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SPECIAL ISSUE:

China in the Global Economy

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Policymakers, academics, and market participants have raised many questions in recent years over the accuracy of China's official economic growth rates, both in terms of levels and volatility. This issue is of considerable importance for policymakers because fluctuations in China's economic activity can have significant impacts on growth, employment, inflation, and other policy objectives, given China's large shares of world output, trade, and commodity demand, and its rapidly growing role in global financial markets. This study addresses the question of growth volatility using a set of alternative growth indicators and concludes that China's official growth rate most likely has been implausibly smooth. Moreover, growth slowdowns during 2014-15 and 2017-19 were about twice as large as officially reported, while a growth rebound in 2016 was scarcely reported at all; the 2017-19 downturn was also shallower than that of 2014-15, by alternative measures. We argue that this picture fits reasonably well with other indicators of the global economy, China's own domestic data, and policy developments in China. Economic cycles in the period after the global financial crises have shown much shorter upturns and much longer downturns compared with the first decade after China joined the World Trade Organization. These cycles are likely to continue around a substantial slowdown in trend growth.

39 Alternative Indicators for Chinese Economic Activity Using Sparse PLS Regression

Jan J. J. Groen and Michael B. Nattinger

Official Chinese GDP growth rates have been remarkably smooth over the past decade, in contrast with alternative Chinese economic data. To better identify Chinese business cycles, we construct a sparse partial least squares (PLS) factor from a wide array of Chinese higher-frequency data, targeted toward variables that are highly correlated with important aspects of the Chinese economy. Our resulting alternative growth indicator clearly identifies Chinese business cycle fluctuations and it performs well both in out-of-sample testing for China as well as when applied to other economies. Using this indicator, we decompose deviations from growth trends into global growth, credit supply, and monetary policy components, and this decomposition suggests that, in contrast to China's 2015-16 slowdown, the country's 2018-19 slowdown was mainly due to deteriorating domestic credit conditions.

69 China's Growth Outlook: Is High-Income Status in Reach?

Matthew Higgins

Can China build on its development success to achieve high-income status in the decades ahead? To shed light on this question, we examine the past and prospective future sources of growth in China through the lens of the neoclassical growth model. Our key finding is that China would need to sustain total factor productivity growth at the top end of the range achieved by its high-income Pacific Rim neighbors in order to match their success in raising living standards. While fast-growing working-age populations boosted per capita income growth elsewhere in the Pacific Rim, a rapidly aging population will act as a powerful drag on income growth in China's case. Moreover, China's already capital-intensive production structure will make it difficult to match those countries' gains from capital deepening. These restraints mean that a sustained and exceptionally high pace of productivity growth will be needed for Chinese per capita incomes to reach even 50 percent of the U.S. level by 2040. We argue that lagging institutional development represents the chief obstacle to the needed productivity gains.

Over the course of 2018, economic activity in major advanced foreign economies and emerging markets—including the Euro area and China—decelerated noticeably. In parallel, foreign growth projections for 2019 and 2020 were revised down, signaling potentially large headwinds for the U.S economy over the medium term. In this article, we use a multi-country simulation model to quantify economic spillovers to the United States from a slowdown originating in the Euro area. Next, we compare these results with spillovers from a slowdown originating in China. We find that spillovers to the U.S. economy from a slowdown in the Euro area are sizable, mainly due to lack of monetary policy space in the region along with greater financial integration between Europe and the United States. Standard trade-related spillovers from a slowdown in China to the United States, instead, are quantitatively limited.

How Stable Is China's Growth? Shedding Light on Sparse Data

Hunter Clark, Jeff Dawson, and Maxim Pinkovskiy

OVERVIEW

- China faces skepticism about the accuracy of its GDP growth statistics, fueled by incidents of data falsification, secrecy around methodological processes, and press censorship, especially during periods of economic stress.
- Against this backdrop, the authors present alternative indicators for measuring China's business cycles using variables that are closely related to China's "true" economic growth, but unlikely to be subject to manipulation.
- Those proxies, which employ index- and factor-based statistical methodologies and data on nighttime lights usage, production, trade, investment, and credit, suggest that China's economic growth has been more volatile in recent years than is portrayed in the official GDP statistics.
- These fluctuations have occurred around a trend growth rate that has been slowing and that is likely to slow substantially in coming years.

There is widespread agreement among both market participants and China's policymakers that China's economic growth slowed in 2018. However, there is much less consensus on the magnitude of the slowdown and even on when it started. Similar disagreements over the magnitude and timing of Chinese business cycles have occurred periodically since at least the early 1990s. In contrast to earlier years, these issues are now of major importance for policymakers in other large economies because China's role in the global economy has increased dramatically. Indeed, on the eve of China's accession to the World Trade Organization (WTO) in 2001, China accounted for 3.6 percent and 7.3 percent of global GDP and merchandise trade, respectively. Those shares have now increased to 16 percent and 23.8 percent as China has become the world's second largest economy and largest trading country. Moreover, China plays a dominant role in world demand for many key energy, metal, and agricultural commodities, and possesses one of the world's largest financial systems, which is poised to become more globally integrated as its domestic markets gain inclusion in important global benchmark indexes (Sin 2019).

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Disagreements on China's business cycle stem from differing views on the reliability and accuracy of China's official economic statistics and on differing approaches to addressing perceived shortcomings in the official data. In this article, we seek to add some alternative indicators to policymakers' toolbox for measuring China's cyclical fluctuations, which, in turn, can be used as inputs for making relevant policy decisions. In contrast to much of the previous academic literature, we focus almost exclusively on relatively high-frequency (monthly) indicators of changes in China's growth rate, as opposed to growth-rate levels. However, we offer some observations on what the indicators say about cyclical fluctuations in longer-term trend growth.

We group our alternative indicators into two buckets. The first revolves around satellite nighttime lights (NTL), based on a methodology described in Clark, Pinkovskiy, and Sala-i-Martin (2020). That article focused on growth-rate levels through the fourth quarter of 2015 and found no convincing evidence that the growth rate at the end of 2015 had been slower than officially reported, though it was noted that there was evidence that the change in the growth rate (marking a slowdown) had been more than reported. In this article, we focus entirely on the changes in growth, at monthly frequency from 2001 or 2006 (depending on data availability) through the middle of 2019. The second set of indicators we refer to as "factor based." This includes an indicator based on principal component analysis (PCA) and a novel approach using sparse partial least squares regression (SPLS), which is discussed in detail in a companion article in this special issue (Groen and Nattinger 2020).

Our results suggest that China's economic growth has been more volatile over the past five years than portrayed in the official GDP statistics. By our measures, growth slowed by substantially more than reported over the course of 2014 and 2015 and then staged a rebound in 2016, to peak in early 2017, a pattern that was scarcely evident in the official data. During the most recent cycle, growth slowed beginning in 2017, but may have been more stable in 2018 and the first half of 2019 than portrayed in the financial press at the time. Our analysis also suggests that cyclical growth upturns (accelerations) have become significantly shorter-lived in the period after the global financial crisis, while growth slowdowns have become much longer. These fluctuations have occurred around a trend growth rate that has been slowing, and which is likely to slow substantially in coming years.

The rest of this article is organized as follows: Section 1 provides some background on long-standing controversies over the accuracy of China's GDP data. Section 2 provides a high-level overview of methodologies most frequently employed to calculate alternative growth indicators, and then introduces the methods used in this article. Section 3 discusses the results, focusing on what they say about the contours of China's business cycle and growth performance since the beginning of 2014. Section 4 broadens the focus to how the alternative indicators correlate with global data and provides additional analysis focused on which alternative indicators provide the best fit to the global data. Section 5 takes a longer-term view on the cyclical fluctuations around China's longer-term trend. Section 6 concludes. The appendixes provide details on the satellite nighttime light methodology used in two of our alternative indicators and the data employed in our analysis.

1. China Faces Perennial Questions over the Reliability and Accuracy of Its Data

During 2018 and up through the beginning of 2019, the financial press was awash with sometimes conflicting stories on China's economic performance, ranging from pessimistic to sanguine. On the more pessimistic side were those arguing that China's growth was much weaker than reported, by some accounts less than half of the official figure (Shane 2019; Pettis 2019). On the more sanguine side were views that the economy had slowed only modestly and was poised for a near-term rebound (Rothman 2019). In 2018, China's own official growth statistics showed only a small decrease in the four-quarter growth rate, from 6.7 percent at the end of 2017 to 6.4 percent at the end of 2018, and the decrease occurred entirely in the last two quarters of the year. That translated to official growth slowing only marginally, having ended 2016 at 6.8 percent (Chart 1).

The fundamental reasons for the wide range of views revolve around long-standing skepticism about the accuracy of the official statistics. Indeed, market participants have raised questions about the official data for many years, including during 1998–2000 (the Asian financial crisis), 2003–04 (the severe acute respiratory syndrome crisis), 2008–09 (the global financial crisis), and 2015–16 (China's currency and equity market stress). Uncertainty about the data has been fueled by well-publicized instances of falsification of data at the local level, nontransparency and secrecy around methodological processes, including but not limited to price deflators, limited independence of the statistical authorities, and censorship of the domestic financial press, especially during periods of economic stress (Holz 2013; Wu 2014; Wee and Yuan 2018). In the eyes of many critics, the remarkably low, and declining, volatility of China's growth rate also appears implausible (Chart 2).

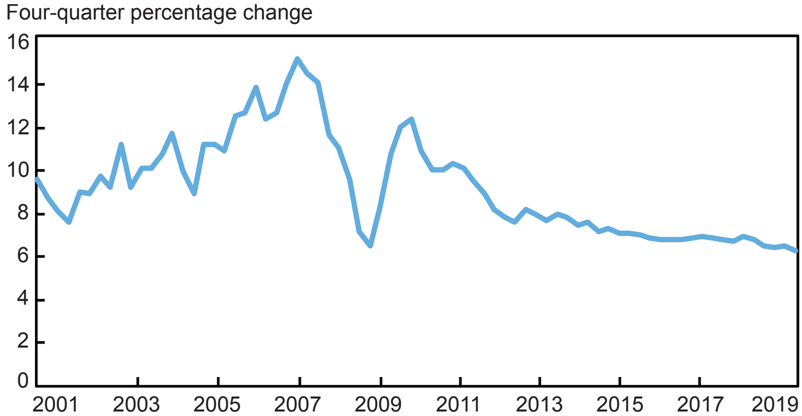
There is an expansive academic literature on the accuracy of China's official data. These studies most often focus on relatively low-frequency data—for example, annual data—as opposed to the intra-year business cycle that we primarily focus on in this article.[1] Of direct relevance to this article, Clark, Pinkovskiy, and Sala-i-Martin (2017; 2020) used satellite nighttime lights to estimate quarterly growth rates from 2004 to 2015. The results in that analysis suggest that growth-rate levels were lower than reported in the years prior to the global financial crisis, but usually higher than reported thereafter. The authors also found that growth had a shallower decline in 2008 and a stronger recovery in 2009 than reported, and a steeper decline than reported during 2014 and 2015. That analysis did not find convincing evidence that growth was weaker than reported in the final quarter of 2015.

2. Using Alternative Growth Indicators to Gauge the Business Cycle in China

Against a backdrop of doubt surrounding official statistics, there is a long history among market participants, policymakers, and academic researchers of using alternative indicators as proxies for the business cycle in China. In this article, we hope to add to the array of such indicators. Our approach is to select variables that are closely related to China's "true" economic growth, but that are either reported independently of China's statistical system,

Chart 1

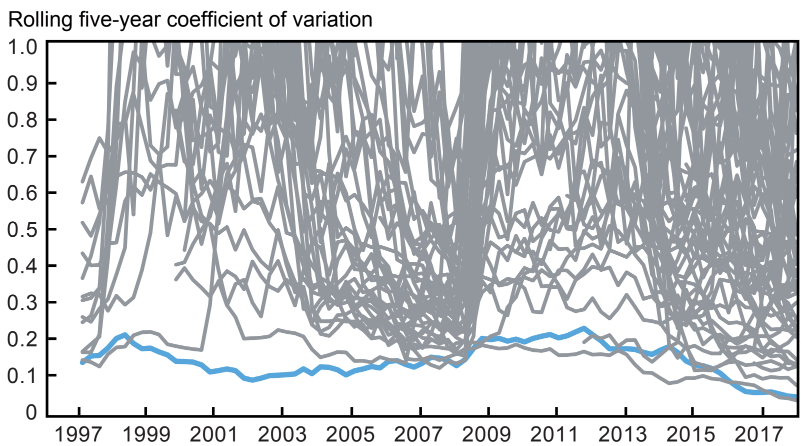
China's Official GDP Growth Rate



Sources: National Bureau of Statistics of China and national authorities via CEIC Data and Haver Analytics; authors' calculations.

Chart 2

China's GDP Volatility versus That of Other Countries



Sources: National Bureau of Statistics of China and national authorities via CEIC Data and Haver Analytics; authors' calculations.

Notes: The gray lines show the GDP volatility of seventy-eight other countries. The coefficient of variation is calculated as the ratio of the rolling five-year standard deviation of the four-quarter GDP growth rate to the absolute value of the rolling five-year compounded quarterly annualized growth rate. The vertical axis is cropped at 1. Data are through the second quarter of 2018.

or cover such a wide range of variables that they are unlikely to be subject to much manipulation or "smoothing." Our focus is on constructing relatively high-frequency indicators that can be updated fairly easily, so as to be useful in real-time policy analysis.

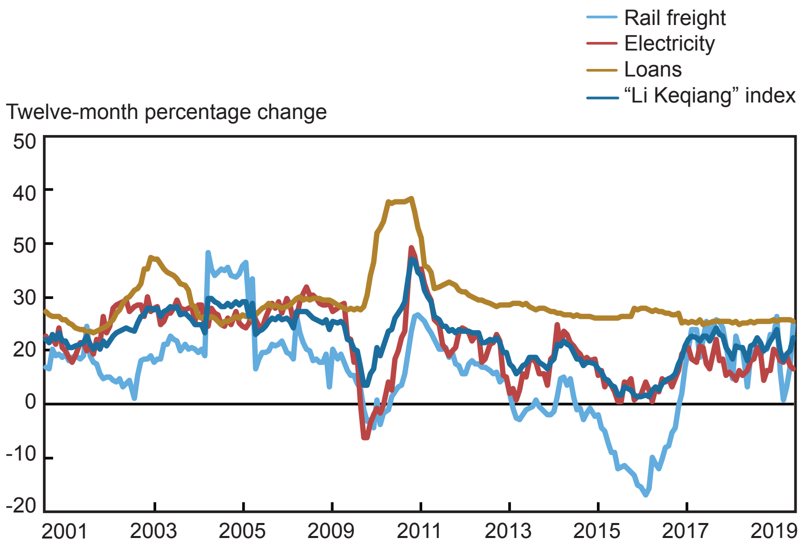
Alternative indicators in the literature—both academic and market-analyst—tend to group into two categories: direct adjustment of official data and index-based approaches, typically involving various econometric techniques. One line of analysis among the direct-adjustment methods computes alternative deflators for GDP, which are then typically applied to nominal GDP to obtain the measure in real terms (Keidel 2001; Kerola 2018). Another line of direct-adjustment analysis works "bottom up" from a detailed sectoral level, often relying heavily on data oriented around the industrial sector within GDP (Wu 2014; Reserve Bank of Australia 2015; Wigram Capital Advisors 2019; Chen et al. 2019). All of these direct-adjustment methods yield results that suggest that GDP growth sometimes differs substantially from officially reported levels, and has usually been lower than reported since the global financial crisis. However, the direct-adjustment methods are quite difficult to implement on a high-frequency basis without making strong simplifying assumptions that themselves may not be plausible.

Among the index-based approaches, the simplest, and possibly the best known in recent years, is the so-called "Li Keqiang index," which is named after China's premier and second-ranking member of the Politburo Standing Committee of the Communist Party. The index gets its inspiration from WikiLeaks' publication of remarks made by Premier Li in 2007 (then still a provincial party secretary) to the effect that he tracked economic activity in his province by monitoring electricity, bank loans, and rail freight. This index is frequently implemented as a simple average of the three indicators. Chart 3 shows an example of this index—computed as a simple average—and each of its components. A sample of other statistical approaches can be found in Clark, Pinkovskiy, and Sala-i-Martin (2017).

Our own alternative indicators follow the index-based statistical methodologies. Our first approach uses indexes computed from a satellite nighttime lights (NTL) methodology (Clark, Pinkovskiy, and Sala-i-Martin 2017; 2020). Appendix 1 to this article covers the details of this approach, and the interested reader can find further information in the studies cited. It is well-established that lights are strongly correlated with measures of economic activity, such as national accounts GDP, in levels and growth rates (Henderson, Storeygard, and Weil 2012). In broad-brush terms, our methodology uses satellite-recorded nighttime lights to aggregate multiple indicators of economic activity into a best unbiased linear predictor of the underlying unobserved true income process.

As discussed in Appendix 1, we exploit variations of provincial growth within China to calculate weights for our indexes. We calculate two sets of NTL-based indicators, which we refer to as "NTL-Narrow" and "NTL-Broad." The NTL-Narrow index comprises the "Li Keqiang" variables mentioned above as well as GDP itself, while the NTL-Broad index comprises those variables covered by Fernald, Hsu, and Spiegel (2015) that are available at the provincial level, including electricity, rail freight, loans, retail sales, floor space construction newly started, real estate investment, air passenger traffic, and exports. As discussed in Appendix 2, in order to operationalize these indicators for policy work, we make an important modification to their composition, substituting M2 for loans in constructing both the NTL-Narrow and NTL-Broad indexes. We make this substitution to be a bit more conservative in how we capture credit conditions in our model, as the relative stability of loan growth does not adequately reflect the on-again, off-again tightening of government policy over the "shadow finance" sector.[2]

Chart 3
Rail Freight, Loans, Electricity, and the "Li Keqiang" Index



Sources: National Bureau of Statistics of China via CEIC Data; authors' calculations.

The predicted growth rates for the NTL proxies are calculated in a three-step process. First, weighted indexes are constructed using national-level variables, in which the weights are derived from the provincial nighttime lights regressions mentioned above. Then, a constant and a regression coefficient are calculated for each index by regressing official quarterly GDP on them through the end of 2013.[3] In the final step, we use the changes in the out-of-sample predicted values from the beginning of 2014 onward as our alternative indicator.

Our second set of approaches revolves around what we refer to as "factor-based" methods. The first of these, labeled PCA in the charts and tables that follow, is calculated from the first principal component of the twelve-month (log) percentage change in a very wide range of variables of a data sample that begins in April 2005 (see the table in Appendix 2).[4] The sixty-two variables we choose range from production and trade to investment and credit. For all variables except the purchasing managers' indexes (PMIs), we take the log year-over-year difference in seasonally adjusted data. In order to account for structural shifts in the data, we first detrend the data using a biweight filter (Stock and Watson 2012). We then normalize the data so that the mean and standard deviation of each series are equal to zero and one, respectively. In order to scale this index to units of official GDP, we regress the detrended year-over-year (log) percentage change growth rates of Chinese GDP on our principal component, excluding all data after 2013, and then add the trend from official GDP back into the calculation of predicted GDP growth.

The second factor-based approach is labeled "SPLS" and uses sparse partial least squares regression techniques. This methodology is covered in detail in a companion article (Groen and Nattinger 2020). Broadly, this method extracts a set of common factors, via partial least squares regression, that best reflects the correlations between a set of economic activity proxy variables—which can be thought of as "training variables"—and a wider set of candidate data. The "sparse" component of the methodology refers to the technique by which this wider range of candidate data is first narrowed to a subset that has relatively strong individual correlations with the proxy variables, so as to reduce the risk that noisy variables create "weak" or "near-strong" factors.

In the first instance, the SPLS method is trained on Chinese real imports from the United States, Japan, and the European Union, reported by the exporting countries' statistical agencies as exports to China and Hong Kong. This approach follows Fernald, Hsu, and Spiegel (2015; 2019) and is similarly motivated by the assumptions that China's imports are closely related to its true growth and that exporting countries' statistics should not be influenced by China's domestic statistical problems. On further refinement, the SPLS indicator used in this article is trained on China's imports (as reported by exporting countries), a diffusion index of the twelve-month change in a wide range of gross industrial production values in physical units (covering about 118 industries at present), and Chinese retail sales.[5]

3. China's Economic Performance over the Past Two Cycles

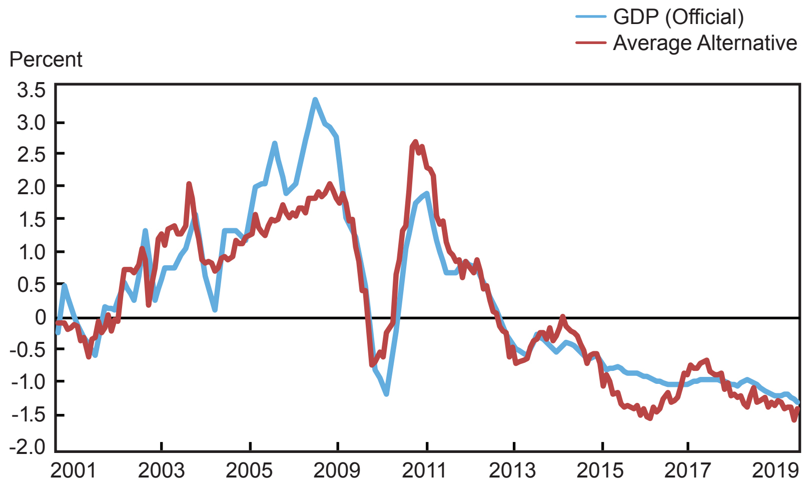
Following the methods discussed in the previous section, we have four alternative indicators, two of which are factor-based—the PCA and SPLS indicators—and two of which are nighttime-lights-based—NTL-Narrow and NTL-Broad. In many of the tables and charts that follow, we will average the PCA and SPLS indicators and refer to this indicator as the "Average Factor"; similarly, we will average all four indicators and label the result the "Average Alternative."

First, we examine what these alternatives say about China's business cycle over the history of the respective series. Charts 4 and 5 plot the Average Alternative indicator against official GDP and China's imports from the United States, Japan, and the European Union (as reported by the trading partners), all normalized and at a monthly frequency. Chart 6 plots the four alternatives separately.

On the whole, official GDP tracks the alternative indicators, but with clear deviations. For example, official growth generally is higher than the Average Alternative in the first half of the 2000s, and the downturn during and subsequent rebound after the global financial crisis are shallower and stronger, respectively.[6] The official and alternative indicators of growth track each other quite closely in the aftermath of the global financial crisis until 2013, when the official figures become much smoother. It is thus readily apparent that the alternative indicators show more cyclical variation in growth than has been reported in official GDP over at least the past five years. By contrast, the alternatives correlate quite well with China's imports over the same period, as they had in the past. This provides visual evidence that the alternative indicators are plausible indicators of China's true growth, and perhaps more so than official GDP growth in recent years.

We now turn to what these alternatives say about China's GDP growth. We will focus on relative changes in growth rates in terms of units of official GDP. The reason for this is that we cannot identify the "true" growth rate under any of our methodologies, since it is unobserved.

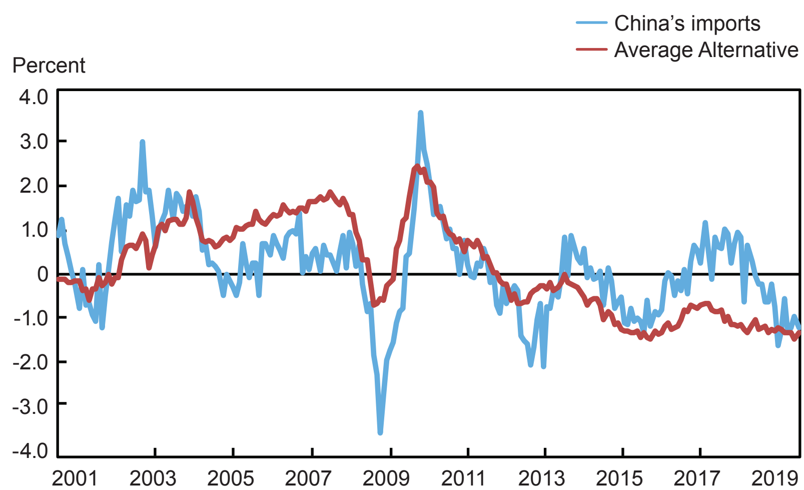
Chart 4
Official GDP and the Average Alternative



Sources: National Bureau of Statistics of China via CEIC Data; authors' calculations.

Notes: The Average Alternative is the average of two nighttime-lights-based indicators and two factor-based indicators, as described in the text. All data are computed from a twelve-month log difference of seasonally adjusted monthly data, with monthly GDP linearly interpolated from quarterly data. The data are monthly and normalized with a mean of 0 and a standard deviation of 1.

Chart 5
China's Imports and the Average Alternative



Sources: National Bureau of Statistics of China via CEIC Data; authors' calculations.

Notes: China's imports are as reported by exporting countries. The Average Alternative is calculated from two nighttime-lights-based indicators and two factor-based indicators, as described in the text. All data are computed from a twelve-month log difference of seasonally adjusted monthly data.

