What helps forecast U.S. Inflation?- Mind the Gap!*

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Abstract

In macroeconomic analysis and inflation forecasting, the traditional Phillips curve has been widely-used to exploit the empirical relationship between inflation and domestic economic activity. Atkeson and Ohanian (2001), among others, cast doubt on the performance of Phillips curve-based forecasts of U.S. inflation relative to naïve forecasts. This indicates a difficulty for policy-making and private sector's long-term nominal commitments which depend on inflation expectations. The literature suggests globalization may be one reason for this phenomenon. To test this, we evaluate the forecasting ability of global slack measures under an open economy Phillips curve. The results are very sensitive to measures of inflation, forecast horizons and estimation samples. We find however, terms of trade gap, measured as HP-filtered terms of trade, is a good and robust variable to forecast U.S. inflation. Moreover, our forecasts based on the simulated data from a workhorse new open economy macro (NOEM) model indicate that better monetary policy and good luck (i.e. a remarkably benign sample of economic shocks) can account for the empirical observations on forecasting accuracy, while globalization plays a secondary role.

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1 Introduction

Forecasting inflation –accurately and reliably- plays a critical role for policy-making and for the decisions of the private sector in making long-term nominal commitments. In macroeconomic analysis and inflation forecasting, the traditional Phillips curve has been a widely used model that captures broadly the empirical relationship between inflation and unemployment rate, capacity utilization or output gap.

As documented by Atkeson and Ohanian (2001), the Phillips curve has flattened since 1984. Their finding was that the Phillips curve-based models did not yield more accurate forecasts than the naïve, 4 quarter random walk benchmark. Stock and Watson (2007) emphasized the role of lower volatility in inflation in the U.S. and in the world in this period. Hence the risk of naive forecasts, computed as the mean square forecast error, declined. Forecasts under a Phillips curve specification have become less accurate. A survey by Stock and Watson (2008) suggest recent forecasts based on univariate specifications including the Phillips curve performed well only occasionally.

A prominent explanation to the break in the Phillips curve suggested in the literature is globalization - the integration of global markets in goods, labor and capital. The recent literature postulated the 'global slack hypothesis', i.e. foreign slack as well as domestic slack drives inflation in the short-run. Hence, a more relevant specification, the open economy Phillips curve that ties inflation to global measures of economic activity has become a focus of investigation. However, the evidence on the role of global slack is mixed. Binyamini and Razin (2007) and Martinez-Garcia and Wynne (2010) made theoretical explanations and Borio and Filardo (2007) provided empirical evidence for the global slack hypothesis. On the other hand, Milani (2010, 2012) among others, argue that the foreign economic activity has a role on domestic supply and demand, but its effect on domestic inflation is negligible, finding weak evidence for the global slack hypothesis.

Even when the theoretical validity of an open economy Phillips curve is assured, forecasting inflation under the open economy framework is a challenging task. It is in general difficult to find sufficiently long, reliable and robust time series of global slack -global output gap or capacity utilization. This has been documented in the current paper as well as in previous studies. Therefore, it gains particular importance to evaluate forecast accuracy with various global slack measures and to compare their performances to those from alternative measures.

In this paper, we test whether global slack measures have predictive power for U.S. inflation. These measures are constructed by mostly theoretically-consistent output gap or capacity utilization series of the U.S. and several different groups of countries combined. In addition, following a recent theoretical finding in Martinez-Garcia and Wynne (2010), we test the performance of a global slack measure defined as a combination of two variables: domestic slack and terms of trade gap. The measure of terms of trade gap is HP-filtered terms of trade, while the domestic slack series are the U.S. measures of output gap, capacity utilization and HP-filtered GDP.

Our first finding is that, perhaps in agreement with the existing literature, these global slack variables yield mixed results in predicting different inflation measures. However, a striking result in this paper is that the terms of trade gap, alone, is a good forecasting variable for U.S. inflation. It yields more accurate forecasts relative to the naive autoregressive process of inflation and it is also robust to various forecast horizons, inflation measures and estimation samples, including the late 1980s –the period of break in the Phillips curve pointed out by Atkeson and Ohanian (2001). On the other hand, we document that most global slack measures yield relatively more accurate forecasts for core inflation while the forecast with terms of trade gap and domestic slack perform well at short horizons for headline inflation measures. Overall, the forecasting performances are not very robust to forecast horizons and estimation samples.

We conduct pseudo out-of-sample forecasts for six measures of U.S. inflation at horizons varying between 1-quarter to 12-quarter ahead. Our benchmark estimation and sample periods are 1980:1-1991:4 and 1992:1-2011:4, respectively. For robustness analyses we go back as far as to 1949:1 and perform rolling forecasts, to the extent that data series are available. Our metric for forecast accuracy is the mean square forecast error (MSFE) of a reduced form new open economy Phillips curve with distributed lags of inflation and slack, relative to the MSFE of the 'restricted' forecast described as a univariate, autoregressive process of inflation. We compute bootstrap standard errors for the MSFEs following Clark and McCracken (2006).

Another major contribution of this paper is our extensive robustness analyses where we compare the performance of a selected measures of slack to a set of widely used variables in the forecasting literature. We test the predictive performances of a domestic slack series (CBO U.S. slack), a global slack series (OECD Total slack), a measure of domestic liquidity growth (U.S. M2 growth) and global liquidity growth (G7 average of monetary aggregates) and two variables of terms of trade gap (HP-filtered U.S. terms of trade, and HP-filtered U.S. terms of trade ex. oil). We report the following stylized facts:

- Forecasts with the domestic slack perform significantly better than the simple AR process of inflation until late 1960s and particularly at short horizons. The global slack measure outperforms the simple AR process significantly only in late 1980s and at short horizons.
- In episodes where domestic liquidity growth performs well in forecasting U.S. inflation, global liquidity growth does not; and vice versa. This result is in general robust to several inflation measures and horizons for the rolling forecasts starting in 1963 through early 1980s. After that period, the relative MSFEs of the forecasts are insignificant for both variables.
- Forecasts with HP-filtered terms of trade perform significantly better relative to the naïve forecast with the estimation samples starting in 1950s till late 1980s (with the exception in 1980-1983, where the performance deteriorates). At some occasions where terms of trade performs relatively weak, terms of trade ex. oil does significantly better.

Therefore, we show that many conventional alternatives do not improve upon the naïve forecast especially in recent years, while HP-filtered terms of trade stands out as a relatively successful variable.

In the remainder of the paper, we try to understand these patterns in the light of a workhorse New Open Economy Macroeconomics (NOEM) model. Our strategy is to use a model that can capture the effects of two other competing (or complementary) hypotheses in addition to globalization –good luck and good monetary policy - that are commonly discussed in the literature as plausible explanations for the observed strengths and weaknesses in the forecasting performances. To this end, we simulate data based on the model and use the data to conduct forecasts similar to those in the empirical section. We estimate MSFEs for many plausible parameter values that capture changes in trade openness, volatility in TFP or monetary shocks (which we call 'good luck') and effectiveness of monetary policy reflected in Taylor rule parameters.

For most of these patterns of forecast accuracy, we find that globalization seems to be a relatively weak channel, while anti-inflationary monetary policy and good luck seem to be the plausible reasons.

2 Methodology

2.1 Data

Figure 1 plots the series employed throughout the paper. The U.S. inflation rate is calculated as annualized log-differences of quarterly series of six price indices: consumer price index (CPI), core CPI (CPI ex. food and energy), personal consumption expenditure deflator (PCE), trimmed-mean PCE, GDP deflator and producer price index (PPI).

We perform inflation forecasts using a wide range of domestic and global slack measures. Our domestic measures consist of CBO U.S. slack, FRBD U.S. slack, OECD U.S. slack, IMF U.S. slack and HP-filtered U.S. real GDP. For global slack measures, we use FRBD G7, FRBD G39, OECD G7, OECD Total and IMF Advanced series. All series are available quarterly, except for the IMF measures of domestic and global slack, which is available in annual frequency. We therefore disaggregate these series into quarterly frequency using quadratic match average.

Terms of trade series is calculated as the ratio of U.S. export price index of goods and services and U.S. import price of goods and services. For terms of trade ex. oil, however, we use the price indices for exported goods and nonpetroleum imported goods due to limited data availability. We HP filter these two series in order to obtain a measure of the terms of trade gap.

We define global money growth as the average of the percentage growth rates of broad money stock in G7 countries. While we pick the series for monetary aggregates that are most similar in definition, we are constrained by quarterly data availability for Canada, France, Germany, Italy and Japan particularly for late 1960s or early 1970s. Since we would like to extend the robustness analysis of forecasting experiments to a large estimation sample, we make our primary decision on selection based on data availability. Therefore our series start in the second quarter of 1963 and we use M2 for U.S., M4 for UK. We splice two short series of M3 for Canada, M2 for Germany, Italy and Japan. For France, we also use a spliced series, which combines M2R up to the first quarter of 1970 and M3 afterwards. (A more detailed explanation is available in the appendix.)

2.2 Models

We specify three models to forecast inflation. Following Stock and Watson (2003), we refer the models with explanatory variables as economic models and we assess to what extent these economic models represent an improvement over the univariate model of forecasting inflation. The first model is a univariate model where we test the predictive power of various regressors. Stock and Watson (1999a, b, 2008) provide some empirical evidence in favor of the Phillips curve as a forecasting tool, suggesting that inflation forecasts produced by the Phillips curve generally are more accurate than forecasts based on other macroeconomic variables (including interest rates, money and commodity prices). Consider first the traditional backward-looking Phillips curve relating inflation to aggregate real economic activity as typically specified by the previous literature

$$\hat{\pi}^h_{t+h|t} = a_1 + \lambda_{11}(L)\hat{\pi}_t + \lambda_{12}(L)\hat{x}_t + \hat{\epsilon}_{1,t+h} \quad \text{(Model 1)}$$

Denoting the quarterly forecast horizon by h, it is possible to forecast h-quarter ahead inflation, $\hat{\pi}^h_{t+h|t}$

with the distributed lag of earlier inflation rates, $\hat{\pi}_t$ as a proxy for expected inflation, and the distributed lag of the domestic slack measure, $\hat{x}_t$. We start with assessing the predictive performance of domestic slack in order to compare our results with those of the earlier studies using this specification in the literature. We define h-quarter ahead (annualized) inflation $\hat{\pi}^h_{t+h|t} = \frac{400}{h} \times [log(P_{t+h}/P_t)]$ and forecast inflation for horizons ranging from 1 quarter-ahead to 12-quarters ahead. The number of lags for each variable is selected based on SIC. To keep the model parsimonious and since the frequency of the variables is defined as quarterly, the maximum possible lags allowed for each variable is set as four.

As the global financial integration substantially increased in the past 30 years, its consequences on inflation, and the consequences of foreign economic activity in particular, has become a focus of attention in inflation forecasting. Martinez-Garcia and Wynne (2010, 2012), among others argued that the Phillips curve on economies open to trade depends on global economic activity and leading or contemporaneous predictors of domestic inflation should include not just domestic but foreign economic activity. We therefore include global measures of slack—as well as domestic slack—among our representative series. Hence, we test the predictive performance of global slack measures in an open economy Phillips curve, similar to the one specified above, where $\hat{x}_t$ is now defined as global slack.

We further evaluate the performance of other variables such as domestic and global liquidity growth[1] and terms of trade gap measures under the same framework. While the long-run relationship between the growth rate of monetary aggregates and the rate of inflation is established by the quantity theory of money and therefore testing the forecasting performance of liquidity growth has analytical content, we test the performance of terms of trade gap measures in light of the theoretical results in Martinez-Garcia and Wynne (2010a). We perform these forecasting exercises here to readdress the role of these measures in order to provide with a comparison with our main forecasting strategy and also to make an extensive robustness analysis of the earlier work.[2]

The issue of how to measure the output gap—both domestic and foreign—has been known as a major challenge. For purely statistical approaches, which in most cases derive potential output using actual (real) output series through a filtering technique (most commonly the HP filter), the choice of the filter is usually an arbitrary decision. In addition, applying these techniques are known to create end-point problems. For structural estimates of the output gap, relying on a production function (such as Cobb-Douglas) and quantifying the total factor productivity, the capital stock or labor employed tend to pose measurement problems (Gerlach, 2011).

Measuring the foreign output gap, however is an even more challenging task since for the emerging market economies that are believed to potentially affect the U.S. inflation, the data series to measure unemployment rates or capacity utilization in manufacturing are usually either too short or they are not available. Furthermore, there is also not a clear idea on how the dynamics of foreign output gap affects the domestic inflation. Therefore, estimating the open-economy Phillips curve based on the combination of domestic and foreign slack as a measure of the global slack becomes a difficulty.

To circumvent the problem of measuring the foreign slack, we follow the theoretical approach taken

[1] D'Agostino and Surico (2009a) evaluate the forecasting performance of the average growth rate of broad money in G7 economies and find that the results are significantly more accurate compared to forecasts with US money growth.

[2] Stock and Watson (1999?) forecast U.S. inflation with a large set of variables, including economic indicators other than the variables of real economic activity. These include U.S. effective exchange rate and a number of foreign exchange rates. They report that exchange rates do not yield better inflation forecasting performance than a Phillips curve specification.

in a previous work by Martinez-Garcia and Wynne (2010) and define global slack in reduced form as a combination of domestic slack and terms of trade gap. To estimate this new formulation of the open-economy Phillips-curve, we follow the literature, and take a backward-looking approach for the reduced-form estimate of the curve. The regression equation in this case can be described as an autoregressive distributed lag model which is our first model to forecast inflation:

$$\hat{\pi}^{h}_{t+h|t} = a_2 + \lambda_{21}(L)\hat{\pi}_t + \lambda_{22}(L)\hat{x}_t + \lambda_{23}(L)\hat{z}_t + \hat{\epsilon}_{2,t+h} \qquad \text{(Model 2)}$$

Under this specification, $\hat{x}_t$ denotes one of the domestic output gap measures and $\hat{z}_t$ denotes one of the terms of trade gap measures (all variables in levels).

Having suggested two different 'unrestricted' reduced-form models, we finally introduce the 'restricted' model. Under this specification, we estimate a univariate autoregressive (AR) process:

$$\hat{\pi}^{h}_{t+h|t} = a_3 + \lambda_3(L)\hat{\pi}_t + \hat{\epsilon}_{3,t+h} \qquad \text{(Model 3)}$$

2.3 Forecast scheme

We perform forecasts based on the pseudo out-of-sample forecasting method and particularly focus on recursive samples. Therefore, at any given date t, we forecast inflation at date $t+h$ using all available data up to date t. The models are estimated by OLS.

We assess the multi-step pseudo out-of-sample forecasting performance of a model that incorporates the variables commonly thought as contemporaneous or leading indicators of inflation relative to the forecast of a univariate autoregressive process. Our forecast evaluation metric, the relative MSFE, is the ratio of MSFE of the economic model (Model 1 or Model 2) relative to that of the benchmark AR model (Model 3). Let T_0 denote the starting date of the data series and T_1 denote the end. The estimation sample starts at T_0 and ends in t_0. We start by using all data up to date t_0 to forecast inflation at date t_0+h. By adding data to the estimation sample, we keep estimating the parameters of the model of interest. The $h-$step recursive forecast continues until period T_1-h with a total of T_1-h-t_0+1 steps. For a given model j, this procedure yields a sequence of forecast errors which helps us construct the MSFE of the model at horizon h and from date t_0 to T_1-h

$$MSFE_j(h) = \frac{1}{T_1-h-t_0+1}\sum_{t=t_0}^{T_1-h}\hat{\hat{\epsilon}}^2_{j,t+h}$$

2.4 Inference and samples

Inference is based on the F-statistics against critical values based on a bootstrap algorithm described in Clark and McCracken (2006)[3].This procedure involves resampling from the residuals of a vector autoregressive (VAR) equations. In order to test the predictive ability of a single variable forecast as in Model 1, we define an equation for inflation (as governed by the restricted model) and an equation for the predicting variable, where the lag length for the predicting variable and inflation is determined based on SIC. The

[3]The construction of F-statistics as well as t-statistics are described in Clark and McCracken (2001, 2002a, b). Inference can also be based on t-statistics, however, as Clark and McCracken (2001, 2002a, b) suggest, F-type tests are more powerful than the corresponding t-type tests and therefore we focus on F-statistics only.

equations of the data generation process (DGP) are estimated by OLS with a number of bootstrap iterations equal to 5000. For a bivariate forecast involving an additional predicting variable as in Model 2, we suggest a similar methodology. In this case, the DGP involves the estimation of a 3-equation VAR. The first equation is the AR process of inflation, as defined in the bootstrap algorithm of the univariate forecast. The remaining two equations are the equations for the predicting variables where we include the lagged values of all three variables (inflation and two predicting variables) as regressors in each equation. Again, the lag length selection is based on SIC. We have a one-sided test with the null hypothesis that an economic model (Model 1 or 2) does not yield more accurate forecasts than the AR process (Model 3), i.e. $MSFE_{AR} \leq MSFE_{EM}$, against the alternative $MSFE_{AR} > MSFE_{EM}$. Throughout the paper, we report the MSFE of the benchmark model and the relative MSFEs of a particular economic model and the benchmark. The null hypothesis is expressed as 'the relative MSFE is greater than or equal to 1'. We report the p-values of the F-test at 1%, 5% and 10% significance levels.

In our benchmark experiments, the estimation sample begins in the 1980:Q1 and ends in 1991:Q4 and the pseudo out-of-sample forecasting period begins in 1992:Q1 and 2011:Q4 leaving us with an estimation sample of 48 quarters and the pseudo out-of-sample forecasting sample of 80 quarters)[4].

In addition to our benchmark forecasting experiment, we conduct a series of other experiments going back in time to the extent that the series are available in order to make a robustness analysis. More specifically, starting with the initial observation in the sample, we shift the estimation and forecast samples backward by one quarter and obtain the relative MSFEs of the forecasts for each 'rolling window'[5]. Each window spans 48 quarters of an estimation sample and 48 quarters of a forecasting sample.

Finally, in order to gain insight about our findings and our potential explanations for them, we also run forecasts with the simulated data consistent with the model in Martinez-Garcia and Wynne (2010a). Under various parameterizations of the model, we try to understand how factors such as trade openness, the stance of monetary policy towards inflation and the size of the monetary and productivity shocks to the economy affect the predictive ability of these variables. The forecast scheme for this group of experiments is also recursive[6]. We discuss the details of these experiments in section 4.

3 Empirical Findings

The results of the pseudo out-of-sample forecast with one variable over the benchmark sample are reported in Tables 2 and 3; while the results with two variables are summarized in Tables 4 and 5. Our findings can be listed as follows:

1. Based on the one-variable forecast results, it is not possible to say that global slack measures outperform the domestic slack measures. In general, both measures almost equally yield more accurate predictions compared to an AR process when the inflation measure is core CPI and trimmed mean PCE. For other measures of inflation however, we conclude that the AR process of inflation performs better.

[4] Our selection of the size of the estimation and pseudo out-of-sample forecasting samples in the benchmark experiments follow that of D'Agostino and Surico (2009) which enables us a comparison of the measures used to forecast inflation with their measures of money. In our robustness analyses we make a symmetric allocation of the observations for the two samples.

[5] The starting dates are provided in more detail in the appendix.

[6] The bootstrap procedure for the F-test in these experiments involves 500 iterations.

2. Global money growth (measured as G7 average) exhibits a better forecasting performance relative to U.S. money growth, at all horizons for CPI, core CPI and PCE deflator. Both variables have a significantly poor performance compared to the AR process in all other inflation measures. Under the forecasts of CPI and PCE inflation, G7 money growth does also better compared to domestic or global slack measures. However, this is not true for the other measures of inflation.

3. Forecasting performance of terms of trade (HP-filtered) is comparable to those of domestic and global slack measures. Terms of trade ex. oil has no significant improvement over the AR specification across any of the inflation measures and at any horizon.

4. Our results of the two-variable forecasts are rather mixed. Forecasts with domestic slack and terms of trade provide higher accuracy at short horizons for CPI and PCE compared to the forecasts with domestic or global slack alone. For GDP deflator and core CPI, one-variable forecasts do better. When domestic slack and terms of trade ex. oil are evaluated, it can be concluded that the two variables combined improve forecasting performance for GDP deflator especially at short horizons and for PPI at long horizons. Results with two-variable forecasts using domestic or global money growth measures in addition to terms of trade or terms of trade ex. oil, do not improve the predictions.

   We perform rolling window experiments for three groups of variables: a domestic slack measure vs. global slack measure; terms of trade vs. terms of trade ex. oil and finally domestic vs. global liquidity growth. Among several alternatives, we choose CBO measure as the domestic slack variable and 'OECD Total' as our global slack measure. Our selection of the two measures is based mainly on the length of the series and relatively better performance compared to other slack measures at hand. In Figures 2a-4b, we show how the forecasting performances of these pairs of variables evolve over time. In these figures, several interesting points emerge:

5. The predictive ability of money growth measures vary significantly over time (Figures 2a-b). In particular, we observe a pattern such that whenever domestic money growth has a poor performance, global money growth performs well and vice versa. During late 1970s, there is a remarkable deterioration in the forecasting power of global money growth, which is outperformed by domestic money growth especially in long-horizon forecasts. After this period, forecasting ability of global money growth recovers rapidly although its performance compared to the AR process is not necessarily superior. This is interesting, because our empirical results based on the benchmark sample are in line with those in D'Agostino and Surico (2009) where they analyze the 1990:1-2006:2 period and show that global money growth-based forecasts seem to be a strong forecasting variable relative to domestic money as well as the naive forecasts of inflation. However, these results do not seem to be robust to sample selection after 1980s as shown in Figures 2a-b.

6. For slack measures however, and with limited data availability, the patterns mentioned above can no longer be pronounced (Figures 3a-b). Our comparison of domestic and global slack measures show that the predictive power of the two measures move almost together through time, and with rare occasions they become significantly more powerful than the AR process in forecasting inflation. In forecasts starting from 1949 through 1970s (where global slack measures are not available) the CBO measure of U.S. slack has a significantly better performance than the AR specification, especially at short horizons.

7. Terms of trade and terms of trade ex. oil produce a similar (albeit slightly weaker) 'switching' pattern in terms of forecasting performance over time (Figures 4a-b). Except for core measures of inflation (core CPI and trimmed mean PCE, which are also relatively short series), terms of trade yields significantly more accurate forecasts starting in late 1950s through mid 1970s and its performance deteriorates in general during late 1970s. The MSFEs of the forecasts with terms of trade ex. oil follow a not so uniform pattern and shows a great variability in performance across horizons or inflation measures while outperforming terms of trade at certain intervals. Particularly for the 1980s however, terms of trade and terms of trade ex. oil appear to be doing better in forecasting inflation compared to monetary aggregates or output gap measures.

   In the next section, we aim to investigate the causes behind these puzzles. First, we would like to understand why domestic and global slack measures do not perform well and global money growth comes out as a superior measure to forecast U.S. inflation. Second, and related to the previous puzzle, we are not clear as to why domestic slack measures along with terms of trade (or terms of trade ex. oil) do not improve forecasting accuracy as much as expected. Third, in theory, we would expect the HP-filtered slack measures to perform not as great as the slack measures that are calculated with a production function approach.

4 Interpreting the results

In order to understand the empirical results more clearly, we simulate the model in Martinez-Garcia and Wynne (2010a) which is a variant of the New Open Economy Macro model of Clarida, Gali and Gertler (2002).We briefly mention the building blocks of this model.

4.1 The New Open Economy Macro Model

There are two countries, Home and Foreign. The current model consists of four basic structural equations for each country and two exogenous shocks. We denote Foreign variables with an asterisk (*). To denote the deviation in logs from its steady state, $\hat{v}_t \equiv \ln(V_t/V)$, for a variable V_t at its steady state V. Similarly, we denote the deviation of the potential (or frictionless) value of a variable from its steady state as $\hat{v}_t^n \equiv \ln(V_t^n/V)$.

Aggregate demand is described by an equation that links the output gap, $\hat{x}_t$ to domestic and foreign interest rates, $\hat{\imath}_t$ and $\hat{\imath}_t^*$, natural rates $\hat{\imath}_t^n$ and $\hat{\imath}_t^{n*}$, and inflation $\hat{\pi}_t$ and $\hat{\pi}_t^*$

$$\gamma(2\xi-1)(E_t\hat{x}_{t+1}-\hat{x}_t) \approx [((2\boldsymbol{\xi}-1)+\Gamma)[(\hat{\imath}_t-\hat{\imath}_t^n)-E_t\hat{\pi}_{t+1}]-\Gamma[(\hat{\imath}_t^*-\hat{\imath}_t^{n*})-E_t\hat{\pi}_{t+1}^*] \tag{1}$$

Aggregate supply is defined as a Phillips curve relating inflation gap to domestic and foreign output gaps

$$\hat{\pi}_t \approx \beta E_t\hat{\pi}_{t+1} + \Phi\left[(\varphi\xi+\Theta\gamma)\hat{x}_t + ((1-\xi)\varphi+(1-\Theta)\gamma)\hat{x}_t^*\right] \tag{2}$$

As shown in a previous work by Martinez-Garcia and Wynne (2010a), under the producer currency pricing (PCP) assumption, it is possible to express the dynamics of the domestic (cyclical) inflation, $\hat{\pi}_t$, in terms of the domestic output gap, $\hat{x}_t$ and the terms of trade gap, $\hat{z}_t$

$$\hat{\pi}_t = \beta E_t \hat{\pi}_{t+1} + \Phi[(\varphi + \gamma)\hat{x}_t + \Psi_{\pi,z}\hat{z}_t] \tag{3}$$

Monetary policy rule is expressed à la Taylor (1993)

$$\hat{\imath}_t \approx \rho_i \hat{\imath}_{t-1} + (1 - \rho_i)[\Psi_\pi \hat{\pi}_t + \Psi_x \hat{x}_t] + \hat{m}_{t.} \tag{4}$$

Domestic money growth is derived by first differencing the ad hoc log-linear *money demand* equation

$$\Delta \hat{l}_t \approx \Delta \hat{y}_t - \eta \Delta \hat{\imath}_t + \hat{\pi}_t. \tag{5}$$

We also define the natural interest rate as the weighted average of expected domestic and foreign productivity growth,

$$\hat{\imath}_t^n \approx \left(\frac{1+\varphi}{\gamma+\varphi}\right)\left[\Theta_{i,a} E_t[\Delta \hat{a}_{t+1}] + \Theta_{i,a^*} E_t[\Delta \hat{a}^*_{t+1}]\right] \tag{6}$$

the potential output as the weighted average of domestic and foreign productivity gap,

$$\hat{y}_t^n \approx \left(\frac{1+\varphi}{\gamma+\varphi}\right)[\tilde{\lambda}_a \hat{a}_t + \tilde{\lambda}_{a^*} \hat{a}^*_t] \tag{7}$$

output gap,

$$\hat{x}_t = \hat{y}_t - \hat{y}_t^n$$

and finally terms of trade and terms of trade gap,

$$\widehat{tot}_t \approx \frac{\gamma(\hat{y}_t - \hat{y}^*_t)}{\sigma\gamma - (\sigma\gamma - 1)(2\xi - 1)^2} \text{ and } \hat{z}_t \equiv \widehat{tot}_t - \widehat{tot}_t^n \tag{8}$$

respectively. For Foreign, the equations of the model can be described symmetrically.

Finally, the law of motion for productivity shocks and monetary shocks is governed by

$$\begin{pmatrix} \hat{a}_t \\ \hat{a}^*_t \end{pmatrix} \approx \begin{pmatrix} \delta_a & \delta_{a,a^*} \\ \delta_{a,a^*} & \delta_a \end{pmatrix} \begin{pmatrix} \hat{a}_{t-1} \\ \hat{a}^*_{t-1} \end{pmatrix} + \begin{pmatrix} \hat{\varepsilon}^a_t \\ \hat{\varepsilon}^{a*}_t \end{pmatrix} \tag{9}$$

$$\begin{pmatrix} \hat{\varepsilon}^a_t \\ \hat{\varepsilon}^{a*}_t \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_a^2 & \rho_{a,a^*} \\ \rho_{a,a^*} & \sigma_a^2 \end{pmatrix}\right) \tag{10}$$

$$\begin{pmatrix} \hat{m}_t \\ \hat{m}^*_t \end{pmatrix} \approx \begin{pmatrix} \delta_m & 0 \\ 0 & \delta_m \end{pmatrix} \begin{pmatrix} \hat{m}_{t-1} \\ \hat{m}^*_{t-1} \end{pmatrix} + \begin{pmatrix} \hat{\varepsilon}^m_t \\ \hat{\varepsilon}^{m*}_t \end{pmatrix} \tag{11}$$

$$\begin{pmatrix} \hat{\varepsilon}^m_t \\ \hat{\varepsilon}^{m*}_t \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_m^2 & \rho_{m,m^*} \\ \rho_{m,m^*} & \sigma_m^2 \end{pmatrix}\right) \tag{12}$$

where the composite parameters are given by

$$\Phi \equiv \frac{(1-\alpha)(1-\beta\alpha)}{\alpha}$$

$$\Psi_{\pi,z} \equiv -\sigma(1-\xi)(\varphi+\gamma) + (\sigma - \frac{1}{\gamma})(\xi-\xi^*)(\varphi(1-\xi)(\eta-\eta^*) - \gamma(1-\eta))$$

$$\Gamma \equiv (1-\xi)\left[\sigma\gamma + (\sigma\gamma-1)(2\xi-1)\right]$$
$$\Theta \equiv \xi\left[\tfrac{\sigma\gamma-(\sigma\gamma-1)(2\xi-1)}{\sigma\gamma-(\sigma\gamma-1)(2\xi-1)^2}\right]$$
$$\Theta_{i,a} \equiv \gamma\left[\left(\tfrac{\sigma\gamma-(\sigma-\frac{1}{\gamma})(\xi-\xi^*)(1-\tilde{\eta})}{\sigma-(\sigma-\frac{1}{\gamma})(\xi-\xi^*)(\tilde{\eta}-\tilde{\eta}^*)}\right)\tilde{\lambda}_a + \left(\tfrac{\sigma(1-\xi)-(\sigma-\frac{1}{\gamma})(\xi-\xi^*)(1-\tilde{\eta})}{\sigma-(\sigma-\frac{1}{\gamma})(\xi-\xi^*)(\tilde{\eta}-\tilde{\eta}^*)}\right)\tilde{\lambda}_a^*\right]$$

$$\Theta_{i,a^*} \equiv \gamma\left[\left(\frac{\sigma\gamma-(\sigma-\frac{1}{\gamma})(\xi-\xi^*)(1-\tilde{\eta})}{\sigma-(\sigma-\frac{1}{\gamma})(\xi-\xi^*)(\tilde{\eta}-\tilde{\eta}^*)}\right)\tilde{\lambda}_{a^*} + \left(\frac{\sigma(1-\xi)-(\sigma-\frac{1}{\gamma})(\xi-\xi^*)(1-\tilde{\eta})}{\sigma-(\sigma-\frac{1}{\gamma})(\xi-\xi^*)(\tilde{\eta}-\tilde{\eta}^*)}\right)\tilde{\lambda}_{a^*}^*\right]$$

$$\begin{aligned}
\tilde{\lambda}_a &\equiv 1 + (\sigma - \frac{1}{\gamma})\left[\frac{\gamma((1-\xi)+(\xi-\xi^*)(1-\tilde{\eta}))}{\varphi(\sigma-(\sigma-\frac{1}{\gamma})(\xi-\xi^*)(\tilde{\eta}-\tilde{\eta}^*))+1}\right] \\
\tilde{\lambda}_{a^*} &\equiv -(\sigma - \frac{1}{\gamma})\left[\frac{\gamma((1-\xi)+(\xi-\xi^*)(1-\tilde{\eta}))}{\varphi(\sigma-(\sigma-\frac{1}{\gamma})(\xi-\xi^*)(\tilde{\eta}-\tilde{\eta}^*))+1}\right] \\
\tilde{\lambda}_a^* &\equiv -(\sigma - \frac{1}{\gamma})\left[\frac{\gamma(\xi^*+(\xi-\xi^*)(1-\tilde{\eta}^*))}{\varphi(\sigma-(\sigma-\frac{1}{\gamma})(\xi-\xi^*)(\tilde{\eta}-\tilde{\eta}^*))+1}\right] \\
\tilde{\lambda}_{a^*}^* &\equiv 1 + (\sigma - \frac{1}{\gamma})\left[\frac{\gamma(\xi^*+(\xi-\xi^*)(\tilde{\eta}^*)}{\varphi(\sigma-(\sigma-\frac{1}{\gamma})(\xi-\xi^*)(\tilde{\eta}-\tilde{\eta}^*))+1}\right]
\end{aligned}$$

$$\begin{aligned}
\tilde{\eta} &\equiv \frac{n\xi}{n\xi+(1-n)\xi^*} \\
\tilde{\eta}^* &\equiv \frac{n(1-\xi)}{n(1-\xi)+(1-n)(1-\xi^*)}
\end{aligned}$$

The model parameters are summarized in Table 1a below. Under the benchmark parameterization, the structural parameters of the model are chosen as $\beta = 0.99$, $\gamma = \varphi = 5$, $\sigma = 1.5$, $\xi = 0.06$, and $\alpha = 0.75$, in the light of Chari, Kehoe and McGrattan (2002). This is also similar to the closed economy model of Neiss and Nelson (2003) and Neiss and Nelson (2005). We assume that countries are equal in population, $n = 0.5$ and the allocation of home and foreign goods in the consumption basket of each country is symmetric, $\xi = 1 - \xi^*$. We set $\eta = 4$ as described in Gali (2008). We assume that the Taylor rule is inertial and the policy rule is identical in both countries. Following Rudebusch (2006), we set monetary policy parameters estimated to match the U.S. data such that $\rho_i = 0.78$, $\Psi_\pi = 1.24$ and $\Psi_x = 0.33$, and the AR(1) monetary shock process parameters of persistence and volatility such that $\delta_m = 0$ and $\sigma_m = 0.36$, respectively. For the productivity shock process, these parameters are chosen as $\delta_a = 0.97$, and $\sigma_a = 0.73$, as in Heathcote and Perri (2002). Based on their estimates, the cross-country spillover parameter δ_{a,a^*} is set at 0.025.The correlations of domestic and foreign productivity and monetary innovations are $\rho_{a,a^*} = 0.29$ and $\rho_{m,m^*} = 0.5$, following Chari, Kehoe and McGrattan (2002). We assume further that the monetary and productivity innovations are uncorrelated with each other.[7]

Table 1a: Model parameters	
Structural parameters	
Intertemporal discount factor	$0 < \beta < 1$
Inverse of the intertemporal elasticity of substitution	$\gamma > 0$
Inverse of the Frisch elasticity of labor supply	$\varphi > 0$
Interest semi-elasticity of money demand	$\eta > 0$
Elasticity of substitution across varieties within a country	$\theta > 1$
Elasticity of substitution between Home and Foreign bundles	$\sigma > 0$
Share of Home goods in the Home basket	$0 < \xi < 1$
Share of Home goods in the Foreign basket	$0 < \xi^* < 1$
Home population size, Mass of Home varieties	$0 < n < 1$
Foreign population size, Mass of Foreign varieties	$0 < 1 - n < 1$
Calvo (1983) price stickiness parameter	$0 < \alpha < 1$
Monetary policy parameters	
Monetary policy inertia	$0 < \rho_i < 1$
Sensitivity to deviations from the inflation target	$\Psi_\pi > 1$
Sensitivity to deviations from the potential output target	$\Psi_x > 0$
Shock parameters	
Persistence of the productivity shock	$-1 < \delta_a < 1$
Volatility of the productivity shock	$\sigma_a > 0$
Correl. between Home and Foreign productivity innovations	$-1 < \rho_{a,a^*} < 1$
Persistence of the monetary policy shock	$-1 < \delta_m < 1$
Volatility of the monetary policy shock	$\sigma_m > 0$
Correl. between Home and Foreign monetary innovations	$-1 < \rho_{m,m^*} < 1$

4.2 Simulated forecasts

We run a Monte Carlo simulation of the model with 100 trials and with a subsample of 160 periods for each trial. Using the simulated data, we forecast inflation using one-variable recursive forecasts. We split 160 periods equally between estimation and pseudo out-of-sample forecast samples and conduct forecasts using *i)* domestic and global money growth, *ii)* terms of trade gap and HP-filtered terms of trade, and *iii)* domestic and global output gap. In particular, we calculate the (relative) MSFEs at a grid of points that spans the space for selected parameters, while keeping other parameters at their benchmark values. (We

[7] Unlike Benati and Surico (2008), where they estimated the model before running their experiments, we have calibrated the model. One possible argument in favor of calibration is that the model is too simplified so we are concerned that estimating it would lead to misspecification bias and, therefore, would complicate the interpretation of our estimates and our subsequent experiments even more.

select an interval for the grid search so that the benchmark values of these parameters fall in that interval.) In these 100 trials, we evaluate forecasting performance based on the median (relative) MSFE, median p-value of the hypothesis that the relative MSFE is greater than or equal to 1, and the fraction of statistically significant trials with p-values less than or equal to 10%.

