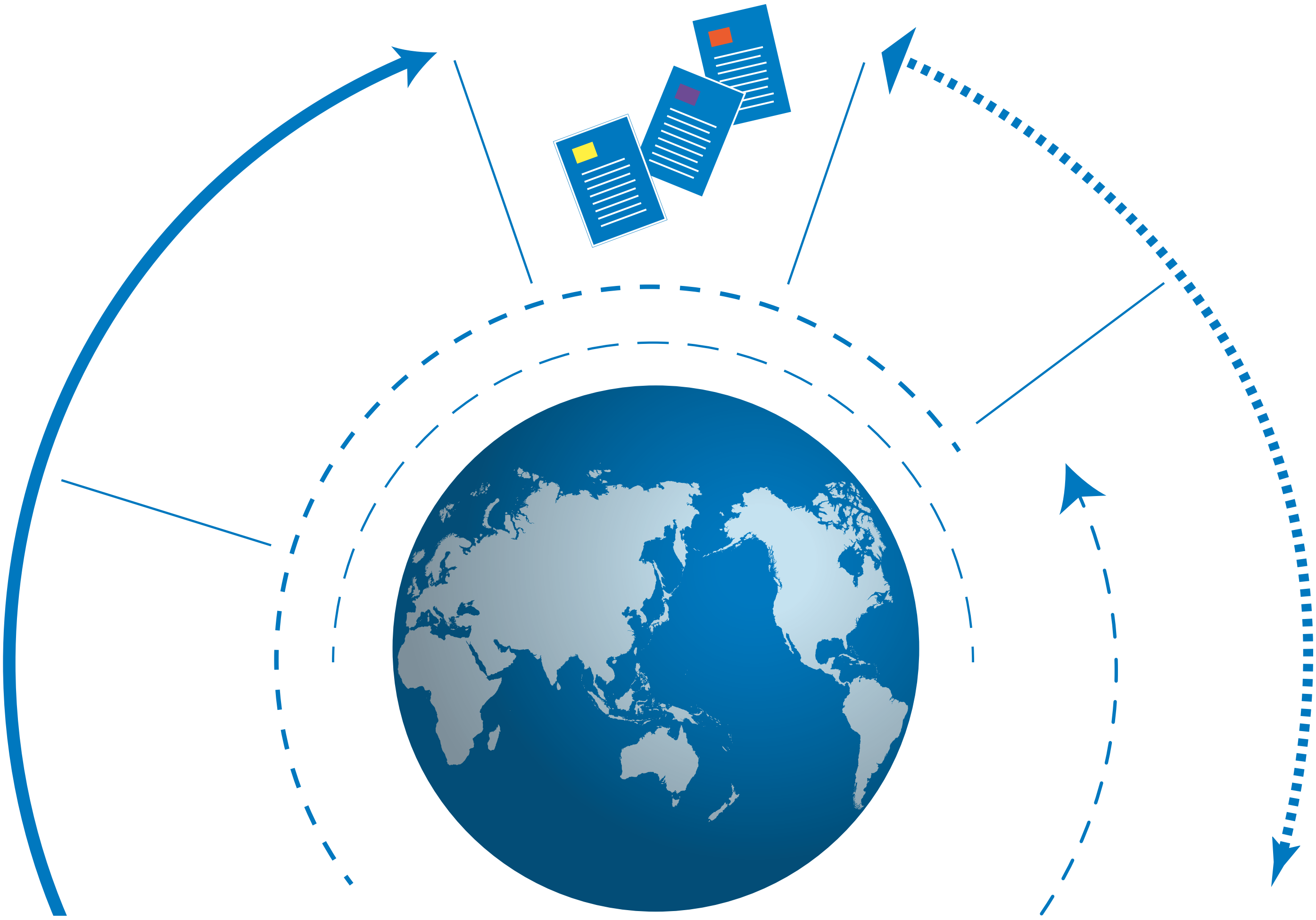

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All remaining errors are the author's responsibility.

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Preface

Accurate forecasts of economic trends are essential for effective policy decisions, yet major external shocks (such as large-scale natural disasters and pandemics) pose challenges to commonly used forecasting models, as they may not perform as well under extreme conditions. Analysing and considering multiple forecasting approaches in conditions of external shocks can be of significant help to policy makers having to navigate the complex challenges brought about by the COVID-19 pandemic.

The paper examines the challenges associated with each approach, with a focus on forecasting issues in Emerging Asia, especially during major external shocks. In this context, the report takes a detailed look at the *Medium-term Projection Framework* (MPF); the basis used for projections in the *OECD Economic Outlook for Southeast Asia, China, and India,* since it was first launched in 2010.

The paper identifies several avenues of research and development in macroeconomic forecasting that deserve more attention. Forecasting frameworks must become flexible enough to cope with big external shocks, enable policies that maintain financial stability, and consider national economies as contributors to a global economy with spillover effects, rather than as self-contained units. In addition, researchers should seek to develop models that incorporate new information such as Big Data and nowcasts.

This paper is a background document for the 2021 edition of the *OECD Economic Outlook for Southeast Asia, China and India*, a Development Centre biannual flagship and best-selling OECD publication that examines the macroeconomic conditions of ASEAN countries, China and India, providing an overview of regional economic trends and policy challenges. The Development Centre is grateful for the financial support provided to this project by the governments of Japan, Korea, Switzerland, and by the European Union.

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Abstract

Predicting future economic trends appropriately is essential to economic policy making. Currently, the DSGE model approach is a benchmark economic forecasting technique widely employed. However, large external shocks, such as large-scale natural disasters and COVID-19, challenge current approaches to economic forecasting. Multiple approaches will be needed in this situation, including reduced-form model and indicator-based approaches. This paper discusses different forecasting approaches, by comparing forecasts during normal times and crisis periods. The Medium-term Projection Framework (MPF), used in the Economic Outlook for Southeast Asia, China and India series, receives particular attention. The paper also examines challenges unique to developing Asia and large external shock periods. The measurement of potential output, difficulties in modelling the credit channel, and the incorporation of Big Data pose challenges regarding developing Asian countries, and large external shocks may force deviation from assumptions of traditional frameworks such as rational expectations. Finally, this paper points out that natural disasters will be a useful proxy for large shocks in Developing Asia.

JEL classification: C53, E17, O53, O20, Q54.

Keywords: Forecasting, large external shocks, natural disasters, DSGE model, time series analysis, Developing Asia, COVID-19.

Résumé

Il est essentiel de prévoir de manière appropriée les futures tendances économiques pour étayer les décisions de politique économique. Actuellement, l'approche modèle DSGE (d'équilibre général dynamique et stochastique) est une technique de prévision économique de référence largement utilisée. Cependant, les chocs externes importants, tels que les catastrophes naturelles à grande échelle et le COVID-19, posent des défis dans les prévisions économiques. L'utilisation de diverses approches, en particulier celle en forme réduite et celles fondées sur des indicateurs, sera grandement utile. Ce papier examine différentes approches de prévision, en comparant les prévisions en temps normal et en période de crise. Il observe notamment le cadre de projection à moyen terme (MPF) utilisé dans les projections de la série Perspectives économiques de l'Asie du Sud-Est, la Chine et l'Inde de l'OCDE. Le papier examine ensuite les défis de la prévision qui sont uniques aux pays asiatiques en développement ou aux grandes périodes de chocs externes. La mesure des résultats potentiels, des difficultés à modéliser le canal du crédit bancaire et l'intégration du « Big Data » sont des défis pour les pays d'Asie en développement, tandis que les chocs externes importants peuvent forcer la distanciation des cadres économiques traditionnels, tels que les anticipations rationnelles. Le papier montre enfin que les catastrophes naturelles représentent un indicateur utile des chocs importants dans l'Asie en développement.

Classification JEL: C53, E17, O53, O20, Q54.

Mots clés: Prévisions, chocs externes importants, catastrophes naturelles, modèle DSGE, analyse de séries chronologiques, pays asiatiques en voie de développement, COVID-19.

1 Introduction

Measuring growth prospects during large external shocks poses various challenges. The *OECD Economic Outlook for Southeast Asia, China and India* (hereafter the *Outlook)* has been providing economic forecasts for Emerging Asian countries, since 2010 up to the present day, but during large external shocks such as the COVID-19 pandemic, the projection methodology employed under usual circumstances needs to be adjusted. The purpose of this paper is to discuss the different forecasting approaches in particular for Emerging Asian economies, by comparing normal times and crisis periods.

The first section of this paper examines the details of different forecasting methods, including the *Medium-term Projection Framework* (MPF) used in the *Outlook*, and explores the challenges they face in normal times. In the next section, further forecasting challenges specific to Emerging Asian countries and during large external shocks are discussed. Large-scale natural disasters can be used as a reference for these shocks. Incomplete data for some key variables, difficulty modelling the credit channel in the financial sector, and incorporation of Big Data are discussed as key challenges.

2 Structural, reduced-form model approach and indicator-based approach

Predicting future economic trends appropriately is essential to economic policy making. Economic forecasting literature can be divided into three broad categories – structural model approach, reduced-form model approach and indicator-based approach. The structural model approach aims to produce models that attempt to explain the economy first by a theoretical model and then provide forecasts only as a by-product of their main aim, such as the DSGE approach. An ideal model would explain the economy perfectly and forecast well based on that explanation, however, real-world complexities require models to hold strong assumptions that weaken the accuracy of forecasts. The reduced-form approach is not to attempt full structural modelling, but to follow what real data says using a reduced-form model (Diebold, 1998[1]; Carriero, Galvão and Kapetanios, 2019[2]). In general, this approach has better forecasting performances, but has difficulty to provide structural explanation behind the forecasts. The indicator-based approach involves constructing composite indicators based on the statistical description of real-time series data. This approach has advantages particularly for very near-term forecasting. Each approach has pros and cons and it is important for policy makers to use the most appropriate approach for their objectives. In general, all these approaches are complementary.

Structural model approach

Dynamic stochastic general equilibrium models (DSGE) have been successfully brought to the forecasting arena, becoming one of the most widely used approaches, particularly in normal times. The development of a new generation of DSGE models incorporated various structural issues with micro-foundations with optimising agents. However, in contrast with appropriate theoretical foundations, such models were not necessarily considered useful tools for accurate forecasting until recently, partly as their forecasting performance was undermined by their inability to track and predict co-movements of aggregate time series over the business cycle (Martinez-Martin et al., 2019[3]).

The DSGE approach has a number of characteristics that render it particularly suitable for addressing various policy questions. As argued by Smets and Wouters (2004[4]; 2003[5]), the DSGE structure lends itself to telling economically coherent stories due to its strong theoretical underpinnings. Off-model information about structural parameters can be used to calibrate or estimate the model. Furthermore, the structural nature of the model together with its ability to account explicitly for the role of expectations renders the output less subject to the Lucas critique and more suitable for policy analysis. DSGE models also give a better feel for which parameters are likely to be policy-invariant and which ones are not (Smets and Wouters, 2004[4]; 2003[5]). Moreover, Blanchard (2018[6]) thinks that a major potential strength of DSGE models is that they can be used not only for descriptive, but also for normative purposes due to its microfoundations. For instance, these models could shed a light on distribution effects or distortions that affect the composition rather than the size of output, or effects of current policies on future rather than current output (Blanchard, 2018[6]).

Other researchers emphasise some of the limitations inherent in the DSGE modelling approach. One of the most prominent critiques is that DSGE models are not suitable for studying large crisis events (Stiglitz, 2018[7]; Vines and Wills, 2018[8]; Wright, 2018[9]). For instance, as argued by Stiglitz (2018[7]), the core failings of DSGE models can be traced to their erroneous microfoundations. The source of the 2008 crisis was not appropriately accounted for in most DSGE models; economic downturns are caused by an exogenous technology shock, while the 2008 shock was an endogenous one. Additionally, inadequate modelling of the financial sector meant DSGE models were ill-equipped for predicting or responding to a financial crisis (Stiglitz, 2018[7]). Other inadequacies of the DSGE approach highlighted in the literature include the inherent simplifications (Blanchard, 2018[6]; Stiglitz, 2018[7]) and inability of these models to account for large shocks (Stiglitz, 2018[7]). Wright (2018[9]) goes even further, arguing that DSGE models should also allow for frictions in trade from searching and matching, incomplete information, and imperfect commitment, which can fundamentally change how the model works. Furthermore, in Blanchard's (2018[6]) view, DSGE models' standard method of estimation, which is a mix of calibration and Bayesian estimation, may be an issue. The problems inherent in this estimation method are related to misspecification and the complexity of mapping from parameters to data.

Reduced-form model approach

Contrary to the structural model approach, reduced-form model approaches, such as autoregressive integrated moving average (ARIMA), the Factor Augmented Autoregressive Distributed Lag (FADL), Mixed-data sampling (MIDAS), vector autoregressions (VARs) and Bayesian VAR (BVAR), have advantages in estimation and generation of out-of-sample forecasts (Webb, 1984[10]; Sims, 1980[11]). Being credited with good forecasting properties, these models have become established benchmarks in forecasting contexts (Stock and Watson, 1999[12]; Angelini et al., 2019[13]). On the other hand, these models embed weak theoretical foundations, compared with the DSGE approach. (Chari, Kehoe and McGrattan, 2005[14]). The Bayesian estimation of a typical VAR model works as briefly explained hereafter (Ciccarelli and Rebucci, 2003[15]). Given the probability density function (*PDF*) of the data conditional on the model's parameters (the information contained in the data in the form of a likelihood function),

$$L(Y|\beta,\Sigma)\alpha|\Sigma|^{-T/2}exp\left\{-\frac{1}{2}\sum_{t}(Y_t-X_t\beta)'\Sigma^{-1}(Y_t-X_t\beta)\right\},$$

and a joint prior distribution on the parameters, $p(\beta,\Sigma)$, the joint posterior distribution of the parameters conditional on the data is obtained through Bayes' rule,

$$p(\beta,\Sigma|\mathrm{Y})=\frac{p(\beta,\Sigma)L(Y|\beta,\Sigma)}{p(Y)}$$

Autoregressive integrated moving average (ARIMA) models belong to the class of reduced-form approaches. Briefly, ARIMA models can be used to forecast a time series that can be rendered stationary by differencing. In an ARIMA framework, a given time series is explained based on its past values. The equation can therefore be used to forecast the series' future values.

Additionally, FADL can be used for assessing the effects of various shocks on a number of variables. An important feature of the FADL is that it estimates the impulse responses using minimal restrictions from the factor model (Ng and Stevanovic, 2012[16]). For instance, Carriero, Galvão and Kapetanios (2019[2]) propose a forecasting approach using the following $FADL(p,k)$ equation for each horizon *h:*

$$\Delta q_t = \beta_0 + \sum_{i=0}^{p-1} \beta_{i+1} \Delta q_{t-h-i} + \sum_{j=1}^{r} \sum_{i=0}^{k-1} \gamma_{j,i+1} f_{j,t-h-i} + \varepsilon_t$$

where *r* counts the number of factors *f*. Factors are estimated by principal components applied to either a medium-sized (around 14 variables) or large (around 100 variables) dataset of predictors of q_t.

