THE EFFECT OF GLOBAL OUTPUT ON U.S. INFLATION AND INFLATION EXPECTATIONS: A STRUCTURAL ESTIMATION

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Abstract. Recent research has suggested that globalization may have transformed the U.S. Phillips curve by making inflation a function of global, rather than domestic, economic activity.

This paper tests this view by estimating a structural model for the U.S., which incorporates a role of global output on the domestic demand and supply relations and on the formation of expectations. Expectations are modeled as near-rational and economic agents are allowed to learn about the economy's coefficients over time.

The estimation reveals small and negative coefficients for the sensitivity of inflation to global output; moreover, the fit of the model improves when global output is excluded from the Phillips curve. Therefore, the evidence does not support altering the traditional closed-economy Phillips curve to include global output.

The data suggest, instead, that global output may play an indirect role through the determination of domestic output. But the overall impact of global economic conditions on U.S. inflation remains negligible.

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1. Introduction

To model the behavior of U.S. inflation, researchers typically use some version of the New Keynesian Phillips curve, a relation that states that the current domestic inflation rate depends on expectations about future inflation and on a measure of resource utilization in the economy.

The rapid increase in the pace of global economic integration in recent years, however, has led a number of researchers, policymakers, and commentators to argue that these conventional Phillips curves, which were derived under the assumption of a closed-economy, may have become obsolete. Not only, in fact, globalization may have contributed to lower the level of inflation in recent decades, but it may have also deeply altered the form of the Phillips curve. First, several studies have documented how globalization may affect the slope of the curve (although the sign of the effect is still controversial, as Rogoff, 2003, 2006, claims that globalization should lead to a steeper curve, while Razin and Loungani, 2005 and Razin and Binyamini, 2007, show analytically that openness to trade causes the Phillips curve to become flatter). Moreover, others have argued that globalization may have even deeper implications by making inflation mostly a function of global – rather than domestic – economic conditions. Borio and Filardo (2007) estimate reduced-form inflation equations and offer evidence that "global slack" has become a significant determinant of U.S. inflation in the post-1985 sample (while domestic slack appears to have become irrelevant). Ihrig et al. (2007) use a similar reduced-form econometric approach, but find opposite results.

This paper aims to contribute to the debate about the consequences of globalization by providing empirical evidence on the effect of global output on U.S. inflation. While Borio and Filardo (2007) and Ihrig et al. (2007) use backward-looking single-equation regressions in their empirical analysis, this paper tries to assess whether global output affects the U.S. economy using a microfounded general equilibrium model, which is estimated by full-information Bayesian techniques. The model is based on Clarida, Galí, and Gertler (2002, hereafter CGG) and Woodford (2007)'s two-country setting and it incorporates potential effects from global output on the aggregate demand and supply blocks of the economy. By using a general equilibrium model, the paper can provide a different way to control for some factors – as the possible endogeneity of global output to U.S. output, the simultaneous effects of global output on domestic output and inflation, the various influences of domestic monetary policy and disturbances, and so forth – that can affect the estimated size of the elasticity of inflation to global slack.

One factor that has emerged in the literature as possibly important in accounting for the divergence in the results is the treatment of inflation expectations. Expectations here are formed from the general equilibrium model's solution, while previous studies assumed either a smooth trend to account for expectations (Borio and Filardo, 2007) or a backward-looking Phillips curve (Ihrig et al., 2007).

The paper relaxes the assumption of rational expectations and allows economic agents to form subjective, although near-rational, expectations, and to learn the parameters of the economy over time (the assumed learning process is in the spirit of Marcet and Sargent, 1989, and Evans and Honkapohja, 2001). In this way, the paper tries to disentangle the effect of global output on the economy from the extent to which it affects the evolution of expectations. Moreover, learning allows the model to match the persistence in inflation and output without changing the model's microfoundations to include features as indexation in price-setting and habit formation in consumption. Having a framework that is able to match the inertia in macroeconomic data is crucial, since it is possible that a large role for global output can simply arise because it captures the omitted persistence in the system.

Adding learning to the model may lead to worries about whether we enter the "wilderness of irrationality". Therefore, here the learning process is not arbitrarily chosen and the estimation results conditioned on its validity. Instead, the best-fitting learning process is inferred from the data along with all the structural parameters. The estimation remains parsimonious as the only free learning parameter is the constant gain.

The main scope of the empirical analysis is to assess the effect of global output on the U.S. economy. In particular, the empirical estimates can shed some light on the recent argument that closed-economy Phillips curves should be abandoned in favor of more global-centric specifications.

The posterior estimates are suggestive of small and slightly negative values for the sensitivity of inflation to global output. When this coefficient is restricted to zero the fit of the model improves. Therefore, there doesn't seem to be much evidence that the New Keynesian Phillips curve should be altered yet to assign a central role to global output as a driver of domestic inflation rates. Global output may still play a role, however, as the estimates indicate that it affects domestic output through the IS equation. The models that incorporate an influence of global output on domestic output, but neither on the Phillips curve nor on expectations, achieve the best fit of the data. Other versions of the open economy model, instead, fail to improve the fit over the standard closed-economy specification.

Shocks to global output account for a very limited fraction of U.S. economic fluctuations. There is no evidence that economic agents would improve their forecasting performance about inflation by exploiting information about global conditions, while these may slightly improve forecasts about domestic output.

The paper mainly aims to contribute to the literature that studies the effects of global factors on U.S. inflation. Besides Borio and Filardo (2007) and Ihrig et al. (2007), other papers by Gamber and Hung (2001), Wynne and Kersting (2007), and Milani (2009a) provide some supportive evidence on the global slack hypothesis, while Tootell (1998) and Ball (2006) find either limited or no role for foreign capacity utilization as a determinant of U.S. inflation.[1] Castelnuovo (2007) focuses, instead, on the influence of global slack on U.S. inflation expectations, finding it unimportant in the post-Volcker sample. This paper reaches similar conclusions. D'Agostino and Surico (2009) identify global liquidity, rather than capacity utilization, as another global factor that may affect domestic inflation. Several papers focus, instead, on the impact of globalization on the slope of the domestic Phillips curve and on the level of inflation: Sbordone (2007), for example, models how the increased competition induced by globalization may affect the slope of the Phillips curve; Guerrieri et al. (2008) derive an open economy New Keynesian Phillips curve under the assumption of a variable elasticity of demand and show that an increase in foreign competition leads to lower inflation. Zaniboni (2008) uses calibration to study the effects of globalization on the level of inflation, on the slope of the Phillips curve, and on the sensitivity of inflation to global slack. His conclusion of a limited impact of globalization on inflation are supported by the empirical results in this paper.

This paper can also be seen as an empirical application of models with adaptive learning (e.g., Evans and Honkaphja, 2001, for an overview). The constant gain and the initial beliefs coefficients are all estimated from the data, rather than fixed a priori, and different learning specifications are estimated and chosen based on fit. The empirical results illustrate the evolution of agents' beliefs in the post-1985 sample in the U.S. and conclude that they were not

[1]Calza (2008) and Milani (2009b) also find results that are not entirely supportive of the global slack hypothesis, but focusing on the Euro area and the set of G-7 countries, respectively.

sensitive to global developments. Other papers that incorporate learning to fit macroeconomic data are Adam (2005), Milani (2007a,b, 2008a,b), and Slobodyan and Wouters (2007). Finally, the paper can provide evidence on whether the closed-economy settings that have been typically estimated as a description of the U.S. economy (e.g., Ireland, 2001, Giannoni and Woodford, 2003, Rabanal and Rubio-Ramirez, 2005, Smets and Wouters, 2007, An and Schorfheide, 2007) may have now become misspecified because of the omission of global factors.

2. A Two-Country Framework

The effect of global output on U.S. macroeconomic variables is investigated using the two-country New Keynesian model derived in CGG (2002). Woodford (2007) uses a similar setting to evaluate the impact of globalization on the effectiveness of national monetary policies.[2] In the model, the U.S. are regarded as the Home country, while an aggregate of several of its trading partners represents the Foreign block.

