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Potential Growth in Emerging Asia

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Potential Growth in Emerging Asia

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Abstract

Using three distinct approaches—statistical filtering, production function, and multivariate model— this paper estimates potential growth for China, India, and five ASEAN countries (Indonesia, Malaysia, the Philippines, Thailand, and Vietnam) during 1993–2013. The main findings include: (i) both China and India have recently exhibited a slowdown in potential growth, largely reflecting a decline of total factor productivity (TFP) growth; (ii) by contrast, trend growth for the five ASEAN countries has been rather stable and might even have increased marginally, with the notable exception of Vietnam; (iii) over the longer term, demographic factors will be much more supportive in India and some ASEAN economies than in China, where working-age population should start shrinking, with the overall dependency ratio climbing by the end of this decade. Improving or sustaining potential growth calls for broad structural reforms.

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I. INTRODUCTION

Medium-term growth prospects for China, India, and other emerging Asian economies have recently become a focus of economic debates in the region. Both China and India have shown a declining growth trajectory since the global financial crisis (GFC): growth in China has slowed from a rate of over 10 percent in the 2000s to below 8 percent in the past two years while growth in India has slowed from around 8 to below 6 percent during the same period. For other emerging Asian economies, while there has been no obvious slowdown in the past few years, growth rates have been significantly lower than those observed prior to the Asian crisis.

A key policy issue is whether some of these recent growth patterns may reflect structural factors, and what they hold for the future. As a region with a high share of rapidly growing middle-income countries, emerging Asia is particularly susceptible to the “middle-income trap,” a phenomenon of rapidly growing economies stagnating at middle-income levels and failing to graduate into the ranks of high-income countries. Indeed recent papers find that middle-income economies are significantly more at risk of experiencing a sustained growth slowdown than their lower- and higher-income counterparts (Aiyar and others, 2013; Eichengreen and others, 2013).

Furthermore, there is concern that sluggish growth in advanced economies in recent years partly is structural and would continue over the medium term, spilling over to emerging Asian economies through trade and technology diffusion linkages. Assessing the trend growth of the countries in the region can help diagnose early signs of such a slowdown, identify the drivers and thereby provide further support for policy actions to fend it off.

Existing literature on the potential growth in emerging economies in the post-GFC era is relatively small, although there have been numerous studies on the impact of crisis on potential growth in advanced economies and emerging economies in other regions. For example, Barrera and others (2009) find that potential output in the United States has been reduced by about 6 percent since the GFC. Furceri and Mourougane (2009) find similar evidence on loss of potential output after the financial crisis for OECD countries based on pre-GFC data. This begs the questions of whether emerging countries are also affected. Based on pre-GFC data, Cerra and Saxena (2008) find that emerging market economies would also suffer from a loss of potential output after a financial crisis. Sosa and others (2013) study potential growth in Latin America, finding that the recent pickup in growth is mainly driven by higher TFP growth. Recently, Lee and Hong (2010) have studied the drivers of potential growth in Asia using a growth accounting framework, but based on pre-crisis data.

This paper shed light on potential growth in selected emerging Asian economies, including China, India, and five ASEAN economies (Indonesia, Malaysia, Philippines, Thailand, and Vietnam) before and after the GFC. It also touches on broad reform priorities to minimize

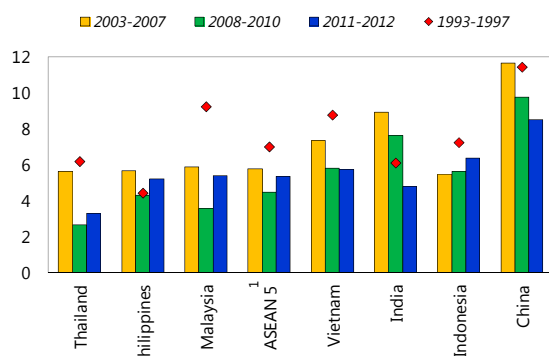
the risk of a sustained slowdown in trend growth in the future. Given that potential growth is unobservable and the various existing approaches are conceptually different and could yield different results, a large set of standard estimation techniques are used to cross-check each other and ensure robustness of the findings.

The rest of the paper will be organized as follows: Section II presents stylized facts about growth and inflation in emerging Asia; Section III lays out various techniques and results; Section IV interprets the findings; while Section V concludes with some policy implications.

II. STYLIZED FACTS ABOUT TREND GROWTH AND INFLATION

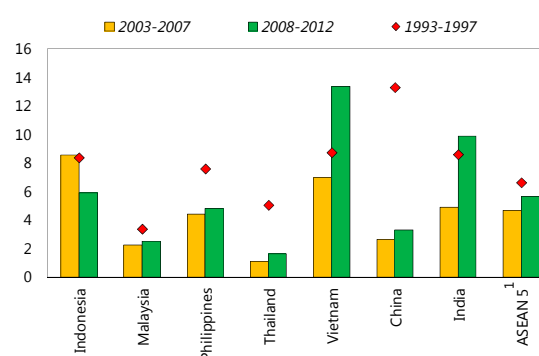
Since the GFC, headline growth has slowed substantially in both China and India, although the inflation picture differs. Growth in China has slowed from 12 percent in 2010:Q1 to around 8 percent, while growth in India has decelerated more sharply from above 10 percent to 4 percent during the same period (Figure 1). Despite much lower growth, India's inflation has come down only little (Figure 2). One explanation for why inflation has remained high and sticky could be that potential growth has come down. In China, the slowdown in GDP growth has been milder and largely policy engineered, and inflation has declined since mid-2011. It is therefore less clear whether the observed slowdown reflects lower potential growth.

Figure 1. Stylized Fact: GDP Growth Rate
(In percent; year-over-year average)



Sources: IMF, *World Economic Outlook*; and IMF Staff Calculations.
¹ PPP GDP weighted average used for ASEAN 5.

Figure 2. Stylized Fact: Consumer Price Inflation
(In percent; year-over-year average)



Sources: IMF, *World Economic Outlook*; and IMF Staff Calculations.
¹ Simple Average used for ASEAN 5.

Growth developments in the five ASEAN economies are more nuanced with a mixed inflation picture. On the one hand, since the GFC, most of these economies have not gone back to their pre-2008 growth rates, and even less so to their pre-Asian crisis growth performance. On the other hand, most recently, in contrast to the sustained slowdown in China and India, some of the ASEAN economies—particularly Indonesia, the Philippines and Malaysia as well as, to a lesser extent, Thailand—have shown a modest pickup of growth. The only exception is Vietnam, where growth has been very sluggish since the GFC. On the inflation front, the picture in ASEAN economies is mixed but inflation declined in

2012 despite broadly stable growth in some countries, in particular in Malaysia and Indonesia.

III. ESTIMATING POTENTIAL GROWTH

A. Methodology

“Trend” or “potential” growth can be broadly defined in a number of ways. First, it can literally refer to a purely statistical estimation of the tendencies in GDP data. Typically, estimation is accomplished by decomposing or filtering raw GDP data into a cyclical/noise component and a trend component using various statistical specifications. Second, “potential growth” can also be defined, in a macroeconomic sense, as the rate of growth consistent with the natural rate of unemployment and stable inflation. In this connection, trend growth is usually estimated by exploiting the link between inflation and output gaps. Finally, “potential growth” can also be defined as the long-term potential growth rate given the productive capacity, technology, as well as factor inputs of the economy.