MIDAS regressions represent another approach in this class. Ghysels, Santa-Clara and Valkanov (2004[17]) first described MIDAS regressions as reduced-form regressions that involve processes sampled at different frequencies. Highly parsimonious distributed-lag polynomials are used to bridge the higher-frequency variable to the low-frequency one. These polynomials are very flexible, allow for various shapes and only require the estimation of a limited number of parameters. The basic MIDAS model for a single explanatory variable and *h*-step-ahead forecasting is given by (Aastveit, Foroni and Ravazzolo, 2016[18]):

$$y_t = \beta_0 + \beta_1 b(L_m;\theta) x_{t_m+w-h_m}^{(m)} + \varepsilon_t$$

Where $b\left(L^{1/m};\theta\right) = \sum_{k=0}^{K} c(k;\theta)\, L_m^k$ and $L_m^x x_{t_m}^{(m)} = x_{t_m-x}^{(m)} * x_{t_m+w}^{(m)}$ is skip-sampled from the high-frequency indicator x_{t_m}. w represents the number of high-frequency observations that lead to the release of the low-frequency variable.

An additional approach in this stream, based on "bridge equations", is presented in Angelini et al. (2008[19]). Bridge equations are regressions of quarterly GDP growth on a small set of preselected key monthly indicators. In order to exploit information of many monthly releases to obtain an early estimate of quarterly GDP growth, Angelini et al. (2008[19]) use estimated common factors as regressors, as an alternative to averaging many bridge equations, along the lines of Giannone, Reichlin and Small (2006[20]). Giannone, Reichlin and Small (2006[20]) have proposed the method that consists of combining predictors in few common factors, which are then used as regressors in the bridge equation via the Kalman filter. Factors are averaged to obtain quarterly series, which are subsequently used as regressors in the GDP equation.

Vector autoregressive (VAR) models are multivariate linear models that provide a systematic way to capture dynamics in multiple time series. In short, in a VAR framework, each variable is in turn explained by its own lagged values, plus current and past values of the remaining variables (Stock and Watson, 2001[21]). (This approach will be discussed in more detail in a later Section 6.)

Nevertheless, no single method can be considered the best at forecasting over all horizons. While simple autoregressive models tend to perform better at short horizons, DSGE models are more accurate at long horizons when forecasting output growth, while the results are reversed for inflation forecasts (Gurkaynak, Kisacikoglu and Rossi, 2013[22]). Monte Carlo comparisons of the various methods are typically conducted to provide guidance as to which of these techniques have the best power properties.

Indicator-based approach

An alternative forecasting approach relies on composite indicators. A composite indicator is formed when individual indicators are compiled into a single index, based on an underlying model of the multi-dimensional concept that is being measured (OECD, 2008[23]). Approaches based on composite indicators may have some challenges. First, the production of composite leading indicators (CLIs) generally entails the use of an incomplete set of component series. In addition, these indicators are revised over time, which makes it difficult, when looking at previous observations, to distinguish turning-point signals from erratic signals. Furthermore, industrial production accounts for a shrinking share of GDP. Finally, the components of CLIs often need to be updated.

As an example of an approach based on composite indicators, the OECD developed in the 1970s a system of composite leading indicators (CLI) for its member countries based on the 'growth cycle' approach to give early signals of turning points of economic activity. Fichtner, Ruffer and Schnatz (2009[24]) use the OECD CLI indicators to assess empirically the ability of CLIs to predict economic activity, in particular through the lens of globalisation. The authors find evidence that the CLI encompasses useful information for forecasting industrial production, particularly over horizons of four to eight months ahead.

The *Asian Business Cycle Indicators* (ABCIs) (OECD, 2010[25]), developed in 2010 and produced during 2010-13 also belong to the category of indicator-based approaches to forecasting. The purpose of these indicators was to provide comparable information on the very short-term (i.e. the following quarter) economic climate and potential macroeconomic risks of Asian economies. The ABCIs rest on the concept of 'growth cycles' approach like the CLIs, defined as recurrent fluctuations in the series of deviations from trend. This approach yields different results from the 'classical' approach of cycles (i.e. the one used by NBER). More precisely, growth cycle contractions include slowdowns as well as absolute declines in activity, as opposed to classical contractions, which include only absolute declines (recessions). Fluctuations in economic activity are measured as the variation in economic output relative to its long-term potential. The output gap is estimated as part of the overall ABCIs production process. The fluctuation in the output gap is interpreted as the business.

ABCIs identify cycles by using both composite indicators and diffusion indices. The ABCIs were constructed for five ASEAN member countries (i.e. Indonesia, Malaysia, the Philippines, Singapore and Thailand), plus People's Republic of China (hereafter 'China') and India. A technical description of the Asian Business Cycle Indicators is provided in Box 2.1 hereafter.

Box 2.1. Asian Business Cycle Indicators (ABCIs)

The *Asian Business Cycle Indicators (ABCIs)*, which were released in 2010-13, identify cycles by using both composite indicators (i.e. leading and coincident indicators) and diffusion indices (i.e. leading and coincident indices). The two components are complementary. The composite index reveals change in economic fluctuations, whereas the diffusion index provides a broader picture of the overall economic activity of the country. Coincident indicators are selected mainly by economic relevance and statistical fitness to quarterly GDP. The list of variables used to construct the composite coincident indicators varies by country, but some common variables include the industrial production index, retail sales, exports and imports. Leading indicators are created based on the coincident indicators and the lead-time is in general 5-6 months. The composite leading indicators draw information from consumer and business surveys, monetary aggregates and financial markets. The list of variables in the composition of leading indicators is country-specific. The evaluation of the phase of the business cycle was done comprehensively by using four sets of information: i) leading indicators of both composite and diffusion; and ii) coincident indicators of both composite and diffusion.

Source: OECD (2010[26]), *Asian Business Cycles Quarterly* and OECD (2013[27]), *This Quarter in Asia.*

Central banks, research institutes and international organisations construct several types of leading indicators. As early as 1937, Wesley Mitchell, Arthur Burns, and their colleagues at the National Bureau of Economic Research (NBER) developed a set of leading, coincident, and lagging indicators of economic activity in the United States as part of the NBER research program on business cycles. Since their development, these indicators have played an important role in summarising and forecasting the state of macroeconomic activity. Mitchell and Burns (1938[28]) considered the minimum period for a full business (reference) cycle to be one year. Some of the variables considered for the construction of the leading indicator include: total liabilities of business failures; stock prices; various indicators of the real estate market; average hours worked; industrial production; department store sales; factory employment; etc. (Mitchell and Burns, 1938[28]). An example of approach used in Emerging Asia is the Composite Coincident Index (CCI) developed for Singapore, which is an aggregate of macroeconomic indicators that move in tandem with business cycles, to track the state of the economy. Trend estimation of the reference series and other economic indicators is performed using a modified version of the Phase-Average Trend (PAT) method. Conceptually, the PAT method uses moving averages to separate the long-term trend from shorter-term cycles to obtain a series that has its trend component removed. The cyclical component that remains, known as “Deviation from Trend” cycles, represents alternating periods of growth rates above and below the long-term trend. Identification of peaks and troughs in economic time series is performed using the Bry-Boschan procedure, which uses rules and specifications from the Burns-Mitchell definition of business cycles. This method first identifies tentative turning points from highly smoothed time series and subsequently, refines such turning points through less smoothed series.

3 Examples from countries and international organisations

An example of a structural model used in forecasting by an international organisation is the IMF's *Financial Programming Model.* In its basic structure, the model is formulated in terms of the demand and supply of goods, money and foreign exchange. The overall domestic inflation and medium-term output growth are set as exogenous targets for the program, while the exchange rate is assumed flexible and determined by market forces. The long-run domestic supply of goods is determined using a neoclassical production function and the demand side is determined from consumption, investment and net exports of goods and services. Private investment is determined from the production function as the growth rate of output is given as an exogenous target. The money market is specified by the supply and demand for money, with the supply linked to the stock of reserve money of the central bank (Mikkelsen, 1998[29]).

Another example of an approach is a forecasting FRB/US model, developed by the Federal Reserve Board. The model describes the economic behaviour of three main sectors, namely households, firms and financial markets. First, households choose equilibrium aggregate consumption based on the lifecycle model, but are assumed quite risk-averse. Second, firms choose investment, inventories, labour hours, and prices based on profit maximisation under imperfect competition. Finally, financial markets set bond rates, stock prices, and the exchange rate by standard arbitrage conditions. FRB/US also contains equations for imports, exports, non-residential construction, employment, labour force participation, and the relative price of consumption (Federal Reserve Board, 1996[30]).

The European Central Bank (ECB) has used the FRB/US model as a source of inspiration for its projection process. Titled "ECB-BASE", the new model developed by the ECB is a large-scale, estimated, semi-structural model that features a high level of detail and an elevated number of endogenous variables. The model can be broadly sketched into a demand, a supply and a financial block. The demand block groups households, firms, government and foreign sector behaviours, whereas consumption is modelled differentiating between optimising agents and liquidity-constrained agents. Forward-looking firms optimising their investment plans based on user costs and the expected value of investment and output growth determine private investment behaviour. The block for the government sector provides a detailed accounting of the main fiscal variables. The foreign sector affects domestic prices and real activity through equations for imports and exports of goods and services and their deflators. Similar to the FRB/US model, expectations in the ECB-BASE model can be either based on projections from an estimated small-scale auxiliary VAR model, or consistent with a full knowledge of the dynamics of the model (Angelini et al., 2019[31]).

The Bank of England in 2011 adopted a new central organising model, the *Central Organising Model for Projection Analysis & Scenario Simulation* (COMPASS), to assist with the production of forecasts. COMPASS is an open economy, New Keynesian DSGE model, estimated on UK data using Bayesian methods. COMPASS comprises five types of economic agents: households, firms, the government, the rest of the world and the monetary policy maker. The model includes two types of households, namely "constrained" or "rule-of-thumb" households and "unconstrained" or "optimising" households. Firms in the value added and final output sectors operate under monopolistic competition. They set their prices as a mark-up over the marginal cost of production. Government expenditure is assumed to follow a simple autoregressive process and is financed by lump-sum taxes levied on unconstrained households. Finally, exporters supply whatever quantity of exports the rest of the world demands (Burgess et al., 2013[32]).

Other semi-structural models deployed by monetary authorities include the Large Empirical and Semi-structural model (LENS) operated by the Bank of Canada and the Quarterly Japanese Economic Model (Q-JEM) in use at the Bank of Japan (BoJ). Bank of Canada has also developed the Terms-of-Trade Economic Model (ToTEM) in 2005; ToTEM was updated in June 2011. The LENS model is a new large-scale Canadian macroeconomic forecasting model similar in structure to the Federal Reserve Board's FRB/US model. LENS models both stocks and flows. On the demand side, LENS distinguishes between household spending, business investment, government spending, international trade and inventories. Business fixed investment is decomposed into spending on two complementary capital goods: machinery and equipment, and structures. In the government block, public spending and revenues are decomposed into federal versus provincial and local components, while government expenditures are further disaggregated into transfer spending, spending on goods and services and interest payments on debt. The frictionless level of exports depends on foreign demand and relative prices. Finally, firms adjust their inventories to meet a target for the stock-to-sales ratio. On the supply-side, a key variable in LENS is potential output, which is based on a Cobb-Douglas production function (Gervais and Gosselin, 2014[33]).

Bank of Japan's Q-JEM model is a large-scale semi-structural model of the Japanese economy. It includes detailed modelling of GDP expenditure components, financial markets and determinants of inflation. Q-JEM employs a small open economy structure and foreign blocks (the US and the rest of the world blocks) are exogenous to the Japanese economy. In Q-JEM, nominal GDP is the sum of domestic expenditure components and net exports, namely: nominal private consumption, nominal private non-residential investment, nominal residential investment, change in nominal inventories, nominal government consumption, nominal public investment, nominal exports and nominal imports. Expenditure components are driven by the real interest rate, the exchange rate and other factors. Core inflation is determined by the Phillips curve (Hirakata et al., 2019[34]).

In Emerging Asia, the Monetary Authority of Singapore (MAS) has developed the Monetary Model of Singapore (MMS) to derive official economic forecasts each quarter, generate alternative scenarios, and conduct macroeconomic and industry policy analysis. The MMS is a fully-integrated macro-Computable General Equilibrium (CGE) model that fully accounts for the interrelationships between the supply and demand sides of the economy. Production GDP (GDP(P)), is modelled in detail alongside Expenditure GDP (GDP(E)). GDP(P) is disaggregated into five sectors, linked together through the Input-Output table: manufacturing, construction, ownership of dwellings, financial and business services and other goods and services. The MMS has a production function for each of its sectors. Both the government and the private sector are subject to their respective intertemporal budget constraints. Given the fact that Singapore is a very open economy, the MAS uses the exchange rate as the instrument of monetary policy. To close off the financial sector, the MMS also includes a term structure equation for interest rates (MAS, 2014[35]).

In the Philippines, Bangko Sentral ng Pilipinas (BSP) uses several models to forecast inflation over a policy horizon of two years and to conduct policy simulations and analysis. A DSGE model had been in use to complement BSP's workhorse models, namely the Single-Equation Model (SEM) and the Multiple-Equation Model (MEM). In 2012, the BSP utilised the Macroeconomic Model for the Philippines (MMPH) as a complement to SEM and MEM in lieu of the DSGE model, in order to capture the fundamental interlinkages among various sectors of the economy and to improve forecasting and policy simulations. Given the extent of interconnectedness in the global market, the BSP also considers international economic and financial data, especially those in other Asian countries and countries with extensive economic and financial linkages with the Philippines. In this regard, the BSP uses the following models and indicators to measure the significance of these developments: the Philippines Financial Stress Index (PFSI), the Asset Price Bubble Index, the Bank Distress Index, Network Analysis, Stress Testing and an Early Warning System (Gunigundo, 2014[36]).

The Bank of Thailand Macroeconomic Model (BOTMM) is the main model used by the Bank of Thailand (BOT) in the forecasting area. BOTMM is a system of equations that represents the dynamics of the Thai economy by capturing various interdependencies between key economic variables. Guided by theory and obtained from econometric estimations based on an error correction mechanism, such relationships depict both short and long-term dynamics. The model comprises 25 behavioural equations and it covers four sectors, namely: the real sector, the monetary sector, the external sector and the public sector. BOTMM has a particularly important role in the forecasting process, as well as in the assessments of the impacts of changes in the policy interest rate and in the projected paths of exogenous variables such as public spending, oil prices and the outlook of trading partners' economies (BOT, 2015[37]).

A summary of approaches is provided in Table 3.1 below.

Table 3.1. Examples of forecasting approaches in use at central banks/financial regulators

Example of approach	Description of approach
Financial Programming Model of the International Monetary Fund (IMF)	In its basic structure, the model is formulated in terms of the demand and supply of goods, money and foreign exchange. The overall domestic inflation and medium-term output growth are set as exogenous targets for the program, while the exchange rate is assumed flexible and determined by market forces.
FRB/US model of the Federal Reserve Board	Large-scale model of the US economy, developed by the Federal Reserve Board. The model describes the economic behaviour of three main sectors, namely households, firms and financial markets.
ECB-BASE model of the European Central Bank (ECB)	Large-scale, estimated, semi-structural model that features a high level of detail and an elevated number of endogenous variables. The model can be broadly sketched into a demand, a supply and a financial block.
Central Organising Model for Projection Analysis & Scenario Simulation (COMPASS) of the Bank of England	COMPASS is an open economy, New Keynesian DSGE model, estimated on UK data using Bayesian methods. COMPASS comprises five types of economic agents: households, firms, the government, the rest of the world and the monetary policy maker.
Large Empirical and Semi-structural model (LENS) of the Bank of Canada	New large-scale Canadian macroeconomic forecasting model. LENS models both stocks and flows. One of the main features of LENS is the high degree of disaggregation of output into various aggregate spending components.
Quarterly Japanese Economic Model (Q-JEM) of the Bank of Japan	Large-scale semi-structural model of the Japanese economy. It includes detailed modelling of GDP expenditure components, financial markets and determinants of inflation.
Monetary Model of Singapore (MMS) of the Monetary Authority of Singapore	Fully-integrated macro-Computable General Equilibrium (CGE) model that fully accounts for the interrelationships between the supply and demand sides of the economy.
Macroeconomic Model (BOTMM) of the Bank of Thailand	System of equations that represents the dynamics of the Thai economy by capturing various interdependencies between key economic variables. It covers four sectors, namely: the real sector, the monetary sector, the external sector and the public sector.
Medium-term projection framework (MPF) for OECD Economic Outlook for Southeast Asia, China and India	MPF is composed of baseline models and economic projection models. Baseline models determine potential output and the output gap by the DSGE approach, while the economic projection models (medium-scale demand-driven forecasting models) provide the components of output, based on the five sectors of the economy.

