Preliminary draft
25 May 2009

Challenges for estimating and forecasting macroeconomic trends during financial crises: implications for counter-cyclical policies

Pingfan Hong[1]
Chief for Global Economic Monitoring
UN/DESA/DPAD

International Seminar on Timeliness, Methodology and Compatibility of Rapid Estimate of Economic Trends

May 27-29

Ottawa, Canada

[1] Views expressed here are those of the speaker. They do not necessarily represent the views of the United Nations.

1. Introduction

I would like to thank the organizers for inviting me to this very interesting conference.

I am an econometrician. As Nobel Laureate Professor Lawrence Klein, my PhD supervisor, once said, an econometrician would wear two hats: one hat of an economist and another of a statistician. I guess most participants at this conference are statistician, so I should speak with my second hat on top of the first one. Indeed, my talk will focus mostly on statistical issues, but I will also discuss briefly their implications for economic policies.

I will concentrate on four issues.

First, I would like to share with you a brief evaluation of the forecasting performance of the UN/LINK global modeling system in the past three decades. The evaluation attests the difficulties in predicting the eruption of a large-scale financial crisis and its impact on the real economy.

Secondly, I will introduce to this audience a high-frequency modeling exercise that some of the LINK experts have been working on in recent years, which shows how to use the weekly data stream to estimate and forecast quarterly GDP growth on a rolling basis. I will also evaluate their estimating performance in recent quarters during this global financial crisis.

Thirdly, I would like to compare two different indicators for quarterly GDP growth. One is the Over-Year-Ago (OYA) quarterly GDP growth and another is the Seasonally Adjusted Annual Rate (SAAR) of Quarterly GDP growth. The second indicator is better in defining the “turning point” for economic trends. Most developing countries have not adopted SAAR yet, and the international statistical community should help developing countries set up the SAAR GDP indicator.

My last point will be on the importance of adopting a correct estimate of the potential output gap for the economy. I would argue that the commonly used H-P filter method may not reflect the true potential GDP in economic sense. In comparison, an estimate of potential GDP based on production function should reflect better the gap in capacity utilization, particularly in employment.

A correct estimate of both the "turning point' and the potential GDP is very crucial for policymakers during financial and economic crises, especially for their stipulating and implementing counter-cyclical macroeconomic policies.

Before I start with my first point, let me clarify the difference between "'estimating" and "forecasting".

Assume y_t is a macroeconomic indictor, such as GDP, or other indicators, I_t is a set of information.

By estimating y_t, we mean we try to ascertain, or to "form our expectation (E) on", the value of y in period t, conditioned on the information available in the same period. For example, we are in May, and if we would like to ascertain GDP for the second quarter, we have at least some information about the economy for the months of April and May, such as, the monthly industrial production. We can "estimate" GDP for the second quarter by using the information available in the same quarter:

$$y_t^e = E_t(y_t / I_t)$$

In comparison, by forecasting y_t, we mean we try to ascertain the value of y for period t, conditioned on the information available only in period t-1. For example, we are in May, and if we would like to forecast GDP for the third quarter, we have information about the economy only up to part of the second quarter, but nothing about the third quarter, so we "forecast" GDP for the third quarter:

$$y_t^f = E_{t-1}(y_t / I_{t-1})$$

2. Evaluation of the forecasting performance of the UN/LINK global modeling system[2]

Since the early 1970s, the UN Secretariat has annually published forecasts for the world economy based on the exercise of Project LINK.[3]

[2] This section is based on, with some updates, a box in the *World Economic Situation and Prospects 2007*, United Nations Sales No. E07.II.C.2

[3] The forecasts were published in part one of the *World Economic and Social Survey* before 2000 and have since been published in the *World Economic Situation and Prospects*.

Project Link consists of some 80 individual country models, linked together through trade and other international linkages, to model the global economy, for forecasting and policy simulation studies.

We evaluate the forecasts for the growth rates of aggregate GDP of three groups: world, developed countries and developing countries respectively. Forecasts for GDP growth rates for year t made at the beginning of the year, namely, one-year-ahead forecasting, are compared with the corresponding data officially released by year t+2.

Figure 1-3 show the forecasts, observed data and errors for these three groups respectively, and table 1 summarizes some key statistics for the forecasting errors.