To encompass these various definitions, we use three broad approaches (see Appendix I for more details):

- **Statistically based filtering methods.** We use both purely statistical filters—such as the commonly used Hodrick-Prescott, Baxter-King, and Christiano-Fitzgerald filters—as well as univariate and bivariate state-space models with the Kalman filter. These approaches are consistent with the first definition of trend growth above, except for the bivariate state-space model that also partly relies on the link between output gaps and inflation. An important advantage of this class of approaches is that it is simple and transparent. The main drawback is that, as purely statistical techniques, these filters estimate trend growth without a firm mapping to economic theory and in particular disregard economic relationships such as the Phillips curve and Okun’s law—with the partial exception of the bivariate state-space model. Furthermore, the filtering approach can be sensitive to the specific choice of smoothing parameters and, more fundamentally, it is often criticized as a backward-looking technique that ultimately tracks actual output developments.
- **Macroeconomic model-based multi-filter method.** This approach encompasses both the first and second definitions of trend growth above and brings consistency between the estimation of trend growth and the observed values of other key macroeconomic variables including inflation and non-accelerating inflation rate of unemployment (NAIRU). In addition, by using a Bayesian estimation method, this approach better allows the data to “speak for themselves.” A drawback is lack of transparency: it is not straightforward to immediately dissect the inter-relationship between various factors and trend growth. In addition, while incorporating complex short-term time-series dynamics, this method is not suited for estimating future trend growth, as the latter quickly converges by construction to an arbitrarily assumed steady-state growth rate.

- Production function approach.** This approach relates to the third definition of trend growth and is implemented here in three steps: first, within a growth accounting framework with a Cobb-Douglas production function featuring both physical and human capital,² actual TFP growth is calculated as the residual contribution to GDP growth once the contributions of physical capital, human capital, working age population, labor participation and the unemployment rate are taken into account. Second, a number of variables—such as TFP, capital stock, unemployment rate, labor force participation rate³—are filtered using the Hodrick-Prescott approach to obtain their trends. Third, trend output is calculated as a sum of six components (i) trend capital stock;⁴ (ii) human capital stock; (iii) working age population; (iv) trend labor force participation; (v) natural rate of unemployment NAIRU (using trend unemployment rate); (vi) trend TFP. This approach is transparent but, like the filtering techniques, it does not explicitly link the estimation of trend growth to the relationship between the output gap and inflation. Its main advantage is to estimate trend growth while also decomposing it into different components. As such, the production function approach can identify the proximate drivers of past shifts in trend growth and provide a framework for thinking about future shifts, for example, through scenario analysis. The main criticism is that this approach filters the inputs, thereby indirectly suffering from the same shortcomings as the statistical filtering methods that directly filter output.

B. Results

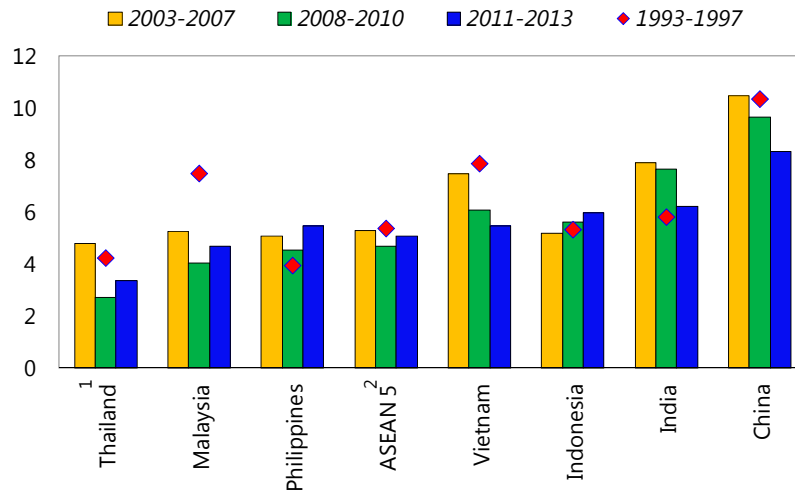
Keeping in mind the limitations of all these estimation techniques—not least their intrinsically backward-looking nature—results suggest that potential growth has declined in China and India since the GFC (Figure 3). Although the three different approaches can produce markedly different results on an annual basis, they consistently point to a gradual decline in trend growth in recent years for both countries (Figure 4). More specifically, consistent with Barnett and others (2013), China’s trend growth appears to have peaked around 2006–07 at around 11 percent and have slowly declined thereafter to below 8 percent by 2013.⁵ Similarly, the analysis suggests that India’s trend growth peaked just before the GFC at about 8 percent and has recently declined to around 6–7 percent.

² Human capital is calculated as a weighted average of years of primary schooling, years of secondary schooling and years of higher schooling from the Barro-Lee dataset, with the weights comprising Mincerian coefficients obtained by Psacharopoulos (1994).

³ A linear trend is used to calculate the trend labor force participation rate.

⁴ In some cases, unfiltered capital stocks are used to check for robustness (see Appendix II).

⁵ In the production function approach, results for China using the unfiltered capital stock would only slightly differ from those using the filtered capital stock. Specifically, trend growth is estimated to have been over 0.5 percentage point higher in 2009 when using the unfiltered capital stock—reflecting the stimulus-driven rise in investment that year— but this difference comes down to 0.2 percentage point in 2013.