The analyses conducted here can be grouped under three main experiments: *i)* Good luck, *ii)* Monetary policy, and *iii)* Openness.

i) Good luck[8] experiment focuses on how forecasting performance of the regressors listed above is altered when the parameters of innovations, specifically the volatility of shocks, σ_m and σ_a take on different values. We run two versions of this experiment. In the first version, we conduct the experiment symmetrically for both countries. Hence for σ_m and σ_a, and σ_{m^*} and σ_{a^*}, we set values both varying within $(0, 2]$. In the second one, we change the parameterization of U.S. only, keeping the ROW parameters constant.

The literature on Great Moderation provides with important empirical findings on the evolution of these variables over time. The Great Moderation era is mainly characterized by reductions in the conditional variance in time-series models. The variance reduction is generally attributed to a smaller error variance, not to changes in the autoregressive coefficients, as suggested by Stock and Watson (2003a), Ahmed, Levin, and Wilson (2002), Blanchard and Simon (2001) and McConnell and Perez-Quiros (2000). Stock and Watson (2003a) calculated a sharp decline in the volatility of the U.S. GDP growth in the first quarter of 1984. Volatility is highest in 1970s, and considerably high in 1960s and early 1980s[9]. They calculate similar volatility declines in macroeconomic variables, including nominal variables such as inflation (GDP deflator) and 90-day T-bill rate. Moreover, Stock and Watson (2005) and Fogli and Perri (2006) document that the moderation is a world-wide phenomenon, also observed in Japan and EU, but the greatest moderation was observed in the U.S. Taking into account this evidence, an asymmetric experiment seems more relevant.

Stock and Watson (2003a) provide a helpful comparison of the monetary shock volatilities for the pre-1983 and post-1984 era. Using structural VAR and implementing the methodologies of Christiano, Eichenbaum and Evans (1998) and Bernanke and Mihov (1997)[10], they compute the implied money shocks. Volatility of these monetary shocks exhibited a decline in the great moderation era, following a high level of volatility in 1960-83 and having a peak during 1979-83[11]. Similarly, Smets and Wouters (2007), report a decline in the volatility of both shocks in the US in an extended DSGE model for the Great Moderation era (1984-2004) relative to the Great Inflation era (1966-79).

ii) Our *monetary policy* experiments pay attention to forecasting performance under changes in the monetary policy parameters Ψ_π and Ψ_x, one with high monetary policy inertia, $\rho_i = 0.78$ and one with low inertia, $\rho_i = 0$. For Ψ_π, we try values of grid points in the interval $(1, 3]$ and Ψ_x, in the interval $(0, 2]$. Coibion and Gorodnichenko (2011), among others[12], provide historical estimates of the coefficients of a

[8]In the current terminology, 'good luck' is used in order to explore the possibility of exogenous changes in the distribution of the shock process. These changes might cause a draw of unusually benign shocks to the economy. Good luck might be the result of an unusual draw of shocks from the right-tail of distribution but that is not the interpretation we give here. Rather, we interpret good luck as the shift in the distribution of shocks.

[9]Stock and Watson (2003a) report the standard deviations of four-quarter growth rate of real GDP. The standard deviation in the post-1984 period is 0.59 times that of the pre-1984 period. (Standard deviation in the 1970-1980 period is highest, but still comparable to its 1960-1970 level.)

[10]They take into account that the monetary policy shifted over the sample period.

[11]Volatility of money shocks during 1984-2001 is about 0.50 times the volatility in 1960-1983 and about 0.76 times the volatility in 1960-1978 period according to CEE methodology.

[12]See also Stock and Watson (2003) for a summary of historical estimates of Taylor Rule coefficients in the US calculated by Judd and Rudebusch (1998), Taylor (1999) and Clarida, Gali and Gertler (2000).

generalized Taylor rule. Their estimates of Ψ_x do not show much variation from late 1960s to early 2000s. They indicate that both the inertia of the monetary policy and the parameter on inflation gap have increased recently. Their time varying estimate for Ψ_π is relatively high in late 1960s as well as early 1980s and onwards, but low during 1970s. A similar pattern is observed for the inertia parameter, ρ_i. The case $\rho_i = 0.78$ in our simulated forecasts is close to the upperbound estimated by Coibion and Gorodnichenko (2011) while $\rho_i = 0$ is not comparable to their lower bound. Rudebusch (2006) provides evidence that for 1990s, a positive inertia parameter in the policy rule is more plausible. However, a non-inertial policy rule is a common benchmark in the literature (e.g. Taylor (1993) and Yellen (2004)) and is therefore a natural case to investigate especially to understand the patterns before 1990s.

iii) The final experiment, *trade openness*, involves a grid search over the parameters of share of Home goods in the Home basket, ξ and elasticity of substitution between Home and Foreign bundles, σ. For ξ we try the values in the intervals $(0, 0.5]$, hence, under the case ξ is close to 0, the economy is almost closed and there is home bias, while under $\xi = 0.5$ there is no bias between consumption and production and the economy is open. For σ, we try values within the range $(0, 2]$ where $\sigma = 1$ implies the consumption aggregator is Cobb-Douglas type.

4.3 Results

We illustrate our results from the symmetric *good luck* experiment in Figures 5a-5f and 6a-6c in the Appendix. The key results are:

1. If a symmetric change in the volatility of productivity and monetary shocks in the U.S. and the ROW has a significant effect on the forecasting performance of variables, it is on domestic slack only.

2. Starting from the benchmark parameterization ($\sigma_a = 0.73$ and $\sigma_m = 0.36$) and for a given σ_m (and σ_{m^*}), a decline in σ_a (and σ_{a^*}) might deteriorate the forecasting ability of domestic slack; for a given σ_a (and σ_{a^*}), a decline in σ_m (and σ_{m^*}) might deteriorate the forecasting ability of domestic slack (Figures 5a and 6a)— However, it would require a large swing from the benchmark parameterization to see the changes in the forecast accuracy observed in the data.

3. The experiment shows that only in a small fraction of instances (less than 40%) some variables (global slack, domestic money growth and terms of trade gap) seem to be marginally statistically significant.

Hence, in theory, we can conclude that the performance of the traditional Phillips curve based forecasts of U.S. inflation might have changed due to Great Moderation—if it is interpreted as a world-wide phenomenon that affected most countries equally. If we allow for asymmetries à la Fogli and Perri (2006), then HP-filtered terms of trade starts to matter in forecasting U.S. inflation. The results from the asymmetric good luck experiment are depicted in Figures 7a-7f and 8a-8c:

1. Relative to the symmetric experiment, we observe larger statistically significant regions for domestic slack, global slack, HP-filtered terms of trade and terms of trade gap and very weak results for domestic and global money supply growth.

2. The volatility changes in productivity and money might make HP-filtered terms of trade a key variable in forecasting inflation.

3. The statistically significant regions for domestic slack and HP filtered terms of trade do not overlap, so if the volatility driving the productivity and monetary shocks change over time, the forecasting performances of these different variables may have been affected in an opposite way: domestic slack's value as a forecasting variable might decline while HP filtered terms of trade gains value and vice-versa.

Since we do not have actual measures of terms of trade gap, in the empirical analysis we use the HP-filtered terms of trade. An interesting point is on the differences between the forecasting power of HP-filtered terms of trade and the terms of trade gap and there is a strong negative correlation between these two variables for the benchmark parameters (Figure 15a).

We show our results from the *monetary policy* experiment with low inertia in Figures 9a-9f and 10a-10c. The benchmark values for $\Psi_\pi = 1.24$ and $\Psi_x = 0.33$, respectively. We summarize the findings as follows:

1. With low inertia, more aggressive monetary policy on inflation (for a given Ψ_x) increases the percentage of instances in which the forecasting power is statistically significant. A high anti-inflationary bias of monetary policy can make domestic and global slack stronger in forecasting inflation—while this is also valid for domestic money, global money and terms of trade gap but the effect seems statistically less significant on these variables.

2. For a given Ψ_π, increases in Ψ_x do not seem to have much of an effect on forecast accuracy of variables.

In turn, the pattern is somewhat reversed when we look at the high inertia case (see Figures 11a-11f and 12a-12c):

1. In this case, the policy does not seem to have a high influence on forecasting ability except for domestic slack—which is also not very strong. For a given Ψ_x increases in the anti-inflation bias of policy (Ψ_π) tend to reduce the share of statistically significant samples. Whenever Ψ_x increases, then the share of statistically significant samples tends to increase for a given Ψ_π.

2. Changes in inertia parameter appear to be key, and perhaps the most influential channel on predictive ability of variables tested in these experiments. When inertia is high, the response of policy is very delayed and using current variables as predictors of inflation can be a bad proxy for what monetary policy does and therefore for how inflation will be in the future.

Our results from the *openness* experiment are shown in Figures 13a-13f and 14a-14c. The benchmark values for the parameters of interest are $\xi = 0.06$ and $\sigma = 1.5$, respectively.

1. This is the only channel that explains the switches between domestic and foreign variables— however, for the slack variables only. Keeping σ constant, an increase in the share of Home goods in the Home basket, ξ, causes a weaker performance for the domestic output gap, i.e. the traditional closed-economy Phillips curve predicts domestic inflation less accurately while implying a better performance for the open economy Phillips curve.

2. This experiment is silent on why domestic money supply growth may be a good predictor of U.S. inflation while global money supply growth is poor and vice versa.

3. Forecast accuracy is almost invariant to changes in the elasticity of substitution between Home and Foreign bundles, σ (for a given ξ) especially in the neighborhood of the benchmark parameterization.

We provide a summary of results in Table 1b where we show which channels in the model might play a statistically significant effect in forecasts in at least 50% of the time. We draw three important conclusions from these experiments (if we consider movements relative to the benchmark parameterization):

- Phillips curve based forecasts of inflation may be affected by a combination of all three channels: good luck, monetary policy and openness.
- Asymmetric changes in volatilities of productivity and monetary shocks can be responsible for the high performance of HP-filtered terms of trade.
- There is nothing that matters more than monetary policy in the performances of all variables tested here except for HP-filtered terms of trade. And it is clear that it is the systematic part that is the key determinant of when and how these variables become more useful for forecasting. It is not only the response to inflation that matters a lot (the response to the output gap has only minor effects in our current experiments), but the fact that policy responses could be gradual or abrupt.

Table 1b: Predictive performances of variables

		Domestic slack	Global slack	ToT HP-filtered	ToT gap	Domestic money growth	Global money growth
Good luck	σ_m	✓					
(symmetric)	σ_a	✓					
Good luck	σ_m	✓	✓	✓	✓		
(asymmetric)	σ_a	✓	✓	✓	✓		
Monetary policy	Ψ_π	✓	✓		✓	✓	✓
(low inertia)	Ψ_x						
Monetary policy	Ψ_π	✓					
(high inertia)	Ψ_x	✓					
Openness	ξ	✓	✓				
	σ						

Note: This table reports whether changes in a given parameter have a statistically significant impact on predictive ability of a variable (at least at 10% significance level) in at least 50% of the trials of the experiment.

Having established the main findings from the simulated forecasts, we move to the next section where we aim to explain how primary domestic and global macroeconomic phenomena since 1960s affected the predictive accuracy of our variables and what accounts for these changes.

4.4 Relating theory to stylized facts

Now we turn to Figures 2a-4b in order to explain how major episodes for the U.S. economy can be related to forecasting performances. We analyze these figures paying particular attention to CPI inflation, since the model at hand is consistent with this measure of inflation. However, forecasting patterns are robust to other measures of inflation to a great extent.

- *Domestic (US) and global (G7) money supply growth:* Figures 2a-b reveal that especially at long horizons, US money supply growth helps forecast US inflation starting in late 1960s until mid 1970s. In samples starting earlier or later than this period, we obtain lower forecast accuracy for this variable relative to naive forecasts. Interestingly, the periods that US money supply growth does not perform well in general coincide with the periods G7 money supply growth performs well. Our model suggests that these variables can matter for forecasting only because of monetary policy and especially when monetary policy is non-inertial ($\rho_i = 0$), and highly anti-inflationary (i.e. high Ψ_π). On the other hand, the historical estimates for the monetary policy parameters during the 1970s reveal that inertia was low but the monetary policy was not anti-inflationary. Hence, none of these variables should have high performance during the 1970s as well as outside the 1970s. Therefore, periods during which any of these variables perform well are puzzling in light of our model and we only explain why they do not perform well.

- *Domestic (CBO) and global (OECD) slack:* Figures 3a-b show that forecasts with domestic slack (i.e. the traditional closed-economy Phillips curve-based forecasts) perform well until 1960s, but any forecast that is based on a sample starting after 1960s in general is less accurate than a naive forecast. According to our model, one channel that can explain this is openness. The model suggests that under low trade openness, we should expect a high predictive performance by U.S. slack. In addition, a combination of high monetary policy shock volatility (σ_m) and high productivity shock volatility (σ_a) might have improved this performance while the stance of monetary policy (high anti-inflation bias of policy (Ψ_π) with high monetary policy inertia (ρ_i)) could have reduced it. Overall, the net effect of these channels might have resulted in a high forecast accuracy in the 1960s.

In the 1970s, both the anti-inflation bias and inertia of monetary policy were low, so this would cause a low performance both domestic and global slack according to our theory especially at long horizons which should be the leading explanation for the low performance of Phillips curve-based forecasts. The volatility of shocks, σ_a and σ_m, remained high in this period which could revert the low performance of slack measures, but monetary policy appears to be a stronger channel that dominates any positive effect in this period. Increasing openness should be another reason for lower forecast accuracy of domestic slack.

In the 1980s where openness is highest, the open economy Phillips curve-based forecast starts to outperform both the traditional Phillips curve and the naive forecast. Global slack starts to perform well occasionally in late 1980s and at short horizons, which can be explained only by higher openness. Highly persistent and highly anti-inflationary policy during the Volcker era (starting 1979) can be shown to weaken the accuracy of both domestic and global slack in this era. The deterioration in forecast accuracy becomes more serious when we also take into account the great moderation era starting in mid-1980s, where the volatility of shocks decline. Our results are in line with Benati and Surico (2008), who suggest, based on a time-varying VAR, that inflation's predictability fell as the persistence of inflation and as the Taylor rule coefficient on the inflation gap rose during the Volcker era. We confirm these results under *high inertia* particularly in forecasts with domestic and global slack measures.

- *Terms of trade gap* (*HP-filtered terms of trade and terms of trade ex. oil):* While in the empirical analysis we use HP-filtered terms of trade and HP-filtered terms of trade ex. oil as proxies for the terms of trade gap, in the NOEM framework we do not separate between these two variables and therefore we only focus on HP-filtered terms of trade in this section. HP-filtered terms of trade kicked in as a good forecast variable starting in late 50s and the performance went well until present except for a break with the estimation samples starting in the early 1980s. The monetary policy and openness experiments do not help us understand the performance of this variable, while the good luck (asymmetric) experiment stands out as the only relevant and important case that can explain the patterns in Figures 4a-b. A sufficiently high combination of the volatility shocks, σ_a and σ_m, during 1960 and 1970s might have caused a high performance by HP-filtered terms of trade (and in theory, terms of trade gap). In the late 1970s, the volatility of shocks peaked, which might have caused the variable to move to the insignificant region in Figure 8b. During the Great Moderation era, the decline in the volatility of shocks might be responsible for a weak performance.

Going back to the first question raised in the previous section, we now have a more clear understanding on what determines the accuracy of forecasts with domestic and global slack measures. While globalization seems to be the only channel to make global slack a better forecasting variable than domestic slack, the conduct of monetary policy and particularly the monetary policy inertia matter most in forecasting U.S. inflation can become a significant determinant of forecast accuracy of all other variables tested here.

We also understand to a great extent why terms of trade can be a good forecasting variable—it is basically due to good luck. Our simulated forecasts obviously cannot explain the occasionally good performance of terms of trade ex. oil and we leave this as an open question to be investigated in the future.

We also document an interesting puzzle regarding the forecasts with domestic and global money supply growth, an alternating pattern in the relative MSFEs of the two variables especially until mid-1980s. This is one case the current model cannot explain. We believe that a plausible explanation is that the strong connection between the US and global money supply during the Bretton Woods era might have weakened by the collapse of the system in 1971 (therefore its relationship between US inflation also weakened) causing the weak performance of G7 money supply growth during 1970s which was a useful forecasting variable before the 1970s. Also, in a recent study, Sargent and Surico (2011) provide results on the empirical evidence of the quantity theory of money that may explain the performance of US money growth in forecasting US inflation. Our empirical findings are consistent with their estimates for 1970s where the quantity theory of money seemed to exist but then broke down starting in late 1970s. We believe that the current model does not help us see this connection exactly since the NOEM model does not capture a strong role for money supply. However, this should not be viewed as a serious issue since both domestic and global money growth seem to have lost their significances in forecasting U.S. inflation during the post-1984 period.

Finally, we still leave an open question on why the HP-filtered slack measures perform as good as the slack measures that are calculated with a production function approach. While we believe that this question must be handled with a more formal analysis (which will be left as future work) we provide some interesting findings in Figures 15a, 15b, 15c and 15d. Lack of structural estimates of output gap might be by-passed by using HP-filtered output in certain cases; however we show that it may not always be a good proxy for output gap. Changes in the structural parameters of the models may significantly affect the correlations between output gap and its HP-filtered counterpart.

5 Conclusion

Beating the naive forecasts of U.S. inflation with a traditional Phillips curve specification has become difficult over the past three decades. The major contribution of our paper is to help solve this problem, introducing a variable, HP-filtered terms of trade, to forecast U.S. inflation. We documented that it yields highly accurate forecasts relative to the naive forecasts of U.S. inflation. It also does well compared to forecasts with several conventional measures: domestic slack, global slack, domestic money supply growth and global money supply growth.

Our second contribution is to bring together and compare three channels regarding forecast accuracy that are widely discussed in the literature -globalization, monetary policy and good luck- under a single NOEM framework to explain our empirical findings. We provide three key insights: (i) monetary policy inertia is an important parameter in raising the significance of a given variable to forecast U.S. inflation, and the conduct of monetary policy appears to be the most important channel, (ii) volatilities of shocks to productivity and money can be a particularly important determinant of the accuracy of forecasts with HP-filtered terms of trade (iii) and a combination of these three channels might have improved the performance of HP-filtered terms of trade while deteriorating that of the Phillips curve-based forecasts during the Great Moderation era.

6 Appendix

A Data Description

Abbreviations

BEA = U.S. Bureau of Economic Analysis; BLS = U.S. Bureau of Labor Statistics; BBK =German Federal Bank; BIS = Bank for International Settlements; CAO = Cabinet Office (Japan); CBO = Congressional Budget Office; FRB = Federal Reserve Board; FRBD = Federal Reserve Bank of Dallas; FRED = Federal Reserve Economic Data (St. Louis Fed); IMF = International Monetary Fund; INSEE = National Institute of Statistics and Economic Studies (France); ISTAT = Istituto Nazionale Di Statistica (Italy); OECD= Organisation for Economic Cooperation and Development; OECDMEI= OECD Main Economic Indicators; ONS = Office for National Statistics (UK); SAAR = Seasonally adjusted at an annual rate; SA=Seasonally adjusted; SCAN = Statistics Canada

All series are quarterly unless indicated otherwise and obtained from Haver Analytics. In general, we indicate the original source if the series is available outside Haver Analytics. While we try to be consistent in terms of the definitions across countries, under cases in which data availability is limited, we use the series with the closest definition.

1. **Price indices**

Series used for U.S. inflation: All series are seasonally adjusted. Start dates of the series vary across different measures and they all end in 2011:4. Base years and start dates of each series are indicated in parentheses. We take CPI (all items) (82-82=100, 1947:1) from the BLS, core CPI (all items ex. food and energy) (82-84=100, 1957:1) from the BLS, GDP implicit price deflator (82-84=100, 1947:1) from the BEA; PCE chain price index (2005=100, 1959:1) from the BEA, trimmed mean PCE chain price index (2004-5=100, 1977:1) from FRBD and PPI (finished goods) (1982=100, 1947:2) from the BLS. Series used for terms of trade gaps: We use exports and imports under the heading 'price indexes for GDP' in National Income and Product Accounts in BEA to calculate U.S. terms of trade. Both series are seasonally adjusted, with the base year 2005=100 and cover periods 1947:1-2011:4. Terms of trade series is calculated as 100 $\times$export price index/import price index. Terms of trade gap is the HP-filtered ($\lambda = 1600$) terms of trade series. Terms of trade gap ex. oil is calculated similarly (with the same base year and seasonally adjusted), using imports of non-petroleum goods (chain price index) and exports of goods (chain price index) from BEA (1967:2-2011:4).

2. **Monetary aggregates**

All series are seasonally adjusted and quarterly (end-of-period aggregates of monthly series). For UK and U.S., we have M4 and M2 data available from OECD and FRB (1963:1-2011:4), respectively. For other countries, data become limited for certain periods and sources and therefore we splice two series. Therefore we obtain M3 for Canada from BIS (1962:1-1981:4) and OECD (1982:1- 2011:4); M2 for Germany from BIS (1963:1-1990:4) and BBK (1980:1-2011:4); M2 for Italy from Bank of Italy (1963:1-1997:1/1997:2-2011:4); M2 for Japan from Bank of Japan (1963:1-1966:4) and FRED (1967:1-2011:4). For France, we splice M2R and M3 from BIS (1963:1-1969:4 and 1970:1-2011:4, respectively). For France, Germany and Italy, the first part of the series is converted from the national currency to Euros using the European Currency Unit (1999).

3. **Slack measures**

All measures used cover the period 1980:1-2011:4 unless stated otherwise.

CBO U.S. slack: Defined as 'Output Gap in Percentage of Real GDP', and is calculated as

$$\frac{100 \times \ (RPGDP_t - RGDP_t)}{RGDP_t}$$

where $RPGDP_t$ and $RGDP_t$ are real potential GDP and real GDP at quarter t, respectively (SAAR, Billions of Chained 2005 Dollars). We take our real GDP series from BEA and real potential GDP series from CBO. U.S. HP-filtered series is simply quarterly U.S. real GDP series with HP filter ($\lambda = 1600$) applied. Then the logs of the cyclical component is taken and multiplied by 100.

FRBD U.S. slack: The series is constructed by the FRBD, and the methodology can be described as follows. First, the Phillips Curve is estimated with annualized quarterly inflation (specifically, core CPI) and unemployment rate/capacity utilization rate. The regression equation for this is specified as is constructed as follows.

The regression is specified as

$$\pi_t = \alpha_1 + \alpha_2 \pi_{t-1} + \alpha_3 \pi_{t-2} + \alpha_4 \pi_{t-3} + (1 - \alpha_2 - \alpha_3 - \alpha_4)\pi_{t-4} + \alpha_5 ur_t + \epsilon_t$$

where $\pi_t = 400 \times \log(p_t/p_{t-1})$, p_t is the price index, ur_t is unemployment rate where we define the potential unemployment rate as $ur^* = -\hat{\alpha}_1/\hat{\alpha}_5$. We run a similar regression with capacity utilization rate, $capu_t$ and define the potential rate of capacity utilization, $capu^* = -\hat{\alpha}_1/\hat{\alpha}_5$, similarly.

Then the slack measure is computed as follows by running the following regression

$$\pi_{t+4} - \pi_t = -\beta_1(ur_t - ur^*) + (1-\beta_1)(capu_t - capu^*) + \epsilon_t$$

and the slack measure is calculated as $slack_t = -\hat{\beta}_1(ur_t - ur^*) + (1-\hat{\beta}_1)(capu_t - capu^*)$.

FRBD G7 slack: Produced by the FRBD and calculated by applying the procedure described above for each member of the G7 economies. After obtaining the 'domestic slack measure for a given country, the GDP shares of each country is calculated so that for country i at quarter t, $share_{i,t}$=$GDP_{i,t}$ / $\sum_i GDP_{i,t}$. The G7 slack is the GDP-weighted average of the slack measures of individual countries.

The data series we use here are as follows:

- GDP series to construct the GDP shares of each country (sources indicated in parentheses): Canada (SCAN), France (INSEE), Germany (BBK), Italy (ISTAT), Japan (CAO), UK (ONS), U.S. (BEA).

All series are in billions of U.S. Dollars, seasonally adjusted (1978:1-2011:4). For France, Germany and Italy, the series are working day adjusted.

- Manufacturing capacity utilization rates (%) come from manufacturing surveys, covering the period 1978:1-2011:4 and are seasonally adjusted for the following countries: France, Germany and U.S. For Italy, the data come from OECDMEI; for Japan, we use manufacturing operation rate; for Canada, we do splicing for capacity utilization rate from OECDMEI (1978:1-1986:4) and the manufacturing survey from SCAN (1987:1-2011:4); while we apply a similar procedure for UK with capacity utilization rate series from Datastream (1978:1-1985:1) and the manufacturing survey from OECDMEI (1985:2-2011:4).

- As a measure of inflation, we use core CPI. All series are seasonally adjusted, come from OECDMEI and the base year is 2005=100 for all countries with the exception that the base year is 2010=100 for Japan and 82-84=100 for the U.S..

FRBD G39 Slack: This measure is calculated by HP filtering ($\lambda = 1600$) of FRBD G39 index which uses constant 2005 (PPP adjusted) weights to aggregate GDP series of the 39 countries: Argentina, Australia, Austria, Belgium, Brazil, Canada, China, Czech Republic, Denmark, Finland, France, Germany, Greece, Hong Kong, Hungary, India, Indonesia, Italy, Ireland, Japan, Korea, Luxembourg, Malaysia, Mexico, Netherlands, New Zealand, Norway, Peru, Poland, Singapore, South Africa, Spain, Sweden, Switzerland, Taiwan, Thailand, Turkey, UK and U.S. GDP series used are quarterly; and for some countries for which only disaggregated (annual) data are available, we apply quadratic match average method to interpolate these series. We use 2005 PPP data from the IMF.

IMF U.S. and IMF Advanced Slack: Both slack measures are defined as 'Output Gap in Percentage of Real GDP (%)' for the U.S. and for a group of advanced countries (Australia, Austria, Belgium, Canada, Cyprus, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, UK and U.S.). These measures are published by IMF WEO, annually and available between 1980-2011. Therefore we interpolate the series by ‘quadratic match average’ method to disaggregate into quarterly frequency.

OECD U.S., OECD G7 and OECD Total Slack: All three measures are defined as the ‘Output Gap of the Total Economy (%)’, published by OECD Economic Outlook. OECD Total consists of 30 OECD countries: Australia, Austria, Belgium, Canada, Cyprus, Czech Republic, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Japan, Korea, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Portugal, Slovakia, Spain, Sweden, Switzerland, Turkey, UK and U.S. and the series go back to 1970:4.

U.S. HP-filtered GDP: Calculated using quarterly U.S. real GDP series from BEA. First, the logs of the series is taken and multiplied by 100 and then Hodrick-Prescott filter ($\lambda = 1600$) is applied.

B Tables and Figures

Table 2. Relative MSFEs– 1992Q1:2011Q4

Horizon	1	4	6	8	10	12	1	4	6	8	10	12
	Consumer Price Index						**Consumer Price Index (ex. Food & Energy)**					
Autoregressive	4.704	1.881	1.334	1.164	1.065	0.958	0.295	0.418	0.626	0.828	0.954	1.036
CBO U.S. Slack	0.990*	1.042	1.059	1.070	1.100	1.168	1.135	0.974*	0.873**	0.827**	0.840**	0.870*
FRBD U.S. Slack	0.878***	0.936*	0.924*	0.936*	1.001	1.073	1.333*	0.955**	0.788**	0.737**	0.733**	0.751**
IMF U.S. Slack	1.005	1.054	1.068	1.072	1.101	1.170	1.060	1.110	1.106	1.082	1.073	1.079
OECD U.S. Slack	0.984*	1.028	1.038	1.046	1.068	1.118	1.018	0.801***	0.741***	0.739**	0.768**	0.798**
U.S. HP-filtered	0.997	1.045	1.036	1.022	1.032	1.069	1.103	0.916**	0.851**	0.838**	0.861**	0.882*
U.S. Money Growth	0.996	1.017	1.030	1.075	1.100	1.147	1.027	0.969	0.893	0.898	0.920	0.923
	PCE Price Index						**Trimmed Mean PCE Price Index**					
Autoregressive	2.329	1.190	0.930	0.885	0.875	0.899	0.142	0.169	0.229	0.313	0.386	0.436
CBO U.S. Slack	0.999	1.026	1.041	1.051	1.069	1.082	0.960**	0.882**	0.869**	0.887*	0.904*	0.922*
FRBD U.S. Slack	1.006	1.032	1.037	1.030	1.024	1.023	0.933***	0.888**	0.826**	0.822**	0.822**	0.808**
IMF U.S. Slack	1.005	1.024	1.032	1.038	1.055	1.067	1.018	1.047	1.029	1.018	1.004	0.986
OECD U.S. Slack	0.995	1.012	1.020	1.027	1.040	1.048	0.899***	0.798***	0.820**	0.860**	0.890*	0.918
U.S. HP-filtered	1.004	1.020	1.018	1.024	1.038	1.045	0.932***	0.904**	0.922*	0.939*	0.954	0.959
U.S. Money Growth	1.002	1.020	1.045	1.078	1.091	1.125	1.017	1.070	1.084	1.109	1.123	1.131
	GDP Deflator						**Producer Price Index**					
Autoregressive	0.508	0.376	0.423	0.498	0.545	0.575	19.431	7.829	4.724	3.127	2.207	1.786
CBO U.S. Slack	1.005	0.996	1.030	1.040	1.055	1.066	0.980*	1.007	1.032	1.039	1.073	1.119
FRBD U.S. Slack	0.949**	0.910**	0.962*	0.997	1.036	1.050	1.005	1.064	1.102	1.137	1.188	1.250
IMF U.S. Slack	1.037	1.057	1.059	1.048	1.057	1.065	0.996	1.024	1.053	1.082	1.143	1.227
OECD U.S. Slack	0.970**	0.951*	0.999	1.022	1.037	1.047	0.974**	0.989	1.001	0.999	1.006	1.013
U.S. HP-filtered	1.013	1.032	1.042	1.031	1.046	1.056	0.909***	0.980*	1.016	1.030	1.073	1.116
U.S. Money Growth	1.004	1.033	1.057	1.074	1.090	1.108	1.000	1.011	1.035	1.068	1.101	1.157

This table reports the forecasting performances with an estimation sample covering 1980Q1:1991Q4 and a pseudo out-of-sample forecasting sample over 1992Q1:2011Q4. The first row of each panel shows the MSFEs of forecasts with the simple univariate AR process of inflation (restricted model) and are therefore in absolute terms. The remaining entries are the MSFEs of the forecasts under the unrestricted model relative to the MSFEs of the restricted model. Asterisks denote that the relative MSFEs are statistically different and (more accurate) than the MSFEs of the benchmark (restricted) model at 1 (***), 5 (**), and 10 (*) percent significance levels.

Table 3. Relative MSFEs– 1992Q1:2011Q4

Horizon	1	4	6	8	10	12	1	4	6	8	10	12
	Consumer Price Index						**Consumer Price Index (ex. Food & Energy)**					
Autoregressive	4.704	1.881	1.334	1.164	1.065	0.958	0.295	0.418	0.626	0.828	0.954	1.036
FRBD G7	0.977*	1.049	1.014	1.017	1.049	1.076	0.947**	0.912**	0.776**	0.740**	0.745**	0.769**
FRBD G39	1.008	1.080	1.076	1.067	1.081	1.135	1.165	0.905**	0.872**	0.871**	0.889*	0.906*
IMF Adv.	1.005	1.050	1.054	1.046	1.041	1.059	1.018	1.054	1.058	1.039	1.023	1.014
OECD G7	0.981	1.036	1.049	1.060	1.067	1.087	0.905***	0.769***	0.680***	0.668***	0.699**	0.735**
OECD Total	0.989*	1.045	1.061	1.073	1.081	1.101	0.968**	0.816***	0.701***	0.677***	0.703**	0.738**
G7 Money Growth	1.020	0.962*	0.919**	0.892**	0.835**	0.779***	1.027	0.969*	0.893**	0.898**	0.920*	0.923*
	PCE Price Index						**Trimmed Mean PCE Price Index**					
Autoregressive	2.329	1.190	0.930	0.885	0.875	0.899	0.142	0.169	0.229	0.313	0.386	0.436
FRBD G7	0.934***	1.059	1.045	1.083	1.130	1.131	1.001	0.895**	0.830**	0.845**	0.869*	0.891*
FRBD G39	1.009	1.029	1.026	1.039	1.063	1.079	0.994*	0.875**	0.847**	0.879**	0.885*	0.891*
IMF Adv.	1.006	1.013	0.993	0.977	0.966	0.960	0.975**	0.707***	0.659***	0.677***	0.707**	0.757**
OECD G7	0.994	1.018	1.018	1.017	1.016	1.014	0.870	0.686	0.701	0.764	0.823	0.878
OECD Total	0.999	1.024	1.023	1.022	1.022	1.021	0.914	0.704	0.696	0.764	0.836	0.898
G7 Money Growth	1.028	0.903**	0.915**	0.889**	0.820***	0.796***	0.982*	1.004	1.054	1.068	1.059	1.066
	GDP Deflator						**Producer Price Index**					
Autoregressive	0.508	0.376	0.423	0.498	0.545	0.575	19.431	7.829	4.724	3.127	2.207	1.786
FRBD G7	1.053	0.989	0.991	1.013	1.059	1.074	1.009	1.050	1.052	1.061	1.050	1.023
FRBD G39	1.056	1.078	1.067	1.044	1.072	1.094	0.947**	1.046	1.074	1.154	1.313	1.389
IMF Adv.	0.996	0.780***	0.811**	0.887*	0.951	1.000	0.990*	1.020	1.051	1.078	1.106	1.134
OECD G7	0.992	1.001	1.026	1.026	1.029	1.029	0.964**	0.994	1.018	1.031	1.039	1.034
OECD Total	1.005	1.015	1.035	1.032	1.037	1.038	0.971**	1.003	1.027	1.040	1.047	1.041
G7 Money Growth	1.009	1.012	1.006	0.988	0.950	0.927	1.023	1.009	1.005	1.018	1.056	1.048

This table reports the forecasting performances with an estimation sample covering 1980Q1:1991Q4 and a pseudo out-of-sample forecasting sample over 1992Q1:2011Q4. The first row of each panel shows the MSFEs of forecasts with the simple univariate AR process of inflation (restricted model) and are therefore in absolute terms. The remaining entries are the MSFEs of the forecasts under the unrestricted model relative to the MSFEs of the restricted model. Asterisks denote that the relative MSFEs are statistically different and (more accurate) than the MSFEs of the benchmark (restricted) model at 1 (***), 5 (**), and 10 (*) percent significance levels.