Figure 1. Forecasting world GDP

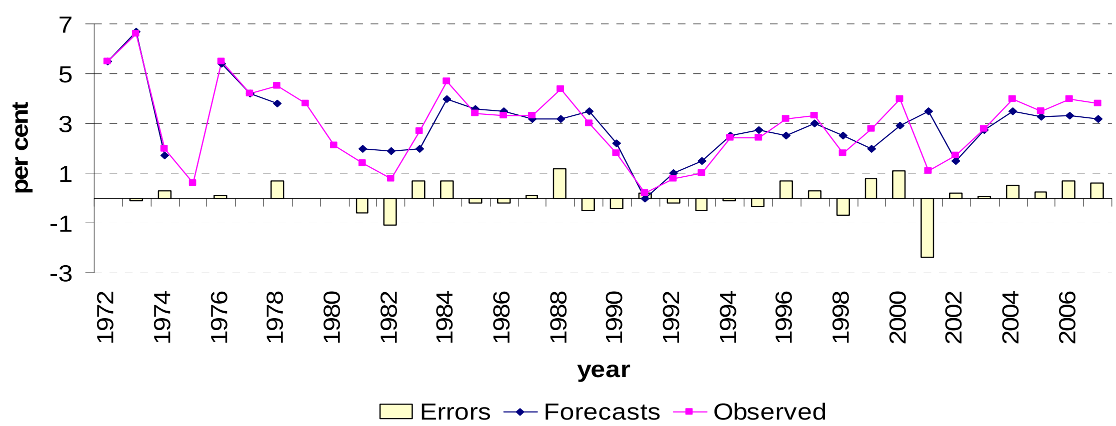


Figure 2. forecasting GDP for developed countries

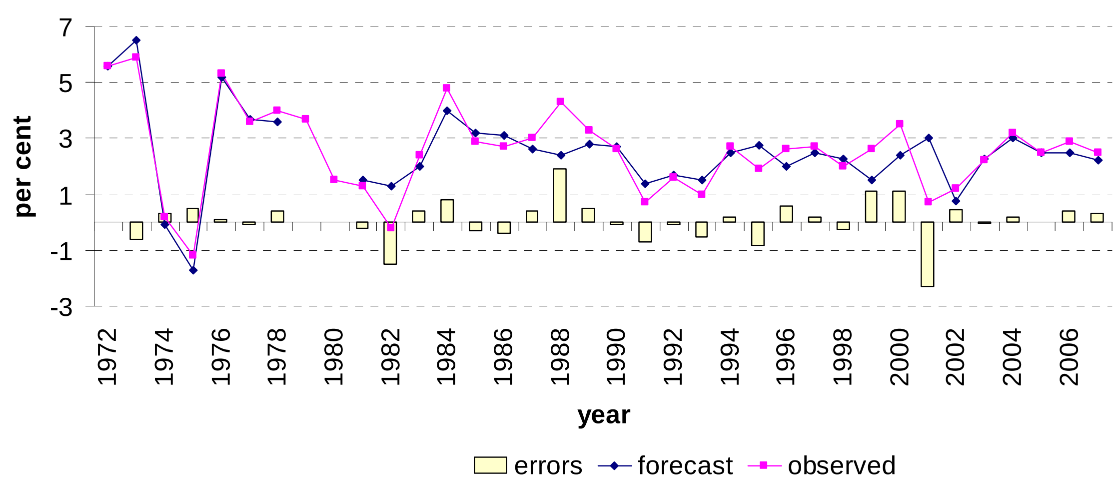


figure 3. forecasting GDP for developing countries

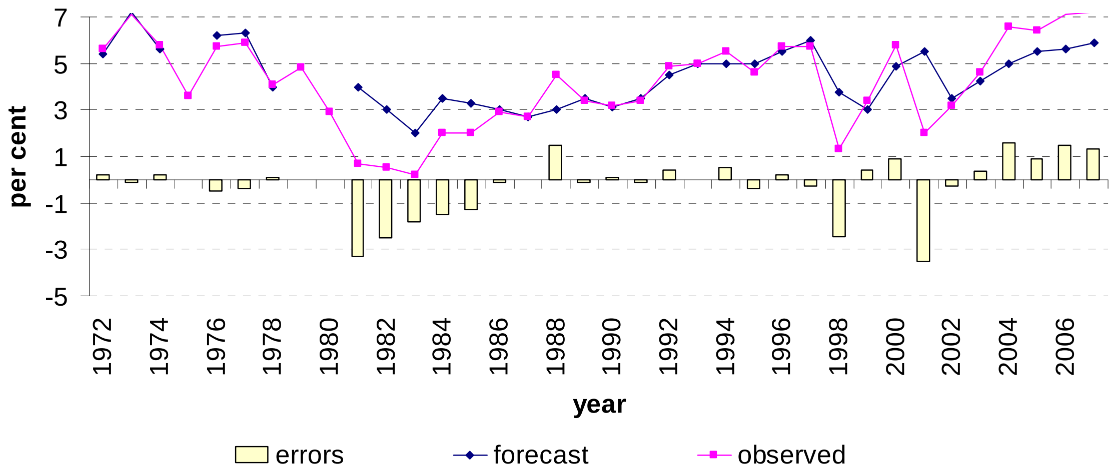


Table 1. Key statistics for the forecasting errors

	world	developed economies	developing countries
Mean	0.02	0.04	-0.36
Median	0.05	0.05	-0.1
Standard Deviation	0.7	0.76	1.25
Fraction of positive errors	0.52	0.5	0.42
Serial correlation	-0.2	-0.1	0.29

Source: DESA

No systematical bias is found in the forecasts for all the three variables, as the means and the medians of the errors are not statistically significant from zero. The forecasts have neither under-predicated nor over-predicated GDP growth rates for all the three groups, as indicated by the sign test. Meanwhile, serial correlations (first order) in the forecasting errors are not found to be significant either, suggesting that the forecasts are efficient in terms of using information available when the forecasts were produced.

Further analysis shows that forecasting errors are not found to be significantly different, or heterogeneous, across the sub-samples of three decades, in terms of the means and the standard deviations of the errors. This finding implies that the forecasting approaches, namely, the reliance on Project LINK, including both the structural models and the experts' opinions, were able to adapt to most structural changes in the world economy over the past three decades.

However, as shown in the figures, the forecasting errors for a couple of years were saliently large, particularly for 2001, when the growth of the world economy was falling substantially in the aftermath of the burst of the investment bubbles associated with ICT stocks. Forecasts for the current global financial crisis (2008-2009) are not included in the evaluation, because the official data of GDP growth rates for many countries are not complete yet.

