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How influential are COVID–19 data points? A fresh look at an estimated small scale DSGE model for the Philippines

Lawrence B. Dacuycuy*
De La Salle University

Shocks emanating from the global pandemic continue to reshape the macroeconomic landscape—dimming national growth prospects, prolonging widespread financial distress among households, firms, and governments and heightening uncertainty. Using a small-scale New Keynesian Dynamic Stochastic General Equilibrium (DSGE) model for the Philippines, we examine the model's sensitivity to COVID-19 datapoints or extreme observations. Relative to estimates during the base period (2002Q1 to 2019Q4), the inclusion of extreme datapoints worsens the model's log data density progressively, from the consideration of the first quarter of 2020 to the full sample – an indication that shock propagation mechanisms associated with COVID–19 and other natural disasters should be integrated into the model. Even with the inclusion of said extreme observations, however, the model's parameters are identified, provided identification schemes are evaluated at posterior median estimates. Judging from the sets of parameter estimates relative to the base sample, the effects of extreme observations are found to be non–uniform, especially the size of the shocks. But there are other parameters, notably those that are embedded in the Taylor rule, which are relatively as stable as some household related parameters. These results imply that the size of standard errors for demand, supply, and monetary policy shocks adjust to partially capture the impact of extreme datapoints.

JEL classification: E12, E32, E52
Keywords: small-scale DSGE model, Philippines, Bayesian estimation, historical decomposition

1. Introduction

The Philippines' growth performance prior to the onset of the COVID-19 pandemic has been robust, spanning two decades since registering the last known recession in the late 90s. Weeks prior to the start of quarantine regimes, the country saw how destructive and disruptive the eruption of Taal volcano was. Official economic accounts indicated that the eruption's effects have been amplified by tourism declines partly attributable to brewing pandemic concerns at that time. With the country experiencing significantly negative growth from

* Address all correspondence to lawrence.dacuycuy@dlsu.edu.ph.

the second to fourth quarters of 2020, several stylized business cycle facts have emerged. First, the pandemic has spawned unprecedentedly large demand (drastic reductions in consumption) and supply (reduction in labor supply) shocks, both of which resulted in contractions that have been quick, deep, and staggering– a sizeable 16.5 percent contraction in the second quarter of 2020 followed by a 11.5 percent contraction in the third quarter. Fourth quarter growth did not offer any respite either, as the economy plunged by 9.5 percent. Non-pandemic emergencies such as the African Swine Fever epidemic, which started to devastate the hog stock starting in the first quarter of 2020, caused price spikes. Second, the speed with which the pandemic has affected industries–even the traditionally sheltered ones, has been unprecedentedly rapid. Third, the country, as the rest of the world, reacted strongly to counter pandemic effects through aggressive monetary, fiscal, and health policy interventions, resulting in mobility restrictions, massive social expenditures and historically low interest rates.

Several models of varying degrees of sophistication came out during the pandemic. Such models have integrated epidemiological features into macroeconomic models belonging to the neoclassical and DSGE strands. Various papers by Eichenbaum, Rebelo, and Trabandt [2020a; 2020b; 2020c] showed how several susceptible-infected-recovered (SIR)- based scenarios (e.g., reproduction rates, social distancing, quarantine rules, vaccination rates) associated with the pandemic could sway macroeconomic fortunes.

In contrast to the aforementioned model features, this paper's main objective is to account for the empirical performance of the New Keynesian DSGE model when influential pandemic datapoints are included in the estimation sample. It is beyond this paper to formally include COVID-19–related processes that identify the nature of demand and supply shocks. Notwithstanding such limitations, the paper endeavors to measure the size of the shocks. In a way, this paper is related to the recent work of Lenza and Primiceri [2020] who were among the first researchers to investigate the empirical implications of extreme observations associated with COVID-19 on vector autoregression estimates. We believe that this is a worthy empirical undertaking for two reasons. First, relative to the base sample (2002Q1–2019Q4), evidence may be informative as to how extreme observations or COVID-19 datapoints can induce changes in the structural parameters of an estimated small–scale DSGE model that does not formally incorporate well-known transmission mechanisms for health contagion and natural disasters (e.g., Taal volcano eruption and Typhoon Goni in the fourth quarter of 2019). Second, we could also examine the respective contributions of supply, demand, and monetary policy shocks to observed output growth using historical decompositions to highlight robustness considerations when extreme observations are accounted for. In these exercises, we analyze historical decompositions pertaining to observed output growth outcomes generated using the base (2002Q1–2019Q4) and full (2002Q1–2020Q4) samples, respectively.

Given influential datapoints, we need to be able to ascertain the degree of model sensitivity and verify adequacy. We are interested in measuring the respective sizes of demand, supply, and monetary policy shocks, as more extreme observations are added. Given the aggressive role of the Bangko Sentral ng Pilipinas (BSP)[1], we would like to know whether there have been significant changes in the parameters of the Taylor rule. For firms, the duration of the pricing cycle may also be of interest, given that crises could potentially alter the timing of price changes. On the part of households, it may be worth examining whether elasticity–based measures such as the Frisch labor supply elasticity and intertemporal elasticity of substitution have changed due to shifting preferences or expectations induced by uncertainties spawned by the pandemic.

The paper follows the usual organizational design. Section 2 details the structure of the New Keynesian DSGE model. Section 3 discusses some preliminaries associated with the Bayesian estimation framework and identifies some issues. Discussions pertaining to parameter estimates and other dynamic outcomes are found in Section 4. Section 5 details some robustness strategies and results associated therewith. The final section concludes, identifies limitations, and provides directions for future research.

2. The model

We follow the small–scale, closed economy New Keynesian DSGE model used in An and Schorfeide [2007]; Rubaszek and Skrzypczyński [2008]; and Herbst and Schorfeide [2016]. The artificial economy is populated by three well–known actors, namely: homogeneous households, firms, and monetary policymakers. Households consume the final good, generate earnings by working in a perfectly competitive labor market, and invest their savings by purchasing bonds. They also own firms and as a result, derive dividend income therefrom. Firms are of two types, namely: intermediate goods firms, which operate with market power, and a final goods firm, which remains competitive. The final goods firm bundles together intermediate goods to produce the final good. Cognizant of the role of output and inflation gaps in interest rate determination, monetary policymakers use the Taylor rule.

Three core equations constitute the New Keynesian DSGE model, namely: a dynamic IS curve, a Phillips curve, and a monetary policy rule.[2] Together, they determine the dynamic path of output, prices, and short–term nominal interest rates [Rubaszek and Skrzypczyński 2008].

[1] BSP is the central monetary authority and the institution that regulates the currency and monetary policy of the Republic of the Philippines.

[2] As noted in Herbst and Schorfeide [2016], iterating the consumption Euler equation forward implies that output is a function of the sum of expected future real returns on bonds (p. 16). The New Keynesian Phillips curve links real economic activity to inflation. Iterating the New Keynesian Phillips curve forward implies that inflation is a function of the expected discounted sum of the future output gap.

2.1. Households

Following usual treatment in the literature (Herbst and Schorfeide [2016]; Rubaszek and Skrzypczyński [2008]), there is a continuum of households indexed by $i \in (0,1)$. Households maximize utility subject to a budget constraint. Households are assumed to form external, not deep habits, thereby necessitating the inclusion of the habit–adjusted level of consumption in the utility function.