Figure 3. Trend Growth Across Countries*(Average across methods; in percent)*

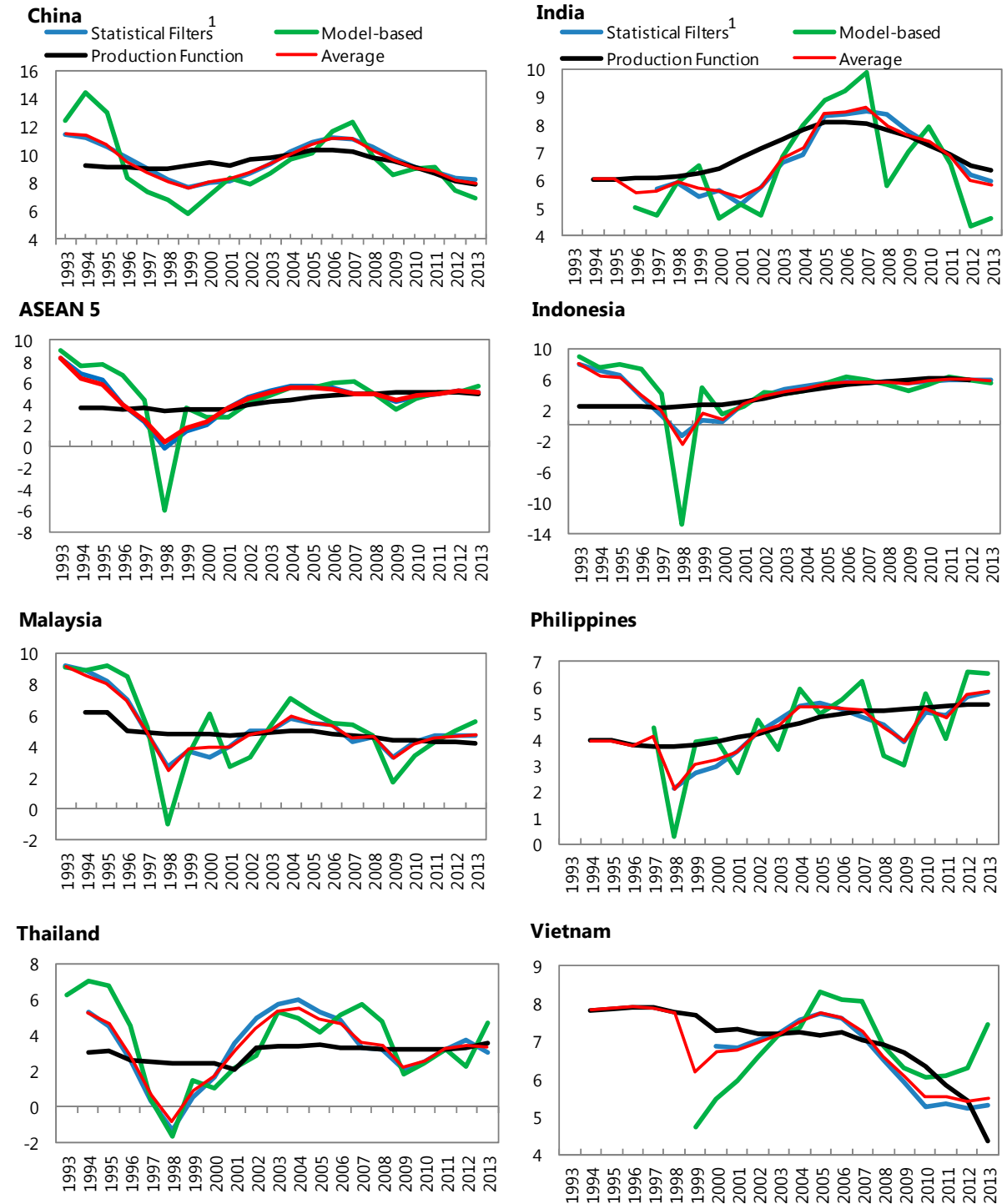
Sources: IMF, *World Economic Outlook*; World Development Indicators; CEIC data Company Ltd.; Haver Analytics; U.N. Population Database; and IMF Staff Calculations.
¹ 1993-1997 average excludes 1997 as Thailand's precrisis boom ended in 1996.
² PPP GDP weighted average used for ASEAN 5.

On the contrary, potential growth for ASEAN 5 as a whole shows no decline since the GFC. Indeed, while trend growth for the five ASEAN countries taken as a whole is still significantly below its pre-Asian crisis level, and marginally below its pre-GFC level, it remains solid and even shows a tentative pickup in recent years⁶. This has largely reflected strong domestic demand, intra-regional integration, improved governance and structural reforms. Notably, Indonesia and the Philippines have been shielded from global shocks given their low trade and financial openness, while Malaysia has benefited from the commodity boom after the crisis (Isnawangsih et al, 2013). However, there is some disparity across the different countries in the group:

- **Indonesia** has registered strong and rising trend growth until its most recent slowdown. After plummeting due to output destruction by the Asian crisis in the late 1990s, growth has been on a steady upward trend since then. Indeed, trend growth during 2011–12 has surpassed the average rates recorded prior to both the 2008 GFC and the late 1990s Asian crisis.
- **Malaysia, the Philippines, and Thailand show a small pickup in** trend growth in most recent years, but only for the Philippines has this trend growth surpassed its pre-GFC rate. Malaysia and Thailand, which were hit hard by the late-1990s Asian crisis, have not achieved their pre-1997 trend growth rates in recent years, and seem to have undergone a further slowdown following the GFC.

⁶ Admittedly, the slowdown in the two regional giants, China and India, might have an impact on growth prospects in the ASEAN region over the medium term.

Figure 4. Trend Growth Estimates
(In percent)



Sources: IMF, *World Economic Outlook*; World Development Indicators; CEIC data Company Ltd.; Haver Analytics; U.N. Population Database; and IMF Staff calculations.

¹ Hodrick-Prescott, Baxter-King, Christiano-Fitzgerald and Kalman filters are applied.

- **Vietnam**'s trend growth has been on a declining trajectory since the GFC and is currently estimated to be at its lowest since the early 1990s.⁷

IV. INTERPRETATION

A. Growth Accounting Exercise

A growth accounting exercise decomposes trend growth into the various factors that drive its evolution over time. Specifically:

- For China and India, the slowdown appears to have been driven largely by the decline in trend TFP growth (Figures 5–6). In theory, a declining capital utilization rate could also play a role in the estimates. Since it is not taken into account in the contribution of physical capital accumulation, it could unduly overstate the decline in TFP in economies such as China where the capital utilization ratio has been declining rather rapidly in recent years. In practice, however, an alternative growth accounting exercise accounting for declining capital utilization still points to some (albeit smaller) decline in trend TFP growth for China.⁸

For the five ASEAN economies as a whole, the most recent uptick in trend growth has largely reflected an increased pace of capital accumulation, with the notable exception of Vietnam where both capital accumulation and TFP have declined. TFP growth rates for the remaining ASEAN economies appear to have been rather stable, with the exception of some tentative uptick in Thailand and some decline in Malaysia.⁹ Nevertheless, trend TFP growth remains typically low in these five economies, particularly compared to China, and also, to a lesser extent, India. This could reflect a host of factors, ranging from: low Research and Development (R&D) expenditure (particularly Indonesia, the Philippines, Vietnam, and Thailand), poor infrastructure (particularly Indonesia and Thailand), low levels of economic complexity (particularly Vietnam, Indonesia, and the Philippines), and difficulty in doing business and stringent regulations in product markets (particularly Malaysia and Thailand)¹⁰ (Figures 7–10).