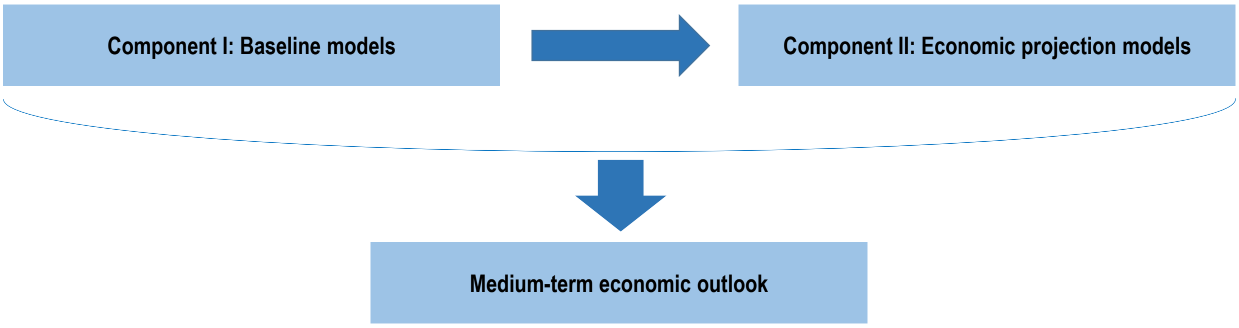
Source: Author's compilation.

4 Forecasting approach used in OECD Economic Outlook for Southeast Asia, China and India: Medium-term projection framework (MPF)

The economic forecasts for Emerging Asian countries that are regularly published in the *OECD Economic Outlook for Southeast Asia, China and India* are derived from the Medium-Term Projection Framework for Growth and Development (MPF). The MPF is an analytical tool developed in 2010 (OECD, 2012[38]) for the first edition of the *Outlook* and updated in 2015 (OECD, 2015[39]). Concisely, the MPF has two components, namely baseline models (for medium-term projections) and economic projection models. Baseline models determine potential output and the output gap, while the economic projection models provide the components of output and other variables.

The following figures summarise the MPF framework. As shown in Figure 4.1, the Framework has two components: i) baseline models for medium-term projections and ii) economic projection models.

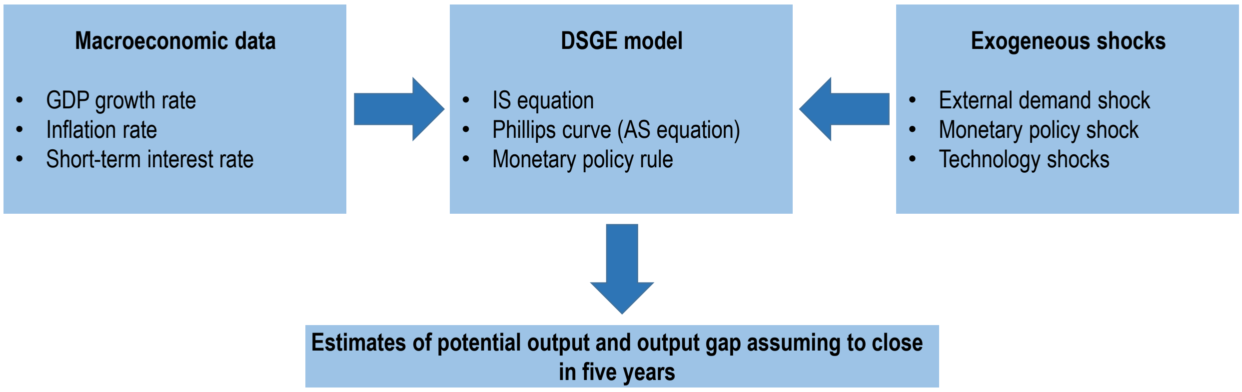
Figure 4.1. Building blocks of the MPF framework



Source: Author.

Baseline models determine potential output and the output gap, while the economic projection models provide the components of output and other variables. First, the baseline models derive the GDP series that are consistent with the output gap closing in five years. Then these reference series are used as inputs to economic projection models to obtain a set of variables from the models (Figure 4.2).

Figure 4.2. Baseline models of the MPF framework



Source: Author.

Theoretical framework of baseline model

A detailed technical description of the MPF framework is provided in the 2011/12 edition of the Outlook (OECD, 2012[38]). Zooming in on the baseline model of MPF, the model for each country is based on a New Keynesian framework that consists of a dynamic Investment-Savings (IS) equation, a Phillips curve (aggregate supply equation), and a monetary policy reaction function. Equilibrium dynamics are driven by three exogenous shocks: total factor productivity (TFP), demand, and monetary policy shocks. The baseline models' parameters are estimated using Bayesian methods. It is assumed that the shocks in the last sample period gradually converge to zero following the estimated stochastic processes. A summary of the theoretical framework of the baseline model is provided below, while more details on its building blocks can be found in (OECD, 2012[38]) and (OECD, 2015[39]).

The measure of the potential output is the stochastic trend level of output expected to prevail in the long run without any other temporary shocks. The potential output A_t evolves according to the following law of motion:

$$\log A_t = \log \gamma + \log A_{t-1} + z_t^a ,$$

Where γ represents the long-run growth rate and z_t^a is the permanent technology shock that affects the potential output growth rate. According to this definition, the output gap is defined as the deviation of output from its stochastic trend:

$$GAP_t = \log(Y_t / A_t) ,$$

Where Y_t is the actual output:

The baseline model of MPF, updated in 2015, is derived from the optimising behaviour of a) households, b) monopolistically competitive firms that face price stickiness, and c) monetary policy follows an interest-rate feedback rule (OECD, 2015[39]). For empirical validity, the model features stochastic trend for real variables and gradual adjustment in consumption, inflation and the interest rate. The equations presented below are the linear approximation of the model, and the variables are denoted as deviations from the balanced growth path.

a) **Households** derive utility from consumption goods and disutility from labour supply. The optimality conditions for utility maximisation are given by:

$$\left(1-\frac{\beta b}{\gamma^{\sigma}}\right)\left(1-\frac{b}{\gamma}\right)\lambda_t = -\sigma\left(c_t-\frac{b}{\gamma}c_{t-1}+\frac{b}{\gamma}z_t^a\right)+\frac{\beta b}{\gamma^{\sigma}}\sigma\left(Ec_{t+1}-\frac{b}{\gamma}c_t-z_{t+1}^a\right)$$

$$\lambda_t = E_t\lambda_{t+1}+r_t^n-E\pi_{t+1}-\sigma z_{t+1}^a\,,$$

Where β is the subjective discount factor, *b* represents habit persistence in consumption preferences, σ measures the risk aversion. λ_t is the Lagrange multiplier interpreted as the marginal utility of consumption and c_t is private consumption, r_t^n is the nominal interest rate, and π_t is inflation.

According to these equations, consumption increases (decreases) when the real interest declines (rises). As observed in the data, however, the adjustment of consumption is gradual because of the habit persistence in consumption.

The market-clearing condition for final-goods is:

$$y_t = \frac{c}{y}c_t+\frac{g}{y}z_t^g\,,$$

Where $\frac{c}{y}$ and $\frac{g}{y}$ are the steady-state share of private consumption and the other demand components. z_t^g is the external demand shock that captures government expenditure and net export.

Combining these three equations above, a dynamic IS equation is obtained that characterises the demand side of the economy.

b) Monopolistically competitive firms maximise their profits by setting the prices of their product. It is assumed that not all firms adjust prices every period. In each period, a fraction $1-\theta$ of firms reoptimises prices, while the remaining fraction θ keeps prices unchanged or indexes prices to past inflation.

The profit maximisation gives a dynamic AS equation called the New Keynesian Phillips curve:

$$\pi_t-\omega\pi_{t-1} = \beta\gamma^{1-\sigma}(E\pi_{t+1}-\omega\pi_t)+\frac{(1-\theta)(1-\theta\beta\gamma^{1-\sigma})}{\theta}(\eta y_t-\lambda_t)+z_t^p\,,$$

Where ω is the weight of price indexation to past inflation and η is the inverse of the labour supply elasticity in the households' utility function. The term $\eta y_t-\lambda_t$ represents the real marginal cost that is equivalent to real wage derived from households' maximisation problem. z_t^p is the marginal cost shock that captures an exogenous cost push to the firms' price setting such as the changes in oil prices and taxes.

This equation means that the current inflation is determined by past and expected future inflation, the real marginal cost, and the exogenous cost shock. Both backward and forward-looking features of the equation enable the model to replicate realistic dynamics.

c) The **monetary authority** follows the Taylor-type inflation targeting rule:

$$r_t^n = \rho_r r_{t-1}^n+(1-\rho_r)\left(\psi_\pi\frac{1}{4}\sum_{j=0}^{3}\pi_{t-j}+\psi_y y_t\right)+\varepsilon_t^r\,,$$

Where ρ_r determines the degree of policy smoothing, ψ_π and ψ_y measure the responsiveness of the interest rate against inflation and the output gap respectively. ε_t^r is the monetary policy shock interpreted as an unsystematic component of the monetary policy. This means that the monetary authority gradually adjusts the short-term nominal interest rate in response to the derivation of annual inflation from its target and the output gap.

Empirical framework

The data used for estimation is the real GDP growth rate ($\Delta \log GDP_t$), the CPI inflation rate ($\Delta \log CPI_t$), and the short-term interest rate (SR_t). These data are related to model variables by the following measurement equations:

$$\begin{bmatrix} \Delta \log GDP_t \\ \Delta \log CPI_t \\ SR_t \end{bmatrix} = \begin{bmatrix} 100(\gamma - 1) \\ \bar{\pi} \\ \bar{\pi} + \left(\frac{\beta b}{\gamma^{\sigma}} - 1\right) \end{bmatrix} + \begin{bmatrix} y_t - y_{t-1} + z_t^a \\ \pi_t \\ r_t^n \end{bmatrix},$$

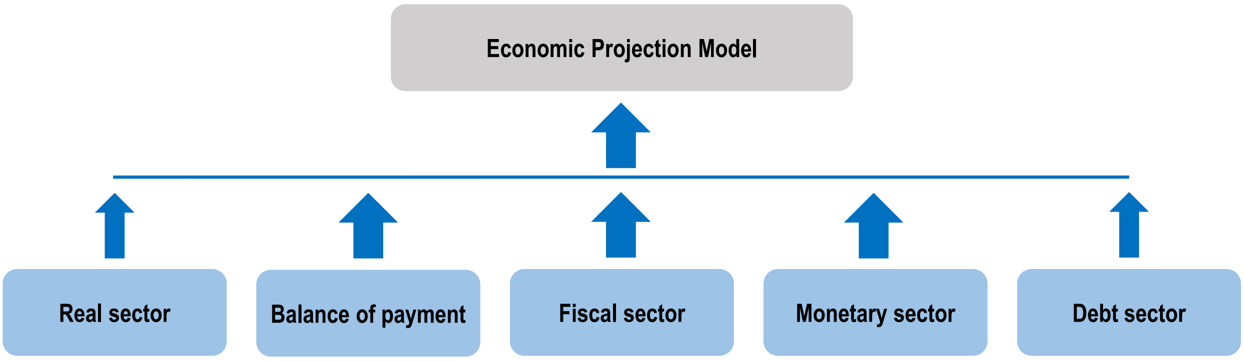
Where $100(\gamma - 1), \bar{\pi}$ and $\bar{\pi} + \left(\frac{\beta b}{\gamma^{\sigma}} - 1\right)$ are the GDP growth rate, inflation rate and nominal interest rate that prevail in the long run respectively.

Baseline models of the MPF apply Bayesian methods to estimate model parameters. Given the estimated parameters, series of potential output and output gaps are estimated so that the estimates are consistent with both the model and data.

Economic projection models of MPF

Using as reference the GDP projections derived from the baseline models, economic projection models are used to provide further details of the forecasts (Figure 4.3). Economic projection models are medium-scale demand-driven economic forecasting models that comprise a set of equations describing the five sectors of the economy: the real sector, the monetary sector, the fiscal sector, the balance of payments sector and the debt sector. The projection results are derived through iterations to identify a set of economic variables in all sectors including the current account, the fiscal balance, investment and private consumption. The Economic Projection Models take into account national development plans subject to their feasibility given the budgetary and other circumstances.

Figure 4.3. Economic projection models of MPF



Source: Author.

5 Key challenges for forecasting developments in Emerging Asia

There are several forecasting challenges particular to Emerging Asian countries.

- estimation of potential output and lack of capital stock data
- bank-based financial systems in Emerging Asia and incorporation into forecasting model
- quality and reliability of data including lack of high frequency data
- measurement of elasticities
- inclusion of Big Data
- adaptation to the changing economic environments, in particular, changing policy stances and globalisation
- inclusion of financial stability considerations.

First, the concept of "potential output" is critical for economic forecasting; yet, the lack of suitable capital stock data in Emerging Asian countries poses material challenges to output gap estimations. Second, macroeconomic forecasting models do not necessarily capture the credit channel of the economy – i.e. the interactions between the banking sector and the real economy – well. This is a major issue in bank-based financial systems such as those prevalent in Emerging Asian countries. A third challenge stems from the quality and reliability of data, which may be inconsistent across sources. In addition, some of the challenges inherent in the measurement of elasticities in macroeconomic models will be an issue.

Other challenges documented in the literature are broader in nature and are applicable not only to Emerging Asian countries, but important to pay attention to. Challenges related to the inclusion of "Big Data" in the modelling framework include nowcast and natural language processing techniques. Moreover, forecasting approaches are sometimes difficult to capture the latest policy changes and the increasing use of unconventional policies. Finally, forecasting models are generally poorly equipped to account for financial stability issues.

Potential output and lack of capital stock data in Emerging Asian countries

The concepts of "potential output" and "output gap" are critical for economic forecasting, in particular its usefulness in identifying longer-term trends in the economy. An output gap emerges when actual output diverges from potential output and different explanations have been provided in the specialised literature as to why an output gap often emerges. One theory is that the economy is best characterised by real business cycle models, where actual output differs from potential output due to random productivity shocks. In this case, the output gap reflects temporary disturbances triggered by the adjustment of the production process to technological changes and unexpected developments on the supply side (Fernald, 2014[40]; Giorno, Richardson and Suyker, 1995[41]). Another theory is that an output gap appears because rigidities in the economy mean that it takes time for prices and wages to adjust (Aiyar and Voigts, 2019[42]).