However, we can make comparisons of the values of our alternative growth indicators over periods of time. Put another way, we can make statements such as "Chinese growth in the fourth quarter of 2018 was higher than that in the same period of 2015," or "the decline in Chinese growth through the second quarter of 2019 has been smaller than the decline in Chinese growth during 2015," without relying on any scaling assumptions.

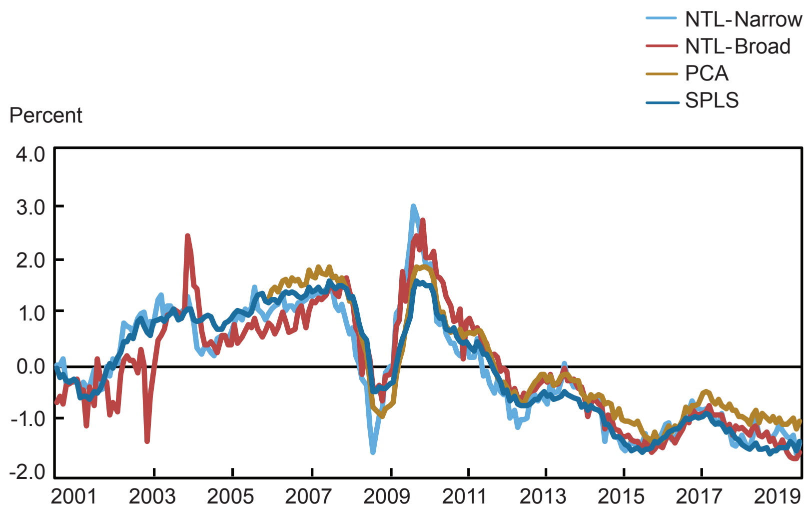
We have chosen to measure changes in growth rates relative to the end of 2013. This starting period coincides with the starting point of our out-of-sample regressions in the previous sections. Moreover, this period encompasses a number of seemingly significant macroeconomic shocks that one would expect, a priori, to affect GDP growth performance. For example, from 2014 through early 2016, China experienced a major property-sector slump and recovery, a stock market boom and bust, large capital outflows, sales of foreign exchange reserves, and exchange-rate volatility, and large policy-driven fluctuations in credit. Throughout this period, market participants were acutely concerned about "hard landing"—a large and abrupt growth slowdown—in China. Similarly, after 2016, the Chinese government initiated a tightening of financial and fiscal conditions in order to reduce financial vulnerabilities, but was buffeted by trade tensions and volatility of domestic equity markets and shifted again to a loosening of macroeconomic policies. Market participants remained highly attuned to "hard landing" risks, albeit perhaps not to the same degree as in the earlier period.

Chart 7 plots the change in official growth implied from the Average Alternative and the official growth rate itself. There is little correlation between official growth and the alternative, at least until the middle of 2018, after which the two measures become more similar. The alternative shows a downturn that bottomed at the end of 2015, followed by a rebound that peaked in early 2017, and then another downturn. The more recent downturn appears to have occurred mainly in 2017; growth in 2018 slowed comparably little for the year as a whole, as it rebounded a bit in the first half of the year but turned down again in the second half. Growth in the first half of 2019 was quite stable aside from a temporary downward spike in May, according to the alternative measure.

During the downward cycle through the end of 2015, the Average Alternative suggests that growth fell by almost 2 percentage points, approximately double the slowdown that was shown in the official statistics. Growth then is estimated to have rebounded by a bit over 1 percentage point using the alternative methodology, versus approximately zero change in the official data. The most recent slowdown through the end of 2018 measures a bit over 1 percentage point, more than double the slowdown in the official statistics. This decline cumulates to 1.2 percentage points by the second quarter of 2019, still about double the official slowdown. Interestingly, the change in growth rates in the final two quarters of 2018 through the first two quarters of 2019 is quite close in the official data and in the Average Alternative, suggesting that the official figures may have been more accurate since the middle of 2018.

The cyclical pattern shown in the alternative indicators appears to be consistent with the "story" told by credit and industrial production in China. Chart 8 plots China's aggregate credit growth and "credit impulse" against the average of our alternative growth indicators. Credit growth is simply the percentage change in the stock of aggregate credit, while the credit impulse follows Biggs, Mayer, and Pick (2009) and is defined as the change in the flow of aggregate credit—$\Delta(\Delta D(t))$—relative to GDP. The correlation between the credit cycle and our alternative indicators is a reassuring robustness check on the usefulness of the alternatives as cyclical indicators. China's economy is highly investment-intensive and credit-driven, and

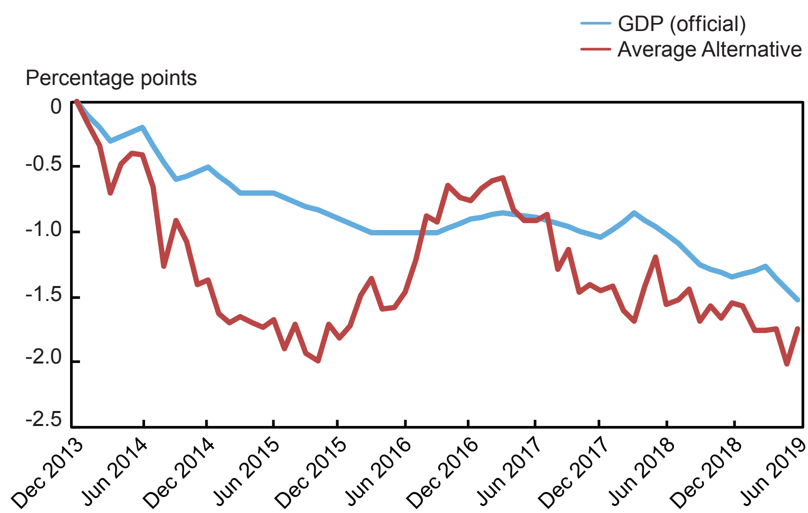
Chart 6
Alternative Indicators for China's GDP Growth



Sources: National Bureau of Statistics of China via CEIC Data; authors' calculations.

Notes: NTL is nighttime lights. PCA is principal component analysis. SPLS is sparse partial least squares. All data are computed from a twelve-month log difference of seasonally adjusted monthly data, with monthly GDP linearly interpolated from quarterly data. They are monthly and normalized with a mean of 0 and a standard deviation of 1.

Chart 7
Change in Official and Alternative GDP Growth
Cumulative difference relative to December 2013



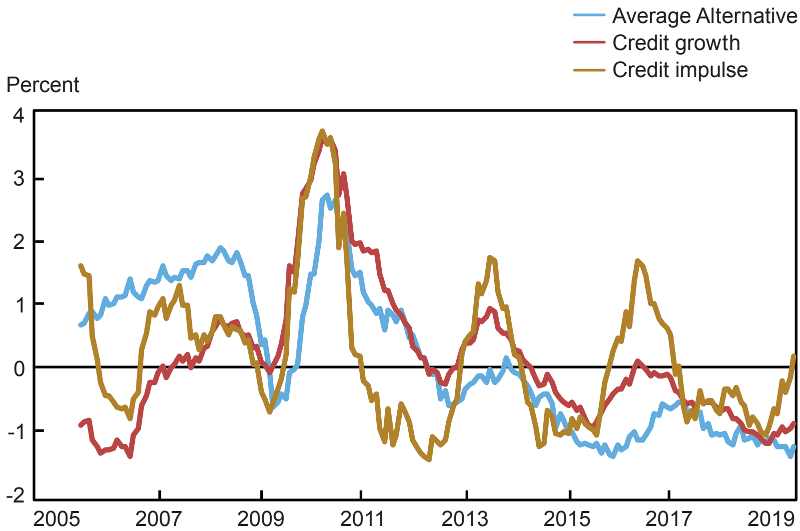
Sources: National Bureau of Statistics of China via CEIC Data; authors' calculations.

against such a backdrop, one should expect to see a strong correlation between credit availability and growth. It is interesting to note that the upturn in the credit impulse in early 2019 coincides with very little change in growth momentum as proxied by the Average Alternative indicator. This attenuated response might reflect impairments to the credit intermediation process, such as tight credit conditions for China's private sector and other sectors reliant on nonloan financing channels as well as external headwinds from U.S. tariffs.

Next we move to industrial production. This variable is important because industry remains by far China's single largest sector as a share of GDP. This share has held fairly steady at about one-third of GDP since 2015, somewhat lower than an average 40.6 percent of GDP during 2000–10. Chart 9 plots the twelve-month percentage change and a rolling three-month percentage change (seasonally adjusted at an annual rate). The illustration shows that industrial production growth hit a low in 2015, recovered by about 2.5 percentage points by May 2017, and then slowed again. The latest business cycle slowdown occurred in two phases: the first in 2017, followed by a partial recovery in early 2018, and then a further slowdown in the second half of 2018. The total slowdown in the recent cycle through the end of 2018 measured about 2.1 percentage points, with growth still above the low point in 2015. Interestingly, industrial production accelerated noticeably in early 2019, but this was driven by very strong monthly readings in March and June that apparently did not coincide with a sustained upturn in economic activity.

Finally, the picture painted by the alternatives is consistent with the macroeconomic policy stance in China. The rebound in the economy from the low point of the 2014–15 cycle was primarily driven by an easing of macroprudential policies in the housing sector and a de facto loosening of fiscal policy at the local government level. As early as May 2016, statements in the government-controlled press attributed to an anonymous senior official signaled a potential shift toward tighter macroeconomic policies (Murray 2016; Zhang 2017), which were followed over the remainder of 2016 by various reforms to control risks in the financial sector. By February 2017, China's leader, Xi Jinping, was quoted in the official press as ordering that local and central government authorities "unswervingly" crack down on financial irregularities (Wu 2017), a directive that was followed in later months by monetary tightening, increasingly stringent macroprudential policies in the financial sector, and tighter restrictions on local government borrowing. By the beginning of 2018, policy had begun to loosen again, as the People's Bank of China implemented a cut to required reserve ratios in January and initiated substantial reductions in market-determined interest rates. The shift toward looser policies was formally acknowledged in a Politburo communique in April 2018 (Zhang 2018), though the authorities continued to rein in riskier types of "shadow finance" lending.[7] The renewed deceleration of growth in the latter part of 2018 coincided with increasingly large declines in shadow finance and in intensification of the trade conflict with the United States.

Chart 8
The Credit Cycle and a Growth Proxy



Sources: People's Bank of China via CEIC Data; authors' calculations.

Note: Credit growth and credit impulse are pulled forward by four months.

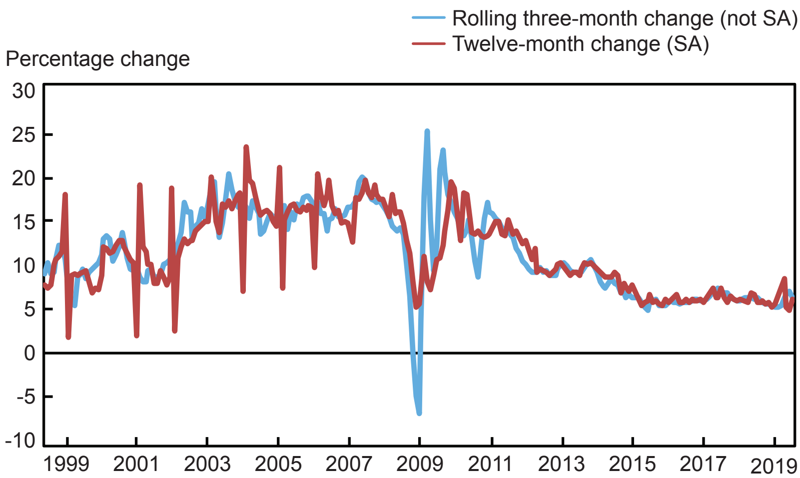
4. Global Data Correlate with Alternative Indicators

We next turn to how the alternative indicators correlate with a wider set of variables, including indicators of activity outside of China. Again, the basic idea is that unobserved true growth of the Chinese economy manifests itself through variables that are measured outside of the Chinese statistical system. The most direct proxy used here is real Chinese imports (as independently reported by exporting countries); we also examine global commodity prices and foreign countries' industrial production and manufacturing surveys.[8]

Table 1 shows the results from simple regressions of monthly data on China's imports, commodity prices, and foreign-country manufacturing activity.[9] For each dependent variable, the table shows the results of a regression on China's official GDP, followed by the results of the same regression on the Average Alternative. (Appendix Table 3A plots the same information but breaks out detail for the NTL-Narrow, the NTL-Broad, the Average Factor, and the Average Alternative.) The data are normalized with a mean equal to zero and a standard deviation equal to one; the table shows Newey-West *t*-statistics, adjusted R2, and the root-mean-square errors (RMSEs) of the regressions. The three sets of columns show results from regressions over 2001–13, 2014–18, and then 2014 through June 2019. The regressions involving imports also factor in China's real effective exchange rate, which is not shown in the table, while the others are simple bivariate regressions.[10]

The table illustrates that over the earliest period both official GDP and the alternatives have explanatory power over the various dependent variables. By contrast, during the more recent periods, official GDP has little explanatory power over China's imports and the other macro

Chart 9
Industrial Production
Value added of industry



Source: National Bureau of Statistics of China via CEIC Data.

Note: The chart plots industrial production data as a twelve-month percentage change (not seasonally adjusted (SA)) and as a rolling three-month percentage change (SA at an annual rate).

indicators considered here. The time window that includes the first six months of 2019 shows the re-emergence of explanatory power over China's imports and German manufacturing production, though less so than in the earliest period. That pattern makes sense since from the middle of 2018, China's official GDP has tracked our alternative indicators reasonably closely. By contrast, it is notable how well the alternative indicators retain explanatory power in the two most recent time periods for China's imports, global commodity prices, and industrial production in Japan, Germany, and emerging-market Asia, excluding China and India. This relationship does not hold true for the U.S. data shown in the table; however, as will be discussed below, there are correlations between the U.S. data and certain lags of the alternative indicators.

Chart 6 shows that the output from these alternative models all paints a rather similar picture of China's economic cycles over the long term, though it does deviate at shorter time horizons. For policy formulation, it is often desirable to have a view of economic performance in close to real time, in which case these shorter-term differences can be important. Indeed, the more detailed results shown in Appendix Table 3A suggest that there is a fair amount of heterogeneity among the alternatives. For example, for German manufacturing production in the regressions through mid-2019, the R2s range from a low of 0.06 (NTL-Narrow) to 0.29 (NTL-Broad). Most of the other rows also show a fair amount of variability between R2s and RMSEs as well. This divergence raises the issue of which models truly provide the most accurate picture of Chinese economic activity, and whether the choice of model depends on context.

To explore these issues further, we regressed the dependent variables shown in Table 1 on contemporaneous or lagged (up to six months) alternative indicators.[11] For this exercise, we

Table 1

China Monthly Growth Indicators (Average Alternative Indicator)

		2001 to 2013			2014 to 2018		2014 to 2019m6		
Dependent Variable	**Proxy Indicators**	***t*-stat**	R^2	**RMSE**	***t*-stat**	R^2	***t*-stat**	R^2	**RMSE**
China's imports	Official GDP	3.96	0.56	0.66	1.32	0.33	2.65	0.34	0.81
	Average Alternative	4.63	0.59	0.64	3.27	0.41	4.60	0.41	0.77
Commodity prices	Official GDP	5.69	0.43	0.75	-0.16	-0.02	0.55	-0.01	1.01
	Average Alternative	8.37	0.50	0.71	3.37	0.43	3.96	0.44	0.75
U.S. manufacturing industrial production	Official GDP	2.70	0.17	0.91	-0.72	0.00	-0.70	-0.00	1.00
	Average Alternative	2.24	0.12	0.94	0.56	-0.00	0.71	-0.00	1.00
U.S. ISM index	Official GDP	2.76	0.16	0.92	-0.91	0.01	-0.53	-0.01	1.01
	Average Alternative	3.94	0.28	0.85	0.73	0.00	1.08	0.01	0.99
Germany manufacturing industrial production	Official GDP	3.78	0.26	0.86	0.85	0.01	2.54	0.17	0.91
	Average Alternative	2.86	0.16	0.92	2.39	0.07	3.11	0.15	0.92
Japan industrial production	Official GDP	3.06	0.23	0.88	0.84	0.03	1.50	0.08	0.96
	Average Alternative	3.39	0.24	0.87	3.73	0.35	4.28	0.37	0.79
Emerging-market Asia industrial production, excluding China and India	Official GDP	3.10	0.24	0.87	-1.09	-0.00	0.85	-0.00	1.00
	Average Alternative	4.47	0.38	0.79	2.30	0.16	3.19	0.22	0.88

Source: Authors' calculations.

Notes: This table shows the results of ordinary-least-squares regressions of the dependent variable, measured independently of China's statistical system, on the Average Alternative proxy indicator. The regression of "China's imports" factors in the real effective exchange rate. All data are monthly and normalized over the regression windows shown. The *t*-values are Newey-West and R^2 values are adjusted R^2. RMSE is root-mean-square error. "China's imports" are exports to China and Hong Kong reported by the United States, the European Union, and Japan. Official GDP is as reported by China. The Average Alternative is the arithmetic average of NTL-Narrow, NTL-Broad, and the Average Factor (itself an average of the PCA and SPLS factor-based indicators).

also separate out the PCA and SPLS indicators. We ran regressions on all the data from the beginning of 2014 through June 2019, and then sorted for each dependent variable the resulting 294 models by their highest R2. The panels in Chart 10 plot the resulting "best fit" alternative indicators against each of the dependent variables. In order to help control for shocks to global demand, we conducted a similar exercise in which we calculated a partial R2 from regressions of the same dependent variables on the Chinese alternative indicators, holding constant the impacts of a global demand factor.[12] We also sorted these results by the highest partial R2 for each dependent variable. Table 2 summarizes these results, showing just the top-ranked model for each dependent variable. Appendix Table 3B shows the same for the top five ranked models for each dependent variable.

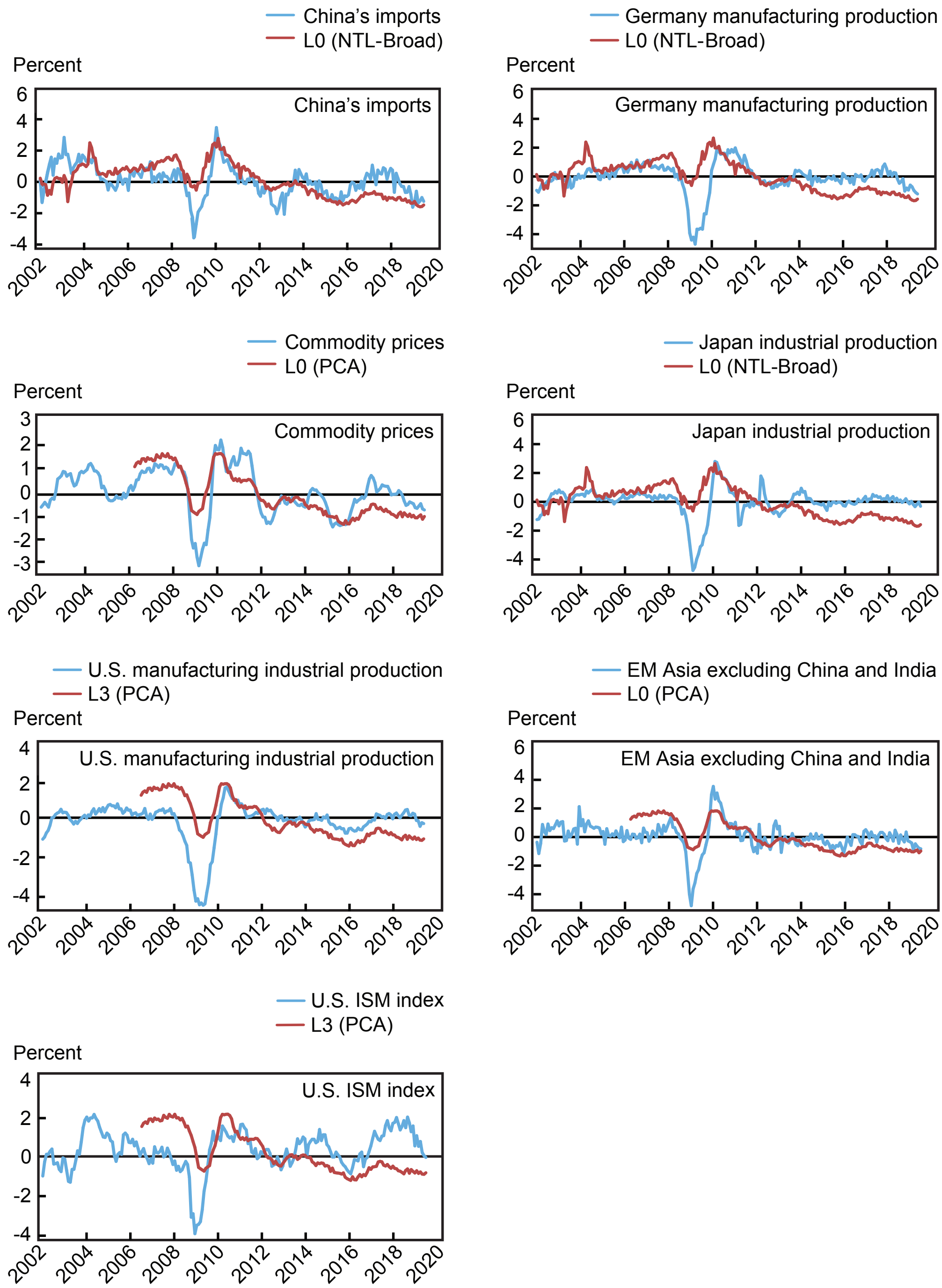
The results warrant several observations. First, the simple regressions do show explanatory power between the alternatives and the U.S. variables once one accounts for a lagged relationship, though this relationship disappears after we control for global demand. Second, it is notable how well the simple PCA indicator performs, showing up with the highest explanatory power in four of the seven dependent variables, and completely dominating the rankings in the models for U.S. manufacturing. However, once we try to control for global demand, the PCA model performs less well and is dominated by the other models, most frequently the broader models (SPLS, NTL-Broad); the NTL-Narrow ranks at the top of the regressions involving Japanese industrial production but generally does not place in the top five.

These results raise questions about the use of models such as the simple PCA as a proxy for Chinese growth. The broad PCA used here—covering sixty-two Chinese data series—clearly is correlated with Chinese activity and enjoys the advantage of being easy to compute in a policy setting. But, at the same time, it is perhaps overly influenced by industrial activity and China's central role in global value chains and, hence, economic activity outside of China. This result supports the use of the more targeted approaches taken in the SPLS and NTL indicators, which tailor the indicators to data that more directly measure Chinese growth. Another approach is the methodology of Fernald, Hsu, and Spiegel (2019; 2015), which addresses the problem by tailoring variables for a principal component based on their explanatory power over Chinese imports.

Our results also caution against overreliance on narrow indicators such as the popular Li Keqiang index, which forms the core of the NTL-Narrow indicator. As discussed in Section 2, the Li Keqiang variables—loans, rail freight, and electricity—consistently show statistically significant coefficients in satellite nighttime lights regressions for economic growth, virtually the only variables that do so, incorporating data over the period 2004 to 2013. This performance supports the use of these variables, with appropriate weighting, as Chinese growth proxies. However, the relationships between these indicators and growth likely are not stable given China's rapid pace of structural change, including in the financial sector. Moreover, a narrow set of indicators may not adequately proxy for China's consumer sector, which has been growing rapidly. Against this backdrop, the broader models considered here—SPLS and NTL-Broad—appear to have the edge in terms of their correlations with other indicators of Chinese growth.

Nonetheless, the "best" model of Chinese activity is likely to vary over time and circumstance. For example, data on labor markets, household and government consumption, the retail sector, and services in China are quite sparse, of questionable quality, or in some cases possibly "politically smoothed" (Goldman Sachs 2017). Models that use retail sales as a proxy for consumption—as do the SPLS and NTL-Broad—may understate a growth slowdown if

Chart 10
Global Variables and the Best-Fit Alternative Indicators



Source: Authors' calculations.

Notes: EM is emerging market. LO indicates that the regressors are contemporaneous and L3 denotes a lag of three months.

Table 2
The Best-Fit Models among All Regressions
Based on the highest R^2 or partial R^2

Dependent Variable	Simple Regression	Global Demand Partialed Out
China's imports	L0.(NTL-Broad)	L0.(NTL-Broad)
Commodity prices	L0.(PCA)	L0.(PCA)
U.S. manufacturing industrial production	L3.(PCA)	L0.(SPLS)
U.S. ISM index	L3.(PCA)	L0.(NTL-Narrow)
Germany manufacturing industrial production	L0.(NTL-Broad)	L0.(NTL-Broad)
Japan industrial production	L1.(NTL-Broad)	L1.(NTL-Narrow)
Emerging-market Asia industrial production, excluding China and India	L0.(PCA)	L0.(PCA)

Source: Authors' calculations.

Notes: This results are based on iterative regressions of the dependent variable on the alternative growth indicators for China: NTL-Narrow, NTL-Broad, principal components analysis (PCA), sparse partial least squares (SPLS), the Average Alternative (an average of the prior four models), and the Average Factor (an average of the PCA and SPLS factor-based models). The regressors were either contemporaneous (LO) or lagged from 1 to 6 months (L1 … L6). ISM is Institute for Supply Management. See Appendix Table 3B for full details.

consumption weakens by more than captured in official statistics. However, models that are heavily influenced by developments in the industrial sector may overstate a slowdown if household consumption is otherwise relatively stable. Policy analysts and market participants typically have a point of view on these developments based on experience and close following of the Chinese economy, news stories, social media, and other such indicators. For these reasons, we would caution against reliance on a single alternative indicator.