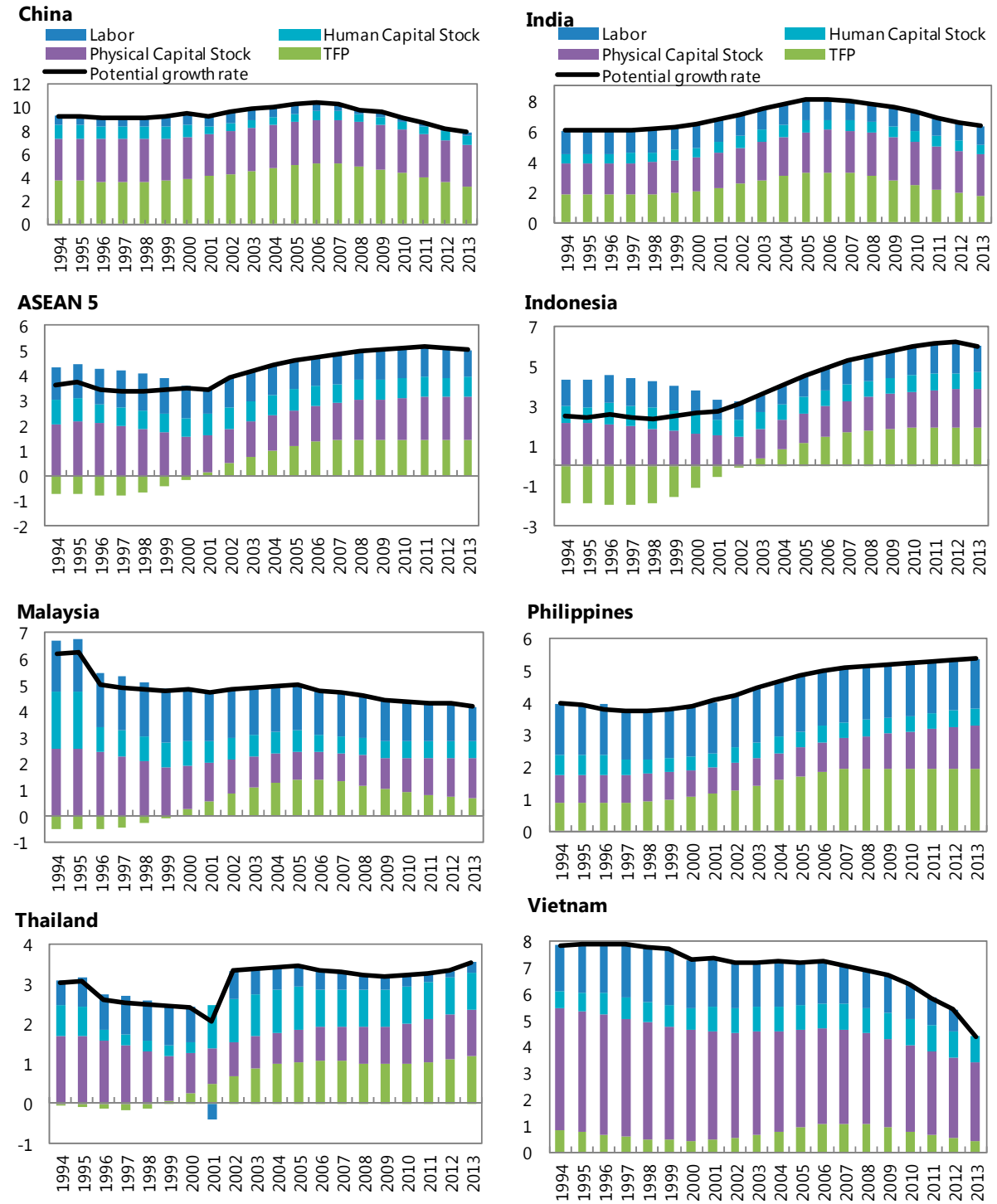
⁷ For Vietnam, the early 1990s estimates based on the production approach should be read with caution given the wide uncertainty surrounding capital stock estimates back then, which in turn reflect short available time series for investment. Nonetheless, the decline in trend growth is robust across other models.

⁸ While the finding of a decline in trend TFP growth and overall potential growth is qualitatively robust to whether and how capital utilization is accounted for, it depends quantitatively on the actual assumption made regarding the “equilibrium” capital utilization rate (e.g., whether the latter is obtained by filtering the actual capacity utilization series or whether some constant number such as the historical average is considered). For more details, see Appendix II.

⁹ To ensure consistency across countries, Indonesia's capital stock is estimated using the same perpetual inventory method applied for other countries. Using official data instead would yield some decline in trend TFP growth.

¹⁰ It is important to emphasize, however, that here the observed correlations between TFP and various factors do not necessarily reflect causality.

Figure 5. Estimated Contributions to Trend Growth
(In percent)



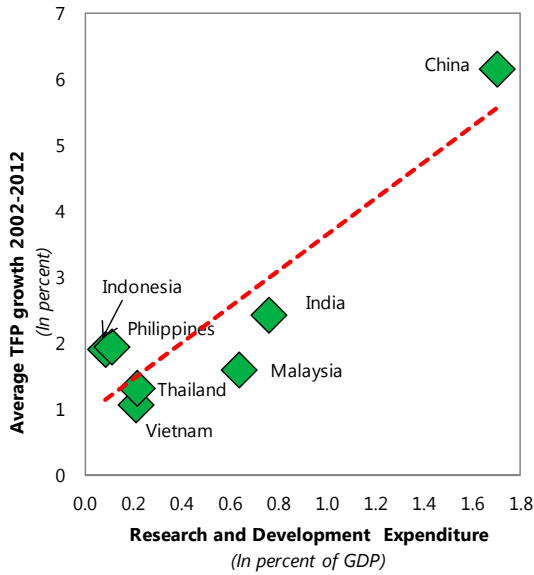
Sources: IMF, *World Economic Outlook*; World Development Indicators; CEIC data Company Ltd.; Haver Analytics; U.N. Population Database; and IMF Staff calculations.

Figure 6. Estimated Growth Rate of Different Components
(In percent)



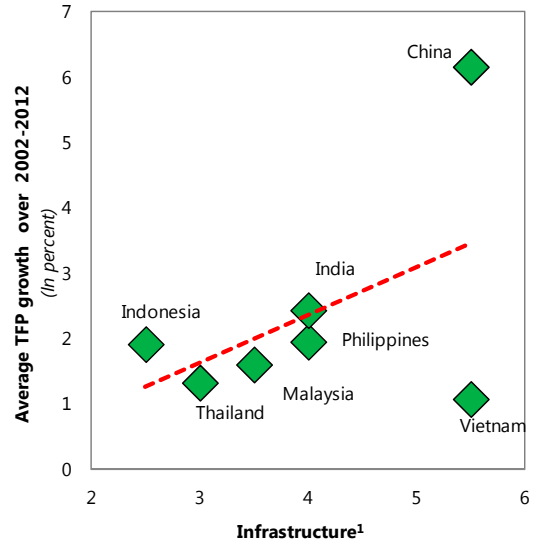
Sources: IMF, *World Economic Outlook*; World Development Indicators; CEIC data Company Ltd.; Haver Analytics; U.N. Population Database; and IMF Staff calculations.

Figure 7. Research and Development Expenditure and Total Factor Productivity¹



Sources: World Development Indicators; UNESCO Database; National Authorities.

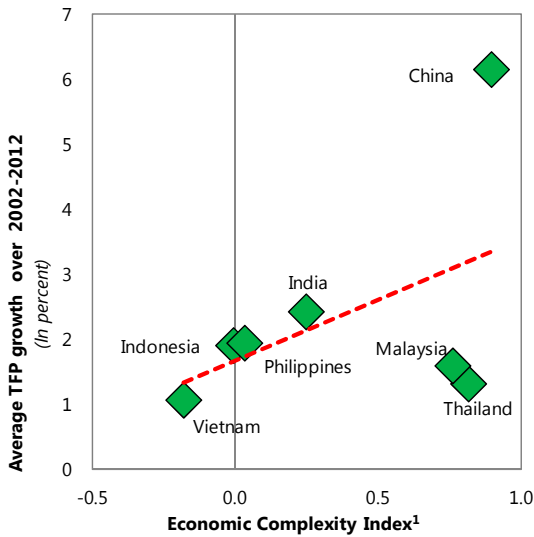
Figure 8. Infrastructure and Total Factor Productivity¹



Source: IMF staff estimates.

¹Infrastructure includes telephone lines and road networks. See Aiyar and others (2013) for details.

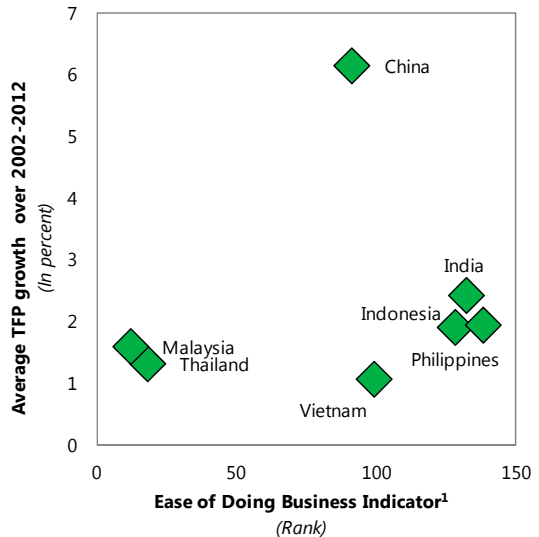
Figure 9. Economic Complexity and Total Factor Productivity¹



Source: IMF staff estimates.