The representative household in the Home country maximizes the discounted sum of future expected utilities

$$E_0 \sum_{t=0}^{\infty} \beta^t \left[\frac{C_t^{1-\sigma^{-1}}}{1-\sigma^{-1}} - \frac{1}{1+\varphi} \left(\frac{H_t}{\zeta_t} \right)^{1+\varphi} \right], \tag{2.1}$$

where $0 < \beta < 1$ denotes the household's discount factor, $\sigma > 0$ denotes the elasticity of intertemporal substitution in consumption, $\varphi > 0$ is the inverse of the Frisch elasticity of labor supply, ζ_t is an aggregate preference shock, H_t denotes hours of work, and C_t is an index of consumption of both domestic and foreign goods

$$C_t \equiv C_{H,t}^{1-\gamma} C_{F,t}^{\gamma}, \tag{2.2}$$

where $C_{H,t}$ is a Dixit-Stiglitz index of Home-produced goods and $C_{F,t}$ is an index of Foreign-produced goods. The coefficient γ denotes the share of foreign-produced goods in the domestic consumption basket (households in both countries are assumed to consume an identical basket of goods).[3] As in CGG (2002), this specification assumes a unit elasticity of substitution

[2] A similar framework has also been used in Benigno and Benigno (2006, 2008) to study issues related to international monetary cooperation. This section will simply sketch the main features of the model; full details on the derivation can be found in the original papers.

[3] The model is presented here under the assumption of rational expectations. Near-rational expectations and learning will be introduced later in the model. The log-linearized laws of motion under rational expectations and learning will be equivalent under the conditions discussed in Honkapohja, Mitra, and Evans (2003). Preston (2008) and Milani (2006) offer a different approach of incorporating learning in which infinite-horizon expectations also matter.

between Home and Foreign goods. Financial markets are complete. Optimization gives the following intra- and intertemporal first-order conditions

$$P_{H,t}C_{H,t} = (1-\gamma)P_tC_t \tag{2.3}$$

$$P_{F,t}C_{F,t} = \gamma P_tC_t \tag{2.4}$$

$$\beta E_t\left[\left(\frac{C_{t+1}}{C_t}\right)^{-\frac{1}{\sigma}}\frac{P_t}{P_{t+1}}\right] = (1+i_t)^{-1}, \tag{2.5}$$

where $P_t \equiv k^{-1}P_{H,t}^{1-\gamma}P_{F,t}^{\gamma}$ denotes the aggregate price level, $k \equiv (1-\gamma)^{1-\gamma}\gamma^{\gamma}$, and $P_{H,t}$ and $P_{F,t}$ are price indices for domestically and foreign-produced goods.

A continuum of monopolistically-competitive firms also populates the economy; each firm produces the differentiated good i according to the production function

$$y_t(i) = A_t h_t(i)^{\phi^{-1}} \tag{2.6}$$

where A_t denotes technology, $h_t(i)$ denotes the labor input for firm i, and $\phi \geq 1$ allows for diminishing returns to the labor input. Firms are assumed to set prices à la Calvo (i.e., in a given period a firm has a probability α of not being able to revise its price). When allowed to revise their price, firms select the new optimal price $p_t(i)$ by maximizing the expected discounted sum of future profits[4]

$$E_t\left\{\sum_{T=t}^{\infty}\alpha^{T-t}Q_{t,T}\left[p_t(i)y_T(i) - W_T\left(\frac{y_T(i)}{A_T}\right)^{\phi}\right]\right\}, \tag{2.7}$$

subject to the demand for each good given by $y_t(i) = Y_t\left(\frac{p_t(i)}{P_{H,t}}\right)^{-\theta}$, where $Q_{t,T}$ denotes the stochastic discount factor, W_t denotes the nominal wage, Y_t denotes aggregate domestic output, and $\theta > 1$ denotes the elasticity of substitution among differentiated goods. Profit maximization leads to the first-order condition

$$E_t\left\{\sum_{T=t}^{\infty}\alpha^{T-t}Q_{t,T}\left[p_t(i) - \mu MC_T(i)\right] = 0\right\} \tag{2.8}$$

where $\mu \equiv \theta/(\theta-1)$ denotes the firm's markup of prices over marginal costs and $MC_t(i)$ denotes the nominal marginal cost for firm i, which can be expressed as $MC_t(i) = MC_t\left(y_t(i)/Y_t\right)^{\phi-1}$, where MC_t is the average marginal cost for domestic firms. The stochastic discount factor and

[4]The paper assumes producer-currency pricing. The impact of globalization on the Phillips curve in the alternative assumptions of local-currency pricing and dollar-dominant pricing have been analyzed in Zaniboni (2008).

the marginal cost are given by

$$Q_{t,T} = \beta \left(\frac{Y_t}{Y_T}\right)^{\frac{1}{\sigma}+\gamma(1-\frac{1}{\sigma})} \left(\frac{Y_t^*}{Y_T^*}\right)^{\gamma(\frac{1}{\sigma}-1)} \frac{P_{H,t}}{P_{H,T}} \tag{2.9}$$

$$MC_t = \phi k^{\left(\frac{1}{\sigma}-1\right)} P_{H,t} \frac{Y_t^{\left[\omega+\frac{1}{\sigma}+\gamma(1-\frac{1}{\sigma})\right]} Y_t^{*\left(\frac{\gamma}{\sigma}-\gamma\right)}}{A_t^{1+\omega}\zeta_t^{\varphi}} \delta_t^{\varphi}, \tag{2.10}$$

where $\omega \equiv [(1+\varphi)\phi - 1]$ and δ_t is a measure of price dispersion for domestic goods. Through its effect on the stochastic discount factor and on marginal costs in (2.9) and (2.10), therefore, foreign (or global) output Y_t^* will affect the aggregate supply block of the economy, which is obtained by log-linearizing the first-order condition (2.8) along with the law of motion for the domestic price index $P_{H,t}^{1-\theta} = \alpha P_{H,t-1}^{1-\theta} + (1-\alpha)p_t(i)^{1-\theta}$, where $p_t(i)$ is the same for each firm i that reoptimizes in t. The sign of the global output impact on marginal costs is, however, ambiguous as a result of two countervailing effects: a positive effect, since an increase in foreign output leads in the model to higher domestic consumption, lower marginal utilities of consumption and income, and higher marginal costs, and a negative effect, since an increase in foreign output also causes an appreciation of the Home country's terms of trade, a higher relative marginal utility of income in units of domestic goods with respect to the marginal utility in units of the world goods, and hence lower marginal costs.

2.1. **Linearized Model.** After log-linearization of the model's equilibrium conditions around a zero-inflation steady state, the U.S. economy can be summarized by the following equations (as in Woodford, 2007):

$$\pi_t = \beta \hat{E}_t \pi_{t+1} + \kappa^H y_t + \kappa^F y_t^* + u_t \tag{2.11}$$

$$y_t = \hat{E}_t y_{t+1} + \vartheta \left(y_t^* - \hat{E}_t y_{t+1}^*\right) - \tilde{\sigma}\left(i_t - \hat{E}_t \pi_{t+1}\right) + \eta_t \tag{2.12}$$

$$i_t = \rho i_{t-1} + (1-\rho)[\chi_\pi \pi_{t-1} + \chi_y y_{t-1}] + \varepsilon_t. \tag{2.13}$$

Equation (2.11) is a New Keynesian Phillips curve (extended to the open economy case), in which the domestic inflation rate π_t depends on the expected one-period ahead inflation rate and on both domestic and foreign output (denoted by y_t and y_t^*). β denotes the household's discount factor, while coefficients κ^H and κ^F denote the sensitivity of inflation to domestic and global output. Global output enters the aggregate supply relation through its effect on the marginal utility of income and on firms' marginal costs. This Phillips curve is similar to the specifications estimated in Borio and Filardo (2007) and Ihrig et al. (2007), which are, however, purely backward-looking: Borio and Filardo (2007) use a smooth trend for inflation to proxy for changing inflation expectations and lagged values for domestic and global slack variables, while Ihrig et al. (2007) use lagged inflation as a proxy for expectations and current slack measures. Here, the formation of expectations will be explicitly modeled. One of the main coefficient of interest in the estimation will be κ^F. Borio and Filardo (2007)'s estimate for κ^F is positive, large, and significant, while κ^H is not significantly different from zero; Ihrig et al. (2007), instead, find negative estimates for κ^F (with a large standard error).

Equation (2.12) is the log-linearized Euler equation. Domestic output depends on expectations about future output, on the ex-ante real interest rate ($i_t - \hat{E}_t\pi_{t+1}$), and on current and expected foreign output. Foreign output affects the economy's IS curve since domestic households are assumed to consume a basket that includes both domestically and foreign-produced goods. The coefficients ϑ and $\tilde{\sigma}$ denote the sensitivity of domestic output to foreign output and domestic real interest rates.