5. What about the Longer Cycle?

In this article, we have focused on the Chinese business cycle as opposed to its longer-term trend growth. In fact, the methodologies employed by the PCA and SPLS are calculated from detrended data, after which the trend from official GDP is reintroduced to make the models' output comparable to the NTL indicators as well as to official GDP. As a result, the factor-based indicators discussed in this article do not provide information on trend GDP independent of the official figures themselves. Nonetheless, parsing trend from cycle is important from many perspectives. For example, there is a risk of conflating a general trend-growth slowdown in China with a "hard landing." In the period after the global financial crisis, concerns over hard landings in China have periodically contributed to global market volatility and tightening of financial conditions.

On the trend side, a key observation is that China's growth is clearly slowing. In fact, the alternative indicators and China's own official GDP are consistent on this point. In a related article in this special issue, Higgins (2020) sketches out three scenarios for China's growth over the next twenty years, referred to as Humdrum, Pretty Good, and Golden. The Humdrum scenario shows real per capita income growth slowing to an average 2.7 percent in the first decade and 0.9 percent in the second. The equivalent growth rates for the Pretty Good scenario are a respective 3.8 percent and 2.1 percent in the first and second decades; for the Golden scenario, they are 4.9 percent and 2.6 percent, respectively. Without taking a stand on which scenario will come to pass, Higgins notes that all three scenarios put real per capita income growth well below the rate of about 6 percent in 2018 (based on the official growth rate). Thus, it appears likely that cycles in China's "true" growth will fluctuate around a substantially declining trend.

On the cycles themselves, the first observation to make is to stress the key point of this article: that China's economy has shown clear cyclical variation and there is no evidence that these cycles have largely disappeared, as portrayed in the official data. These cycles can have a large influence over the global economy as China's economy has grown to become a major powerhouse.

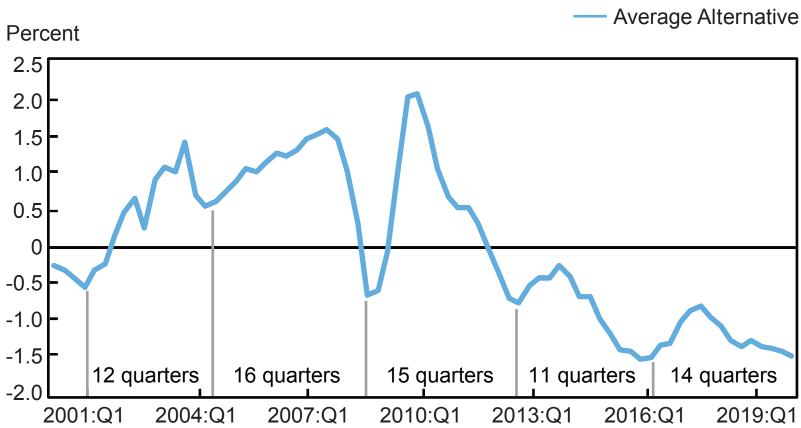
The alternative indicators suggest that there have been five complete business cycles in the post-WTO period, and that China entered a new cycle beginning in the second quarter of 2017, the end of which had not yet been apparent through mid-2019. The troughs of these cycles occurred in the fourth quarter of 2001, the fourth quarter of 2004, the fourth quarter of 2008, the third quarter of 2012, and the fourth quarter of 2015. As illustrated in Chart 11, the data indicate that the frequency of these cycles (as measured peak to peak or trough to trough) has been fairly steady at about fourteen quarters. However, upturns in growth have been much shorter in duration in the last three cycles than in the first two, while slowdowns have lasted much longer. In the last three cycles, upturns (trough to peak) have lasted, on average, only a bit more than four quarters, compared with ten to twelve quarters in the early cycles. Downturns lasted a year or less in the first two cycles but for over two years in the more recent three slowdowns.

The timing of these cycles is certainly influenced by global factors outside of China's control, but nonetheless is heavily determined by domestic policy choices as well. China's leadership has been grappling with fallout from years of overinvestment in heavy industry and real estate, and build-ups of debt in the corporate, government, and household sectors. As a result, the authorities have been trying to manage financial stability risks and economic growth goals by alternately tightening and loosening credit and fiscal policies. Given growing concerns over financial stability risks, in the period after the global financial crisis the authorities evidently have been more willing to tolerate longer periods of slowing economic growth than they were in the past. At the same time, though, concerns over social stability make the authorities resistant to allowing slowdowns to last too long or become too deep, prompting the eventual reversions to stimulus that is evident in the data.

Chart 11

China's Post-WTO Business Cycles

As measured by the Average Alternative



Source: Authors' calculations.

Notes: WTO is World Trade Organization. Data are normalized with a mean equal to zero and a standard deviation of 1.

Against this backdrop, it is reasonable to expect continued growth fluctuations around a substantially slowing trend. China's policymakers historically have had ample tools to boost growth quickly whenever needed, but these tools may become weaker over time. The most powerful policy tools are oriented around investment and credit, but as noted by Higgins (2020), contributions to growth from capital accumulation ultimately are self-limiting, since ever-greater shares of new investment outlays are needed to simply keep the capital stock from shrinking. In this context, China's credit impulse will have less "bang for the yuan" as time passes; indeed, China is already witnessing substantial declines in contributions to growth from capital accumulation. Of course, China's government could choose to "double down" on its investment-intensive growth model and increase the share of capital expenditure in GDP, but such a strategy would lead to a build-up in financial stability risks—an acute concern for authorities.

6. Conclusion

In this article, we have argued that China's official data on GDP growth appear implausibly smooth in recent years. This steadiness calls into question the usefulness of China's official growth data in forecasting and in making policy and business decisions, at least in recent years. Accordingly, we have constructed a set of alternative growth proxies, the methodologies of which revolve around satellite nighttime lights, principal component analysis, and sparse partial least squares regression. These proxies are more volatile than China's official data, show changes that are plausible with respect to domestic economic data and policy developments, and retain considerable explanatory power over other global economic variables that China should influence. In terms of magnitude, growth slowdowns during 2014–15 and 2017–19 were about twice as large in percentage points of growth as those officially reported, while a growth rebound in 2016 seen in the alternative indicators was scarcely reported in official statistics. The growth slowdown during 2017 through mid–2019 was not as deep as the 2014–15 slowdown—measuring somewhat more than half the size of the slowdown as the previous period. Official GDP data have tracked the alternative indicators relatively closely from the third quarter of 2018 through the second quarter of 2019.

While our analysis indicates that cyclical movements in China's economy have remained quite pronounced over the past half-decade, it does not necessarily imply that the growth rates themselves are much lower than officially reported. Indeed, Clark, Pinkovskiy, and Sala-i-Martin (2020) found little basis for such an assertion. Nonetheless, it is already evident, both from the alternative indicators and from official GDP, that average growth rates have slowed substantially, and the outlook over the next few decades is for trend growth to slow by significantly more. At the same time, policymakers will have less room for stimulus as the efficacy of capital accumulation fades. Eventually, trend growth may be low enough that "growth recessions" may materialize into actual contractions—an outcome not yet evident in our alternative indicators.

The fluctuations in growth suggested by the alternative indicators are large enough to have economically significant impacts on global commodity markets and emerging-market economies. As discussed in Akinci, Benigno, and Pesenti (2020), a slowdown similar to that in 2017-18 should have fairly moderate impacts on the U.S. economy through normal trade channels. However, the impact of any slowdown in the Chinese economy would become larger as the country's financial system becomes more integrated into global markets or if such a slowdown triggered adverse shocks to financial markets and business confidence. Moreover, a higher-magnitude Chinese slowdown, such as occurred during 2014–15, could have a meaningful impact even through normal trade channels alone.

Appendix 1: Additional Detail on Nighttime Lights Methodology

In this appendix we summarize the methodology described in detail in Clark, Pinkovskiy, and Sala-i-Martin (2017; 2020), and discuss a few additional details of how this methodology was operationalized at a monthly frequency in this article to support real-time policy work.

The nighttime lights satellite data are collected by the Defense Meteorological Satellite Program Operational Linescan System (DMSP-OLS). These data are maintained and processed by the National Oceanic and Atmospheric Administration's National Centers for Environmental Information (formerly National Geophysical Data Center). Satellites orbit the Earth, sending images of every location between 65 degrees south latitude and 65 degrees north from 8:30 p.m. to 10 p.m. local time. The images are processed to remove cloud cover, snow, and ephemeral lights (such as forest fires). They are then averaged over time for stability and to limit seasonality. The final product is publicly available for download at an annual frequency for years between 1992 and 2013.[13]

Each pixel (1 square kilometer) in the luminosity data is assigned a digital number (DN) representing its luminosity. The DNs are integers that range from 0 to 63. We construct our lights proxy for aggregate income by summing up all the digital numbers across the pixels. This method has been widely used in the literature on nighttime lights in economics, including Henderson, Storeygard, and Weil (2012) and Michalopoulos and Papaioannou (2013; 2014). For years with multiple satellites available, we average the logarithms of our aggregate luminosity measure, following Henderson, Storeygard, and Weil (2012).

Although it is well-established that lights are strongly correlated with measures of economic activity, such as national accounts GDP, in levels and growth rates, there are also well-known problems with the relationship between nighttime lights and economic development that need to be taken into account. When the data from the DMSP-OLS satellites are used, pixels with DN equal to 0 or 63 are top- or bottom-censored. For example, the lights data are also affected by overglow and blooming, meaning that light tends to travel to pixels outside of those in which it originates, and that light tends to be magnified over certain terrain types such as water and snow cover (Doll, Muller, and Morley 2006). Given that this research is based on national-level estimates of aggregate lights, it is unlikely that these sources of error will be large enough or sufficiently correlated with important variables to confound our analysis. Another problem may be that satellites age in space and are eventually retired. Hence, they might give inconsistent readings from year to year, or new satellites may give fundamentally different readings from old ones. While some evidence of this problem exists, the mathematical framework in the next section suggests that our calculations are supported by assumptions that allow nighttime lights to have all of the data problems described above, so long as nighttime lights are correlated with true income. We also address this problem by including year fixed effects (sometimes additionally interacted with cross-sectional variation) in all specifications.

We now turn to summarizing the mathematical framework for our methodology, which was developed in Pinkovskiy and Sala-i-Martin (2016a; 2016b).

Appendix 1 (Continued)

Let $y^{*}_{i,t}$ be the unobserved, true value of GDP in location i in time period t, $y^{A}_{i,t}$ and $y^{B}_{i,t}$ be observed proxies of economic activity, and $y^{L}_{i,t}$ be the amount of nighttime light. We can always write:

$$y^{L}_{i,t} = f_{i,t}(y^{*}_{i,t}) + \varepsilon^{L}_{i,t}$$
$$y^{A}_{i,t} = \alpha_A + \beta_A y^{*}_{i,t} + \varepsilon^{A}_{i,t}$$
$$y^{B}_{i,t} = \alpha_B + \beta_B y^{*}_{i,t} + \varepsilon^{B}_{i,t}$$

where $f_{i,t}\,(y^{*}_{i,t})$ may be some nonlinear function of the unobserved true $GDP\ y^{*}_{i,t}$, and the epsilons are measurement errors. To discipline this structure, we make the following assumptions:

$$\text{A0)}\quad cov(y^{*}_{i,t}, f_{i,t}(y^{*}_{i,t})) \neq 0,$$

(lights are correlated with true income)

$$\text{A1)}\quad E(\varepsilon^{L}_{i,t}|y^{*}_{i,t}) = E(\varepsilon^{A}_{i,t}|y^{*}_{i,t}) = E(\varepsilon^{B}_{i,t}|y^{*}_{i,t})$$

(measurement errors are uncorrelated with true income)

$$\text{A2)}\quad E(\varepsilon^{A}_{i,t}\varepsilon^{L}_{i,t}|y^{*}_{i,t}) = E(\varepsilon^{B}_{i,t}\varepsilon^{L}_{i,t}|y^{*}_{i,t}) = 0$$

(measurement error in lights is uncorrelated with other measurement errors).

Under assumptions A0-A2, Clark, Pinkovskiy, and Sala-i-Martin (2020) show that running the regression

$$y^{L}_{i,t} = \alpha + b_A y^{A}_{i,t} + b_B y^{B}_{i,t}$$

will yield coefficients b_A and b_B that are proportional to the weights on $y^{A}_{i,t}$ and $y^{B}_{i,t}$ in the best unbiased linear predictor of $y^{*}_{i,t}$ based on the proxies $y^{A}_{i,t}$ and $y^{B}_{i,t}$.

Clark, Pinkovskiy, and Sala-i-Martin (2020) found that running regressions on the 2005-13 sample of Chinese provinces with the Li Keqiang variables and log real GDP as the candidate proxy measures gave an optimal weight of about 60 percent on loan growth, 30 percent on electricity growth, and 10 percent on railroad freight growth. Running this regression on a broader subset of variables used by Fernald, Hsu, and Spiegel (2015) generated no new additional variables with statistically significant weights, with the exception of retail sales if price deflators were included in the regressions. We concluded that an optimal estimator of Chinese economic performance should put considerable weight on loan growth.

One challenge of comparing the resulting best unbiased linear predictor of Chinese growth to the official GDP series is that our methodology does not identify the location or scale of GDP. Clark, Pinkovskiy, and Sala-i-Martin (2020) addressed this problem by calculating the

Appendix 1 (Continued)

fitted values of the regression of official national quarterly GDP growth rates on the optimally weighted national quarterly candidate proxy growth rates as our best unbiased linear predictor. The fit of this regression is quite good. However, even without relying on the assumption that official GDP is a good measure of "true" growth, we can compare the values of our best unbiased linear predictor in one time period to the values in another time period. Therefore, we can make statements such as "Chinese growth in the fourth quarter of 2018 was higher than Chinese growth in the fourth quarter of 2015," or that "the decline in Chinese growth over 2018 has been smaller than the decline in Chinese growth during 2015," without relying on any scaling assumptions.

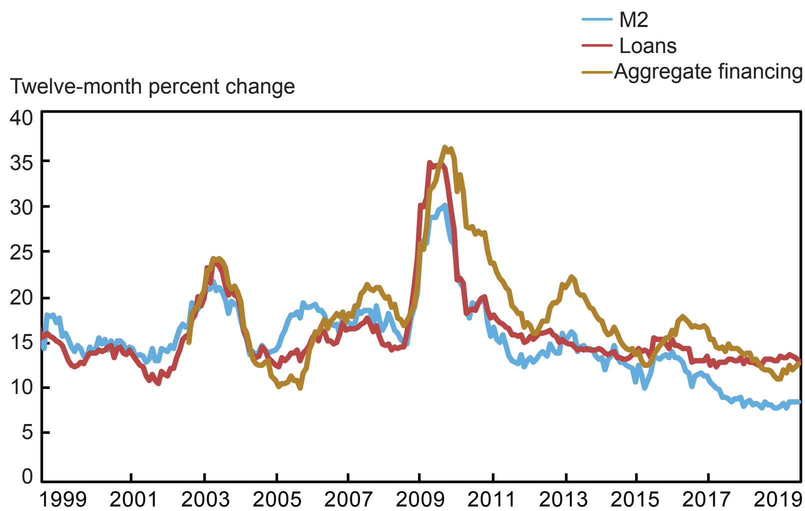
Another important challenge for using these indicators for current policy work is that financial conditions are likely not as well captured by loans as they were over our in-sample period. For reasons of data availability, we had to use data on loans in the provincial regressions. However, within the past decade the broader concept of "aggregate financing"—of which "shadow credit" is an important component—has taken on greater importance in China's credit cycle. The use of loans in our NTL growth indexes would therefore likely misrepresent financial conditions in China during both the 2014–15 and the most recent cycles. This is because the authorities have alternately tightened and loosened credit in the so-called "shadow finance" sector, leading to substantial fluctuations in aggregate financing, and hence tightening and loosening of credit conditions. By contrast, bank loan growth has been much more stable as the authorities have taken measures to move off-balance-sheet financial activities back onto bank balance sheets.

As a workaround for this problem, the NTL-based alternative indicators in this article use M2 instead of loans in the calculation of the indexes used to make in and out-of-sample estimates of GDP growth. The reason for this substitution is that we can be a bit more conservative in how we capture credit conditions. We believe that changes in M2 growth serve as a useful "middle ground" between aggregate financing and loans in representing true credit conditions in our period of interest. Appendix Charts 1A and 1B show the twelve-month growth rates of M2, loans, and aggregate financing and their rolling correlations. For most of China's history—including the period in our estimation sample—money, loans, and aggregate financing have been quite strongly correlated, with correlations usually ranging from 0.8 to 0.95. However, in more recent years, the relationship between M2 and loans has weakened, while the one between M2 and aggregate financing has remained higher. In the most recent cycle, from the first quarter of 2017 to the second quarter of 2019, M2 growth has fallen by about half as much as aggregate financing, while loan growth was little changed overall. We argue that true credit availability for the "real economy" was likely not as steady as implied by loan growth, nor as tight as implied by aggregate financing, and hence is better represented by M2 growth.

Appendix 1 (Continued)

Chart 1A

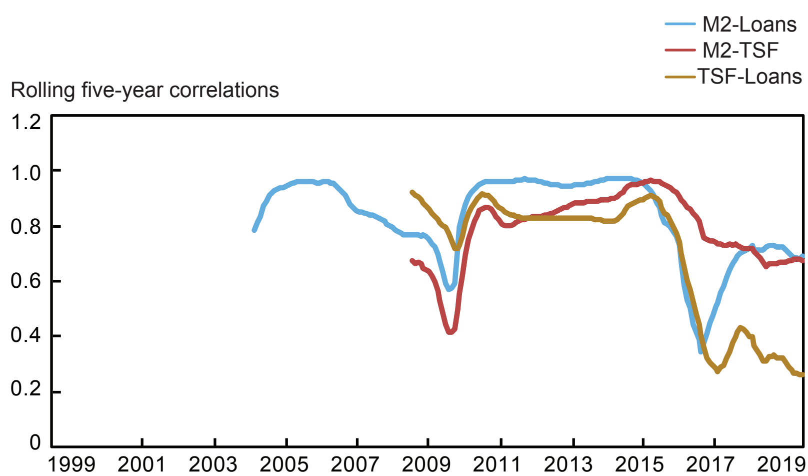
M2 Growth Serves as a Middle Ground for Gauging Credit Conditions



Sources: People's Bank of China via CEIC Data; authors' calculations.

Chart 1B

Relationships between Credit Condition Measures Have Weakened Somewhat



Sources: People's Bank of China via CEIC Data; authors' calculations.

Appendix 2: Notes on the Data

1. General Observations

The data used in this article come from official sources (National Bureau of Statistics of China and People's Bank of China) and are accessed via the CEIC Data's Premium China Database. The underlying frequency of the data used here is monthly, except for GDP and the fixed asset investment (FAI) price deflator, which are quarterly and converted to monthly frequency via linear interpolation. Data published in year-to-date format are converted to monthly frequency by subtracting the current from the previous observation. All twelve-month changes are computed from seasonally adjusted data, for which measures are taken to control for the timing of the Chinese New Year. Certain series are problematic in that the availability of data for January and/or February varies over the history of the series (for example, data for January and February are published in some years, some years exclude January, and some years exclude both). For these series, we discard January and February from the entire series, linearly interpolate the gaps, and seasonally adjust the modified data.[14] With the exceptions of value-added by private industry (VAI) and the purchasing manager's index (PMI), all data are seasonally adjusted by the authors using the TRAMO-SEATS algorithm within the U.S. Census Bureau's X13-ARIMA program. The VAI and PMI data are seasonally adjusted by the authorities.

2. Specific Notes

Credit: Data problems make it difficult to construct consistent time series for credit. China most recently revised its aggregate credit series in July 2018 and again in September 2018; revisions for the outstanding levels of aggregate credit were not carried back further than 2016, and the stocks implied from the flows, in general, have not been internally consistent. As a simple workaround, we construct credit levels derived from reported flows, for which there is a more consistent historical series. We also make additional adjustments for the inclusion of certain local government bond issuance and the exclusion of equity financing and loan write-offs.

Fixed asset investment (FAI): China's FAI data suffer from many well-known statistical shortcomings (Orlik 2012). The major problems include coverage of investment expenditure on both new and existing machinery and structures; purchases of land; publication only in year-to-date nominal terms; inclusion of expenditure on not-yet completed investments; and periodic, highly nontransparent data revisions. Data revisions were particularly problematic during 2017–18, when large discrepancies developed between officially published twelve-month percentage changes and directly calculated changes from the published levels, with the former reportedly "adjusted" by the authorities to make them comparable to previous data. In this article, we calculate index levels from the official twelve-month percentage changes. Specifically, we identify years during which there is little or no discrepancy between twelve-month percentage changes, and using those official levels, we extrapolate forward and backward using the official data on percentage change. These calculated index levels are then fed into our seasonal adjustment and subsequent modeling procedures.

Appendix 2 (Continued)

Summary of Data Employed for Each Growth Proxy Indicator

	Sparse Factor					
	V1	V2	V3	Simple Factor	NTL - Narrow	NTL - Broad
Consumer confidence index			x	x		
Consumer expectation index	x			x		
Value added of industry	x	x	x	x		
Electricity production	x	x	x	x	x	x
Iron ore production	x		x	x		
Pig iron production	x			x		
Crude steel production	x			x		
Steel product production	x			x		
Apparent crude demand				x		
Apparent refined demand	x			x		
Copper production	x			x		
Aluminum production	x		x	x		
Cement production	x		x	x		
Plate glass production	x			x		
Real estate investment production	x		x	x		
Floor space started	x			x		x
Floor space under construction (Residential)	x		x	x		
Floor space completed	x			x		

Table continued on next page

Appendix 2 (Continued)

	Sparse Factor			Simple Factor	NTL-Narrow	NTL-Broad
	V1	V2	V3			
Floor space sold				x		
Imports of iron ore (Volume)			x	x		
Steel product imports (Volume)	x			x		
Imports of unwrought copper	x		x	x		
Imports of copper waste	x		x	x		
Imports of unwrought aluminum	x		x	x		
Steel products exports	x		x	x		
Unwrought copper export volume				x		
Unwrought aluminum export volume	x			x		
Nominal retail sales				x		x
Real retail sales				x		
Nominal fixed-asset investment				x		
Real fixed-asset investment				x		
Real estate investment				x		x
Auto sales	x	x	x	x		
Rail freight				x	x	x
Air pass-through	x			x		x
Total pass-through				x		
Petrol imports	x		x	x		
Foreign reserves			x	x		
Exchange rate (USD)	x			x		

Table continued on next page

Appendix 2 (Continued)

	Sparse Factor V1	Sparse Factor V2	Sparse Factor V3	Simple Factor	NTL-Narrow	NTL-Broad
Shanghai Stock Exchange index			x	x		
Shenzhen Stock Exchange index			x	x		
PE ratio for Shanghai Stock Exchange	x		x	x		
PE ratio for Shenzhen Stock Exchange			x	x		
Producer price index	x	x	x	x	x	
Consumer price index	x		x			
M1	x		x	x		
M2				x		
Official PMI				x		
Export PMI				x		
Nominal exports				x		x
Real exports				x		
Nominal imports				x		
Real imports				x		
Processing exports				x		
Processing imports				x		
Non-processing exports				x		
Non-processing imports				x		

Table continued on next page

Appendix 2 (Continued)

	Sparse Factor V1	Sparse Factor V2	Sparse Factor V3	Simple Factor	NTL-Narrow	NTL-Broad
Trade balance				x		
Shanghai-Shenzhen 300 index				x		
Truck sales				x		
Bank loans				x	x	x
Official GDP					x	

Notes: V1, V2, and V3 refer to the versions of the Sparse Factor Model described in Groen and Nattinger (2020). The nighttime lights (NTL) calibration regressions use bank loan data, which is available at the provincial level. The NTL alternative indexes serving as growth proxies in this article use the coefficients from earlier regressions using loans, but apply them to M2, to better capture the tightening of financial conditions. See the main text for further explanation.