Table 4. Relative MSFEs– 1992Q1:2011Q4

Horizon	1	4	6	8	10	12	1	4	6	8	10	12
	Consumer Price Index						**Consumer Price Index (ex. Food & Energy)**					
Autoregressive	4.704	1.881	1.334	1.164	1.065	0.958	0.295	0.418	0.626	0.828	0.954	1.036
Terms of Trade	0.963**	0.937**	1.055	1.132	1.247	1.312	1.120	1.221	1.173	1.086	1.057	1.061
CBO U.S. & ToT	0.981*	1.016	1.227	1.339	1.508	1.623	1.179	1.133	1.030*	0.929**	0.921*	0.958*
FRBD U.S. & ToT	0.903***	0.987*	1.177	1.283	1.461	1.568	1.302	1.015	0.872	0.810*	0.802*	0.829
IMF U.S. & ToT	0.995**	1.011*	1.215	1.332	1.504	1.612	1.030	1.009	0.922*	0.879**	0.873*	0.885*
OECD U.S. & ToT	0.973**	0.986*	1.187	1.295	1.456	1.557	1.079	0.974*	0.904*	0.843**	0.851*	0.890*
U.S. HP-filt. & ToT	0.992**	1.034	1.216	1.292	1.453	1.558	1.225	1.137	1.021	0.926*	0.926*	0.955
U.S. Money Growth & ToT	0.953**	0.974*	1.098	1.215	1.351	1.448	1.116	1.327	1.305	1.228	1.218	1.248
G7 Money Growth & ToT	1.014	1.005	1.096	1.169	1.221	1.206	1.127	1.161	1.050	0.984	0.987	1.007
	PCE Price Index						**Trimmed Mean PCE Price Index**					
Autoregressive	2.329	1.190	0.930	0.885	0.875	0.899	0.142	0.169	0.229	0.313	0.386	0.436
Terms of Trade	0.916***	0.892**	0.974	1.116	1.252	1.283	0.963	0.911**	0.864**	0.828***	0.833**	0.843**
CBO U.S. & ToT	0.899	0.883	0.980	1.126	1.274	1.318	1.053	0.873**	0.777***	0.790**	0.784**	0.783**
FRBD U.S. & ToT	0.907	0.898	0.989	1.139	1.276	1.305	0.950**	0.899**	0.828**	0.803**	0.834**	0.867*
IMF U.S. & ToT	0.912***	0.882**	0.976*	1.128	1.278	1.319	1.029	0.967*	0.877**	0.843**	0.848**	0.863*
OECD U.S. & ToT	0.896***	0.873**	0.965*	1.108	1.251	1.293	0.992**	0.809***	0.742***	0.768**	0.768**	0.774*
U.S. HP-filt. & ToT	0.916***	0.917**	1.004	1.153	1.302	1.341	1.001*	0.892**	0.802**	0.804**	0.788**	0.765**
U.S. Money Growth & ToT	0.909***	0.956*	1.089	1.303	1.459	1.479	1.039	0.972	0.890	0.914	0.902	0.854
G7 Money Growth & ToT	0.980**	0.876**	0.986	1.088	1.144	1.157	1.044	0.946*	0.898**	0.907*	0.886*	0.853**
	GDP Deflator						**Producer Price Index**					
Autoregressive	0.508	0.376	0.423	0.498	0.545	0.575	19.431	7.829	4.724	3.127	2.207	1.786
Terms of Trade	1.072	1.155	1.129	1.105	1.158	1.200	0.968**	0.967*	1.034	1.141	1.315	1.377
CBO U.S. & ToT	1.028	1.027	1.108	1.133	1.199	1.261	0.965**	0.997	1.085	1.207	1.431	1.550
FRBD U.S. & ToT	0.982	1.089	1.139	1.141	1.206	1.255	0.980**	1.040	1.145	1.304	1.550	1.676
IMF U.S. & ToT	1.088	1.163	1.150	1.125	1.178	1.226	0.971**	0.999	1.101	1.259	1.530	1.687
OECD U.S. & ToT	0.988	0.993	1.086	1.123	1.189	1.247	0.961**	0.969*	1.039	1.146	1.335	1.409
U.S. HP-filt. & ToT	1.053	1.110	1.158	1.154	1.212	1.260	0.970**	1.011	1.091	1.226	1.467	1.602
U.S. Money Growth & ToT	1.081	1.252	1.231	1.224	1.269	1.306	0.961**	0.971*	1.078	1.248	1.479	1.582
G7 Money Growth & ToT	1.077	1.190	1.171	1.124	1.142	1.171	1.008	1.003	1.059	1.178	1.372	1.411

This table reports the forecasting performances with an estimation sample covering 1980Q1:1991Q4 and a pseudo out-of-sample forecasting sample over 1992Q1:2011Q4. The first row of each panel shows the MSFEs of forecasts with the simple univariate AR process of inflation (restricted model) and are therefore in absolute terms. The second entry in each panel reports the relative MSFEs of the univariate forecasts with terms of trade. The remaining entries are the MSFEs of the bivariate forecasts relative to the MSFEs of the restricted model. Asterisks denote that the relative MSFEs are statistically different and (more accurate) than the MSFEs of the restricted model at 1 (***), 5 (**), and 10 (*) percent significance levels.

Table 5. Relative MSFEs– 1992Q1:2011Q4

Horizon	1	4	6	8	10	12	1	4	6	8	10	12
	Consumer Price Index						**Consumer Price Index (ex. Food & Energy)**					
Autoregressive	4.704	1.881	1.334	1.164	1.065	0.958	0.295	0.418	0.626	0.828	0.954	1.036
ToT ex.oil	1.013	0.980	1.000	1.025	1.038	1.069	1.002	1.018	1.026	1.030	1.030	1.027
CBO U.S. & ToT ex. oil	1.029	1.020*	1.083	1.128	1.114	1.177	1.153	0.952	0.853	0.815	0.828	0.851
FRBD U.S. & ToT ex. oil	0.905***	0.871**	0.810**	0.794**	0.805**	0.866*	1.393	0.954**	0.773**	0.710**	0.690**	0.691**
IMF U.S. & ToT ex. oil	1.039	1.009*	1.054	1.076	1.057	1.120	1.073	1.125	1.122	1.096	1.081	1.076
OECD U.S. & ToT ex. oil	1.021	1.013*	1.076	1.127	1.114	1.165	1.026	0.784***	0.729***	0.737**	0.768**	0.793*
U.S. HP-filt. & ToT ex. oil	1.023	1.032	1.092	1.127	1.106	1.153	1.103	0.873**	0.821**	0.824**	0.852*	0.872*
U.S. Money Gr. & ToT ex. oil	1.041	1.027	1.075	1.137	1.119	1.159	1.062	1.068	1.112	1.144	1.167	1.194
G7 Money Gr. &ToT ex. oil	1.040	0.883**	0.937**	0.990	0.933*	0.928*	1.036	0.966*	0.895**	0.920*	0.960	0.975
	PCE Chain Price Index						**Trimmed Mean PCE Price Index**					
Autoregressive	2.329	1.190	0.930	0.885	0.875	0.899	0.142	0.169	0.229	0.313	0.386	0.436
ToT ex.oil	1.043	1.036	1.039	1.065	1.076	1.083	1.008	1.045	1.046	1.047	1.047	1.040
CBO U.S. & ToT ex. oil	1.057	1.075	1.080	1.119	1.096	1.102	0.968	0.938	0.936	0.940	0.966	0.978
FRBD U.S. & ToT ex. oil	0.941***	0.981*	0.938*	0.946	0.943	0.964	0.925***	0.907**	0.854**	0.843**	0.850**	0.831*
IMF U.S. & ToT ex. oil	1.057	1.053	1.045	1.076	1.054	1.065	1.033	0.954**	0.886**	0.869**	0.860**	0.855*
OECD U.S. & ToT ex. oil	1.052	1.069	1.071	1.109	1.083	1.084	0.913***	0.841**	0.872**	0.903*	0.941*	0.964
U.S. HP-filt. & ToT ex. oil	1.059	1.077	1.071	1.108	1.082	1.083	0.938***	0.961**	0.984*	0.987	1.009	1.006
U.S. Money Gr. & ToT ex. oil	1.075	1.073	1.085	1.136	1.109	1.165	0.997	1.127	1.117	1.127	1.142	1.139
G7 Money Gr. &ToT ex. oil	1.088	0.942**	0.980*	0.996	0.915*	0.916*	1.055	1.217	1.364	1.393	1.414	1.304
	GDP Deflator						**Producer Price Index**					
Autoregressive	0.508	0.376	0.423	0.498	0.545	0.575	19.431	7.829	4.724*	3.127	2.207	1.786
ToT ex. oil	0.993	1.061	1.049	1.056	1.058	1.063	1.035	0.981	0.949	0.982	1.051	1.152
CBO U.S. & ToT ex. oil	0.917***	0.819**	0.886**	0.970	1.016	1.057	1.051	0.988*	0.967*	1.012	1.118	1.224
FRBD U.S. & ToT ex. oil	0.891***	0.895**	0.920*	0.948*	0.976	0.999	1.078	1.047*	1.033*	1.089	1.191	1.293
IMF U.S. & ToT ex. oil	1.013	1.093	1.073	1.055	1.052	1.064	1.070	1.010*	0.992*	1.053*	1.173	1.306
OECD U.S. & ToT ex. oil	0.881***	0.779***	0.858**	0.955*	1.007	1.047	1.039	0.963*	0.935*	0.977	1.073	1.153
U.S. HP-filt. & ToT ex. oil	0.917***	0.874**	0.925*	0.991	1.043	1.079	1.044	0.985	0.965	1.031	1.151	1.271
U.S. Money Gr. & ToT ex. oil	1.000	1.110	1.099	1.106	1.108	1.125	1.082	0.997*	0.959*	1.024	1.128	1.249
G7 Money Gr. &ToT ex. oil	0.988*	1.042	1.038	1.037	1.022	1.026	1.109	0.967**	0.930**	0.991*	1.086	1.162

This table reports the forecasting performances with an estimation sample covering 1980Q1:1991Q4 and a pseudo out-of-sample forecasting sample over 1992Q1:2011Q4. The first row of each panel shows the MSFEs of forecasts with the simple univariate AR process of inflation (restricted model) and are therefore in absolute terms. The second entry in each panel reports the relative MSFEs of the univariate forecasts with terms of trade ex. oil. The remaining entries are the MSFEs of the bivariate forecasts relative to the MSFEs of the restricted model. Asterisks denote that the relative MSFEs are statistically different and (more accurate) than the MSFEs of the restricted model at 1 (***), 5 (**), and 10 (*) percent significance levels.

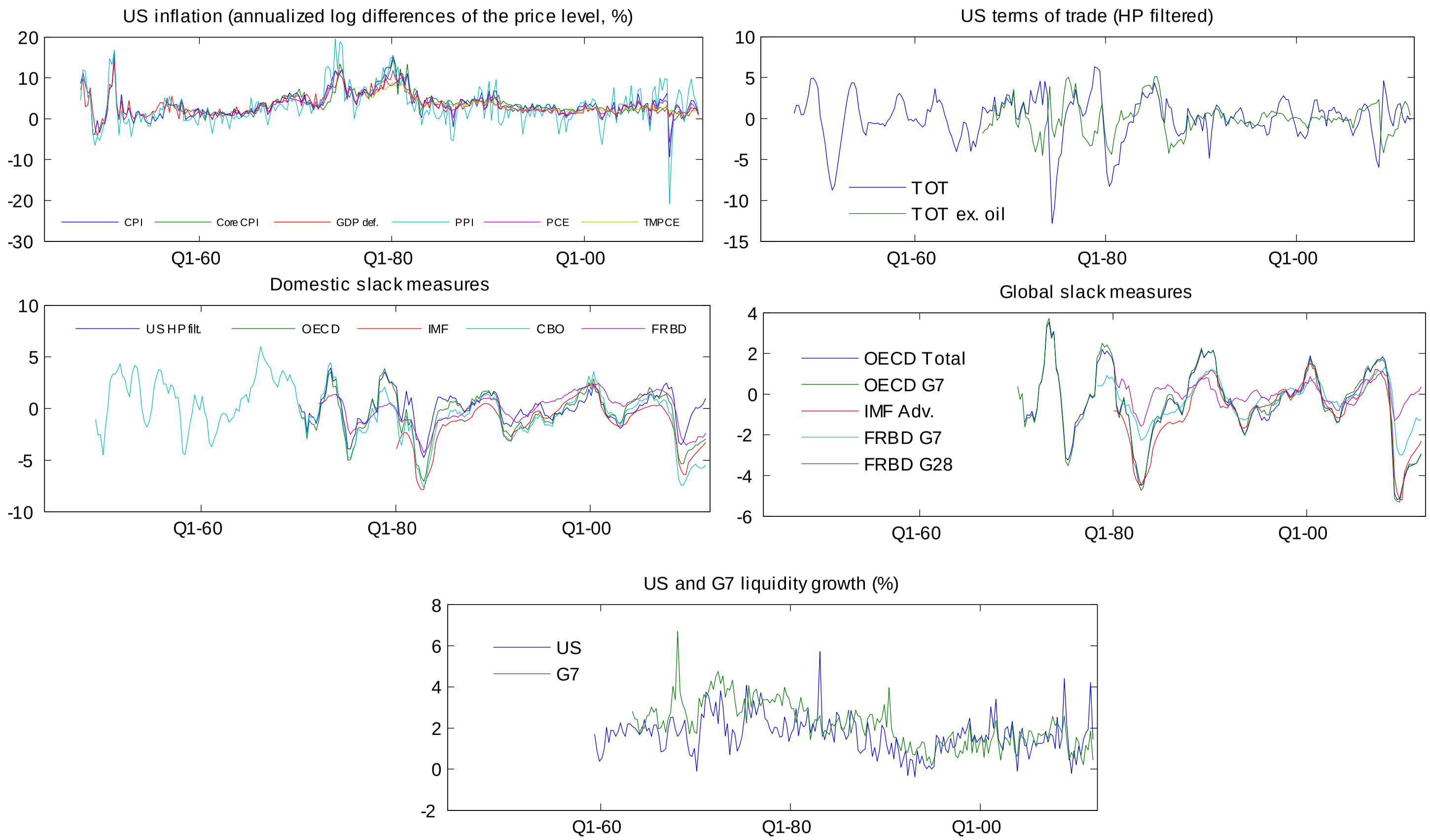

FIGURE 1. Time series plots of the data

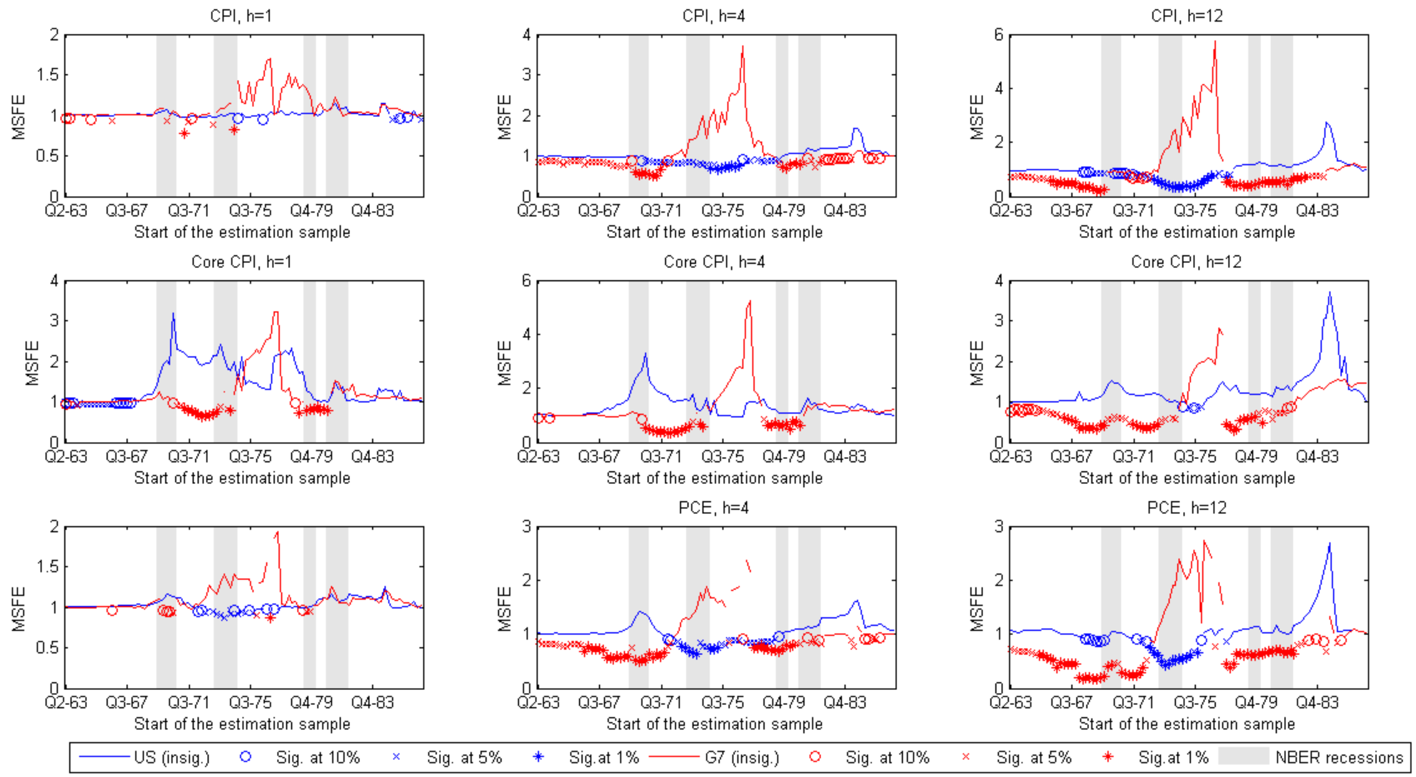

FIGURE 2A. Evolution of the relative MSFEs of the forecasts with the U.S. vs. G7 money growth

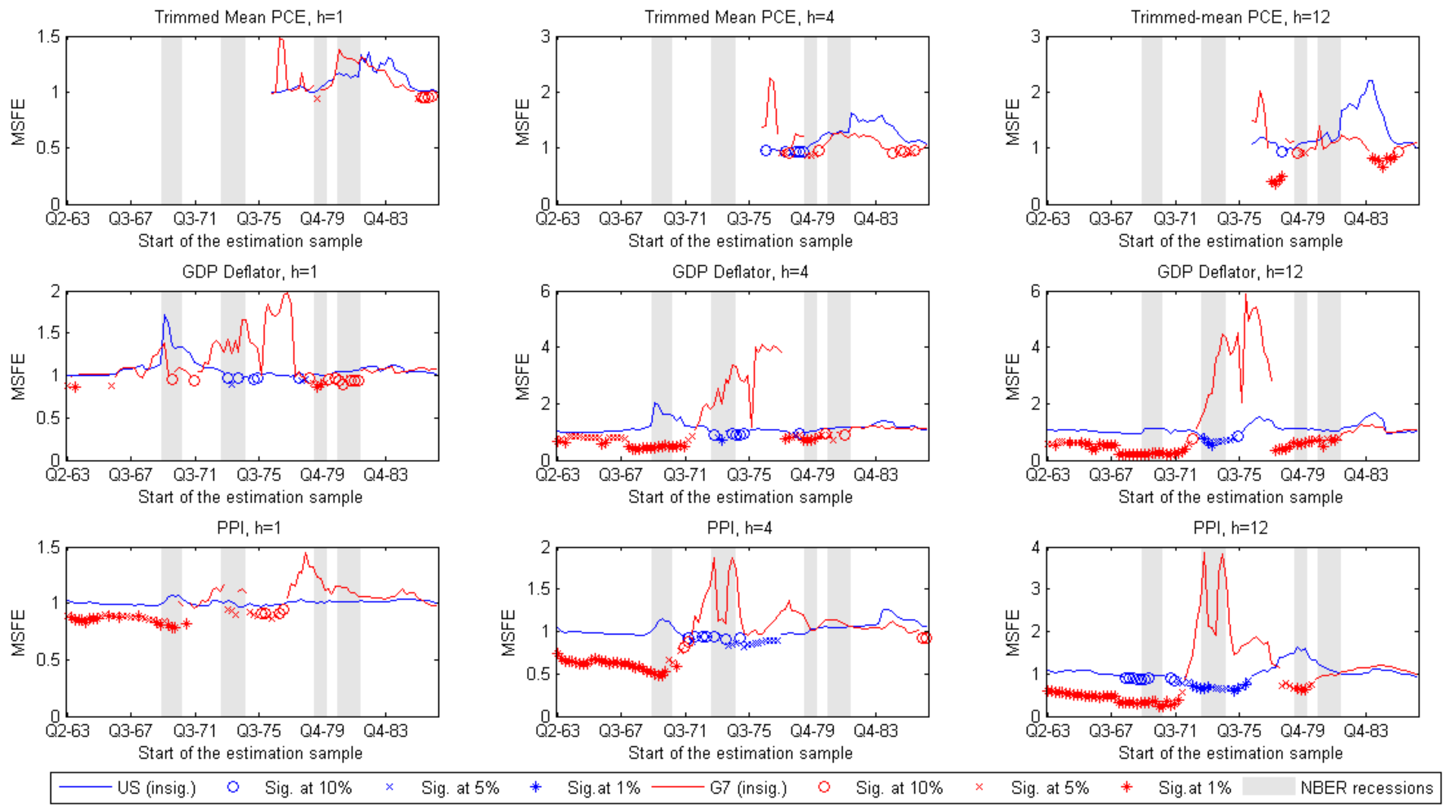

FIGURE 2B. Evolution of the relative MSFEs of the forecasts with the U.S. vs. G7 money growth

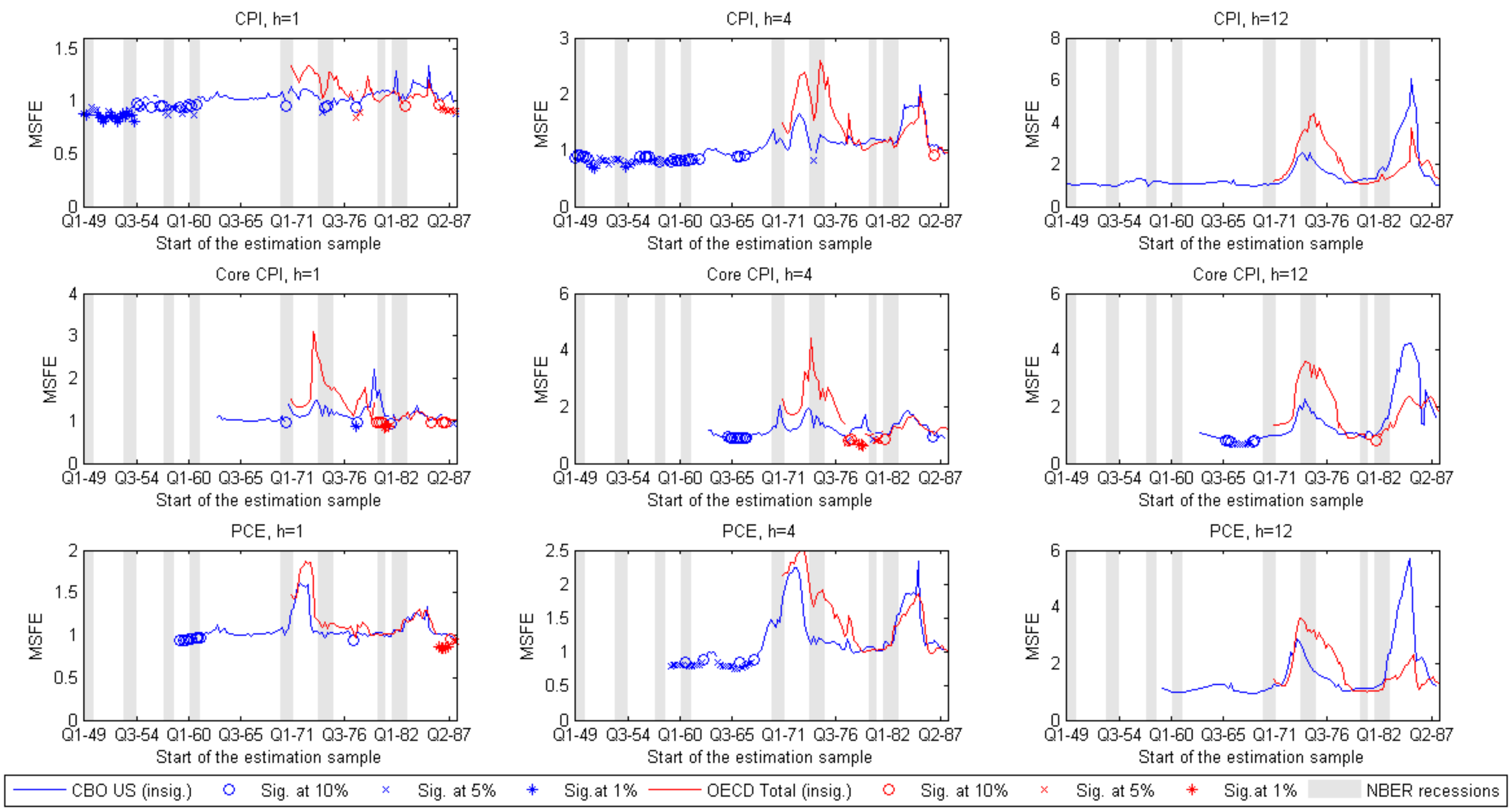

FIGURE 3A. Evolution of the relative MSFEs of the forecasts with the CBO U.S. slack vs. OECD Total slack

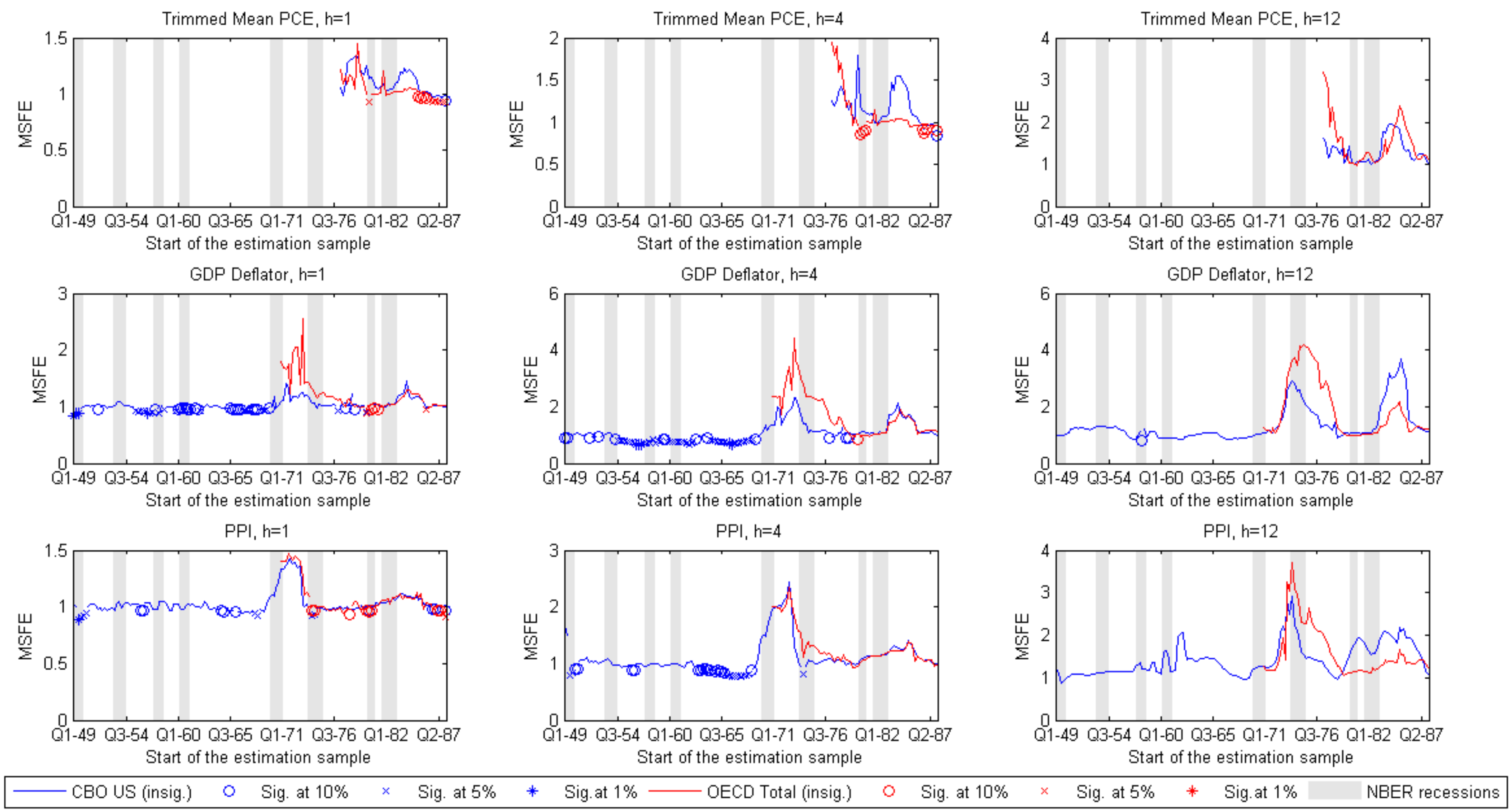

FIGURE 3B. Evolution of the relative MSFEs of the forecasts with the CBO U.S. slack vs. OECD Total slack

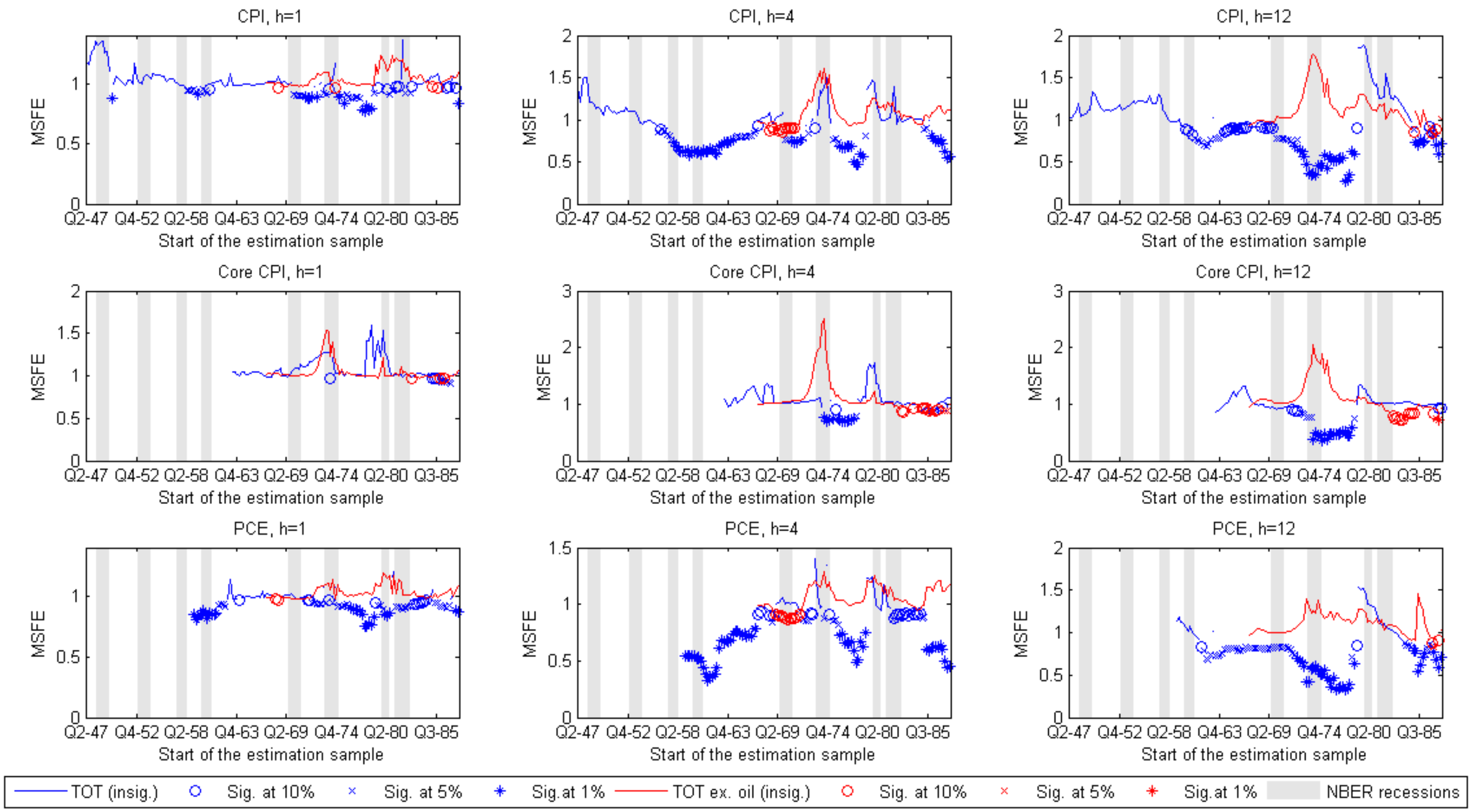

FIGURE 4A. Evolution of the relative MSFEs of the forecasts with terms of trade vs. terms of trade ex. oil

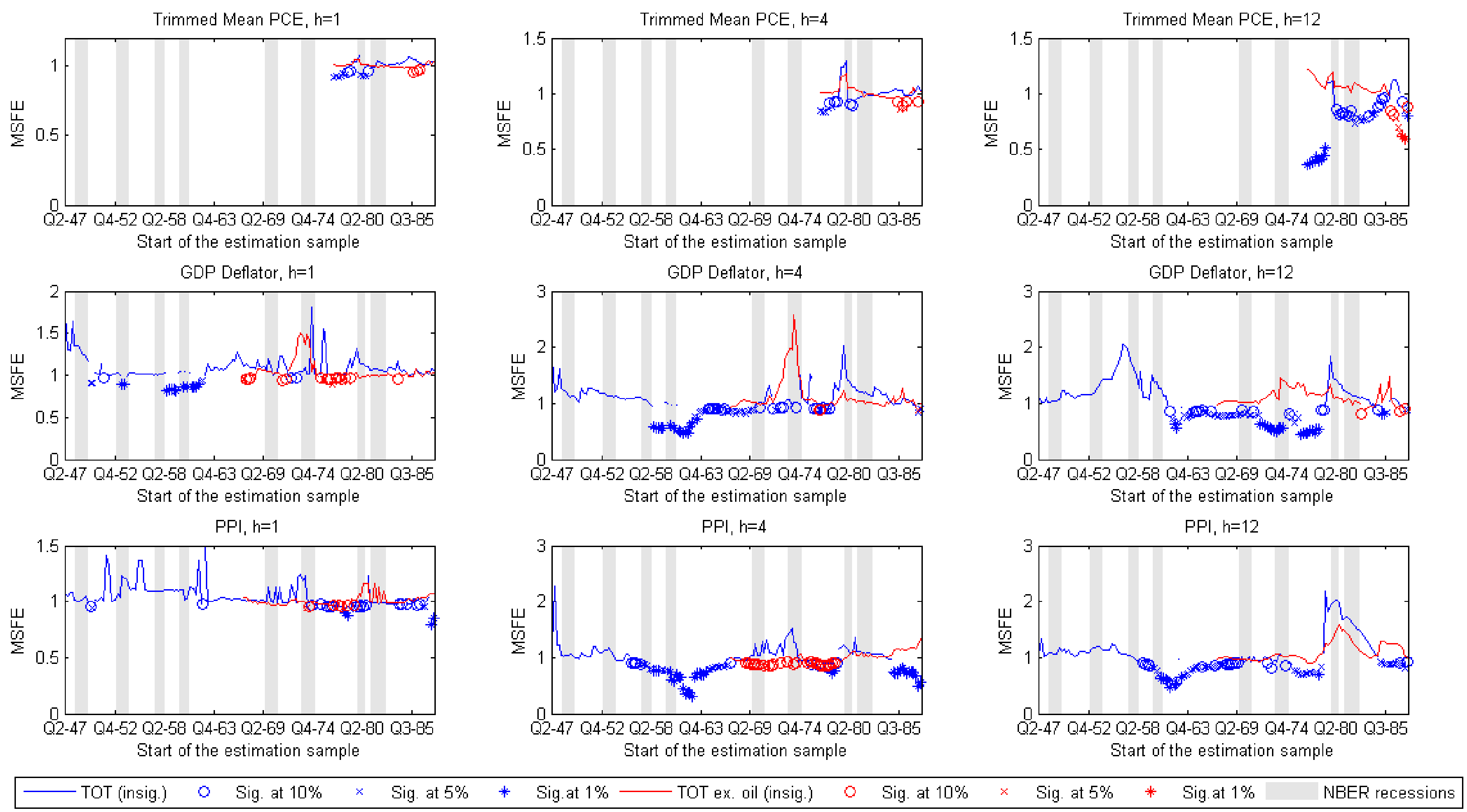

FIGURE 4B. Evolution of the relative MSFEs of the forecasts with terms of trade vs. terms of trade ex. oil

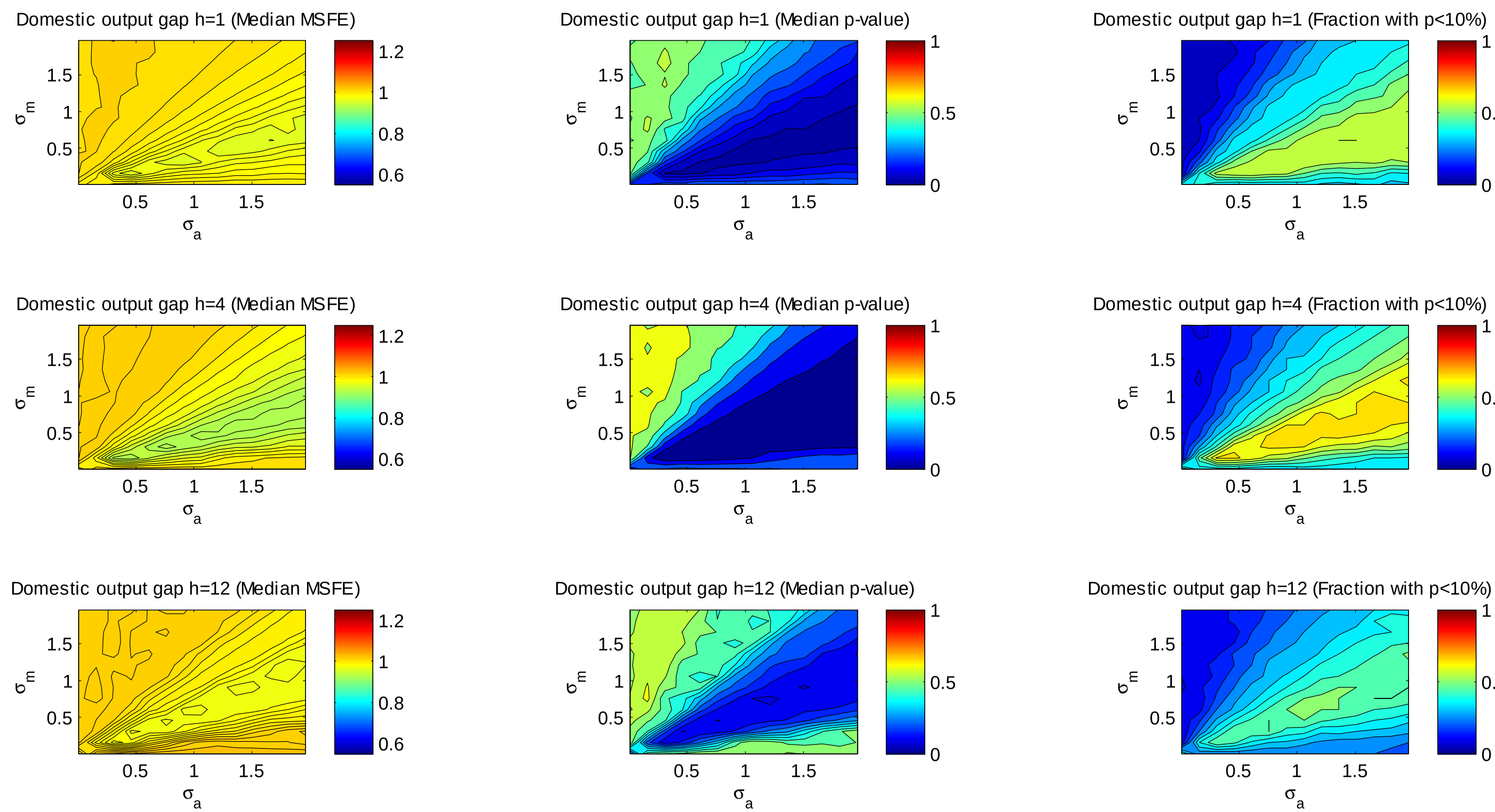

FIGURE 5A. Model's prediction of the relative MSFEs of forecasts with domestic slack as a function of the parameters of *good luck*

Note: MSFEs are relative to the MSFEs of the univariate AR process of inflation (restricted model). Median MSFEs, median p-values and fraction of statistically significant MSFEs in 100 simulations are reported.