¹Economic complexity index is a measure of the overall knowledge and sophistication as implied by a country's production and export structure. See Hausmann and others (2011) for details.

Figure 10. Ease of Doing Business and Total Factor Productivity¹



Sources: World Development Indicators; UNESCO Database; National Authorities.

¹Ease of doing business ranks economies from 1 to 185, with number 1 being the best. A high ranking (a low numerical rank) means that the regulatory environment is conducive to business operation.

B. Specific Country Policies Circumstances

At a deeper level, the evolution of trend or potential growth can be partly traced back to policy developments as discussed below:

For **China**, a recent study (Nabar and N'Diaye, 2013) points out that China's growth has slowed despite high levels of investment and credit growth. This would imply diminishing returns to investment, a misallocation of resources, and a limit to how far an economy can grow by reallocating labor from the country side into factories. The study casts doubt on the extensive growth model and suggests that a failure to adapt this model could eventually lead to further macroeconomic and financial imbalances and a further slowdown in trend growth. Barnett and others (2013) have also confirmed the slowdown of potential growth in China.

India's trend growth slowdown in last two years appears to result in part from heightened regulatory and policy uncertainties, delayed project approvals and implementation, continued bottlenecks in the energy sector as well as reform setbacks, contributing to a lower investment rate and sluggish TFP growth. Investment as a ratio of GDP declined by 3 percentage point between 2007 and 2012. Data from a corporate database on investment projects suggest a large decline in new capex projects and an increase in shelved projects. The sharpest decline in project announcements has occurred in infrastructure, which is most susceptible to policies and regulatory uncertainties. A sharp decline in infrastructure investment is likely to have lowered productivity growth in many sectors.

For **ASEAN**, the picture is more mixed:

- In some **ASEAN** economies, such as **Indonesia**, strong credit growth and supportive monetary policy boosted demand and spurred investment and capital accumulation until the recent slowdown —underlining the difficulty of fully disentangling cyclical and structural factors in trend growth estimation. Higher investment ratios relative to pre-GFC levels partly reflect that ASEAN economies have made progress towards addressing their “infrastructure gap.” To some extent, this progress has reflected government-sponsored and -financed projects, which may have helped not only increase capital accumulation but also sustain TFP gains.
- By contrast, the lackluster developments in **Vietnam's** trend growth may have reflected tighter macroeconomic stabilization policies amid heightened macroeconomic and financial risks as well as inefficiencies associated with the dominance of state-owned enterprises (SOEs).
- For the **Philippines**, improved macro management and governance has built investor confidence, and together with the government's PPP (public-private partnership) initiative, has led to faster accumulation of physical capital.
- In **Malaysia**, overall potential growth has been broadly stable and capital accumulation has slightly gained pace owing to the investments made under the

Economic Transformation Program (ETP). However, these investments have not been accompanied by structural reforms in areas such as governance and education which may have had a negative impact on TFP growth in recent years.

- For **Thailand**, TFP growth changes largely explain the variability in trend growth overtime. Employment has been growing steadily in line with changing demographics. Capital accumulation has picked up reflecting the government's expansionary fiscal policy and reconstruction activities following the 2011 floods.¹¹

C. Longer-term Issues: Demographic Factors

Over the longer term, demographic factors will play an increasingly important role, which can affect trend GDP growth both directly through the rate of growth of the working-age population (Table 1), and indirectly through the age profile of the population—in particular the overall dependency ratio, which can adversely affect aggregate saving and possibly innovation and has been found to increase risks of a sustained slowdown in GDP per capita growth (Aiyar and others, 2013):

- **Working-age population growth.** Working-age population growth has already slowed down across emerging Asian economies, and will continue to do so in the coming decades (Figures 11 and 12). However, it will make a greater contribution to growth in India and ASEAN 5 than in China, where it is already turning negative. Within the group of ASEAN economies, demographic trends are significantly better in Malaysia and the Philippines than in Thailand and, to a lesser extent, Indonesia and Vietnam.

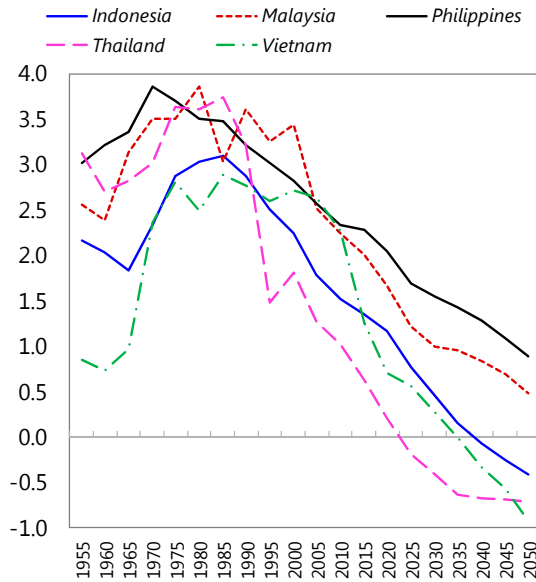
Table 1. Contribution of Working Age Population to Potential Growth per annum (in percent) ¹

	Indonesia	Malaysia	Philippines	Thailand	Vietnam	China	India
1990-2012	1.3	1.9	1.7	0.8	1.6	0.9	1.4
2013-2032	0.5	0.9	1.2	0.0	0.4	-0.1	0.9

¹ Calculated as two-thirds of the average annual growth rate.

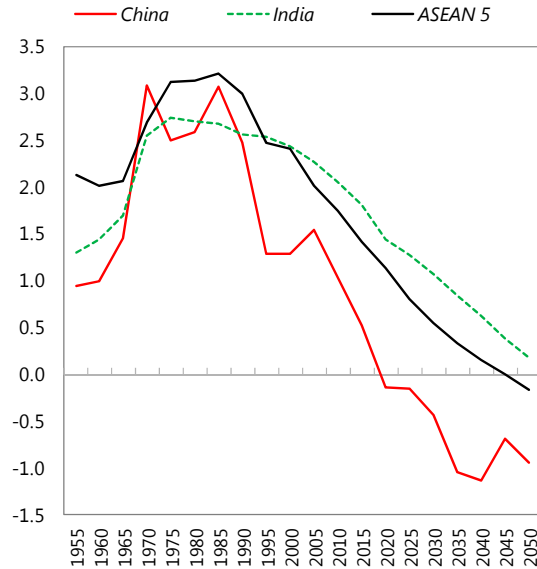
¹¹ The rate of capacity utilization may have dropped at the onset of the crisis and due to the floods, and the numbers of hours worked per worker may also have fallen. However, there are no data to document this.

Figure 11. Growth of Working Age Population¹
(Population aged 15-64; in percent)



Sources: U.N. Population Database; and IMF staff calculations.
¹ Projections based on the medium fertility U.N. scenario.