Appendix 3: Supplementary Tables

Table 3A
China Monthly Growth Indicators (Individual Proxy Indicators)

		2001 to 2013			2014 to 2018		2014 to 2019m6		
Dependent Variable	Proxy Indicators	*t*-stat	R^2	RMSE	*t*-stat	R^2	*t*-stat	R^2	RMSE
China's imports	Official GDP	3.96	0.56	0.66	1.32	0.33	2.65	0.34	0.81
	Average Alternative	4.63	0.59	0.64	3.27	0.41	4.60	0.41	0.77
	NTL-Narrow	3.98	0.57	0.65	1.29	0.32	2.35	0.27	0.86
	NTL-Broad	3.61	0.56	0.66	4.49	0.48	6.24	0.51	0.70
	Average Factor	4.66	0.58	0.64	3.32	0.43	4.49	0.41	0.77
Commodity prices	Official GDP	5.69	0.43	0.75	-0.16	-0.02	0.55	-0.01	1.01
	Average Alternative	8.37	0.50	0.71	3.37	0.43	3.96	0.44	0.75
	NTL-Narrow	5.98	0.36	0.80	2.56	0.23	3.06	0.25	0.87
	NTL-Broad	6.22	0.37	0.79	3.16	0.41	3.68	0.40	0.78
	Average Factor	7.61	0.53	0.68	4.00	0.51	4.69	0.52	0.69
Emerging-market Asia industrial production, excluding China and India	Official GDP	3.10	0.24	0.87	-1.09	-0.00	0.85	-0.00	1.00
	Average Alternative	4.47	0.38	0.79	2.30	0.16	3.19	0.22	0.88
	NTL-Narrow	4.16	0.33	0.82	1.79	0.07	2.47	0.11	0.94
	NTL-Broad	4.29	0.31	0.83	2.10	0.15	3.25	0.25	0.87
	Average Factor	4.23	0.37	0.79	2.77	0.20	3.69	0.24	0.87
Japan industrial production	Official GDP	3.06	0.23	0.88	0.84	0.03	1.50	0.08	0.96
	Average Alternative	3.39	0.24	0.87	3.73	0.35	4.28	0.37	0.79
	NTL-Narrow	2.59	0.16	0.92	3.05	0.30	3.49	0.31	0.83
	NTL-Broad	2.83	0.16	0.92	4.20	0.36	4.96	0.40	0.77
	Average Factor	3.64	0.29	0.84	3.46	0.30	3.83	0.32	0.83

Table 3A continued on next page

Appendix 3 (Continued)

		2001 to 2013			2014 to 2018		2014 to 2019m6		
Dependent Variable	**Proxy Indicators**	***t*-stat**	R^2	**RMSE**	***t*-stat**	R^2	***t*-stat**	R^2	**RMSE**
Germany manufacturing industrial production	Official GDP	3.78	0.26	0.86	0.85	0.01	2.54	0.17	0.91
	Average Alternative	2.86	0.16	0.92	2.39	0.07	3.11	0.15	0.92
	NTL-Narrow	1.49	0.05	0.97	1.29	0.02	2.07	0.06	0.97
	NTL-Broad	2.27	0.10	0.95	3.42	0.15	4.12	0.29	0.84
	Average Factor	3.74	0.24	0.87	2.08	0.06	2.77	0.11	0.94
U.S. manufacturing industrial production	Official GDP	2.70	0.17	0.91	-0.72	0.00	-0.70	-0.00	1.00
	Average Alternative	2.24	0.12	0.94	0.56	-0.00	0.71	-0.00	1.00
	NTL-Narrow	1.38	0.05	0.97	-0.32	-0.01	-0.26	-0.01	1.01
	NTL-Broad	1.81	0.06	0.97	0.93	0.02	1.21	0.02	0.99
	Average Factor	2.76	0.18	0.90	0.75	0.01	0.84	0.01	1.00
U.S. ISM index	Official GDP	2.76	0.16	0.92	-0.91	0.01	-0.53	-0.01	1.01
	Average Alternative	3.94	0.28	0.85	0.73	0.00	1.08	0.01	0.99
	NTL-Narrow	3.56	0.21	0.89	-0.23	-0.02	-0.03	-0.02	1.01
	NTL-Broad	4.82	0.31	0.83	1.16	0.04	1.70	0.05	0.97
	Average Factor	3.52	0.24	0.87	0.93	0.02	1.22	0.03	0.99

Source: Authors' calculations.

Notes: This table shows the results of ordinary-least-squares regressions of the dependent variable, measured independently of China's statistical system, on the proxy indicators individually. The regression of "China's imports" factors in the real effective exchange rate. All data are monthly and normalized over the regression windows shown. The *t*-values are Newey-West and R^2 values are adjusted R^2. RMSE is root-mean-square error. "China's imports" are exports to China and Hong Kong reported by the United States, the European Union, and Japan. Official GDP is as reported by China. The Average Alternative is the arithmetic average of NTL-Narrow, NTL-Broad, and the Average Factor (itself an average of the PCA and SPLS factor-based indicators).

Appendix 3 (Continued)

Table 3B

Top Five Alternative Growth Indicators for Each Global Variable

Sorted by R^2 or partial R^2

	Simple Bivariate Regressions			Regressions with Global Demand Partialed Out		
	Five Best Models	***t*-stat**	R^2	**Five Best Models**	***t*-stat**	Partial R^2
China's imports	L0.(NTL-Broad)	6.24	0.51	L0.(NTL-Broad)	5.63	0.32
	L1.(NTL-Broad)	4.96	0.46	L1.(NTL-Broad)	4.73	0.25
	L6.(SPLS)	3.95	0.45	L6.(SPLS)	4.54	0.23
	L2.(NTL-Broad)	4.88	0.45	L3.(SPLS)	4.47	0.23
	L3.(NTL-Broad)	4.54	0.43	L5.(SPLS)	4.34	0.22
Commodity prices	L0.(PCA)	6.58	0.59	L0.(PCA)	7.51	0.46
	L0.(Average Factor)	4.69	0.52	L0.(Average Factor)	7.43	0.45
	L1.(Average Factor)	4.03	0.46	L0.(SPLS)	6.63	0.40
	L1.(PCA)	4.58	0.46	L0.(Average Alternative)	6.36	0.38
	L0.(Average Alternative)	3.96	0.44	L1.(SPLS)	6.28	0.37
U.S. manufacturing industrial production	L3.(PCA)	2.83	0.26	L0.(SPLS)	-1.96	0.04
	L2.(PCA)	2.83	0.24	L0.(NTL-Narrow)	-1.80	0.03
	L4.(PCA)	2.64	0.23	L1.(SPLS)	-1.53	0.02
	L1.(PCA)	2.92	0.21	L3.(PCA)	1.50	0.02
	L5.(PCA)	2.50	0.20	L2.(SPLS)	-1.25	0.01

Table 3B continued on next page

Appendix 3 (Continued)

	Simple Bivariate Regressions			Regressions with Global Demand Partialed Out		
	Five Best Models	***t*-stat**	R^2	**Five Best Models**	***t*-stat**	**Partial** R^2
U.S. ISM index	L3.(PCA)	3.08	0.25	L0.(NTL-Narrow)	-1.80	0.03
	L4.(PCA)	2.96	0.24	L0.(SPLS)	-1.46	0.02
	L1.(PCA)	3.33	0.24	L2.(NTL-Narrow)	-1.24	0.01
	L2.(PCA)	3.05	0.22	L1.(SPLS)	-1.12	0.00
	L5.(PCA)	2.75	0.20	L2.(SPLS)	-1.11	0.00
Germany manufacturing industrial production U.S. ISM index	L0.(NTL-Broad)	4.12	0.29	L0.(NTL-Broad)	4.66	0.24
	L1.(NTL-Broad)	3.53	0.25	L1.(NTL-Broad)	4.01	0.19
	L2.(NTL-Broad)	3.42	0.24	L2.(NTL-Broad)	3.87	0.18
	L5.(SPLS)	3.35	0.22	L5.(SPLS)	3.69	0.16
	L6.(SPLS)	3.10	0.21	L6.(SPLS)	3.55	0.15
Japan industrial production	L1.(NTL-Broad)	4.99	0.46	L1.(NTL-Narrow)	5.97	0.35
	L1.(Average Alternative)	4.47	0.43	L1.(NTL-Broad)	5.88	0.34
	L2.(NTL-Broad)	4.54	0.41	L1.(Average Alternative)	5.79	0.33
	L0.(NTL-Broad)	4.96	0.40	L0.(NTL-Narrow)	5.54	0.31
	L2.(Average Alternative)	4.13	0.39	L0.(NTL-Broad)	5.37	0.30

Table 3B continued on next page

Appendix 3 (Continued)

	Simple Bivariate Regressions			Regressions with Global Demand Partialed Out		
	Five Best Models	***t*-stat**	R^2	**Five Best Models**	***t*-stat**	Partial R^2
Emerging-market Asia industrial production, excluding China and India	L0.(PCA)	4.92	0.30	L0.(PCA)	4.21	0.20
	L0.(NTL-Broad)	3.25	0.25	L0.(Average Factor)	3.85	0.18
	L0.(Average Factor)	3.69	0.24	L0.(NTL-Broad)	3.85	0.18
	L0.(Average Alternative)	3.19	0.22	L0.(Average Alternative)	3.70	0.16
	L2.(NTL-Broad)	2.57	0.21	L0.(SPLS)	3.34	0.14

Source: Authors' calculations.

Notes: The left side of this table presents the results from iterative regressions of the dependent variable on the alternative growth indicators for China: NTL-Narrow, NTL-Broad, principal components analysis (PCA), sparse partial least squares (SPLS), the Average Alternative (an average of the prior four models), and the Average Factor (an average of the PCA and SPLS factor-based models), with the regressors either being contemporaneous (LO) or lagged from 1 to 6 months (L1 … L6). The right side presents the results of the same set of regressions, but partials out a global demand factor. All regressions involving China's imports include the real effective exchange rate.

Notes

[1] See, for example, Rawski (2001), Maddison and Wu (2006), Wu (2014), Holz (2013), Martinez (2018), Hu and Yao (2019), Clark, Pinkovskiy, and Sala-i-Martin (2017; 2020), and references therein.

[2] While we prefer using M2 growth in place of loan growth, both generate very similar predictions for Chinese GDP growth over our in-sample estimation period. In the post-sample period, the level of growth implied by loans is somewhat higher than implied by M2, while the changes in growth are somewhat smaller.

[3] Monthly alternative indicators are calculated using linearly interpolated quarterly GDP growth.

[4] After taking the twelve-month change, the estimation sample begins in April 2006.

[5] This SPLS indicator is referred to as model "V3" in Groen and Nattinger (2020).

[6] This characterization holds for the alternative indicators individually as well.

[7] The cut to required reserves totaled 100 basis points and had been preannounced in September 2017. It did not result in a reduction in the headline official rate, since as it applied only to selected institutions.

[8] Satellite data in principle could also be a good candidate. However, the high-frequency data are of relatively limited time span and extremely volatile.

[9] Chinese imports follows Fernald, Hsu, and Spiegel (2015) and are defined as exports to China and Hong Kong reported by the United States, Japan, and the European Union. The data are deflated according to the methodology described in the article cited.

[10] This specification follows Fernald, Hsu, and Spiegel (2015). In all the regressions, the real effective exchange rate is statistically significant with the expected negative coefficient.

[11] As in Table 1, each regression included the dependent variable, a constant, and the alternative indicator, with the regressions iterating over lags of zero through six months of the alternative indicators. The regression for China's imports also included the real effective exchange rate. Each regression for the dependent variables contains the same number of variables.

[12] The global demand factor was calculated as the first principal component of an index derived from ocean dry bulk cargo freight rates (Kilian and Zhou 2018) and from data derived in the oil price decomposition published in the Federal Reserve Bank of New York's Oil Price Dynamics Report.

[13] National Oceanic and Atmospheric Administration's National Centers for Environmental Information (formerly National Geophysical Data Center) 2010 Nighttime Lights Time Series (Version 4 DMSP-OLS; accessed September 2013), https://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html.

[14] The series include: industrial production of electricity, copper, aluminum, iron ore, pig iron, crude steel, steel products, cement, plated glass, refrigerators, air conditioners, and washing machines; retail sales above designated size; and apparent demand of crude and refined petroleum, which are computed as production minus exports plus imports.

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Alternative Indicators for Chinese Economic Activity Using Sparse PLS Regression

Jan J. J. Groen and Michael B. Nattinger

OVERVIEW

- According to official GDP data, China's economy has experienced a remarkably—and perhaps unrealistically—smooth deceleration since the Great Recession. Alternative data sources suggest greater volatility, however, with many China watchers seeing evidence that cyclical downturns occurred in 2015-16 and 2018-19.

- To better track Chinese business cycle fluctuations, the authors construct an economic activity indicator using factors from a sparse partial least squares (PLS) regression on a wide array of high-frequency data. The resulting indicator points to a greater degree of cyclicality in Chinese economic growth than official statistics reflect.

- Decomposing deviations from trend growth, the authors also find that domestic factors have eclipsed external factors as the primary driver of Chinese economic activity since 2018, citing a deterioration in domestic credit conditions as the main cause of the 2018-19 slowdown.

While Chinese GDP growth rates remain impressive compared to those seen in developed market economies, the Chinese economy has been decelerating since the 2007-09 Great Recession. Remarkably, this slowdown seems to be proceeding in a smooth fashion.[1] However, alternative, higher-frequency data, as well as reports about firm and household behavior, suggest that Chinese growth has been more cyclical over this period than the official numbers imply.

For example, market participants and academics believe that China has experienced two cyclical downturns in the Xi Jinping era (2013-present)—one in 2015-16 and another in 2018-19. However, neither of these downturns appears in the official GDP data, which have continued to reflect a gradual and orderly deceleration in China's economy throughout this period. Consequently, there is widespread doubt about the reliability of official Chinese GDP data. Chen et al. (2019), for example, look at changes in VAT receipts to quantify over- and underreporting in official GDP numbers, finding that such errors occur frequently and are quantitatively large—problems they attribute to data collection and construction issues within statistical authorities at both the local and national levels.[2]

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In an attempt to better track Chinese business cycles, China watchers have constructed a wide array of growth indicators based on alternative data. The most well-known of these alternative indicators is the so-called Li Keqiang index, which is essentially an arithmetic average of the growth rates of electricity production, railroad freight, and bank loans in China.[3]

Academic studies, such as Clark, Pinkovskiy, and Martin (2019) and Fernald, Hsu, and Spiegel (2019), have used more extensive data sets and more sophisticated aggregation schemes to construct alternative views of Chinese economic performance. Similarly, we propose a methodology that efficiently draws and combines indicator variables from a large pool of candidate variables to quantify an alternative view of the state of the Chinese economy.

Our methodology has several advantages as an alternative growth indicator. First, our indicator draws from an extensive pool of high-frequency data, all potentially related to Chinese economic performance. Our methodology then weeds out series that provide less information about underlying economic growth. Next, we target the underlying data to a set of economic indicators that are highly correlated with various important aspects of the Chinese economy. The end results are factors from a sparse partial least squares (PLS) regression that appear to track Chinese business cycles at a high frequency, perform well out-of-sample, and, as shown in Clark, Dawson, and Pinkovskiy (2019), correlate well with an array of growth indicators from around the world. Finally, our factor model enables us to decompose China's deviations from trend growth into global growth, credit supply, and monetary policy components.

1. Modeling Approach

As noted above, a number of studies indicate that Chinese GDP data might suffer from a number of measurement issues, which make them a less reliable indicator of fluctuations in economic activity. We shall treat Chinese economic activity as not observable and approximate it by making use of higher-frequency correlations between proxies of Chinese economic activity and an array of survey, production, sales, and financial market variables.

To model these correlations, we start with the following relationship:

$$\Delta y_t = \alpha_0 + \alpha' x_t + \epsilon_t; \quad t = 1, \ldots, T, \tag{1}$$

where t represents an observation at the monthly frequency, $\Delta y_t = 100(\ln(Y_t) - \ln(Y_{t-12}))$, with Y_t being a $k \times 1$ vector of economic activity proxies and x_t an $N \times 1$ vector of normalized variables (either in terms of percentage changes or log levels, depending on what yields an $I(0)$ series). Given the size of our data set, N in (1) becomes quite large. A common way to deal with large dimensionality in the context of (1) is to extract a limited number of common factors from x_t; see the discussion in Groen and Kapetanios (2016). However, only those common factors that best reflect the correlations between the economic activity proxy variables and the variables in x_t, both contemporaneously as well as dynamically, are of interest for our exercise. Hence, only specific methods of common factor estimation can be used and one of those approaches is PLS regression.

To execute the PLS regression described in (1), one constructs r independent, linear combinations of x_t that have the highest covariance with Δy_t: $f_t = (f_{1,t}, \ldots, f_{r,t})'$. This implies that

PLS factors can be defined as $(f'_1, \dots f'_T)' = XW$, $X = (x'_1 \cdots x'_T)'$, $W = (w_1 \cdots w_r)$ (see also Groen and Kapetanios [2016]). For each factor, the corresponding loadings, w_r, can be estimated as

$$w_r = \max_{w} w'(X'\Delta\tilde{y})(X'\Delta\tilde{y})'w \quad \text{s.t.} \quad w'w = 1 \quad \text{and} \quad w'(X'X)w_j = 0, \tag{2}$$

with $\Delta\tilde{y}_t$ being the *normalized* activity proxies, $\Delta\tilde{y} = (\Delta\tilde{y}'_1 \dots \Delta\tilde{y}'_T)'$ and $j = 1, \dots, r-1$. (2) boils down to estimating w_r using the eigenvector corresponding to the largest eigenvalue of the squared covariance matrix of the activity proxies, with the variables in X conditional on the effect of the previous $r - 1$ factors.

In its standard setup, as described above, PLS regression estimates factors that have contributions from all N variables in x_t. One disadvantage of using factor models to summarize the information in a relatively large, heterogeneous data set is that when N expands—and x_t contains noisy variables—the factors could become imprecise, generating a case of "weak" or "near-strong" factors. In contrast to more standard factor estimation methods that solely maximize the fit for x_t and do not target a dependent variable, such as principal component analysis, PLS regression can be a useful tool for estimating appropriate factors, even when these are weak, just because it also targets a dependent variable. However, when using PLS regression, there is also the risk of overfitting the data, in particular when N is large.

Groen and Kapetanios (2016, Theorem 2) formally explore the behavior of PLS regression in the weak factor case, showing that it works as long as the number of variables underlying the factors grows at a slower rate than the number of time series observations. One way to impose this condition in practice is to use sparse PLS regression as devised by Chun and Keles (2010), which in essence builds a group least absolute shrinkage and selection operator (LASSO) restriction into the standard PLS estimation approach (2), that is,

$$w_r = \max_{w} w'(X'\Delta\tilde{y})(X'\Delta\tilde{y})'w \quad \text{s.t.} \quad w'w = 1, \quad |w| \geqq \lambda \quad \text{and} \quad w'(X'X)w_j = 0, \tag{3}$$

with $\lambda = \bar{\lambda} \times \max|w_r|$ and $0 < \bar{\lambda} < 1$. Intuitively, a group LASSO restriction, through λ in (3), yields the relevant subset of the N variables, given the strength of the individual correlations with the activity proxies. Standard PLS estimation is then applied in a final step to get the appropriate factors f_t in (4). This LASSO restriction also reduces the potential risk of overfitting that comes with applying PLS regression. Hence, variables, and the common factors derived from these, are selected and rotated based on their relevance to the correlation with activity proxies.

In order to be able to estimate a sparse PLS factor model, one needs to determine the number of PLS factors, r, and the degree of sparsity, $\bar{\lambda}$, in (3). This is done with the Bayesian Information Criterion (BIC) using a stochastic degrees of freedom measure for PLS regression, as developed in Krämer and Sugiyama (2011). For a given set of r and $\bar{\lambda}$ values, we fit

$$\Delta y_t = \beta_0 + \beta' f_t + \varepsilon_t; \quad t = 1, \dots, T, \tag{4}$$

and compute the corresponding BIC criterion

$$BIC - PLS = T\ln(|\Sigma_{\hat{\varepsilon}}|) + \left(\sum_{m=1}^{k}\left(1 + r + \text{trace}\left(\frac{\partial\Delta\hat{y}_{m,t}(r)}{\partial\Delta y_{m,t}}\right)\right)\right)\ln(T), \tag{5}$$

where $\Sigma_{\hat{\varepsilon}}$ is the matrix of the mean squared fitting errors of (4) and $\frac{\partial\Delta\hat{y}_{m,t}(r)}{\partial\Delta y_{m,t}}$ is the first derivative of the fitted value for the activity proxy variable *m* based on r PLS factors, since the estimated PLS factors themselves depend on the activity proxies. The lower the collinearity among the x_t variables used in the sparse PLS estimation, the higher this derivative will be, and this collinearity will be partly regulated by the number of variables selected for the PLS factor estimated through the value of sparsity parameter, $\bar{\lambda}$, in (3).

After recasting all variables as year-over-year growth rates, we then purge very low-frequency variation from the data underlying Δy_t and x_t; because our activity indicator is intended to measure the current state of Chinese economic activity, we filter out the effects any underlying trends. Following Stock and Watson (2012), each of the series underlying Δy_t and x_t is computed as a deviation from a time-varying mean that is approximated through a bi-weight kernel-based filter with a bandwidth of five years. Each series is then normalized and utilized in our sparse modeling approach.[4]

Under the assumption that the covariation between Δy_t and x_t is driven by a single primitive shock, we use $\hat{\gamma}'f_t$, with $\hat{\gamma}$ being the result of the regression

$$\sigma\left(\Gamma'\left(\Delta y_t - \Delta\bar{y}_t\right)\right) = \gamma' f_t + \varepsilon_t; \quad t = 1, \ldots, T. \tag{6}$$

In (6), $\Delta\bar{y}_t$ collects the bi-weight kernel-based filtered trends of the variables in Δy_t; Γ is the $k \times 1$ loading vector corresponding to the largest principal component of $(\Delta y_t - \Delta\bar{y}_t)$; and σ is a scaling variable that guarantees that the standard deviation of $\Gamma'\ (\Delta y_t - \Delta\bar{y}_t)$ equals that of similarly de-trended, monthly interpolated, official GDP data. Our Chinese economic activity indicator thus equals:

$$\Delta\text{pseudoGDP}_t = \alpha_t + \hat{\gamma}' f_t, \tag{7}$$

where α_t is the bi-weight kernel-based filtered time-varying mean of the year-over-year GDP growth rate extracted from the official Chinese GDP data (interpolated to a monthly frequency), using a five-year window for the kernel.

2. Results

2.1 Data

We employ three versions of our sparse PLS factor model-based activity indicator, depending on the composition of the target variables, Δy_t. The first version utilizes a univariate growth target variable (so $k = 1$ in (4)) and consists of the year-over-year growth rate of a proxy of

Chinese imports; the second version adds a proxy of Chinese manufacturing activity to the imports measure as the target variables for (4); and the final version adds a proxy for Chinese retail sales to those activity proxies, bringing the total number of target variables in (4) to three. For the first and second versions of the indicator, x_t contains forty-four Chinese economic activity variables, while the third version moves retail sales to the left-hand side of the equation, resulting in an x_t containing forty-three variables. All three versions of the indicator are estimated on a monthly sample from January 2001 to March 2019.

For our first targeted growth proxy, we approximate Chinese import volumes with real exports as reported by China's largest trade partners: Japan, the United States, and the euro area. Fernald, Hsu, and Spiegel (2019) show that such figures are a strong proxy for Chinese economic growth.

One argument for that conclusion is that the proxy theoretically avoids the entire issue of incorrect or incomplete data, since there is less incentive for China's trade partners to falsify their data on China-bound exports. Another advantage is that these countries are likely to measure the exports leaving their ports more accurately than Chinese authorities measure the imports arriving at theirs.

When we tally up Chinese imports, we include imports to Hong Kong because, as Fernald, Hsu, and Spiegel (2019) have pointed out, a large proportion of these flows have China as their final destination. This relationship was especially true during the first few years of our sample, but for consistency we use the sum of exports from Japan, the United States, and the euro area to both Hong Kong and China over the entire sample. To account for inflation, we construct a U.S.-China trade deflator. After summing U.S. agricultural and nonagricultural exports (based on NAICS product-level categories) to China, we use the agricultural and nonagricultural U.S. export price indexes to create a weighted price deflator. We then apply this indicator to Chinese import data—as reported by all of the country's trade partners.

Our second target variable is a Chinese industrial production diffusion index. One main reason to focus on such a diffusion index is that, as a measure of dispersion of change, it quantifies the breadth of growth across the manufacturing sector, which is important in assessing the overall state of China's economy. There are two additional reasons why we focus on a manufacturing growth diffusion index as a target variable in our sparse PLS-based factor model. First, it is possible that Chinese industrial production data are biased at several levels of aggregation. China's National Bureau of Statistics (NBS) does not publish an index of industrial production, but instead releases estimates of value-added by industry (at current prices) and year-over-year growth rates (at constant prices). Local authorities gather a large portion of these real value-added estimates from firms, data that are then adjusted when the NBS aggregates the figures at the national level. Chen et al. (2019) report significant biases in the data-gathering procedures at the local level, as well as in the aggregation process. These biases are especially large for firms in industrial sectors.

In addition, there are inconsistencies and gaps in the Chinese industry-level data, with some sectors dropping out of the sample in certain months and reappearing in other months. A diffusion index can easily deal with the latter issue, and assuming that these aggregation biases are more or less equally distributed across industries, a diffusion index should still yield reasonably reliable insight on the breadth of an expansion or contraction in China's manufacturing sector. We therefore construct a diffusion index by determining, for a given month, the percentage of industrial sector-level series that have data exhibiting a higher year-over-year growth rate of real value-added than they did in the previous month. The diffusion index is thus similar to an industry-level purchasing managers' index (PMI). We exclude mining from our main index because mining activity is much more dependent on global commodity prices than the state of the domestic economy.[5]

Finally, the third target variable is a retail sales variable constructed from Chinese industry-level retail sales data, deflated using the relevant retail price indexes. As we exclude auto and petrol sales, we aggregate the remaining groupings into an overall real retail sales series, and construct a growth proxy by compiling the year-over-year growth rates of our real retail sales series.[6]

For the first two versions of our sparse PLS factor model-based activity indicator, the right-hand side of (4) involves forty-four variables covering Chinese survey, production, sales, and financial market data, spanning everything from electricity production and sectoral production data to M2 and stock price data. In the third version, x_t consists of the same variables, with the exception of retail sales, which is moved to the left-hand side. These variables, as well as the three target variables described above, are seasonally adjusted using the U.S. Census Bureau's X-13 methodology (the financial variables are not adjusted). We then take the log year-over-year difference where appropriate, filter out remaining outliers, and de-trend our data using a bi-weight filter in the spirit of Stock and Watson (2012).[7] Finally, we set all variables to unit variance.