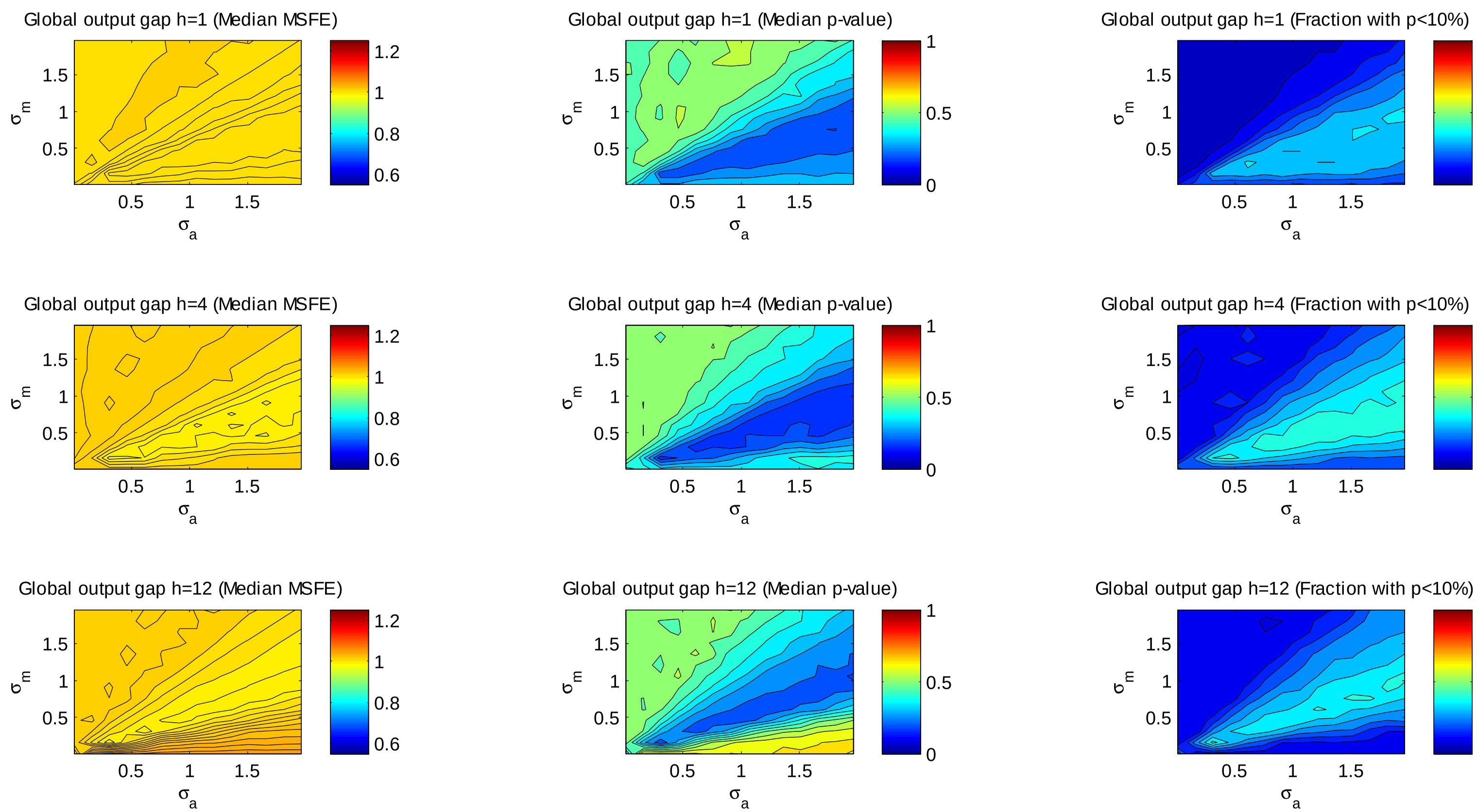

FIGURE 5B. Model's prediction of the relative MSFEs of forecasts with global slack as a function of the parameters of *good luck*

Note: MSFEs are relative to the MSFEs of the univariate AR process of inflation (restricted model).
Median MSFEs, median p-values and fraction of statistically significant MSFEs in 100 simulations are reported.

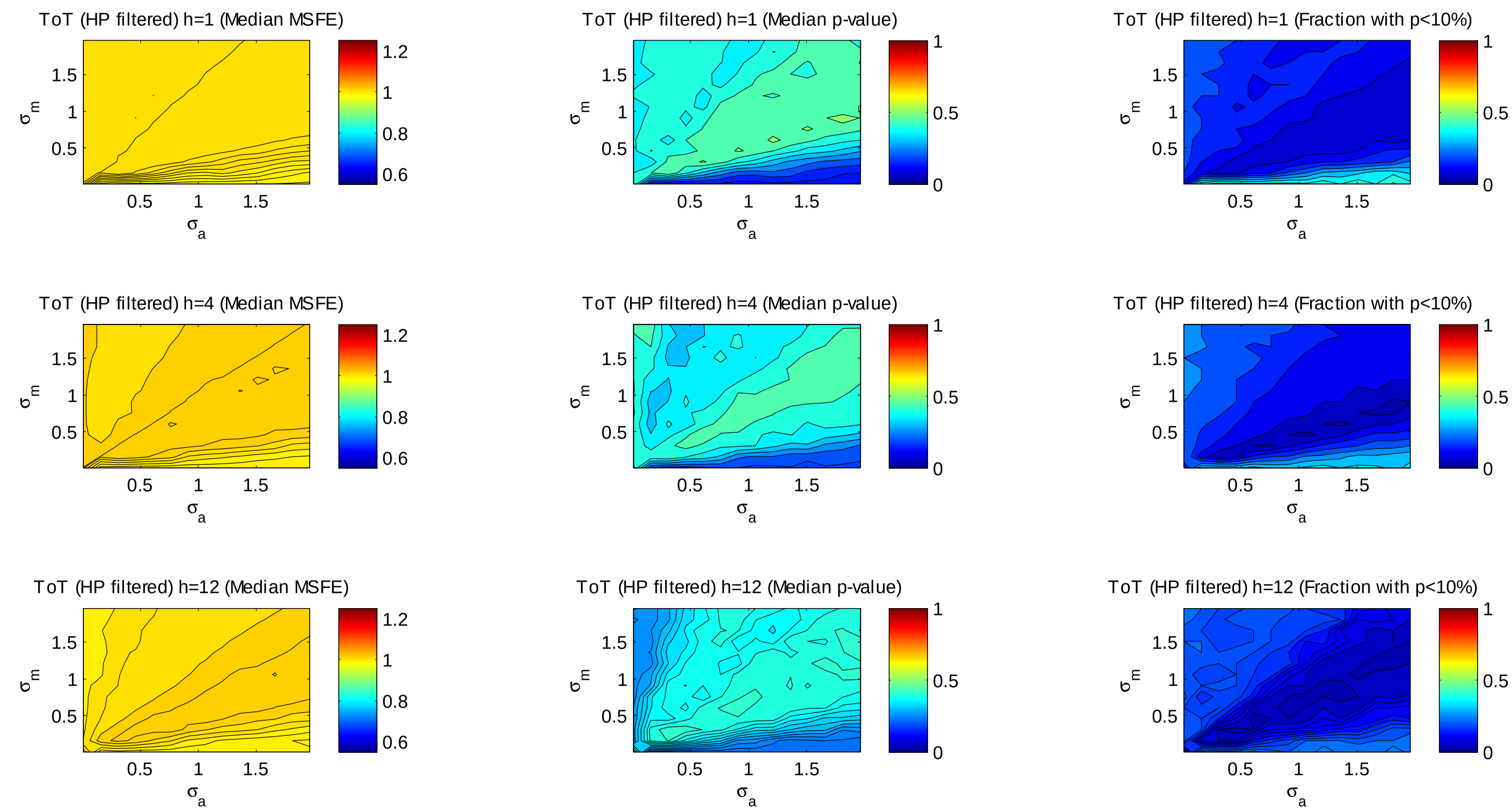

FIGURE 5C. Model's prediction of the relative MSFEs of forecasts with HP-filtered terms of trade as a function of the parameters of *good luck*

Note: MSFEs are relative to the MSFEs of the univariate AR process of inflation (restricted model).

Median MSFEs, median p-values and fraction of statistically significant MSFEs in 100 simulations are reported.

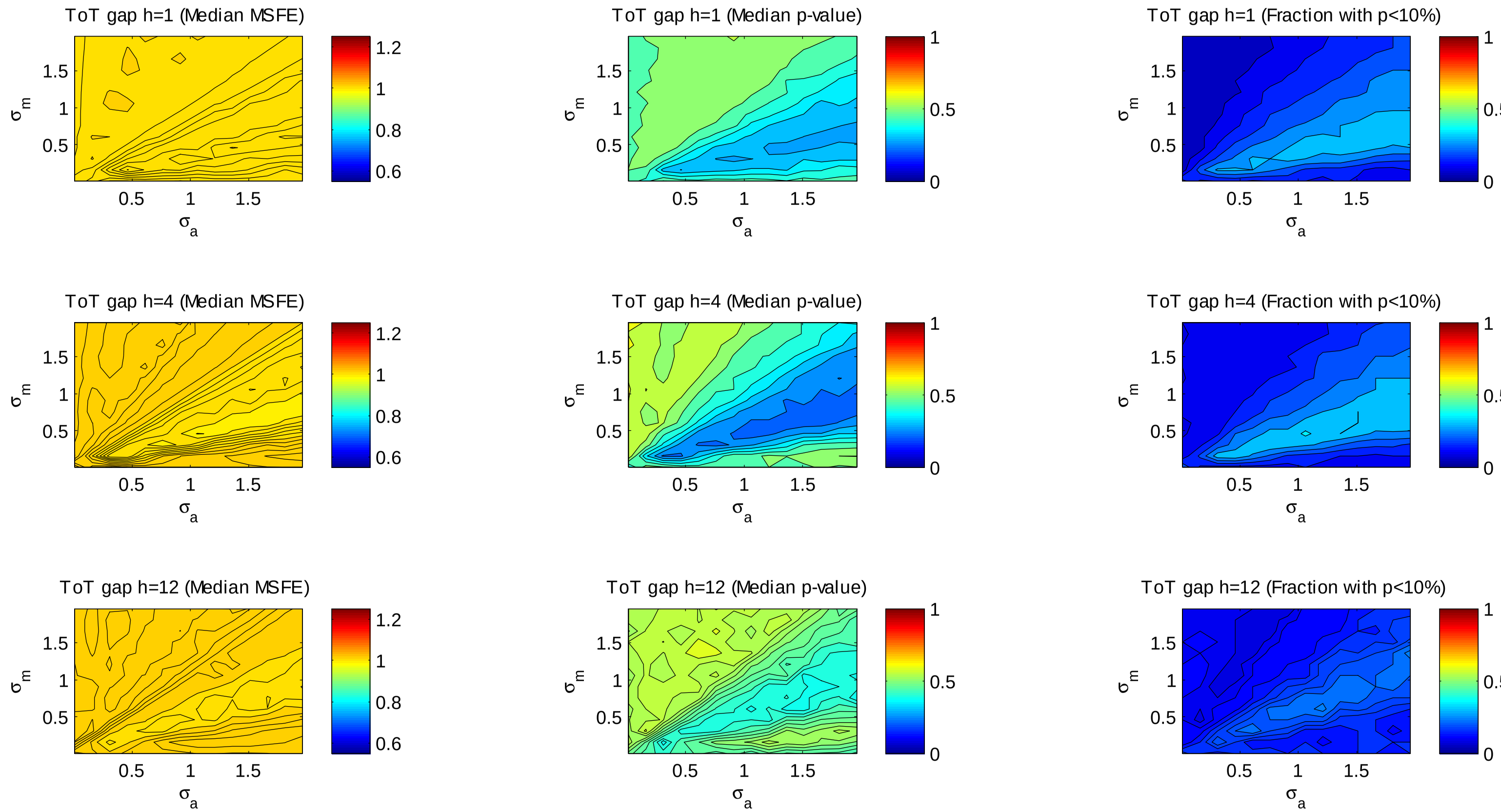

FIGURE 5D. Model's prediction of the relative MSFEs of forecasts with terms of trade gap as a function of the parameters of *good luck*

Note: MSFEs are relative to the MSFEs of the univariate AR process of inflation (restricted model).
Median MSFEs, median p-values and fraction of statistically significant MSFEs in 100 simulations are reported.

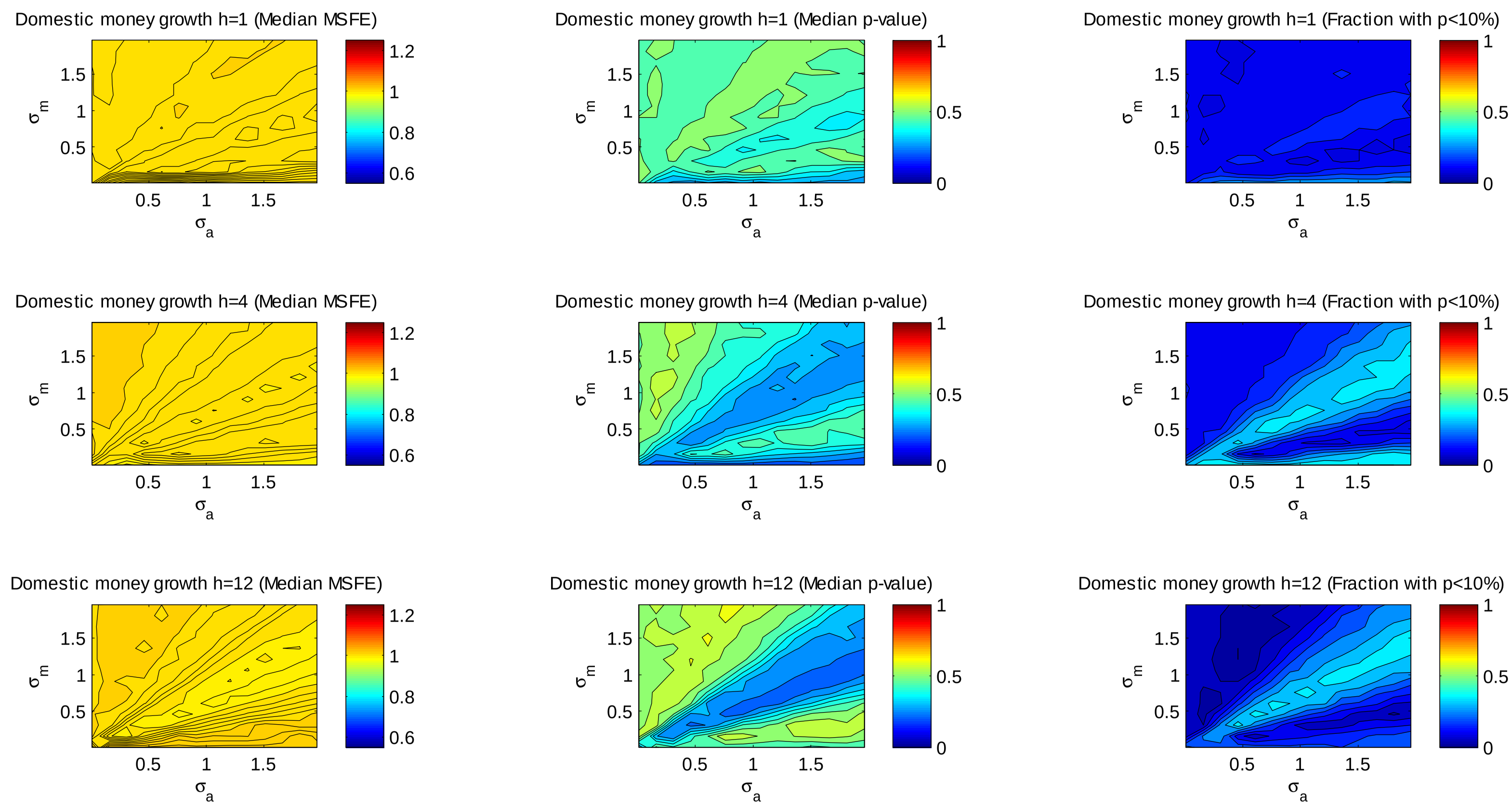

FIGURE 5E. Model's prediction of the relative MSFEs of forecasts with domestic money supply growth as a function of the parameters of *good luck*

Note: MSFEs are relative to the MSFEs of the univariate AR process of inflation (restricted model).

Median MSFEs, median p-values and fraction of statistically significant MSFEs in 100 simulations are reported.

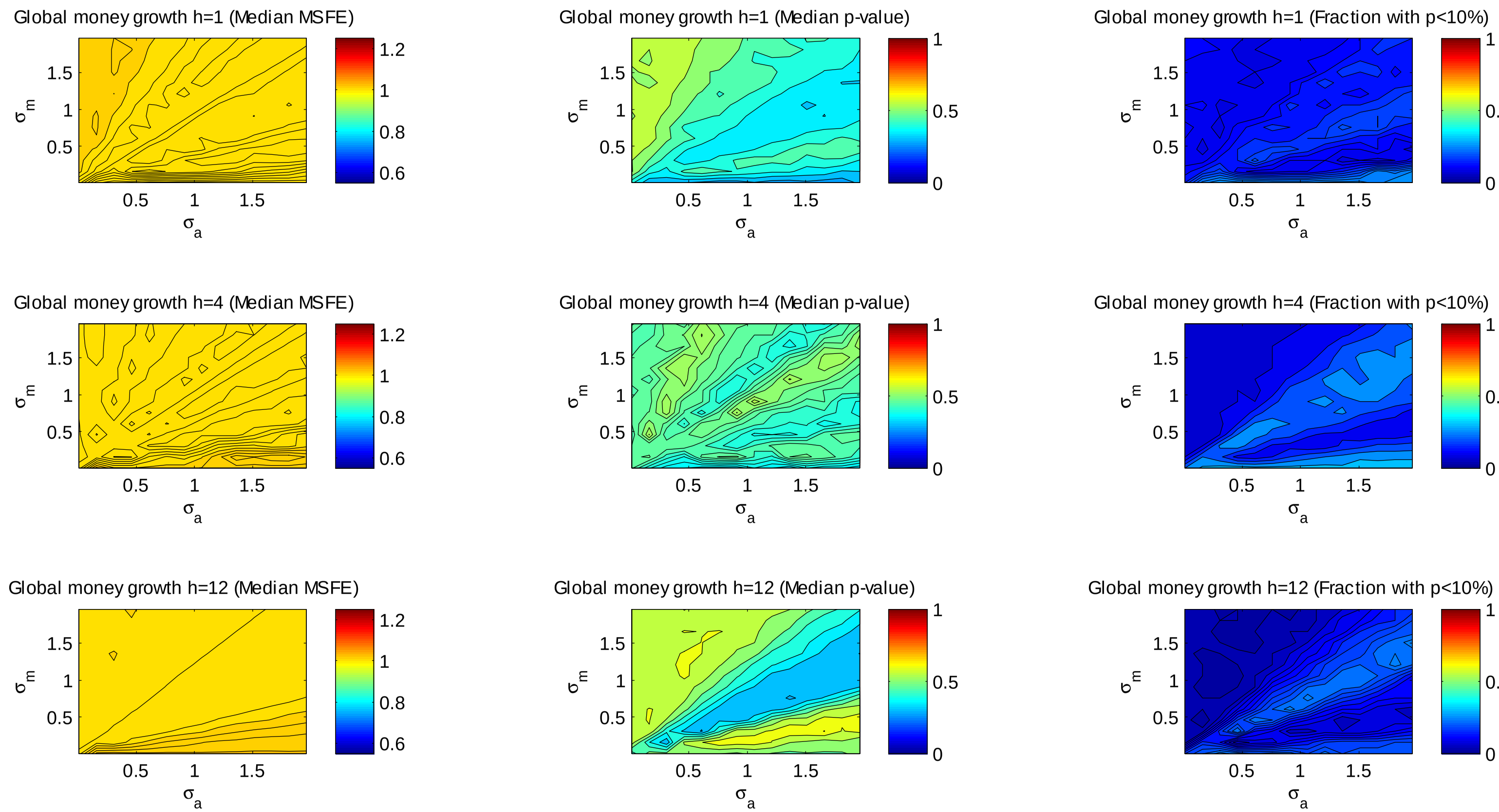

FIGURE 5F. Model's prediction of the relative MSFEs of forecasts with global money supply growth as a function of the parameters of *good luck*

Note: MSFEs are relative to the MSFEs of the univariate AR process of inflation (restricted model).
Median MSFEs, median p-values and fraction of statistically significant MSFEs in 100 simulations are reported.

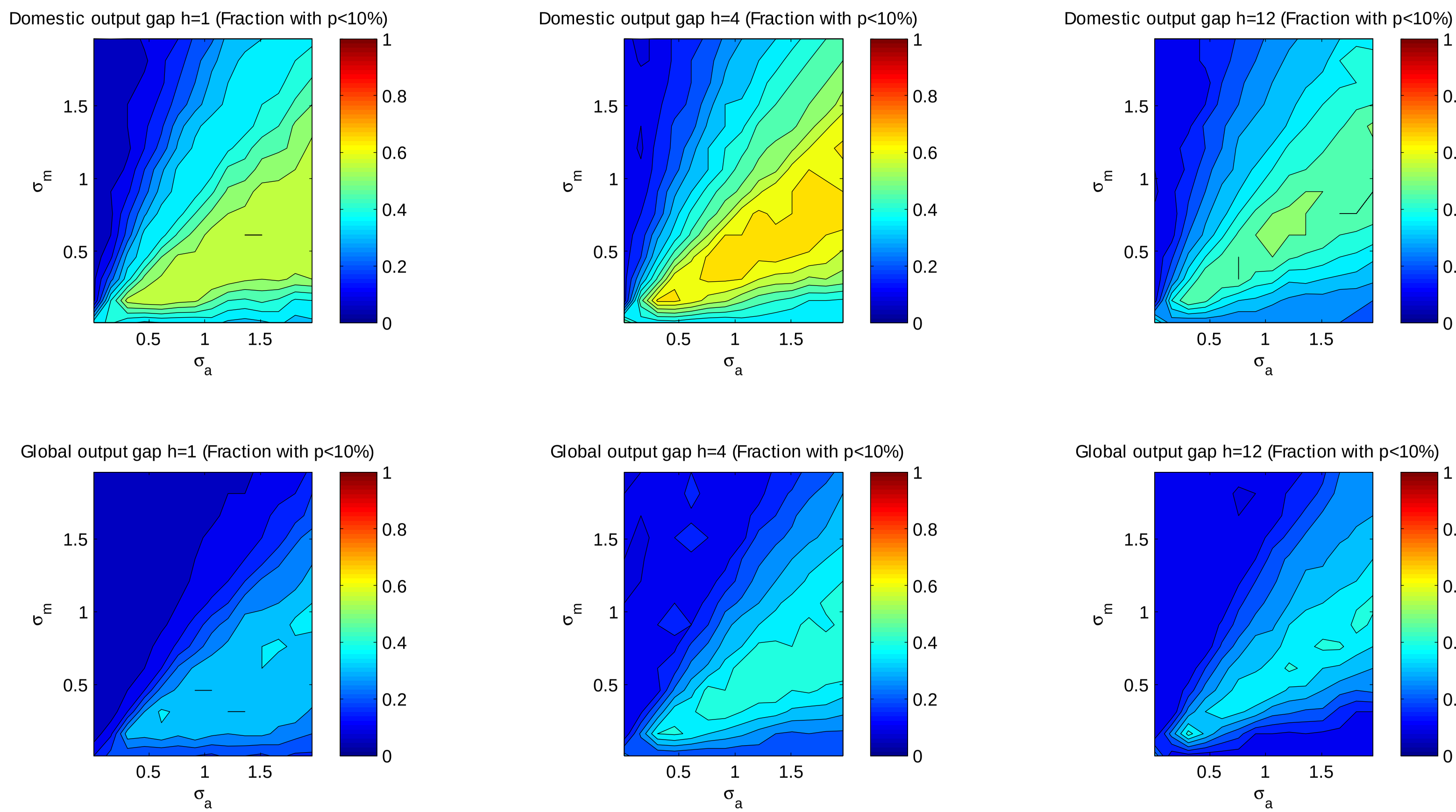

FIGURE 6A. Comparison of the forecasting performances of simulated domestic and global output gap as a function of the parameters of *good luck*

Note: Fraction of statistically significant MSFEs in 100 simulations are reported.

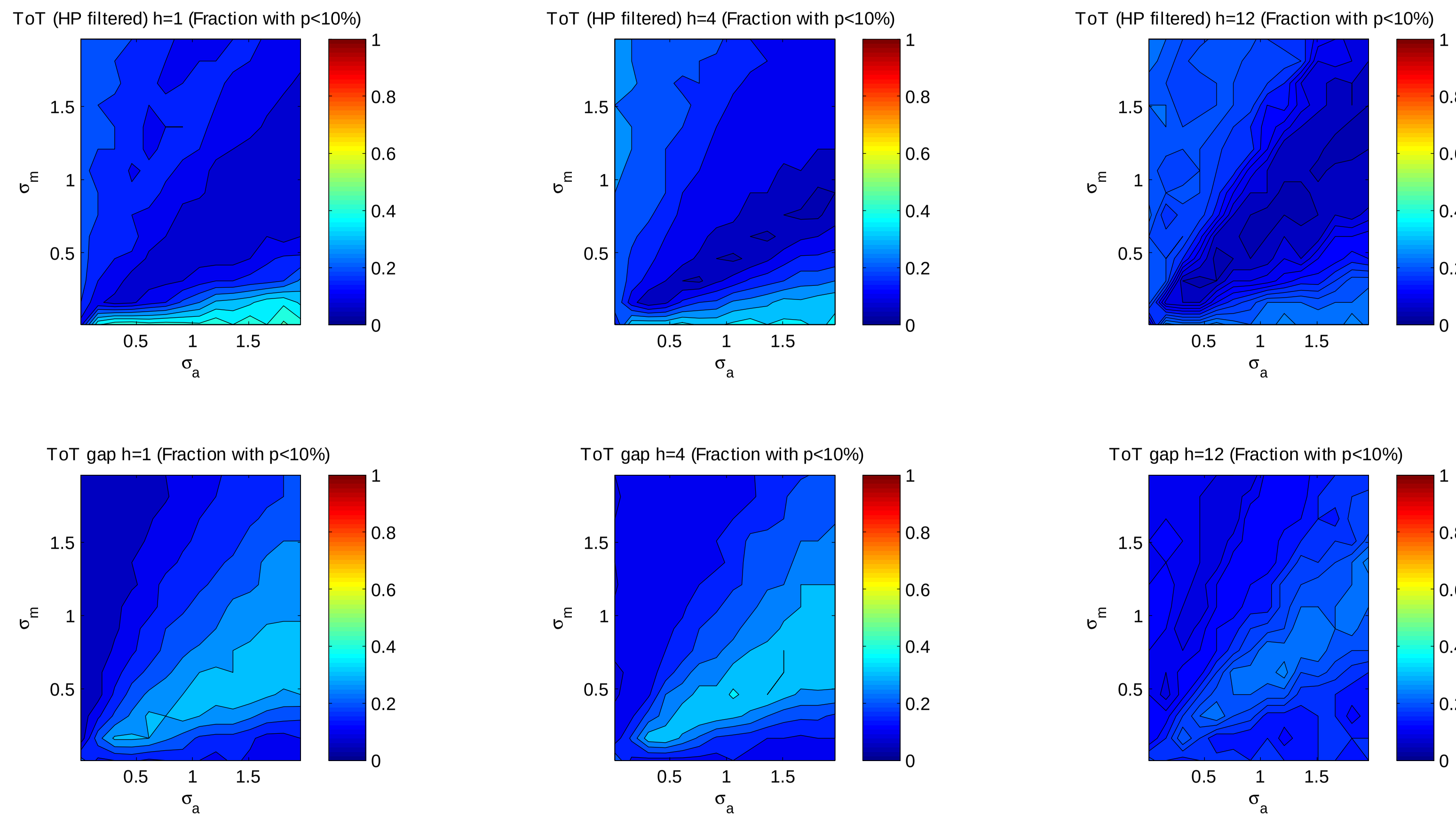

FIGURE 6B. Comparison of the forecasting performances of simulated HP-filtered ToT and ToT gap as a function of the parameters of *good luck*

Note: Fraction of statistically significant MSFEs in 100 simulations are reported.

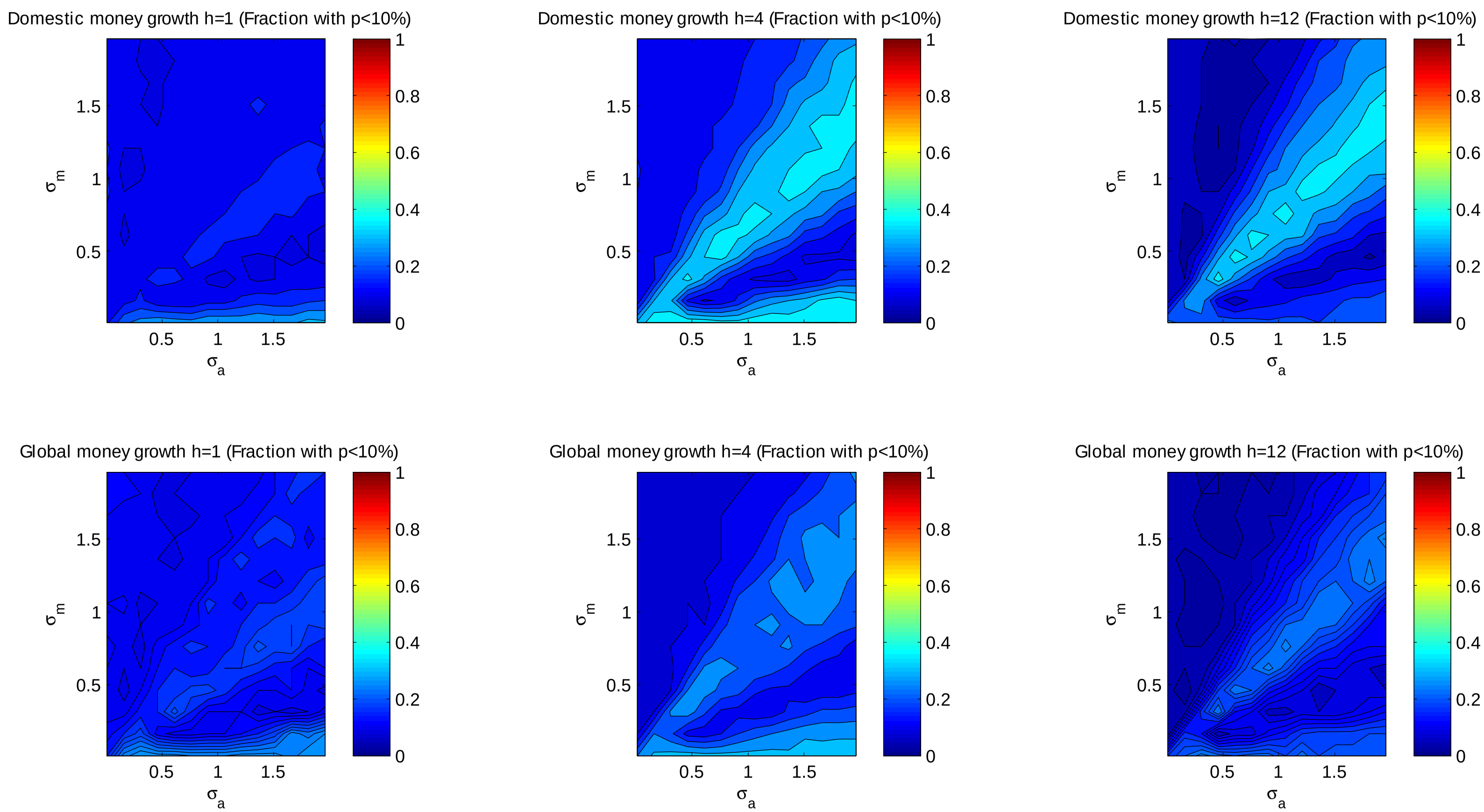

FIGURE 6C. Comparison of the forecasting performances of simulated domestic and global money supply growth as a function of the parameters of *good luck*

Note: Fraction of statistically significant MSFEs in 100 simulations are reported.