In comparison of the forecasts for these three groups, the forecasting errors for the group of developing countries are larger than those for the group of developed countries, with the standard deviation of the errors for the former almost twice as large as that of the latter. One obvious reason for the poorer forecasting performance for developing countries is inextricably attributable to the much lower information-to-noise ratio in the economic data for these countries. Other reasons include the fact that many developing countries have experienced a number of periods of high volatility in their GDP growth over the past three decades, such as those during the debt crisis for Latin America in the early 1980s and the Asian financial crisis in the late 1990s. As indicated in figure 3, the forecasts for developing countries have missed or under-predicated the adverse impact of these crises on the growth of these economies.

More generally, the large forecasting errors for the downturns are rooted in the weakness of those structural macro-econometric models used to produce these forecasts, as those models are not powerful to predicate precisely and timely the occurrence of financial shocks in the first place, such as those financial crises in developing countries in the 1980s (debt crisis in Latin America) and in late 1990s (Asia financial crisis) and the one in the developed market in 2000-2001 (hi-tech bubble).

Once a financial crisis occurs, these models seem to fare well in forecasting the growth in the aftermath by incorporating the impact of the financial shocks, as well as the effects of policy responses.

There are a number of other factors for explaining the forecasting errors, such as assumptions on exogenous variables and on policies, which would deserve a thorough investigation.

Another approach to evaluating the forecasts is to compare these forecasts with the forecasts generated by a random-walk process, to see if the conditional LINK forecasting performs better than a mechanic unconditional forecasting. The analysis shows that the forecasts of GDP growth for the three groups as released in the UN publications are all superior to the forecasts generated by a random-walk process, in terms of smaller value of the means of forecasting errors and smaller value of standard deviation. For instance, the mean value of the forecasting errors for the world GDP growth from the UN forecasts is about 0.5 in comparison with the mean of 1.3 from the random-walk forecasting, and the standard deviation is about 0.7 in comparison with 1.7.

There are other more sophisticated mechanic forecasting approaches, such as vector-auto-regression modeling, which may perform better than the LINK forecasts, but such comparability is limited as the LINK approach posses other merits, such as alternative scenarios. A more meaningful study is to compare the UN forecasts with the forecasts produced by other international organizations, but this would involve nontrivial work to assure the comparability in such issues as the different time of releasing the forecasts by different organizations and the exchange of information among these organizations.

The forecasting errors are also tested for normal distribution. Since the forecasts for the world GDP and the GDP of the two country groups are the aggregate of the forecasts for individual countries, the forecasting errors for these aggregate variables should be the linear combination of the forecasting errors for the individual GDP; therefore, by the law of large number, the forecasting errors for the aggregate variables should theoretically follow a normal distribution. However, statistic tests have rejected normal distribution for the forecasting errors of all three GDP variables: all have positive kurtosis and negative skew. This non-normality will affect the accuracy for testing the mean of the errors, but should not affect the sign test.

Another caveat is that all the evaluation above is based on the premise of symmetric cost function of the forecasting errors. In reality, downside forecasting errors, namely, under-predication of the growth downturns may have higher economic costs than upside forecasting errors.

In short, the conventional large-scale econometric models have limitations in forecasting precisely the timing of the eruption of the financial crisis, but once the crisis occurs, they can still be a good tool for forecasting the impact of the financial crisis on the real economic growth.

3. High-frequency estimating and forecasting of quarterly macroeconomic indicators[4]

Many national statistical authorities release their preliminary quarterly data of national account, including the GDP growth, one month after the quarter is over, or even later. However, every week, there are releases of new data related to the performance of the overall economy at higher frequency: some are monthly, for example, the monthly construction spending, sales, international trade, and some are weekly or even daily.

A few LINK experts, led by Professor Klein, have engaged in recent years in developing high-frequency national models to estimate and forecast the quarterly GDP growth on a rolling basis every week, by incorporating the weekly data stream. Table 2 shows some weekly data for the US economy.

<u>Table 2 weekly data steam for the US</u>

Date	Economic Indicator	For	Latest	Prior Month
May 04	**Construction Spending**	**March**	**0.3%**	**-1.0%**
May 08	**Nonfarm Payroll Employment**	**April**	**-539,000**	**-699,000**
May 01	Auto Sales	April	9.3 Million	9.8 Million
May 07	**Consumer Credit Outstanding**	**March**	**-\$11.1 billion**	**-\$8.1 billion**
Apr 09	Export/Import Price Index	March	-0.6%, 0.5%	-0.3%, -0.1%
Apr 15	Producer Price Index, Total & Core	March	-1.2%, 0.0%	0.1%, 0.2%
Apr 14	Retail Sales, Total & Ex-Auto	March	-1.1%, 0.9%	0.3%, 1.0%
Apr 15	Industrial Production	March	-1.5%	-1.5%
Apr 14	Business Inventories	February	-1.3%	-1.3%
Apr 15	Consumer Price Index, Total & Core	March	-0.1%, 0.2%	0.4%, 0.2%
Apr 16	Housing Starts	February	510,000	572,000
Apr 09	Trade Balance	February	-\$26.0 billion	-\$36.2 billion
April 24	Durable Goods Orders & Shipments	March	-0.8%, -1.5%	1.6%, -0.9%
May 01	Manuf Ships, Inv, & Orders	March	-1.2%, -0.8%, -0.9%	-0.5%, -1.3%, 0.7%

The high-frequency modeling exercise is based on two statistical techniques: principle component analysis and ARIMA time-serials analysis. It is also based on economic analysis.

The modelers would select a large number of high-frequency indicators, based on their economic relationship with both the supply side and demand side of producer and consumer behavior, as well as public sector. For example, the Japan H-F model consists of more than 50 high-frequency indicators and the US H-F model has even more.