Monetary policy in the model is described by the Taylor rule (2.13). The policy instrument i_t is adjusted in response to fluctuations in inflation and output, and it is characterized by inertial adjustment (the rule is operational in the sense of McCallum, 1999, since the monetary authority is assumed to dispose of information up to $t-1$ when setting policy in t); χ_π and χ_y denote the policy reaction coefficients to inflation and output, while ρ captures the inertia of central bank's policy.

The variable u_t denotes a cost-push shock, η_t denotes a demand shock (preference or government spending), and ε_t is a policy shock. The supply and demand shocks are assumed to evolve as AR(1) processes $u_t = \rho_u u_{t-1} + \nu_t^u$ and $\eta_t = \rho_\eta \eta_{t-1} + \nu_t^\eta$, where ν_t^u and ν_t^η are Normally-distributed with mean zero and standard deviations σ_u and σ_η, while the policy shock ε_t is assumed to be *i.i.d.* Normal with mean zero and standard deviation σ_ε.

The foreign economy is not modeled as structural (if it was, it would follow a system of equations similar to (2.11) to (2.13)).[5] Global output, however, is not taken as exogenous, since it is likely to be affected by U.S. macroeconomic conditions. It will be, therefore, allowed to depend on U.S. variables, as

$$y_t^* = \rho^* y_{t-1}^* + \delta_y y_{t-1} - \delta_r(i_{t-1} - \pi_{t-1}) + \upsilon_t, \tag{2.14}$$

[5]As the main focus in the empirical analysis lies in inferring the effect of global output on the U.S. economy, I prefer here to avoid the risk of biasing the main coefficients of interest by imposing cross-equation restrictions from a potentially misspecified structural model for the foreign aggregate.

where the coefficients δ_y and δ_r denote the sensitivity of global output to U.S. output and real interest rates. The shock to global output is allowed to be AR(1) with autoregressive coefficient ρ_ν and standard deviation σ_ν.

Expectations are modeled as near-rational and denoted by $\hat{E}_t$, which may differ from model-consistent rational expectations E_t. The agents are assumed to form expectations using a Perceived Law of Motion (PLM) of the economy that has the same structural form of the model's Minimum State Variable (MSV) solution under rational expectations. It is assumed, however, that economic agents are unable to observe the structural disturbances and that they lack knowledge about the model parameters. Therefore, agents use the available historical data to learn about the reduced-form coefficients of the economy over time (similar expectations formation mechanisms are extensively analyzed in Evans and Honkapohja, 2001).

They estimate the specification:

$$\begin{bmatrix} \pi_t \\ y_t \\ i_t \\ y_t^* \end{bmatrix} = \begin{bmatrix} a_t^\pi \\ a_t^y \\ a_t^i \\ a_t^{y^*} \end{bmatrix} + \begin{bmatrix} b_t^{\pi,\pi} & b_t^{\pi,y} & b_t^{\pi,i} & b_t^{\pi,y^*} \\ b_t^{y,\pi} & b_t^{y,y} & b_t^{y,i} & b_t^{y,y^*} \\ b_t^{i,\pi} & b_t^{i,y} & b_t^{i,i} & b_t^{i,y^*} \\ b_t^{y^*,\pi} & b_t^{y^*,y} & b_t^{y^*,i} & b_t^{y^*,y^*} \end{bmatrix} \begin{bmatrix} \pi_{t-1} \\ y_{t-1} \\ i_{t-1} \\ y_{t-1}^* \end{bmatrix} + e_t \tag{2.15}$$

where e_t is a vector of residuals. Agents update their coefficient estimates over time according to the constant-gain algorithm

$$\widehat{\phi}_t = \widehat{\phi}_{t-1} + \overline{\mathbf{g}} R_t^{-1} X_t (Y_t - X_t' \widehat{\phi}_{t-1}) \tag{2.16}$$

$$R_t = R_{t-1} + \overline{\mathbf{g}} (X_t X_t' - R_{t-1}) \tag{2.17}$$

where $Y_t \equiv [\pi_t, y_t, i_t, y_t^*]'$, $X_t \equiv \{1, Y_{t-1}\}$, and where $\widehat{\phi}_t = \left([a_t^\pi, ..., a_t^{y^*}]', [b_t^{\pi,\pi}, ..., b_t^{y^*,y^*}]' \right)'$ describes the updating of the learning rule coefficients, and R_t the updating of the matrix of second moments of the stacked regressors X_t. The coefficient $\overline{\mathbf{g}}$ denotes the constant gain, which governs the rate at which agents discount past information when forming their beliefs.[6]

The learning algorithm needs to be initialized by choosing initial beliefs $\widehat{\phi}_{t=0}$ and $R_{t=0}$. In the empirical analysis, these will not be arbitrarily chosen, but, as the estimation sample will start from 1985, they will be inferred using pre-sample data from 1960:I to 1984:IV. It is assumed that agents start the sample (in 1985:I) with initial beliefs that are also estimated

[6]There is experimental and time series evidence in support of similar models of learning as a reasonable description of the economic agents' expectations formation mechanism. Adam (2007) shows that forecast rules including lagged inflation approximate the inflation expectations of his experimental subjects. Branch and Evans (2005) find that constant gain models of learning fit forecasts from surveys better than the alternatives (such as models that use an optimal constant gain, the Kalman Filter, or Recursive Least Squares learning) for both inflation and output.

through constant-gain learning as[7]

$$\widehat{\phi}_\tau = \left[\sum_{i=1}^{\tau}(1-\mathbf{\overline{g}})^{(i-1)} X_{\tau-i}X'_{\tau-i}\right]\left[\sum_{i=1}^{\tau}(1-\mathbf{\overline{g}})^{(i-1)} X_{\tau-i}Y'_{\tau-i+1}\right] \quad (2.18)$$

$$R_\tau = \mathbf{\overline{g}}\sum_{i=1}^{\tau}(1-\mathbf{\overline{g}})^{(i-1)} X_{\tau-i}X'_{\tau-i}, \quad (2.19)$$

where τ denotes the last quarter of the pre-sample period. Hence, the estimation will not be conditioned on a given chosen learning process, but the empirical analysis will try to extrapolate the best-fitting learning dynamics along with the best-fitting structural and policy parameters from time series data. The initial values of the vector of beliefs $\widehat{\phi}_\tau$ and the initial precision matrix R_τ, in fact, are not fixed, but their values will be inferred from the data by estimating the constant gain parameter $\mathbf{\overline{g}}$ (this is important since Carceles-Poveda and Giannitsarou, 2007, show how different initial beliefs may affect the dynamics of artificially-simulated economies). Therefore, there is only a single free parameter that is added in the model by introducing learning.

Economic agents use (2.15) and the updated parameter estimates in (2.16) and (2.17), obtained starting from initial beliefs (2.18) and (2.19), to form their expectations for $t+1$ as

$$\widehat{E}_{t-1}Y_{t+1} = a_t(1+b_t) + b_t^2 Y_{t-1}, \quad (2.20)$$

where it is assumed that agents dispose of information up to $t-1$, when forming expectations in t, and which can be substituted in (2.11) to (2.13) to obtain the Actual Law of Motion of the economy (ALM):

$$\xi_t = A_t + F_t\xi_{t-1} + G\varpi_t \quad (2.21)$$

$$Y_t = H\xi_t \quad (2.22)$$

where $\xi_t = [Y'_t, u_t, \eta_t, \nu_t]'$ is a vector of state variables, Y_t is the vector of observable variables, ϖ_t is a vector of Normally-distributed exogenous innovations, A_t is a vector of intercept terms, F_t is a matrix of coefficients that depends on structural and beliefs coefficients, G collects the standard deviations of the innovations, and H is a 4×7 matrix of zeros and ones, which simply selects the observables from the vector of state variables ξ_t; A_t and F_t are time-varying as an implication of agents' real-time learning.

[7]Since economic agents learn using a constant gain in the model, it is assumed that also the initial beliefs are derived in the same way, rather than by OLS. In this way, older observations are potentially discounted.