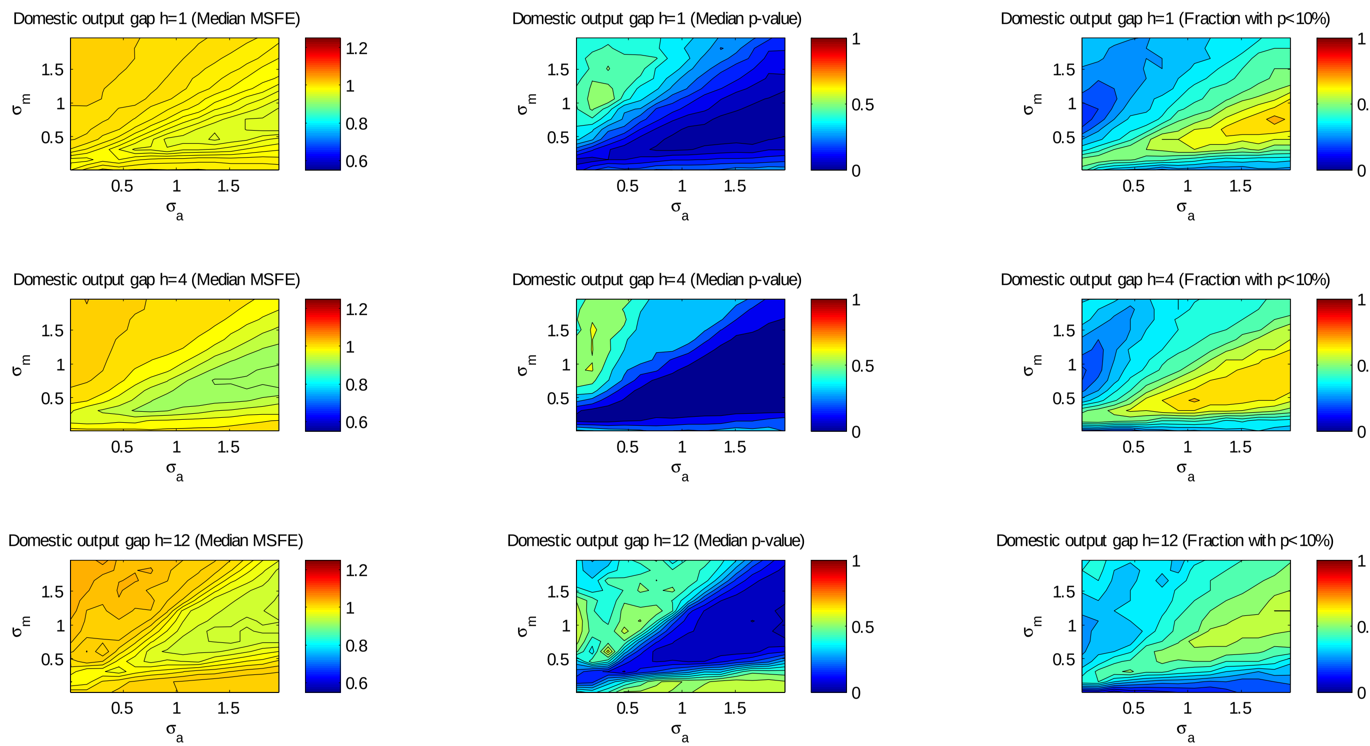

FIGURE 7A. Model's prediction of the relative MSFEs of forecasts with domestic slack as a function of the parameters of *good luck (asymmetric experiment)*

Note: MSFEs are relative to the MSFEs of the univariate AR process of inflation (restricted model). Median MSFEs, median p-values and fraction of statistically significant MSFEs in 100 simulations are reported.

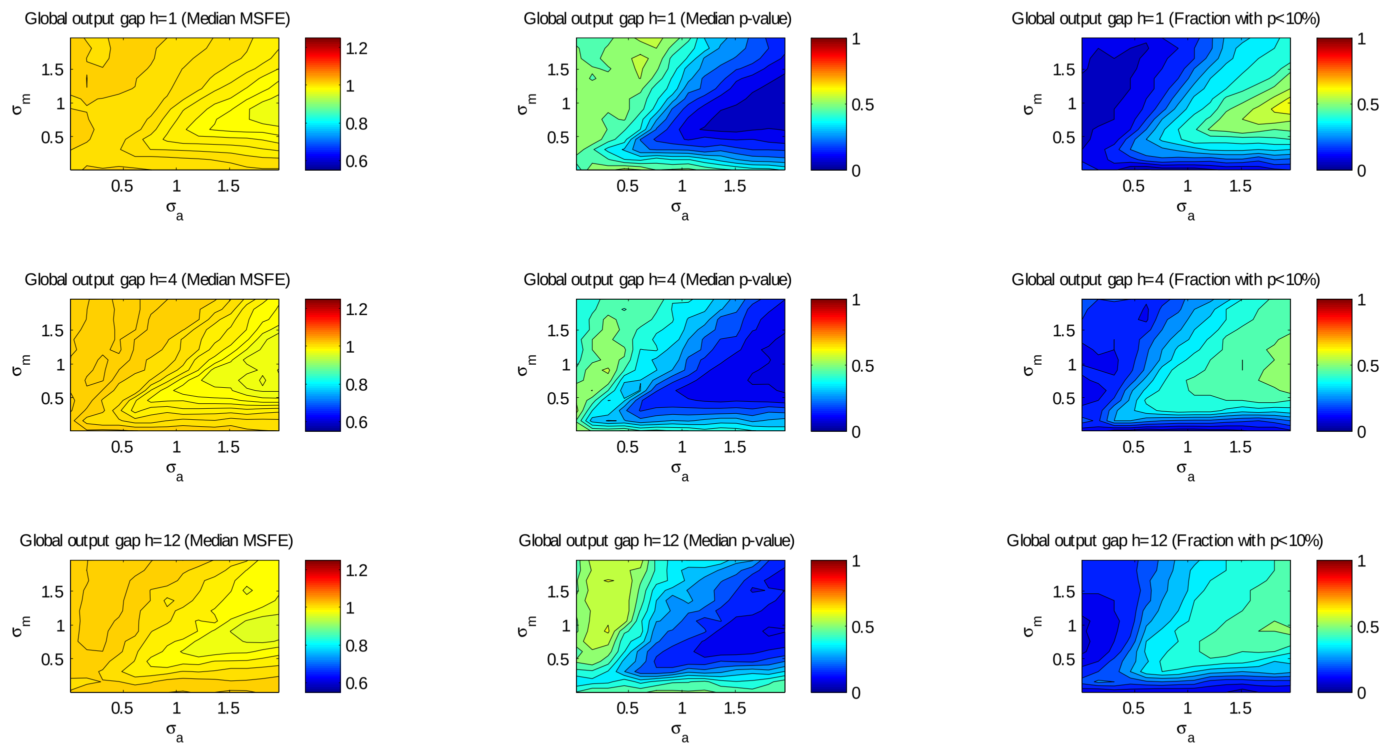

FIGURE 7B. Model's prediction of the relative MSFEs of forecasts with global slack as a function of the parameters of *good luck (asymmetric experiment)*

Note: MSFEs are relative to the MSFEs of the univariate AR process of inflation (restricted model). Median MSFEs, median p-values and fraction of statistically significant MSFEs in 100 simulations are reported.

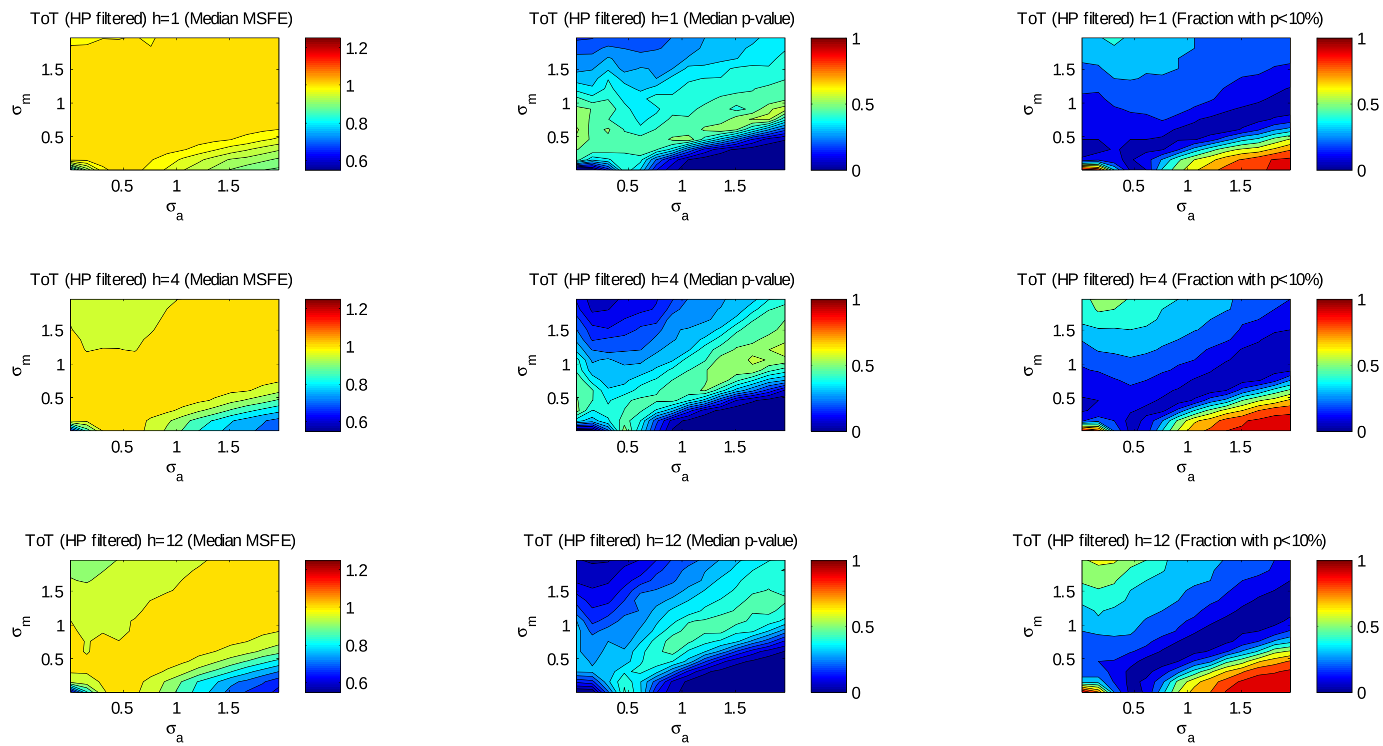

FIGURE 7C. Model's prediction of the relative MSFEs of forecasts with HP-filtered terms of trade as a function of the parameters of *good luck (asymmetric experiment)*

Note: MSFEs are relative to the MSFEs of the univariate AR process of inflation (restricted model).

Median MSFEs, median p-values and fraction of statistically significant MSFEs in 100 simulations are reported.

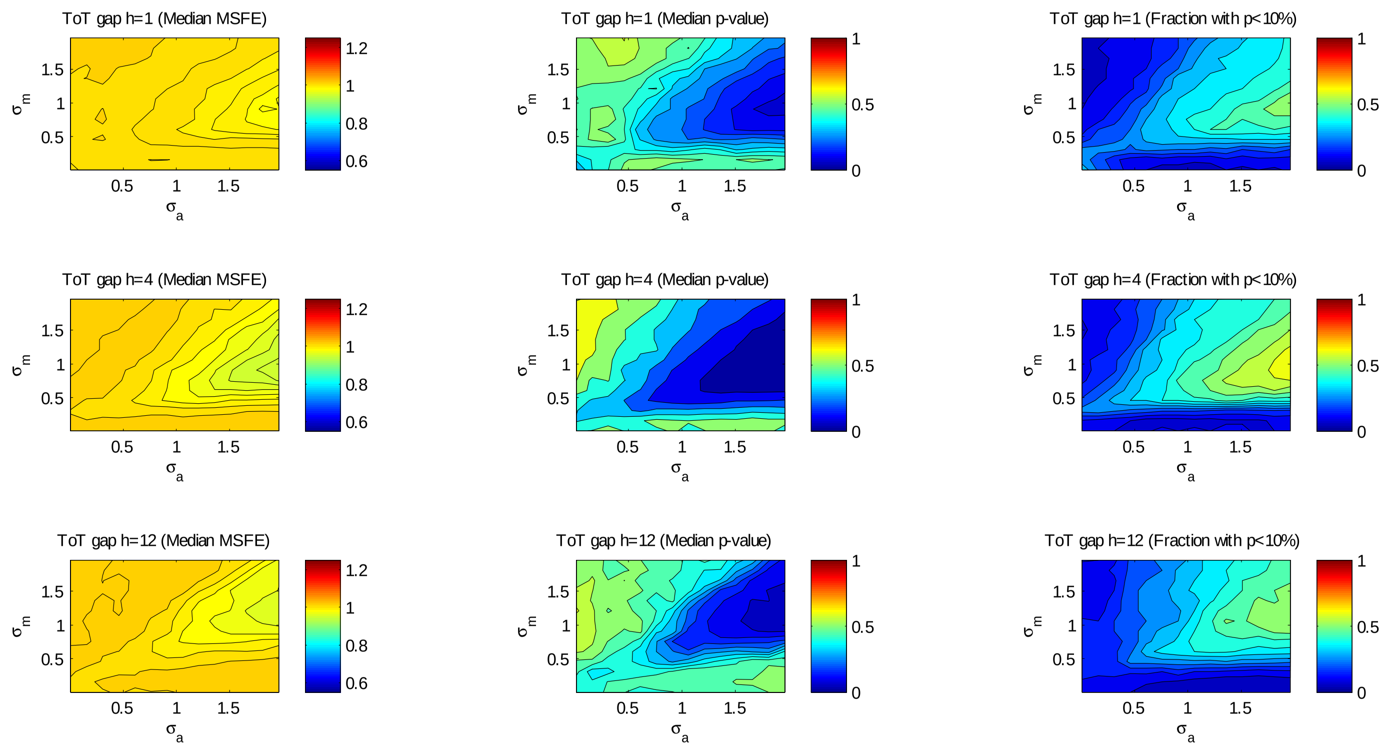

FIGURE 7D. Model's prediction of the relative MSFEs of forecasts with terms of trade gap as a function of the parameters of *good luck (asymmetric experiment)*

Note: MSFEs are relative to the MSFEs of the univariate AR process of inflation (restricted model).

Median MSFEs, median p-values and fraction of statistically significant MSFEs in 100 simulations are reported.

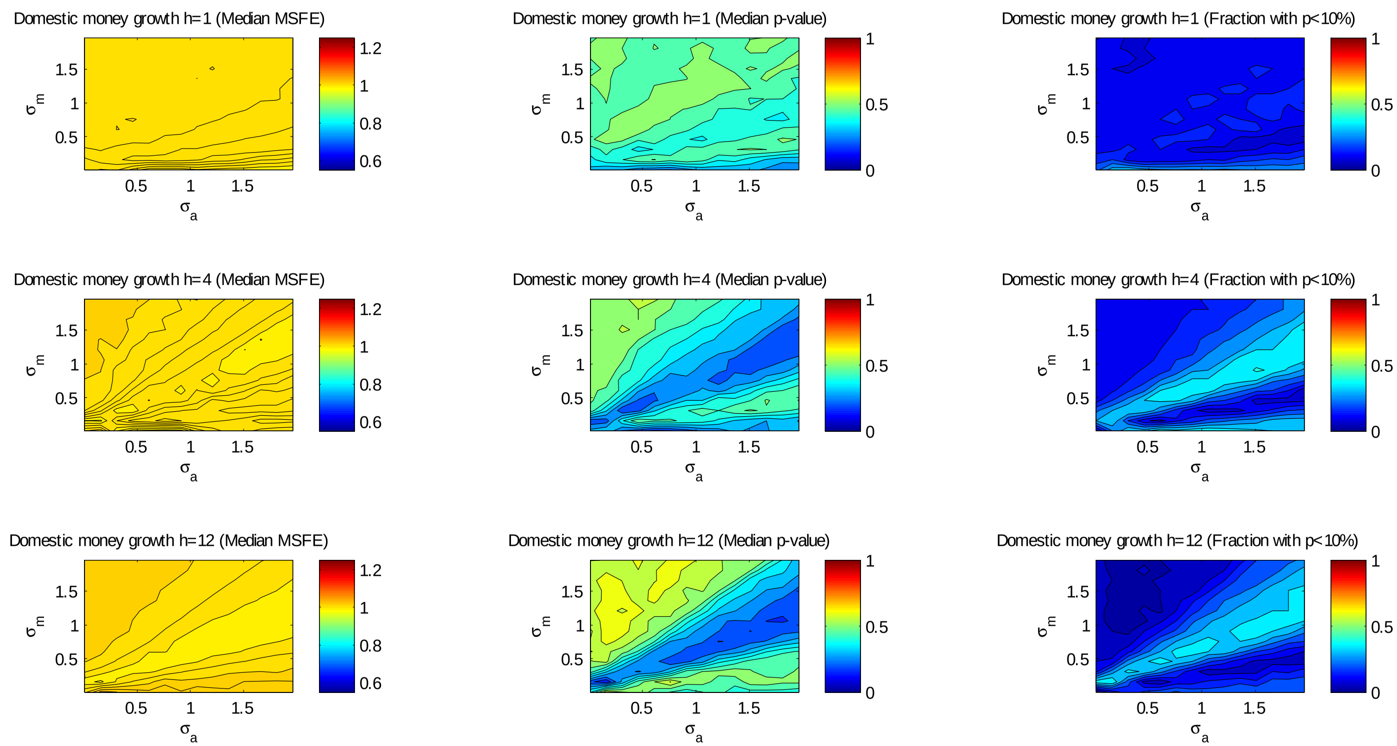

FIGURE 7E. Model's prediction of the relative MSFEs of forecasts with domestic money supply growth as a function of the parameters of *good luck (asymmetric experiment)*

Note: MSFEs are relative to the MSFEs of the univariate AR process of inflation (restricted model).

Median MSFEs, median p-values and fraction of statistically significant MSFEs in 100 simulations are reported.

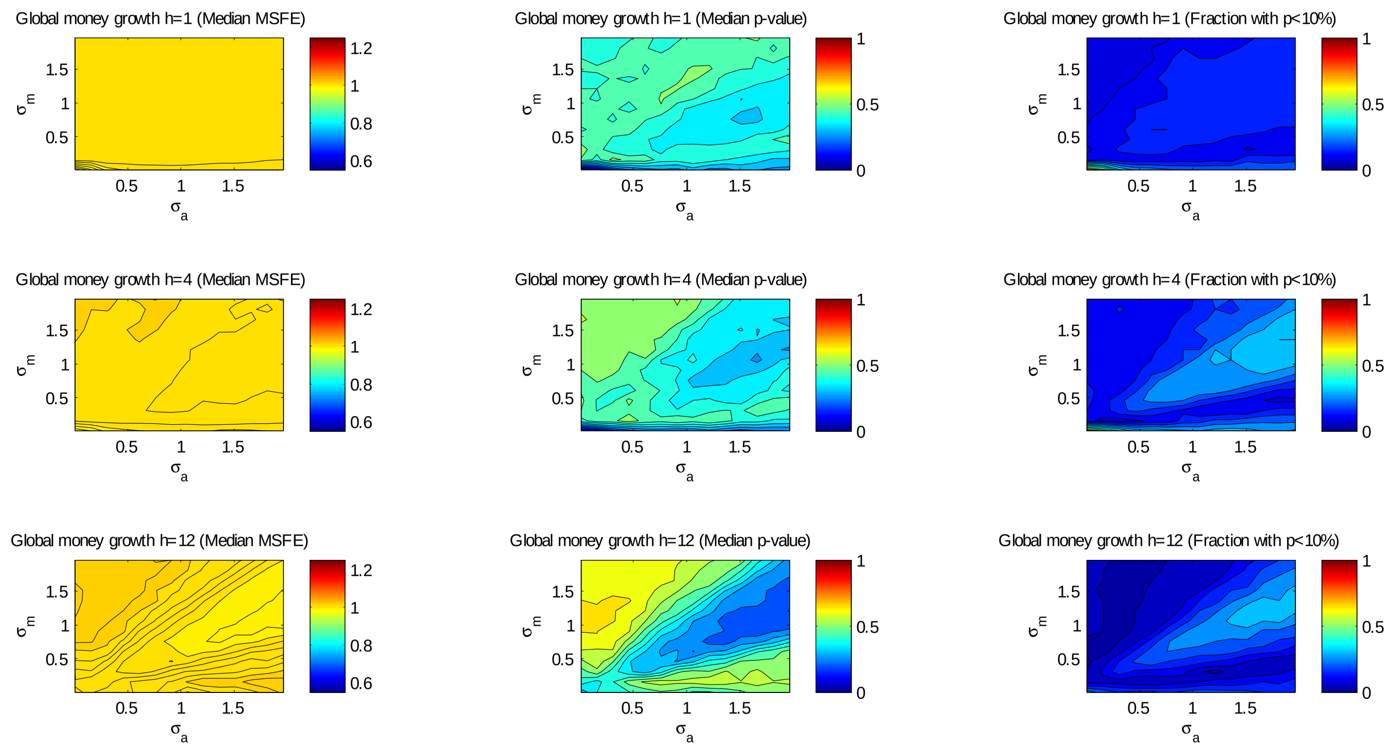

FIGURE 7F. Model's prediction of the relative MSFEs of forecasts with global money supply growth as a function of the parameters of *good luck (asymmetric experiment)*

Note: MSFEs are relative to the MSFEs of the univariate AR process of inflation (restricted model).

Median MSFEs, median p-values and fraction of statistically significant MSFEs in 100 simulations are reported.

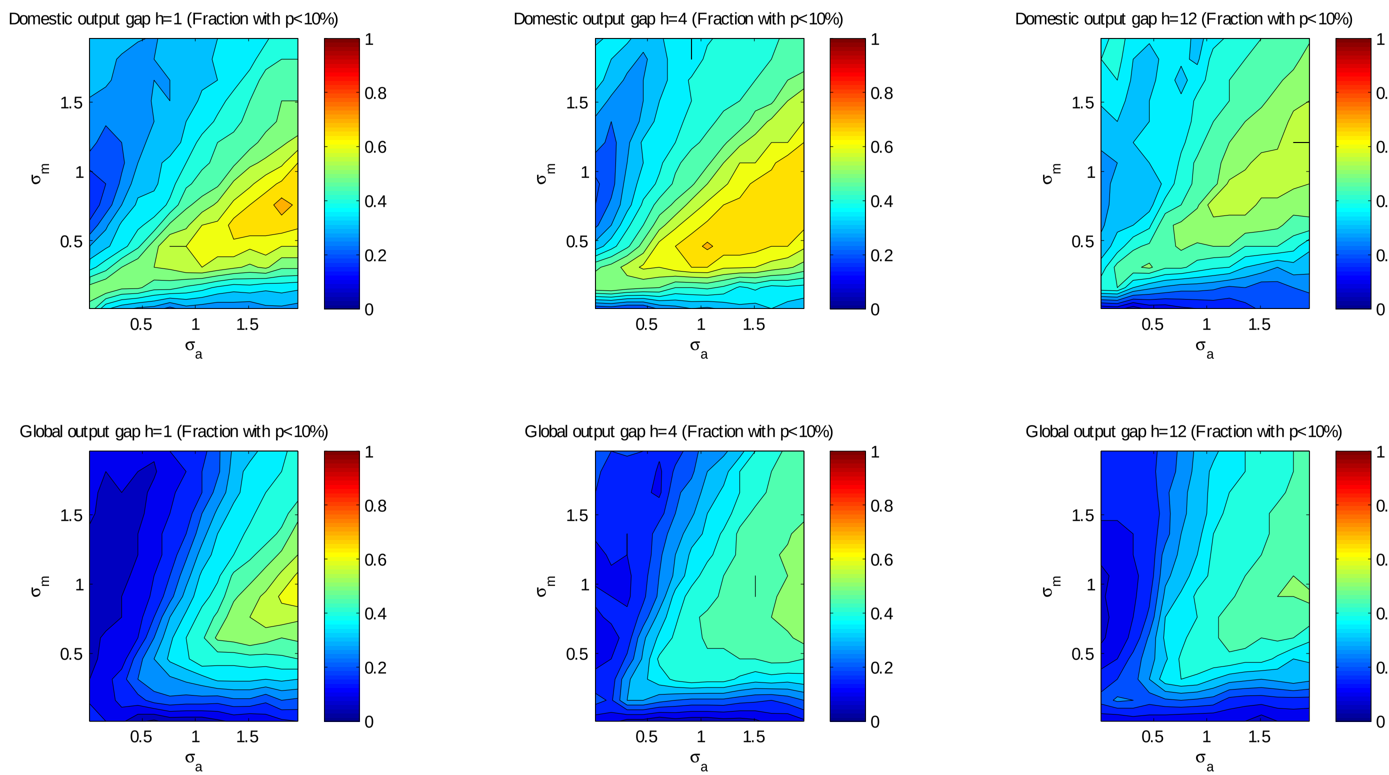

FIGURE 8A. Comparison of the forecasting performances of simulated domestic and global output gap as a function of the parameters of *good luck (asymmetric experiment)*

Note: Fraction of statistically significant MSFEs in 100 simulations are reported.

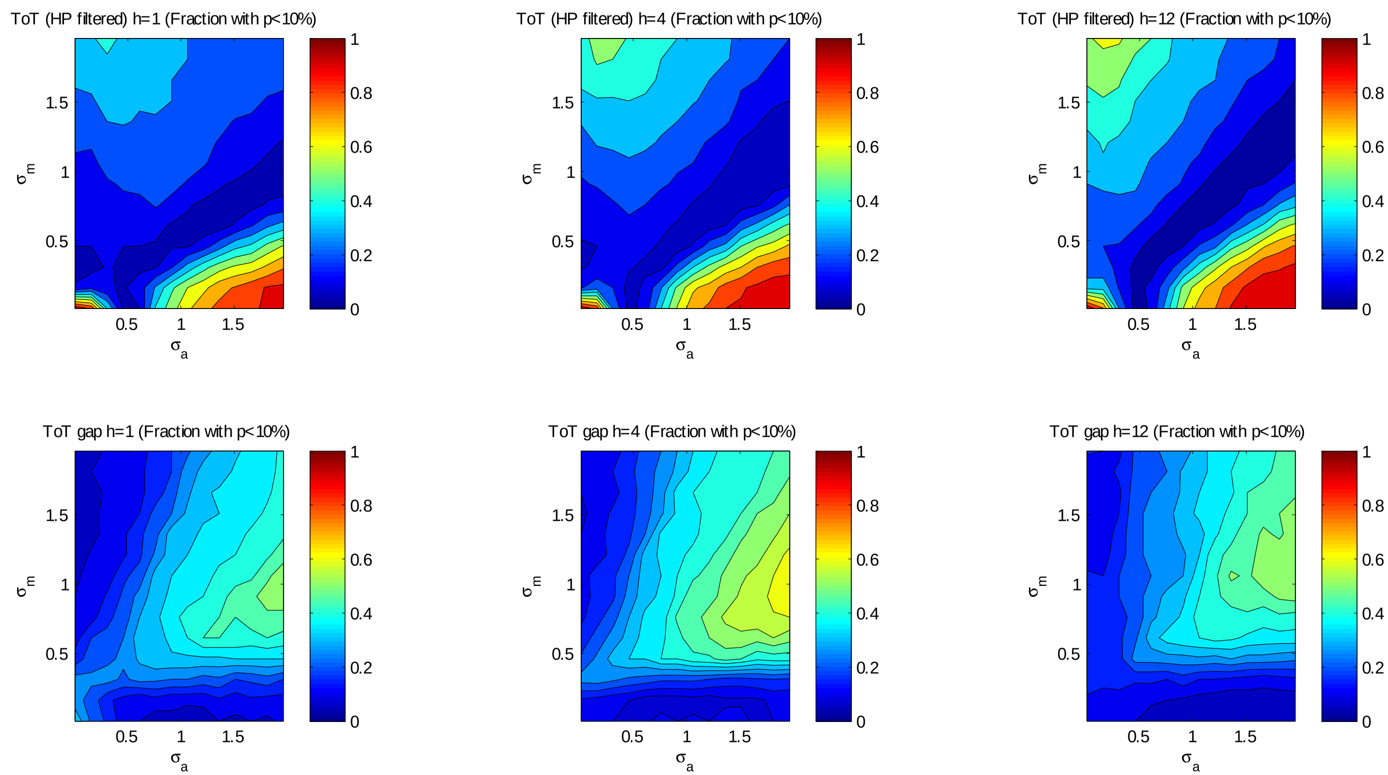

FIGURE 8B. Comparison of the forecasting performances of simulated HP-filtered ToT and ToT gap as a function of the parameters of *good luck (asymmetric experiment)*

Note: Fraction of statistically significant MSFEs in 100 simulations are reported.

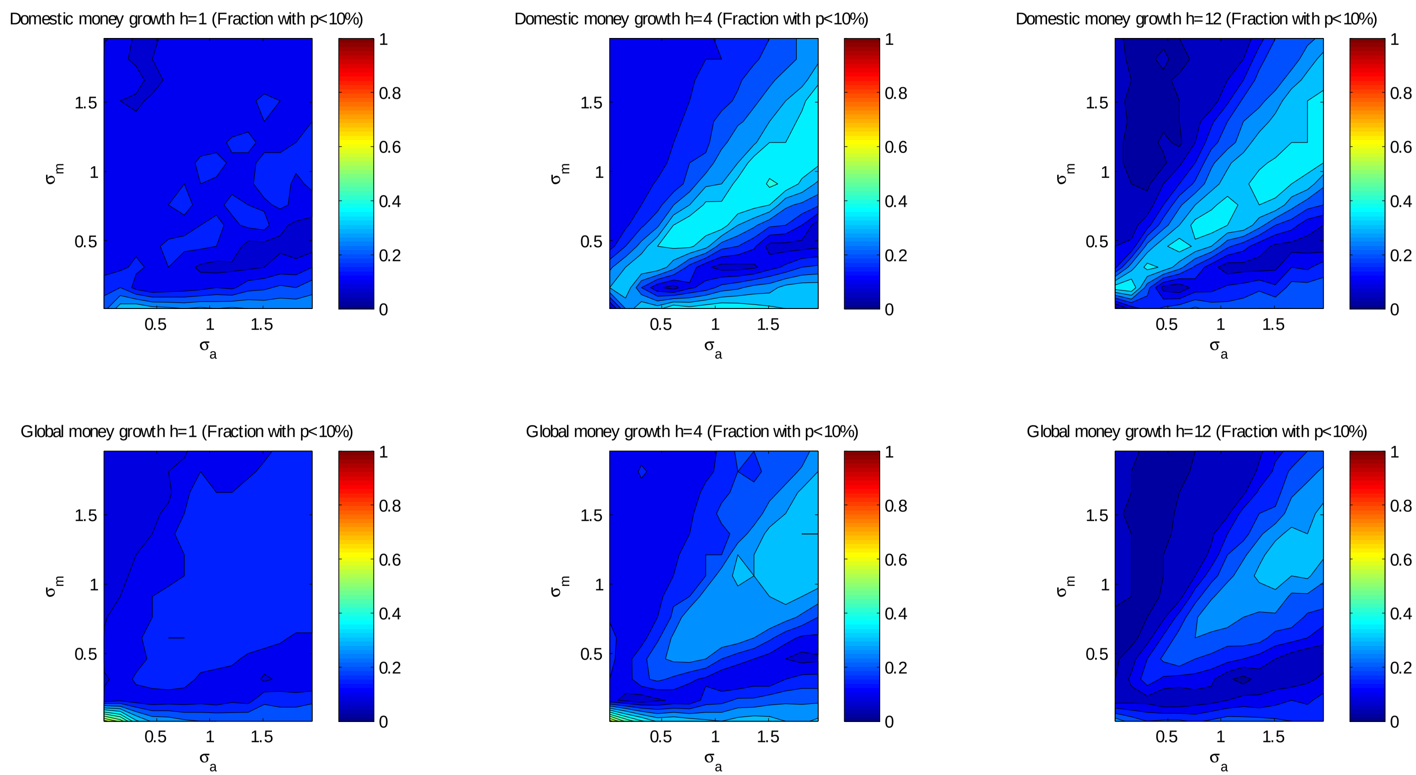

FIGURE 8C. Comparison of the forecasting performances of simulated domestic and global money supply growth as a function of the parameters of *good luck (asymmetric experiment)*

Note: Fraction of statistically significant MSFEs in 100 simulations are reported.

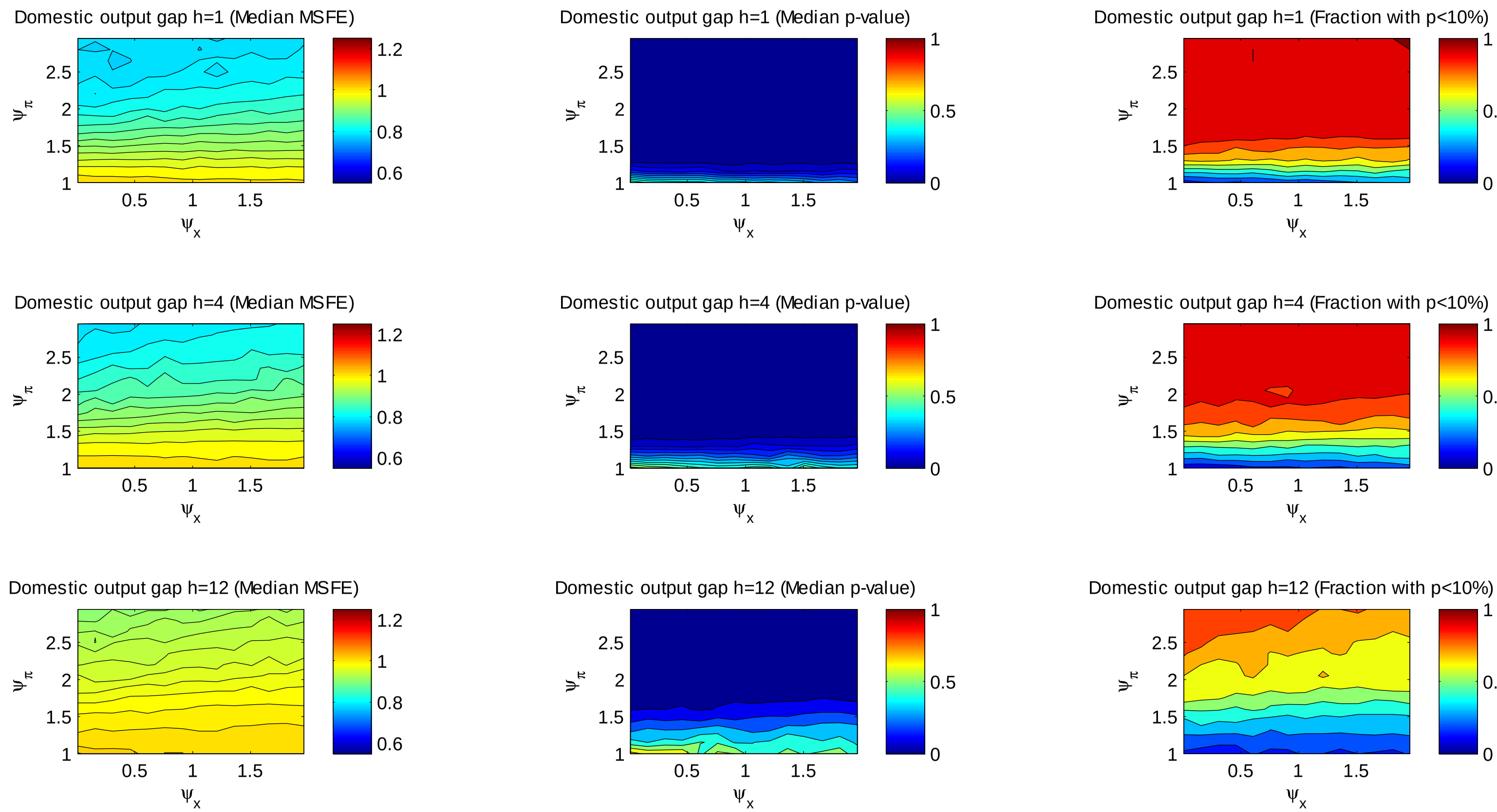

FIGURE 9A. Model's prediction of the relative MSFEs of forecasts with domestic output gap as a function of the parameters of *monetary policy (low inertia)*

Note: MSFEs are relative to the MSFEs of the univariate AR process of inflation (restricted model).