Our data are collected from a wide variety of sources made available through Haver Analytics and CEIC Data.

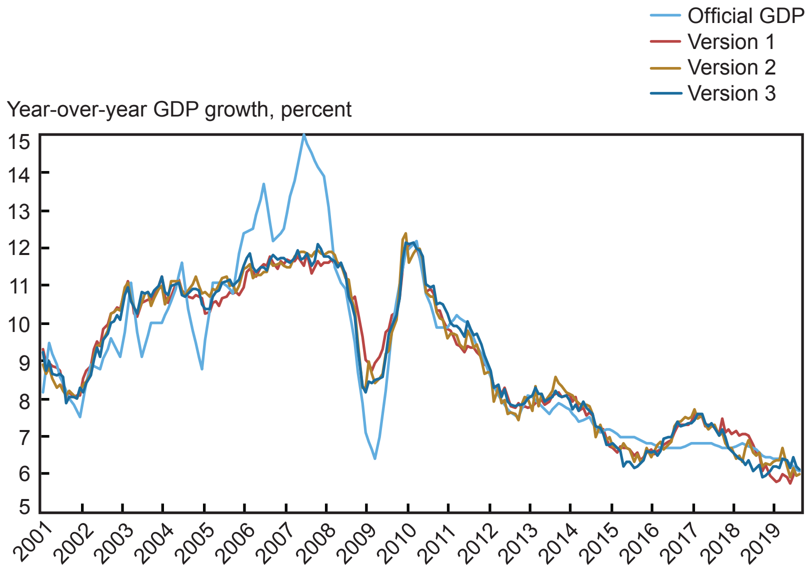
2.2 Chinese Official GDP Data vs. the Alternative Indicators

For the three versions of our sparse PLS factor model-based activity indicator, we minimize (5) on the data using a grid of $r = 1, \ldots, 10$ and $\bar{\lambda} = 0.11, 0.12, 0.13, \ldots, 0.99$ in order to get optimal values for r and $\bar{\lambda}$ that can be used in the corresponding (3) and (4) for each of these three versions. This specification search indicates that when only the Chinese import growth target variable is used (version 1), the optimal specification for the corresponding full sample sparse factor model should be based on $\bar{\lambda} = 0.6$ and $r = 3$; when both Chinese imports and the manufacturing production diffusion index are targeted (version 2), the sparse PLS model is based on $\bar{\lambda} = 0.88$ and $r = 3$; and finally, when imports, the manufacturing production diffusion index, and real retail sales are targeted, the underlying sparse PLS specification should be $\bar{\lambda} = 0.77$ and $r = 8$.

In terms of the number of variables used, these differences in specifications between the three versions of the sparse PLS factor model indicate that twenty-nine variables are used to construct an economic activity measure when targeted toward real import growth only; a mere four variables constitute the activity measure when targeted jointly toward import growth and the manufacturing growth diffusion index, whereas the sparse PLS model uses twenty-three variables to construct the activity measure when targeted toward import growth, the manufacturing growth diffusion index, and the real retail sales growth proxy (see Table 1A in Appendix 1). Some variables—electricity production, value-added by industry, auto sales, and PPI—are included in all three versions of our sparse factor model, but versions 1 and 3 also incorporate additional survey, financial, price, and trade variables.

Chart 1

Comparing China's Official GDP Growth to Alternative Indicators



Source: Authors' calculations; National Bureau of Statistics of China, accessed through CEIC.

Note: Chart shows three versions of the authors' sparse PLS factor model-based activity indicator.

We compare our three sparse PLS-based indicators of economic activity with the official Chinese GDP data in Chart 1. A first observation from this chart is that our three alternative activity indicators behave rather similarly despite the specification differences. What also becomes apparent from Chart 1 is that before 2010, the alternative indicators suggest that economic activity was less volatile than the official GDP data suggest, whereas from 2010 onward this pattern reverses, with official Chinese GDP data becoming far less volatile than our indicators.

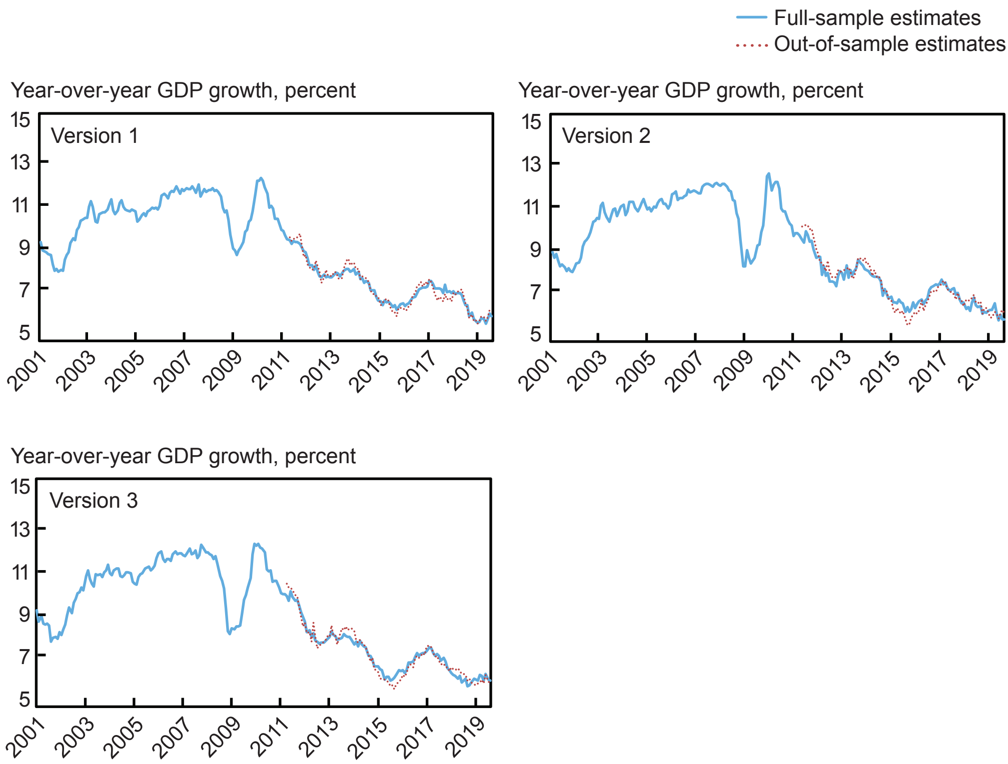
For example, between 2005 and 2008, official statistics show a sharp acceleration in growth—from 9 percent to 15 percent—whereas the alternative indicators point to a far more gradual growth acceleration. Likewise, for the 2014-19 period, these indicators suggest significant growth accelerations and slowdowns, but the official GDP growth data remain essentially flat.

To get an idea of how a real-time application of the sparse PLS factor model-based indicators would perform, and also to get a sense of the stability of the underlying models, we can recursively re-estimate the sparse PLS models and generate out-of-sample estimates of Chinese economic activity.

More specifically, we start off with a subsample of data from January 2001 to March 2011, which we use to estimate our three sparse PLS models (including cross-validating the appropriate number of factors and the number of variables used for this subsample). Keeping the estimated model parameters constant, data for the next month are then used in the models to generate projections of Chinese economic activity in that month. We then add that month of

Chart 2

Chinese Economic Indicators: Full Sample vs. Out-of-Sample



Source: Authors' calculations.

Note: The panels show full-sample and out-of-sample estimates for each version of the authors' sparse PLS factor model-based activity indicator.

data (April 2011) to the initial subsample (January 2001-March 2011), then go through the previous steps once again. All of this is repeated until we reach the end of our full data sample.

Chart 2 depicts both the full-sample estimates (as also shown in Chart 1) and the out-of-sample evolutions for all three variations of our sparse PLS-based economic indicators. Compared to the full-sample estimates, the recursive projections for all three versions of the model at times appear to reflect a slightly more optimistic or pessimistic view on growth in China, but they nonetheless converge fairly quickly toward the full-sample estimates. In summary, the model structures underlying our estimates of Chinese economic activity seem to be relatively stable over time.

Another way to assess the usefulness and robustness of our approach is to apply our methodology for China to economies for which high-quality data are available. As an example of a large economy, we use the United States, and as an example of an East Asian export-oriented economy that has outgrown developing economy status fairly recently, we use South Korea.

For both economies, we apply our sparse PLS-based factor approach in the same manner as we did for China—that is, we use an identical monthly 2001-19 sample, all variables are de-trended using the bi-weight kernel-based filter with a five-year window for the kernel, and we use the same three versions of our model based on similar sets of target variables. Inconsistencies in data availability, however, result in some subtle differences relative to our application of the model to China.

For the United States, we use real imports (excluding oil), the headline industrial production diffusion index from the Board of Governors of the Federal Reserve System, and real retail sales (excluding motor vehicle and petrol sales) as target variables. In the case of South Korea, the target variables comprise real imports (including oil), industrial production (in log year-on-year changes, since industrial production diffusion indexes are not available for South Korea), and real retail sales.

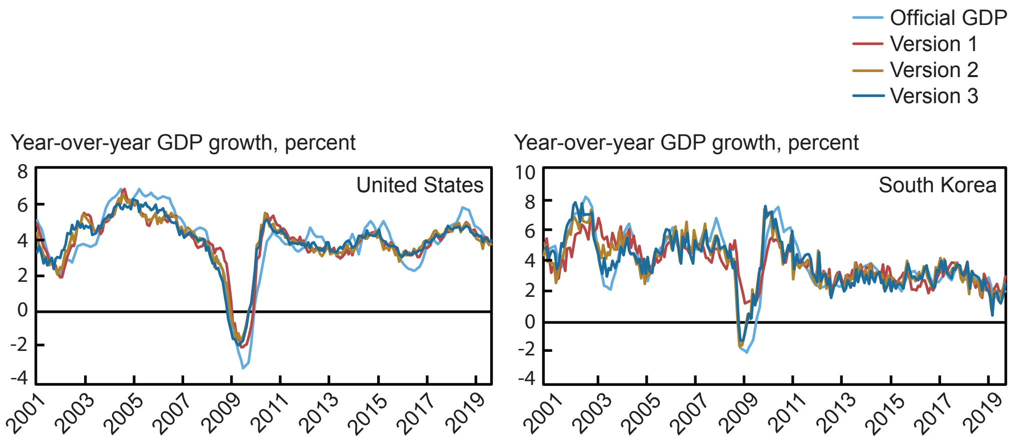
Regarding the factor-extraction process, we use the same panel of right-hand side variables for the United States and South Korea as we had for China; these variables were also treated in the same manner with respect to seasonal adjustment and transformations to stationarity. However, because better data are available for the U.S. and South Korean economies, we ended up with more than forty-three variables in most cases (see Appendix 1 for more details). None of these minor data differences should devalue the usefulness of applying our methodology to the United States and South Korea as a robustness check for our China results.

Chart 3 plots, for both the United States and South Korea, the three versions of sparse PLS factor-based estimates of economic activity relative to official year-over-year GDP growth rates. The chart makes clear that these estimates track variations in GDP growth quite accurately for both economies and that the economic activity estimates are less volatile than official GDP growth. In addition, note that in the case of South Korea, targeting more than just real import growth in the factor extraction seems to result in a slightly more accurate tracking of official GDP growth, whereas for the United States, differences between the three approaches are less marked. In summary, applying the same modeling and factor-extraction process to South Korea and the United States generates economic activity estimates that closely track official GDP growth data without being excessively volatile. In fact, for the United States and South Korea, the economic activity estimates are somewhat less volatile and smoother than the official GDP growth data, which is similar to the pattern we observed for China in the pre-2010 period in Chart 1. Given that our estimated economic activity indicators are likely to be less volatile than official GDP growth data when the methodology behind the latter is of reasonably good quality, it would seem that since 2010 China's official GDP figures have become a less dependable gauge of Chinese business cycles. We therefore consider our sparse PLS factor model-based economic activity trackers to be reliable gauges for the strength of economic growth in China.

2.3 Interpreting the Alternative Indicators

To better interpret movements in the sparse PLS factor model-based alternative indicators of Chinese economic activity, one could attempt to relate these movements to what are deemed to be relevant shocks for the Chinese economy. In this subsection, we do just that, using version 3 of our sparse PLS factor-based activity indicator, in which the variable selection and factor extraction are done by targeting import growth, the manufacturing production growth diffusion index, and real retail sales growth. Notice from Table 1A in Appendix 1 that real retail sales is not part of the selected variable set for versions 1 and 2 of the sparse factor model,

Chart 3
Official GDP Growth vs. Alternative Indicators: U.S. and South Korea



Sources: Authors' calculations; Bank of Korea, accessed through Haver Analytics.

Note: The panels show three versions of the authors' sparse PLS factor model-based activity indicator.

suggesting that including it as a third target variable adds separate, additional information in tracking economic activity in China, particularly with respect to capturing the domestic drivers of the Chinese business cycle more precisely.

Following Bai and Ng (2007) and Stock and Watson (2012), we posit a vector autoregressive model for the r PLS factors, f_t , that are estimated by means of SPLS,[8]

$$\underbrace{f_t}_{r\times 1} = \underbrace{D_0}_{r\times 1} + \sum_{i=1}^{p} D_i \underbrace{f_{t-i}}_{r\times 1} + \underbrace{\varepsilon_t}_{r\times 1}; \quad \varepsilon_t \sim iid\left(\mathbf{0}, \Omega^{\varepsilon}\right). \tag{8}$$

As in a standard structural VAR model, restrictions can be placed on the covariance matrix Ω^{ε} of the errors in (8) in order to identify a limited number of structural shocks (see also Appendix 2). Therefore, it can be seen from (8), (4), and (3) that different combinations of r (the number of PLS factors, which for version 3 equals 8) and $\bar{\lambda}$ (the sparsity parameter) determine in a flexible but parsimonious manner the heterogeneity of the dynamic impact of these identified structural shocks on the retained variables from our initial sample of forty-three activity variables and their correlations with our target variables (real imports, the manufacturing production diffusion index, and real retail sales).

Next, we need to get an idea of the potential number of shocks to underlie the eight factors in version 3 of the sparse PLS factor model-based indicator. Bai and Ng (2007) propose test procedures that can be used to determine to what degree a VAR model of factors such as (8) has a reduced rank, with the rank being equal to the number of underlying shocks. The procedures, as well as the results of applying them to our case, are described in more detail in Appendix 2, but the tests do suggest that the dynamics in version 3 of the sparse PLS factor model-based indicator seem to be driven by at least three structural shocks.

To identify these three structural shocks, we need to impose restrictions in the disturbance covariance matrix of VAR model (8), and there are a variety of ways to do this, such as recursive ordering, sign restrictions, and so on. Here we follow Stock and Watson (2012) and Mertens and Ravn (2013), whose approach consists of two steps: First, a VAR model is estimated; then, one or more instrument variable regressions are used to quantify the impact of a shock; this is done by regressing the other VAR residuals on the residual of the VAR equation of the causal variable of interest using an external instrument variable (external in the sense of coming from outside the VAR system) within an instrument variable (IV) regression.

The resulting coefficients measure the impact of the shocks of interest. Their impact beyond the current period can be traced out using the estimated VAR system. In the context of this study, the VAR system is the VAR model in (8) of the PLS factors, and our aim is to quantify up to three shocks—related to global economic activity, Chinese credit supply, and Chinese monetary policy—with three external instrument variables. It is worth noting that in this IV-VAR approach, the IV regression used to determine the structural parameters can be applied to just a subsample of the VAR residuals—if, for example, an external instrument variable is only available for part of the total sample.

The Chinese economy is highly dependent on the state of global economic activity, which can be measured in a number of ways. First, drawing on world trade volume data (2000-present) from the CPB World Trade Monitor, we use the monthly change in the year-over-year growth rate of world trade volume as an instrument for shocks to global economic activity. Another useful gauge in this context is the JP Morgan Global PMI (produced by IHS Markit), which is a GDP-weighted average of monthly outlook surveys for firms in forty-five countries (developed and emerging) that starts in 2004; we use the monthly change in this global PMI as an additional instrument variable for global activity shocks.

The Federal Reserve Bank of New York's weekly *Oil Price Dynamics Report* provides a third means of identifying global activity shocks. The *Report* uses correlations between the price of Brent crude oil and an array of financial variables to decompose oil price movements into components related to demand and supply shocks in the global oil market. The third instrument variable for global activity, therefore, is a monthly aggregate of the demand component of oil prices, as identified in the *Report*, since this metric should reflect market participants' views regarding the global economic outlook.

The first principal component of these three variables—world trade volume growth, the change in the global PMI, and the demand component of oil prices—is then used to aggregate the three instrument variables into a common proxy variable to identify global activity shocks in the PLS VAR model (8), with the corresponding IV regression for the VAR residuals covering a subsample starting in 2004.[9]

Fluctuations in Chinese economic activity could also stem from shifts in domestic monetary policy. Measuring changes in the policy stance of the People's Bank of China (PBoC) is challenging, however, since the PBoC does not designate a single policy rate as its operating target. Rather, the PBoC uses multiple tools to implement policy: (i) interest rates, such as one-year lending and deposit rates, interest rates on required and excess reserves, and the lending rate on PBoC refinancing; (ii) quantity-based instruments, such as reserve requirement ratios (RRR) and open market operations (OMO); and (iii) administrative window guidance (a means of influencing bank lending, which is unobserved). Girardin, Lunven, and Ma (2017) construct a composite policy rate measure that attempts to reflect the changing mix of policy instruments utilized by the PBoC over the 1993-2013 period. This is obviously easier to do for the interest rates under the PBoC's control than for the quantitative instruments it employs. As a result, Girardin, Lunven, and Ma (2017) make a number of assumptions, equating, for example, each 50 basis point change in RRRs to a 27 basis point policy rate change. In the case of OMOs, a monthly net injection or withdrawal of 200 billion yuan in liquidity is converted into a 27 basis point policy rate change, with changes of 350 and 500 billion yuan equivalent to movements of 54 and 81 basis points, respectively. (For more details see Girardin, Lunven, and Ma [2017], Box 1.)

We extend the Girardin, Lunven, and Ma (2017) measure of monthly monetary policy changes, which ends in 2013, to the end of our sample. In doing so, we notice that the volatility and size of the PBoC's OMOs increased drastically after 2015, in line with an increased effort to use OMOs to influence the Chinese seven-day repo rate. Thus, from 2016 onward, we multiplied each of the earlier mentioned threshold sizes of 200, 350, and 500 billion yuan by a factor of 3.6855, in line with the increased volatility of monthly net changes in liquidity during the 2016-19 period. The resulting extended monthly monetary policy change index is then used as a monetary policy instrument variable in the PLS VAR model (8).

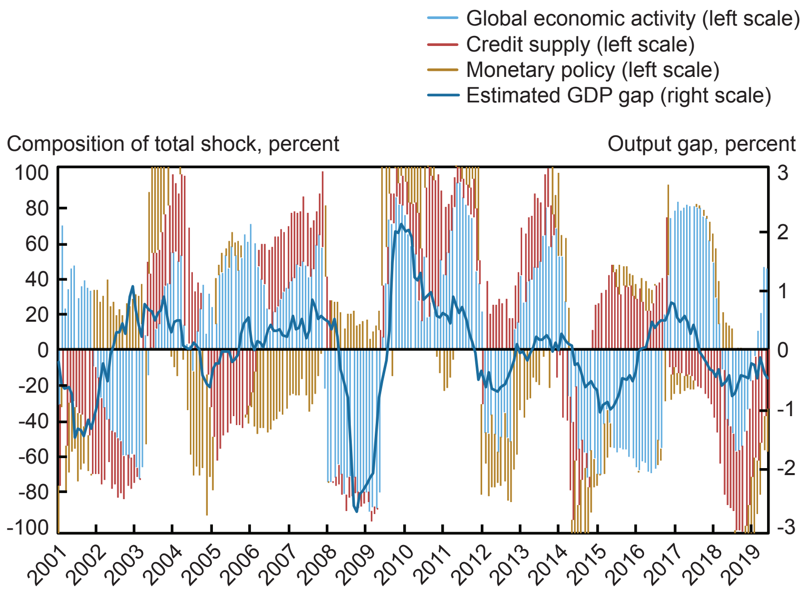
As described in Clark, Dawson, and Pinkovskiy (2019), China's economic growth is highly dependent on investment growth, which in turn is primarily financed by loans and other forms of credit. Shocks to the credit supply could therefore be an important driver of the Chinese business cycle. Chinese credit data present a number of difficulties owing to revisions and significant gaps between reported stocks and flows. As a result, Clark, Dawson, and Pinkovskiy (2019) construct a credit stock measure based on reported flows that have more consistent historical series. This adjusted total social financing (TSF) measure includes local currency and FX loans, various forms of off-balance-sheet bank-related lending, nonbank lending (trust loans), and corporate and local government bonds.

This adjusted TSF series is the basis for our credit supply instrument. To strip out demand effects as much as possible, we take the monthly change in the year-over-year growth rate of the adjusted TSF series and regress it on our instrument variables for global economic activity and Chinese monetary policy; the resulting residuals are then used as the credit supply instrument variable in the PLS VAR model (8).

So, if valid, the combination of global activity, credit supply, and monetary policy shocks identified through the IV-VAR approach should explain the bulk of the deviations from trend in the case of the version 3 specification. Chart 4 graphs the resulting decomposition. Unsurprisingly, global economic activity is a dominant driver of fluctuations in Chinese economic activity, with credit supply also a major factor, particularly during boom periods. Monetary policy seems to have had a more profound impact in the pre-2013 era, especially in the post-Great Recession recovery period. When we zoom in on the more recent period beginning with the Great Recession, we notice that up to 2017, slowdowns and accelerations in Chinese growth were led by slowdowns and accelerations in global economic activity, with credit supply mostly supporting growth and Chinese monetary policy having a relatively small, counter-cyclical impact.

From the second half of 2017 onward, however, we observe that credit supply has become the dominant determinant of growth. In addition, since the advent of China's deleveraging campaign in 2018, a slower rate of credit growth has posed a significant drag on growth, and credit supply shocks have recently been somewhat amplified by monetary policy due to a

Chart 4
Shock Decomposition of the Version 3 Sparse Factor-Based Activity Indicator



Source: Authors' calculations.

Note: Using version 3 of the sparse PLS factor model-basd activity indicator, the authors decompose deviations from China's trend growth into three components: shocks to global growth, domestic credit supply, and domestic monetary policy.

limited response by the PBoC. Hence, the 2018-19 growth slowdown appears to have been mostly driven by internal rather than external factors—the first such episode of the post-Great Recession era.

3. Conclusions

China's official GDP growth rates over the past decade have been remarkably, and perhaps unrealistically, smooth. In an attempt to model Chinese business cycle fluctuations, we created a sparse PLS factor from a large array of high-frequency data. The resulting factor demonstrates the cyclicality expected of China's economic growth, and performs well in out-of-sample testing. For robustness, we tested our model on the United States and South Korea. Our model holds up well, with versions 2 and 3 both providing a good estimate of official GDP growth in each country. Overall, we believe that our sparse PLS model provides an accurate measure of Chinese economic growth at a high frequency.

Focusing on the version of our indicator that conducts variable selection and factor extraction in relation to real import growth, the diffusion index of manufacturing production growth, and real retail sales growth, we decompose the deviation from trend growth into global economic activity growth, credit supply, and monetary policy components. We found that global economic activity was the primary driver of Chinese economic activity from the beginning of the Great Recession through 2017. Throughout most of this period, credit supply provided a consistent positive impulse to the economy, while monetary policy had a small and mainly countercyclical effect. Since the beginning of China's deleveraging campaign in 2018, a slowdown in credit supply growth has been a massive drag on the Chinese economy, and monetary policy has posed an additional drag owing to limited PBoC reaction. China's 2018-19 deceleration marks the first time since the beginning of the Great Recession that internal factors, rather than external factors, have been the primary driver of a slowdown in the country's economy.

Appendix 1: Data Sources and Construction

The data are retrieved from Haver Analytics and CEIC Data. In order to have $I(0)$ predictor variables, the underlying raw series need to be appropriately transformed.