[4] This section draws materials from L.R. Klein and W. Mak, *University of Pennsylvania Current Quarter Model of the United States Economy*, and Y. Inada, *Konan University Current Quarter Model Forecast for the Japanese Economy*. More detailed information can be found in L.R. Klein (edit) *The Making of National Economic Forecasts*, forthcoming. I would like to thank Professor Klein and Professor Inada for sharing their papers and materials, but I should solely be responsible for any errors in my presentation and interpretation.

The modelers would apply principle component analysis to the historical quarterly values of these high frequent indicators, for identifying the co-movement among these indicators, in terms of their principal components.

Afterward, the modelers would build the statistical relationship between the expenditure side GDP components and the principle components of these indictors, as well as the relationship between the income side GDP components and the principle components of these indicators. For example, the two equations for GDP and GDP deflator in terms of their direct relationship with some principle components of the high-frequency indicators are shown below.

$$\begin{aligned}\textbf{Dlog (QGDP)} = \mathbf{0684} &- \mathbf{0.954\ Dlog\ C1} \\ &+ \mathbf{0.304\ Dlog\ C2} \\ &- \mathbf{0.0661\ Dlog\ C6} \\ &- \mathbf{0.295\ Dlog\ C7} \\ &+ \mathbf{0.581\ AR(1)} \\ &- \mathbf{0.677\ MA(1)}\end{aligned}$$

$$\begin{aligned}\textbf{Dlog (QPGDP)} = \mathbf{0.817} &- \mathbf{2.463\ Dlog\ C1} + \mathbf{0.925\ Dlog\ C2} \\ &+ \mathbf{1.383\ Dlog\ C3} - \mathbf{5.113\ Dlog\ C4} \\ &+ \mathbf{4.189\ Dlog\ C5} - \mathbf{2.233\ Dlog\ C6} \\ &+ \mathbf{0.908\ MA(4)}\end{aligned}$$

The modelers would also apply ARIMA analysis to those high-frequency indicators to identify their dynamic time-series features.

The estimating and forecasting process will follow these steps:

In step 1, the modelers would update the high-frequency indicators every week, with the latest data collected in this week.

In step two, the modelers would run the ARIMA model to reproduce all the monthly values of these indicators for the rest period of this quarter, as well as for the next quarter, and also sum up their quarterly values.

In step three, the modelers would run the model based on the principle component analysis, and the regression relationship between these principle components and the quarterly GDP, to produce the estimate for expenditure side GDP and income side GDP for the current quarter and the forecasts for the next quarter.

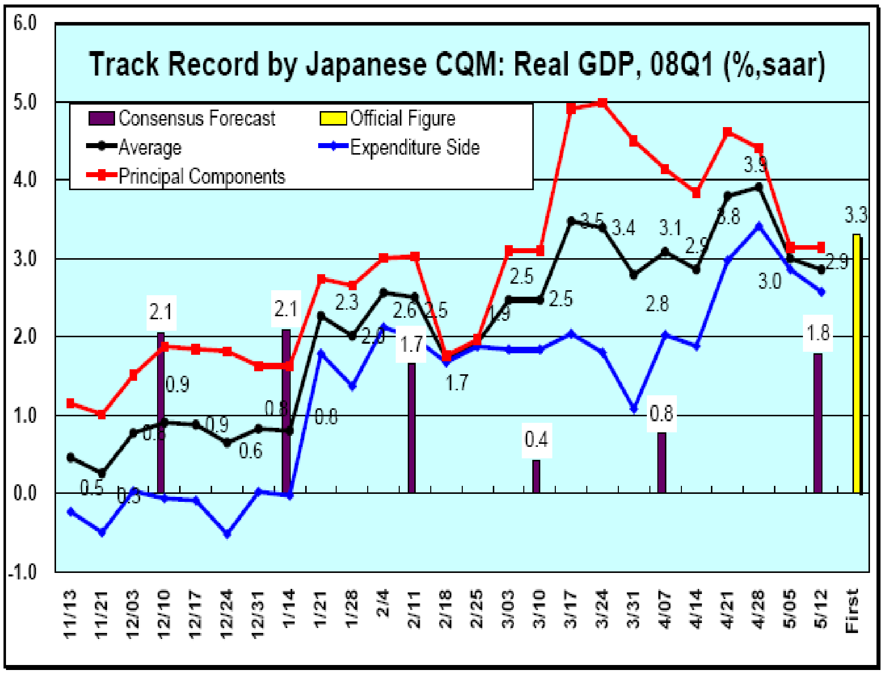
The modelers will keep this process rolling on, continuously updating the database, the model parameters, and the estimate of the quarterly GDP every week.

What is the performance of these models in estimating and forecasting, particularly during this global financial crisis?

According to a recent study of Professor Inada, his H-F Japanese model seems to perform better than the "consensus forecast", in terms of standard deviation of forecasting errors, as shown in figure 4 below (duplicate from Inada's paper).

<u>Figure 4. performance of Japanese H-F model</u>

Figure 7-2 Forecast Dynamics of High Frequency Model Forecast: 2008 Q1



I take a different approach to evaluating both the US and the Japan H-F models.

I focus on the convergence of the rolling estimating of these models, to find out if the estimates made in the later weeks of the quarter are better than the estimates made in the earlier weeks. In other words, we would like to see if this rolling estimating process would converge to the official GDP released by the government, along with the increase in the information set of the high frequency indicators over time.