3. Structural Estimation

3.1. **Data and Global Output Calculation.** I use quarterly data on U.S. domestic inflation, U.S. output, the Federal Funds rate, and 'global' output, as observable variables in the estimation. Inflation is calculated as the log quarterly change in the GDP Implicit Price Deflator, output is obtained as log Real GDP, detrended using the Hodrick-Prescott filter (with $\lambda = 1,600$), and the Federal Funds rate represents the monetary policy instrument in the model.[8] The sample spans the period from 1985:q1 to 2007:q1 (the starting date is chosen to be consistent with Borio and Filardo, 2007, and Ihrig et al., 2007, and because a rapid increase in the pace of globalization took place starting roughly from the mid-1980s).

To obtain the relevant measure of global output for the U.S. economy, I identify the largest 50 U.S. trading partners at the end of the sample and use quarterly data on their real GDP, and their bilateral exports and imports with the U.S. over the sample (the data for the trading partners have been obtained from IHS Global Insight).[9] All GDP, imports, and exports series have been seasonally adjusted when already seasonally-adjusted series were not available.

For each country, I derive a detrended output series using the HP filter. Global output y_t^* is then obtained as a weighted average of the countries' detrended output series in period t:

$$y_t^* = \sum_{i=1}^{N} w_t^i y_t^i \tag{3.1}$$

where $i = 1, ..., N$ is an index for the different trading partners, y_t^i is the detrended output of trading partner i, and where the weights w_t^i are given by the sum of U.S. imports and exports with country i in each period t as a fraction of total U.S. imports and exports with the set of trading partners

$$w_t^i = \frac{(Imports_t^i + Exports_t^i)}{\sum_{i=1}^{N}(Imports_t^i + Exports_t^i)}. \tag{3.2}$$

Similar global output measures have been adopted by Borio and Filardo (2007), although they use a changing weighted average of the top 10 trading partners, and by Ihrig et al. (2007),

[8]The U.S. data were obtained from FRED®, the Federal Reserve of St. Louis Economic Database.

[9]Data are not always available for each of the 50 countries. In some cases, only annual GDP series are available: these countries are dropped from the analysis. As they typically occupy positions between 35 and 50 in the trading partners' rankings, their omission is unlikely to have any sizeable effect on the results. Global output is, therefore, calculated using data on about 40 countries: Argentina, Australia, Austria, Belgium, Brazil, Canada, Chile, China, Colombia, Costa Rica, Denmark, Ecuador, Finland, France, Germany, Hong Kong, India, Indonesia, Ireland, Israel, Italy, Japan, South Korea, Malaysia, Mexico, Netherland, Norway, New Zealand, Philippines, Russia, South Africa, Singapore, Spain, Sweden, Switzerland, Thailand, Turkey, U.K., Venezuela.

who consider the top 35 partners. The large set of trading partners permits to account for the influence of emerging market economies, which may be important in the recent part of the sample. Moreover, the use of trade weights in the construction of global output is motivated by the observation that bilateral trade flows still represent the main source of global linkages (e.g., Forbes and Chinn, 2004, and Frankel and Rose, 1998).

Figure 1 shows global output along with detrended U.S. output. The two series clearly comove: their correlation is equal to 0.546, which remains nevertheless far from levels that would create problems of near multicollinearity in the estimation.

3.2. **Bayesian Estimation.** The vector Θ collects the coefficients that need to be estimated:

$$\Theta = \left\{\kappa^H, \kappa^F, \vartheta, \tilde{\sigma}, \rho, \chi_\pi, \chi_y, \rho_u, \rho_\eta, \rho_\nu, \rho^*, \sigma_u, \sigma_\eta, \sigma_\varepsilon, \sigma_\nu, \overline{\mathbf{g}}\right\}. \tag{3.3}$$

The only parameter that is fixed is β, which is assumed equal to 0.99. The priors for the other parameters (assumed to be independent) are specified in Table 1. For κ^H, which denotes the sensitivity of inflation to domestic output, I assume a Gamma prior distribution with mean 0.1 and standard deviation 0.08. The coefficient regarding the effect of global output on inflation, denoted by κ^F, follows a Normal prior distribution with mean 0 and standard deviation 0.15, while the coefficient regarding the effect of global output on domestic output, denoted by ϑ, follows a Normal prior distribution with mean 0 and standard deviation 0.5. The priors incorporate sizeable uncertainty, as there is no clear-cut evidence about the value of these coefficients from previous studies; moreover, the priors are centered at zero, which will be the value of κ^F and ϑ in the closed-economy New Keynesian model. I choose a Gamma prior distribution with mean 1 and standard deviation 0.75 for $\tilde{\sigma}$, the sensitivity of domestic output to the ex-ante real interest rate, and Normal distributions with mean 1.5 and standard deviation 0.25 for the monetary policy reaction coefficient to inflation and with mean 0.25 and standard deviation 0.125 for the reaction coefficient to output. A non-informative Uniform distribution is assumed for the constant-gain coefficient (the estimation was also repeated, however, under alternative Beta or Gamma prior distributions for the gain). Beta and inverse gamma prior distributions are, finally, selected for all autoregressive coefficients in the model and for the standard deviations of the shocks.

The model is estimated using Bayesian methods. The estimation techniques are reviewed in An and Schorfheide (2008), for rational expectations models, and have been used to estimate models with near-rational expectations and learning in Milani (2007a,b, 2008a,b) and Slobodyan and Wouters (2007). Draws from the posterior distribution are generated using the Metropolis-Hastings algorithm. I run 600,000 draws, discarding the first 25% as initial burn-in. Convergence is evaluated by looking at trace plots, CUSUM plots, and performing the tests proposed by Geweke (1992) and Raftery and Lewis (1995);[10] I use bivariate scatter plots to assess the mixing of the chain and to check whether strong dependence exists among some parameters.

4. Empirical Results

4.1. **Posterior Estimates.** Table 2 reports the posterior mean estimates for the structural coefficients in Θ along with the corresponding 95% highest posterior density (HPD) intervals.

The first three columns (columns (1a), (1b), and (1c) in the table) refer to the baseline model, described by equations (2.11) to (2.14), in which global output is allowed to have an effect on the aggregate demand and supply of the economy and on the formation of expectations, through the PLM (2.15). The posterior mean estimate for the sensitivity of inflation to global output κ^F is equal to -0.015 (column 1a). In reduced-form inflation regressions, Borio and Filardo (2007) estimate this sensitivity to be positive, significant, and relatively large. The estimates in the structural model, instead, point to small and slightly negative coefficients: this evidence is, therefore, more consistent with the estimates in Ihrig et al. (2007), who also often obtain negative elasticities (equal to -0.048 in their baseline U.S. estimation, with a large standard error), and with the theoretical arguments in Woodford (2007), who discusses how negative signs may be more natural within the model. The 95% HPD interval is rather large and contain the value of zero for the elasticity. The estimate for ϑ, instead, falls entirely in positive range and has posterior mean equal to 0.558. The posterior mean for the elasticity of inflation to domestic output κ^H equals 0.015, while the posterior mean for the elasticity of domestic output to the ex-ante real interest rate is equal to 0.096. The estimates of the monetary policy

[10] Geweke's test compares the partial means $\widehat{\mu}_1 = \frac{1}{D_1}\sum_{j=1}^{D_1} g(\Theta_j)$ and $\widehat{\mu}_2 = \frac{1}{D_2}\sum_{j=D_1+1}^{D_2} g(\Theta_j)$ obtained from the first D_1 and last D_2 simulation draws. The null hypothesis of equal means can then be tested using the fact that the quantity $(\widehat{\mu}_1 - \widehat{\mu}_2) \,/ \left(\frac{\widehat{S}_g^1(0)}{D_1} + \frac{\widehat{S}_g^2(0)}{D_2}\right)^{1/2} \Longrightarrow N(0,1)$, for $D \to \infty$. Raftery and Lewis (1995)'s diagnostics, instead, suggests a minimum number of total draws, a thinning parameter, and a minimum burn-in, by computing the autocorrelation of the draws.

rule coefficients are in line with the existing evidence ($\rho = 0.91$, $\chi_\pi = 1.421$, and $\chi_y = 0.39$). The estimate of the constant gain coefficient falls on the low side: the posterior mean for $\overline{\mathbf{g}}$ is 0.011. A low value for the gain coefficient is expected since there is evidence that its value is lower in the post-1985 sample than in the previous decades (see Milani, 2007b), as periods of turbulence in the economy, which typically lead agents to increase their gain coefficient, have been far less frequent.