A variety of methods can be deployed for estimating potential output and consequently the output gap. These methods can be grouped into two broad categories, namely theoretical approach (typically represented by the production function approach) and statistical approaches (or filtering approaches) (Guisinger, Owyang and Shell, 2018[43]). In Emerging Asian countries, in most cases, the production function approach is difficult to implement due to poor capital stock data (Anand et al., 2014[44]; OECD, 2012[38]). The production function approach attempts to create an explicit model of the supply-side of the economy by relating output to the level of technology and factor inputs, such as labour and capital. Production functions can have several functional forms, including the Cobb-Douglas form widely used by international organisations (Chalaux and Guillemette, 2019[45]; De Masi, 1997[46]) to derive estimates of potential output. The merits of the approach lie in its ability to provide a comprehensive analytical framework for estimating potential output, by establishing a clear link between output and its long-term determinants. It can therefore be used to evaluate the impact of structural changes and policies on potential output (Epstein and Macchiarelli, 2010[47]).

An additional and new approach to measure potential output is the one used in the MPF. The baseline model of the MPF is estimated by the DSGE approach, mentioned in the previous section. A clear advantage of the DSGE approach is that it can provide comparable information on potential output and output gaps by using relatively easily available data, such as GDP, inflation, and interest rates, without relying on weak capital stock data in developing Asian countries (OECD, 2012[38]). At the same time, strong assumptions related to model setting need to be interpreted carefully. The properties of potential output and output gap fluctuations derived from the DSGE approach can be different from those derived from the production function approaches or statistical approaches.

The statistical approaches of estimating potential output are based on the idea of extracting the trend from the output series using statistical techniques. These techniques can be categorised into two. First, the univariate approaches encompass methods that extract the trend from the information contained in the output series in isolation, without using the information inherent in other variables (Clark, 1987[48]; Watson, 1986[49]). Several univariate methods can be utilised, such as deterministic trend methods (De Brouwer, 1998[50]) and the Hodrick-Prescott filter (Hodrick and Prescott, 1997[51]). A second class of statistical methods is the multivariate approaches, with a large number of studies focusing on the use of multivariate filters to estimate potential output. These methods typically attempt to derive the trend using information contained in other variables (Fleischman and Roberts, 2011[52]; Benes et al., 2010[53]). More specifically, multivariate techniques take into account empirical relationships, such as the short-run Phillips curve (Alichi et al., 2017[54]) and inflation (Basistha and Startz, 2008[55]). The statistical approaches have better performance in very near-term forecasting but lack of theoretical foundations makes the story telling difficult. In short, depending on the availability of data, in particular capital stock data and purposes, the use of various approaches is important, in particular for Emerging Asian economies.

Treatment of the banking sector in forecasting models

One of the challenges of traditional theoretical model approach is that they could not capture the interactions between the banking sector and the real economy in an appropriate manner. Particularly, in many Emerging Asian economies the banking sector played a prominent role in financial system.

There are several early contributions to analysis of the credit channel of the economy, for instance, Bernanke and Gertler (1989[56]), and Kiyotaki and Moore (1997[57]). Bernanke and Gertler (1989[56]) develop a neoclassical model of the business cycle in which the condition of borrowers' balance sheets is a source of output dynamics, under asymmetric information. The mechanism at work in this study is that higher borrower net worth reduces the agency costs of financing real capital investments. Business upturns improve net worth, lower agency costs, and increase investment, amplifying the upturn. The opposite occurs during a downturn (Bernanke and Gertler, 1989[56]). Kiyotaki and Moore (1997[57]) construct a model with dynamic interactions between credit limits and asset prices, which turns out to be a transmission mechanism by which the effects of shocks persist, amplify and leak to other sectors. The authors also show that small, temporary shocks to technology or income distribution can generate large, persistent fluctuations in output and asset prices (Kiyotaki and Moore, 1997[57]). More recently, Adrian and Shin (2008[58]) show that investment banks' leverage has been highly pro-cyclical and increased about threefold in the run-up to the crisis. These developments took place alongside the growth in importance of investment banks in the supply of credit to the real economy. Meh and Moran (2010[59]), present a benchmark DSGE model where the standard moral hazard problem between entrepreneurs and banks is supplemented with another moral hazard problem between banks and households. The incentive constraints in the model ensure that entrepreneurs select "good" projects and banks decide to monitor. Consequently, the capital position of banks affects their ability to attract loanable funds and influences the business cycle through a bank-capital transmission channel (Meh and Moran, 2010[59]). Other studies pay attention to the liquidity shortage problems of the financial sector and the liquidity spirals that compounded it. Gertler and Kiyotaki (2010[60]) incorporated the interbank market within DSGE models.

Existing macroeconomic forecasting models in use at central banks have incorporated the financial sector differently, according to their economic systems, though financial sector is mostly limited to the equity market. For example, in the Federal Reserve Board's FRB/US model, financial markets set bond rates, stock prices, and the exchange rate by standard arbitrage conditions. As a result, bond yields depend on values of short-term interest rates expected to prevail over the maturity of the bond, and the stock market valuation depends on expected dividends. Term premiums in the bond equations vary countercyclically, whereas the risk premium in the equity market is modelled as a constant. Unlike non-financial behaviour, where frictions make it too costly to move immediately to equilibrium values, in the FRB/US model asset prices are assumed to be in equilibrium continuously (Federal Reserve Board, 1996[30]). Similarly, the ECB-BASE model used at the ECB allows for an explicit role of the financial sector. In particular, the model features a risk-free term structure determined by the expectations hypothesis. This provides the basis for the construction of the lending rates, affecting various parts of the economy. In addition to interest rates, a special role is given to housing and financial wealth (Angelini et al., 2019[31]). In the case of the MMS model developed by the Monetary Authority of Singapore (MAS), expectations in financial markets are assumed rational. To allow for forward-looking behaviour in financial markets, the MMS incorporates the Uncovered Interest Parity (UIP) condition. The UIP equation introduces a positive relationship between the local three-month interest rate and the strength of the spot exchange rate. Besides the UIP equation, a second relationship reflecting the conduct of monetary policy, which involves the local three-month interest and the spot exchange rate, is defined. The outcome for the exchange rate is fed into the UIP equation to determine the local three-month interest rate. (MAS, 2014[35]).

The incorporation of theoretical insights of the credit channel into forecasting will continue to pose challenges in developing Asia, owing to the evolving role of the banking sector.

Data availability and quality issues may hamper the forecasting process

Economic projections for Emerging Asian countries take into account the rich, but sometimes diverse, set of national data sources. This hampers comparability across different variables and across the same variables of different countries. Another challenge encountered in forecasting stems from the frequency of data releases. The projections typically rely on high-frequency data. However, quarterly data are published with different delays, while for some countries in Emerging Asia quarterly data are not available at all. Sometimes, unpredictable revision practices could also damage the reliability of data.

Missing data is usually a result of failure in the data collection process. There are various types of missing data patterns. The fact that the missing data is often not missing at random and is characterised by long periods where no data is observed further complicates matters. The performance of traditional univariate forecasting methods tends to decrease with the length of the missing data period because they do not have access to local temporal information. An option for dealing with data gaps is to calculate estimates of the missing values. Certain types of missing data can often be modelled effectively using univariate methods due to their short length. However, some types are more difficult to handle due to the presence of extended gaps where no local temporal information is available. (Haworth and Cheng, 2012[61]).

Elasticity measurement gives rise to a number of challenges

The measurement of elasticities poses various challenges in macroeconomic models. The types of elasticities being modelled are manifold, ranging from demand elasticity to trade and labour supply elasticities. Various approaches pertaining to each of these areas will be summarised below.

One common way to estimate demand elasticity is to rely on instruments that trace out demand. For instance, Berry, Levinsohn and Pakes (1995[62]) develop techniques for empirically analysing demand and supply in differentiated products markets and then apply these methods to assess equilibrium in the US automobile industry. On the demand side, they estimate own- and cross-price elasticities as well as elasticities of demand with respect to vehicle attributes. The general approach posits a distribution of consumer preferences over products. These preferences are then explicitly aggregated into a market-level demand system that, in turn, is combined with an assumption on cost functions and on pricing behaviour to generate equilibrium prices and quantities. The primitives to be estimated are parameters describing firms' marginal costs and the distribution of consumer tastes. The distribution of tastes determines elasticities, and these, together with marginal cost and a Nash assumption, determine equilibrium prices (Berry, Levinsohn and Pakes, 1995[62]).

An alternative approach is to make parametric assumptions regarding the shape of supply and demand. Broda and Weinstein (2010[63]) use a panel dataset and assume that demand and supply elasticities are constant over different categories of Universal Product Codes (UPCs). This strategy allows the identification of the "within" demand elasticities. In particular, Broda and Weinstein (2010[63]) define a set of moment conditions for each brand module and product group by using the independence of the unobserved demand and supply disturbances for each UPC over time. This implies that there are as many moment conditions as the number of UPCs in a particular product group. To estimate demand elasticities across brand modules, the authors use market shares and unit prices at the brand level across modules and assume that the across brand elasticities in all modules within a product group are the same. They aggregate prices to form brand-level prices. Thus, estimates can be obtained for the two sets of elasticities per product group that are key to estimating the impact of product turnover.

Additionally, Bussière et al. (2011[64]), inter alia, propose an approach to estimating trade elasticities. More specifically, the study re-evaluates the relation between trade flows and macroeconomic dynamics by developing a new methodology for the estimation of trade elasticities, namely the elasticity of import demand to aggregate demand, which takes into account the different import content and cyclical behaviour of the different components of aggregate demand. The authors use the OECD Input-Output tables to show that the most procyclical components of demand (investment and exports) have a particularly rich import content, whereas the other components (private consumption and, especially, government spending) have lower import content. Bussière et al. (2011[64]) construct a new measure of aggregate demand, called Import-intensity-Adjusted Demand (IAD) as a weighted average of traditional aggregate demand components (investment, private consumption, government spending, and exports) using as weights the import contents of demand computed from the OECD Input-Output tables.

The literature on how to estimate the labour supply elasticities is equally vast. The first empirical effort known to estimate labour supply pertains to Rowe and Douglas (1934[65]). Rowe and Douglas (1934[65]) build up an index of the growth in the volume of fixed capital in the United States from 1899 to 1922 together with a series representing the growth of labour supply. Subsequently, the author develops an equation of production showing the quantitative influence of labour and capital upon production. Over the period as a whole, labour is found to contribute three quarters and capital a quarter of the total product, while their marginal productivities are computed on a yearly basis. Rowe and Douglas (1934[65]) find a labour supply elasticity that lies somewhere between -0.1 and -0.2. Subsequent labour supply studies often separate the income and substitution effects and make use of microeconomic data instead of macroeconomic data (for instance, (Blundell, Meghir and Neves, 1993[66]; Kimball and Shapiro, 2008[67]; Saez, 2002[68]).

Central bank models account for elasticities in various ways. For instance, in the Federal Reserve Board's US/FRB model, the equilibrium condition also specifies that the optimal price margin may vary with the aggregate unemployment rate to allow for possible cyclical variations in perceived demand elasticities and marginal costs of production. In the model's foreign trade block, each trade equation contains a time trend and is formulated as an error correction; long-run income elasticities are constrained to unity and long-run price elasticities to minus unity (Federal Reserve Board, 1996[30]). In a similar vein, Bank of Canada's LENS models exports using the standard rational error-correction specification along with the contemporaneous change in the foreign output gap to help improve short-term forecast performance and capture the fact that the income elasticity of trade variables is typically higher in the short term (Gervais and Gosselin, 2014[33]). In the Bank of England's COMPASS model, one of the structural parameters is the intertemporal elasticity of substitution. In the model, exports have a unit world-demand income elasticity, while imports have a unit price elasticity (Burgess et al., 2013[32]).

In the Banque de France FR-BDF macroeconomic model, the production function technology is assumed to be a Constant Elasticity of Substitution (CES) production function. This makes it possible to have a non-unitary elasticity of labour and investment to labour cost and capital user cost. In the long run, the wage elasticity of supply is assumed to be zero. As regards external trade, the FR-BDF model provides estimates for the price elasticities in equations of exports and non-energy imports. This is achieved by including the weight of emerging countries in the former case and a goods variety indicator in the latter. These elasticities play a pivotal role in the long-run convergence of the FR-BDF model (Lemoine et al., 2019[69]).

As part of a projection exercise, it may also be necessary to evaluate the impact of last-minute changes in the assumptions underlying the projections or to assess the impact of alternative assumptions in a consistent manner. The ECB developed a tool called *Basic Model Elasticities* (BMEs) to provide a mechanical "rule of thumb" assessment of the impact on the economy from certain changes in assumptions. BMEs can be thought of as a smaller version of a multi-country model, but linearised around a specific baseline. BMEs are presented by a set of tables that, for each country, provide the impulse responses of endogenous variables to shocks in certain exogenous variables. The BME process involves two steps. First, an alternative path for an exogenous variable is specified in terms of deviations from its baseline. The BME tool first calculates, for each quarter, the related direct impact of the shock in the exogenous variables on the endogenous variables for each country and for the euro area as a whole. In a second step, the tool uses an incorporated linearised trade link block to calculate the effect of changes in import demand and the export deflator on other countries, namely spillover effects. The result is given by adding up the direct impact and the spillover effects (ECB, 2016[70]).

The role of Big Data in economic forecasting

Following the development of AI, “Big Data” provides some avenues for unveiling knowledge that might be relevant to the task of macroeconomic forecasting. The use of search engine data, for example, could hint at potentially statistically significant relationships between search terms and certain dependent variables. For instance, Scott and Varian (2015[71]) show that search engine queries in the “vehicle shopping” category could be useful in forecasting automobile sales, while searches for terms like “file for unemployment” could be good candidates for forecasting initial claims for unemployment benefits. Although often applied in other social sciences, text mining has been less frequently used in economics and in policy circles. Bholat et al. (2015[72]) discuss how text mining is useful for addressing research topics of interest to central banks, and provide a walkthrough primer on how to mine text, including an overview of unsupervised and supervised techniques. However, there are several methodological challenges in using Big Data for forecasting purposes. First, there is a need to avoid drawing unreliable conclusions. For example, the use of search engine data in an unstructured way can lead to spurious results. Second, solutions need to be designed for reducing the dimensionality of the information inherent in Big Data in ways that enable its conversion into meaningful knowledge (Nyman et al., 2014[73]).

Remaining in the realm of Big Data, some countries in Emerging Asia have yet to explore fully the benefits of “nowcasting”. Indeed, Emerging Asian countries could more actively exploit the information that is published early and at higher frequencies than the target variable of interest. This would allow obtaining an early estimate before the official figures become available. For instance, if the focus is on tracking GDP, one may look at its expenditure components, like for example personal consumption, or variables related to the supply-side, such as industrial output. In addition, the information contained in surveys may also be considered. Surveys are particularly valuable sources of information owing to their timely release. Furthermore, one may also consider forward-looking indicators such as financial variables, which are available at very high frequency and may carry information on expectations of future economic developments (Bańbura et al., 2013[74]).

Luciani et al. (2015[75]) have attempted to overcome some of the obstacles outlined above and developed a nowcasting framework for Indonesia. The authors estimate a Dynamic Factor Model on a dataset of 11 indicators over the period 2002-2014 in order to generate nowcasts of the Indonesian economy. To gauge the current state of the Indonesian economy, the authors construct a prediction of GDP growth before the official data is released. The set of variables used in the nowcasting exercise is determined according to data availability and expert judgement and includes some of the following items: central bank policy rate, exports, car sales, cement consumption, imports, money supply, etc. Luciani et al. (2015[75]) demonstrate, by means of a pseudo-real-time forecasting exercise, that incorporating high-frequency data in a rigorous framework leads to an improvement in the forecast accuracy of Indonesia’s economy compared to simple univariate benchmarks. The authors also argue that their model does well in predicting quarterly GDP growth when compared with private forecasters and does well in predicting annual GDP growth when compared with institutional forecasts.