I have selected a sample period from the first quarter of 2008 to the first quarter of 2009. For each quarter, I have collected five pieces of data: (1) the estimate of the quarterly GDP made at the beginning week of the first month of this quarter, for instance, the estimate of GDP growth for the first quarter of 2008, made at the first week of January of 2008; (2) the estimate made at the beginning week of the second month; (3) the estimate made at the beginning week of the third month; (4) the estimate made at the beginning week of the month immediately after the quarter is over; and (5) the official GDP growth for that quarter released at the end of the month immediately after the quarter, for example, the official US GDP growth for the first quarter as released by the end of April (but Japan would release its GDP even later, in late May).

As indicated by figures 5-6, and tables 3-4, the rolling estimates indeed converge, in terms of gradually narrowing root-mean-squared errors as the estimating process moves toward the date of the official GDP release.

Figure 5 Convergence in the rolling estimate of US H-F model

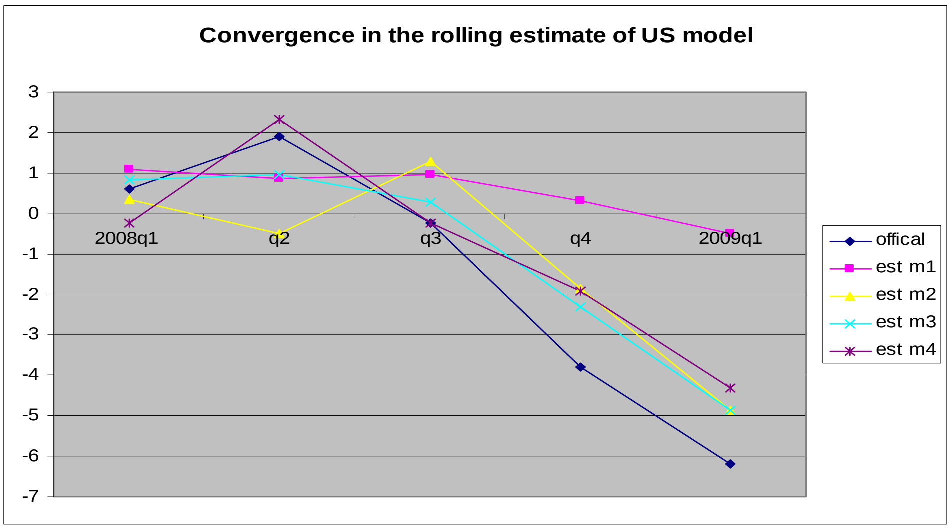


Table 3. Estimate errors of the US H-F model

Mean Error	-2.625	-0.5475	-0.665	-0.8375
RMSE	3.607652	1.853126	1.144312	1.4058

Figure 6. Convergence in the rolling estimate of Japan H-F model

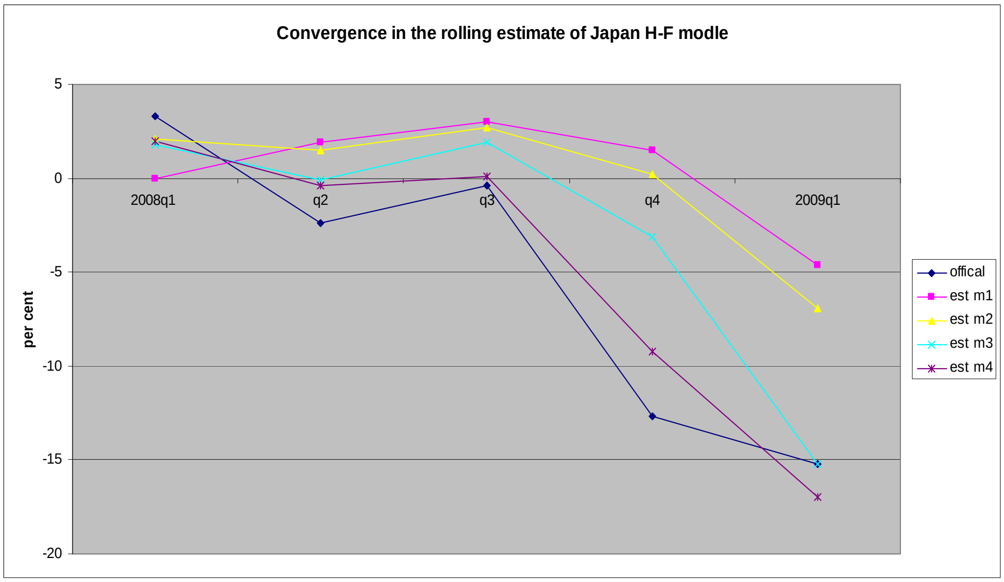


Table 4. Estimate errors of the US H-F model

Mean error	-7.3	-6.75	-3.175	-0.725
RMSE	8.425438	7.232704	4.582357	2.070266

In terms of forecasting errors, the performance of the US H-F model seems to fare much better than the Japanese model, as the former shows much smaller mean errors and RMSE than the latter. However, the Japan H-F model seems to show a more monotonic converging property than the US model. In the Japanese model, the estimating errors narrow monotonically as the point of forecasting is moving close to the date of the official release. In the US model, the estimating errors made in the first three months are converging, but the errors for the estimate made in the fourth month would increase slightly.

We should keep it in mind that the period I have selected, from the first quarter of 2008 to the first quarter of 2009, was the most volatile period for these economies in the history, as the eruption of the financial crisis had brought these economies into the most severe recession since WWII, with uncertainties heightening significantly for estimating and forecasting.

4. Indicators for the "turning point" in macroeconomic trend: OYA versus SAAR?

It is crucial for policymakers to ascertain the major "turning point" of the economy for both the downturn and the upturn associated with financial crises and economic cycles, in order for them to adopt timely policy actions. A prompt and correct identification of the turning point will depend both on sound economic analysis and on properly defined statistical measures of the economy.