It is important to notice that learning seems able to capture most of the persistence in the model. The autoregressive coefficient for the exogenous cost-push shock u_t is, in fact, estimated equal to 0.076. This suggests that when the existing inflation inertia is fully captured, the role of global output as a significant determinant of inflation is diminished. Estimations that fail to account for the inertial adjustment of expectations may hence overestimate the importance of those variables – such as global output – that can capture the omitted inertia.

Finally, there seems to be evidence against the assumption of exogeneity of global output to the U.S. business cycle: global output, in fact, depends positively on past U.S. output ($\delta_y = 0.207$) and negatively on past U.S. real interest rates ($\delta_r = 0.077$).[11]

The evidence about the role of global output seems robust to alternative assumptions about the learning rule. In the baseline model, economic agents were assumed to know the steady state of the variables (i.e., they recognize that $a_t = 0$ for all t's), although they were learning about the parameters of the model. This assumption can be relaxed and the new estimation results are reported in column (1b) in the table: economic agents now need to learn about the steady states as well (i.e., they also estimate a vector of intercept terms a_t). Column (1c), instead, refers to the case in which economic agents are assumed to start the sample with an initial belief that global output does not affect domestic variables (rather than leaving this belief unrestricted and estimated from pre-sample data): agents start from beliefs $b_{t=0}^{\pi,y^*} = b_{t=0}^{y,y^*} = b_{t=0}^{i,y^*} = 0$, but they update their beliefs as new data become available. In both cases, the results remain very similar. In the learning about the steady state case, the mean estimate for κ^F remains negative and equal to -0.019, while the estimate for ϑ is unchanged (as learning about the intercept seems to matter more in the inflation equation than in the output equation). When the initial beliefs assign a zero weight to global output, the estimated value for ϑ is reduced ($\vartheta = 0.349$) and the posterior estimate for κ^F is still negative ($\kappa^F = -0.012$).

[11]The model has also been re-estimated taking global output as exogenous. The fit of the model becomes substantially worse. The estimates of the main coefficients of interest remain similar.

So far, I have assumed that global output affects both the determination of output and inflation in the model and formation of economic agents' expectations, through their PLM (2.15). The effects of globalization, however, may not have been incorporated yet in the expectations formation of agents. Hence, I repeat the estimation allowing global output to affect the IS and Phillips curves, but assuming it does not affect expectations (b_t^{π,y^*}, b_t^{y,y^*}, and b_t^{i,y^*}, are now all equal to zero in the PLM for all t's). Again, the resulting estimates (reported in column (2) of Table 2) are absolutely similar ($\kappa^F = -0.023$, $\vartheta = 0.322$).

The best-fitting values of the gain coefficient are somewhat dependent on the learning rule specification (ranging from 0.006 when agents need to learn about the constant and the effect of global output as well, to 0.035 when they know the steady state and simply use a VAR in inflation, domestic output, and interest rates). For the purposes of the paper, however, even under different constant gain values and PLM specifications, the estimates regarding the effects of global output remain remarkably similar.

The evidence on the role of domestic and global economic conditions in the Phillips curve is, in fact, not particularly sensitive to the specific assumptions about economic agents' learning rules. Figure 2 shows the posterior distributions for the coefficients denoting the sensitivity of inflation to domestic output κ^H and the sensitivity of inflation to global output κ^F, across the different estimated models in Table 2. The shapes of the distributions remain similar across all cases; the distributions for κ^F are substantially more diffuse, which can help explain the difficulty in pinning down the value of this parameter in the literature.

4.2. **Posterior Odds Ratios.** To assess whether it would be desirable for macroeconomic models of the U.S. economy to be revised to incorporate a role for global output, I can compare the fit to the data of the baseline specification compared with the fit of alternative specifications in which some of the channels through which global output affects the system are shut down. Table 2 reports the posterior odds ratios among the estimated models, calculated with respect to the baseline model with global output, whose estimates are shown in column (1a).[12] Requiring agents to also learn about the steady state levels of the variables leads to a worsening in the model fit. A substantial improvement is, instead, obtained by assuming that agents start the sample in 1985 with an initial belief that global output has a zero effect on

[12] The log marginal likelihoods are computed using Geweke's modified harmonic mean estimator. According to Jeffreys (1961), strong evidence of one model specification versus the other is typically obtained when the ratios are above 10; posterior odds ratios above 100 are typically considered decisive evidence.

domestic variables, which means that they didn't include global output in their PLM in the 1960-1984 period (the posterior odds ratio with respect to the baseline model is 41.6). If the expectations channel is shut down (by assuming that global output does not affect the agents' PLM at all t's), the model fit further improves: the posterior odds ratio in this case is 345.5. Therefore, the data strongly suggest that U.S. expectations respond to domestic conditions, but not (yet) to global developments.

Figure 3 illustrates the evolution of economic agents' beliefs under the alternative learning assumptions. If global output is included in the PLM for domestic variables, the perceived effect is often negative in the sample (with an estimated initial belief close to zero in the inflation equation, and negative in the output equation). As seen, fixing the initial beliefs to zero or dropping global output from the PLM improves the model's fit. The best-fitting specification is characterized by a more rapidly declining perceived persistence in inflation compared with the other cases, by a lower perceived persistence in output, by a belief of a more aggressive monetary policy reaction at the beginning of the sample, which drops in the second half, and by a lower perceived policy reaction to output deviations.

To test if global output plays any role for the U.S. economy, I also estimate a closed-economy version of the model, setting $\kappa_F = \vartheta = 0$, as well as $b_t^{\pi,y^*} = b_t^{y,y^*} = b_t^{i,y^*} = 0$ in the PLM. The model fits the data better than the baseline model with global output (posterior odds ratio = 393.07). The fit of the closed economy model, however, is comparable to the fit of the alternative model in which global output is allowed to affect the economy, but not the formation of expectations. The slight prevalence of the closed economy model in Table 2 is sensitive to assumptions about the priors: if the model is re-estimated assuming a less diffuse prior distribution for ϑ (with standard deviation equal to 0.25, for example), or one with a positive prior mean (equal to 0.25, for example), the relative fit of the two models would be reversed. The data, therefore, cannot clearly favor one specification over the other.

The model is finally re-estimated by fixing in turn either κ_F or ϑ equal to zero. The estimates are shown in column (4) and (5) in the table. The estimation results suggest a role for global output fluctuations in affecting domestic output through the IS equation; the effect of global output on marginal costs and hence on inflation does not seem, however, central in fitting the data (as including it leads to a worse fit than the closed-economy specification). The specification with $\kappa_F = 0$ and $\vartheta \neq 0$, in fact, attains the highest fit among all the estimated models, with a posterior odds ratio of 2,599.31. In this case, the model rankings are robust to different choices about the prior distributions: extending the IS curve to allow for an effect of global output improves the fit, while altering the Phillips curve appears to worsen it.

4.3. **Impulse Responses and Variance Decomposition.** Even if the direct effect of global output on inflation is unimportant, global output can still have potentially important effects on inflation through its estimated influence on domestic output.

Figure 4 displays the impulse responses of the domestic inflation rate to one standard deviation positive shocks to both domestic and global output, obtained for the model in which global output is assumed not to enter the agents' PLM (this case is selected as it is the best-fitting specification among those that allow for a role of global output in column (1a) through (2) in Table 2). The impulse responses are time-varying in the sample as a result of learning dynamics: the figure shows the median impulse response functions over the sample, along with 16% and 84% percentile bands (no clear pattern is apparent from the time variation in the impulse responses, which is modest). Shocks to domestic output have a sluggish effect on inflation. The response of inflation to shocks to global output is substantially smaller: the impact is initially negative and then it turns positive after few quarters. Global output shocks have a positive effect on domestic output with a peak after two-three quarters.

The contribution of global output to the domestic economy is, however, limited. The forecast error variance decomposition indicates that shocks to global output can account for only 1% of the fluctuations in domestic inflation at five or ten-year horizons (while the variance share explained by domestic output shocks reaches 20%), and for 9% of the domestic output fluctuations (median values over the sample). The other direction of causality is probably stronger: shocks to U.S. output can explain roughly 30% of fluctuations in the global output variable.

Finally, although the effect of global output is still relatively small, the openness of the U.S. economy may change the transmission of domestic shocks. Figure 5 shows the response of U.S. inflation and output to domestic shocks, i.e. the response of inflation to a one standard deviation shock to domestic output and the response of output to a one standard deviation contractionary monetary policy shock. The impulse responses are shown in the cases in which the economy is open (the specification refers to column (2) in Table 2) and in which the same economy is, instead, closed (by setting κ^F and ϑ equal to zero). The comparison is important since, even though the data favor the closed economy specification, the fit of the two models is still similar (the posterior model probabilities would be 0.532 for the closed economy and 0.468 for the open economy specification in column (2)) and their relative fit is dependent on the prior selections. It is hence necessary to check whether omitting open economy features would lead to a serious misspecification of the dynamics of U.S. variables.