Broader in nature than text mining, natural language processing could help policy makers to understand and analyse unstructured data. Kalamara et al. (2020[76]) present some ways to extract timely economic signals from newspaper text. The text is drawn from three popular UK newspapers and it is subsequently incorporated into forecasts by combining counts of terms with supervised machine learning. The results lend support to the idea that exploiting newspaper text can improve economic forecasts both in absolute and marginal terms. These improvements tend to be more pronounced during periods of economic stress when, arguably, forecasts matter even more than in normal times (Kalamara et al., 2020[76]).

Models must become more flexible to cope with changing economic environments

The need for forecasting frameworks to be adaptable to unconventional monetary and fiscal policies often deployed in and following crises poses a key challenge. For instance, Thach, Oanh and Chuong (2018[77]) study the impact of fiscal policy and macroprudential policy as well as their interaction on financial stability in Viet Nam during the global financial crisis of 2007-08 (GFC). The results of the study suggest that both fiscal policy and macroprudential policy have a great impact on financial stability. In particular, fiscal policy is shown to have a negative impact, while macroprudential policy has a positive impact on financial stability in Viet Nam (Thach, Oanh and Chuong, 2018[77]). Policy makers should therefore carefully consider the interactions between various policy functions in order to ensure their effectiveness.

Indeed, forecasting frameworks may sometimes not be able to capture the latest policy trends and a serious treatment of unconventional policies (large-scale asset purchases and quantitative easing) in policy models. For instance, quantifying the impact of quantitative easing (QE) on the real economy is not straightforward, as standard tools cannot be easily applied. To overcome this issue, Meinusch and Tillmann (2016[78]) use an alternative approach, the Qual VAR model, which is a combination of a standard VAR system with the event-studies literature that uses binary policy announcements. Rather than including QE announcements as an exogenous variable in an event study or panel model, Meinusch and Tillmann use the Qual VAR framework to model the interaction of QE announcements with business cycle variables in the US. The resulting impulse response functions suggest that QE does indeed have a significant and sizeable effect on both real economic activity and the financial sector (Meinusch and Tillmann, 2016[78]).

To adapt to rapidly changing economic environments, countries might need to adopt unconventional policies more often. Therefore, designing models with increased flexibility in terms of policy inputs remains a key area of econometric and modelling research and development.

Inclusion of financial stability considerations

Apart from analysing unconventional policies, there is an increasing need to be able to integrate financial stability considerations into forecasting models. This involves stress testing exercises and the creation of an environment with an effective role for various macroprudential tools (Linde, Smets and Wouters, 2016[79]). In addition, macroeconomic models necessarily exclude some economic sectors and do not explicitly recognise the probability of default. Effort has been increasingly devoted to modelling the financial system. The integration of financial markets explicitly into general equilibrium is of outmost importance, for both households and firms. Iacoviello (2005[80]), for example, develops and estimates a monetary business cycle model with nominal loans and collateral constraints tied to housing values. In the model, demand shocks move housing and nominal prices in the same direction, and are amplified and propagated over time. Other models suggest that strong endogenous risk and feedback channels between the real and the financial sector can play an important part in explaining the change in volatility and correlations between tranquil and turmoil periods. In this regard, Brunnermeier and Sannikov (2014[81]) study the full equilibrium dynamics of an economy with financial frictions. In the study, endogenous risk, driven by asset illiquidity, persists in crisis even for very low levels of exogenous risk (i.e. “the volatility paradox”). Endogenous leverage determines the distance to crisis, while securitisation and derivatives contracts that improve risk sharing may lead to higher leverage and more frequent crises (Brunnermeier and Sannikov, 2014[81]). Another important avenue is the incorporation of default for both the financial and non-financial sectors, as in Clerc et al. (2015[82]). The authors develop a dynamic general equilibrium model for the positive and normative analysis of macroprudential policies. For all borrowers (households, firms, and banks), external financing takes the form of debt which is subject to default risk. This “3D model” shows the interplay between three interconnected net worth channels that cause financial amplification and the distortions due to deposit insurance (Clerc et al., 2015[82]).

Acknowledging the importance of better understanding macrofinancial linkages for enhancing financial stability, Ghilardi and Peiris (2014[83]) develop an open-economy DSGE model with an optimising banking sector to assess the role of capital flows, macrofinancial linkages and macroprudential policy in Emerging Asia. In the model, financial frictions affect real activity via the impact of funds available to the banking sector, while there is no friction in the transfer of funds between banks and non-bank financial intermediaries. Financial instability or a shock to bank capital triggered by non-performing loans, for example, is shown to have a pervasive and significant impact on the economy through macrofinancial linkages. The model developed by Ghilardi and Peiris (2014[83]) therefore sheds light on the key transmission mechanism of a financial crisis by showing how bank leverage amplifies the initial shock to capital and tightens the bank's borrowing constraint, effectively inducing asset sales at fire-sale prices. The crisis then feeds into real activity as the decline in asset values is considered responsible for the magnified drop in investment and output (Ghilardi and Peiris, 2014[83]).

The strong interlinkages between the banking sector and the real economy, especially in Emerging Asia, necessitate the inclusion of financial stability measures in models. It is critical that these measures are harmonised with the other inputs of the model, so that impacts of financial stability on the real economy can be well observed.

Adaptation to globalisation

Macroeconomic forecasting models are rather poorly equipped to account for increasingly globalised world and changing nature of the impact of global shocks. This appears as a major shortcoming in a world characterised by increasingly globalised trade and integrated financial markets. For instance, a key challenge is to account for the relationship between interest rate differentials and exchange rate movements, what is known as the uncovered interest rate parity condition, more precisely. For instance, Eichenbaum and Evans (1995[84]) assess the effects of shocks to US monetary policy on exchange rates. Three measures of these shocks are considered, namely: orthogonalised shocks to the federal funds rate, orthogonalised shocks to the ratio of non-borrowed to total reserves and changes in the Romer and Romer index of monetary policy. The results of the study are twofold. First, a contractionary shock to US monetary policy leads to persistent and significant appreciations in US nominal and real exchange rates. Second, a contractionary shock to US monetary policy is shown to trigger significant and persistent deviations from uncovered interest rate parity in favour of US interest rates (Eichenbaum and Evans, 1995[84]). In another study of US monetary spillovers to other economies, Brauning and Ivashina (2018[85]) report that the availability of foreign bank credit to firms in emerging market economies is strongly connected to the conduct of US monetary policy.

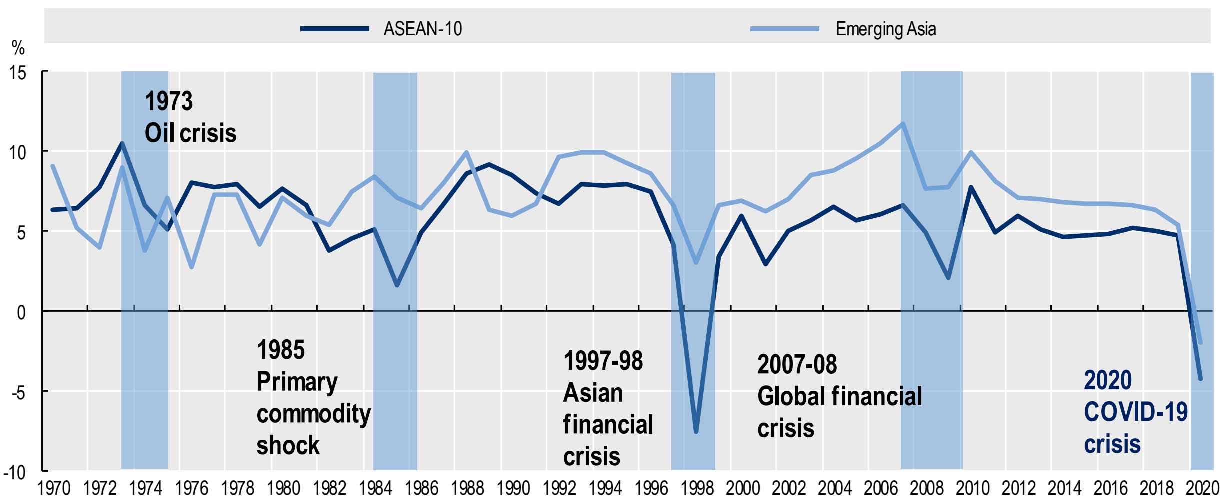
Some studies have attempted to shed light on how Emerging Asian economies respond to global policy shocks, but they are mostly focused on the spillover effects of US monetary policy decisions. For instance, Choi et al. (2017[86]) use a panel factor-augmented vector autoregressive (FAVAR) model to assess the effect of US and domestic monetary policies on emerging market economies. They conclude that a US policy rate hike outstrips an equivalent increase in domestic policy rates and also document that bond and equity markets in emerging economies are prone to outflows when US monetary policy tightens (Choi et al., 2017[86]). Similarly, Miyajima, Mohanty and Yetman (2014[87]) employ a panel VAR model to evaluate the impact of a very low US term premium on small open Asian economies. The results show that unconventional US monetary policy spills over to Asia mainly through low domestic bond yields and rapid growth of domestic bank credit. These spillovers compromise national monetary authorities' control over long-term interest rates, which are key determinants of economic activity in small open Asian economies (Miyajima, Mohanty and Yetman, 2014[87]).

Foreign shocks are increasingly relevant to a country's welfare as globalisation accelerates shock transmission. Forecasting models need to incorporate these trends in a flexible way.

6 Forecasting in times of large-scale external shocks: Implications for COVID-19

The COVID-19 crisis has caused both supply and demand shocks, making it different from other large shocks, such as the Asian financial crisis of 1997-98 (AFC) and the global financial crisis of 2007-08 (GFC), which mainly stemmed from demand shock. During AFC and GFC, the turmoil began with disruptions to the financial sector and only spread to the real economy with a certain delay. During the COVID-19 crisis, the shocks are mainly exogenous and large, similar to large-scale natural disasters. In many parts of the world, the pandemic has put the real economy out of action almost immediately, depressing both supply and demand with unparalleled force. For instance, Triggs and Kharas (2020[88]), among others, point out that the pandemic is unlike a standard recessionary (i.e. aggregate demand) shock or a typical inflationary supply shock. As argued by Triggs and Kharas (2020[88]), the demand shock was clear and obvious, stemming from the lockdown measures and other restrictions that dealt a blow to consumer services. Similarly, the supply shock was triggered by disruptions to supply chains. In addition, the impact of the COVID-19 outbreak on GDP has been more acute compared to the GFC (Figure 6.1). Several economic sectors will take longer to recover from the losses they incurred.

Figure 6.1. Real GDP growth rate of ASEAN-10 and Emerging Asia, 1970-2020



Source: OECD (2020), *Economic Outlook for Southeast Asia, China and India 2020 – Update: Meeting the Challenges of COVID-19*, https://doi.org/10.1787/e8c90b68-en.

Forecasting in times of large external shocks may require different approaches compared to normal times. Several key issues need to be addressed in this context:

- inclusion of “uncertainty”, such as that induced by COVID-19, in forecasting models
- natural disasters as a reference for large external shocks
- bounded rationality in times of large external shocks
- existence of indirect cost, in addition to direct cost
- effective use of epidemiological models (as appropriate).

Acknowledgement of heightened uncertainty is essential for forecasting in times of large external shocks, such as the COVID-19 pandemic. In this regard, the section reviews some attempts at forecasting the impact of large external shocks by using large-scale natural disasters as a reference. Third, the possible invalidity of the rational expectations assumption is discussed. Fourth, techniques for measuring direct and indirect costs and their limitations are examined. The section concludes with a review of a baseline epidemiological model. The model may be modified to reflect the conditions of a particular scenario (such as COVID-19 outbreaks).

Including “uncertainty” in forecasting models will be a key challenge

Indeed, obtaining reliable forecasts during crises is more challenging than in normal times. In an assessment of forecasts in the run-up to recessions, An, Tovar Jalles and Loungani (2018[89]) find that forecasters typically miss the magnitude of a recession episode by a wide margin until the year is almost over, with forecasts of the private sector and the official sector being virtually identical. Strong booms are also missed, suggesting that behavioural factors (i.e. the reluctance to absorb either good or bad news) play a role in the evolution of forecasts (An, Tovar Jalles and Loungani, 2018[89]). In addition, conventional approaches to constructing forecast intervals, based on Gaussian shocks, appear inappropriate for many macroeconomic variables in the presence of large stochastic changes in trends. The paper by Phillips (1996[90]) constitutes an early attempt at estimating extreme values under general conditions. In the framework developed by Phillips (1996[90]), once the parameters of the process are estimated, the estimated model can be used to develop parametric bootstrap forecast intervals that reflect the possibility of large stochastic shocks in the future. The model is estimated for several series of macroeconomic variables, for some of which changes only occur in the conditional variance of the innovation process, while the conditional variances are not dependent. The evidence provided in this study suggests that the usual method of constructing forecast intervals, based on assuming Gaussian innovations, produces intervals that are too short (Phillips, 1996[90]).

Other approaches to analysing the impact of external shocks are proposed in Bloom (2009[91]) and Jurado, Ludvigson and Ng (2015[92]). Bloom (2009[91]) builds a model with a time-varying second moment, which is numerically solved and estimated using firm-level data and subsequently uses it to simulate a macroeconomic uncertainty shock. The simulation exercise shows that macroeconomic uncertainty shocks generate short sharp recessions and recoveries. Jurado, Ludvigson and Ng (2015[92]) also attempt to provide new measures of uncertainty, by modelling a variable’s *h*-period uncertainty as the conditional volatility of the purely unforecastable component of the future value of the series. The findings are manifold. First, the estimates by Jurado, Ludvigson and Ng (2015[92]) imply far fewer larger uncertainty episodes than what is inferred from common uncertainty proxies. Second, their estimate of macroeconomic uncertainty appears to be far more persistent than stock market volatility. This implies that most movements in common uncertainty proxies, such as stock market volatility, and measures of cross-sectional dispersion, are not associated with a broad-based movement in economic uncertainty (Jurado, Ludvigson and Ng, 2015[92]).

In a similar vein, Baker et al. (2020[93]) aim to assess the near and medium-term macroeconomic effects of the COVID-19-induced uncertainties. To achieve this goal, the authors identify three indicators (i.e. stock market volatility, newspaper-based economic uncertainty and subjective uncertainty in business expectation surveys) that provide real-time forward-looking uncertainty measures. In order to quantify the macroeconomic impact of the COVID-19 crisis, Baker et al. (2020[93]) feed COVID-19 pandemic induced first-moment and uncertainty shocks into an estimated empirical model of disaster effects. The empirical model is a vector autoregression (VAR) with shock identification using natural disasters as instruments. The authors show that approximately half of the forecasted US real GDP contraction in the second quarter of 2020 reflects a negative effect of COVID-induced uncertainty (Baker et al., 2020[93]).

Even some of the most sophisticated econometric approaches tend to perform poorly in predicting the depth of past downturns, and in particular of the COVID-19 recession. A growing number of studies have stressed the importance of nowcasting during crisis times. Nowcasting is important because current-quarter forecasts of GDP growth and inflation provide useful summaries of recent news on the economy. Nowcasts are also important because these forecasts are commonly used as inputs to forecasting models, such as some of the DSGE models in use at central banks, which are effective in medium-term forecasting but not necessarily short-term forecasting (Carriero, Clark and Marcellino, 2020[94]). Moreover, when the economy experiences sudden headwinds such as the COVID-19 shock, conditions can evolve rapidly. Monitoring the high-frequency evolution of the economy in real time cannot be achieved with DSGE models, for instance, but other techniques need to be designed. For example, Lewis, Mertens and Stock (2020[95]) propose a Weekly Economic Index (WEI) that measures real economic activity at a weekly frequency and that can be updated relatively quickly. Some of the weekly series that compose the WEI are the initial unemployment insurance claims, raw steel production, US railroad traffic and electricity utility output.