Following An and Schorfeide [2007], the household derives utility from consumption relative to a habit stock A_t. The utility function of the i^{th} household follows the CRRA specification:

$$U_{i,t} = E_t \sum_{s=0}^{\infty} \beta^{t+s} \epsilon^{D}_{t+s} \left\{ \frac{\left(C^h_{i,t+s}/A_{t+s}\right)^{1\text{-}\sigma}}{1\text{-}\sigma} \text{-} \upsilon_L \frac{N^{1+\varphi}_{i,t+s}}{1+\varphi} \right\} \tag{1}$$

where $N_{i,t}$ is the household's labor supply, φ is the inverse of the Frisch labor supply elasticity, and σ is the inverse of the intertemporal elasticity of substitution (IES). As explained in Rubaszek and Skrzypczyński [2008], $U_{i,t}$ is an increasing function of $C_{i,t}$ after having accounted for the fraction of past consumption and adjusted for technology growth, g. This is shown by the following process:

$$C^h_{i,t} = C_{i,t} - \theta_h (1+g) C_{t\text{-}1} \tag{2}$$

where θ_h is a fraction of past consumption. When the fraction θ_h equals zero, the objective function reverts to the familiar one.

$$U_{i,t} = E_t \sum_{s=0}^{\infty} \beta^{t+s} \epsilon^{D}_{t+s} \left\{ \frac{\left(C_{i,t+s}/A_{t+s}\right)^{1\text{-}\sigma}}{1\text{-}\sigma} \text{-} \upsilon_L \frac{N^{1+\varphi}_{i,t+s}}{1+\varphi} \right\} \tag{3}$$

The demand shock is specified as an autoregressive linear process:

$$\epsilon^D_t = \left(1\text{-}\rho_D\right)\bar{\epsilon}^D + \rho_D \epsilon^D_{t\text{-}1} + \sigma_D \eta^D_t \tag{4}$$

which has the following log–linearized form:

$$\hat{\epsilon}^D_t = \rho_D \hat{\epsilon}^D_{t\text{-}1} + \sigma_D \eta^D_t \tag{5}$$

The household receives labor payments and dividends. They consume and pay $P_t C_t$ or invest in securities. The constraint is specified as

$$P_t C_{i,t} + B_{i,t} = R_{t\text{-}1} B_{i,t\text{-}1} + W_t N_{i,t} + Div_{i,t} \tag{6}$$

Maximizing (1) with respect to consumption and bonds, subject to the constraint (6), leads to the specification of the dynamic IS curve. The first order condition associated with $B_{i,t}$ is

$$\mu_t = E_t \beta R_t \mu_{t+1} \tag{7}$$

The first order condition for $C_{i,t}$ is

$$\beta^t \epsilon_t^D (C_{i,t}^h/A_t)^{-\sigma} (1/A_t) = \mu_t P_t \tag{8}$$

Performing the necessary substitutions, we have

$$\beta^t \epsilon_t^D \frac{1}{P_t} \frac{1}{A_t} \left(C_{i,t}^h/A_t\right)^{-\sigma} = E_t \left\{ \beta^{t+1} \epsilon_{t+1}^D \frac{1}{P_{t+1}} \frac{1}{A_{t+1}} R_t \left(C_{i,t+1}^h/A_{t+1}\right)^{-\sigma} \right\} \tag{9}$$

Equation 9 can be expressed as

$$\left(C_{i,t}^h/A_t\right)^{-\sigma} = \beta E_t \left\{ \frac{A_t}{A_{t+1}} \frac{\epsilon_{t+1}^D}{\epsilon_t^D} \pi_{t+1}^{-1} R_t \left(C_{i,t+1}^h/A_{t+1}\right)^{-\sigma} \right\} \tag{10}$$

The intra-temporal condition for labor is given by

$$\beta^t \epsilon_t^D \upsilon_L N_{i,t}^{\varphi} = \mu_t W_t \tag{11}$$

Combining Equation 11 with 8, we have

$$\upsilon_L N_{i,t}^{\varphi} = (C_{i,t}^h/A_t)^{-\sigma} (W_t/A_t P_t) \tag{12}$$

2.2. Firms

This section heavily borrows from Rubaszek and Skrzypczyński [2008], Herbst and Schorfeide [2016], and McCandless [2008]. The goods market is characterized by nominal rigidities in price adjustments. There are two types of firms, namely: final goods and intermediate goods firms. According to Herbst and Schorfeide [2016], the set–up allows the introduction of price– setting. Indexed by $j \in [0,1]$, intermediate goods firms produced differentiated goods which are sold to the competitive final goods firm. However, there are two types of intermediate goods firms. Firms belonging to the first type can set prices optimally per period. The second type of firms follows a certain rule of thumb in setting prices, implying that pricing histories are used. The non–zero probability that a firm is unable to set prices optimally is ζ. The constant returns to scale (CRS) production technology of the perfectly competitive final goods firm is specified as:

$$Y_t = \left[\int_0^1 (Y_{j,t})^{1-\frac{1}{\theta}} dj\right]^{\frac{1}{1-\frac{1}{\theta}}} \tag{13}$$

where $\theta \in (0,\infty)$ represents the elasticity of substitution among intermediate inputs. Given the intermediate goods inputs, the final goods firm maximizes profits, taking as given the prices of intermediate goods. The price at which the final good is sold is

$$P_t = \left[\int_0^1 (P_{j,t})^{1-\theta} dj\right]^{\frac{1}{1-\theta}} \tag{14}$$

Accordingly, the final goods firm's demand for the intermediate good is given by

$$Y_{j,t} = [P_{j,t}/P_t]^{-\theta}\, Y_t \tag{15}$$

For each intermediate goods firm, the production function is assumed to depend only on labor and is subject to constant returns to scale technology.

$$Y_{j,t} = A_t\, \epsilon_t^S\, N_{j,t} - FC_t \tag{16}$$

where A_t represents a deterministic trend gt, ϵ_t^S is a covariance–stationary shock with the form

$$\epsilon_t^S = (1-\rho_S)\bar{\epsilon}^S + \rho_S \epsilon_{t-1}^S + \sigma_S \eta_t^S \tag{17}$$

and $FC_t = Y_t/\theta$ is the fixed costs to ensure that profits are zero in equilibrium.

Technology shocks reduce marginal costs while the input price increases them. The marginal cost of the firm could be derived by minimizing total labor cost subject to the feasibility constraint.

$$MC_{j,t} = W_t/A_t\, \epsilon_t^S \tag{18}$$

Instantaneous profits are given by

$$D_{j,t} = (P_{j,t} - MC_{j,t})\, [P_{j,t}/P_t\,]^{-\theta}\, Y_t - (P_t\, Y_t/\theta) \tag{19}$$

Using the framework on sticky prices by Calvo [1983], some firms can optimize, with nonzero probability, while others follow rules of thumb. The proportion of firms able to set prices optimally is 1-ζ. For those who cannot reoptimize, the Rubaszek and Skrzypczyński [2008] pricing rule next period is

$$P_{j,t+1} = \{(\pi_t)^{\iota}\, (\overline{\pi})^{1-\iota}\} P_{j,t} \tag{20}$$

where non-optimizing firm prices P_{t+1} are indexed to steady–state inflation rate $\bar{\pi}$ and a fraction of the last period's excessive inflation rate. If the said firm has not changed its price s periods into the future, the pricing rule is

$$P_{j,t+s} = (P_{t+s-1}/P_{t-1})^{\iota}\,(\bar{\pi})^{s(1-\iota)}\,P_{j,t} \tag{21}$$