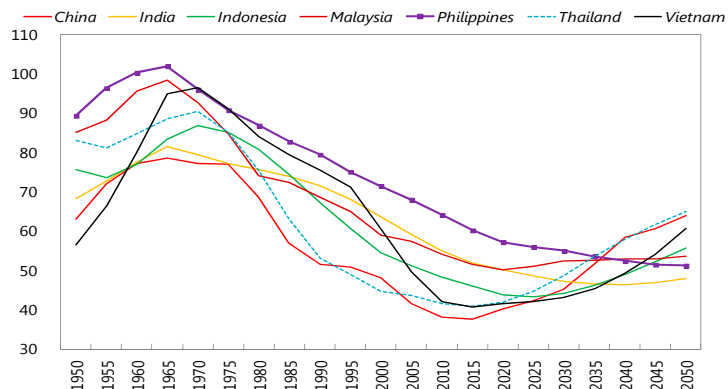
Figure 12. Growth of Working Age Population¹
(Population aged 15-64; in percent)



Sources: U.N. Population Database; and IMF staff calculations.
¹ Projections based on the medium fertility U.N. scenario.

- Dependency ratio.** Until now, overall dependency ratios have been typically low in emerging Asian economies, including compared to those in Latin American and MENA middle-income countries. Dependency ratios are projected to rise sharply throughout the region, but to various degrees and at different horizons (Figure 13). Over the next decade, only China, Thailand and Vietnam should experience a pickup, while by contrast India, the Philippines and to a lesser extent Indonesia will see a decline as they enjoy a “demographic dividend.” Beyond the 10-year horizon, a generalized deterioration is foreseen, with the notable exception of India and the Philippines. The contrast between China and India is especially striking; China’s dependency ratio should increase by about 7 percentage points by 2030, while India’s should decline by 8 percentage points.

Figure 13. Overall Dependency Ratios¹
(Ratio of population aged 0-14 and 65+ to aged 15-64; in percent)



Sources: U.N. Population Database; and IMF staff calculations.
¹ Dependency ratio projected using the medium fertility U.N. scenario.

V. POLICY IMPLICATIONS

These signs of a slowdown demand a closer scrutiny of the policy circumstances that have led to slower GDP growth and in particular the declining contribution of TFP in China, India and Vietnam. As Asia shifts into a lower gear, the case for boosting growth and unleashing productivity gains through broad-based structural reforms has become stronger:

- In China, an accelerated pace of reform implementation is warranted, aimed at enhancing efficient credit allocation, reducing dependence on capital accumulation, supporting the services sector and employment. This can be achieved by greater contestability of markets, financial and services sector reform—in particular telecommunication utilities and health care—and measures to support urbanization reform such as the hukou reform. This will foster gains in productivity and set China on a sustainable and balanced path. In this regard, the comprehensive and ambitious reform agenda recently announced by the Third Plenum of the Central Committee is encouraging.
- India faces a slowdown that could be debilitating if not thwarted with the swift adoption of appropriate policies and reforms. With limited policy space, financial risks emerging in the banking and corporate sector, and slowing investment, productivity gains and trend growth are poised to disappoint in the future unless reforms gain momentum, which would mitigate the negative repercussions emanating from both domestic and external risks. These reforms should include: ensuring sustainable fiscal adjustment, reducing inflation, addressing outstanding supply constraints, and tackling financial sector vulnerabilities. Furthermore, a business climate that is conducive to investment needs to be fostered by streamlining procedures to fast-track infrastructure projects. Reforms to address skill shortages, to ease labor and product market regulations, and to remove binding infrastructure bottlenecks also need to be implemented. Policy logjam has started to break (with projects worth nearly 3 percent of GDP being cleared, the land acquisition bill and the pension bill passed); slow action on key reforms (fiscal reforms and power sector reforms) continues to adversely affect investment. These broad structural reforms will not only boost growth but will bolster potential growth through productivity gains.¹²
- For the selected ASEAN economies covered in this paper, although trend TFP and GDP growth seem stable, they are low in comparison to China or India. Accordingly, there is a need for a comprehensive strategy that allows countries to move up the value chain by investing in infrastructure, education, research and development, and by encouraging efficient allocation of resources and innovation through increased product market competition. For many economies in the region, particularly Vietnam, governments need to accelerate the pace of reforms, especially in bank restructuring, creating a competitive environment which fosters a balanced mix of, and private and foreign companies.¹³

¹² For more details see India's Country Report (2013).

¹³ For more details see Malaysia's Country Report (2012) and Thailand's Country Report (2013).

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APPENDIX I: METHODOLOGY

This appendix briefly explains the methodologies used in the analysis. Before turning to the details of each method, it is important to note that these standard methods provide conceptually different trend growth. First, the statistical filters and the univariate unobserved component method do not impose any structural restriction on trend growth; rather, just use the statistical properties of the GDP. The estimates from these methods can thus be better phrased as “trend growth;” second, the bivariate unobserved component and the multivariate filter both contain the Phillips curve, using inflation as an additional indicator to identify trend growth, these two methods thus yield an “inflation consistent trend growth rate;” lastly, the production function estimates the production capacity of an economy given its factor endowment and total productivity level. The estimates from this method thus focus more on the supply side of the economy without matching the demand side.

A. Statistically-based Approach

The Hodrick-Prescott (HP) Filter

HP filter is a simple statistical smoothing procedure and is one of the most used, as well as the most criticized method of estimating the potential output. HP filter fits a trend line through all the observations of the given series, regardless of any structural breaks that might have occurred, by making the regression coefficients themselves vary over time. This is done by finding a trend output (y^*) that minimizes a combination of the gap between actual output and the trend output at any time and the rate of change in trend output for the whole sample of the observations (T).

$$\text{Min} \sum_{t=1}^T (y_t - y_t^*)^2 + \lambda \sum_{t=2}^{T-1} [(y_{t+1}^* - y_t^*) - (y_t^* - y_{t-1}^*)]^2 ,$$

where λ is a weighting factor that determines the degree of smoothness of the trend. A low value of λ will produce a trend output that follows actual output more closely, whereas a high value of λ reduces sensitivity of the trend output to short term fluctuations in actual output and in the limit the trend tends to the mean growth rate for the whole estimation period.

Following the standard practice for quarterly data, we choose a smoothness parameter equal to 1600.

Band Pass Filters

Unlike HP filter, which is a high-pass filter (removes low frequency cycles from the data), the band-pass (BP) filter is a linear filter that takes a two-sided weighted moving average of the data where cycles in a “band,” given by a specified lower and upper bound, are passed through, and the remaining cycles are filtered out. The band-pass filter is based on the idea that business cycles can be defined as fluctuations of a certain frequency. Fluctuations with a higher frequency are considered as irregular or seasonal, while those of lower frequency are associated with the trend. On the other hand, medium-frequency components of the data are

described as the cyclical component or business cycles which are the main focus of this type of filtering. Given a judgment on the true frequency of the business cycle, the filter extracts frequencies within a specified frequency range from the underlying time series.

In this paper, we use two different types of BP filters—Baxter-King (BK) Filter and Christiano-Fitzgerald (CF) Filter. Standard practice using these filters assumes a cycle lasts from 1.5 to 8 years. In particular, BK is a fixed length symmetric filter, where the weights for lags and leads (of same length) are the same and time-invariant. CF filter is a full sample asymmetric filter, where the weights on the leads and lags are allowed to differ and is time-varying. While BK filter produce stationary filters, the data have to be made stationary before applying CF filter.