In addition, as shown by Estrin, Tang and Subramani (2020[96]), any reliable macroeconomic forecast during the COVID-19 period must accurately capture consumers' changing needs, attitudes and behaviour. In this regard, the authors augment existing models of the US economy by combining forward-looking consumer sentiment with real-time transaction data. The main data source for this study is a database of 500 000 credit and debit accounts with weekly details of transaction patterns, which allows focusing on expense categories that are most likely to be impacted by near and long-term changes in consumer behaviour (i.e. travel, hospitality, recreation, retail, gas, etc.). To gauge the future evolution of spending, Estrin, Tang and Subramani (2020[96]) gather information on how consumers intend to buy under multiple realistic scenarios that include the timing and extent of reopening conditions. These scenarios are updated on a monthly basis to reflect new information. This approach could therefore enhance the accuracy of forecasts, as it combines past credit and debit transaction patterns with consumer feedback that captures anticipated cash, credit and debit expenditures (Estrin, Tang and Subramani, 2020[96]).

A separate line of research has focused on tail risks in macroeconomic outcomes, typically at short horizons (i.e. one quarter or one year ahead). Most of this work has been inspired by the quantile regression methods to estimate tail risks, as developed in Adrian, Boyarchenko and Giannone (2019[97]), or in linear semi-structural models as proposed by Hasenzagl et al. (2020[98]), among others. For example, Reichlin, Ricco and Hasenzag (2020[99]) evaluate the role of financial conditions as predictors of macroeconomic risk, first in the quantile regression framework of Adrian, Boyarchenko and Giannone (2019[97]) and then in the framework developed by Hasenzagl et al. (2020[98]). The authors derive several important conclusions. First, they suggest that credit spreads provide limited advanced information on growth vulnerability. Second, non-financial leverage provides a leading signal for the left quantile of the GDP distribution in the 2008 recession. Third, they document a relatively strong predictive power of measures of excess leverage conceptually similar to the Basel credit-to-GDP gap, but cleaned from business cycle dynamics (Reichlin, Ricco and Hasenzag, 2020[99]).

Other studies explore options for increasing the reliability of nowcasts and forecasts for the COVID-19 period, adjusting them by an amount similar to the nowcast and forecast errors made during the financial crisis and subsequent recovery. Foroni, Marcellino and Stevanovic (2020[100]), for example, build their forecast adjustments for the COVID-19 crisis on the Great Recession. This approach is motivated by the similarities between the two crisis events. First, the uncertainty has increased in both episodes implying negative and long-lasting effects on real activity. Second, the Great Recession is the most similar event to COVID-19 in the past decades in terms of the implied demand and supply shocks. The authors argue that the performance of nowcasting models during the Great Recession could be informative for the COVID-19 crisis. This finding is also supported by empirical evidence, most notably for Q1 2020.

Large-scale natural disasters can be used as a reference for large external shocks

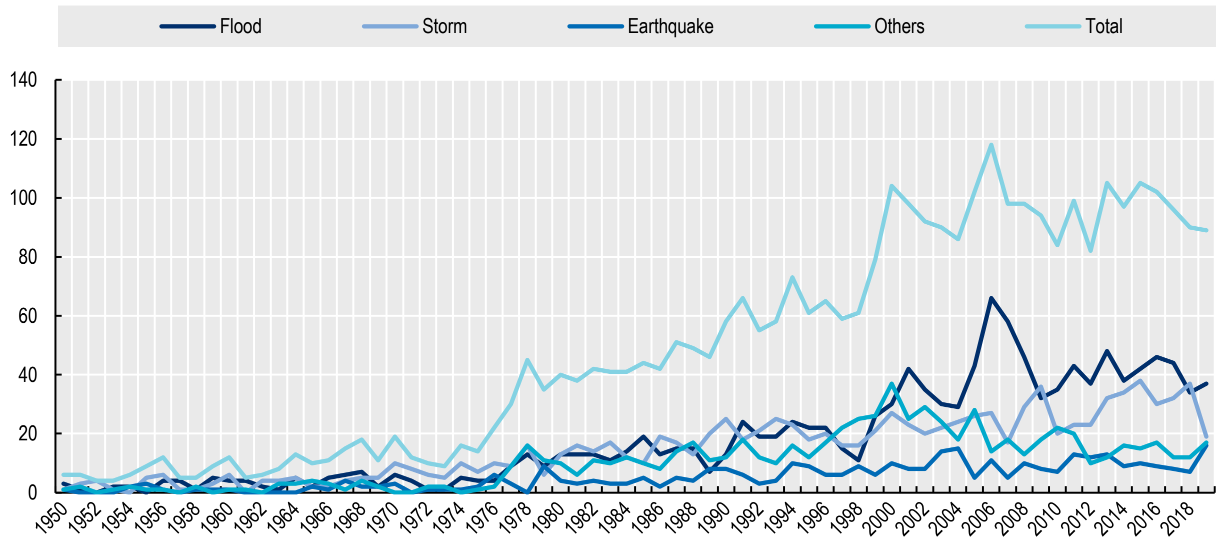
Emerging Asia is prone to natural disasters. Major natural disasters in the region include meteorological disasters such as storms, geophysical disasters such as earthquakes and volcanic activity, hydrological disasters such as flood and landslide, or climatological disasters such as drought. The number of floods and storms has steadily increased in recent decades [(OECD, 2019[101]) and Figure 6.2]. Since the data on past pandemics are very scarce, information on natural disasters can be used as a reference for large external shocks. However, results must be interpreted with care due to differences between the two types of events.

A large number of studies have assessed both the short-term impact and the long-term economic impact of large exogenous shocks, typically focusing on natural disasters. For instance, Noy and Nualsri (2007[102]) show that a natural disaster destroying human capital has a negative impact on growth, while they do not find any statistically significant effect on output with regard to natural disasters leading to a reduction in physical capital. Raddatz (2007[103]), Noy (2009[104]) and Rasmussen (2004[105]) also find that natural disasters can have short-run adverse effects on the economy. Analysing a panel of countries simultaneously, they consider various indicators for measuring the magnitude of a disaster. Their estimation results show that direct damage costs of natural disasters are associated with a 0.5% to 3% decrease of the same-year real GDP growth rate. Furthermore, some studies even suggest that countries affected by a natural disaster are permanently relegated to a lower growth path (Hsiang and Jina, 2014[106]).

Uncertainty is remarkably high during times of large external shocks. While it is crucial to understand its impact on economic activity, measuring uncertainty is hard as it is an increasingly unobservable concept. One of the approaches used in the specialised literature for identifying the causal effects of uncertainty on activity relies on events such as natural disasters to identify uncertainty shocks. Baker and Bloom (2013[107]), for instance, study the causal relationship between uncertainty and growth by using natural disasters, terrorist attacks and unexpected political shocks as instruments for the stock market proxies of first and second moment shocks. The authors find that both the first and second moments are highly significant in explaining GDP growth, with second moment shocks accounting for at least a half of the variation in growth (Baker and Bloom, 2013[107]). In a recent study, Baker et al. (2020[108]) develop a learning model that captures the two channels through which natural disaster shocks affect expectation formation, namely the attention effect whereby the visibly large shocks induce immediate and synchronised updating of information for inattentive agents, and the uncertainty effect, whereby the occurrence of those shocks generates increased uncertainty among attentive agents. Baker et al. (2020[108]) also argue that information rigidity declines significantly in the aftermath of large, unexpected natural disaster shocks.

Guerrieri et al. (2020[109]) develop a modelling framework that suggests severe negative supply shocks (like the COVID-19 shock) can lead to a shortfall in aggregate demand. As posited by the authors, demand may overreact to the supply shock and lead to a demand-deficient recession. The model rests on the hypothesis that supply and demand forces are intertwined: demand is endogenous and affected by the supply shock and other features of the economy. For example, when workers lose their income, due to the shock, they reduce their spending, causing a contraction in demand. This mechanism could be strong enough to cause an overall shortfall in demand. Guerrieri et al. (2020[109]) lay out the conditions for this to happen. Low substitutability across sectors and incomplete markets, with liquidity-constrained consumers, all contribute towards the possibility of Keynesian supply shocks.

Figure 6.2. Recorded occurrences of natural disasters in Emerging Asia, 1950-2019



Note: Other disasters include drought, epidemics, volcanic activity, landslides, extreme temperature, insect infestation, wildfire and mass movements (dry). Events are categorised as disasters if they meet at least one of four criteria: 10 or more persons killed; 100 or more persons affected, injured, or left homeless; an appeal for international assistance; or an official declaration of a state of emergency.
Source: CRED.

Other papers used large-scale natural disasters to assess the growth impact in advanced versus developing economies. Growth in developing countries appears to be more sensitive to natural disasters than in developed ones, with more sectors affected and the effects larger and economically meaningful (Klomp and Valckx, 2014[110]; Loayza et al., 2012[111]). At the same time, several studies explore the impact of natural disasters via a case studies approach. Cavallo et al. (2013[112]) conduct a comparative cross-country study; creating counterfactuals to demonstrate the effect of disasters on GDP growth path. The results show that only very large disasters display an impact on GDP growth in the affected countries in both the short and the long term. For instance, ten years after the disaster, the average GDP per capita of the affected countries is, on average, 10% lower than it was at the time of the disaster, whereas it would be approximately 18% higher in the counterfactual scenario in which the disaster did not take place. For their part, Heger and Neumayer (2019[113]) identify the causal economic impacts of the 2004 Indian Ocean tsunami by observing differences in economic activity between flooded districts/sub-districts and non-flooded districts/sub-districts in the Indonesian province of Aceh, which serve as a counterfactual comparator group to the flooded units. The study provides compelling evidence that the tsunami was only growth depressing in the first year following the disaster, while growth in subsequent years was boosted by the reconstruction effort (Heger and Neumayer, 2019[113]). Another method widely used in economic impact assessment is the event-study approach. While this methodology is typically used in the field of financial markets, several studies have used it for gauging the impact of pandemics on various sectors (Chen et al., 2007[114]).

A large number of academic papers rely on the analysis of time series for quantifying the impact of external shocks, in particular by using structural vector autoregressive (SVAR) methods, whose versatility is widely acknowledged (Ludvigson, Ma and Ng, 2020[115]; Mackowiak, 2006[116]; Canova, 2005[117]; Bordo and Murshid, 2002[118]). Variations of the SVAR model have been utilised, for instance by Gupta et al.

(2020[119]), who develop a time-varying parameter structural vector autoregressive (TVP-SVAR) model to analyse the dynamic impact of uncertainty due to pandemics on output growth.

In light of the considerations outlined in the preceding paragraphs, the 2021 edition of the *Outlook* made an attempt to estimate Emerging Asian countries' growth resilience by using large-scale natural disasters as a reference for external shocks. The results were used as supplementary information for forecasting. The analysis is undertaken within a structural vector autoregressive (SVAR) model, which is suited to capture both the size and the speed of the impact. Insights on the size and speed of external shocks are derived from impulse response functions.

The modelling framework, used in the 2021 edition of the *Outlook*, in a similar vein as in Ludvigson, Ma and Ng (2020[115]) is detailed hereafter. A baseline framework, by the following p-lag vector VAR model:

$$X_t = \sum_{i=1}^{p} \beta_i X_{t-i} + \eta_t$$

where $\beta_i$are 3x3 matrices containing estimation coefficients and $\eta_t$is a 3x1 vector of error terms. Denoting X_t as a vector of three variables including, in this order, measurements of large-scale natural disaster (LND_t), real economic growth (g_t) and economic uncertainty index (U_t):

$$\mathrm{X_t} = \begin{bmatrix} \mathrm{LND_t} \\ \mathrm{g_t} \\ \mathrm{U_t} \end{bmatrix} = \begin{bmatrix} \text{Large} - \text{scale natural disaster} \\ \text{Real economic growth} \\ \text{Economic uncertainty index} \end{bmatrix}$$

The reduced form innovations η_t relate to mutually uncorrelated structural shocks e_t by:

$$\eta_t = Be_t \text{ , } e_t \; N \; (0, \Sigma)$$

In this equation, Σ is a diagonal matrix with the variance of the shocks, and diag(B) = 1. For identification, B is assumed to be lower triangular. The covariance matrix of VAR residuals is orthogonalised using a Cholesky decomposition with the variables ordered as above, i.e. from the most exogenous to the most endogenous.

The resulting structural VAR (SVAR) has the following structural moving average representation:

$$X_t = \mu + \psi_0 e_t + \psi_1 e_{t-1} + \psi_2 e_{t-2} + \cdots$$

where μ is deterministic or steady state value of X_t. ψ_j, 3x3 matrices including the standard deviation of shocks. The impact effect of shock i is measured in the i-th diagonal entry of ψ_j. The dynamic responses of X_{t+h} to one-time change in e_t are summarised by ψ_h, matrices that can be estimated directly from the VAR using Ordinary Least Squares (OLS).

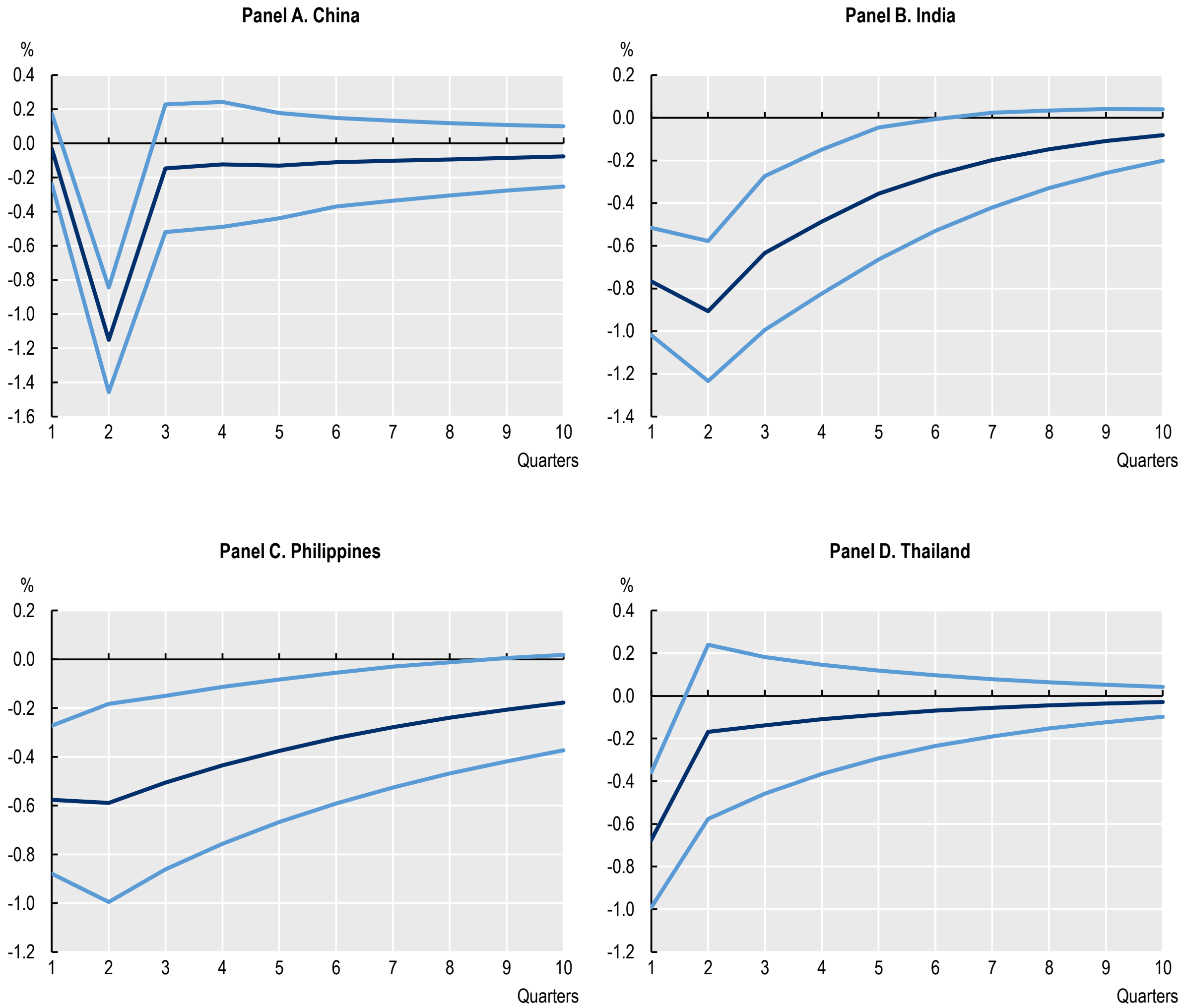
As a measure of economic uncertainty, the quarterly Economic Policy Uncertainty Index (EPU) constructed by Baker, Bloom and Davis (2016[120]) was used. The EM-DAT database from the Centre for Research on the Epidemiology of Disasters records the nature, scope and costs of major disasters globally. Monthly natural disaster data are collected from the Emergency Events Database. The monetary costs of frequently occurring natural disasters in Emerging Asia was used over the period Q1 1960 to Q1 2020 as a measure of natural disasters in units of billions of US dollars. These are disasters such as earthquakes, landslides, floods, storms, droughts, and volcanic activities. Quarterly data by country are obtained by summing the monthly damage costs of all such natural disasters. The resulting observations highlight 660 quarters that have non-zero values, of which 164 occurred in the Philippines alone, 120 in China and 113 in India. Large-scale natural disasters are defined as coinciding with a drop in real GDP during the same quarter or the next one. For instance, from 1960 to 2020, 14 in the Philippines, 8 in Thailand, 8 in India and 4 in China are identified as quarters of large-scale natural disasters.