Note that when $\iota = 0$, we have the following pricing rule:

$$P_{j,t+s} = (\bar{\pi})^{s}\,P_{j,t} \tag{22}$$

For optimizing firms, they choose price such that their present value of discounted intertemporal profits is maximized.

$$\max_{P_{j,t}} E_t\left\{\sum_{s=0}^{\infty} \zeta^s\,Q_{t,t+s} D_{j,t+s}\right\} \tag{23}$$

where $Q_{t,t+s}$ is the stochastic discount factor. Inserting equations (19) and (22) into equation (24), we have

$$\max_{P_{j,t}} E_t\left\{\sum_{s=0}^{\infty} \zeta^s\,Q_{t,t+s}\left[\left(P_{j,t}\left[\frac{P_{t+s-1}}{P_{t-1}}\right]^{\iota}(\bar{\pi})^{s(1-\iota)} - MC_{j,t}\right)\left(\frac{P_{j,t}\left[\frac{P_{t+s-1}}{P_{t-1}}\right]^{\iota}(\bar{\pi})^{s(1-\iota)}}{P_{t+s}}\right)^{\iota} - \frac{P_t Y_t}{\theta}\right] Y_{t+s}\right\} \tag{24}$$

The first order condition associated with the optimizing firm is given by

$$E_t\left\{\sum_{s=0}^{\infty} \zeta^s\,Q_{t,t+s} Y_{t+s}\,\left(\tilde{P}_{j,t}\left[P_{t+s-1/P_{t-1}}\right]^{\iota}(\bar{\pi})^{s} - [\theta/\theta\text{-}1]MC_{t+s}\right)\right\} = 0 \tag{25}$$

The price level is equal to

$$P_t = [\zeta(P_{t-1}(P_{t-1}/P_{t-2})^{\iota} - \pi^{1-\theta} + (1-\zeta)(\tilde{P}_{j,t})^{1-\theta}]^{1/1-\theta} \tag{26}$$

2.3. Monetary policy

The monetary policy maker's objective is to maintain price and output stability.

$$r_t/r = (r_{t-1}/\bar{r})^{\gamma}[(\pi_t/\bar{\pi})^{\gamma_\pi}(Y_t/Y_{t-1})^{\gamma_{AY}}]^{1-\gamma} exp(\sigma_M \epsilon_t^M) \tag{27}$$

where $\bar{r}$ is the steady state interest rate and $\bar{\pi}$ is the inflation target. ϵ_t^M is a monetary policy shock. Note that specification (27) follows the output growth rule version of the Taylor rule as discussed in Schorfeide and An [2007].

2.4. Closing the model

To close the model, we will closely follow Sims [2014]. In equilibrium, B_t=B_{t+1}=0. The real household budget constraint is written as follows:

$$C_t = (W_t/P_t)\, N_t + (Div_t/P_t) \tag{28}$$

Since Div_t/P_t represents the dividends from intermediate goods firms, then

$$Div_t/P_t = \int_0^1 \{(P_{j,t}/P_t)Y_{j,t} - w_t N_{j,t}\}\, dj \tag{29}$$

Since $\int_0^1 = N_{j,t} = N_t$, we have

$$Div_t/P_t = \int_0^1 \{(P_{j,t}/P_t)Y_{j,t}\}\, dj - w_t N_t \tag{30}$$

Substituting $w_t N_t$ into the constraint, we have

$$C_t = \int_0^1 \{(P_{j,t}/P_t)Y_{j,t}\}\, dj \tag{31}$$

Using the optimal demand function and integrating over firms, the following condition closes the model:

$$Y_t = C_t \tag{32}$$

3. Estimation of the New Keynesian System

3.1. Putting them together

Based on Rubaszek and Skrzypczyński [2008], we have the system of log–linearized equations.

$$\hat{\pi}_t = (\beta/1+\iota\beta)\, E_t\hat{\pi}_{t+1} + (\iota/1+\iota\beta)\hat{\pi}_{t\text{-}1} + [(1\text{-}\zeta\beta)(1\text{-}\zeta)/(1+\iota\beta)\,\zeta]\widehat{mc}_t \tag{33}$$

$$\widehat{mc}_t = \sigma\hat{c}_t^h + \varphi\widehat{N}_t \text{-} \sigma_S\hat{\epsilon}_t^S \tag{34}$$

$$\hat{r}_t = \rho\hat{r}_{t\text{-}1} + (1\text{-}\rho)\left(i_\pi\hat{\pi}_t + i_{AY}\left(\hat{y}_t \text{-} \hat{y}_{t\text{-}1}\right)\right) + \sigma_M\eta_t^M \tag{35}$$

$$\hat{c}_t^h = 1/1+\theta_h\left(\hat{y}_t \text{-} \theta\hat{y}_{t\text{-}1}\right) \tag{36}$$

$$\hat{c}_t^h = \text{-}\sigma^{\text{-}1}\left[\widehat{R}_t + E_t\hat{\pi}_{t+1} + \sigma_D\left(\hat{\epsilon}_{t+1}^D \text{-} \hat{\epsilon}_t^D\right)\right] + \hat{c}_{t+1}^h \tag{37}$$

Equation (33) is called the Phillips curve. It establishes the temporal connections between economic activity and price inflation. Equation (35) is called the Taylor rule, which shows how the monetary authority could react to adverse shocks, depending on its sensitivity to inflation gaps and output gaps. The IS curve requires both the habits formation equation (36) and the Euler equation (37).

Log–linearizing the production function, $\hat{y}_t - \hat{\epsilon}_t^S = \hat{N}_t$. Substituting the log–linearized habits equation into (34) and (37), and the modifying the Phillips curve accordingly, we have the 3–equation New Keynesian DSGE model.

$$\hat{\pi}_t = \frac{\beta}{1+\iota\beta} E_t\hat{\pi}_{t+1} + \frac{\iota}{1+\iota\beta}\hat{\pi}_{t-1} + \frac{(1-\zeta\beta)(1-\zeta)}{(1+\iota\beta)\zeta}\left\{\frac{\sigma}{1-\theta_h}\hat{y}_t - \frac{\sigma\theta}{1-\theta_h}\hat{y}_{t-1} + \varphi\left\{\hat{y}_t - \sigma_S\hat{\epsilon}_t^S\right\} - \sigma_S\hat{\epsilon}_t^S\right\} \tag{38}$$

$$\hat{y}_t = \frac{1}{1+\theta_h}\hat{y}_{t-1} - \frac{1-\theta_h}{1+\theta_h}\sigma^{-1}\left[\hat{R}_t + E_t\hat{\pi}_{t+1} + \sigma_D\left(\hat{\epsilon}_{t+1}^D - \hat{\epsilon}_t^D\right)\right] + \frac{1}{1+\theta_h}E_t\hat{y}_{t+1} \tag{39}$$

$$\hat{r}_t = \rho\hat{r}_{t-1} + (1-\rho)\left(i_\pi\hat{\pi}_t + i_{AY}\left(\hat{y}_t - \hat{y}_{t-1}\right)\right) + \sigma_M\epsilon_t^M \tag{40}$$

3.2. Important steps

To set up estimation, the system of three equations consists of log-linearized equations (38), (39), and (40). Solution methods can now be used to determine the equilibrium law of motion for the endogenous variables output, inflation, and interest rates. As noted in Herbst and Schorfeide [2016], the solution should be expressed as a first order vector autoregressive model. In matrix notation, we have

$$\begin{bmatrix}\hat{\pi}_t \\ \hat{y}_t \\ \hat{r}_t\end{bmatrix} = \Phi_{yy}(\theta)\begin{bmatrix}\hat{\pi}_{t-1} \\ \hat{y}_{t-1} \\ \hat{r}_{t-1}\end{bmatrix} + \Phi_\epsilon(\theta)\begin{bmatrix}\epsilon_t^S \\ \epsilon_t^D \\ \epsilon_t^M\end{bmatrix}$$

which could be written as

$$X_t = \Phi_{yy}(\theta)\, X_{t-1} + \Phi_\epsilon(\theta)\epsilon_t,\ \epsilon_t \sim iidN(0,\Omega_t) \tag{41}$$

where the matrices $\Phi_{yy}(\theta)$ and $\Phi_\epsilon(\theta)$ are functions of the structural parameters of the model.