The evidence, however, suggests that the response of output to a monetary policy shock is largely similar in the open and closed economy case, given the estimated parameters (Boivin and Giannoni, 2008, similarly find that global forces have not significantly changed the transmission of U.S. monetary policy shocks). This finding reinforces the argument that the effectiveness of national monetary policies has not been compromised by globalization. The response of inflation to a domestic demand shock is somewhat attenuated in the open economy scenario compared with the closed economy case. The differences, however, are again small.

4.4. **Does Taking Global Output Into Account Improve Forecasting?** Is information about global output developments helpful in forecasting future domestic inflation and output values? The last rows of table 2 show the forecasting performance, expressed by the Mean Absolute Error (MAE) in the 1985-2007 sample, of economic agents that learn using the different PLMs of the economy.

Agents obtain the best forecasting performance for inflation using a PLM in which they are assumed to have knowledge about the intercept, and to disregard information about global output (the specifications estimated in column (2) to (5) lead to lower MAEs). Global output, therefore, doesn't seem particularly helpful in improving inflation forecasting outcomes. As regards output forecasting, instead, the PLM that includes global output as a regressor, but starting from initial beliefs about its effects that equal zero in 1985, outperforms the other learning rules (MAE = 0.500). Models without global output do somewhat worse, and models in which global output enters the PLM with initial beliefs about its effect estimated from pre-sample data have the worst forecasting record. The conclusions from the forecasting exercise match those obtained from the in-sample model comparison: there is some evidence of a role of global output in affecting domestic output, but no clear role of global output on inflation.

5. Conclusions

Various research papers, policy speeches, and press articles have suggested that the increased global integration of national economies may have led to radical changes in the behavior of inflation, even in large economies as the U.S.

This paper has estimated a two-country general equilibrium model with focus on the U.S. to identify the impact of global output on domestic inflation. The results do not provide supportive evidence for abandoning the conventional closed-economy Phillips curve in favor of one in which global output replaces domestic output as the main variable driving U.S. inflation. When expectations are modeled within a general equilibrium setting and the inertia of inflation is fully captured, there doesn't appear to remain a role left for measures of global output as a significant regressor in the U.S. Phillips curve. There is also no evidence that global output has had an important influence through the formation of agents' expectations. Global output can still affect inflation, though, as it is found to have a positive spillover effect on domestic output. But the overall effect is not large. Thus, the empirical results imply that, so far, globalization is unlikely to have substantially altered the conduct and the effectiveness of domestic monetary policy.

There are other possible effects of globalization, however, that have been ignored in the current paper. Globalization may have more radically affected the structure of the models that we use. As one example, the Calvo parameter in the model, which influences the frequency of price changes is typically regarded as exogenous; but it may be argued that it is actually endogenous and that it may vary with the extent of openness to trade. Extending the model to capture all possible channels through which globalization can affect the U.S. economy remains an important direction for future research.

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		Prior Distribution			
Description	Parameter	Distr.	Support	Prior Mean	95% Prior Prob. Interval
Discount Factor	β	-	-	0.99	-
Sensit. Infl. to Dom. Output	κ^H	Γ	$\mathbb{R}^+$	0.1	[0.007,0.30]
Sensit. Infl. to Global Output	κ^F	N	$\mathbb{R}$	0	[-0.29,-0.29]
Sensit. Output to Global Output	ϑ	N	$\mathbb{R}$	0	[-0.98,0.98]
Sensit. Output to Int. Rate	$\tilde{\sigma}$	Γ	$\mathbb{R}^+$	1	[0.099,2.91]
MP Inertia	ρ	B	[0,1]	0.8	[0.57-0.95]
MP Inflation feedback	χ_π	N	$\mathbb{R}$	1.5	[1.01-1.99]
MP Output Gap feedback	χ_y	N	$\mathbb{R}$	0.25	[0.01-0.49]
AR coeff. u_t	ρ_u	B	[0,1]	0.5	[0.11-0.89]
AR coeff. η_t	ρ_η	B	[0,1]	0.5	[0.11-0.89]
AR coeff. ν_t	ρ_ν	B	[0,1]	0.5	[0.11-0.89]
Std. Cost-Push Shock	σ_u	Γ^{-1}	$\mathbb{R}^+$	0.5	[0.1,1.94]
Std. Demand Shock	σ_η	Γ^{-1}	$\mathbb{R}^+$	0.5	[0.1,1.94]
Std. MP Shock	σ_ε	Γ^{-1}	$\mathbb{R}^+$	0.5	[0.1,1.94]
Std. Global Output Shock	σ_ν	Γ^{-1}	$\mathbb{R}^+$	0.5	[0.1,1.94]
Effect of US Output on Y_t^*	δ_y	N	$\mathbb{R}$	0	[-0.98,0.98]
Effect of US Real Rate on Y_t^*	δ_r	Γ	$\mathbb{R}^+$	0.25	[0.03,0.7]
AR coeff. y_t^*	ρ^*	B	[0,1]	0.7	[0.47,0.89]
Constant Gain	$\bar{\mathbf{g}}$	U	[0,0.2]	0.1	[0.005,0.195]

Table 1 - Prior Distributions.