Then, the dynamic responses of real economic growth to a shock are examined. Information on the size and speed of the pass-through of external shocks on economic growth can be derived from impulse response functions (IRFs). Growth resilience could be interpreted as the magnitude and speed of recovery in the aftermath of an external shock, as can be inferred from the analysis of IRFs.

The empirical results show that LNDs have a negative impact on real GDP growth in all economies, in particular, India, Thailand and the Philippines, although the speed at which the impact wanes is different across countries (OECD, 2021[121]). In Thailand and China, the negative effect lasts only a short period and becomes statistically insignificant, while in India and the Philippines, the effect on growth is more persistent (Figure 6.3).

Figure 6.3. Response of real economic growth to large-scale natural disasters

Innovation using Cholesky (d.f. adjusted) Factors (±2 S.E)



Note: The light blue lines are the error bands (lower bound and upper bound) and the dark blue line in the middle is the implus response function.
Source: Author's calculations.

In addition, some large external shocks such as pandemics could be multi-period shocks. To explore these features, large shocks based on our SVAR models taken as baselines.

For instance, for two consecutive shocks of one standard deviation, the dynamic response of *Xt+h* is:

$$\mathrm{E}[X_{t+h}|e_{1t} = \sigma, e_{1t-1} = \sigma, X^t] - \mathrm{E}[X_{t+h}|e_{1t} = 0, e_{1t-1} = 0; X^t] = \psi_h + \psi_{h+1}$$

X^t contains all information in X at time t and at all lags. The left side of the equation denotes the difference between the forecasted variables under and in the absence of a shock of one standard deviation. h is the horizon for which the impulse responses are computed.

The rational expectations assumption may be too strong in times of large external shocks

The dominant approach in macroeconomic modelling has made use of the rational expectations hypothesis, which posits that agents have probability beliefs that coincide with the probabilities predicted by the model. In other words, economic models typically assume agents are rational. However, the assumption is a strong one and may seem inadequate when considering relatively short-run responses to disturbances, or the consequences of newly adopted policies that have not been followed in the past (Woodford, 2013[122]). The same may be true for large shocks. The global financial crisis (GFC) of 2007-08 has raised concerns around the relevance of the standard representative agent framework in macroeconomics. For instance, Vines and Wills (2018[8]) think that one of the main changes required to the core macroeconomic model is to place a limit on the operation of rational expectations.

There is a vast behavioural macroeconomics literature emphasising the role of non-rational expectations and bounded rationality in stylised complexity models. Woodford (2013[122]), for example, discusses the role of non-rational expectations within the New Keynesian modelling framework. One of the approaches discussed by Woodford (2013[122]) involves the definition of classes of reasonable specifications of expectations under a given policy regime, rather than a single correct specification. Additionally, the framework developed by Adam and Marcet (2011[123]) introduces a notion of bounded rationality called “internal rationality”. In this framework, agents are internally rational in the sense that they maximise discounted expected utility under uncertainty given dynamically consistent subjective beliefs about the future. At the same time, agents may not be “externally rational”, which means they may not know the true stochastic process for payoff-relevant variables beyond their control. Adam and Marcet (2011[123]) show that even though this is potentially a deviation from the beliefs of the rational expectations hypothesis, the outcomes of the learning model can be quite different.

One of the ways in which the COVID-19 pandemic has affected the formation of expectations is reflected by economic agents’ herding behaviour; Espinosa-Mendez and Arias (2021[124]) report that the pandemic had an effect on herding behaviour in European capital markets. The authors show that less informed investors have followed the more informed ones, which in turn led to the erratic behaviour seen on capital markets during the second quarter of 2020. As a result of fear and uncertainty over the effects of the pandemic, less informed agents abandoned their beliefs and followed the more informed ones (Espinosa-Méndez and Arias, 2021[124]). Kizys, Tzouvanas and Donadelli (2021[125]) document similar herding behaviour in international stock markets during the COVID-19 pandemic. The study also suggests that government policy responses to the economic fallout somewhat alleviated herding behaviour. In light of the considerations outlined in the preceding paragraphs, we estimate Emerging Asian countries’ growth resilience by using large-scale natural disasters as a reference for external shocks. The modelling framework is detailed hereafter.

Forecasting methods need to account properly for both direct and indirect costs of disasters

The assessment of indirect costs represents an important challenge of forecasting in times of large external shocks. Many typologies of disaster impacts typically distinguish between direct and indirect losses. While direct losses are relatively straightforward to quantify, defining the indirect cost of a disaster poses different theoretical and practical challenges. Indirect costs can be broadly defined as all costs that are not provoked by the disaster itself. The challenge inherent in quantifying indirect costs stems from the fact that they span over a longer period than the event itself and they affect a larger spatial scale or different economic sectors. Another difficulty in disaster indirect cost assessment lies in the definition of the baseline scenario. The baseline scenario is not easy to define and several baseline scenarios are often possible. Furthermore, in cases where recovery and reconstruction do not lead to a return to the baseline scenario, there are permanent disaster effects that are difficult to compare with a non-disaster scenario (Hallegatte, 2015[126]). An attempt at estimating the indirect costs of the COVID-19 lockdowns is the work by Mandel and Veetil (2020[127]), among others. The authors develop a production network model that allows studying the indirect costs that emerge from the reductions in the availability of intermediate outputs. Mandel and Veetil (2020[127]) conclude that the indirect costs of lockdowns can be roughly equivalent to the direct costs, with the relation between the two being determined by the degree of substitutability between intermediate inputs.

In a similar vein, Keogh-Brown et al. (2020[128]) show that the effects of the COVID-19 pandemic on the UK economy are likely to be dominated by the indirect costs of mitigation or suppression of the pandemic. As with previous pandemic outbreaks, economic declines stemming from COVID-19 can cause struggling businesses to fail and result in a longer-term increase in unemployment. Business failures may also affect the degree to which the economy and livelihoods return to normal levels in the aftermath of the pandemic (Keogh-Brown et al., 2020[128]).

Epidemiological models and COVID-19

Finally, the modelling of epidemics can also be addressed through various models pertaining to the domain of mathematical biology (Tanaka and Pezzini, 2020[129]). Various equilibrium models have been developed in this regard, which highlight the crucial role played by the parameter R_0, describing the average number of new infections due to a contaminated individual. A widely used model in epidemiology is the 'SIR' model (Atkeson, 2020[130]), where individuals can belong to one of three states: (1) healthy and susceptible to infection (S); (2) infected and therefore capable of transmitting the disease (I); or (3) recovered and immune or deceased (R). Once a few hundred people are infected, the evolution of the epidemics becomes almost deterministic. For a SIR-type epidemic, which seems to be the case with COVID-19, an exponential growth is observed at the start of the contamination process, followed by saturation and eventually the number of people affected decreases. However, the peak of infection throughout the epidemic or the number of people affected by the virus at the end of the epidemic is highly dependent on the nature and timing of public health policy measures (Atkeson, 2020[130]).

Other deterministic approaches focus on modelling the attainment of herd immunity, for example through vaccination. A population is said to have herd immunity for a disease if enough people are immune so that the disease would not spread if it were suddenly introduced somewhere in the population. The contact number σ captures the average number of adequate contacts (i.e. those which are sufficient for transmission if all contacted people were susceptible) of an infective during the infectious period. In order to prevent the spread of the infection from an infective, enough people must be immune so that the replacement number satisfies the following condition: $\sigma S < 1$. More precisely, the susceptible fraction must be small enough so that average infective transmits the disease to less than one person during the infectious period. Herd immunity could be achieved by vaccination of susceptible people. If R is the fraction of the population that is immune due to vaccination, then herd immunity is achieved if the following condition is met (Hethcote, 1989[131]): $\sigma(1 - R) < 1$ or $R > 1 - \frac{1}{\sigma}$.

7 Conclusion

Accurate forecasts of economic trends are essential for effective policy decisions. This paper discussed different forecasting approaches, comparing forecasts during normal times and crisis periods, based on our experiences of producing the *OECD Economic Outlook for Southeast Asia, China and India* series. In general, the DSGE modelling approach has emerged as a benchmark during normal times, being used by many international organisations and national regulators for forecasting purposes. For instance, the Medium-term Projection Framework (MPF) used for the production of the Outlook belongs to this category of approach.

However, major external shocks (such as large-scale natural disasters and pandemics) pose challenges to commonly used forecasting models. Forecasting for Emerging Asian economies involves several challenges, for instance, the lack of reliable capital stock data, difficulty to model the credit channel, and delays in data release. More granular modelling of the banking sector and of interlinkages in an increasingly globalised world is also essential, while unconventional policies must be better accounted for.

Looking ahead, forecasting models will need to evolve in order to make better use of “Big Data” and nowcasting, keeping pace with the development of AI.

Annex A. Theoretical framework of the baseline model in the MPF

Households

There is a continuum of households $h \in [0,1]$, each of which purchases consumption goods $c_{h,t}$ and one-period riskless bonds $B_{h,t}$ and supplies labour services $l_{h,t}$. Each household's preferences are represented by the utility function:

$$\sum_{t=0}^{\infty} \beta^t \left\{ \frac{(c_{h,t} - bc_{t-1})^{1-\sigma}}{1+\sigma} - \frac{\chi l_{h,t}^{1+\eta}}{1+\eta} \right\} \exp(z_t^d),$$

Where $\beta \in (0,1)$ is the subjective discount factor, $\sigma > 0$ measures the risk aversion, $b \in (0,1)$ represents external habit persistence in consumption preferences, $\eta > 0$ is the inverse of the labour supply elasticity, and $\chi > 0$ is the scale factor. z_t^d represents a shock to the period utility, broadly interpreted as a demand shock. Each household h maximises the utility function subject to the budget constraint:

$$c_{h,t} + \frac{B_{h,t}}{P_t} \leq w_{h,t} l_{h,t} + \frac{\mathrm{R}_{t-1}^{\mathrm{n}} \mathrm{B}_{h,t-1}}{\mathrm{P}_t} + T_{h,t},$$

Where P_t is the aggregate price, $w_{h,t}$ represents real wage R_t^n is the (gross) nominal interest rate, and $T_{h,t}$ consists of a lump-sum public transfer and profits received from firms.

Lagrangian:

$$E_0 \sum_{t=0}^{\infty} \beta^t \left[\left\{ \frac{(c_{h,t} - bc_{t-1})^{1-\sigma}}{1-\sigma} - \frac{\chi}{1+\eta} l_{h,t}^{1+\eta} \right\} exp(z_t^d) + \lambda_t \left\{ w_{h,t} l_{h,t} + \frac{R_{t-1}^n B_{h,t-1}}{P_t} + T_{h,t} - c_{h,t} - \frac{B_{h,t}}{P_t} \right\} \right]$$

FOCs:

$\partial c_{h,t}$: $$(c_{h,t} - bc_{t-1})^{-\sigma} exp(z_t^d) - \lambda_t = 0$$

$\partial l_{h,t}$: $$-\chi l_{h,t}^{\eta} exp(z_t^d) + \lambda_t w_{h,t} = 0 \Leftrightarrow w_{h,t} = \frac{\chi l_{h,t}^{\eta} exp(z_t^d)}{\lambda_t}$$

$\partial B_{h,t}$: $$-\lambda_t \frac{1}{P_t} + \beta \lambda_{t+1} \frac{R_t^n}{P_{t+1}} = 0 \Leftrightarrow 1 = \beta \frac{\lambda_{t+1}}{\lambda_t} \frac{R_t^n}{\pi_{t+1}},$$

Where $\pi_t = \frac{P_t}{P_{t-1}}$

Under the symmetric equilibrium,

$$\lambda_t = (c_t - bc_{t-1})^{-\sigma} \exp(z_t^d) \quad (1)$$

$$w_t = \frac{\chi l_t^{\eta} \exp(z_t^d)}{\lambda_t} \quad (2)$$

$$1 = \beta \frac{\lambda_{t+1}}{\lambda_t} \frac{R_t^n}{\pi_{t+1}} \quad (3)$$

Firms

Final-Good Firm

The final-good firm produces output yt by choosing a combination of intermediate inputs $\{y_{f,t}\}$ so as to maximise profit

$$P_t y_t - \int_0^1 P_{f,t} y_{f,t} df,$$

Subject to the production technology

$$y_t = \left\{\int_0^1 y_{f,t}^{\frac{1}{1+\lambda_t^p}} df\right\}^{1+\lambda_t^p}, \tag{4}$$

Where $P_{f,t}$ is the price of intermediate good *f.* λ_t^p is related to the elasticity of substitution between intermediate goods and turns to be a time-varying price mark-up.