It would usually take several months or longer for macroeconomic policy measures to have their effects on the real economy. The policymaking process itself would also take time, particularly for stipulating any major discretionary fiscal policies, as the process involves a prolonged complex political bargaining.

Relying on annual macroeconomic indicators for determining the turning point of the economy and for making counter-cyclical policy decisions would seem to be too late.

Most countries have quarterly statistical data for macroeconomic indicators, such as quarterly GDP growth rate, but there are two different quarterly measures.

For most developed economies, the Seasonally Adjusted Annual Rate (SAAR) is used:

$$y_t^{saar} = (Y_t^{sa} / Y_{t-1}^{sa})^4 - 1$$

In the equation above, y is the saar growth rate of GDP for quarter t, and Y is the seasonally adjusted level of quarterly GDP.

For most developing countries, quarterly GDP growth, if available, is defined over the same quarter of the previous year, namely, over-year-ago (OYA):

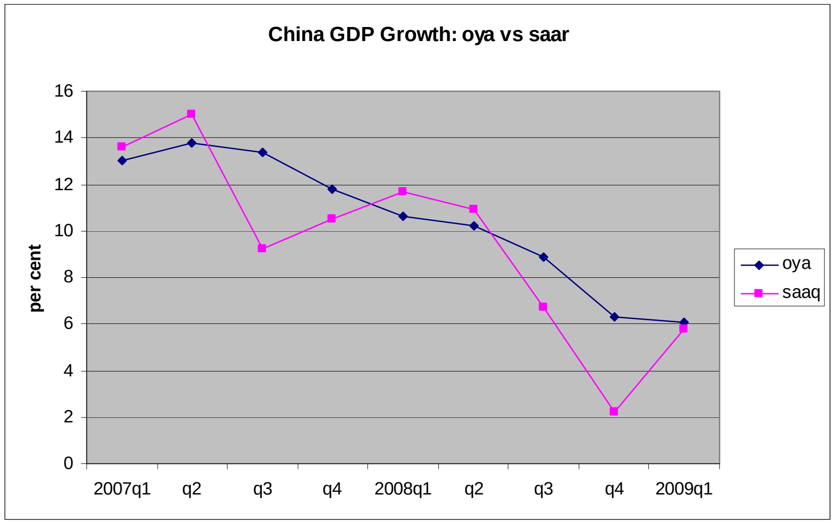
$$y_t^{oya} = (Y_t / Y_{t-4}) - 1$$

In the equation above, y is the oya growth rate of GDP for quarter t, and Y is the level of quarterly GDP without adjusting any seasonality.

Figure 7 shows an example of comparing these two different quarterly GDP indicators for China. The oya growth rate is officially released by the Chinese National

Bureau of Statistics, while the saar growth rate is an unofficial estimate by JP Morgan (other private institutions also provide similar estimate).

Figure 7 oya versus saar quarterly GDP growth of China



It is clear from this chart that the saar growth rate had indicated a significant downturn for the Chinese economy as early as in the third quarter of 2007, but the oya growth rate could not indicate such a significant signal.

Most Chinese economists, as well as the policymakers, had remained complacent about the strength of the Chinese economy until the second half of 2008. In fact, the authorities were tightening macroeconomic policies in 2007 and early 2008. Had they rely on the saar growth rate, they might have acted much earlier in response to the weakening of the economy from the impact of the global financial crisis.

These two indicators also showed a completely different signal most recently for the performance of the Chinese economy in the first quarter of 2009. According to the oya measure, China's GDP in the first quarter of 2009 grew by 6.1 per cent, a further weakening from the 6.3 per cent of the last quarter of 2008. According to the saar measure, however, China's GDP registered a growth of 5.8 per cent in the first quarter of 2009, a notable strengthening from the 2.2 per cent of the previous quarter.

Relying on the oya indicator, some economists in China have continued to call on the government to adopt new stimulus packages. If they had looked at the saar growth rate, they might have found indications that the implementation of the 4 trillion yuan

($580 billion) stimulus package since late 2008, along with the drastic monetary easing, may have started to show some effects, although still tentative.

It is important for developing countries to develop the saar indicators, so as to improve their capacity in measuring the cycles of their economy promptly and properly. The methodology and technology for doing so are not complex. The software X-12 is virtually free. However, nontrivial efforts are needed to make correct adjustment of the raw data by identifying the trend-cycle, seasonal, and irregular components.

5. Estimate of potential output gap: H-P filter versus production function

Another important data issue related to the financial crisis is how to provide the policymakers with correct estimate of the potential output gap of the economy.

For example, if an economy is growing at 2 per cent, we don't know if the economy is weak or strong, unless we know whether it is growing above its potential, or below its potential. 5 per cent GDP growth in China could be considered to be too weak while 2 per cent growth in Japan could be considered to be perfect, because the potential growth of the former is much higher than the latter.

Strictly speaking, a sound macroeconomic policy decision must rely on not only the information about the pace the economy is growing but also the information about the potential growth of the economy.

A common approach used by many economists to describing the relationship between macroeconomic policy action and the potential of the economy is the "Taylor Rule":

$$i_t = \pi_t + r^* + \lambda(\pi_t - \pi^*) + (1-\lambda)(y_t - y^*)$$

The equation above is specifically for monetary policy, where i is the policy interest rate, π is inflation rate, π^* is the target inflation rate, r^* is the long-run real interest rate, y is GDP growth rate, and y^* is the potential GDP growth rate, λ is a fraction. The central bank is expected to adjust its policy interest rate according to the gap between the observed inflation and the target of inflation, and also according to the gap between observed GDP growth and the potential GDP growth. A similar rule can be set for fiscal policy.