Table 1A
China

		Economic Activity Indicator					
		Version 1		Version 2		Version 3	
Variable	Transformation	Percent	Full Sample	Percent	Full Sample	Percent	Full Sample
Consumer confidence index	SA by X-13, levels	27		64		63	x
Consumer expectation index	SA by X-13, levels	52	x	98		91	
Value-added by industry	SA by X-13, log diff	100	x	100	x	100	x
Electricity production	SA by X-13, log diff	100	x	100	x	100	x
Iron ore production	SA by X-13, log diff	100	x	99		100	x
Pig iron production	SA by X-13, log diff	62	x	74		76	
Crude steel production	SA by X-13, log diff	85	x	90		67	
Steel product production	SA by X-13, log diff	51	x	98		84	
Apparent crude demand	SA by X-13, log diff	15		5		53	
Apparent refined demand	SA by X-13, log diff	52	x	70		44	
Copper production	SA by X-13, log diff	60	x	69		45	
Aluminum production	SA by X-13, log diff	70	x	99		99	x
Cement production	SA by X-13, log diff	40	x	65		85	x
Plate glass production	SA by X-13, log diff	45	x	29		35	
Real estate investment	SA by X-13, log diff	100	x	99		93	x

Table 1A continued on next page

Appendix 1 (Continued)

		Economic Activity Indicator					
		Version 1		Version 2		Version 3	
Variable	Transformation	Percent	Full Sample	Percent	Full Sample	Percent	Full Sample
Floor space started	SA by X-13, log diff	33	x	54		52	
Floor space under construction (residential)	SA by X-13, log diff	100	x	98		100	x
Floor space completed	SA by X-13, log diff	91	x	78		47	
Floor space sold	SA by X-13, log diff	45		53		67	
Imports of iron ore (volume)	SA by X-13, log diff	54		41		82	x
Steel product imports (volume)	SA by X-13, log diff	67	x	94		74	
Imports of unwrought copper	SA by X-13, log diff	68	x	43		47	x
Imports of copper waste	SA by X-13, log diff	100	x	87		77	x
Imports of unwrought aluminium	SA by X-13, log diff	100	x	97		93	x
Steel products exports	SA by X-13, log diff	48	x	80		62	x
Unwrought copper export volume	SA by X-13, log diff	74		54		82	
Unwrought aluminum export volume	SA by X-13, log diff	34	x	82		64	
Nominal fixed asset investment	SA by X-13, log diff	84		62		70	
Auto sales	SA by X-13, log diff	100	x	100	x	97	x
Rail freight	SA by X-13, log diff	86		88		85	
Air pass-through	SA by X-13, log diff	46	x	93		60	
Petrol imports	SA by X-13, log diff	92	x	99		91	x

Table 1A continued on next page

Appendix 1 (Continued)

		Economic Activity Indicator					
		Version 1		Version 2		Version 3	
Variable	Transformation	Percent	Full Sample	Percent	Full Sample	Percent	Full Sample
Foreign reserves	Log diff	60		97		84	x
Exchange rate (U.S. dollar)	Log diff	26	x	33		70	
Shanghai Stock Exchange index	Log diff	81		53		90	x
Shenzhen Stock Exchange index	Log diff	73		62		85	x
Price/equity ratio for Shanghai Stock Exchange	Log diff	94	x	95		93	x
Price/equity ration for Shenzhen Stock Exchange	Log diff	80		86		92	x
Producer price index	SA by X-13, log diff	100	x	100	x	97	x
Consumer price index	SA by X-13, log diff	73	x	82		98	x
Seven-day repo rate	Levels	12		46		61	
M1	SA by X-13, log diff	67	x	78		64	x
M2	SA by X-13, log diff	65		98		95	
Real retail sales	SA by X-13, log diff	98		59		0	

Notes: In the "Transformation" column, "SA" stands for "seasonally adjusted;" "X-13" is the U.S. Census Bureau's seasonal adjustment methodology; and "log diff" refers to the following transformation: $X_t = ln(Y_t) - ln(Y_{t-12})$, with X_t being the transformed variable and Y_t being the raw variable. "Percent" denotes the percentage of out-of-sample and full-sample model estimations in which the variable was not dropped. Variables that were not dropped in the full-sample estimation are marked by an x in the "full-sample" column.

Appendix 1 (Continued)

Table 1B
United States

Variable	Transformation	Economic Activity Indicator: Version 1 Percent	Version 1 Full Sample	Version 2 Percent	Version 2 Full Sample	Version 3 Percent	Version 3 Full Sample
Nominal trade-weighted exchange rate for emerging market economies (Federal Reserve Board)	Log diff	79	x	82	x	49	
M2	Log diff	97	x	24	x	82	x
Ratio of nominal GDP to M2	SA by Haver, Levels	26		32	x	23	
Consumer credit	SA by source, log diff	93	x	100	x	32	x
Commercial banks' loan-to-deposit ratio	SA by Haver	28		72	x	100	x
Fixed rate home mortgage loans: Effective rate	Levels	94	x	2	x	71	
Dow 30: Average close	Log diff	4	x	3		1	
Standard & Poor's 500 composite index	Log diff	5	x	11		3	
NASDAQ Composite Index	Log diff	20		7		11	
NYSE Composite Index	Log diff	48	x	10	x	7	
Federal Housing Finance Agency House Price Index: Purchases only	SA by source, log diff	98	x	4		9	
Housing starts	SA by source, log diff	53	x	4		4	
Housing completions	SA by source, log diff	53	x	30	x	4	
Industrial production: Automotive products	SA by source, log diff	0		80	x	29	
Industrial production: Consumer goods	SA by source, log diff	90	x	100	x	80	x

Table 1B continued on next page

Appendix 1 (Continued)

Variable	Transformation	Economic Activity Indicator: Version 1 Percent	Version 1 Full Sample	Version 2 Percent	Version 2 Full Sample	Version 3 Percent	Version 3 Full Sample
Industrial production: Business equipment	SA by source, log diff	100	x	100	x	100	x
Industrial production: Durable goods materials	SA by source, log diff	100	x	97	x	100	x
Industrial production: Nondurable goods materials	SA by source, log diff	58	x	6	x	96	
Industrial production: Energy materials	SA by source, log diff	9		30	x	5	
Civilian unemployment rate (aged 16+)	SA by source, levels	16	x	63	x	29	
Manufacturers' shipments: Machinery	SA by source, log diff	97	x	100	x	62	
Manufacturers' shipments: Primary metals	SA by source, log diff	100	x	10	x	100	x
Manufacturers' shipments: Computers and electronic products	SA by source, log diff	96	x	88		9	
Manufacturers' shipments: Electronic equipment, appliances, and components	SA by source, log diff	100	x	76	x	88	
Manufacturers' shipments: Transportation equipment	SA by source, log diff	82	x	11	x	75	
Manufacturers' shipments: Food products	SA by source, log diff	96	x	2	x	10	
Manufacturers' shipments: Textile products	SA by source, log diff	20		15	x	1	
Manufacturers' shipments: Paper products	SA by source, log diff	96	x	70		14	
Manufacturers' shipments: Petroleum and coal products	SA by source, log diff	63	x	100	x	70	
Manufacturers' shipments: Basic chemicals	SA by source, log diff	100	x	97	x	100	x

Table 1B continued on next page

Appendix 1 (Continued)

Variable	Transformation	Economic Activity Indicator: Version 1 Percent	Version 1 Full Sample	Version 2 Percent	Version 2 Full Sample	Version 3 Percent	Version 3 Full Sample
Manufacturers' new orders: All manufacturing (ex defense)	SA by source, log diff	100	x	12	x	100	x
Manufacturers' inventories: All manufacturing (ex defense)	SA by source, log diff	95	x	98		11	
Manufacturers' shipments: Construction materials and supplies	SA by source, log diff	100	x	2	x	99	x
Manufacturers' shipments: Information technology	SA by source, log diff	59	x	21		1	
Manufacturers' shipments: Capital goods	SA by source, log diff	96	x	24		21	
Manufacturers' shipments: Consumer goods	SA by source, log diff	97	x	82		24	
Average weekly hours: Manufacturing	SA by source, log diff	55	x	19	x	82	
Real M2	SA by source, log diff	95	x	69		18	
Real personal income (less transfer payments)	SA by source, log diff	88	x	99		70	x
Industrial production	SA by source, log diff	100	x	7	x	100	x
Total nonfarm employees	SA by source, log diff	96	x	100	x	7	x
Real manufacturing and trade sales	SA by source, log diff	96	x	10	x	100	x
Average duration of unemployment	SA by source, log diff	25	x	99		10	x
Real manufacturing and trade: Inventories/sales	SA by source, log diff	51	x	9	x	100	x
Bank prime loan rate	Levels	89	x	79		8	

Table 1B continued on next page

Appendix 1 (Continued)

		Economic Activity Indicator					
		Version 1		Version 2		Version 3	
Variable	Transformation	Percent	Full Sample	Percent	Full Sample	Percent	Full Sample
Real commercial and industrial loans outstanding	SA by source, log diff	73	x	95	x	79	
Ratio of consumer credit to personal income	SA by source, levels	100	x	7	x	94	
CPI for services: Six-month change	SAAR (percent) by source	89	x	48		6	
Conference Board: Consumer Confidence Index	SA by source, levels	100	x	92	x	49	x
Conference Board: Consumer Expectations Index	SA by source, levels	31	x	16	x	91	
ISM Composite Index	SA by source, levels	9	x	0		15	

Notes: In the "Transformation" column, "SA" stands for "seasonally adjusted;" "SAAR" stands for "seasonally adjusted annualized rate;" "Haver" refers to "Haver Analytics;" and "log diff" refers to the following transformation: $X_t = ln(Y_t) - ln(Y_{t-12})$, with X_t being the transformed variable and Y_t being the raw variable. "Percent" denotes the percentage of out-of-sample and full-sample model estimations in which the variable was not dropped. Variables that were not dropped in the full-sample estimation are marked by an x in the "full-sample" column.

Appendix 1 (Continued)

Table 1C
South Korea

		Economic Activity Indicator					
		Version 1		Version 2		Version 3	
Variable	Transformation	Percent	Full Sample	Percent	Full Sample	Percent	Full Sample
Bank of Korea Base Rate	Levels	36		78	x	64	x
Ninety-one-day commercial paper yields	Levels	99	x	78	x	64	x
Exchange rate (won/U.S. dollar)	Log diff	75		3	x	48	x
Reserve money	SA by source, log diff	18		0		24	
M2	SA by source, log diff	8		13	x	54	
Bank of Korea assets	SA by Haver, log diff	35		29	x	89	x
Depository corporation assets	SA by Haver, log diff	100	x	81	x	67	x
Depository corporation liabilities and capital	SA by Haver, log diff	100	x	81	x	67	x
Deposit Money Banks: Loans	SA by Haver, log diff	96	x	44	x	71	x
Other Depository Corps Loan to Deposit Ratio	SA by Haver, levels	44		4	x	99	x
Central bank deposits of commercial banks and savings banks	SA by Haver, log diff	14		3		53	x
Stock price index: KOSPI	Log diff	80		4	x	85	x
Stock price index: KOSDAQ	Log diff	77		10		85	x
Stock exchange market cap (won)	Log diff	99	x	43		62	x
Stock exchange market cap (U.S. dollars)	Log diff	95	x	7	x	54	x
MSCI Korea Index, ex dividends (U.S. dollars)	Log diff	47		37	x	60	x

Table 1C continued on next page

Appendix 1 (Continued)

		Economic Activity Indicator					
		Version 1		Version 2		Version 3	
Variable	Transformation	Percent	Full Sample	Percent	Full Sample	Percent	Full Sample
MSCI Korea Index, ex dividends (won)	Log diff	34		3	x	62	x
MSCI Korea Index, with gross dividends (U.S. dollars)	Log diff	48		37	x	60	x
MSCI Korea Index, with gross dividends (won)	Log diff	38		3	x	61	x
Number of listed issues: Bonds	Log diff	100	x	64	x	55	x
Listed issues: Public bonds	Log diff	34		2	x	37	
Listed issues: Corporate bonds	Log diff	86	x	27	x	87	x
Trading volume: Corporate bonds	Log diff	90	x	77	x	65	x
Trading value: Bonds	Log diff	1		0		36	
Trading value: Public bonds	Log diff	2		0		35	
Trading value: Corporate bonds	Log diff	80	x	97	x	92	x
Foreign exchange holdings (gold and special drawing rights)	SA by Haver, log diff	15		2		45	x
International liquidity reserves (minus gold)	SA by Haver, log diff	15		2		44	x
CPI (ex agricultural products and oil)	SA by source, log diff	19		7		67	x
CPI: All	SA by source, log diff	100	x	56	x	93	x
CPI: Agricultural products and oil	SA by source, log diff	20		4		34	x

Table 1C continued on next page

Appendix 1 (Continued)

		Economic Activity Indicator					
		Version 1		Version 2		Version 3	
Variable	Transformation	Percent	Full Sample	Percent	Full Sample	Percent	Full Sample
CPI: Industrial Products	SA by Haver, log diff	24		11	x	96	x
CPI: Services	SA by Haver, log diff	11		11	x	28	x
PPI	SA by source, log diff	30		49	x	85	x
PPI: Commodities	SA by source, log diff	21		41	x	81	x
PPI: Manufacturing	SA by source, log diff	25		47	x	85	x
PPI: Mining	SA by source, log diff	33	x	29	x	92	x
PPI: Services	SA by source, log diff	100	x	100	x	98	x
Unleaded gasoline price	SA by Haver, log diff	35		5	x	37	x
House purchase price composite index	SA by Haver, log diff	92	x	53	x	92	x
Apartment purchase price index	SA by Haver, log diff	36		54	x	89	x
Building permits: Square feet	SA by source, log diff	7		7		20	
Building permits: Units	SA by source, log diff	19		0		48	x
Industrial production, ex construction	SA by source, log diff	100	x	100	x	100	x
Industrial production: Mining and manufacturing	SA by source, log diff	100	x	100	x	100	x
Inudstrial production: Construction	SA by source, log diff	11		100	x	97	x
Industrial production: Services	SA by source, log diff	81	x	100	x	100	x
Industrial production: Public admin	SA by source, log diff	70	x	100	x	96	x

Table 1C continued on next page

Appendix 1 (Continued)

		Economic Activity Indicator					
		Version 1		Version 2		Version 3	
Variable	Transformation	Percent	Full Sample	Percent	Full Sample	Percent	Full Sample
Industrial production: Electricity, gas, and steam supply	SA by source, log diff	33	x	7	x	34	x
Industrial production: Info/tech activity in manufacturing	SA by source, log diff	10		32	x	55	x
Index of equipment investment: Commodities	SA by source, log diff	100	x	39	x	57	x
Index of equipment investment: Other machinery	SA by source, log diff	100	x	86	x	71	x
Index of equipment investment: Transportation	SA by source, log diff	23		12		63	x
Production capacity index	SA by Haver, log diff	25		2		36	x
Capacity utilization index: Manufacturing	SA by source, log diff	96	x	100	x	98	x
Manufacturing operation ratio	SA by Haver, log diff	96	x	100	x	100	x
Electricity consumption	SA by source, log diff	4		2		44	x
Electricity consumption: Manufacturing	SA by source, log diff	100	x	93	x	98	x
Electricity consumption: Agriculture, forestry, fishing, and hunting	SA by Haver, log diff	9	x	1		20	
Electricity consumption: Mining and quarrying	SA by Haver, log diff	15		0		18	
Electricity consumption: Household	SA by Haver, log diff	82	x	61	x	53	x
Electricity consumption: Public	SA by Haver, log diff	60	x	7	x	68	x

Table 1C continued on next page

Appendix 1 (Continued)

		Economic Activity Indicator					
		Version 1		Version 2		Version 3	
Variable	Transformation	Percent	Full Sample	Percent	Full Sample	Percent	Full Sample
Electricity consumption: Service industry	SA by Haver, log diff	63	x	48		31	
Oil and gas production	SA by Haver, log diff	51		1		49	x
Petroleum imports	SA by Haver, log diff	100	x	100	x	86	x
Domestic consumption	SA by Haver, log diff	78	x	48	x	70	x
Exports of petroleum products	SA by Haver, log diff	4		1		25	x
Unemployment	SA by source, log diff	98	x	26		66	x
Not in labor force	SA by source, log diff	46	x	5		33	
Employment	SA by Haver, log diff	10		1		53	
Output per employed person	SA by source, log diff	100	x	100	x	95	x
Shipments	SA by source, log diff	100	x	100	x	100	x
Shipments: Mining and manufacturing	SA by source, log diff	100	x	100	x	100	x
Shipments: Domestic market	SA by source, log diff	86		100	x	100	x
Machinery orders received	SA by source, log diff	100	x	87	x	92	x
Machinery orders received: Domestic demand	SA by Haver, log diff	19		0		25	
Machinery orders received (ex vessels): Domestic	SA by source, log diff	28		0		34	x
Machinery orders received (ex vessels): Government	SA by source, log diff	2		0		2	
Machinery orders received (ex vessels): Private	SA by source, log diff	29		8	x	52	x

Table 1C continued on next page

Appendix 1 (Continued)

		Economic Activity Indicator					
		Version 1		Version 2		Version 3	
Variable	Transformation	Percent	Full Sample	Percent	Full Sample	Percent	Full Sample
Machinery orders received (ex vessels): Private, manufacturing	SA by source, log diff	16		2		39	x
Machinery orders received (ex vessels): Private, nonmanufacturing	SA by source, log diff	1		1		36	
Tourist arrivals	SA by Haver, log diff	34	x	4	x	30	
Tourist arrivals by air	SA by Haver, log diff	39	x	8	x	42	x

Notes: In the "Transformation" column, "SA" stands for "seasonally adjusted;" "Haver" refers to "Haver Analytics;" and "log diff" refers to the following transformation: $X_t = ln(Y_t) - ln(Y_{t-12})$, with X_t being the transformed variable and Y_t being the raw variable. "Percent" denotes the percentage of out-of-sample and full-sample model estimations in which the variable was not dropped. Variables that were not dropped in the full-sample estimation are marked by an x in the "full-sample" column.

Appendix 2: Structural Shocks and the Sparse PLS Factors

To make more explicit the relationship between the r PLS factors and the underlying structural shocks, we augment the VAR model (8) with

$$\begin{aligned} \underbrace{\varepsilon_t}_{r\times 1} &= \underbrace{\Re}_{r\times q}\underbrace{\mathbf{v}_t}_{q\times 1}; \quad r \geq q; \quad \mathbf{v}_t \sim iid\left(\mathbf{0}, I_q\right), \\ \underbrace{\Re}_{r\times q} &= \underbrace{\hat{K}}_{r\times q}\underbrace{\operatorname{diag}\left(\sqrt{\hat{\mu}^{\varepsilon}}_1 \cdots \sqrt{\hat{\mu}^{\varepsilon}}_q\right)}_{q\times q}, \end{aligned} \tag{2A}$$

where ε_t are the errors from VAR model (8), diag $\left(\sqrt{\hat{\mu}^{\varepsilon}}_1 \cdots \sqrt{\hat{\mu}^{\varepsilon}}_q\right)$ is a matrix with the non-zero elements $\sqrt{\hat{\mu}^{\varepsilon}}_1, \ldots, \sqrt{\hat{\mu}^{\varepsilon}}_q$ on its main diagonal and zeros everywhere else, $\hat{\mu}^{\varepsilon}_1, \ldots, \hat{\mu}^{\varepsilon}_q$ are the first q eigenvalues (in descending order) of $\hat{\Omega}^{\varepsilon}$ in (8) and the columns of $\hat{K}$ are the corresponding eigenvectors. All or a subset of the shocks in v_t in (2A) can be found by a correspondingly appropriate rotation of the $\Re$ matrix.

Based on Ω^{ε} in the VAR model of r PLS factors (8), or the corresponding correlation matrix Ω^{ε}_{C}, we follow Bai and Ng (2007) and consider the following transformations of the eigenvalues of Ω^{ε} or Ω^{ε}_{C}:

$$\begin{aligned} D_{1,k} &= \left(\frac{\hat{\mu}^{\varepsilon}_{k+1}}{\sum_{j=1}^{r}\hat{\mu}^{\varepsilon}_j}\right)^{1/2}, \\ D_{2,k} &= \left(\frac{\sum_{j=k+1}^{r}\hat{\mu}^{\varepsilon}_j}{\sum_{j=1}^{r}\hat{\mu}^{\varepsilon}_j}\right)^{1/2}, \end{aligned} \tag{2B}$$

where, as in (2A), $\hat{\mu}^{\varepsilon}_j$ is the j^{th} eigenvalue (in descending order) from either Ω_{ε} or Ω^{C}_{ε}. Then, by comparing for each k^{th} eigenvalue $D_{1,k}$ and $D_{2,k}$ to $\frac{1}{min(N^{0.4},T^{0.4})}$ when the eigenvalues relate to Ω^{ε} or comparing $D_{1,k}$ and $D_{2,k}$ to, respectively, $\frac{1.25}{min(N^{0.4},T^{0.4})}$ and $\frac{2.25}{min(N^{0.4},T^{0.4})}$ when the eigenvalues relate to Ω^{ε}_{C}, one can select to the optimal number of shocks q driving the r PLS factors for those $D_{1,k}$ and $D_{2,k}$ that fall below these threshold values.

Applying this approach to sparse factor model version V3 indicates that this model's eight PLS factors seem to be driven by three or five shocks when applying $D_{1,k}$ to the disturbance covariance matrix or disturbance correlation in (8), respectively, whereas the $D_{2,k}$ in either case suggests two shocks. Bai and Ng (2007) show in simulations that their tests based on the $D_{1,k}$ measure exhibit better finite sample properties than the ones based on the $D_{2,k}$ when either N (the number of variables underlying the factors) or T (the number of time series) is small. In our case, we combine variable selection with factor extraction, resulting in a relatively small N, and thus the Bai and Ng (2007) results suggest that it is more likely that fluctuations in the V3 sparse factor economic activity indicator are driven by *at least* three shocks.

Notes

Acknowledgments: The authors thank New York Fed President John C. Williams and an anonymous referee for helpful comments.

[1] It is worth pointing out that there are no regular publications of revisions to GDP growth.

[2] For further discussion of the low volatility of Chinese GDP growth, refer to our companion paper, "How Stable is China's Growth? Shedding Light on Sparse Data" (Clark, Dawson, and Pinkovskiy 2019).

[3] China's prime minister since 2013, Li Keqiang is known for stating that these three series provide a reliable gauge of the state of the Chinese economy.

[4] The bi-weight kernel-based approach will produce a two-sided filter to approximate underlying trends, which then raises the issue of how to compute such a two-sided filter close to the endpoints of the sample. Following Stock and Watson (2012), we deal with these endpoints by truncating the kernel and rescaling the truncated weights so that they add up to 1.

[5] For robustness, we created a separate index that includes mining, with very similar results.

[6] Like the data on firms' value-added, retail sales data are collected locally and aggregated by the NBS. However, Chen et al. (2019) do show that data collection and aggregation issues are much less of an issue for consumption data. Our main reason to build up our retail sales growth proxy from sectoral data is to be able to strip out the impact of autos and petrol sales.

[7] The main reason to apply the X-13 seasonal adjustment, even if we take year-over-year log differences, is to deal in a quasi-automated manner with a number of floating blocs of public holidays that can span across more than one month (most notably the Lunar New Year), which heavily impact Chinese data releases. Any remaining irregularities in the data are then filtered out by our outlier procedure, which is along the lines of the procedure used in Stock and Watson (2012), in which any observation of a series that is above or below this series' historical median value, plus or minus 5 times the interquartile range, is replaced by the historical median value, plus or minus 5 times the interquartile range.

[8] Note that Bai and Ng (2007) and Stock and Watson (2012) work with factors estimated by means of principal components. Their framework, however, is easily generalizable to our setting, as Kelly and Pruitt (2015) have shown that with an unobserved common factor model PLS regression can be interpreted as selecting those principal component approximations of the unobserved factors that are most relevant for a dependent variable in a regression of this variable on all factors.

[9] Using a version of this global activity instrument where the composing parts are first stripped of contributions of Chinese counterparts (PMI, trade variables) did not materially impact the results as discussed later on in this subsection.

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China's Growth Outlook: Is High-Income Status in Reach?

Matthew Higgins

OVERVIEW

• Decades of rapid economic growth have propelled China out of poverty and into middle-income status. Now the country faces a new challenge: escaping the so-called "middle-income trap."

• To gauge the likelihood of success, the author develops a set of growth projections, drawing on the experience of other countries that have reached China's current income level.

• The results are stark: Given an aging population and diminishing returns to capital, China can only achieve high-income status in the coming decades by sustaining productivity growth at the top end of the range attained by its Pacific Rim neighbors. Further, productivity gains on that scale would likely require extensive institutional development, including a marked reduction in state direction of the economy.

• Though high-income status is probably not just over the horizon, China's years of rapid expansion are hardly over, with "catch-up" effects and continued urbanization offering plenty of fuel for future growth.

Can China build on its development success to achieve high-income status in the decades ahead? The experience of Japan, South Korea, and some smaller Pacific Rim economies suggests that such an outcome is possible. But most economies deliver unimpressive growth after reaching China's current income level, giving rise to the notion of a "middle-income trap." To shed light on what the future may hold for China, we rely on a neoclassical growth framework. Our key finding is that China would need to sustain total factor productivity growth at the top end of the range achieved by its Pacific Rim neighbors in order to match their success in raising per capita incomes. Whereas fast-growing working-age populations boosted per capita income growth in the Pacific Rim, a rapidly aging population will act as a powerful drag on income growth in China. Moreover, China's capital-intensive production structure will make it difficult to match the returns to capital accumulation achieved by those countries at a similar level of income.