Lagrangian:

$$P_t \left\{\int_0^1 y_{f,t}^{\frac{1}{1+\lambda_t^p}} df\right\}^{1+\lambda_t^p} - \int_0^1 P_{f,t} y_{f,t} df$$

FOCs:

$\partial y_{f,t}$:

$$(1+\lambda_t^p) P_t \left\{\int_0^1 y_{f,t}^{\frac{1}{1+\lambda_t^p}} df\right\}^{\lambda_t^p} \frac{1}{1+\lambda_t^p} y_{f,t}^{\frac{1}{1+\lambda_t^p}-1} - P_{f,t} = 0$$

$$\Leftrightarrow y_{f,t} = \left(\frac{P_{f,t}}{P_t}\right)^{-\frac{1+\lambda_t^p}{\lambda_t^p}} y_t, \tag{5}$$

By substituting (5) into (4), we obtain:

$$y_t = \left\{\int_0^1 \left[\left(\frac{P_{f,t}}{P_t}\right)^{-\frac{1+\lambda_t^p}{\lambda_t^p}} y_t\right]^{\frac{1}{1+\lambda_t^p}} df\right\}^{1+\lambda_t^p}$$

$$\Leftrightarrow P_t = \left\{\int_0^1 P_{f,t}^{-\frac{1}{\lambda_t^p}} df\right\}^{-\lambda_t^p} \tag{6}$$

The market clearing condition for final-goods is:

$$y_t = c_t \tag{7}$$

Intermediate-Good Firms

Cost minimisation

Each intermediate-good firm *f* produces output $y_{f,t}$ by choosing a cost-minimising of labour services$\{l_{f,t}\}$, given wage w_t subject to the production function:

$$y_{f,t} = A_t l_{f,t}\,.$$

Where A_t is total factor productivity.

Lagrangian:

$$w_t l_{f,t} + mc_{f,t}\big(y_{f,t} - A_t l_{f,t}\,\big),$$

Where the Lagrange multiplier $mc_{f,t}$ is interpreted as a real marginal cost.

FOCs:

$\partial l_{h,t}$:

$$mc_{f,t} = \frac{w_t}{A_t}$$

Thus,

$$mc_t = \frac{w_t}{A_t} \tag{8}$$

The labour market clearing condition is:

$$\begin{aligned} l_t &= \int_0^1 l_{f,t} df = \int_0^1 \frac{y_{f,t}}{A_t} df \\ &= \frac{y_t}{A_t}\int_0^1 \left(\frac{P_{f,t}}{P_t}\right)^{-\frac{1+\lambda_t^p}{\lambda_t^p}} df \\ &= \frac{y_t d_t}{A_t} \end{aligned}$$

$$\Leftrightarrow y_t d_t = A_t l_t \tag{9}$$

Where $d_t = \int_0^1 \left(\frac{P_{f,t}}{P_t}\right)^{-\frac{1+\lambda_t^p}{\lambda_t^p}} df$ denotes price dispersion across firms.

Price setting

Facing the consumption-good firm's demand, each intermediate-good firm sets the price of its product on a staggered basis à la Calvo (1983[132]). In each period, a fraction $1 - \theta \in (0,1)$ of intermediate-good firms reoptimises prices, while the remaining fraction θ remains prices unchanged or indexes prices to (gross) past inflation $\pi_{t-1} = P_{t-1}/P_{t-2}$. Then, firms which reoptimise prices in the current period maximise the expected profit:

$$E_t \sum_{j=0}^{\infty} \theta^j \beta^j \frac{\lambda_{t+j}}{\lambda_t}\left(\frac{P_{f,t}\prod_{k=1}^{j}\pi_{t+k-1}^{\omega}}{P_{t+j}} - mc_{t+j}\right) y_{f,t+j},$$

Subject to the demand curve for each intermediate good (analogous to (5)).

$$y_{f,t+j} = \left(\frac{P_{f,t}\prod_{k=1}^{j}\pi_{t+k-1}^{\omega}}{P_{t+j}}\right)^{-\frac{1+\lambda_{t+j}^{p}}{\lambda_{t+j}^{p}}} y_{t+j},$$

Where $\omega \in (0,1)$ denotes the weight of price indexation to past inflation.

Lagrangian:

$$E_t \sum_{j=0}^{\infty}\left[\theta^j \beta^j \frac{\lambda_{t+j}}{\lambda_t}\left(\frac{P_{f,t}\prod_{k=1}^{j}\pi_{t+k-1}^{\omega}}{P_{t+j}} - mc_{t+j}\right)\left(\frac{P_{f,t}\prod_{k=1}^{j}\pi_{t+k-1}^{\omega}}{P_{t+j}}\right)^{-\frac{1+\lambda_{t+j}^{p}}{\lambda_{t+j}^{p}}} y_{t+j}\right]$$

$$= E_t \sum_{j=0}^{\infty}\left[(\theta\beta)^j \frac{\lambda_{t+j}}{\lambda_t} y_{t+j}\left\{\left(p_{f,t}\prod_{k=1}^{j}\frac{\pi_{t+k-1}^{\omega}}{\pi_{t+k}}\right)^{1-\frac{1+\lambda_{t+j}^{p}}{\lambda_{t+j}^{p}}} - mc_{t+j}\left(p_{f,t}\prod_{k=1}^{j}\frac{\pi_{t+k-1}^{\omega}}{\pi_{t+k}}\right)^{-\frac{1+\lambda_{t+j}^{p}}{\lambda_{t+j}^{p}}}\right\}\right]$$

Where $p_{f,t} = \frac{P_{f,t}}{P_t}$.

FOCs for the reoptimised price $p_t^o = \frac{P_t^o}{P_t}$

∂p_t^o:

$$E_t \sum_{j=0}^{\infty}\left[(\theta\beta)^j \frac{\lambda_{t+j}}{\lambda_t} y_{t+j}\left\{\begin{matrix}\left(1-\frac{1+\lambda_{t+j}^{p}}{\lambda_{t+j}^{p}}\right)\left(p_t^o\prod_{k=1}^{j}\frac{\pi_{t+k-1}^{\omega}}{\pi_{t+k}}\right)^{-\frac{1+\lambda_{t+j}^{p}}{\lambda_{t+j}^{p}}}\prod_{k=1}^{j}\frac{\pi_{t+k-1}^{\omega}}{\pi_{t+k}} \\ -mc_{t+j}\left(-\frac{1+\lambda_{t+j}^{p}}{\lambda_{t+j}^{p}}\right)\left(p_t^o\prod_{k=1}^{j}\frac{\pi_{t+k-1}^{\omega}}{\pi_{t+k}}\right)^{-\frac{1+\lambda_{t+j}^{p}}{\lambda_{t+j}^{p}}-1}\prod_{k=1}^{j}\frac{\pi_{t+k-1}^{\omega}}{\pi_{t+k}}\end{matrix}\right\}\right] = 0$$

$$\Leftrightarrow = E_t \sum_{j=0}^{\infty}\left[(\theta\beta)^j \frac{\lambda_{t+j}}{\lambda_t}\frac{1}{\lambda_{t+j}^{p}} y_{t+j}\left(p_t^o\prod_{k=1}^{j}\frac{\pi_{t+k-1}^{\omega}}{\pi_{t+k}}\right)^{-\frac{1+\lambda_{t+j}^{p}}{\lambda_{t+j}^{p}}}\left\{p_t^o\prod_{k=1}^{j}\frac{\pi_{t+k-1}^{\omega}}{\pi_{t+k}} - (1+\lambda_{t+j}^{p})mc_{t+j}\right\}\right] = 0 \qquad (10)$$

In this circumstance, the final-goods price is:

$$P_t = \left\{\int_0^1 P_{f,t}^{-\frac{1}{\lambda_t^p}} df\right\}^{-\lambda_t^p}$$

$$\Leftrightarrow 1 = (1-\theta)\left[(p_t^o)^{-\frac{1}{\lambda_t^p}} + \sum_{j=1}^{\infty}\theta^j\left(p_{t-j}^o\prod_{k=1}^{j}\frac{\pi_{t-k}^{\omega}}{\pi_{t-k+1}}\right)^{-\frac{1}{\lambda_t^p}}\right] \qquad (11)$$

Potential output

Potential output is defined as:

$$y_t^* = A_t l,$$

i.e. the equilibrium output when the input of labour and the price dispersion across firms are at the steady-state. The output gap is defined as the percentage deviation of actual output from its flexible-price equilibrium output:

$$GAP_t = \log\left(\frac{y_t}{y_t^*}\right) \tag{12}$$

Monetary Authority

Monetary authority adjusts the short-term nominal interest rate following a Taylor-rule monetary policy rule.

$$\frac{R_t^n}{R^n} = \left(\frac{R_{t-1}^n}{R^n}\right)^{\rho R}\left[\left(\prod_{j=0}^{3}\frac{\pi_{t-j}}{\pi}\right)^{\frac{\psi\pi}{4}}\left(\frac{y_t}{y_t^*}\right)^{\psi y}\right]^{1-\rho R}\exp(z_t^R), \tag{13}$$

Where R^n is the (gross) steady-state nominal interest rate, $\rho R \in [0,1)$ is the degree of interest rate smoothing, $\psi\pi, \psi y \geq 0$ are the degrees of interest policy responses to inflation and the output gap. z_t^R represents the monetary policy shock.

Steady-states

Households

Marginal utility of consumption:

$$\lambda = (c - bc)^{-\sigma}$$

Labour supply:

$$w = \frac{\chi l^\eta}{\lambda}$$

Euler equation:

$$1 = \beta\frac{R^n}{\pi} \Leftrightarrow R^n = \frac{\pi}{\beta}$$

Firms

Final-goods market clearing:

$$y = c$$

Real marginal cost:

$$mc = \frac{w}{A}$$

Labour market clearing:

$$y = Al$$

Since
$d = 1$
Price setting:

$$1 = (1-\theta)\sum_{j=0}^{\infty}\theta^j\,(p^o)^{-\frac{1}{\lambda p}} \Leftrightarrow p^o = 1$$

$$E_t\sum_{j=0}^{\infty}\left[(\theta\beta)^j\frac{1}{\lambda^p}y(p^o)^{-\frac{1+\lambda^p}{\lambda^p}}\{p^o-(1+\lambda^p)mc\}\right] = 0$$

$$\Leftrightarrow mc = \frac{1}{1+\lambda^p}, \text{and } \theta\beta < 1$$

Log-linearised equations

Households

Marginal utility of consumption:

$$\lambda_t = (c_t - bc_{t-1})^{-\sigma}\exp(z_t^d)$$

$$\Rightarrow \lambda\tilde{\lambda}_t = -\sigma(c-bc)^{-\sigma-1}\mathrm{c}\tilde{c}_t - \sigma(\mathrm{c}-bc)^{-\sigma-1}(-b)c\tilde{c}_{t-1} + (\mathrm{c}-bc)^{-\sigma}z_t^d$$

$$\Leftrightarrow \tilde{\lambda}_t = -\frac{\sigma}{1-b}\tilde{c}_t + \frac{\sigma b}{1-b}\tilde{c}_{t-1} + z_t^d$$

Real wage:

$$w_t = \frac{\chi l_t^\eta \exp(z_t^d)}{\lambda_t}$$

$$\Rightarrow \widetilde{w}_t = \eta\tilde{l}_t - \tilde{\lambda}_t + z_t^d$$

Euler equation:

$$\lambda_t = \beta\lambda_{t+1}\frac{R_t^n}{\pi_{t+1}}$$

$$\Longrightarrow \tilde{\lambda}_t = \tilde{\lambda}_{t+1} + \tilde{R}_t^n - \tilde{\pi}_{t+1}$$

Firms

Final-goods market clearing:

$$\tilde{y}_t = \tilde{c}_t$$

Real marginal cost:

$$\widetilde{mc}_t = \widetilde{w}_t - \tilde{A}_t$$

Labour market clearing:

$$\tilde{y}_t = \tilde{A}_t + \tilde{l}_t\,,$$

Since
$\tilde{d}_t = 1$
Price setting:

$$(\tilde{\pi}_t - \omega\tilde{\pi}_{t-1}) = \beta(\tilde{\pi}_{t-1} - \omega\tilde{\pi}_t) + \frac{(1-\theta)(1-\theta\beta)}{\theta}\widetilde{mc}_t\,,$$

Where we exclude the marginal cost shock $z_t^p = \frac{(1-\theta)(1-\theta\beta)}{\theta}\lambda_t^p$ for identifying $\tilde{A}_t$.

Potential Output

$$\tilde{y}_t^* = \tilde{A}_t \,,$$

Output gap:

$$GAP_t = \log\left(\frac{y_t}{y_t^*}\right) = \tilde{y}_t - \tilde{y}_t^*$$

Monetary Authority

$$\frac{R_t^n}{R^n} = \left(\frac{R_{t-1}^n}{R^n}\right)^{\rho R}\left[\left(\prod_{j=0}^{3}\frac{\pi_{t-j}}{\pi}\right)^{\frac{\psi\pi}{4}}\left(\frac{y_t}{y_t^*}\right)^{\psi y}\right]^{1-\rho R} \exp(z_t^R)$$

$$\Rightarrow \tilde{R}_t^n = \rho_R \tilde{R}_{t-1}^n + (1-\rho_R)\left\{\frac{\psi_\pi}{4}\sum_{j=0}^{3}\tilde{\pi}_{t-j} + \psi_y(\tilde{y}_t - \tilde{y}_t^*)\right\} + \varepsilon_t^R$$

Summary

IS equation

$$\tilde{y}_t = \frac{1}{1+b}E_t\tilde{y}_{t+1} + \frac{b}{1+b}\tilde{y}_{t-1} - \frac{1-b}{\sigma(1+b)}\left(\tilde{R}_t^n - E_t\pi_{t+1}\right) + \frac{1-b}{\sigma(1+b)}(z_t^d - E_t z_{t+1}^d)$$

Phillips curve

$$(\tilde{\pi}_t - \omega\tilde{\pi}_{t-1}) = \beta(\tilde{\pi}_{t+1} - \omega\tilde{\pi}_t) + \frac{(1-\theta)(1-\theta\beta)}{\theta}\left[\left(\eta + \frac{\sigma}{1-b}\right)\tilde{y}_t - \frac{\sigma b}{1-b}\tilde{y}_{t-1} - (1+\eta)\,\tilde{A}_t\right]$$

Potential Output

$$\tilde{y}_t^* = \tilde{A}_t$$

Output gap:

$$GAP_t = \tilde{y}_t - \tilde{A}_t$$

Monetary Authority

Monetary Policy rule:

$$\tilde{R}_t^n = \rho_R \tilde{R}_{t-1}^n + (1-\rho_R)\left\{\frac{\psi_\pi}{4}\sum_{j=0}^{3}\tilde{\pi}_{t-j} + \psi_y(\tilde{y}_t - \tilde{y}_t^*)\right\} + \varepsilon_t^R$$

Exogenous shock processes

$$z_t^d = \rho_d z_{t-1}^d + \varepsilon_t^d, \varepsilon_t^d \sim N(0, \sigma_d^2)$$
$$\tilde{A}_t = \rho_A \tilde{A}_{t-1} + \varepsilon_t^A, \varepsilon_t^d \sim N(0, \sigma_A^2)$$
$$z_t^R = \rho_R z_{t-1}^R + \varepsilon_t^R, \varepsilon_t^d \sim N(0, \sigma_R^2)$$

Measurement equations

For each country, we use three time series as observable variables: (1) detrended real GDP (GDP), (2) the consumer price index (CPI) inflation rate, and (3) the short-term interest rate (SR). The corresponding measurement equations are:

$$\begin{bmatrix} 100\ (\log GDP_t - \log \mathrm{GDP}_t^{HP}) \\ 100\Delta \log \mathrm{CPI}_t \\ \mathrm{SR}_t \end{bmatrix} = \begin{bmatrix} 0 \\ \bar{\pi} \\ \bar{r} \end{bmatrix} + \begin{bmatrix} \tilde{y}_t \\ \tilde{\pi}_t \\ \tilde{R}_t^n \end{bmatrix},$$

Where $\mathrm{GDP}_t^{HP}$is an HP filtered series of real GDP, $\bar{\gamma} = 100(\gamma - 1), \bar{\pi} = 100(\pi - 1)$, and $\bar{\mathrm{r}} = 100(R^n - 1) = 100(\frac{\pi}{\beta} - 1)$.

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