Different countries can define their own policy objectives, with different elements in their policy reaction function, but the potential output of the economy must be a key factor in their policy consideration.

During the financial crisis, if the policymakers underestimate the potential output of the economy, their policy response to the economic downturn may come too late and the policy stance may come too small. The policymakers may also withdraw the policy stimuli too early when the economy just starts to recover, but is still far below its potential.

On the other hand, an overestimate of the potential output of the economy can also lead to policy mistakes. When the economy recovers to the level of its potential, if the policymakers keep the expansionary policy for too long, they will be faced with rising inflation and the counter-cyclical policy can metamorphose into a pro-cyclical policy.

A popularly used method to estimate potential GDP is the Hodrick-Prescott (H-P) filter, defined as follows.

$$\min \sum_{t-1}^{T} (y_t - \tau_t)^2 + \lambda \sum_{t=2}^{T-1} [(\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1})]^2$$

The series y is made up of a trend component, denoted by τ and a cyclical component.

Given an adequately chosen positive value of λ, the trend component is so estimated that it will minimize both the deviation of y from its trend (the first term of the formula above) and the variation of the trend component itself (the second term). The larger the value of λ, the higher is the penalty for the variation of the trend itself. For quarterly data, a value of λ equal to 1600 is recommended.

The HP filter is a heady tool to identify statistical trend, but the economic meaning of the estimated potential GDP based on this method is questionable, in addition to a few statistical limitations of this method.

By economic definition, the potential GDP (level or growth) for an economy should be the one when the economy is running at its full capacity of utilizing its labour and capital. This economic meaning is not reflected in the H-P filter at all.

The H-P filter would always impose symmetry of the GDP around the potential, so that the estimated gaps for the economy to run above its potential and the gaps below its potential are cancelled out over the long run. We know, however, in reality, an economy would be running at its potential only when all the factors are well aligned in a perfect condition. In most cases, the economy would be running below its potential.

Meanwhile, economic shocks, such as the external trade and financial shocks would not come in symmetry.

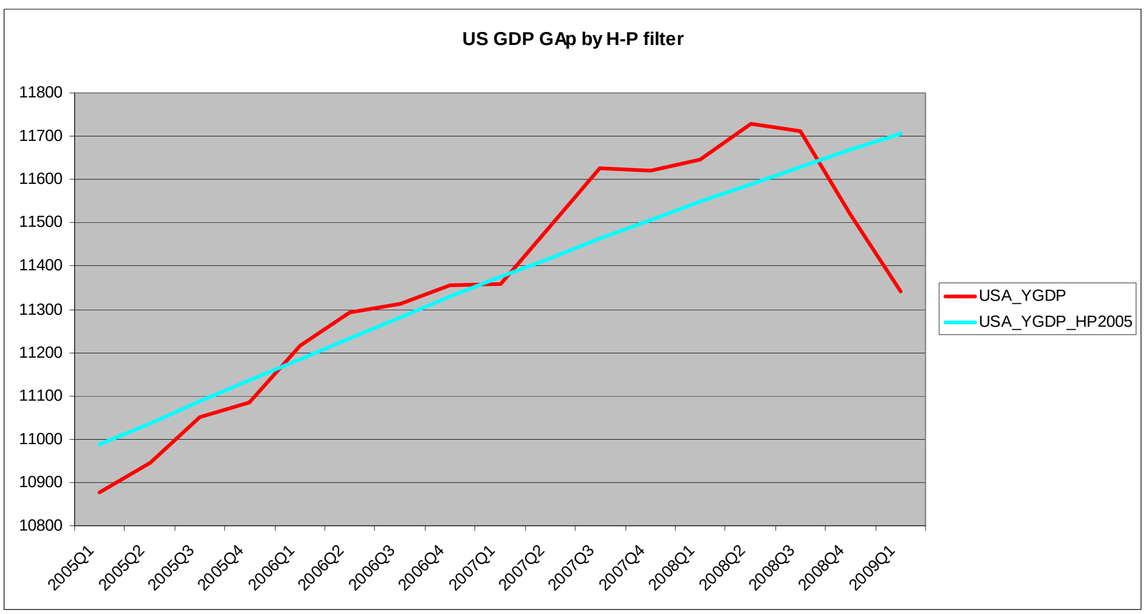
An alternative approach to the estimate of potential GDP is to use a production function. First, we can estimate a production function based on certain economic theory. Then, we can generate the potential GDP corresponding to the full utilization of labour and capital:

$$y^* = f(k^*, l^*)$$

Let's take an example to compare these two different estimates of potential GDP.

Figure 8 shows the estimate of the US potential GDP based on the H-P filter for the period from Q1 2005 to Q1 2009.

Figure 8. H-P filter estimate of GDP output gap for the US



The figure shows from Q2 2007 to Q3 2008, the US economy is running above its potential, and since the financial crisis intensifies, GDP in Q1 2009 was running 3 per cent below its potential.

In comparison, figure 9 shows the estimate of the US potential GDP based on a production function. It shows that for the period from Q1 2005 to Q1 2009, the US economy reached its potential only at the beginning of 2006, when the unemployment rate reached the lowest level of about 4.5 per cent, and for most other quarters, the economy was running below its potential. By this measure, the crisis has led the US economy to a level 7 per cent below its potential in Q1 2009.

The GDP gap estimated in the latter is more than twice as large as in the former, and the policy implications would also be significantly different between these two estimates.