Median MSFEs, median p-values and fraction of statistically significant MSFEs in 100 simulations are reported.

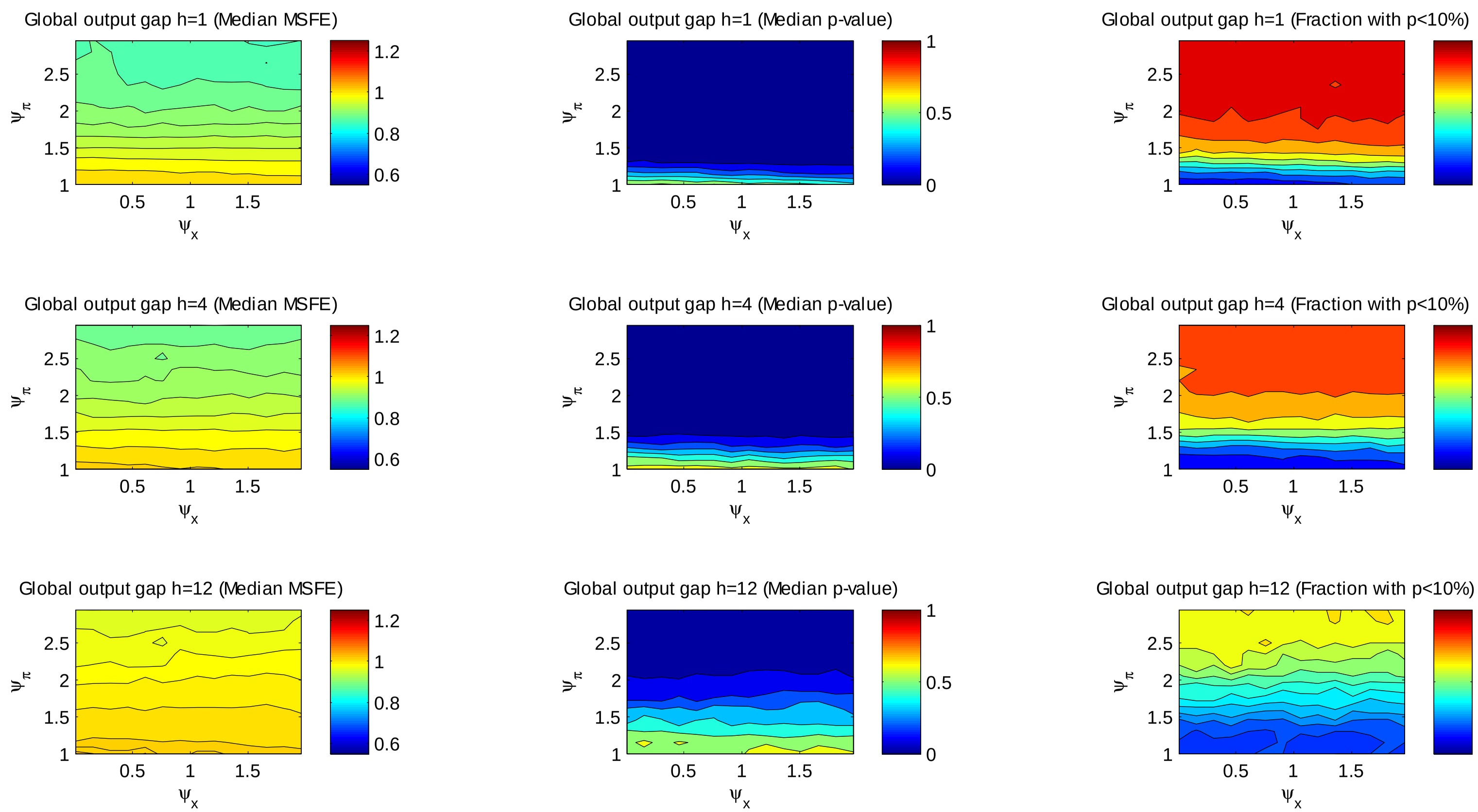

FIGURE 9B. Model's prediction of the relative MSFEs of forecasts with global output gap as a function of the parameters of *monetary policy (low inertia)*

Note: MSFEs are relative to the MSFEs of the univariate AR process of inflation (restricted model). Median MSFEs, median p-values and fraction of statistically significant MSFEs in 100 simulations are reported.

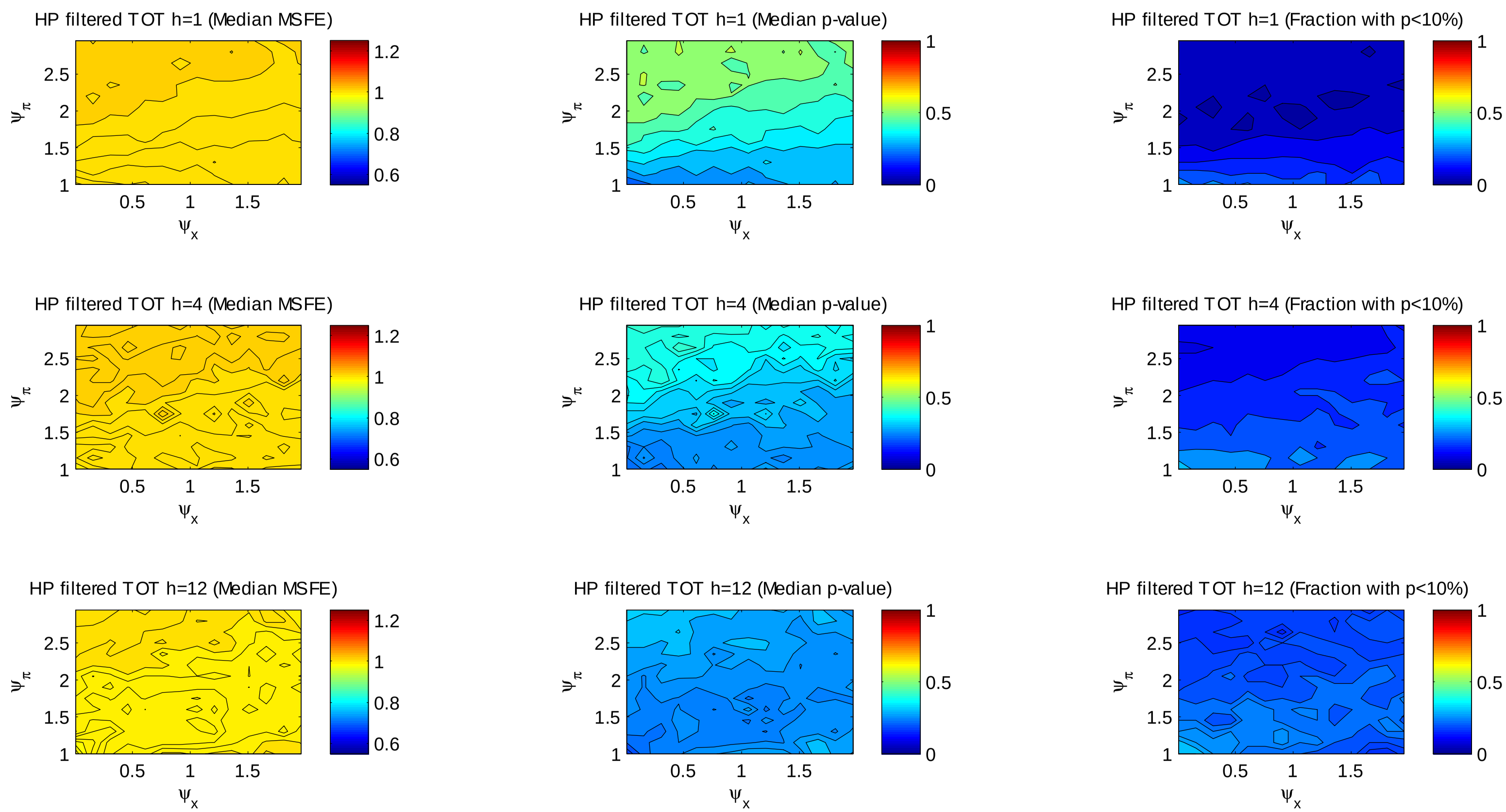

FIGURE 9C. Model's prediction of the relative MSFEs of forecasts with HP-filtered TOT as a function of the parameters of *monetary policy (low inertia)*

Note: MSFEs are relative to the MSFEs of the univariate AR process of inflation (restricted model).
Median MSFEs, median p-values and fraction of statistically significant MSFEs in 100 simulations are reported.

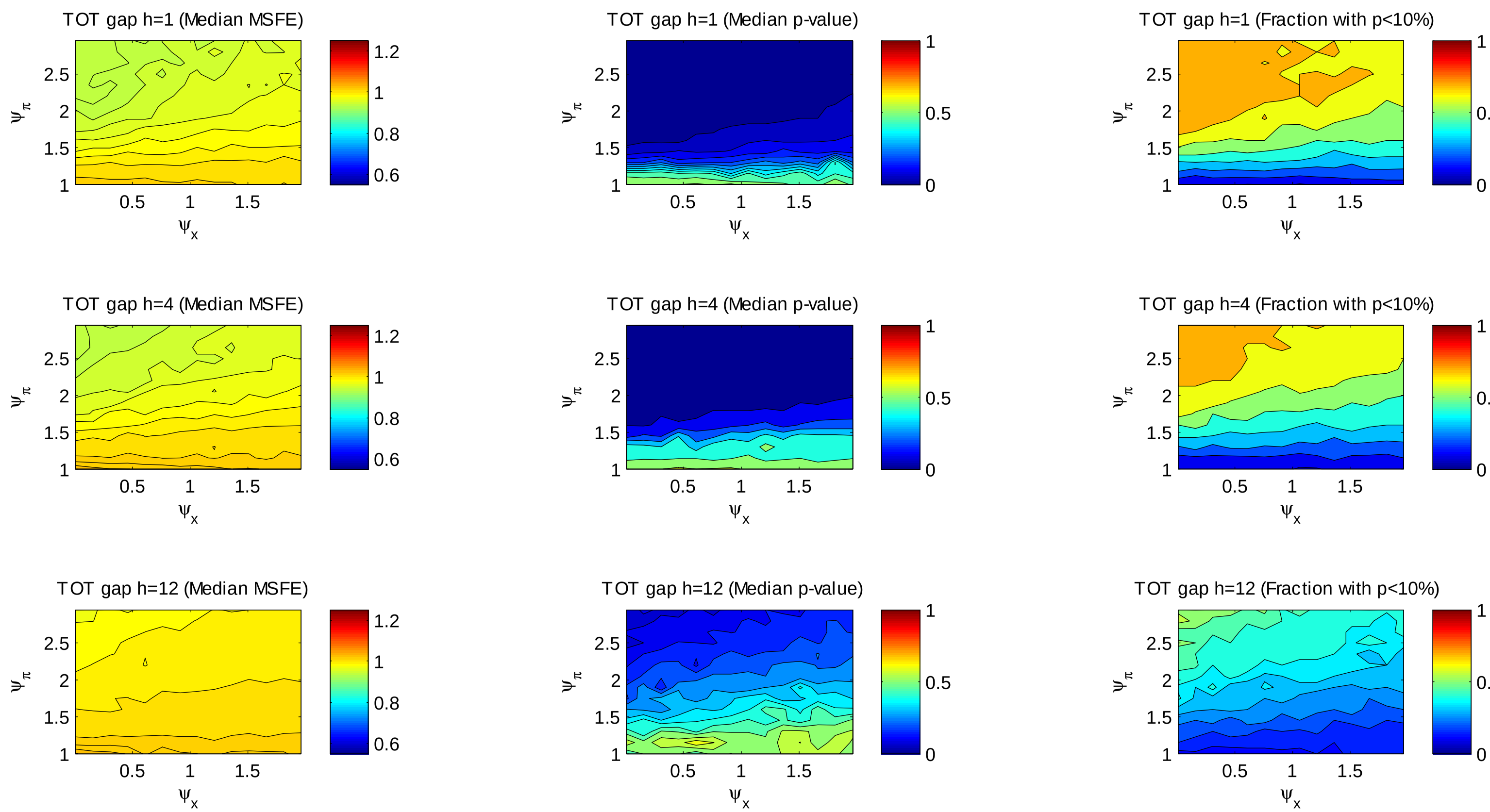

FIGURE 9D. Model's prediction of the relative MSFEs of forecasts with TOT gap as a function of the parameters of *monetary policy (low inertia)*

Note: MSFEs are relative to the MSFEs of the univariate AR process of inflation (restricted model).
Median MSFEs, median p-values and fraction of statistically significant MSFEs in 100 simulations are reported.

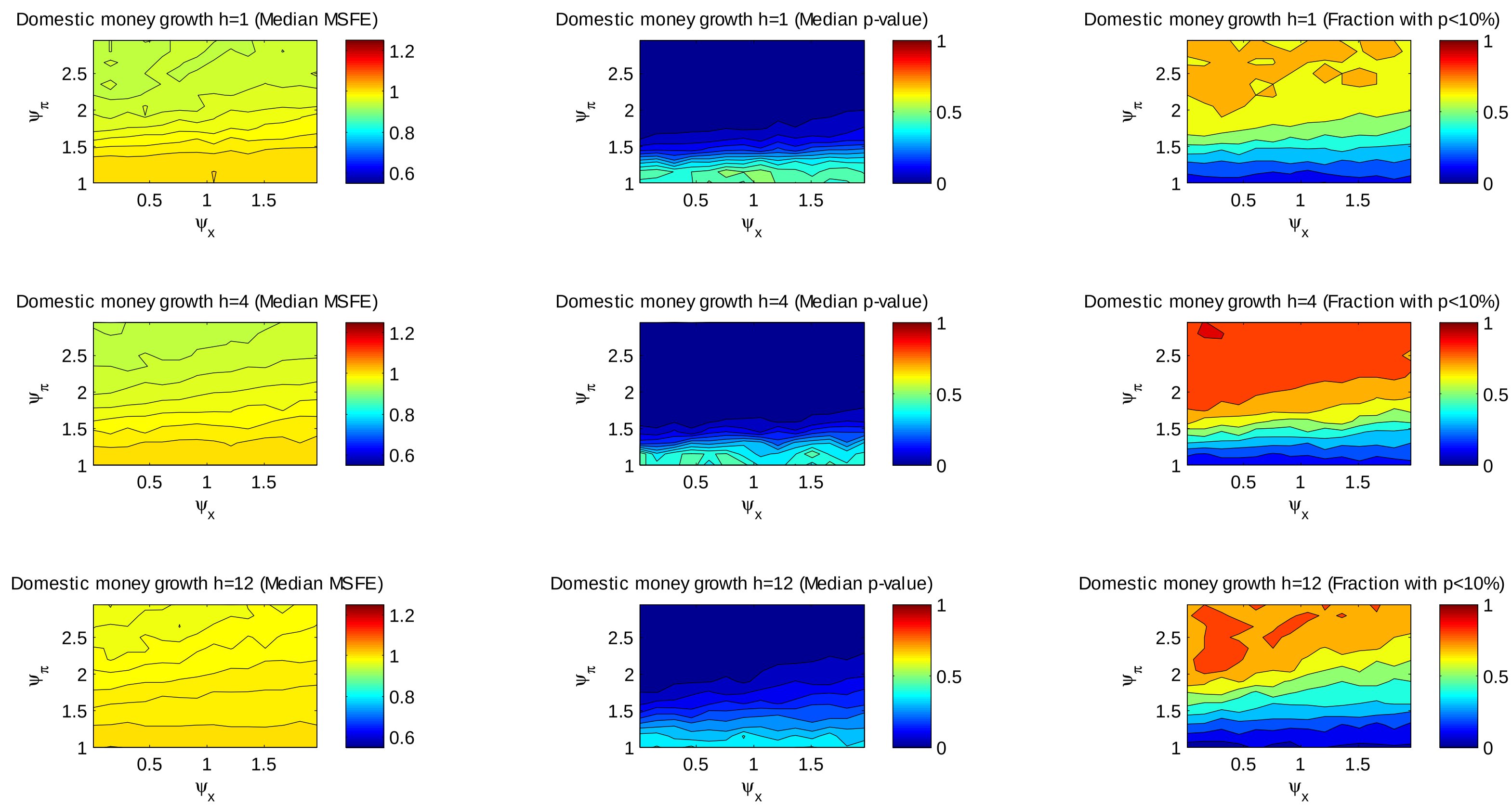

FIGURE 9E. Model's prediction of the relative MSFEs of forecasts with domestic money supply growth as a function of the parameters of *monetary policy (low inertia)*

Note: MSFEs are relative to the MSFEs of the univariate AR process of inflation (restricted model).

Median MSFEs, median p-values and fraction of statistically significant MSFEs in 100 simulations are reported.

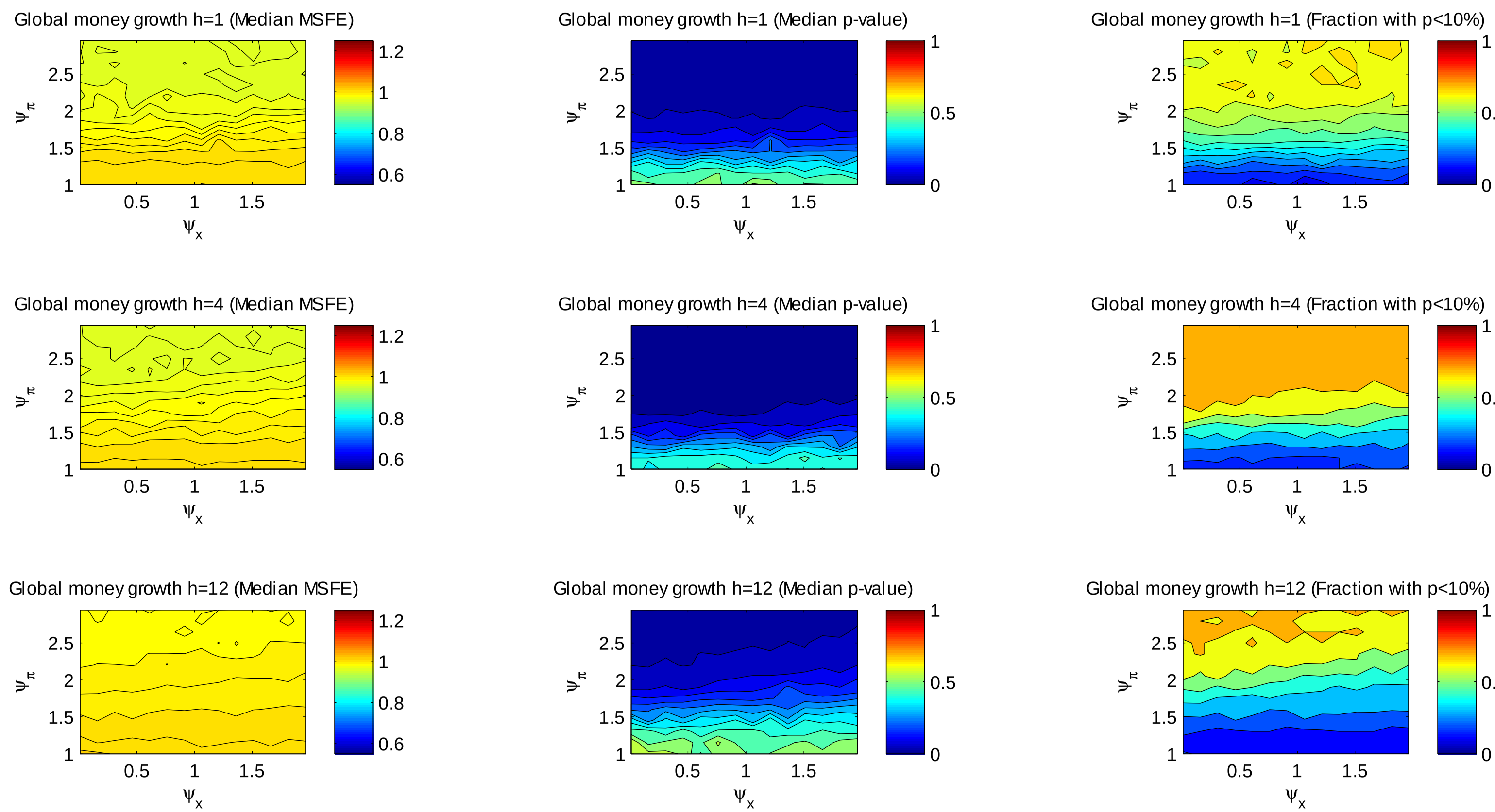

FIGURE 9F. Model's prediction of the relative MSFEs of forecasts with global money supply growth as a function of the parameters of *monetary policy (low inertia)*

Note: MSFEs are relative to the MSFEs of the univariate AR process of inflation (restricted model).
Median MSFEs, median p-values and fraction of statistically significant MSFEs in 100 simulations are reported.

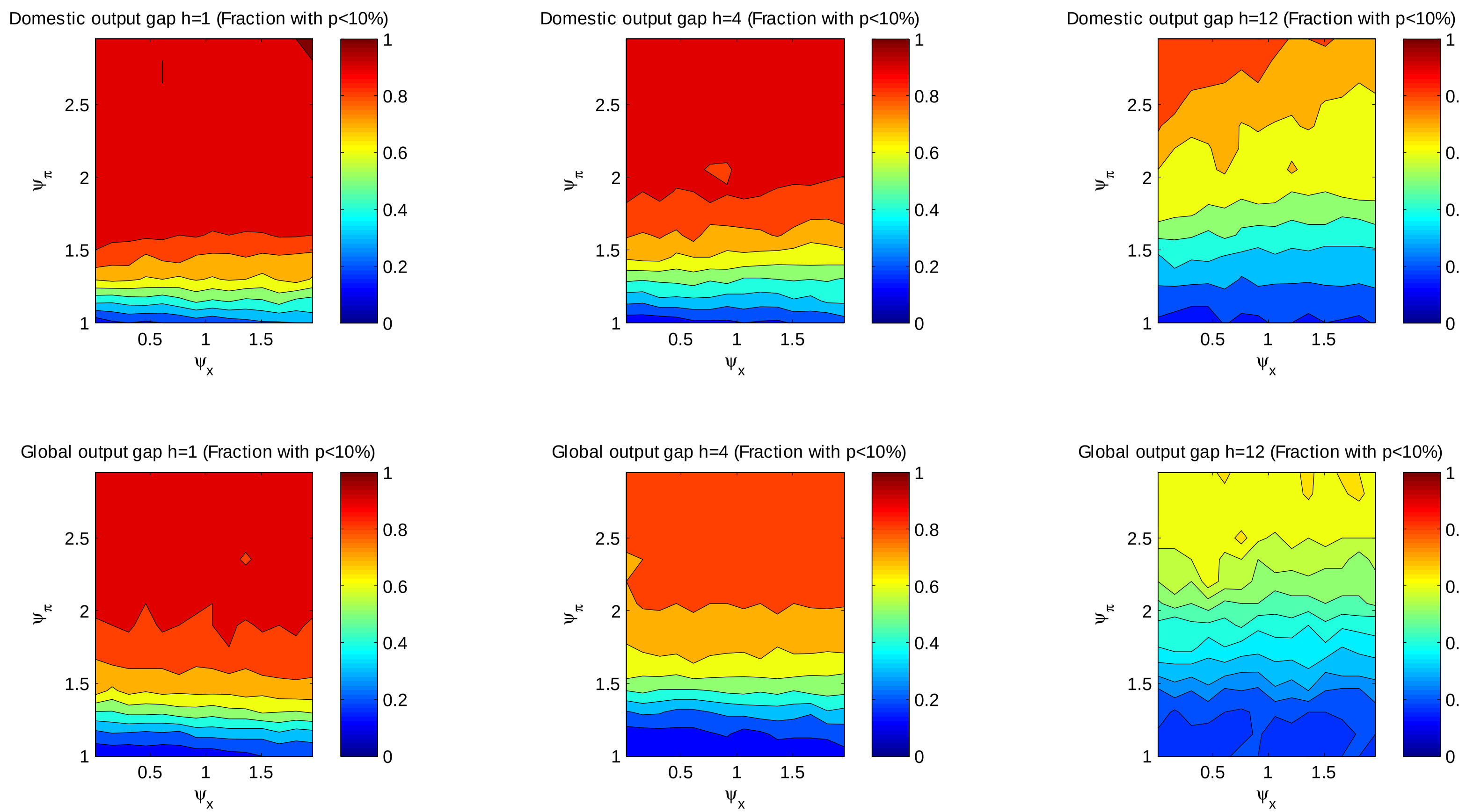

FIGURE 10A. Comparison of the forecasting performances of simulated domestic and global output gap as a function of the parameters of *monetary policy (low inertia)*

Note: Fraction of statistically significant MSFEs in 100 simulations are reported.

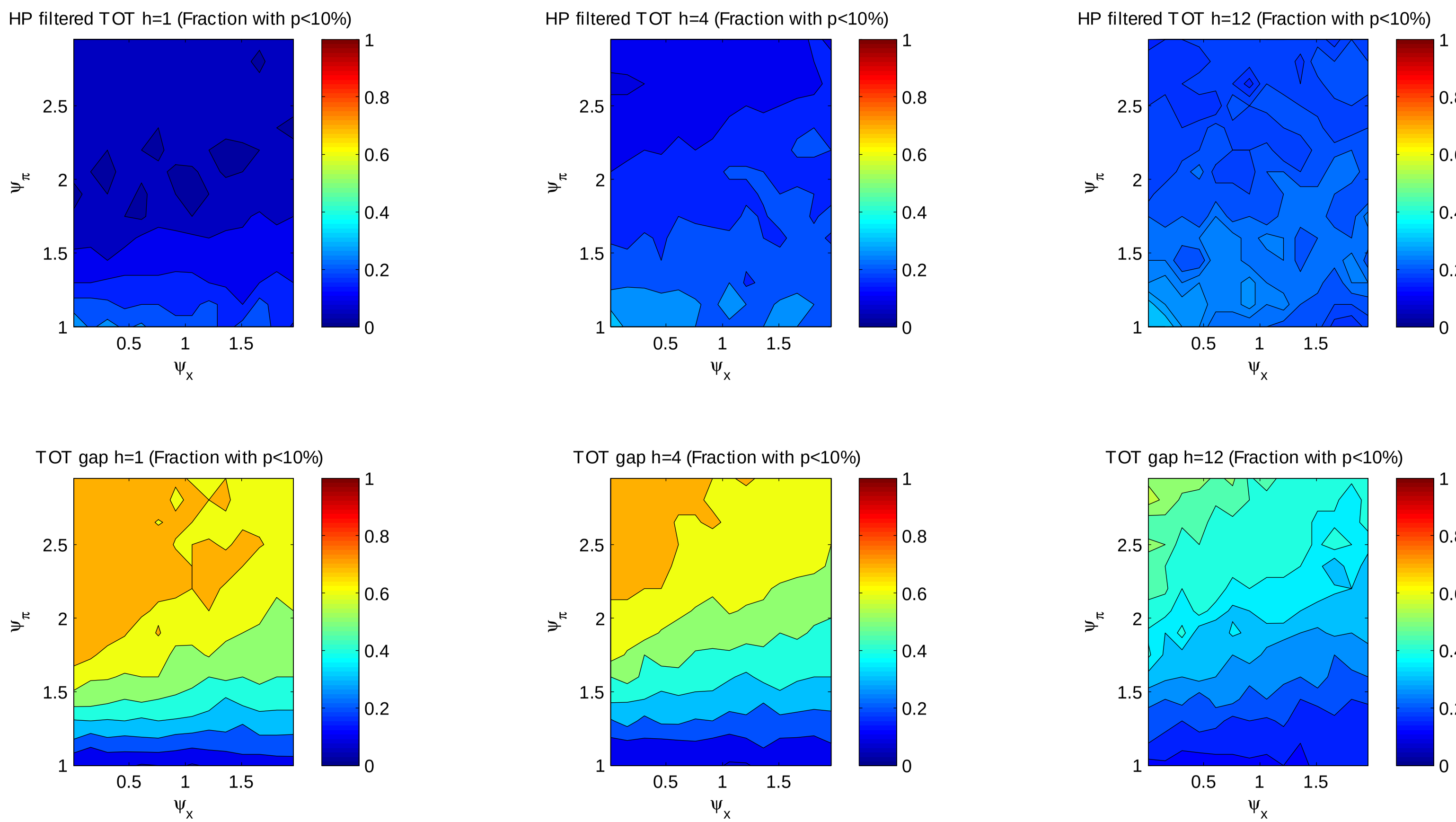

FIGURE 10B. Comparison of the forecasting performances of simulated HP-filtered TOT and TOT gap as a function of the parameters of *monetary policy (low inertia)*

Note: Fraction of statistically significant MSFEs in 100 simulations are reported.

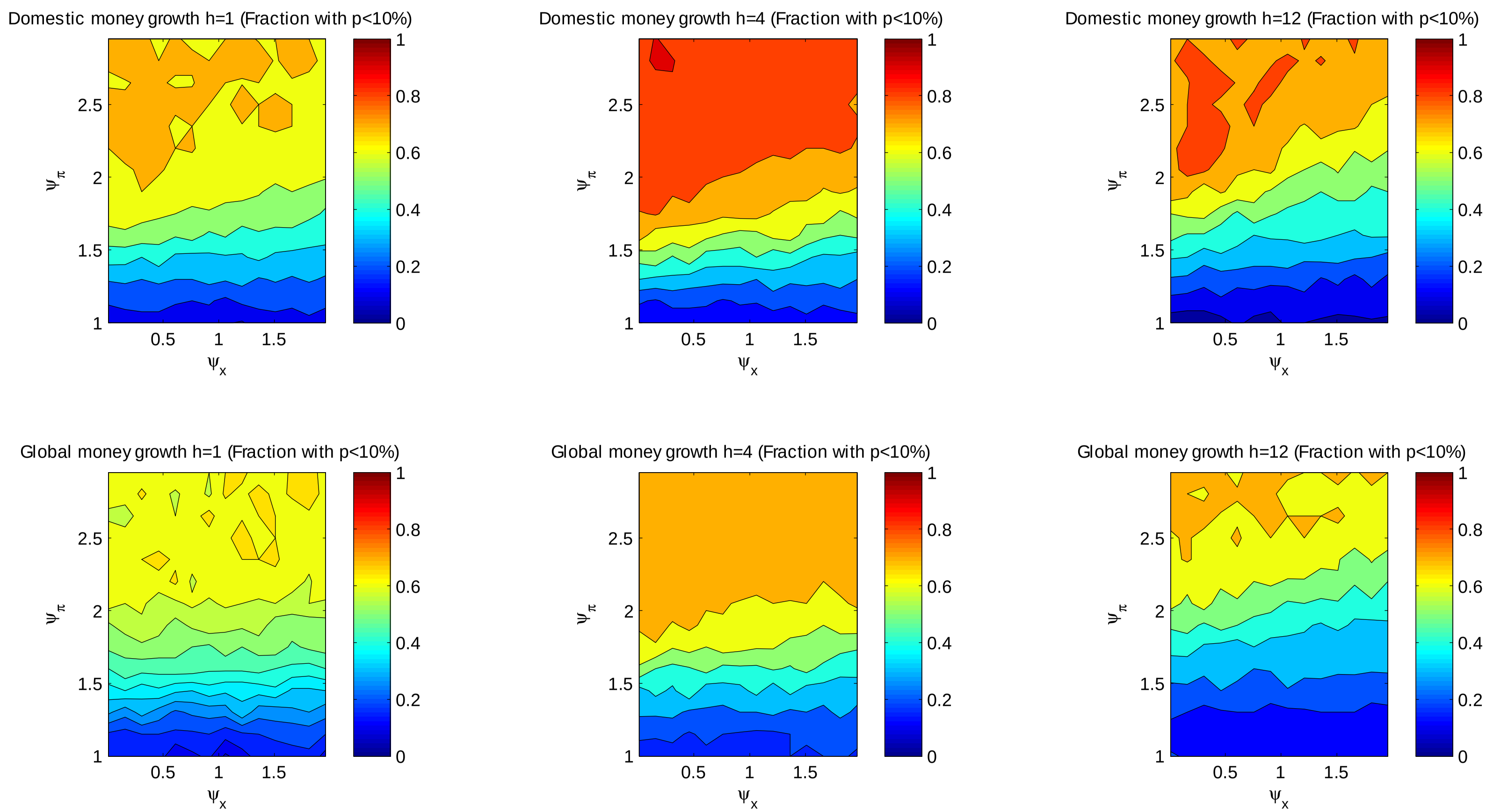

FIGURE 10C. Comparison of the forecasting performances of simulated domestic and global money supply growth as a function of the parameters of *monetary policy (low inertia)*

Note: Fraction of statistically significant MSFEs in 100 simulations are reported.

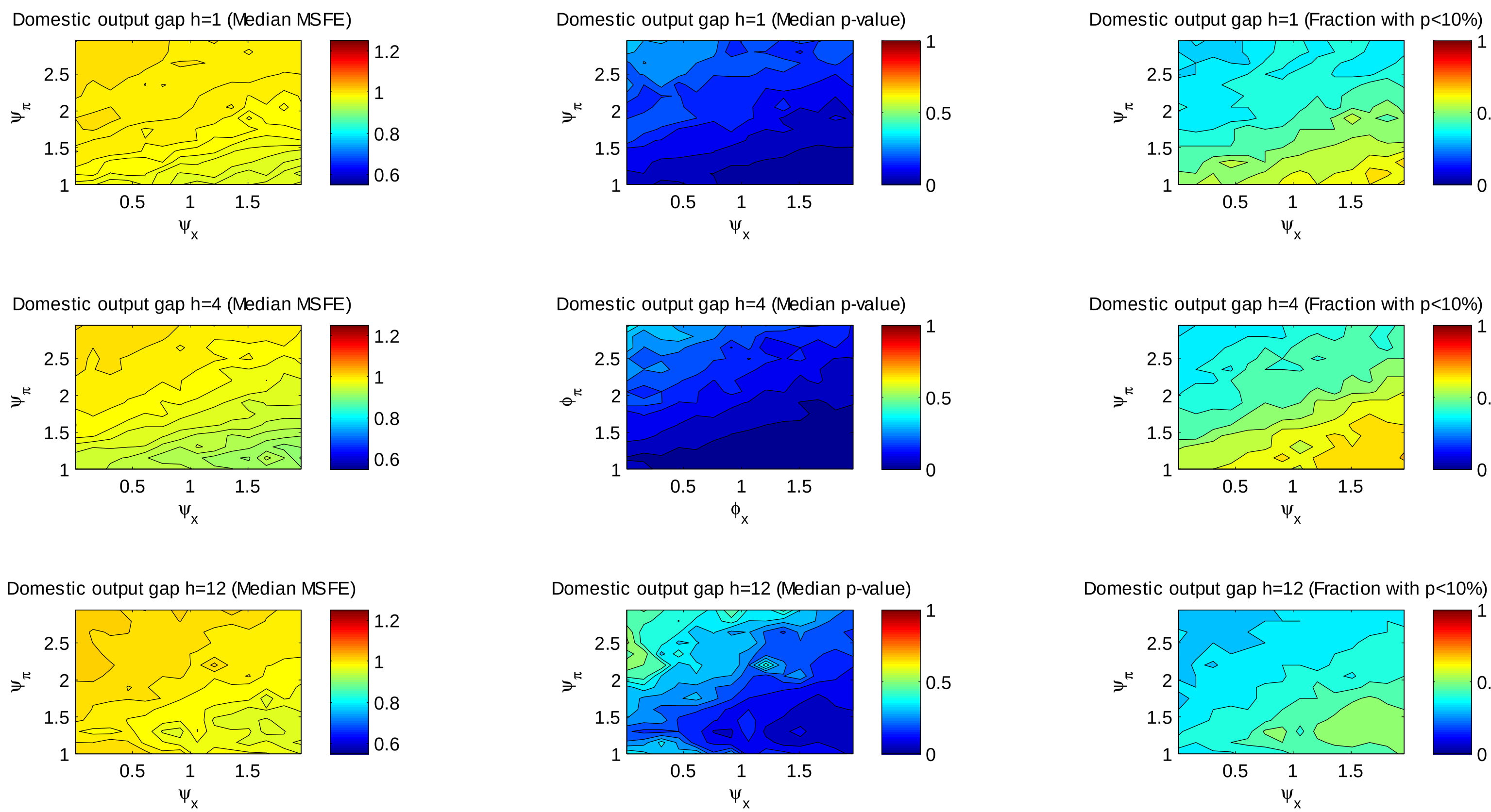

FIGURE 11A. Model's prediction of the relative MSFEs of forecasts with domestic output gap as a function of the parameters of *monetary policy (high inertia)*

Note: MSFEs are relative to the MSFEs of the univariate AR process of inflation (restricted model).