Baxter King Band Pass Filter

The BP filter designed by Baxter and King (1995) passes through the components of time series with fluctuations between 6 (18 month) and 32 (96 month) quarters, removing higher and lower frequencies. The moving average weights depend only on the band specification, and do not use the data. Specified leads/lags of 8 quarters, the filter is thus a weighted moving average of leads/lags up to 8 quarters. The weights are symmetric for leads and lags and time-invariant. By choosing specified leads/lags (K), results in a loss of $K = 8$ observations both in the beginning and in the end of the series. But choosing low values for K results in poor approximation of the filter to the ideal high pass filter.

Christiano-Fitzgerald (CF) Filter

The Christiano-Fitzgerald random walk filter is a BP filter that was built on the same principles as the Baxter and King (BK) filter. While BK filter is constrained to produce stationary filters, the data have to be made stationary before applying CF filter. Here we remove the linear trend in real GDP. The band for business cycle is chosen as 8 to 32 quarters (same as BK). It is worth noting that the weights in CF can differ for leads and lags, and is also time-varying with the weights depending on the data and changing for each observation.¹ Unlike BK, the filter is a moving average of the full sample.

These filters formulate the de-trending and smoothing problem in the frequency domain. Both the BK and CF filters approximate the ideal infinite band pass filter. The Baxter and King version is a symmetric approximation, with no phase shifts in the resulting filtered series. But symmetry and phase correctness comes at the expense of series trimming. Depending on the trim factor a certain number of values at the end of the series cannot be

¹ CF also has a version of fixed-length symmetric filter, but the moving average weights are different due to different objective function when selecting the weights.

calculated. There is a trade-off between the trimming factor and the precision with which the optimal filter can be approximated. On the other hand, the Christiano-Fitzgerald filter uses the whole time series for the calculation of each filtered data point. The advantage of the CF filter is that it is designed to work well on a larger class of time series than the BK filter, converges in the long run to the optimal filter, and in real time applications outperforms the BK filter. For details see Christiano-Fitzgerald (1999).

Unobserved Component Models

The unobserved components model is a method to estimate the unobserved variables such as potential output, trend growth rate and output gap using the information from observed variables. Once the model is specified in the state space form and given the initial values for the unobserved state vector, the unobserved variables can be estimated by a recursive algorithm known as Kalman filter. Kalman filter uses the initial values for the unobserved state vector in order to predict the unobserved variables and then updates the guesses based on the prediction errors. When all the observations have been processed, the smoothing equations give the best estimators of the unobserved variables based on all the information.²

The simplest way of measuring potential output is the univariate methods, in which only the real output data are used. Output is decomposed into a permanent and a transitory component. While in the literature, several different models have been proposed to model trend and transitory components, in this paper, we follow Fuentes and others (2007) and Magud and Medina (2011) with some modifications.

The output Y_t is decomposed into two independent components: a permanent trend component (potential GDP), τ_t and a cyclical component (output gap) C_t

$$Y_t = \tau_t + C_t \quad (1)$$

The stochastic trend is modeled as local linear trend.

$$\tau_t = \tau_{t-1} + g_{t-1} \quad (2)$$

$$g_t = g_{t-1} + \varepsilon_t^g \quad (3)$$

The cyclical component of GDP is assumed to be stationary and follows an autoregressive process AR(1).³

$$C_t = \theta C_{t-1} + \varepsilon_t^c \quad (4)$$

² See Harvey (1985) for the technical details.

³ Initially, following Watson (1986), an AR(2) process for the output gap is tested. However, estimation results indicate that the second term is insignificant.

ε_t^g and ε_t^c are residual terms of mean zero and variances σ_g^2 and σ_c^2 .

The system is estimated by Kalman filter using equation (1) as a signal equation and equations (2) to (4) as the transition equations.

Measurements of the potential output and output gap are shown to be sensitive to the model specification (consequently various assumptions related to initial state vector), estimation period, and the method of estimation.

For the bivariate case, a backward looking Phillips curve has been added to the above state-space model, where inflation depends on past inflation and lagged output gap.

$$\pi_t = \alpha\pi_{t-1} + \beta y_{t-1} + \varepsilon_t^\pi$$

Another measurement equation on inflation is also added to the model, where observed inflation equals to “true” inflation and measurement errors:

$$\pi_t^m = \pi_t + \varepsilon_t^m$$

Data: quarterly GDP and inflation data from WEO database, CEIC Co Ltd. , and Haver Analytics.

B. Production Function Approach

The aggregate production is used where it takes the standard Cobb-Douglas form and then we calculate TFP as a Solow residual is used.

$$Y_t = A_t K_t^\alpha (L_t H_t)^{(1-\alpha)}$$

Where Y_t represents GDP in period t, K_t the physical capital stock, L_t the labor component, H_t the human capital per worker and A_t , the total factor productivity which embodies the efficiency with which factor inputs are used, such as technological progress and other determinants. Human capital is defined as follows:

$$H_i = e^{\mu(E_i)}$$

E_i represents the average years of schooling obtained by a worker in country I , and the derivative $\mu'(E)$ is the return to education estimated in a mincerian wage regression.

Following standard practice, the capital share is assumed to be one-third across all countries.⁴

Capital stock is constructed on the basis of the perpetual inventory method. Initial capital stock is measured as:

$$K_0 = \frac{I_0}{(1+g)-(1+\delta)}$$

⁴ A robustness check for a different value for α would not yield a different result as only the share would change for different factor inputs not the evolution of the trend, which is what we are primarily concerned with in this exercise.

Where the depreciation rate, δ , is assumed to be 0.05 percent for all countries (Bosworth and Collins, 2003) and I_0 is the initial investment expenditure.

This approach contains the following steps:

Step 1: derive historical TFP as output less weighted average of factor inputs

Step 2: using HP filter to derive trend TFP growth

Step 3: using HP filter to derive trend growth of physical capital stock

Step 4: derive trend labor using working age population, trend labor participation rate,⁵ and NAIRU

Step 5: trend output is derived using trend TFP, trend labor and physical capital stock, as well as actual human capital stock.

Data: Annual data from 1993–2018. Real GDP, employment, labor force and investment data are from the WEO database. Working age population and labor force participation rate data are from World Development Indicator (WDI). Human capital is constructed by applying Mincerian coefficients to years of schooling in the 2010 Barro & Lee dataset (For details, see Duval and De La Maisonneuve, 2010).