This article proceeds as follows: Section 1 places China's growth performance of recent decades in international and historical perspective and also wades into the debate concerning the accuracy of China's growth statistics. We find that China's growth performance remains among the

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strongest on record, regardless of whether official figures or skeptics' estimates are closer to the mark. Section 2 shows how the neoclassical growth model can be used to break down GDP growth into contributions from labor force growth, capital accumulation, and technological change. The framework enables us to show how China's growth performance is already feeling the weight of slower labor-force growth and diminishing returns to capital. Section 3 reviews the evidence for a "middle-income trap," confirming the finding from other studies that middle-income countries tend to remain in that category for decades. Section 4 relies on the neoclassical model to analyze countries' growth performance after reaching China's current income level. We find a strong tendency toward growth slowdowns, with notably reduced contributions from capital accumulation and technical change. These results help inform parameter choices for our projection exercise. Section 5 details our projection results, which highlight that rapid growth will require exceptional productivity gains, given drags stemming from demographic pressures and diminishing returns to capital. Section 6 considers factors that could provide scope for continued rapid growth in China as well as factors that could impede it. China's low current per capita income relative to that of global leaders and its low rate of urbanization point to clear upside potential for growth. But to realize this potential, China must overcome challenges stemming from lagging institutional development and the state's pervasive role in the economy. Section 7 concludes.

1. China's Growth in Perspective

China's growth performance has been remarkable following the introduction of economic reforms in the late 1970s. According to the official data, real GDP growth has averaged 9.0 percent since 1978. Growth over the past twenty years has been almost as fast, at 8.7 percent (Table 1).

Table 1

Growth over the Two Decades Prior to Reaching China's 2018 Real Income Level

	GDP Growth (Percent)	GDP Growth Per Capita
China (2018)	8.7	8.1
Singapore (1984)	9.4	7.6
Taiwan (1987)	8.8	6.8
South Korea (1994)	8.7	7.4
Japan (1976)	7.9	6.8
Hong Kong (1983)	7.6	5.4

Sources: Penn World Table version 9.1; The Conference Board, Total Economy Database; national sources.

Notes: Real income relative to China evaluated at constant 2011 purchasing power parities. Figures in parentheses show the year in which each economy first reached $16,100 in real per capita GDP (China's 2018 level).

That makes China the fastest growing economy in a sample of 124 economies during both periods. China's performance stands out all the more for its consistency. When its growth is averaged over rolling five-year periods, China has remained above the 90th percentile of the growth distribution since 1982, a feat no other economy has accomplished.

Rapid economic growth has led to a similar increase in living standards, lifting China out of poverty and into middle-income status. According to official figures, real per capita income has risen by a factor of 25 since 1978. Annual per capita income now stands at about $16,100 measured at purchasing power parity, in "2011 international dollars." (Unless otherwise noted, real income figures rely on this measure throughout this article.) This places China at roughly the 60th percentile of the global income distribution, though still slightly below 30 percent of the U.S. level.

We have to go back to before the start of China's reform period to find clear precedents for the country's growth performance. Singapore's economy grew even faster over the twenty years before it reached China's current real income level, while the economies of South Korea and Taiwan grew just as fast as China's. Growth rates in Hong Kong and Japan over similar twenty-year periods were less than 1 percentage point below China's. On a per capita basis, however, China's growth has outpaced that of all these economies, reflecting its slower rate of population growth.

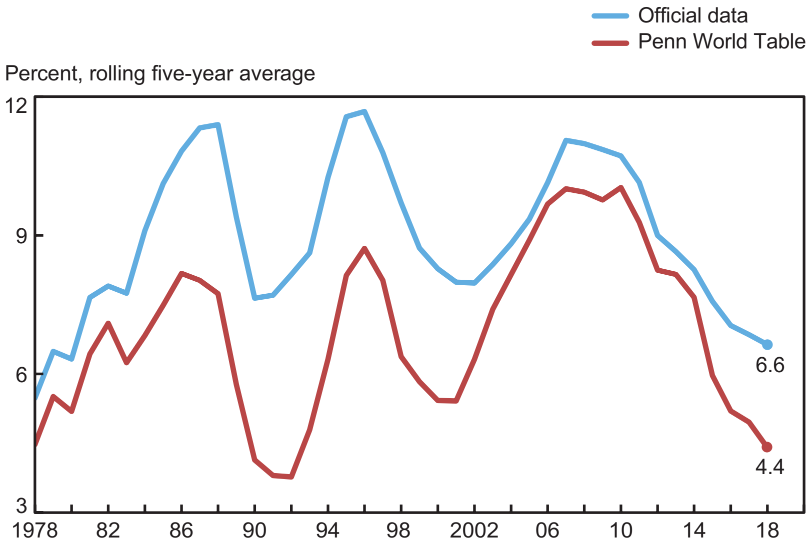
Many observers believe that the official GDP data overstate China's growth performance. The most comprehensive critique of the official statistics comes in a series of papers by Harry Wu of Hitotsubashi University, some written in collaboration with analysts at the Conference Board, and, earlier, with Angus Maddison. Wu goes beyond critique, developing alternative annual GDP estimates for China by drawing on a variety of official and unofficial data. This work has been influential enough for Wu's methods to be employed in the Penn World Table, the leading data source for international growth studies.

According to these data, Chinese real GDP growth has averaged 6.9 percent since 1978, more than 2 percentage points below the official figure. (Chart 1 shows these data as five-year averages.) The estimated overstatement of growth varies considerably over time, from more than 3 percentage points for much of the 1990s to less than 1 percentage point until recently. But China's growth performance remains remarkable. For our sample of 124 economies, China has come in above the 90th percentile of the global growth distribution more than half the time since 1982, and above the 75th percentile until just last year. China's growth over the past twenty years (7.5 percent) somewhat lags that of the high-income Pacific Rim economies listed in Table 1 during the periods in which they rose to China's current income level, but stands in the middle of the pack in per capita terms (6.9 percent).

The debate over the accuracy of China's GDP statistics goes back more than two decades, and some observers believe the official data are basically accurate. It is beyond the scope of this article to provide a detailed assessment of the evidence. In our view, however, the implications for past living standards provide strong evidence that official growth figures for earlier decades are too high.

Given current incomes, the faster China has grown, the poorer it must have been in the past. Official growth rates, together with a consensus estimate for real per capita income in 2011, imply that China was one of the poorest countries in the world well into the 1980s.[1] Indeed, real per capita income at the start of the decade would have been below that of most countries in sub-Saharan Africa as well as neighbors such as Bangladesh, Laos,

Chart 1
Real GDP Growth in China



Sources: Penn World Table (version 9.1); The Conference Board, Total Economy Database; IMF, World Economic Outlook database.

Note: In the Penn World Table series, GDP growth for 2018 (as part of a five-year average) is taken from the Total Economy Database.

and Myanmar. Although China was clearly a poor country at the time, few would have rated it as one of the poorest. Such a ranking is also inconsistent with data on life expectancy, literacy, and other quality-of-life indicators. Growth rates from the Penn World Table, more plausibly, place China at roughly the 30th percentile of the global income distribution in the early 1980s, ahead of most countries in sub-Saharan Africa but still behind neighbors such as Indonesia, the Philippines, and Thailand.

A look at living standards, however, provides little help in judging the accuracy of the recent data. Extrapolating from the consensus figure for 2011 at official growth rates, the International Monetary Fund (IMF) and World Bank place current real per capita income in China at about $16,100. Extrapolating from the same starting point using Wu's methods, the Penn Table places current incomes at about $13,600. This gap is not that large in context, however, barely affecting China's ranking in the global income distribution.[2] In what follows, we will assume that the recent official data are accurate, noting the implications of assuming a lower initial income level where relevant.

In this connection, some recent research implies that the Penn Table might overcorrect the recent official data. An analysis of nighttime lights data shows growth since 2011 slowing less sharply than in the official statistics (Clark, Pinkovskiy, and Sala-i-Martin 2017). So does an analysis of other alternative growth indicators (Clark, Dawson, and Pinkovskiy [2020], also in this special issue). The Penn Table, in contrast, shows growth slowing *more* sharply than in the official statistics.[3] These conflicting signals carry an important lesson: There is irreducible uncertainty as to how fast China has been growing.

2. The Sources of China's Growth

The neoclassical growth model has provided the standard framework for studying long-term economic growth since it was introduced by Robert Solow (1956, 1957) more than six decades ago. Under the model, economic growth comes from two basic sources: increases in capital and labor inputs, and improvements in technology. The basic growth accounting equation is given by:

$$\widehat{Y}_t = \hat{A} + \alpha \widehat{K}_t + (1-\alpha)\widehat{L}_t \tag{1}$$

In equation (1), Y represents real GDP, A the economy's technology level, K the quantity of capital inputs, and L the quantity of labor inputs. The ^ symbol denotes a proportional rate of change or percentage increase. The terms α and 1- α represent the elasticity of output relative to, respectively, capital and labor inputs. (Thus, a 1 percent increase in capital inputs would raise GDP by the factor $\alpha < 1$ percent). The fact that these terms sum to 1 expresses constant returns to scale, so that a 1 percent increase in both inputs results in a 1 percent increase in GDP. In a competitive economy, with factors of production paid their marginal product, these terms also represent the shares of national income accruing to capital and labor. The term A captures the efficiency with which capital and labor inputs are used, or total factor productivity (TFP). A higher value for A means that greater output can be produced from given factor inputs. Given measures for these terms, equation (1) can be used to decompose observed growth into contributions from factor accumulation and technological change.

The evolution of the capital stock is determined by the economy's savings rate and the rate of depreciation:

$$K_{t+1} = (1-\delta)K_t + s_t Y_t, \tag{2}$$

where δ is the rate of depreciation and s_t is the economy's investment rate. Equations (1) and (2), taken together, have a surprisingly powerful implication: An economy's long-run growth rate is independent of its investment rate. To be sure, a high-investment economy will follow a higher income trajectory and will grow faster than its long-term rate if it begins below that trajectory. But high investment is a self-limiting path to growth. Over the long run, the economy settles at an equilibrium with a constant capital-to-output ratio, with GDP growth determined solely by the pace of TFP and labor input growth. This equilibrium takes hold more quickly the faster the existing capital stock depreciates.[4]

Our empirical analysis uses capital input data from the Penn World Table, based on disaggregated investment outlays in nine categories. The composition of investment matters for the aggregate capital stock because some capital assets depreciate more rapidly than others. (Consider structures compared with software.) The latest edition of the Penn Table, released this year, also reports estimates of the flow of services provided by the capital stock.[5] This is the preferred measure of capital inputs from a theoretical perspective. In equilibrium, rapidly depreciating assets must yield a higher service flow to equalize investment returns across asset types. While our growth accounting exercise relies on these capital services data, our results would be basically the same using the capital stock series.

Data on employment and average hours worked are also taken from the Penn Table. In addition, the Penn Table contains data on labor quality, derived from underlying data on average years of schooling and estimates of the economic returns to education (Barro and Lee 2013). Labor inputs here are measured by a composite variable taking in all three of these elements:

$$L_t = hc_t avh_t N_t, \tag{3}$$

where hc_t represents the average level of human capital, avh_t average hours worked, and N_t total employment. This is in line with the emphasis on human capital in the recent growth literature and follows many studies in using the "extended Solow model" introduced by Mankiw, Romer, and Weil (1992).

The expanded Solow model implies that long-term GDP growth depends on the pace of human capital development as well as on TFP and raw labor input growth. A further interesting implication concerns the drivers of per capita income growth (assuming that long-run growth involves constant values for labor force participation and average hours worked). Per capita income growth now depends only on the pace of human capital upgrading and TFP growth.[6]

What about TFP growth? The neoclassical growth model treats this term as a residual—that is, as the part of GDP growth not accounted for by capital and labor accumulation (including human capital accumulation in the extended Solow model). While this is an important limitation of the neoclassical model, growth accounting studies based on the model have yielded important insights.[7] As we'll see, capital and labor accumulation play a diminishing role as growth drivers as economies ascend the global income ladder. Economies that fall into the middle-income trap fail to make the transition from growth based on factor accumulation to growth based on technology and education.

What does the neoclassical model tell us about the sources of growth in China? Table 2 shows the breakdown for the two most recent five-year periods (2008-13 and 2014-18) and for the prior ten years (1998-2007). Growth in total hours worked makes a steadily diminishing contribution to growth, falling to zero for 2014-18. This owes to the aging of China's population. Indeed, the working-age (20-64) population began shrinking in 2017, helping to drag the growth contribution from raw labor inputs below zero in 2017 and 2018.

Improvements in labor quality make a steadily increasing contribution throughout this twenty-year period, reaching 0.8 percentage point for 2014-18. The larger contribution reflects rapid gains in average years of schooling, partly because of the aging out of the labor force of earlier, less-educated population cohorts.

Capital accumulation makes the largest contribution to growth throughout, peaking at 5.0 percentage points for 2008-13 but falling to 3.0 percentage points for 2014-18. The reduced growth contribution from capital comes despite little change in the average share of capital expenditure in GDP (45 percent for 2014-18, compared with 47 percent for 2013-17). China is already seeing the self-limiting nature of capital accumulation as a source of growth. As the capital intensity of production rises, an ever-higher investment rate is needed simply to keep the growth contribution from capital accumulation at its current value. A simple back-of-the-envelope calculation indicates that China would now need an investment rate of roughly 55 percent of GDP to prevent this contribution from continuing to decline.

Since TFP growth is calculated as a residual, the difference in GDP growth between the official data and the Penn Tables falls entirely on TFP. Based on the official data, TFP

Table 2
The Sources of Growth in China

	2014-18	2008-13	1998-2007
1) Labor hours	0.0	0.5	0.6
2) Labor quality	0.8	0.6	0.5
3) Capital	3.0	5.0	4.7
4) Total factor productivity: Official data	2.8	2.6	3.9
5) Total factor productivity: PWT data	0.6	2.1	2.9
GDP: Official data	6.6	8.7	9.7
GDP: PWT data	4.4	8.2	8.7

Sources: Penn World Table (PWT) version 9.1; The Conference Board, Total Economy Database; national sources; author's calculations.

Notes: The Penn World Table ends in 2017; the Total Economy Database is used to fill in values for 2018. Offical GDP growth equals the sum of rows 1 through 4. PWT GDP growth equals the sum of rows 1 through 3 plus row 5. Figures refer to growth *from* 2013 to 2018, or equivalently, *during* 2014 through 2018, and so on for earlier periods.

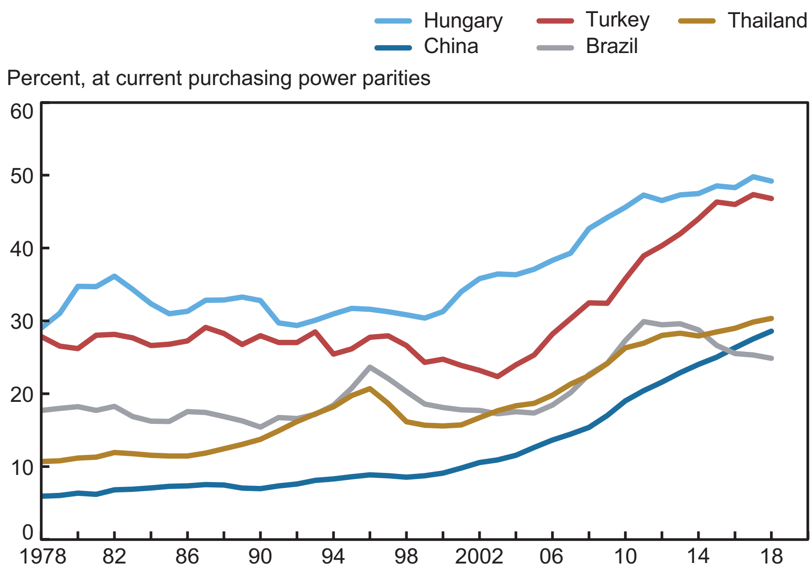
growth stands at 2.8 percent for 2014-18, up slightly from 2008-13. Based on the Penn Table data, TFP stands at just 0.6 percent for 2014-18, down sharply from the prior ten-year period.

In sum, our analysis points to one clear and one possible limit to China's future growth. The growth contribution from capital expenditure is already shrinking fairly rapidly. And if the alternative growth estimates from the Penn World Table are on target, the growth contribution from technological change is falling very rapidly. To gain better insight into what the future might hold, we turn to an analysis of growth experiences in other middle-income countries.

3. The Middle-Income Trap

The "middle-income trap" refers to the fact that many countries have failed to sustain rapid growth after reaching middle-income status. While the general idea of a middle-income trap is plain enough, there is no clear consensus as to how the term should be operationalized. Many studies define the trap in relative terms, that is, as a failure to rise past a certain fraction of income in the richest economies. Other studies define the trap in terms of income levels. (Within this group, studies differ as to where to draw the line between middle-income and upper-income status, whether and how rapidly income thresholds should be adjusted over time, and whether to define thresholds in purchasing power parity or U.S. dollar terms.) Some researchers deny that a middle-income trap even exists, arguing that the risk of a shift to sluggish growth is independent of income level. Agénor (2017) provides a useful and comprehensive review.

Chart 2
Per Capita Income Levels Relative to the United States



Sources: Penn World Table; IMF, World Economic Outlook database.

The notion has penetrated Chinese official circles. Premier Li Keqiang stated that China must "take particular care to avoid falling into the middle-income trap" at the Twelfth National People's Congress in 2016.[8] This statement followed then-Finance Minister Lou Jiwei's remark a year earlier that China faced a "50/50 chance" of sliding into a middle-income trap. Chinese policymakers are intent on avoiding that outcome. Although Premier Li remarked in 2018 that "there is a long way to go before China is a high-income country," he maintains that this outlook provides scope for China "to sustain medium-high growth for a long time to come."

We find a relative metric to be most informative, corresponding to Chinese authorities' stated goal of joining the ranks of the most advanced economies. Our middle-income category includes countries with per capita incomes at 10 to 50 percent of the U.S. level (at current purchasing power parities); our high-income category includes anything above that. The resulting country groupings are similar to the IMF's, but more stringent as to high-income status than the World Bank's.[9]

The global income distribution is roughly stable under our metric. Out of 124 countries, 52 qualified as middle-income in 1978 and 49 in 2018. Of the original cohort of 52 middle-income countries, just 8 had advanced to high-income status by 2018. (Chart 2 displays growth experiences in a handful of these economies as well as in China.) An equal number slipped into low-income status, with per capita incomes falling below 10 percent of the U.S. level.

Advancing to high-income status remains challenging even given a lower, fixed metric. Suppose we freeze income categories in real terms in 1978, the start of our sample. (Thus, middle-income status corresponds to 10 to 50 percent of U.S. real per capita income back then.) Out of 54 middle-income countries in 1978, just half had attained high-income status by 2018; 25 countries remained in the middle-income ranks and 2 slipped back into the low-income ranks, with per capita incomes actually declining in real terms.

The relatively low rate at which countries advance from middle- to high-income status reflects the simple fact that doing so requires sustaining a high growth rate for decades. To take an extreme case, a country with incomes at 10 percent of the U.S. level in 1978 would have needed to sustain growth above 5½ percent to reach 50 percent of the U.S. level in 2018. Even a country starting at 30 percent of the U.S. level would have needed to sustain income growth at a still-impressive 3 percent pace.

That said, similar arithmetic implies that China is well on track to high-income status if the trends in the recent official data can be sustained. After all, per capita income growth has averaged 6.2 percent over the last five years, implying a doubling roughly every eleven years, and per capita income is already close to 30 percent of the U.S. level. But as we'll see, the old investment adage holds true for countries' growth rates: Past performance is no guarantee of future results.

4. The Anatomy of Growth Slowdowns

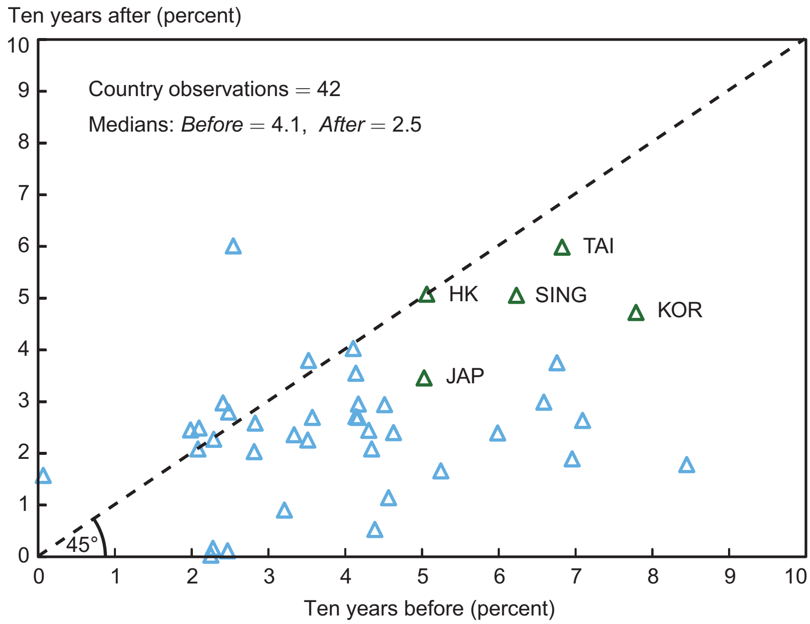
How much is growth in China likely to slow? In what follows, we take a two-part approach to shedding light on this question: first, by looking at growth performance in other countries after they reached China's current real income level; second, by zooming in on the sources of that performance through the lens of the Solow growth model.

Consider countries' growth performance over the ten years after reaching China's current real income level compared with the previous ten years (Chart 3).[10] (We assume for now that China's real per capita income stands at slightly above $16,000, as implied by the official data.) There are 42 country cases with the requisite data. Several features of the historical record stand out.

- Per capita income growth tends to slow after countries reach China's current level. Some 33 of the 42 country cases experienced slowdowns, as evidenced by the preponderance of observations below the 45-degree line, with the median growth rate falling from 4.1 percent to 2.5 percent. Where growth does speed up, the increase tends to be small.
- The decline in growth rates extends across the distribution, with the 90th, 75th, 25th, and 10th percentiles all moving markedly lower.
- The relationship between growth before and growth after reaching China's income level is fairly weak. Indeed, a univariate regression yields an $\bar{R}^2$ of just 0.15. As applied to China, the estimated relationship points to a per capita income growth rate of 3.6 percent over the next decade, but with a roughly one-in-four chance of exceeding 4.5 percent and a similar chance of falling below 2.7 percent.
- The weak relationship between past and future growth implies that slowdowns tend to be sharpest where growth had previously been fastest. This result mirrors the finding in Pritchett and Summers (2014) that regression to the mean is a robust feature of cross-country growth rates.[11]

Chart 3

Real Per Capita GDP Growth, Before and After Reaching China's 2018 Level

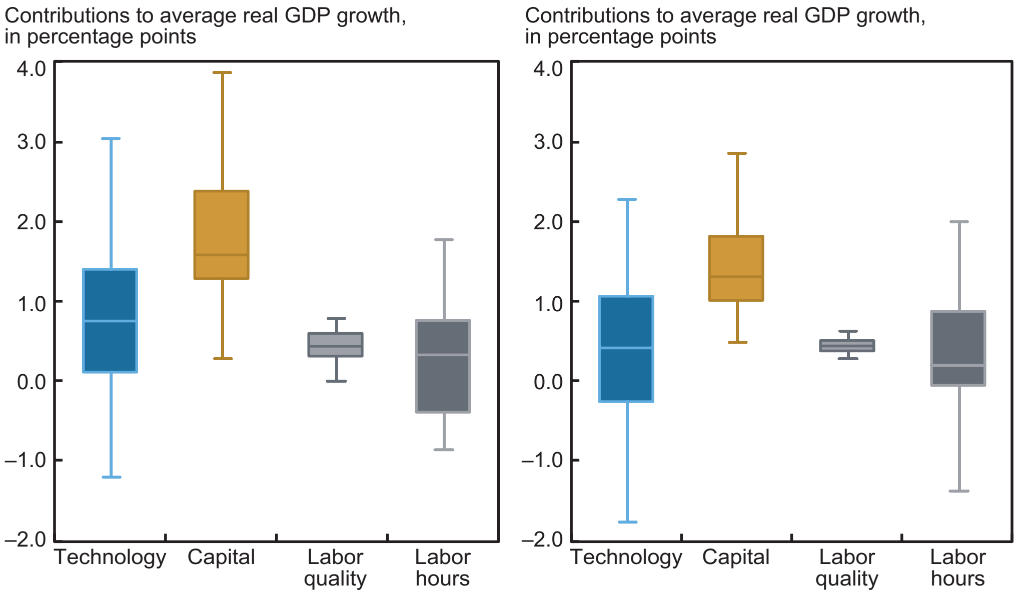


Sources: Penn World Table (version 9.1); IMF, World Economic Outlook database; author's calculations.

Chart 4 contains "box and whiskers" diagrams for the sources of growth after countries reach China's current income level, with the top panel referring to the first ten years. The boxes contain the interquartile range (25th to 75th percentiles) and a line for the median outcome. The whiskers show the upper and lower limits of the distribution after excluding extreme outliers.[12] Note that these distributions do not sum to the distribution for GDP growth. For example, the sum of 75th percentile values for the four categories is well above the 75th percentile for GDP growth.