Median MSFEs, median p-values and fraction of statistically significant MSFEs in 100 simulations are reported.

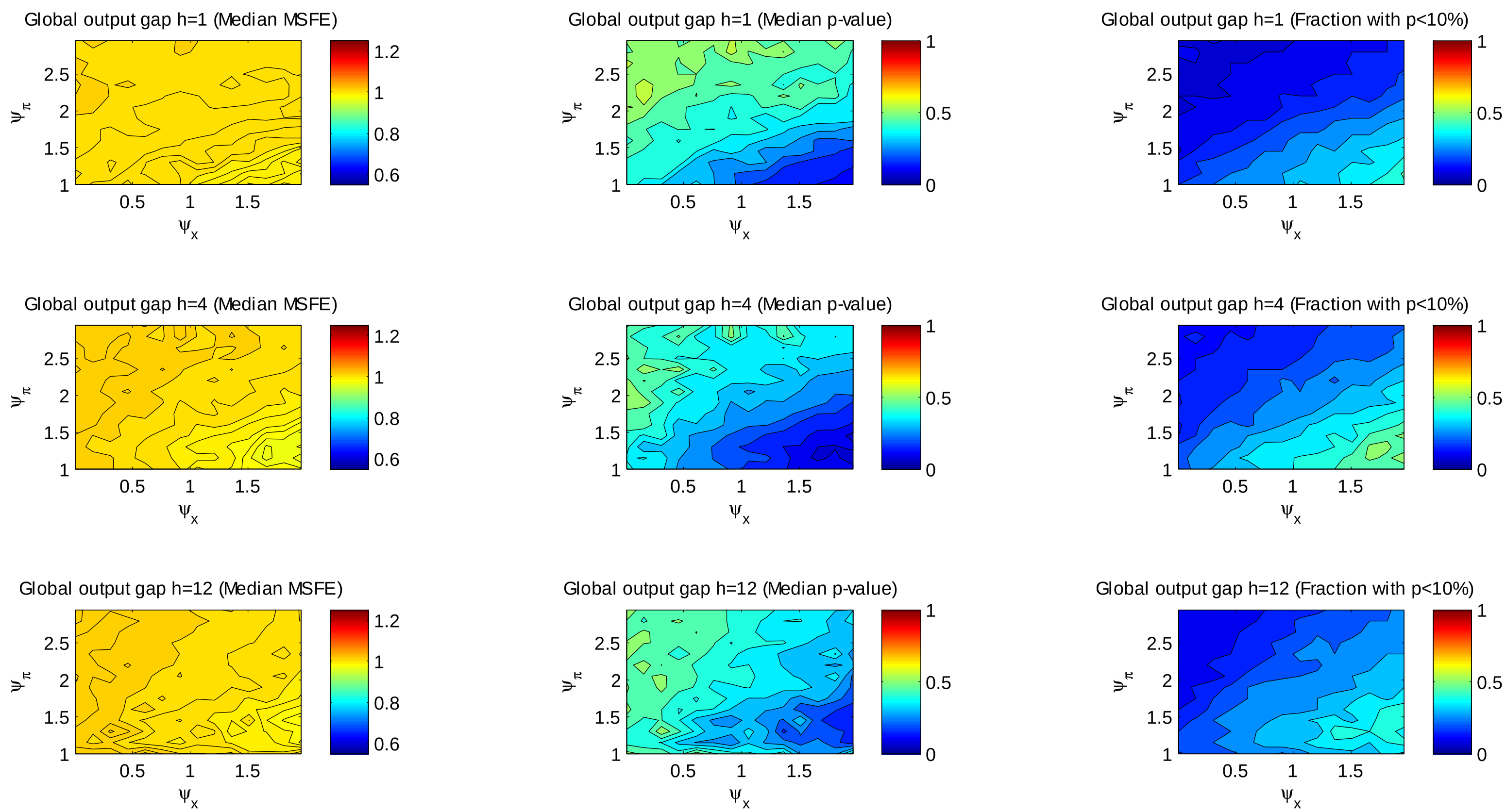

FIGURE 11B. Model's prediction of the relative MSFEs of forecasts with global output gap as a function of the parameters of *monetary policy (high inertia)*

Note: MSFEs are relative to the MSFEs of the univariate AR process of inflation (restricted model).
Median MSFEs, median p-values and fraction of statistically significant MSFEs in 100 simulations are reported.

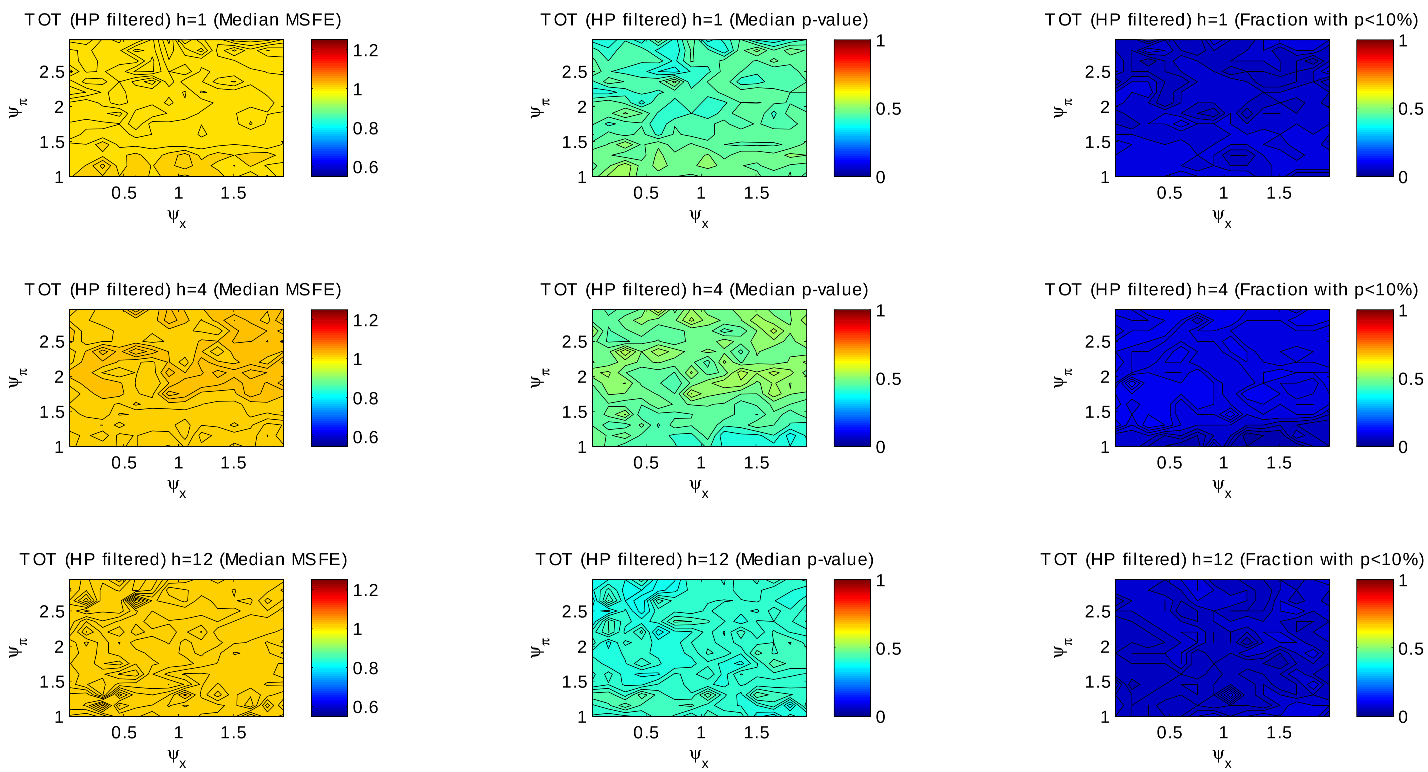

FIGURE 11C. Model's prediction of the relative MSFEs of forecasts with HP-filtered TOT as a function of the parameters of *monetary policy (high inertia)*

Note: MSFEs are relative to the MSFEs of the univariate AR process of inflation (restricted model).

Median MSFEs, median p-values and fraction of statistically significant MSFEs in 100 simulations are reported.

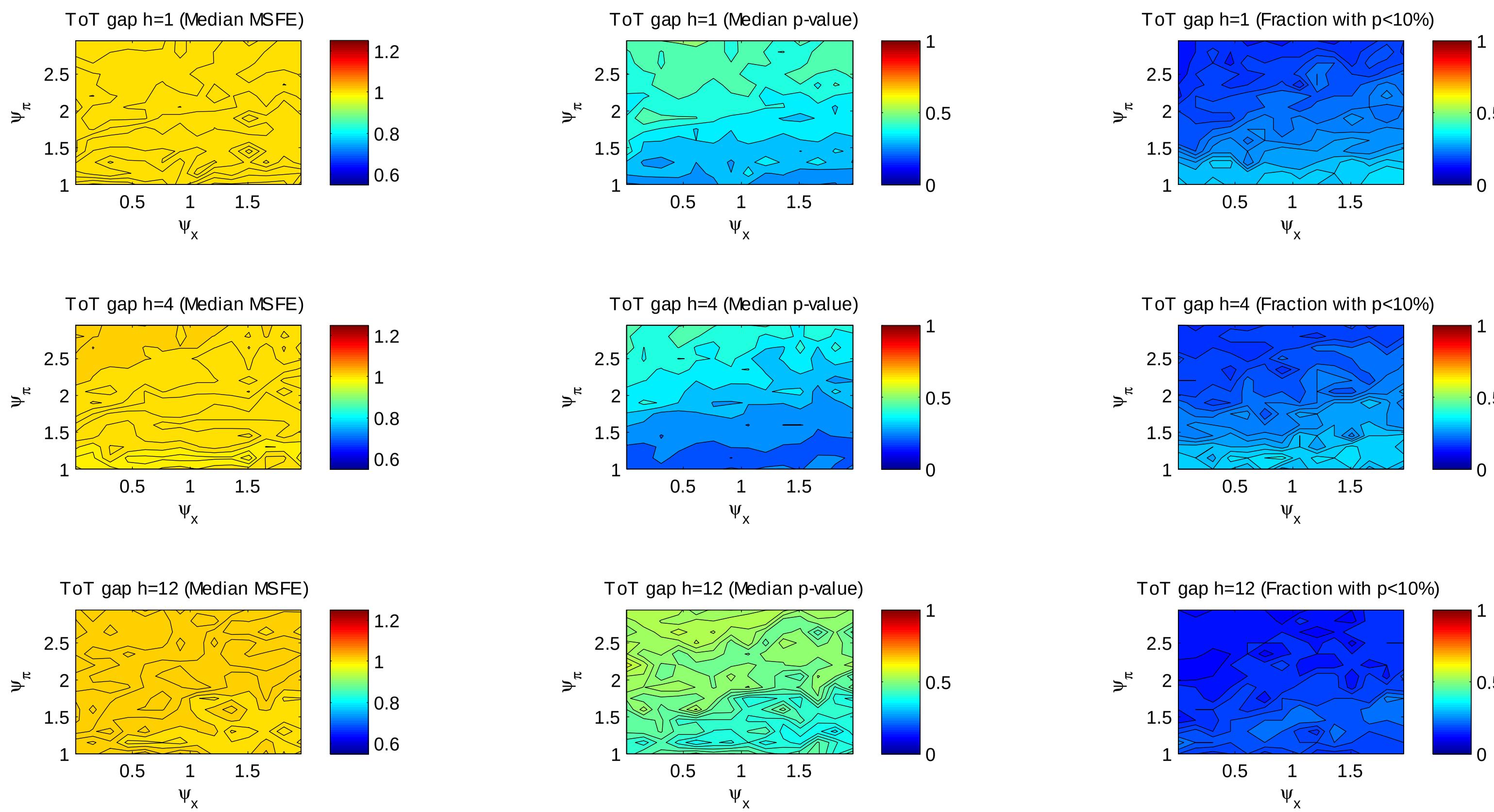

FIGURE 11D. Model's prediction of the relative MSFEs of forecasts with TOT gap as a function of the parameters of *monetary policy (high inertia)*

Note: MSFEs are relative to the MSFEs of the univariate AR process of inflation (restricted model). Median MSFEs, median p-values and fraction of statistically significant MSFEs in 100 simulations are reported.

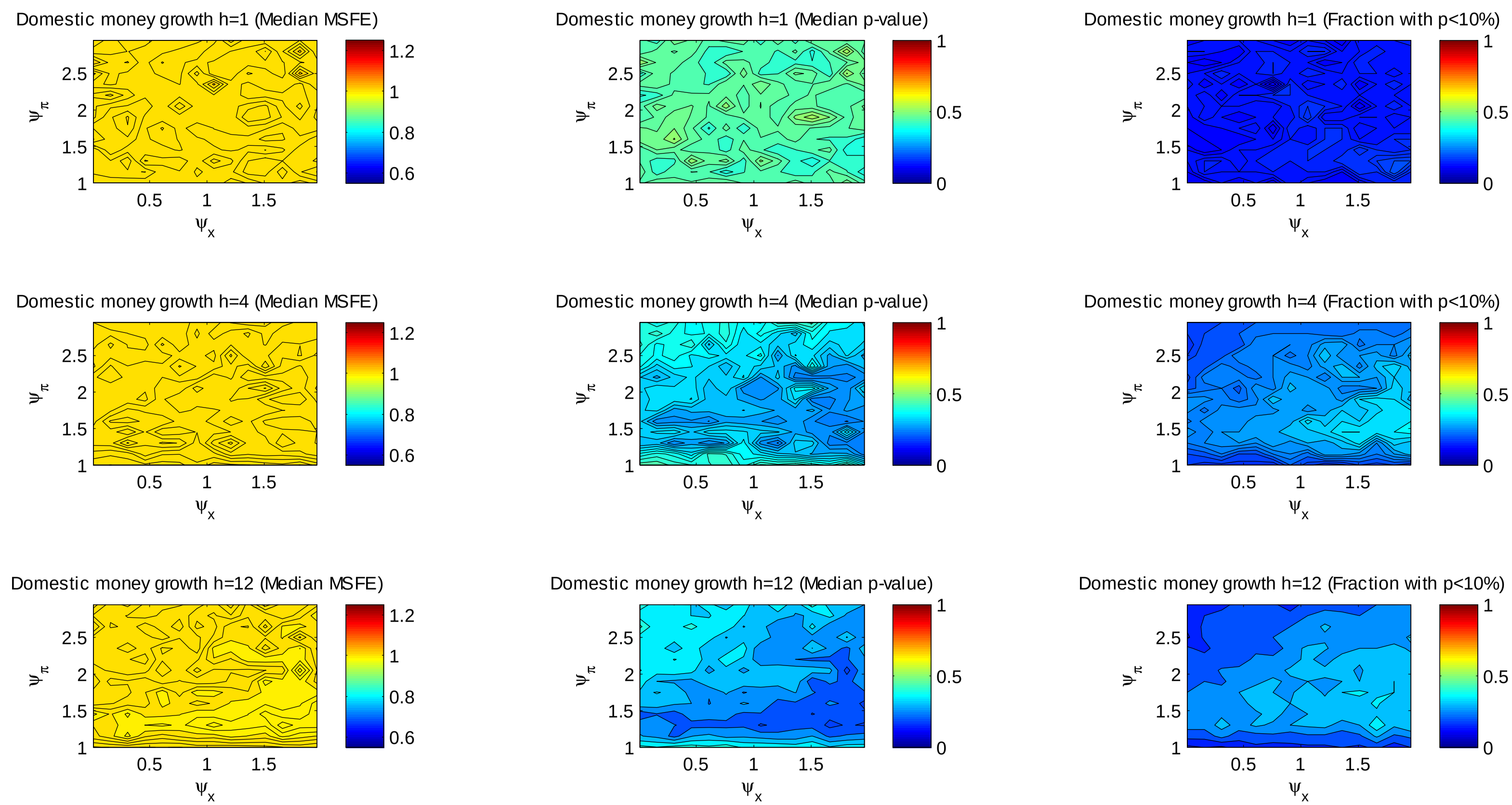

FIGURE 11E. Model's prediction of the relative MSFEs of forecasts with domestic money supply growth as a function of the parameters of *monetary policy (high inertia)*

Note: MSFEs are relative to the MSFEs of the univariate AR process of inflation (restricted model).

Median MSFEs, median p-values and fraction of statistically significant MSFEs in 100 simulations are reported.

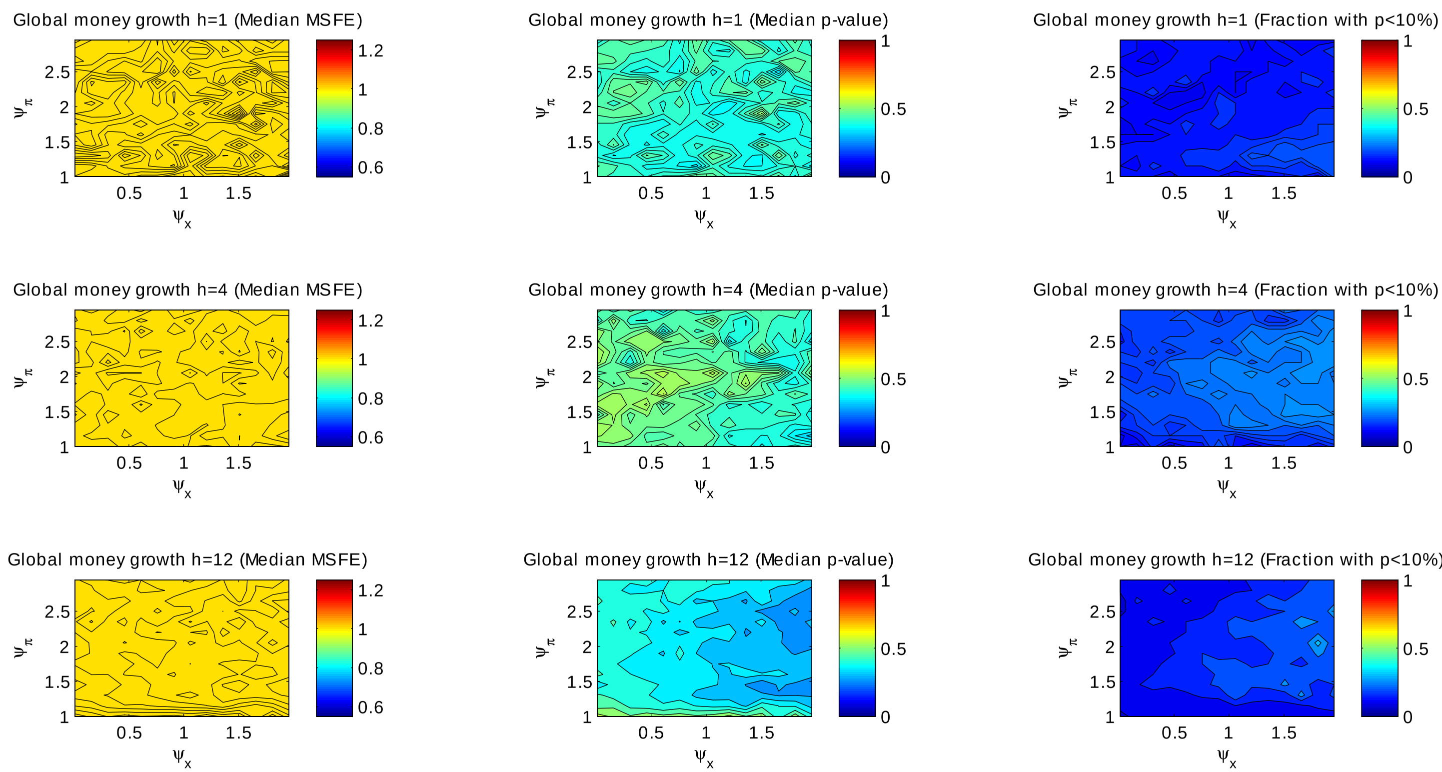

FIGURE 11F. Model's prediction of the relative MSFEs of forecasts with global money supply growth as a function of the parameters of *monetary policy (high inertia)*

Note: MSFEs are relative to the MSFEs of the univariate AR process of inflation (restricted model).

Median MSFEs, median p-values and fraction of statistically significant MSFEs in 100 simulations are reported.

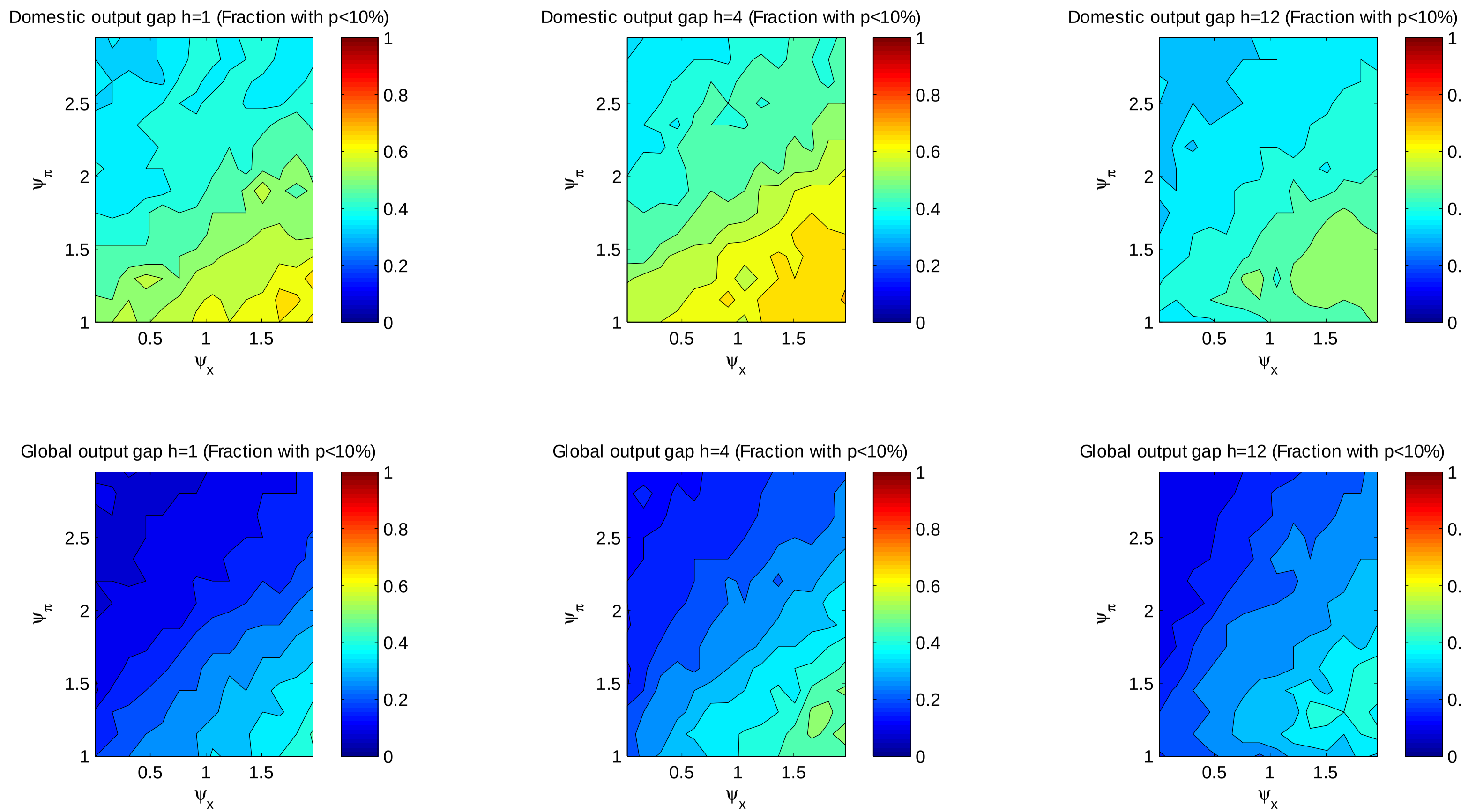

FIGURE 12A. Comparison of the forecasting performances of simulated domestic and global output gap as a function of the parameters of *monetary policy (high inertia)*

Note: Fraction of statistically significant MSFEs in 100 simulations are reported.

Median MSFEs, median p-values and fraction of statistically significant MSFEs in 100 simulations are reported.

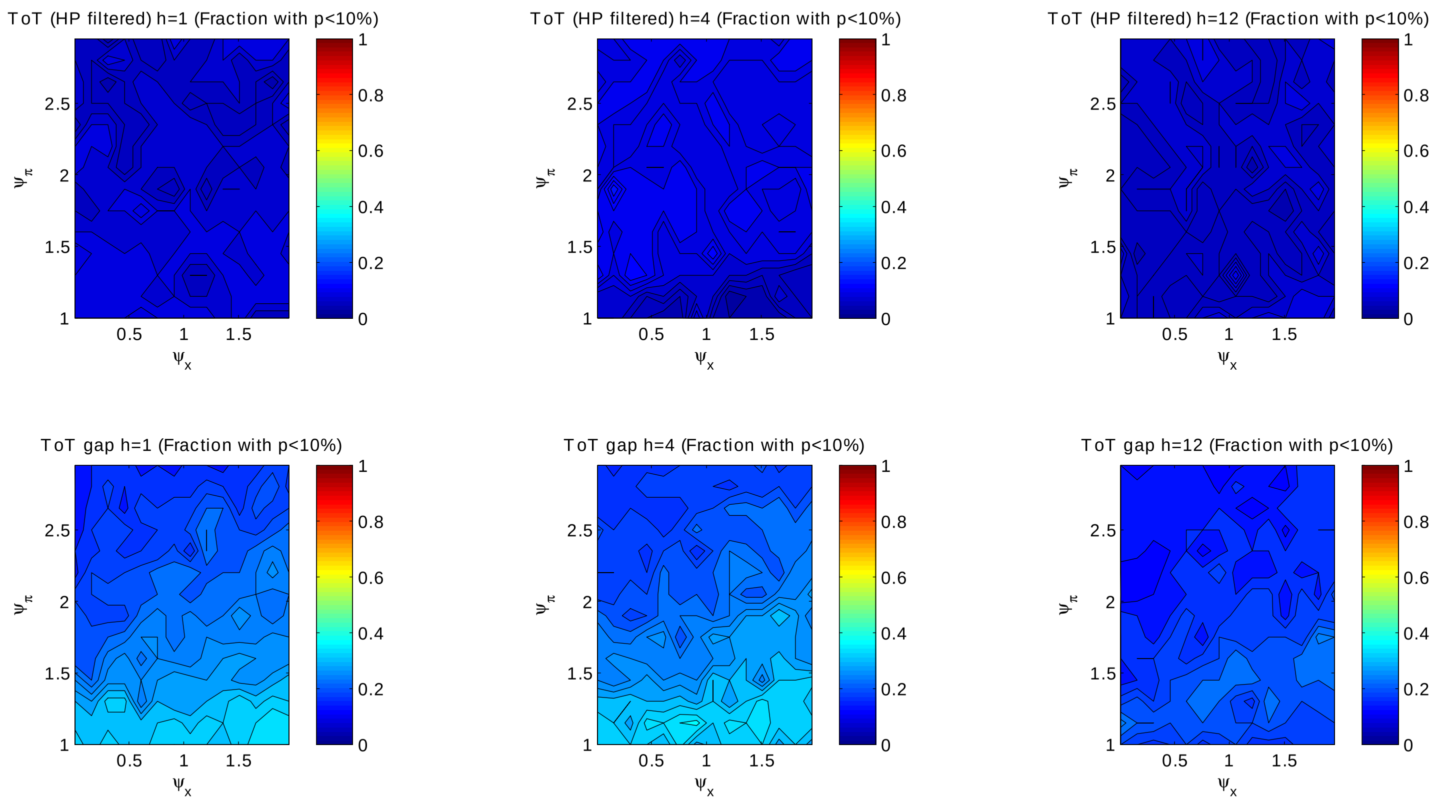

FIGURE 12B. Comparison of the forecasting performances of simulated HP-filtered TOT and TOT gap as a function of the parameters of *monetary policy (high inertia)*

Note: Fraction of statistically significant MSFEs in 100 simulations are reported.

Median MSFEs, median p-values and fraction of statistically significant MSFEs in 100 simulations are reported.

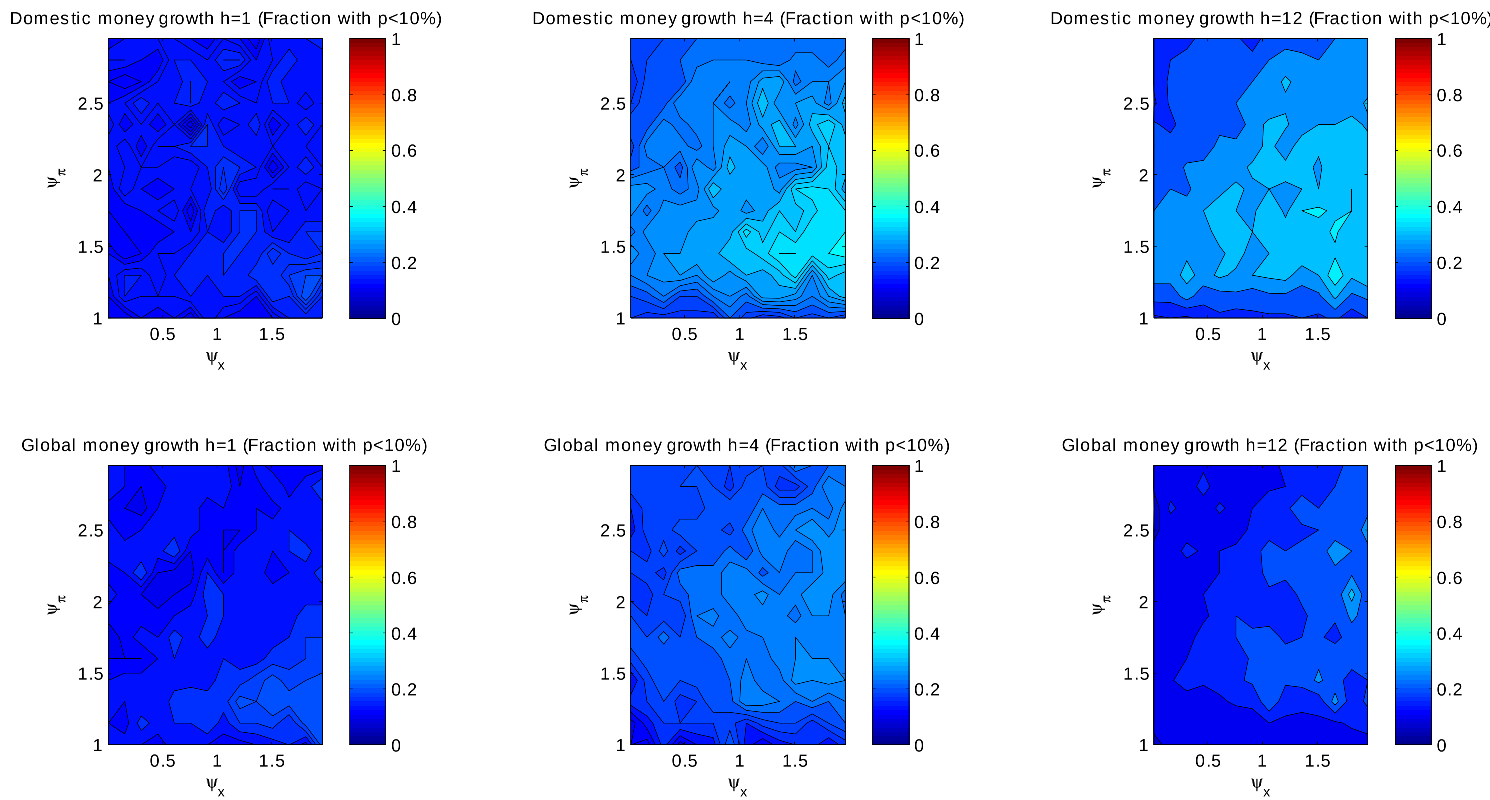

FIGURE 12C. Comparison of the forecasting performances of simulated domestic and global money supply growth as a function of the parameters of *monetary policy (high inertia)*

Note: Fraction of statistically significant MSFEs in 100 simulations are reported.

Median MSFEs, median p-values and fraction of statistically significant MSFEs in 100 simulations are reported.

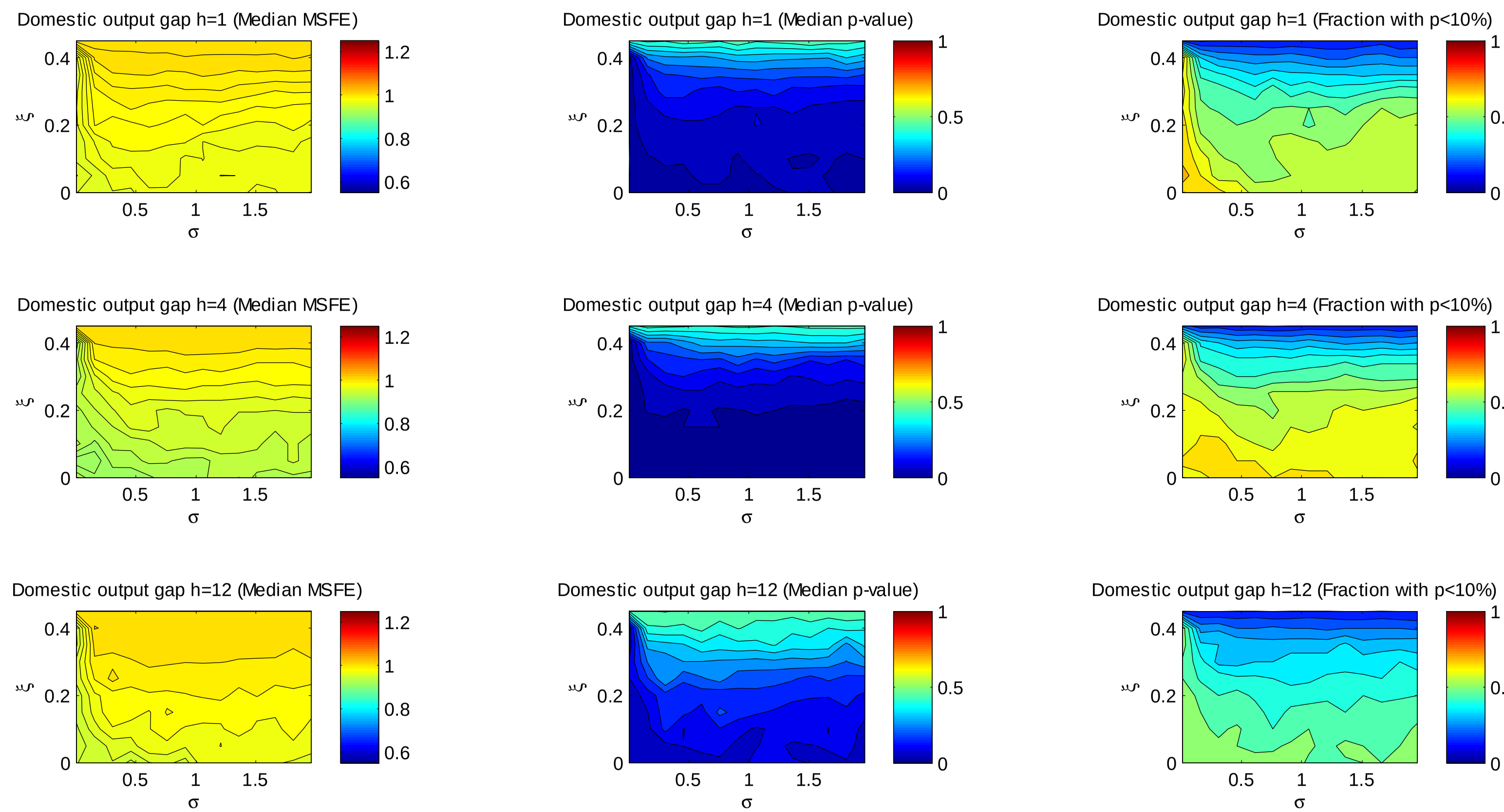

FIGURE 13A. Comparison of the forecasting performances of simulated domestic output gap as a function of the parameters of *openness*

Note: Fraction of statistically significant MSFEs in 100 simulations are reported.