Central to DSGE estimation is the construction of likelihood function which relates the model variables to a set of observables. It combines the vector autoregressive representation of the solution with a set of measurement equations, which link the set of model variables to the set of observables.

The measurement equations could be simply written as:

$$log(y_t^{data}) - log(y_{t-1}^{data}) = \mu_y + 100(\hat{y}_t - \hat{y}_{t-1}) \tag{42}$$

$$R_t^{data} = \mu_R + 100\hat{r}_t \tag{43}$$

$$\pi_t^{data} = \mu_\pi + 100\bar{\pi}_t \tag{44}$$

The probability distribution of the innovations of the exogenous shock processes is deemed important [Herbst and Schorfeide 2016]. The measurement equations could be written collectively as

$$Y_t = \Psi(\theta)X_t + u_t \tag{45}$$

Both state and measurement equations are needed to constitute the state–space representation of the log–linearized DSGE model. As remarked in Herbst and Schorfeide [2016], and Guerron– Quintana and Nason [2013], the specification of the distribution of errors is critical. If the distribution of structural innovations is Gaussian, the Kalman filter can be used to recursively compute for the means and covariance matrices, allowing for the evaluation of the likelihood function.

3.3. The Bayesian method

Bayesian methods will be used to estimate some of the key parameters of the model. In the literature, Bayesian methods are empirically appealing with the parameters assumed to be random, contrary to the classical assumption that the model is generated by an underlying data generating process (DGP). The DSGE model, under the Bayesian framework becomes the DGP.[3]

The objective of classical methods is to estimate unknown parameters that are assumed to be true. Bayesian methods overcome the inherent difficulty in maximum likelihood estimation to include non–sample information and avoid intricacies involved when the distributional assumption is inconsistent with the data. As noted in Villaverde [2010], sometimes it is not interesting to determine the significance of parameter estimates in repeated samples. Bayesian analysis requires the prior distribution, the data and the likelihood function in order to derive the posterior distribution (see Guerron–Quintana and Nason [2013]).

Estimating parameters in a DSGE model relies on the construction of a likelihood function and the prior distribution. Given the data or observables, we would like to construct the posterior, which consists of the sum of two parts, namely: the log likelihood and the log prior. The value of the parameters at which the log posterior is maximized is known as the posterior mode. But the solution is not analytical, and estimation requires simulation methods, specifically the Metropolis-Hastings Markov Chain Monte Carlo, which specifies the posterior distribution as the target distribution, from which Markov Chains are formed.

[3] We are cognizant of the fact that identification problems continue to beset the DSGE framework. We don't address them here but interested readers could learn more from Canova and Sala [2009], and Beltran and Draper [2008].

3.4. The priors

Two components of the posterior distribution are needed to evaluate the Bayesian likelihood function. These are the likelihood of observing the data given parameters and the prior distribution. The latter is associated with the state of knowledge or a priori beliefs about the parameters, which are not found in the sample. The update to this belief is provided by the likelihood function, which proves critical in deriving the posterior distribution. We follow Del Negro and Schorfeide [2008], Guerron–Quintana and Nason [2013], and Herbst and Schorfeide [2016] by dividing the parameters into three sets. The first set collects the intercept parameters in the measurement equations. The second set includes parameters that are associated with primitives such as preferences, technology, and market structure. The third set consists of AR(1) coefficients and standard deviations of shocks.

$$\Theta_{SS} = [\mu_y \;\; \mu_R \;\; \mu_\pi] \tag{46}$$

$$\Theta_{ENDO} = [\theta_h \;\; \sigma \;\; \phi \;\; \iota \;\; \gamma_R \;\; \gamma_\pi \;\; \gamma_{\Delta y}] \tag{47}$$

$$\Theta_{EXO} = [\rho_D \;\; \rho_S \;\; \sigma^S \;\; \sigma^D \;\; \sigma^M] \tag{48}$$

As noted in Guerron–Quintana and Nason [2013], and Rubaszek and Skrzypczyński [2008], parameters associated with habits, price setting, and the persistence parameters have priors defined by the beta distribution, which restricts priors to the open unit interval. The priors on the standard deviations are drawn from the inverse–gamma distribution, which is unbounded, and has support on the open interval excluding zero. The priors on the intercept parameters were taken from the gamma and normal distributions.

We follow Beltran and Draper [2008]. The prior distribution for Calvo pricing should cover low and high estimates of the slope of the Phillips curve. For this purpose, we use the Beta(0.8,0.1) distribution. A uniform distribution with lower bound 0 and upper bound 1 was tried but the model failed to converge. The indexation parameter's prior distribution is Beta(0.7,0.1). This covers the absence of any indexation to full indexation. For the discount rate, we need to ensure that moderately high and high values should be covered. For this reason, we chose Beta(0.9, 0.01). The model requires tight prior for habit persistence parameter. We chose Beta(0.8, 0.05). The risk aversion parameter's prior distribution is Gamma(1,1.2), indicating greater uncertainty. It is centered at 1 and it includes values as large as 10. The Frisch labor supply elasticity's prior distribution is Gamma(2,0.5). This is consistent with micro studies on the said parameter. The interest rate persistence in the Taylor rule has been assumed to have come from the uniform distribution with lower bound 0 and upper bound 1. We followed

Schorfeide and An [2007]. For the response of interest rate to inflation, we chose a tight prior, Gamma(1.5, 0.05). For the response of interest rate to output growth, we also chose a tight prior, Gamma(0.125, 0.05). This is consistent with the robustness of the said parameter. Persistence of demand and supply shocks have uniform prior distributions, with lower bound zero and upper bound 1. These priors are based on Herbst and Schorfeide [2016].