C. Multivariate Model

This model, developed by Benes and others (2010), is built around three gaps—the output gap (y), the unemployment gap (u), and the capacity utilization gap (c)—and three identifying equations:

The *inflation equation* relates the level and the change of the output gap to inflation:

$$\pi_t = \pi_{t-1} + \beta y_t + \Omega(y_t - y_{t-1}) + \varepsilon_t^{\pi}.$$

The dynamic Okun's law defines the relationship between the current unemployment rate and the output gap. Based on Okun's law, an *unemployment equation* links the unemployment gap to the output gap:

$$u_t = \phi_1 u_{t-1} + \phi_2 y_t + \varepsilon_t^u.$$

Finally, the model also relies on a *capacity utilization equation*, on the assumption that capacity utilization contains important information that can help improve the trend output and output gap estimates. The equation takes the following form:

⁵ For China and Vietnam, actual labor participation rates are used. For India, working age population is used as a proxy for employment.

$$c_t = \kappa_1 c_{t-1} + \kappa_2 y_t + \varepsilon_t^c.$$

Given the three identifying equations, the equilibrium variables are assumed to evolve dynamically as follows. A stochastic process including transitory (level) shocks and more persistent shocks guides the evolution of equilibrium unemployment (\bar{U}_t) (the NAIRU equation):

$$\bar{U}_t = \bar{U}_{t-1} + G_t^{\bar{U}} - \frac{\omega}{100} y_{t-1} - \frac{\lambda}{100} (\bar{U}_{t-1} - U^{SS}) + \varepsilon_t^{\bar{U}}$$

Persistent shocks to the NAIRU ($G_t^{\bar{U}}$) follow an autoregressive process:

$$G_t^{\bar{U}} = (1 - \alpha) G_{t-1}^{\bar{U}} + \varepsilon_t^{G^{\bar{U}}} \quad (1)$$

And trend output (\bar{Y}_t) is modeled to be a function of the underlying trend growth rate of trend output ($G_t^{\bar{Y}}$) and changes in the NAIRU. Specifically:

$$\bar{Y}_t = \bar{Y}_{t-1} - \theta(\bar{U}_t - \bar{U}_{t-1}) - (1 - \theta)(\bar{U}_{t-1} - \bar{U}_{t-20})/19 + G_t^{\bar{Y}}/4 + \varepsilon_t^{\bar{Y}} \quad (2)$$

where θ is the labor share in a Cobb-Douglas production function. This specification allows for short- and medium-term growth of trend to differ from trend growth. Note that $G_t^{\bar{Y}}$ is not constant, but follows serially correlated deviations (long waves) from the steady-state growth rate $G_{SS}^{\bar{Y}}$. Similar dynamic equations are specified for equilibrium capacity utilization.

Finally, an output gap equation is added to recognize the fact that monetary policy exerts its influence on inflation through the output gap:

$$y_t = \rho_1 y_{t-1} - \frac{\rho_2}{100} (\pi 4_{t-1} - \pi 4_{t-1}^E) + \varepsilon_t^y$$

where $\pi 4_{t-1}^E$ is the inflation expectation.

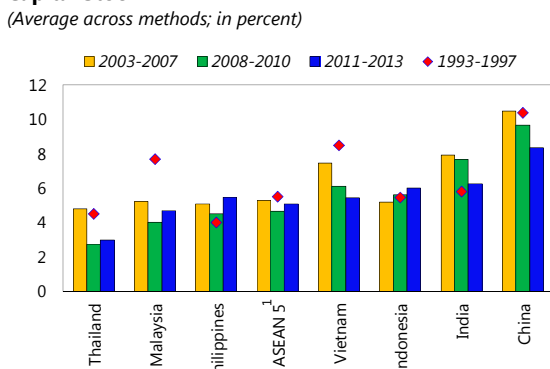
The full model is estimated by regularized maximum likelihood (Ljung, 1999), a Bayesian methodology. This method requires the user to define prior distributions of the parameters. While this can improve the estimation procedure by preventing parameters from wandering into nonsensical regions, the choice of priors has also non-negligible implications for the final estimates as the data are uninformative about some parameters.

Data: Quarterly GDP and inflation data are from the WEO database, inflation expectation is from Consensus Economics Forecast. Capacity utilization and unemployment rate data are from CEIC. The model requires assumptions on the steady state growth rate and unemployment rate, which we assume equal to historical average in most cases.

APPENDIX II: ROBUSTNESS CHECK

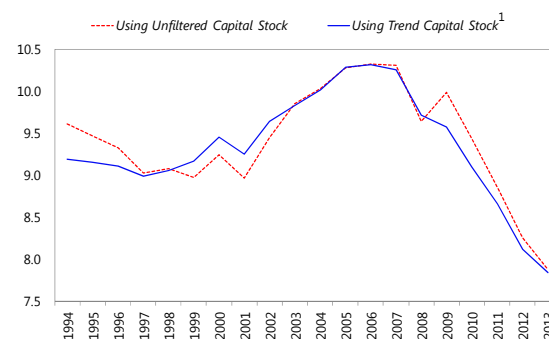
This appendix tests the robustness of growth drivers using an unfiltered rather than filtered capital stock in the production function approach. In other words, the potential capital stock is assumed to be equal to the actual capital stock.

Figure 1. Trend Growth Across Countries using Unfiltered Capital Stock
(Average across methods; in percent)



Sources: IMF, *World Economic Outlook*; World Development Indicators; CEIC data Company Ltd.; Haver Analytics; U.N. Population Database; and IMF Staff Calculations.
¹ PPP GDP weighted average used for ASEAN 5.

Figure 2. China's Trend Growth
(In percent)

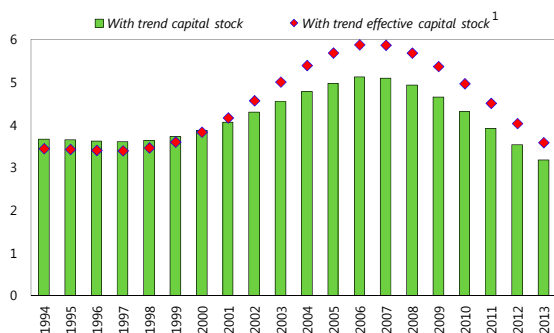


Sources: IMF, *World Economic Outlook*; World Development Indicators; CEIC data Company Ltd.; Haver Analytics; U.N. Population Database; and IMF Staff Calculations.
¹ Using HP filter.

The general trend still holds, where potential growth is picking up in ASEAN 4 after the crisis, while slowing down in China, India and Vietnam. Notably, using unfiltered capital stock implies a higher potential growth in China since the 2009 fiscal stimulus, but also a sharper slowdown afterwards.

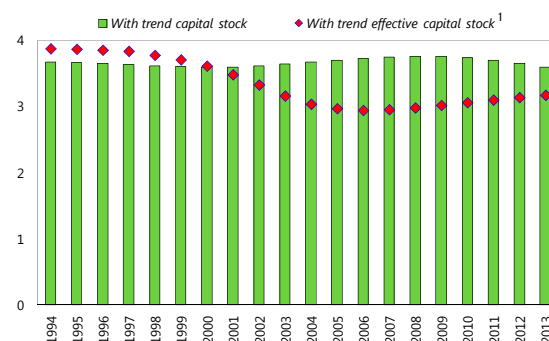
For China, estimating the magnitude of the slowdown in TFP, if any, is challenging. Capacity utilization rate has dropped significantly after the crisis, which can be unduly picked up by TFP as a residual if not included in the production function. We therefore conducted an additional robustness check using the trend effective capital stock, where the potential capital stock is derived by applying the HP filter to the capacity utilisation- adjusted capital stock. This approach yields higher trend TFP growth and lower trend growth of capital stock compared to the case without utilisation, but a slowdown in potential growth driven by TFP still holds.

Figure 3. China's Trend Contribution of TFP
(In percent)



Sources: IMF, *World Economic Outlook*; World Development Indicators; CEIC data Company Ltd.; Haver Analytics; U.N. Population Database; and IMF Staff Calculations.
¹ Calculated as capital stock multiplied by the capacity utilization rate.

Figure 4. China's Trend Contribution of Capital
(In percent)



Sources: IMF, *World Economic Outlook*; World Development Indicators; CEIC data Company Ltd.; Haver Analytics; U.N. Population Database; and IMF Staff Calculations.
¹ Calculated as capital stock multiplied by the capacity utilization rate.