Median MSFEs, median p-values and fraction of statistically significant MSFEs in 100 simulations are reported.

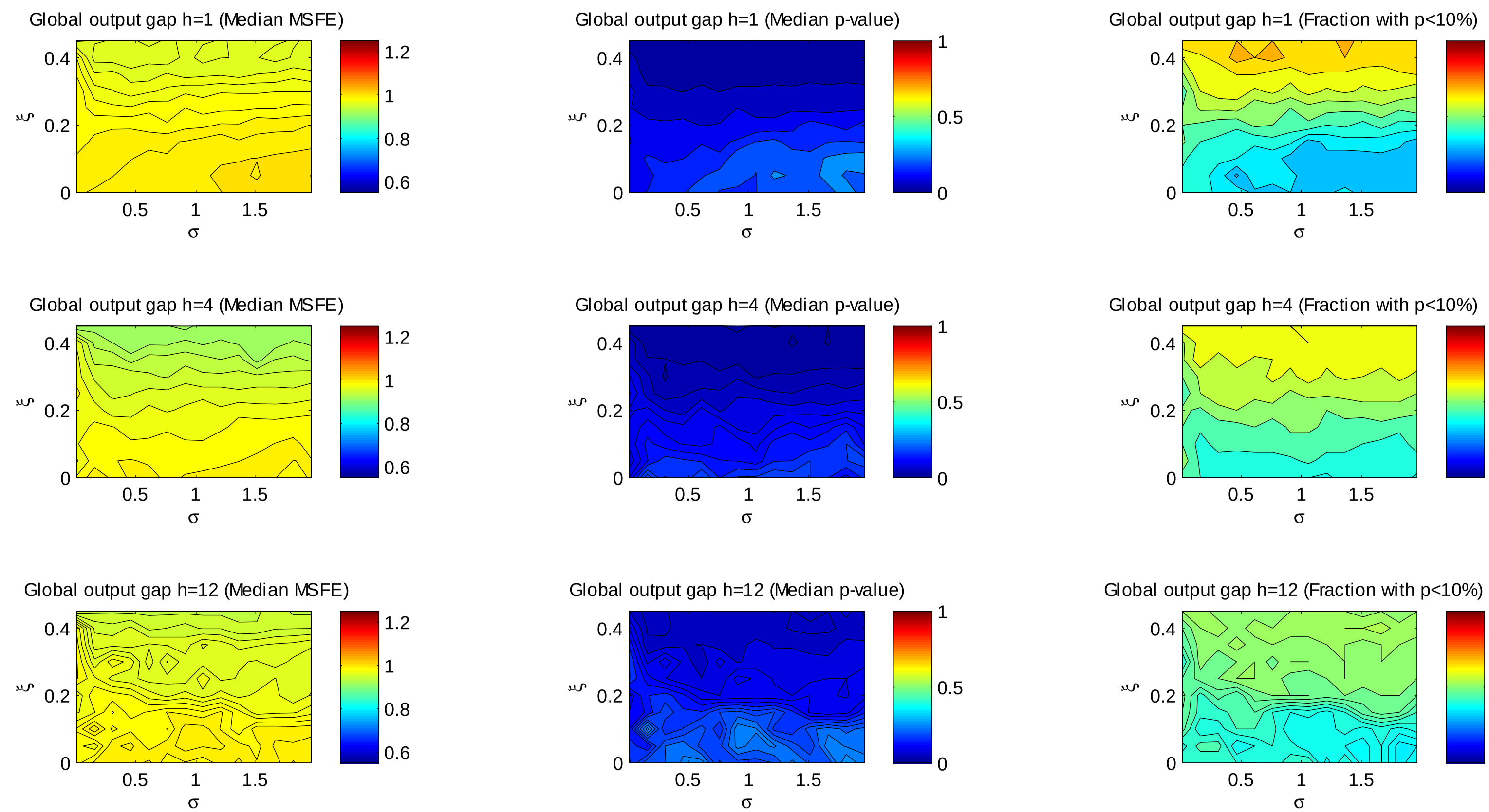

FIGURE 13B. Comparison of the forecasting performances of simulated global output gap as a function of the parameters of *openness*

Note: Fraction of statistically significant MSFEs in 100 simulations are reported.

Median MSFEs, median p-values and fraction of statistically significant MSFEs in 100 simulations are reported.

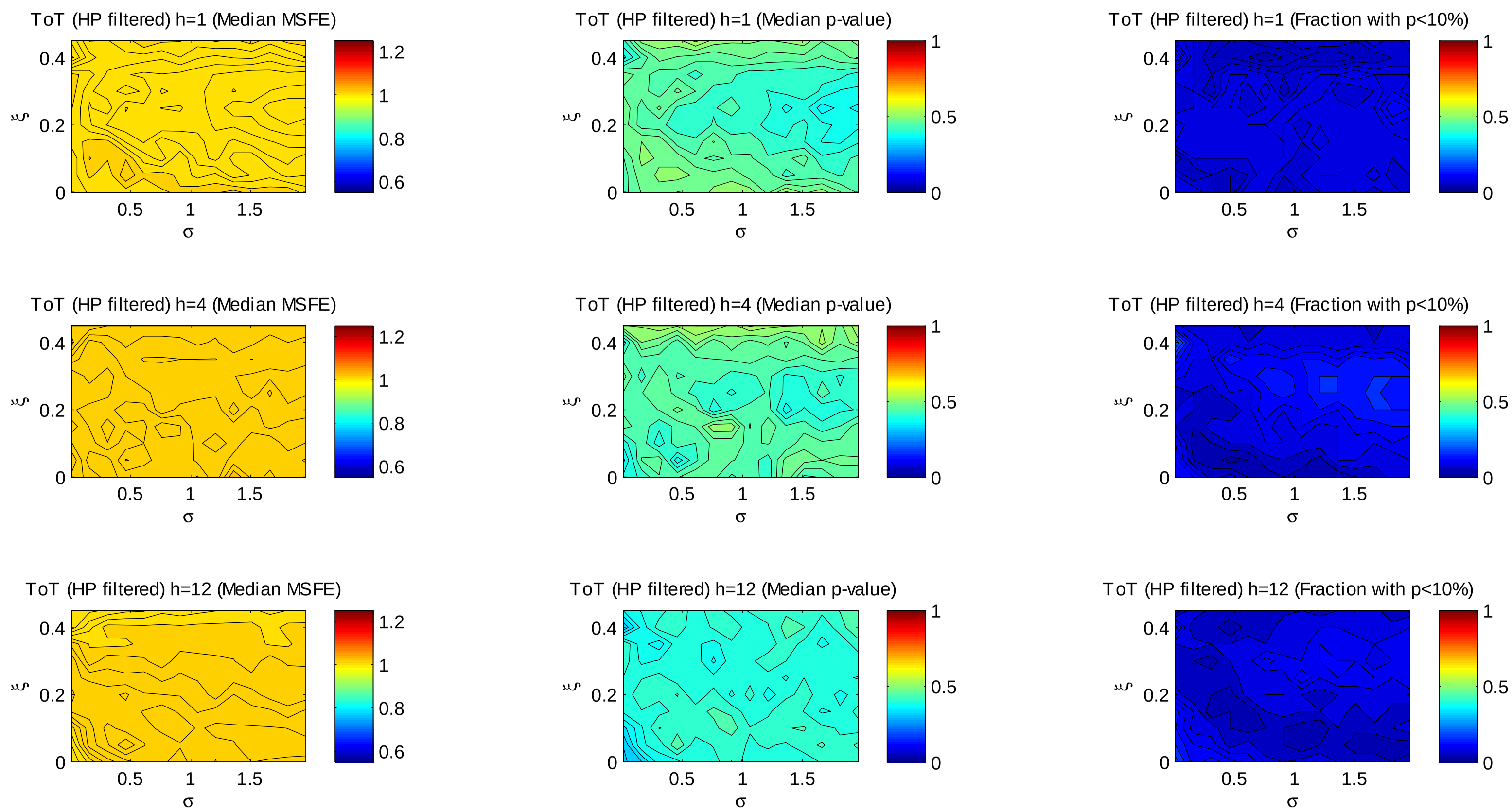

FIGURE 13C. Comparison of the forecasting performances of simulated HP-filtered TOT as a function of the parameters of *openness*

Note: Fraction of statistically significant MSFEs in 100 simulations are reported.

Median MSFEs, median p-values and fraction of statistically significant MSFEs in 100 simulations are reported.

FIGURE 13D. Comparison of the forecasting performances of simulated TOT gap as a function of the parameters of *openness*

Note: Fraction of statistically significant MSFEs in 100 simulations are reported.

Median MSFEs, median p-values and fraction of statistically significant MSFEs in 100 simulations are reported.

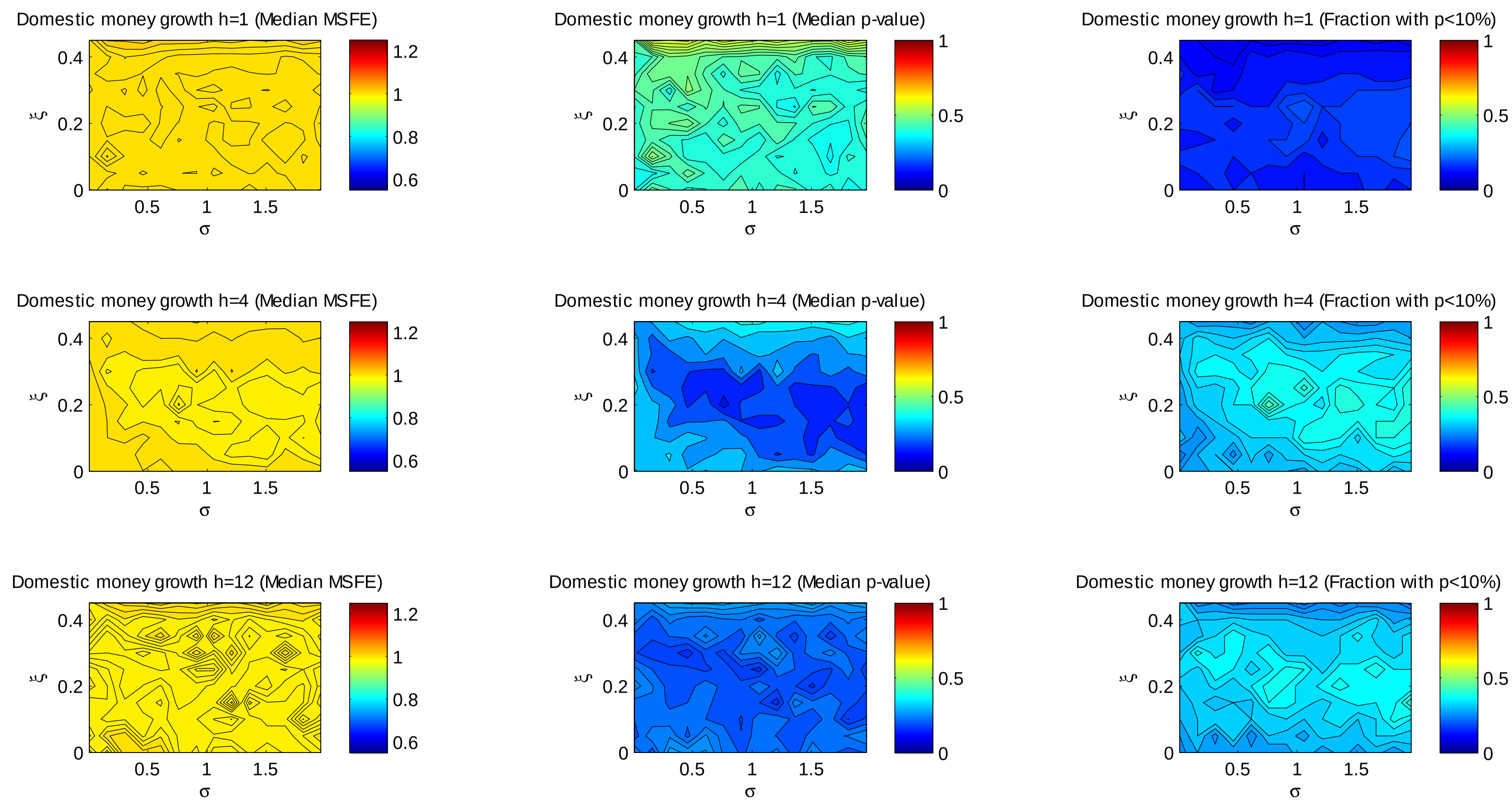

FIGURE 13E. Comparison of the forecasting performances of simulated domestic money supply growth as a function of the parameters of *openness*

Note: Fraction of statistically significant MSFEs in 100 simulations are reported.

Median MSFEs, median p-values and fraction of statistically significant MSFEs in 100 simulations are reported.

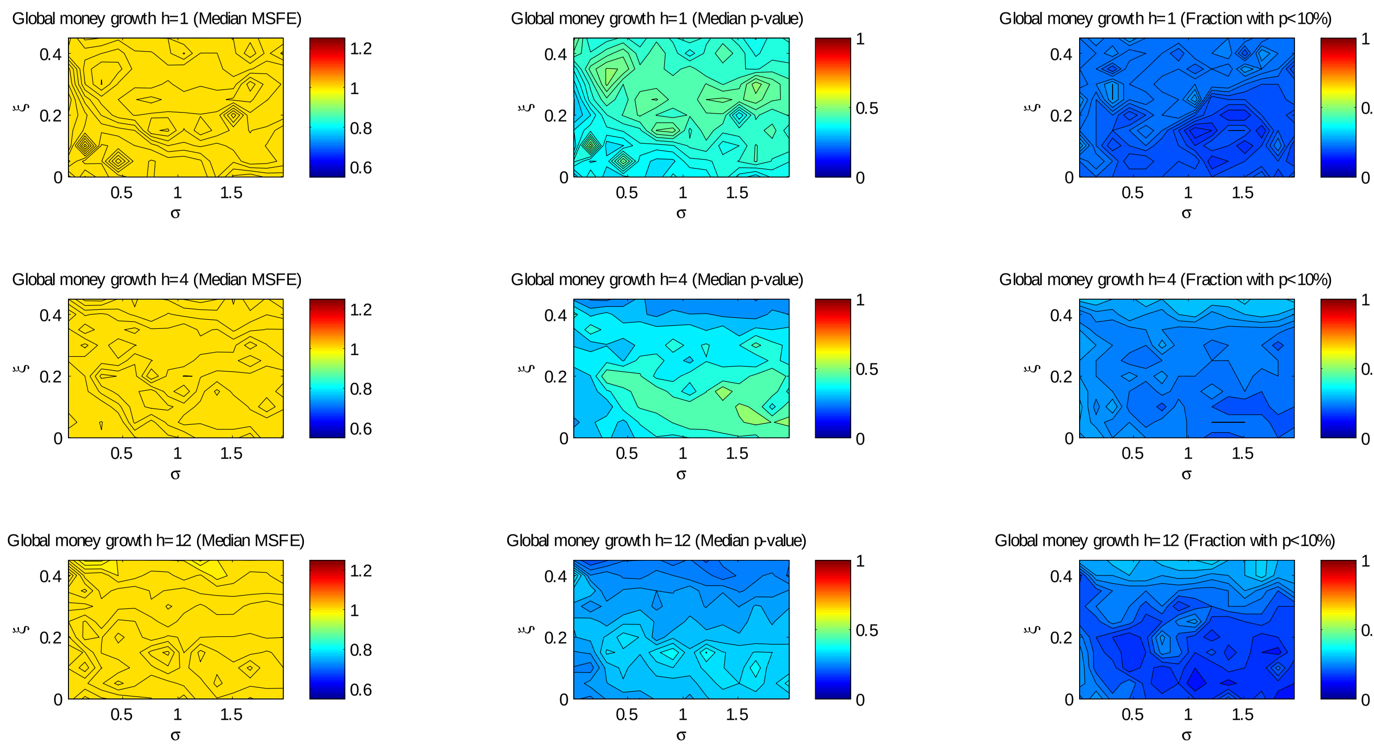

FIGURE 13F. Comparison of the forecasting performances of simulated global money supply growth as a function of the parameters of *openness*

Note: Fraction of statistically significant MSFEs in 100 simulations are reported.

Median MSFEs, median p-values and fraction of statistically significant MSFEs in 100 simulations are reported.

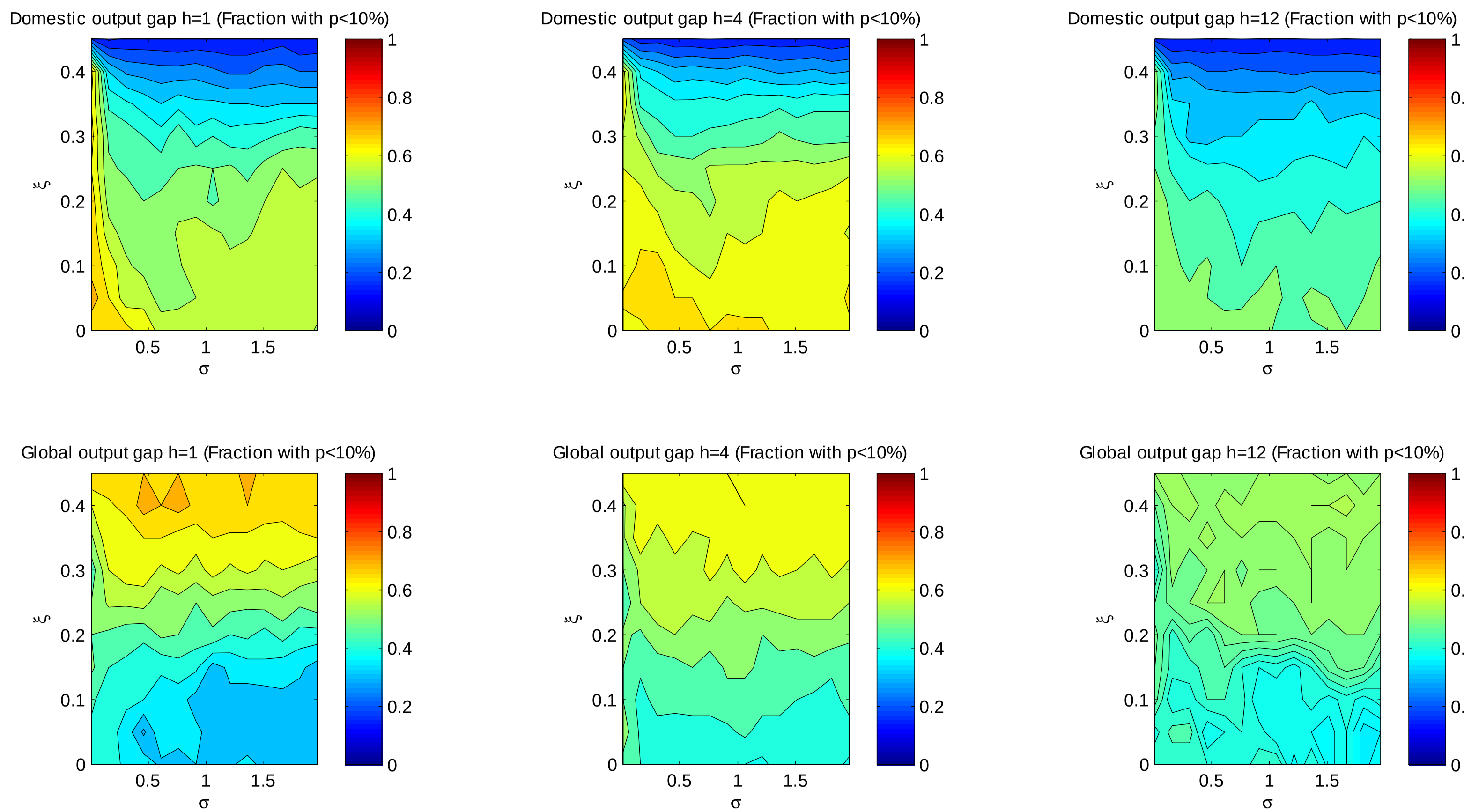

FIGURE 14A. Comparison of the forecasting performances of simulated domestic and global output gap as a function of the parameters of *openness*

Note: Fraction of statistically significant MSFEs in 100 simulations are reported.

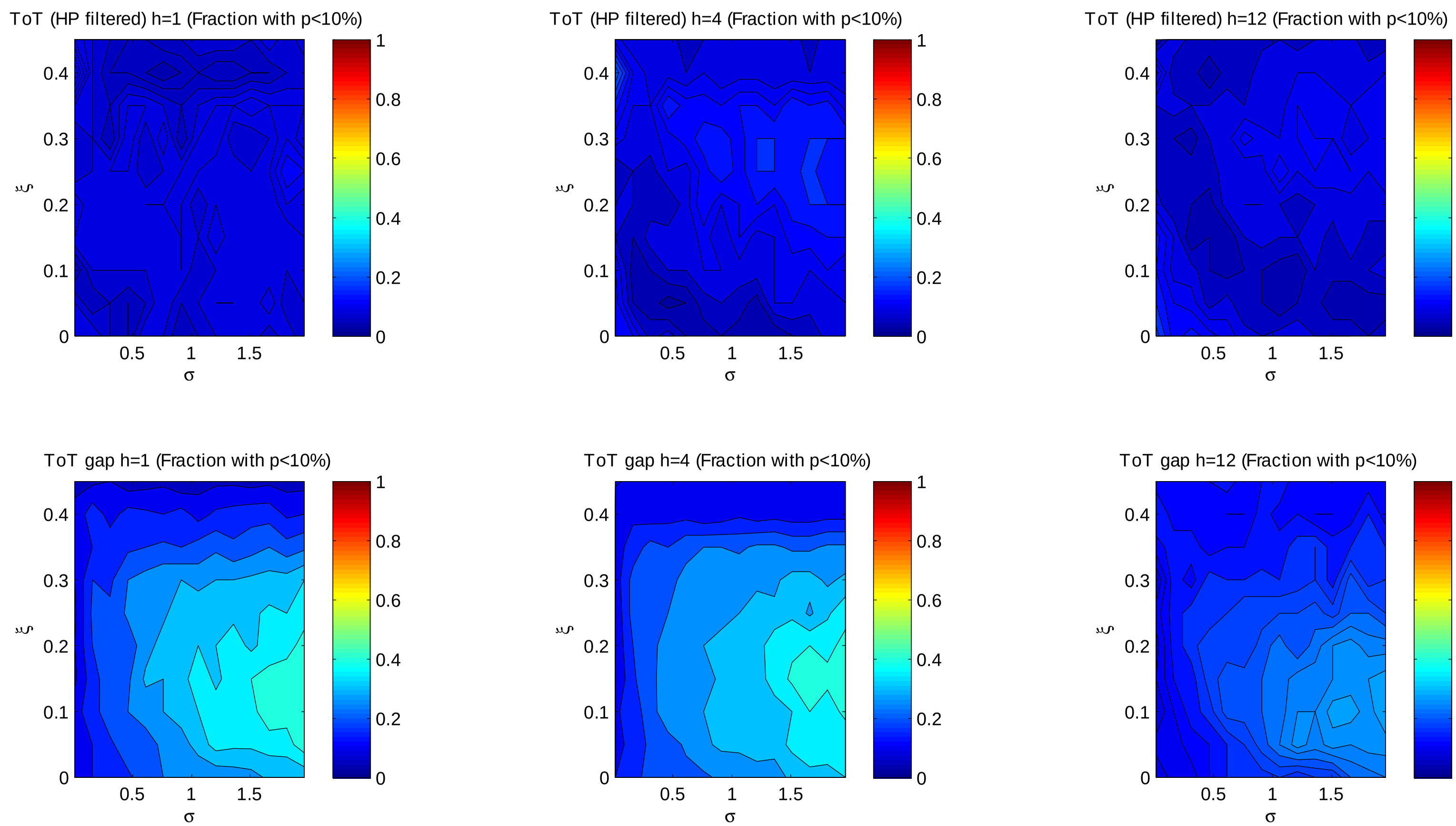

FIGURE 14B. Comparison of the forecasting performances of simulated HP-filtered TOT and TOT gap as a function of the parameters of *openness*

Note: Fraction of statistically significant MSFEs in 100 simulations are reported.

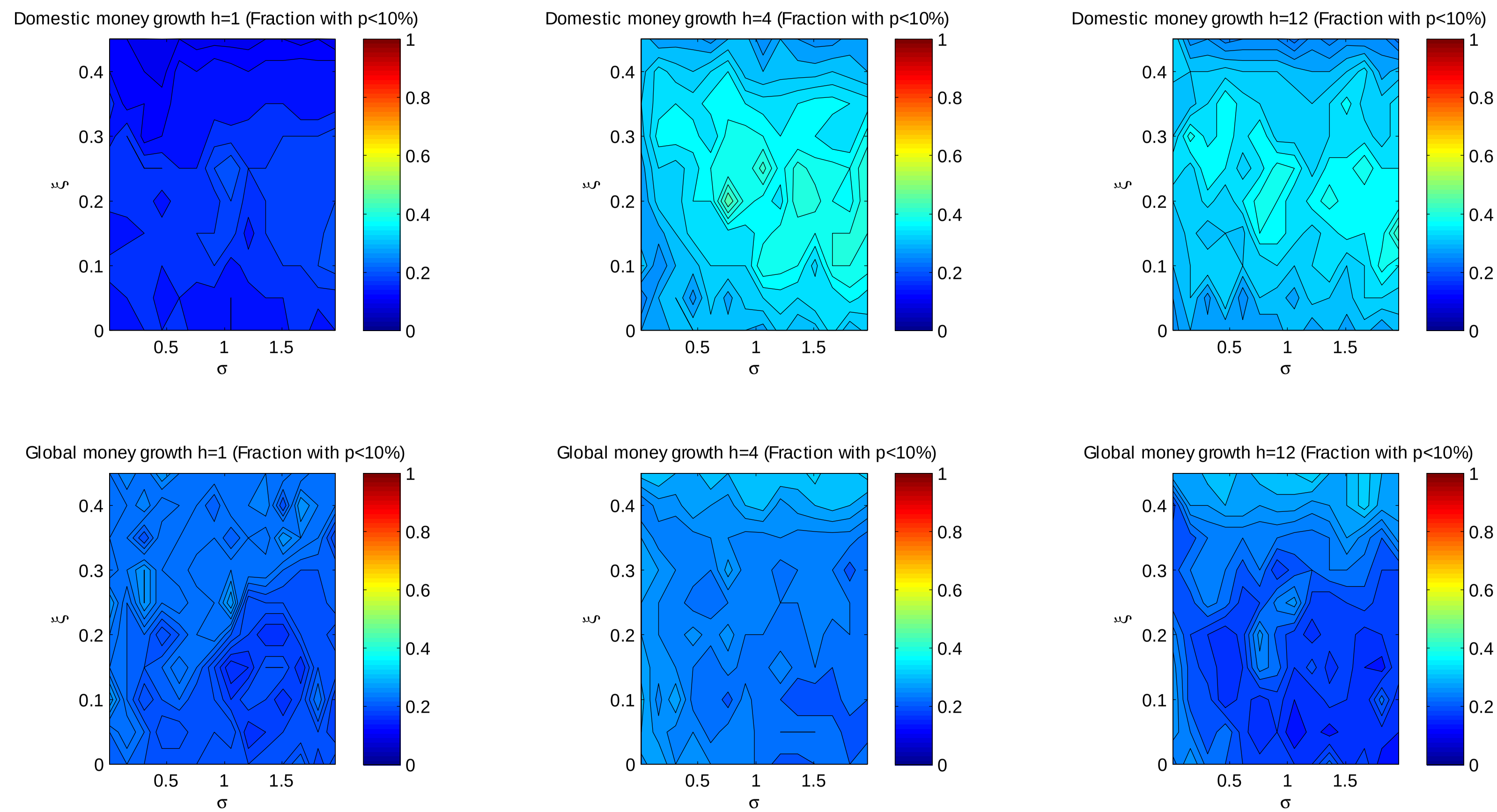

FIGURE 14C. Comparison of the forecasting performances of simulated domestic and global money supply growth as a function of the parameters of *openness*

Note: Fraction of statistically significant MSFEs in 100 simulations are reported.

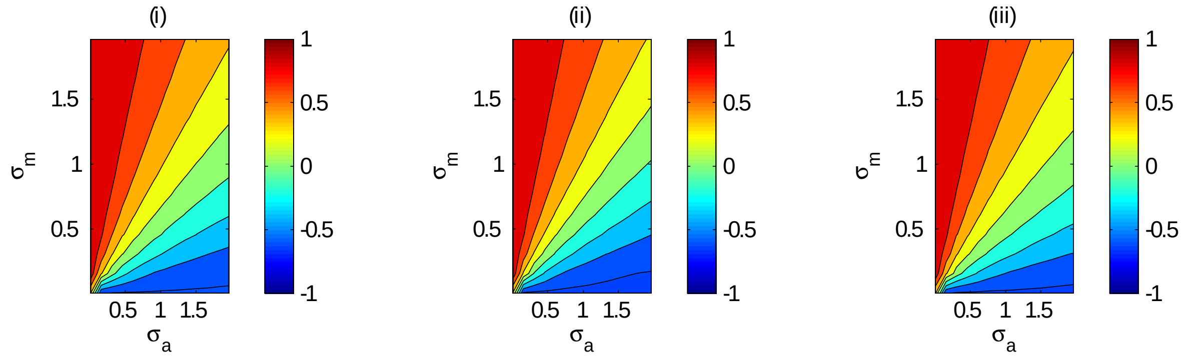

FIGURE 15A. Correlations of (i) model-consistent domestic output gap and HP-filtered domestic output, (ii) model-consistent global output gap and HP-filtered global output, (iii) model-consistent ToT gap and HP-filtered ToT as a function of the parameters of good luck (symmetric experiment)

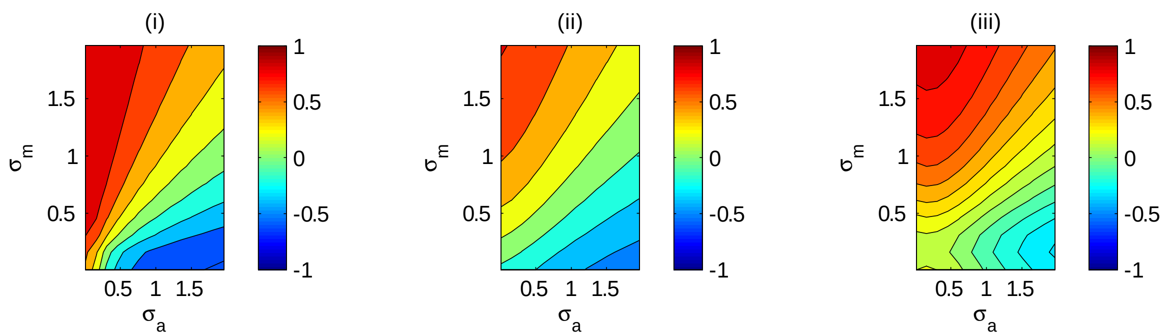

FIGURE 15B. Correlations of (i) model-consistent domestic output gap and HP-filtered domestic output, (ii) model-consistent global output gap and HP-filtered global output, (iii) model-consistent ToT gap and HP-filtered ToT as a function of the parameters of good luck (with U.S. parameters only)

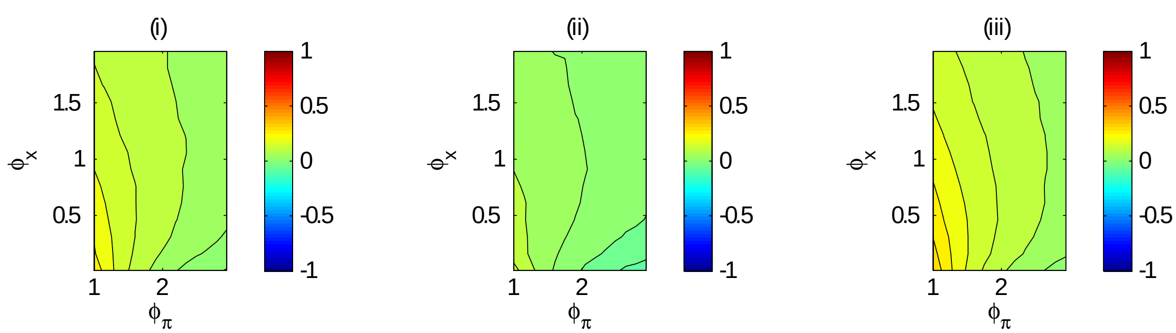

FIGURE 15C. Correlations of (i) model-consistent domestic output gap and HP-filtered domestic output, (ii) model-consistent global output gap and HP-filtered global output, (iii) model-consistent ToT gap and

HP-filtered ToT as a function of the parameters of monetary policy (high *inertia*)

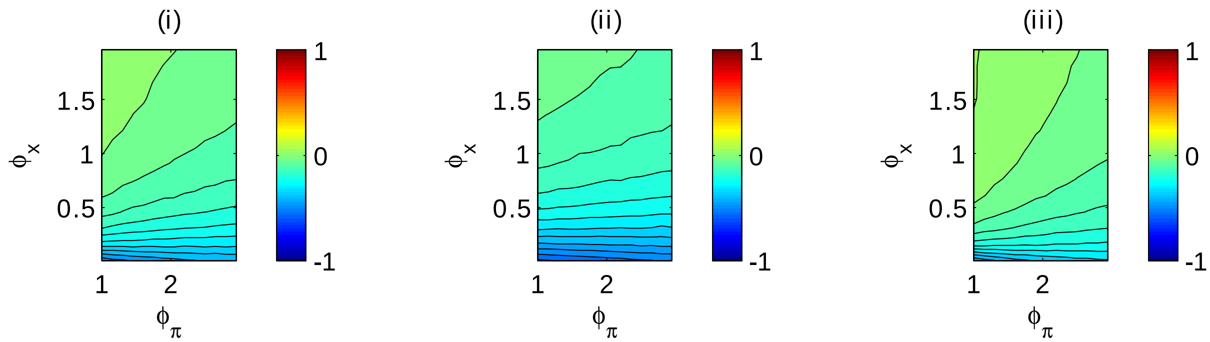

FIGURE 15D. Correlations of (i) model-consistent domestic output gap and HP-filtered domestic output, (ii) model-consistent global output gap and HP-filtered global output, (iii) model-consistent ToT gap and HP-filtered ToT as a function of the parameters of monetary policy (low *inertia*)

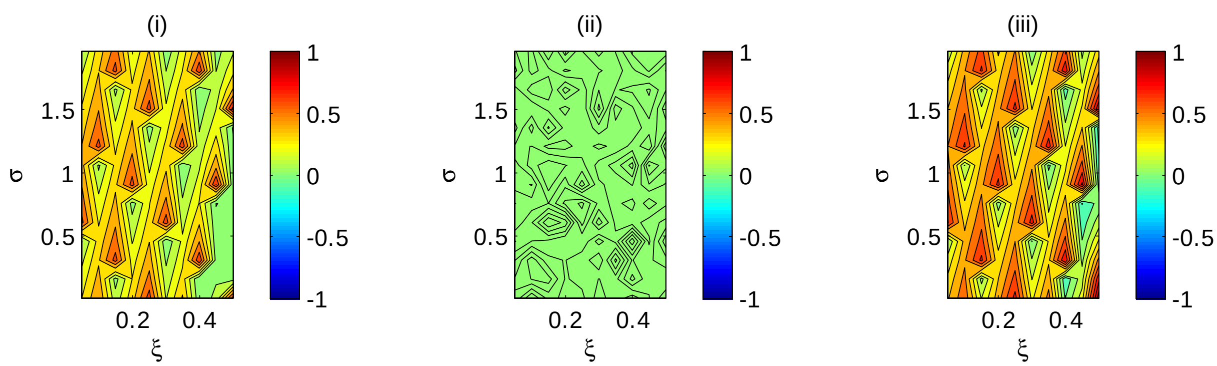

FIGURE 15E. Correlations of (i) model-consistent domestic output gap and HP-filtered domestic output, (ii) model-consistent global output gap and HP-filtered global output, (iii) model-consistent ToT gap and HP-filtered ToT as a function of the parameters of openness

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