Figure 9 Alternative estimate of the US GDP gap (copy from Business Week)

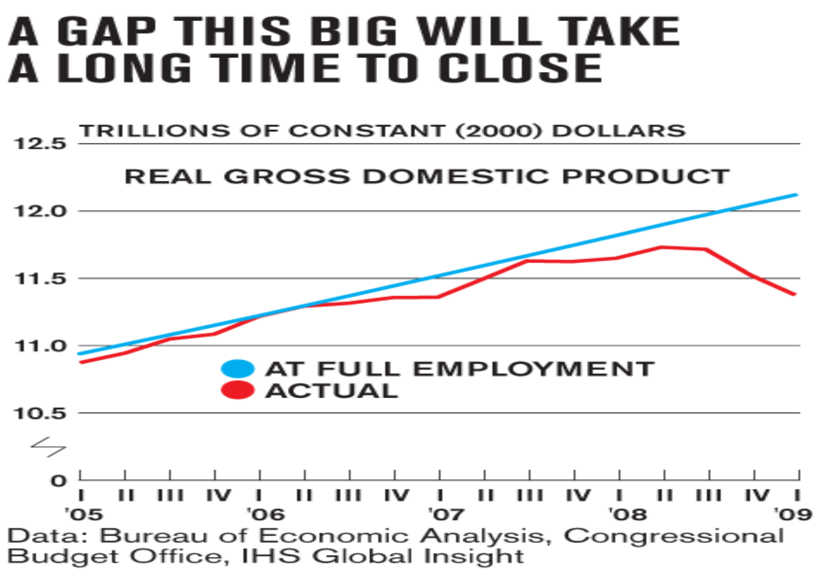
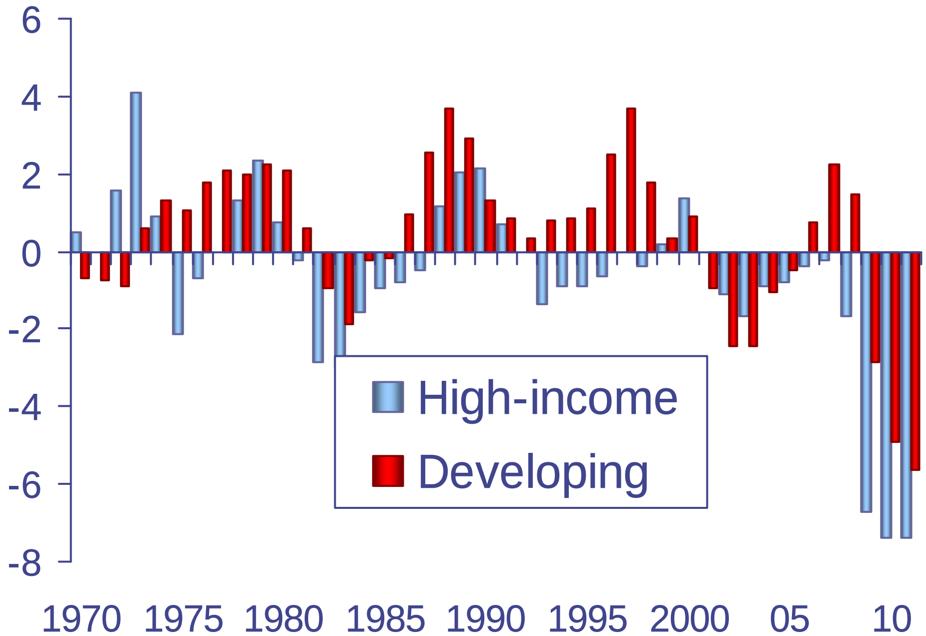


Figure 10 is a copy from a most recent presentation by the World Bank on the global financial crisis, indicating the large slack in global capacity caused by the crisis. I don't know the exact method the World Bank has used for the estimate of the potential output for both the developed and developing countries, but from the symmetric pattern of the output gaps in this figure, I guess the estimate is based on the H-P filter. Intuitively from economic point of view, it is hard to believe developing countries (as in the red color on the slide) have been running in many years above their potential GDP, given the fact that most of them have a high unemployment and under-employment, and the external shocks they have experienced are far from symmetric, namely, more adverse shocks than auspicious shocks. It is also difficult to understand, as the chart indicated, that the crisis has led to a much larger spare capacity in developed countries than in developing countries.

Figure 10. World Bank estimate of output gap % of GDP



In short, if we rely on the H-P filter to estimate the GDP potential, we would most likely underestimate the potential of the economy. If we adopt macroeconomic policies on the basis of this estimate, the policy would error on the tightening side, leading to under-utilization of labour and other resources in the economy in the long run.

6. Concluding remarks and implications for macroeconomic policymaking

From the hindsight, the response of policymakers worldwide to this global financial crisis had been behind the curve, at least prior to October of 2008 (most developed economies have started to scale up their policy stance since then). Policymakers in most developed countries had underestimated the systemic risks of this crisis and its impact on the real economy, while policymakers in many emerging market economies had underestimated the contagion and the spill-over effects of this crisis on their own economies.

Many factors might have led to the delay in policy reaction, including the lack of timely information about the severity of this crisis, the inadequacy in the methodology of economic analysis, particularly in the analysis of the linkages between the financial sector and the real economy, the misjudgment of some policymakers, and the divide ideological concerns about the political implications of economic policies.

Economic policy actions are ultimately taken by politicians, who have to take into account the political implications, which would quiet often go beyond the economic and statistical domains. Economists and statisticians, however, can help in this process by providing more accurate and timely information, and more comprehensive and robust economic analysis, to facilitate the policy debate and the policy making.