4. Data, results & interpretation

4.1. The data

To estimate the structural parameters of the DSGE model, we will use the full–likelihood approach. The number of observables matches the number of shocks. By subscribing to the Bayesian perspective, the DSGE model represents our data–generating process. Data were obtained from the Philippine Statistics Authority's (PSA) OpenStats and BSP websites. For the observables, we computed the quarterly growth rate of deseasonalized real gross domestic product (with 2018 as the base year), used the applicable Consumer Price Index (CPI) to compute for inflation, and 91–day Treasury bill rates converted to quarterly frequency. To establish robustness and align our methodology to BSP's inflation targeting framework, we use CPI data to compute for the quarterly inflation rates, and the overnight reverse repurchase rate (ORRP). For consistency, we rebase CPI using 2018 as the base year. All variables have been demeaned. Dynare was used to construct the likelihood and estimate the parameters.[4]

To know more about the effects of uncertainty emanating from COVID-19 observations, we initially compare parameter estimates that respectively pertain to base and full samples. Our entire sample period covers the quarters 2002Q1 thru 2020Q4 to be consistent with BSP's inflation targeting framework.[5] The first sample pertains to the period 2002Q1–2019Q4. This sample does not factor in the effects of the pandemic quarters yet but may have already captured the impact of natural calamities during the 4th quarter of 2019. The full sample encompasses the entire sample period. We generated 200,000 draws from the target posterior distribution. Following statistical procedures, the usual tests of convergence have been implemented, leading to satisfactory results. The number of Markov Chain Monte Carlo (MCMC) chains is pegged at 2. The posterior means and medians as well as the 5 and 95 percentile values of the High Posterior Density (HPD) for all estimated parameters are shown in Tables 2 to 5 in the Appendix.

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[4] The author benefited from the Matlab and Dynare codes written by Matthias Trabandt, which was shared with participants in CEMFI's Summer School 2020 Course entitled: "Computational Tools for Macroeconomists. The said code has been modified to align it to Rubaszek & Skrzypczyński's model.

[5] I would like to thank the anonymous referee for pointing this out.

4.2. Structural parameter estimates

For some parameters, full sample-based estimates have exhibited minimal deviations relative to their counterparts in the base sample. To learn more about the robustness properties of the NKDSGE model, we created three samples. The first sample expands the base sample by including the first quarter of 2020. The second sample includes 2 quarters of 2020 to the base sample. Apparently, this sample is associated with the onset of the enhanced community quarantine (ECQ) protocol – the highest level of mobility restrictions. The third sample includes the first three quarters of 2020, plausibly capturing the quarantine easing implemented during the third quarter.

Table 1 shows the respective estimates associated with the base sample (2002Q1–2019Q4). We reported both posterior mean and median estimates, but it is the latter that survives standard identification tests in Dynare. In all our discussions, we will use posterior median estimates. First, the estimated discount factor β, which is associated with the growth years is expectedly high at 0.90. With the inclusion of COVID-19 quarters, the subsequently estimated discount factors appear to have minimally deviated from the base sample's posterior median estimates.[6]

TABLE 1. Prior distribution and estimates of structural parameters: base sample

	Prior type	Prior Mean	Prior Std Dev	Post. Mean	Post. Median	95% HPD	
Households							
Discount factor (β)	Beta	0.90	0.05	0.90	0.90	0.80	0.98
Habit persistence (θ_h)	Beta	0.80	0.05	0.94	0.94	0.89	0.97
Inverse of the Intertemporal Elasticity of substitution (σ)	Beta	1.00	1.20	0.60	0.58	0.31	0.92
Frisch labor supply elasticity (φ)	Beta	2.00	0.50	2.21	2.17	1.26	3.21
Firms							
Calvo prices (ζ)	Gamma	0.80	0.10	0.66	0.66	0.51	0.80
Price indexation (ι)	Gamma	0.70	0.20	0.48	0.44	0.10	0.94
Central Bank							
Interest rate smoothing (ρ)	Uniform	0.00	1.00	0.82	0.82	0.76	0.88
Inflation response (γ_π)	Gamma	1.50	0.05	1.55	1.55	1.45	1.65
Output growth response ($\gamma_{\Delta y}$)	Gamma	0.13	0.05	0.13	0.12	0.04	0.23
Persistence							
Persistence parameter Demand (ρ_D)	Uniform	0.00	1.00	0.86	0.87	0.69	0.98

[6] This observation may be attributed to the inability of data to update the prior distribution for the discount factor in samples that included extreme observations.

TABLE 1. Prior distribution and estimates of structural parameters: base sample (continued)

	Prior type	Prior Mean	Prior Std Dev	Post. Mean	Post. Median	95% HPD	
Persistence parameter Supply (ρ_S)	Uniform	0.00	1.00	0.73	0.75	0.49	0.90
Shocks							
Monetary shock std (σ_M)	Inverse Gamma	0.50	Inf	0.41	0.40	0.31	0.51
Demand shock Std (σ_D)	Inverse Gamma	3.00	Inf	2.84	2.62	1.53	4.82
Supply shock Std (σ_S)	Inverse Gamma	3.00	Inf	2.18	2.04	1.01	3.79
Intercepts							
Mean inflation (μ_π)	Gamma	1.00	0.20	0.88	0.87	0.57	1.22
Mean Tbill rate (μ_R)	Gamma	1.00	1.00	0.99	0.99	0.28	1.69
Mean output growth ($\mu_{\Delta y}$)	Normal	0.03	0.09	0.05	0.05	0.00	0.11

Second, the estimate on the degree of habit persistence in normal times is very high at 0.94. Including the third and fourth quarters of 2020 reduced the persistence of past consumption. The significant drop in external habits may be indicative of a much faster economic adjustment [Villaverde 2010].

Third, in contrast to the limited variation in the discount rate, there have been significant changes in household–based elasticities. Our estimate of ϕ shows that the Frisch elasticity of labor supply fell by 44 percent after the inclusion of all extreme observations to the base sample. This means that the pandemic has reduced the degree of responsiveness of labor supply to changes in the wage rate. This is in line with microeconomic evidence (Villaverde [2010]; Chetty, Guren, Manoli and Weber [2011]). In addition, the estimated inverse of the intertemporal elasticity of substitution (IES) parameter σ was halved, from 0.57 to 0.26, implying a 119 percent growth in the IES.[7] The tremendous increase in the IES is consistent with households substituting future consumption in favor of current consumption in the face of tremendous uncertainty.[8]

Fourth, the posterior estimates for the Calvo price parameter highlight stability. The estimated values of the indexation parameters are moderate, with significant reductions occurring when the first two quarters of 2020 are accounted for. The indexation parameter has significantly increased relative to the base estimate of 0.45 to 0.60 plausibly due to the Taal volcano eruption and strict quarantine regimes which were set up during the 2nd quarter. Full sample-based estimates are comparable with the base model estimate.

[7] Hall [1988] remarked that the magnitude of the change in consumption in response to a shift in expectations of the real interest rate determines the elasticity measure.

[8] I am grateful to a referee for pointing this out.

Fifth, the coefficients for the Taylor rule have been consistent with those observed in the literature, and collectively bolster the claim of monetary authority efficiency in dealing with economic crises. The coefficient of inflation across samples exhibits stability. This indicates that the BSP respects the Taylor rule. The coefficient on output is quite low but nonetheless, shows a positive response. As remarked in Villaverde [2010], this is a sign that the central bank smooths changes in nominal interest rates over time.

Finally, no parameter has been more affected by the inclusion of COVID-19 datapoints than the size of the shocks (i.e. standard deviations). According to Lenza and Primiceri [2020], extreme observations are associated with volatility. The inclusion of COVID-19 datapoints has unambiguously increased the volatility of output growth significantly and inflation minimally. Note that the standard deviation estimates are quite high even prior to the inclusion of COVID-19 datapoints. This was due to growth slowdown induced by slow disbursements in 2010, leading to the crafting of a controversial yet effective executive measure known as the Disbursement Acceleration Program (DAP). With the inclusion of COVID-19 datapoints, supply and demand shocks appear to be orders of magnitude higher than monetary policy shocks, thereby largely counteracting the pandemic–mitigating potential of monetary policy. What is noteworthy is that the size of demand and supply shocks appeared to be highest when the first two quarters of 2020 have been included. Results also indicate that shocks have persisted until the fourth quarter of 2020.