Note: Γ= Gamma, N= Normal, B= Beta, Γ^{-1}= Inverse Gamma, U= Uniform,

		Posterior Means and 95% HPD Intervals						
		(1a)	(1b)	(1c)	(2)	(3)	(4)	(5)
Description	Param.	Baseline Model	Learning about s.s.	$b_0^{\cdot,y^*}=0$	No y^* in PLM	Closed Economy	$\kappa^F=0$	$\vartheta=0$
Sensit. π_t to y_t	κ^H	0.015 [0.001,0.043]	0.015 [0.001,0.041]	0.015 [0.001,0.045]	0.017 [0.0001,0.046]	0.015 [0.001,0.042]	0.015 [0.001,0.042]	0.017 [0.002,0.05]
Sensit. π_t to y_t^*	κ^F	**-0.015** [−0.08,0.05]	**-0.019** [−0.09,0.05]	**-0.012** [−0.08,0.06]	**-0.023** [−0.09,0.04]	**0**	**0**	**-0.024** −0.09,0.04
Sensit. y_t to y_t^*	ϑ	**0.558** [0.29,0.82]	**0.558** [0.30,0.81]	**0.349** [0.07,0.63]	**0.322** [0.03,0.62]	**0**	**0.321** 0.03,0.62	**0**
Sensit. y_t to r_t	$\tilde{\sigma}$	0.096 [0.01,0.29]	0.098 [0.01,0.3]	0.108 [0.1,0.30]	0.121 [0.1,0.33]	0.109 [0.01,0.31]	0.123 [0.01,0.33]	0.11 [0.01,0.31]
MP Inertia	ρ	0.91 [0.86,0.95]	0.909 [0.86,0.95]	0.91 [0.86,0.96]	0.909 [0.86,0.95]	0.91 [0.86,0.95]	0.91 [0.86,0.95]	0.91 [0.86,0.96]
MP π_t-feedback	χ_π	1.421 [0.95,1.87]	1.419 [0.96,1.87]	1.418 [0.97,1.89]	1.418 [0.96,1.92]	1.425 [0.95,1.90]	1.425 [0.97,1.88]	1.429 [0.96,1.91]
MP y_t-feedback	χ_y	0.39 [0.19,0.58]	0.397 [0.21,0.58]	0.388 [0.19,0.58]	0.389 [0.20,0.57]	0.388 [0.19,0.57]	0.391 [0.19,0.58]	0.391 [0.19,0.58]
AR coeff. u_t	ρ_u	0.076 [0.01,0.17]	0.077 [0.01,0.18]	0.078 [0.01,0.18]	0.08 [0.01,0.18]	0.081 [0.01,0.19]	0.083 [0.02,0.19]	0.081 [0.02,0.19]
AR coeff. η_t	ρ_η	0.345 [0.15,0.59]	0.353 [0.16,0.57]	0.378 [0.14,0.63]	0.333 [0.13,0.58]	0.324 [0.13,0.57]	0.338 [0.14,0.61]	0.335 [0.13,0.58]
AR coeff. ν_t^*	ρ_ν	0.521 [0.302,0.738]	0.525 [0.29,0.73]	0.518 [0.30,0.73]	0.523 [0.31,0.73]	0.521 [0.29,0.73]	0.516 [0.27,0.74]	0.517 [0.28,0.73]
Std. u_t Shock	σ_u	0.224 [0.19,0.26]	0.225 [0.19,0.26]	0.225 [0.19,0.26]	0.22 [0.19,0.26]	0.219 [0.19,0.26]	0.22 [0.19,0.26]	0.22 [0.19,0.26]
Std. η_t Shock	σ_η	0.476 [0.41,0.56]	0.476 [0.41,0.56]	0.462 [0.4,0.54]	0.463 [0.4,0.54]	0.474 [0.41,0.56]	0.463 [0.40,0.54]	0.474 [0.41,0.55]
Std. ε_t Shock	σ_ε	0.112 [0.1,0.13]	0.111 [0.1,0.13]	0.111 [0.1,0.13]	0.111 [0.1,0.13]	0.111 [0.1,0.13]	0.111 [0.1,0.13]	0.111 [0.1,0.13]
Std. y_t^* Shock	σ_{y^*}	0.303 [0.26,0.35]	0.304 [0.26,0.35]	0.303 [0.26,0.35]	0.303 [0.26,0.35]	0.303 [0.26,0.35]	0.303 [0.26,0.35]	0.303 [0.26,0.35]
Effect of y_t on y_t^*	δ_y	0.207 [0.07,0.34]	0.205 [0.07,0.34]	0.213 [0.09,0.34]	0.214 [0.08,0.35]	0.211 [0.08,0.34]	0.211 [0.08,0.34]	0.212 [0.08,0.36]
Effect of r_t on y_t^*	δ_r	0.077 [0.01,0.21]	0.074 [0.01,0.19]	0.077 [0.01,0.20]	0.076 [0.01,0.20]	0.077 [0.01,0.20]	0.076 [0.01,0.20]	0.075 [0.01,0.21]
AR coeff. y_t^*	ρ^*	0.65 [0.48,0.80]	0.649 [0.48,0.80]	0.645 [0.48,0.79]	0.639 [0.46,0.79]	0.644 [0.47,0.80]	0.65 [0.48,0.80]	0.646 [0.47,0.80]
Constant Gain	$\overline{\mathbf{g}}$	0.011 [0.0006,0.031]	0.006 [0.0002,0.017]	0.019 [0.001,0.05]	0.035 [0.005,0.063]	0.038 [0.01,0.064]	0.036 [0.006,0.063]	0.037 [0.008,0.063]
Model Comparison								
Posterior Odds		**1**	**0.364**	**41.6**	**345.5**	**393.07**	**2,599.31**	**115.93**
Forecasting								
MAE for π_t in agents' PLM		0.1828	0.1835	0.1827	0.1821	0.1822	0.1821	0.1822
MAE for y_t in agents' PLM		0.512	0.517	0.500	0.5069	0.5074	0.5069	0.5072

Table 2 - Empirical Results: Posterior Estimates. The main entries denote posterior mean estimates, while the numbers below in brackets denote 95% Highest Posterior Density (HPD) intervals.

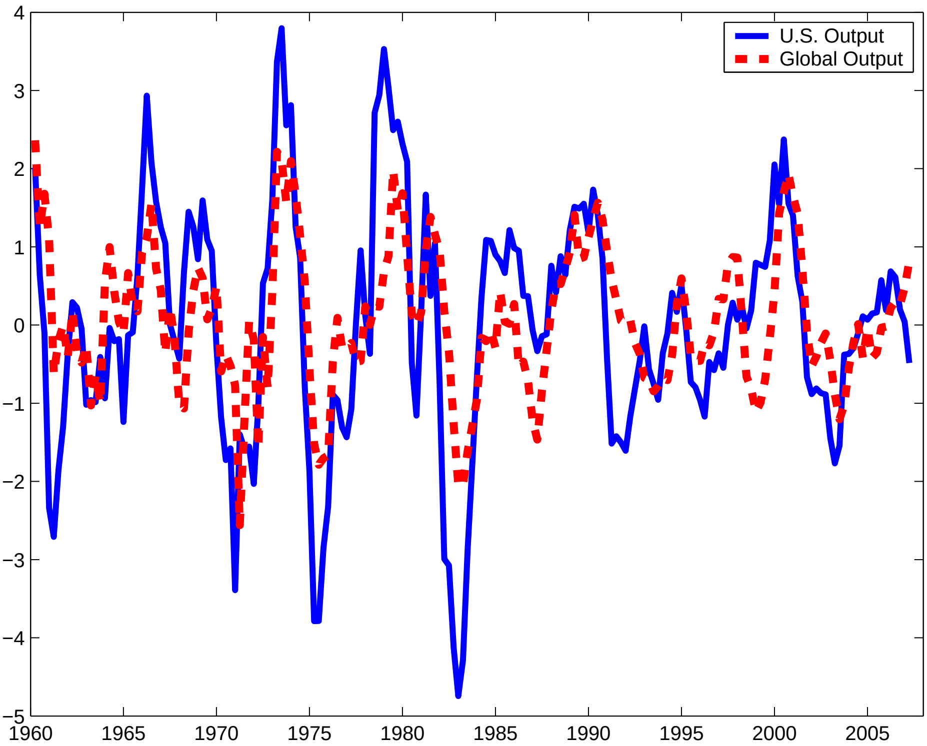

FIGURE 1. U.S. and "Global" Output series.

Note: Data from 1985:q1 to 2007:q1 are used in the estimation of the structural model. Data from 1960:q1 to 1984:q4 are used to calculate initial values for the agents' beliefs at the beginning of the estimation sample.

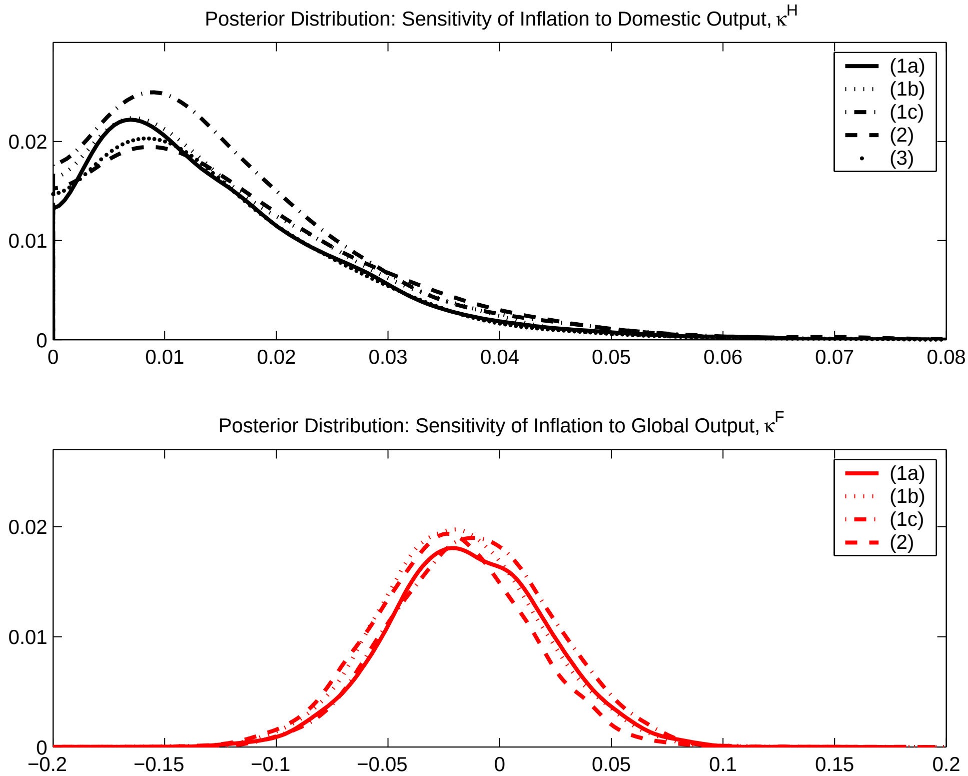

FIGURE 2. Posterior Distibutions for the sensitivity of inflation to domestic output and to global output coefficients κ^H and κ^F, across different model and learning specifications.