4.3. Historical decomposition

Suppose we ask the following question: What would have happened if supply shocks have driven the data exclusively? This kind of counterfactual question requires a tool for structural analysis known as historical decomposition. This is an important tool for understanding the impact of extreme observations. A succinct description of what historical decompositions can do is provided in Wong [2017]. He wrote that "historical decompositions provide an interpretation of historical fluctuations in the modelled time series through the lens of the identified structural shocks" [Wong 2017:1]. The Kalman smoother is a two–sided filter, which implements a backward recursive algorithm. It requires the implementation of the Kalman filter, and through a backward algorithm, estimates are further refined. It decomposes the historical deviations of the endogenous variables (output growth) from their respective steady state values into the contribution coming from demand, supply, and monetary policy shocks. We account for the respective roles of demand, supply, and monetary policy shocks in historical decompositions of observed output growth.

We focus on the dynamics of observed output growth and show how extreme observations affect the ability of shocks to explain output growth trajectory. Figure 1 shows that during the growth years, positive supply shocks played a big role in sustaining growth. Prior to 2020, supply and demand shocks have robust positive contributions as well. As shown in Figure 2, monetary policy shocks alone could not explain the trajectory of output growth. Nor do demand shocks. As shown in Figure 4, evidence seem to affirm the importance of supply shocks in the NKDSGE model. For the full sample, shock components could not individually explain the trajectory of output growth. Large fluctuations in output growth translates into relatively smaller shock contributions. As shown in Figure 8, however, it is clear that supply shocks have done a better job explaining output growth starting in 2019Q3 up to the fourth quarter of 2020.[9]

FIGURE 1. Decomposition of observed output growth: base sample

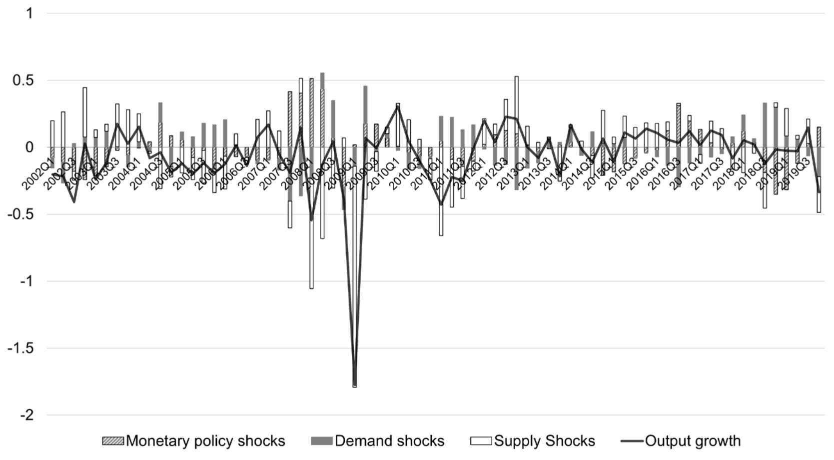
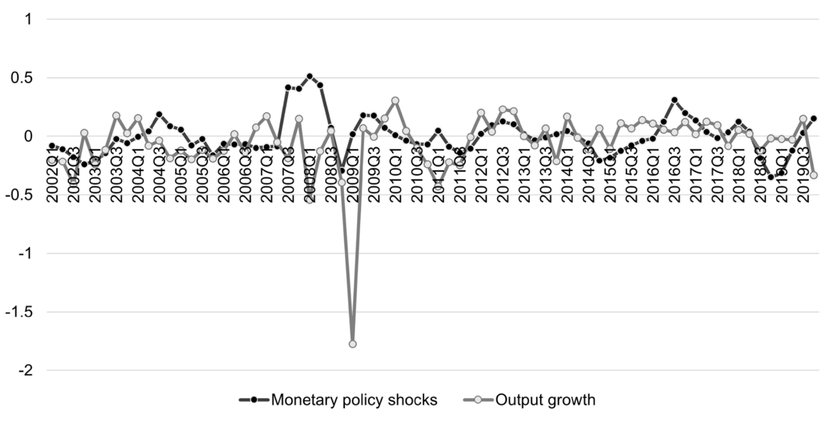


FIGURE 2. Decomposition of observed output growth: monetary policy shocks only



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[9] The results should be interpreted with caution, as the log data likelihood becomes more negative (or deteriorates) once extreme observations are included. This implies that the structure of the DSGE model works well for the base sample but clearly, it is unable to capture important aspects associated with disasters and the pandemic.

FIGURE 3. Decomposition of observed output growth: demand shocks only

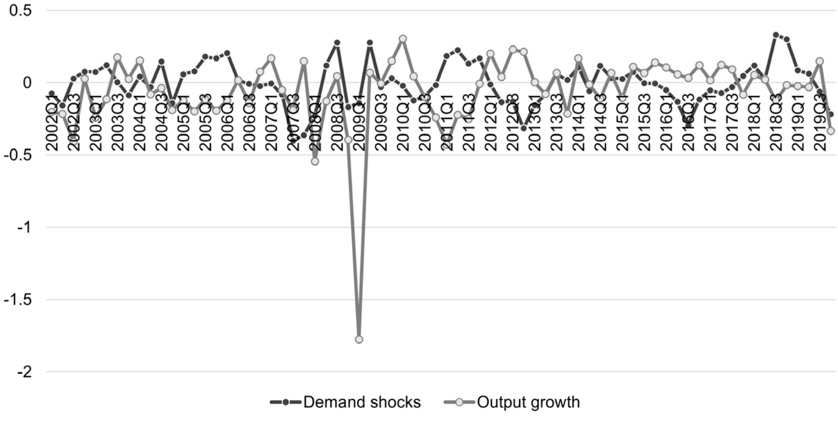


FIGURE 4. Decomposition of observed output growth: supply shocks only

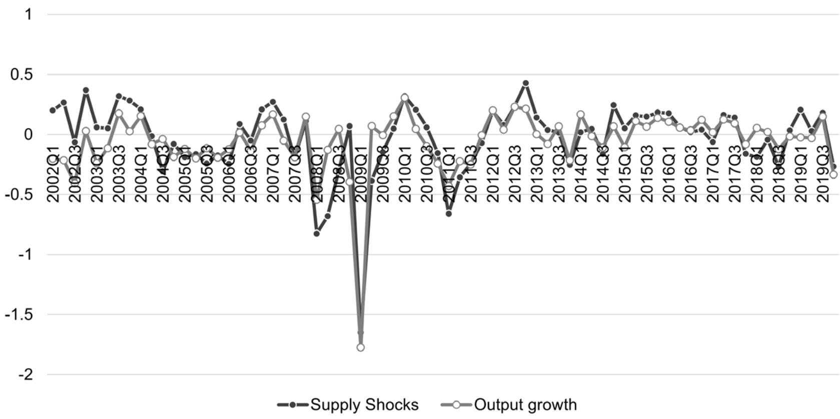


FIGURE 5. Decomposition of observed output growth: base sample

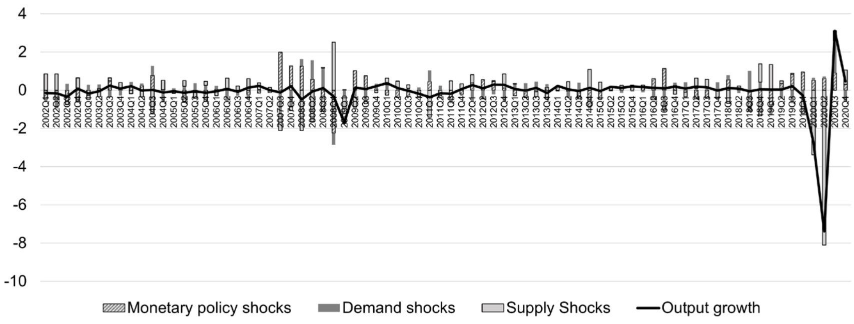


FIGURE 6. Decomposition of observed output growth: monetary policy shocks only

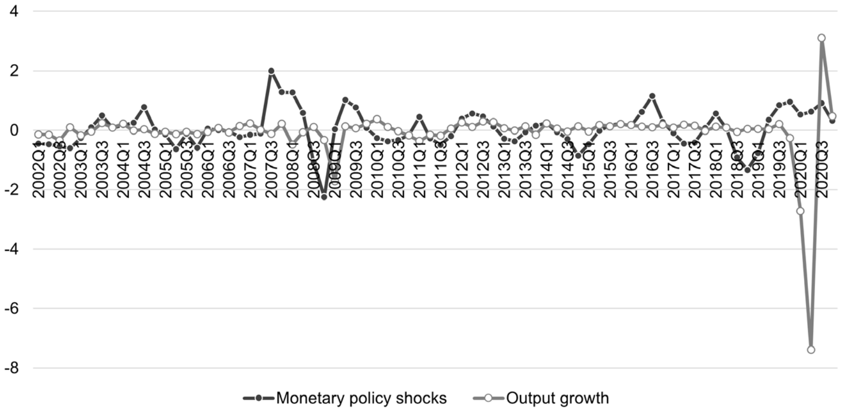


FIGURE 7. Decomposition of observed output growth: demand shocks only

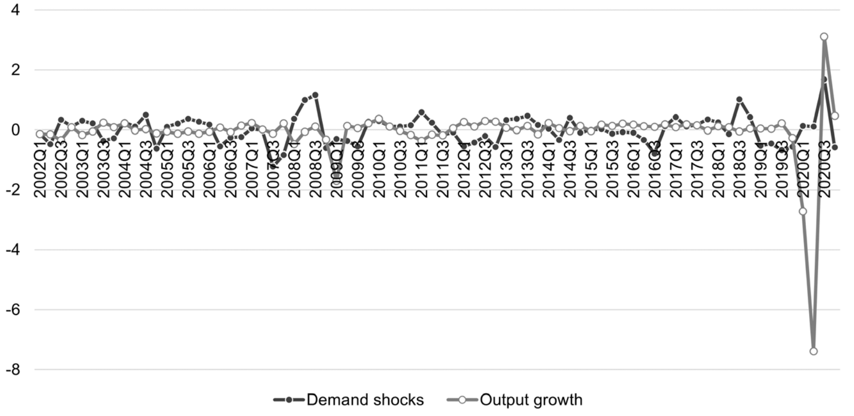
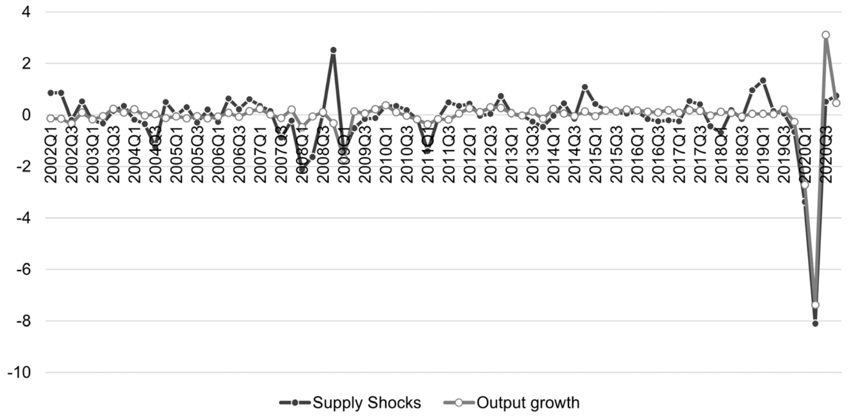


FIGURE 8. Decomposition of observed output growth: supply shocks only



5. Concluding remarks

The main objective of the paper is to empirically ascertain how influential or extreme observations affect key parameters estimates and shock contributions (via Kalman smoother) in an estimated small–scale New Keynesian DSGE model. Expectedly, extreme observations have their own way of influencing results, some of which render the NKDSGE model inadequate. As expected, deep parameters that pertain to the discount factor have been affected minimally. In contrast, habit persistence declined after including pandemic quarters. Relative to base–sample estimates, we find tremendous increase in IES estimates after using the full sample. Key parameters from the Taylor rule have changed minimally as well, plausibly indicating monetary authority efficiency in mitigating adverse shocks propagated by the pandemic. It turns out that one way to account for such extreme observations is to appropriately scale (via Bayesian estimation) demand, supply, and monetary policy shocks.

There are obvious model shortcomings. First, the model does not integrate formal structures that identify how COVID-19 related processes could influence labor supply, consumption, and production decisions. Differences in parameter estimates may be signaling either robust behavior or limited or weak parameter identification. Second, some exogenous shocks have been excluded. This may explain why historical decomposition estimates associated with the base sample fail to track the trajectory of output growth when extreme observations have been admitted. Third, while the parameters were all identified at the posterior median, results also indicate that there is tremendous model uncertainty.

For future work, the model will be refined to properly reflect how the current pandemic has affected macroeconomic outcomes. The labor bloc is envisioned to reflect labor market dynamics in the formal and informal sectors, since the pandemic has affected these sectors differently. We will also strengthen the fiscal bloc of the model by considering the integration of non-Ricardian households and by focusing on endogenous fiscal policy (spending, transfers, and deficits), complementarities between private and public capital, and labor market outcomes–key structures/features that played important roles in shaping Philippine macroeconomic dynamics during the pandemic period.

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Appendix

TABLE 2. Prior distribution and estimates of structural parameters: 2002Q1 – 2020Q1

	Prior type	Prior Mean	Prior Std Dev	Post. Mean	Post. Median	95% HPD	
Households							
Discount factor (β)	Beta	0.90	0.05	0.79	0.90	0.79	0.98
Habit persistence (θ_h)	Beta	0.80	0.05	0.89	0.93	0.89	0.97
Inverse of the Intertemporal Elasticity of substitution (σ)	Gamma	1.00	1.20	0.29	0.56	0.29	0.93
Frisch labor supply elasticity (φ)	Gamma	2.00	0.50	1.33	2.22	1.33	3.32
Firms							
Calvo prices (ζ)	Beta	0.80	0.10	0.55	0.68	0.55	0.80
Price indexation (ι)	Beta	0.70	0.20	0.22	0.60	0.22	0.99
Central Bank							
Interest rate smoothing (ρ)	Uniform	0.00	1.00	0.78	0.83	0.78	0.88
Inflation response (γ_π)	Gamma	1.50	0.05	1.45	1.55	1.45	1.65
Output growth response ($\gamma_{\Delta y}$)	Gamma	0.13	0.05	0.05	0.13	0.05	0.25
Persistence							
Persistence parameter Demand (ρ_D)	Uniform	0.00	1.00	0.73	0.94	0.73	0.99
Persistence parameter Supply (ρ_S)	Uniform	0.00	1.00	0.51	0.73	0.51	0.90
Shocks							
Monetary shock std (σ_M)	Inverse Gamma	0.50	Inf	0.31	0.38	0.31	0.48
Demand shock Std (σ_D)	Inverse Gamma	3.00	Inf	1.81	3.60	1.81	10.19
Supply shock Std (σ_S)	Inverse Gamma	3.00	Inf	1.40	2.53	1.40	4.26
Intercepts							
Mean inflation (μ_π)	Gamma	1.00	0.20	0.56	0.87	0.56	1.23
Mean Tbill rate (μ_R)	Gamma	1.00	1.00	0.26	0.96	0.26	1.67
Mean output growth ($\mu_{\Delta y}$)	Normal	0.03	0.09	0.00	0.07	0.00	0.14