Note: (1a), (1b), (1c), (2), and (3) in the graph refer to the corresponding specifications whose estimates are reported in Table 2.

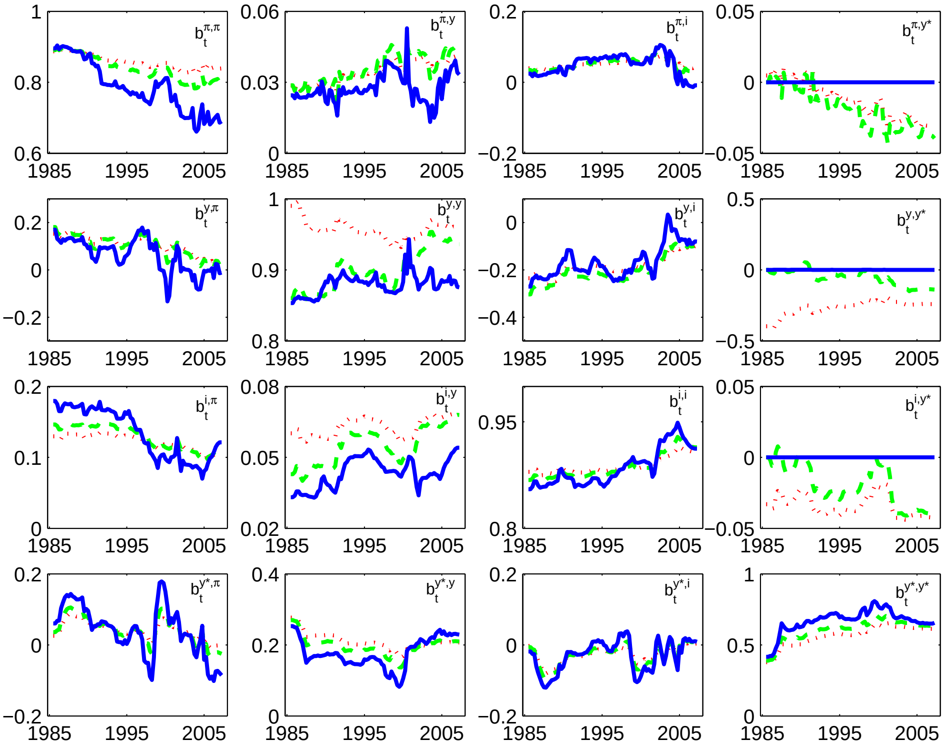

FIGURE 3. Evolution of economic agents' beliefs over the sample, across different estimated PLM specifications.

Note: the dotted red line refers to the model with global output in the PLM with initial beliefs about its effect estimated from pre-sample data (case (1a) in the table), the dashed green line refers to the model with global output in the PLM with initial beliefs about its effect fixed at zero (case (1c) in the table), and the blue line refers to the model in which global output is omitted from the PLM of the domestic variables (case (2) in the table).

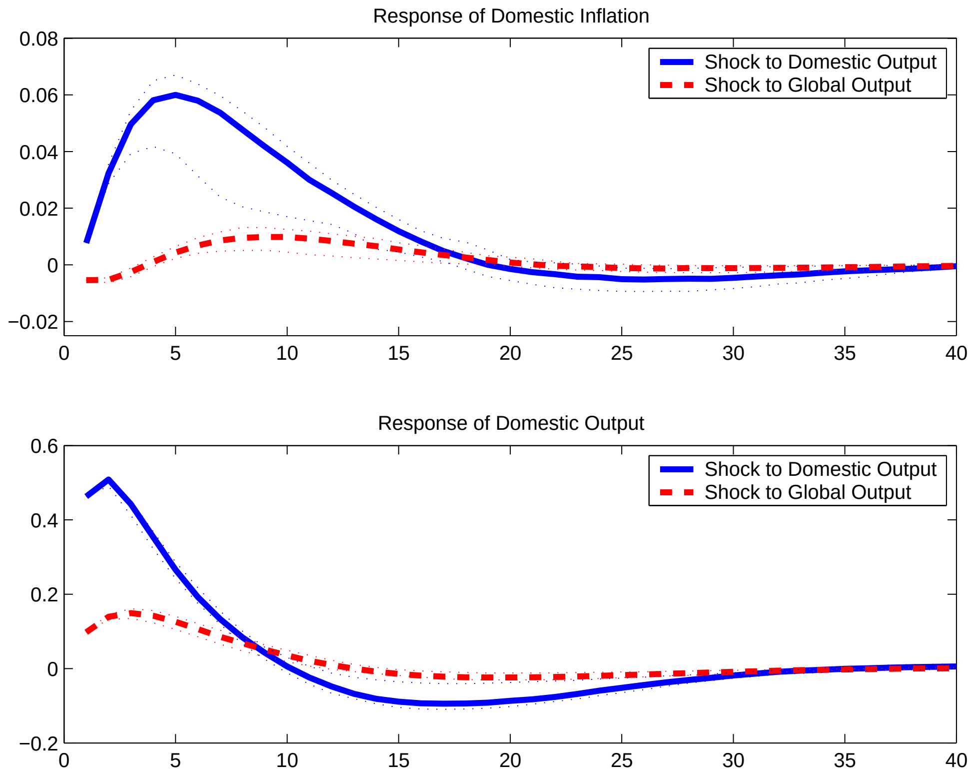

FIGURE 4. Impulse response functions of domestic inflation and output to one standard deviation shocks to global output and to domestic output.

Note: The figure shows the median impulse responses across the sample (denoted by the solid blue line for the response to the domestic shock, and by the dashed red line for the response to the global shock), along with 16% and 84% percentile error bands (dotted lines).

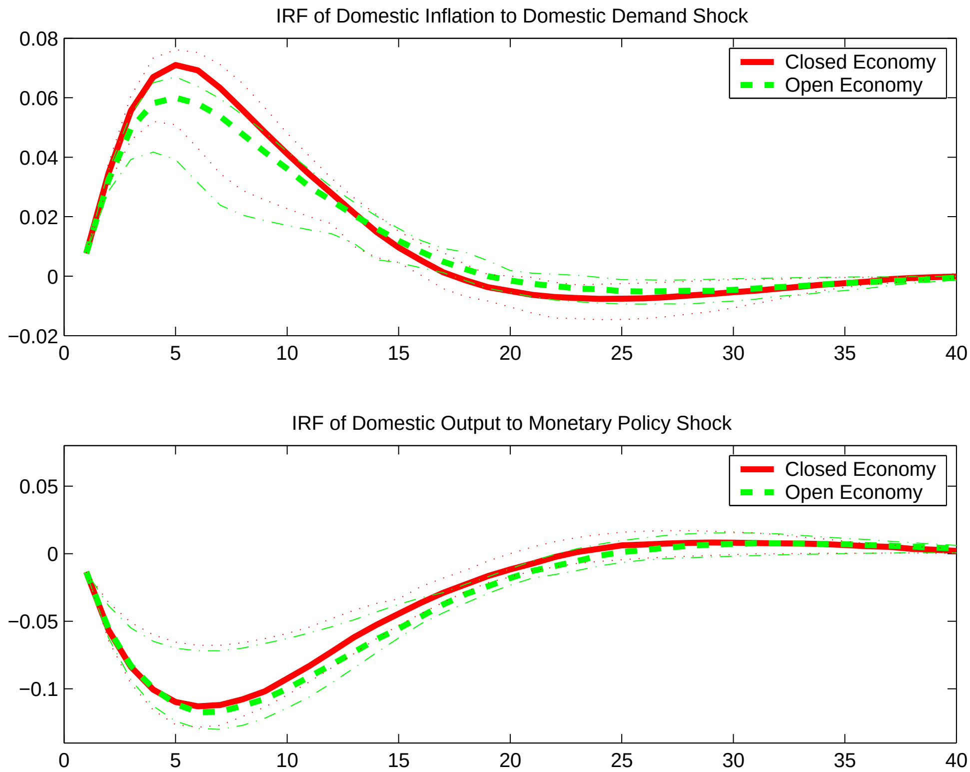

FIGURE 5. Impulse response functions of domestic variables to domestic shocks in closed versus open economy scenario.

Note: The figure shows the median impulse responses across the sample (the dashed green line indicates the median responses of domestic variables in the open economy case, while the solid red line indicates the median responses of domestic variables if the same economy was closed); dotted and dash-dotted lines denote the respective 16% and 84% percentile error bands.