TABLE 3. Prior distribution and estimates of structural parameters: 2002Q1 – 2020Q2

	Prior type	Prior Mean	Prior Std Dev	Post. Mean	Post. Median	95% HPD	
Households							
Discount factor (β)	Beta	0.90	0.05	0.89	0.90	0.78	0.98
Habit persistence (θ_h)	Beta	0.80	0.05	0.93	0.93	0.87	0.97
Inverse of the Intertemporal Elasticity of substitution (σ)	Gamma	1.00	1.20	0.49	0.46	0.22	0.83
Frisch labor supply elasticity (φ)	Gamma	2.00	0.50	2.22	2.18	1.30	3.16
Firms							
Calvo prices (ζ)	Beta	0.80	0.10	0.55	0.68	0.55	0.80
Price indexation (ι)	Beta	0.70	0.20	0.22	0.60	0.22	0.99
Central Bank							
Interest rate smoothing (ρ)	Uniform	0.00	1.00	0.82	0.82	0.77	0.88
Inflation response (γ_π)	Gamma	1.50	0.05	1.55	1.55	1.45	1.65
Output growth response ($\gamma_{\Delta y}$)	Gamma	0.13	0.05	0.16	0.15	0.05	0.28
Persistence							
Persistence parameter Demand (ρ_D)	Uniform	0.00	1.00	0.92	0.96	0.75	0.99
Persistence parameter Supply (ρ_S)	Uniform	0.00	1.00	0.71	0.73	0.41	0.92
Shocks							
Monetary shock std (σ_M)	Inverse Gamma	0.50	Inf	0.40	0.39	0.31	0.49
Demand shock Std (σ_D)	Inverse Gamma	3.00	Inf	4.45	4.21	1.79	7.80
Supply shock Std (σ_S)	Inverse Gamma	3.00	Inf	3.98	3.78	2.01	6.34
Intercepts							
Mean inflation (μ_π)	Gamma	1.00	0.20	0.89	0.88	0.56	1.24
Mean Tbill rate (μ_R)	Gamma	1.00	1.00	0.92	0.91	0.19	1.62
Mean output growth ($\mu_{\Delta y}$)	Normal	0.03	0.09	0.15	0.15	0.04	0.26

TABLE 4. Prior distribution and estimates of structural parameters: 2002Q1 – 2020Q3

	Prior type	Prior Mean	Prior Std Dev	Post. Mean	Post. Median	95% HPD	
Households							
Discount factor (β)	Beta	0.90	0.05	0.89	0.90	0.79	0.98
Habit persistence (θ_h)	Beta	0.80	0.05	0.82	0.83	0.74	0.90
Inverse of the Intertemporal Elasticity of substitution (σ)	Gamma	1.00	1.20	0.30	0.28	0.13	0.48
Frisch labor supply elasticity (φ)	Gamma	2.00	0.50	2.06	2.02	1.17	3.05
Firms							
Calvo prices (ζ)	Beta	0.80	0.10	0.65	0.65	0.51	0.79
Price indexation (ι)	Beta	0.70	0.20	0.48	0.47	0.12	0.90
Central Bank							
Interest rate smoothing (ρ)	Uniform	0.00	1.00	0.80	0.80	0.72	0.86
Inflation response (γ_π)	Gamma	1.50	0.05	1.55	1.55	1.45	1.65
Output growth response ($\gamma_{\Delta y}$)	Gamma	0.13	0.05	0.16	0.15	0.05	0.27
Persistence							
Persistence parameter Demand (ρ_D)	Uniform	0.00	1.00	0.96	0.96	0.92	0.99
Persistence parameter Supply (ρ_S)	Uniform	0.00	1.00	0.73	0.73	0.52	0.92
Shocks							
Monetary shock std (σ_M)	Inverse Gamma	0.50	Inf	0.44	0.43	0.34	0.56
Demand shock Std (σ_D)	Inverse Gamma	3.00	Inf	4.59	3.98	1.90	9.52
Supply shock Std (σ_S)	Inverse Gamma	3.00	Inf	2.16	2.08	1.25	3.35
Intercepts							
Mean inflation (μ_π)	Gamma	1.00	0.20	0.90	0.88	0.57	1.24
Mean Tbill rate (μ_R)	Gamma	1.00	1.00	1.00	0.99	0.30	1.73
Mean output growth ($\mu_{\Delta y}$)	Normal	0.03	0.09	0.08	0.08	0.00	0.17

TABLE 5. Prior distribution and estimates of structural parameters: full sample

	Prior type	Prior Mean	Prior Std Dev	Post. Mean	Post. Median	95% HPD	
Households							
Discount factor (β)	Beta	0.90	0.05	0.89	0.90	0.79	0.98
Habit persistence (θ_h)	Beta	0.80	0.05	0.84	0.84	0.76	0.91
Inverse of the Intertemporal Elasticity of substitution (σ)	Gamma	1.00	1.20	0.27	0.26	0.11	0.46
Frisch labor supply elasticity (φ)	Gamma	2.00	0.50	2.09	2.05	1.21	3.08
Firms							
Calvo prices (ζ)	Beta	0.80	0.10	0.66	0.66	0.52	0.79
Price indexation (ι)	Beta	0.70	0.20	0.47	0.44	0.12	0.90
Central Bank							
Interest rate smoothing (ρ)	Uniform	0.00	1.00	0.80	0.81	0.73	0.87
Inflation response (γ_π)	Gamma	1.50	0.05	1.55	1.55	1.46	1.65
Output growth response ($\gamma_{\Delta y}$)	Gamma	0.13	0.05	0.15	0.15	0.05	0.27
Persistence							
Persistence parameter Demand (ρ_D)	Uniform	0.00	1.00	0.96	0.96	0.91	0.99
Persistence parameter Supply (ρ_S)	Uniform	0.00	1.00	0.76	0.77	0.56	0.96
Shocks							
Monetary shock std (σ_M)	Inverse Gamma	0.50	Inf	0.44	0.43	0.33	0.56
Demand shock Std (σ_D)	Inverse Gamma	3.00	Inf	4.28	3.97	1.85	7.31
Supply shock Std (σ_S)	Inverse Gamma	3.00	Inf	2.22	2.12	1.22	3.48
Intercepts							
Mean inflation (μ_π)	Gamma	1.00	0.20	0.89	0.88	0.56	1.22
Mean Tbill rate (μ_R)	Gamma	1.00	1.00	0.96	0.96	0.27	1.66
Mean output growth ($\mu_{\Delta y}$)	Normal	0.03	0.09	0.08	0.08	-0.01	0.19