- Capital accumulation is typically the largest source of growth in the decade after countries reach China's income level, with the median annual contribution at 1.6 percentage points, and the 25th percentile not that much lower, at 1.3 percentage points. Moreover, the distribution is skewed to the upside, with one-fourth of the sample seeing a contribution greater than 2.4 percentage points.
- Productivity gains are typically the second largest source of growth, with a median annual contribution of 0.8 percent. Dispersion in TFP growth is fairly wide. While nearly a quarter of the sample saw TFP growth of more than 1.4 percent, another quarter saw negligible or even negative growth.
- Improvements in labor quality typically contribute about 0.5 percentage point to annual GDP growth after countries reach China's income level. Dispersion is small. No country saw a negative growth contribution—something that would correspond to a drop in average years of schooling—and only a few saw contributions of above 0.8 percentage point.
- Growth in aggregate hours worked is typically the smallest source of growth, with a median annual contribution of just 0.3 percentage point. Dispersion is relatively wide, with roughly a quarter of the sample seeing contributions above 0.7 percentage point,

Chart 4
Sources of Growth after Reaching China's 2018 Income Level: First Decade



Source: Penn World Table.

Notes: Figures show distributions for the sources of growth in the decade after countries pass China's 2018 real income per capita level. Boxes contain interquartile range (25th to 75th percentiles) and median line. "Whiskers" show minimum and maximum values. Extreme outliers excluded via "Tukey industry standard." Number of observations = 43 (left panel); 26 (right panel).

and another quarter seeing contributions below -0.3 percentage point. Keep in mind, however, that the implications for *per capita* income growth are more muted, given that total and working-age populations tend to move together. More important for our purposes, the evolution of these variables in China over the next two decades is largely predetermined, making other countries' experiences of limited relevance.

Two points are worth noting concerning how growth contributions change relative to the prior decade. First, there is a strong tendency toward declines. Across the four categories, contributions fall for between roughly 60 and 75 percent of the sample. The largest declines are for TFP growth (median = –1.0 percentage point) and capital accumulation (median = –0.4 percentage point). For countries where growth contributions do pick up, the increases tend to be small.

Second, there is a strong tendency toward regression to the mean, with countries putting in the strongest performance in the pre-threshold decade likely to see the sharpest declines in the subsequent decade. Across the four categories, growth contributions move an average of 50 to 70 percent closer to the mean outcome. This fact provides a strong argument against building a growth projection for China by carrying forward its recent history.

Unfortunately, the number of country cases falls to 26 when looking to the second decade after countries reach China's income level. Moreover, the sample narrows in a way that makes it potentially less relevant to prospects in China, now consisting largely of countries in Europe or of European settlement (for example, Australia and Canada) that passed China long ago. Nevertheless, these experiences are our best available guide to China's prospects. What lessons do they provide?

- Growth tends to slow further. In 22 of the 26 countries in our sample, growth slowed in the second post-threshold decade relative to the first, with the median growth rate (on a consistent-sample basis) falling from 2.6 percent to 1.9 percent. The rest of the growth distribution also shifts down, with the upper end of the distribution moving down especially sharply.
- Capital accumulation is typically the largest source of growth in the second decade (Chart 4, bottom panel). The median contribution comes to 1.3 percentage points, though with fairly wide cross-country dispersion. TFP growth comes next, with a median contribution of 0.5 percentage point, again with significant dispersion. Labor quality improvements also make a meaningful contribution (median = 0.4 percentage point), but growth in aggregate hours typically makes a small contribution (median = 0.2 percentage point).
- Contributions from TFP and capital accumulation typically decline relative to the previous decade, falling for about three-fourths of the sample, and with median changes of -0.5 percentage point and -0.4 percentage point, respectively. Contributions from labor quality improvements and growth in hours worked typically remain roughly stable.
- Regression to the mean continues to operate powerfully, both for per capita income growth and for growth contributions. Indeed, TFP growth and the capital contribution in the second post-threshold decade are essentially uncorrelated with their values in the first decade.

If the experience of other countries at China's income level is a good guide, per capita income growth should slow significantly over the next two decades, particularly given the country's earlier high growth rate. The slowdown should feature markedly reduced contributions from TFP growth and capital deepening. But we've left out an important part of the story thus far: China's strikingly unfavorable demographic trajectory.

5. Projections

5.1 Methodology

The key question is how to use the information developed above to inform growth projections for China. We build projections that we term the Humdrum, Pretty Good, and Golden scenarios, as follows.

The Humdrum scenario sets TFP growth over the next two decades at the median values found above, while the Pretty Good and Golden scenarios set TFP growth at the 75th and 90th percentiles, respectively (see again Chart 4). Note that the TFP gains in the latter two scenarios would be extremely difficult to achieve. In our sample of 26 economies, only Taiwan achieved TFP growth above either the 75th or the 90th percentiles in both decades.

We considered but rejected setting the growth contribution from capital accumulation in the same manner. But matching even the 50th percentile of the contribution in our sample would require keeping investment spending as a share of GDP at close to 35 percent through the next two decades, well above the rates in other countries. (Capital expenditure spending in Japan and the Asian Tigers leads our sample, averaging roughly 30 percent of GDP.) Matching the 75th percentile would require capital expenditure spending of 40 percent of GDP, only slightly below its current level and, excepting China, higher than that of any country in the world with a GDP of more than $100 billion.

These high investment rate requirements reflect the diminishing returns to capital accumulation discussed in Section 2. Maintaining them would be inconsistent with the Chinese government's stated goal of rebalancing the economy away from an excessive reliance on investment and toward consumption. Moreover, remaining on a high-investment trajectory would result in an increasingly capital-heavy production structure, an outcome at odds with the necessity of sustaining rapid productivity growth.

In light of these facts, the Humdrum scenario assumes that investment spending as a share of GDP declines gradually from its current level, bottoming out at 25 percent in the early 2030s. This is about the 75th percentile for the 37 economies the IMF classifies as advanced. The Pretty Good and Golden scenarios assume that investment declines still more gradually, bottoming out at 30 percent in the early 2030s.

The Humdrum scenario sets the future pace of labor quality improvement at the 50th percentile of our sample of similar countries. The Pretty Good and Golden scenarios set this parameter at, respectively, the 75th and 90th percentiles.

All three scenarios assume that aggregate hours worked evolves in line with China's working-age population over the projection horizon. This implicitly sets age-specific labor-force participation rates and average hours per worker at current levels. We discuss below whether plausible changes in participation or average hours might materially alter our results.

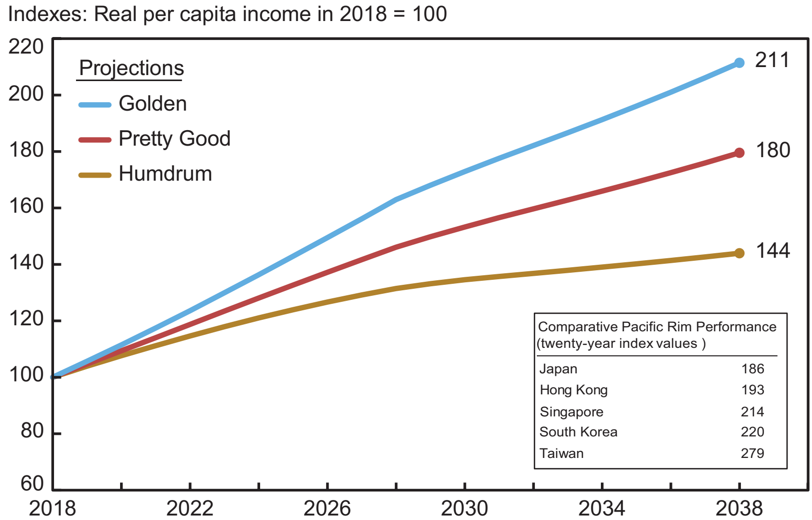
5.2 Results

In the Humdrum scenario, real per capita income growth averages a respectable 2.7 percent over the next decade. But growth falls sharply from 2028 to 2038, averaging just 0.9 percent. This would leave real per capita income 44 percent above its current level (Chart 5). By comparison, China's fast-growing Pacific Rim neighbors achieved gains of between 86 and 179 percent over a similar period. This performance would leave China well short of advanced economy status. At the end of the projection horizon, real per capita income would be just over 40 percent of the current U.S. level, and just over one-third of the future U.S. level, assuming annual increases of 1 percent for the latter.

The slowdown in growth largely reflects a reduced contribution from capital accumulation, from an average of 1.9 percentage points over the first decade of projection to just 0.4 percentage point in the second. About two-thirds of this step-down is the result of the diminishing

Chart 5

Real Per Capita Income Projections for China



Sources: Penn World Table (version 9.1); The Conference Board, Total Economy Database; national sources; author's calculations.

Note: See the text of the paper for details on the three projections.

returns to capital accumulation, and the other third is from the assumed gradual decline in capital spending as a share of GDP. Demography also exerts a greater downward weight over time, with the working-age population declining by a little over 0.2 percentage point per annum over 2018-28 but by almost 0.9 percentage point per annum over 2028-38. Meanwhile, the contribution from TFP growth moves down by 0.3 percentage point, while the contribution from labor quality improvement remains essentially stable, consistent with performance by peer economies at the 50th percentile.

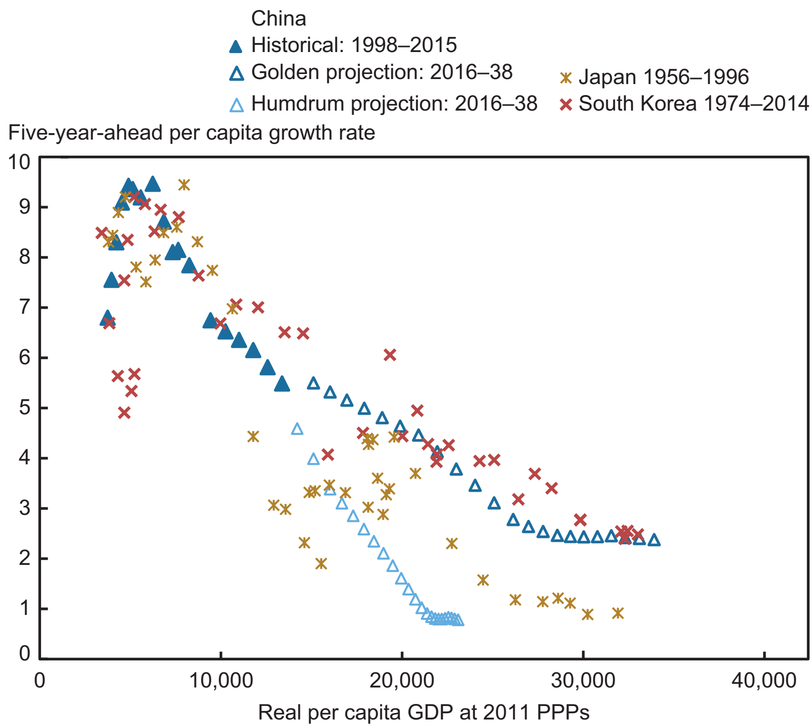
In the Pretty Good scenario, real per capita income growth averages a rapid 3.8 percent over the first decade of the projection and slows to 2.1 percent in the second. This performance leaves real incomes up by 80 percent from their current level, only slightly below what Japan achieved over a similar period. China would now be at the margins of high-income status. Real per capita income would be just above 50 percent of the current U.S. level, but only slightly above 40 percent of the assumed future U.S. level.

As before, a reduced contribution from capital accumulation—from 2.3 percentage points to 1.0 percentage point—explains most of the slowdown between the two decades. The contribution from TFP growth also falls, from 1.4 percentage points to 1.0 percentage point, consistent with peer performance at the 75th percentile. Changes in other factors influencing growth are much the same as in the Humdrum scenario.

In the Golden scenario, real per capita income growth averages a very rapid 4.9 percent from 2018 to 2028, slowing to a still strong 2.6 percent over 2028-38. This leaves real incomes up by 111 percent from their level in 2018, a performance comparable to what the Asian Tigers achieved over a similar period. China now achieves high-income status,

Chart 6

Per Capita Income Growth vs. PPP Income Levels



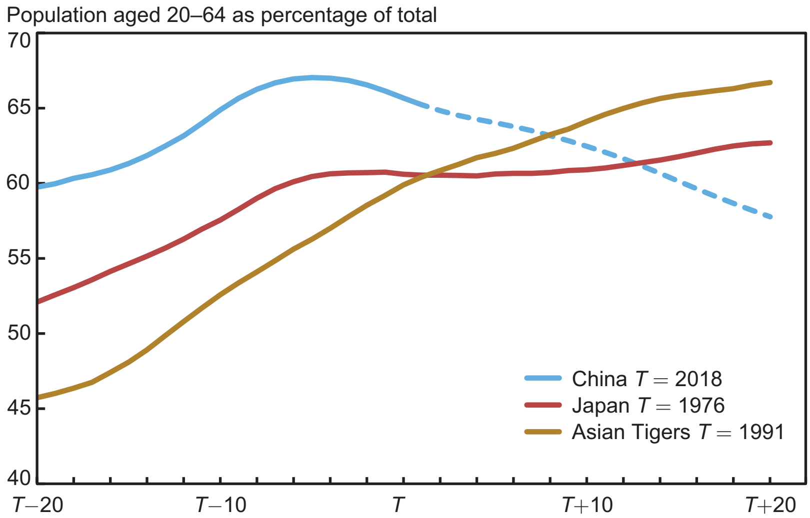
Sources: Penn World Table (version 9.1); The Conference Board, Total Economy Database; national sources; author's calculations.

Note: See the text of the paper for projection details.

with real incomes at slightly above 60 percent of the current U.S. level, or exactly 50 percent of the assumed future U.S. level. As before, the slowing in growth between the two decades mainly reflects a reduced contribution from capital accumulation (from 2.4 to 1.2 percentage points) and a slower assumed pace of TFP growth (from 2.2 to 1.3 percent).

We make no judgment as to the relative likelihood of the various projection scenarios. What the projections do make clear, however, is that events would have to unfold in a strikingly favorable manner for China to approach or reach high-income status over a two-decade horizon. As we've already noted, both the Golden and Pretty Good scenarios build in considerable upside. Among peer economies, only Taiwan placed at or above the 75th percentile for TFP growth in consecutive decades (though it also placed above the 90th). Moreover, in all three scenarios, a gradually declining but still high share of capital spending in GDP works to support growth. It also results in an increasingly capital-heavy production mix, pushing China's real capital-output ratio from near the top to the very top of the current range for major economies. There is good reason to doubt that China could sustain rapid TFP growth with such a production mix, especially given already pressing concerns about the efficiency of new investment spending.

Chart 7
Working-Age Populations, Before and After Reaching China's Current Income Level



Sources: Penn World Table; United Nations Population Database.

Notes: "*T*" indicates the year in which each economy reached China's 2018 level of per capita income at 2011 purchasing power parities. The "Asian Tigers" are Hong Kong, South Korea, Singapore, and Taiwan.

Chart 6 compares the joint evolution of real per capita income growth and per capita income levels in the Humdrum and Golden Scenarios with observed outcomes in Japan and South Korea. Income growth is shown on a leading five-year average basis, in line with the notion that growth will generally slow as an economy climbs the income ladder. The series for Japan and South Korea show outcomes from the two decades before and after the point at which those countries reached China's current real income level (1976 and 1994, respectively).

As can be seen, growth in China has tracked growth at similar income levels in Japan and South Korea fairly closely thus far. Growth in China continues to track growth in South Korea fairly closely in the Golden scenario, but falls well below outcomes in both countries in the Humdrum scenario. Although we don't show the Pretty Good scenario for reasons of legibility, China's growth rates in that case would track slightly below historical outcomes in Japan.

The aging of China's population weighs heavily on projected income growth in all three scenarios. According to U.N. figures, China's working-age population is expected to decline by about 12 percent over the next twenty years even as the total population rises slightly. As a result, the working-age (20-64) population share is on track to decline by roughly 8 percentage points over the next twenty years, from 65 percent to 57 percent (Chart 7). In contrast, the median country reaching China's income level saw its working-age population share increase by 5 percentage points over the next twenty years. The Asian Tigers did even better, with working-age population shares rising by about 7 percentage points. This is a key reason why highly favorable assumptions are needed to support income growth projections that are in line with the achievements of China's neighbors.

Recall that the projections assume that aggregate hours worked will evolve in line with China's working-age population over the projection horizon, thus holding hours per worker and employment-population ratios constant. Could changes in these variables soften the demographic blow?

In fact, any changes are more likely to be a source of additional downside. The average Chinese worker puts in 2,175 hours per year; that's high for a country at China's current income level—100 hours above the 75th percentile for the countries in our sample. Moreover, almost all of those countries saw average hours fall over the next two decades, with the median change at -9 percent. Similarly, labor-force participation in China is quite high for a country that has reached its income level. Total employment stands at 85 percent of the working-age population, above the 90th percentile in our sample. And more than half these countries saw their employment-population ratios drop over the next two decades, although generally by only a few percentage points.

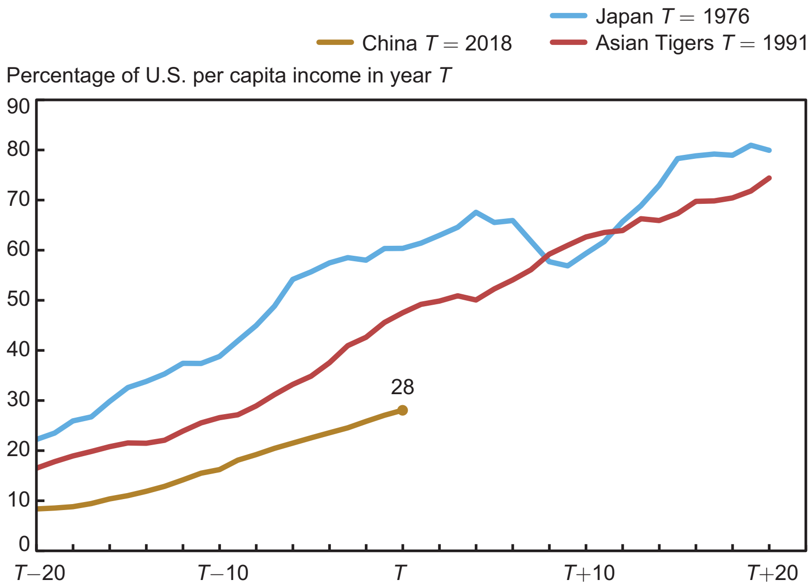
To be sure, the record does contain more hopeful precedents. Employment in Japan is now equivalent to more than 95 percent of the working-age population, up more than 10 percentage points from a decade ago. (The figure is so high because of rising employment among persons 65 and older, who are not normally counted in the working-age population.) It is possible that China will be able to replicate Japan's success. But the upside growth potential is limited. Back-of-the envelope calculations indicate that growth might run 0.3 percentage point higher were China's labor-force participation rate to reach Japan's level over the next two decades. That would raise incomes by about 7 percentage points by the end of our projection horizon—a welcome boost, but not a game-changing development. Moreover, this calculation assumes no decline in average hours worked; Japan has seen a significant drop because so many of the elderly work part-time.

Recall also that the projections assume that China's recent official GDP data are accurate. As we've discussed, the developers of the Penn Table accept the argument from Wu and other critics that recent official growth rates are overstated. As a result, real per capita income from the Penn Table is now about 18 percent lower than estimates derived from official sources (roughly $13,000 compared with $16,000). How would the different "jumping off" point affect our projection results?

Our analysis of growth experiences in other countries that have reached China's income level would now be based on a different and somewhat larger group of countries (53 cases for the first decade). Over the two-decade span, TFP growth and the growth contribution from human capital accumulation would be slightly higher, especially at the 75th and 90th percentiles of the distribution. As a result, our projections would call for a slightly faster pace of income *growth* in China. But this would not be enough to make up for the lower initial *level* of income, leaving it roughly 10 percent lower in 2038 than in the projections above.

While our projections illustrate plausible future paths, they provide only loose guidance on what is likely to occur. We don't know how growth fundamentals will evolve in China in the coming decades (even if we have a fairly good grasp of the demographic outlook). Nor do we know how policy will respond. Take the results with a healthy (unhealthy?) dose of salt.

Chart 8
Income Levels Relative to the United States



Sources: Penn World Table; The Conference Board, Total Economy Database.

Notes: "*T*" indicates the year in which each economy reached China's 2018 level of per capita income at 2011 purchasing power parities. The "Asian Tigers" are Hong Kong, Singapore, South Korea, and Taiwan.

6. Opportunities and Challenges

Prospects for rapid growth in China are buoyed by two key factors: the country's distance behind current global income leaders and its relatively low rate of urbanization. These factors could provide scope for continued rapid growth through "catch-up" effects and structural transformation.

In this connection, China is much further behind global leaders than its Pacific Rim neighbors were when they reached China's income level. At present, real per capita income in China is slightly below 30 percent of the U.S. level (Chart 8). When Japan reached China's current income level in the mid-1970s, real incomes stood at about 60 percent of the U.S. level. When the Asian Tigers reached China's current income level in the early 1990s, real incomes stood at slightly below 50 percent of the U.S. level. This introduces the possibility that China faces greater opportunities for growth via technological upgrading and adopting best practices.

Empirical studies show that there is no general tendency for countries with lower initial income levels to grow more rapidly. (See Johnson and Papageorgiou [2018] for a recent review.[13]) Many studies, however, support "conditional convergence," finding that income growth rates are negatively related to initial income levels subject to appropriate controls. (Mankiw, Romer, and Weil [1992] and many later studies condition on the determinants of steady-state incomes identified in the Solow model.) A common estimate is that countries converge toward their steady-state income levels at a rate of roughly 2 percent a year. Applied to China, this estimate would imply a growth advantage of roughly 2.4 percentage points relative to the United States, although one that would diminish over time as the income gap narrowed.

Other studies, however, find that traditional convergence tests lack power against the alternative of multiple steady states, some involving catch-up with global leaders and some involving falling further behind (Durlauf, Johnson, and Temple 2009). From this viewpoint, countries belong to different "convergence clubs," and the issues for policy purposes concern the sorting process.

Our core point, however, holds regardless of the general power of convergence effects. The wide current income gap between China and global leaders means that China can grow rapidly for a long time before it approaches the technological frontier. There is plenty of upside, just no guarantee that it will be exploited.

China's relatively low rate of urbanization also provides upside for growth. The urban-rural income gap in China is particularly wide, and some of the historical and prospective TFP growth reflects the movement of workers from the rural sector to the higher-productivity urban sector. At present, China's urban population share stands at 58 percent. This compares with an average of 70 percent for our sample of countries reaching China's 2018 income level, and an average of roughly 80 percent among advanced economies. Very likely, China has a lower "natural" urbanization rate than many countries given its sheer size. But even roomy Russia, sprawled across eleven time zones, has a current urbanization rate of 74 percent. Migration from country to city could add to growth in China for the next decade or two.

Perhaps surprisingly, however, empirical studies do not support a clear connection between the pace of urbanization and economic performance (Bloom, Canning, and Fink 2008). While urbanization and per capita income *levels* are strongly correlated, urbanization and per capita income growth rates are not. Indeed, in recent decades, countries falling into stagnation have often seen urbanization continue apace. China will need to maintain a dynamic urban sector if it is to unlock this source of upside growth potential. Not surprisingly, generating urban employment remains a top official priority, highlighted in successive five-year plans.[14]

In short, the take-away here is much the same as for convergence. China's unfinished structural transformation leaves it with plenty of room to run. How fully China exploits this potential will depend largely on its own policies.

In this connection, institutional underdevelopment represents perhaps the biggest roadblock on China's path to high-income status. The World Bank's Worldwide Governance Indicators (WGI) data set is the most comprehensive data source on countries' institutional quality. The WGI draws on a large number of surveys from a variety of sources, normalizes them, and summarizes them according to six governance categories. Importantly, the WGI takes in assessments of norms and practices as well as formal institutional arrangements. Establishing the rule of law, for example, is not simply a matter of putting the right statutes on the books.

A look at China's performance over time, and compared with other upper-middle-income and high-income economies, is far from encouraging (Table 3). Across most governance categories, China's performance in 2017 was little better than in 2005. Moreover, China scores below the average for its upper-middle-income peers in all governance categories. Not surprisingly, then, China scores far below upper-income norms in all categories. Indeed, in five of six categories, China scores below the *worst-performing* high-income economy.[15]

Table 3

Institutional Underpinnings for High-Income Status

World Bank Governance Indicators (mean = 0, standard deviation = 1.0)

	China 2005	China 2017	Upper-Middle Income Average	High-Income Average
Regulatory quality	-0.08	-0.19	0.36	1.53
Rule of law	-0.41	-0.19	0.23	1.61
Control of corruption	-0.45	-0.15	0.10	1.64
Government effectiveness	-0.05	0.42	0.34	1.55
Voice and account-ability	-1.39	-1.48	0.35	1.28
Political stability, control of violence	-0.21	0.00	0.44	1.08

Source: World Bank, World Development Indicators database.

Notes: Each indicator is constructed from a variety of surveys, which are normalized and combined via unobserved components analysis. The sample includes 121 countries, and excludes OPEC countries and those with populations of less then 3 million. Income categories are based on 2017 per capita income (in U.S. dollars). High-income countries occupy the top quintile (>$21,150, about 35 percent of the U.S. level), and upper-middle-income countries occupy the next highest quintile ($6,732 - $21,149).

China's current governance rankings allow for three distinct possibilities:

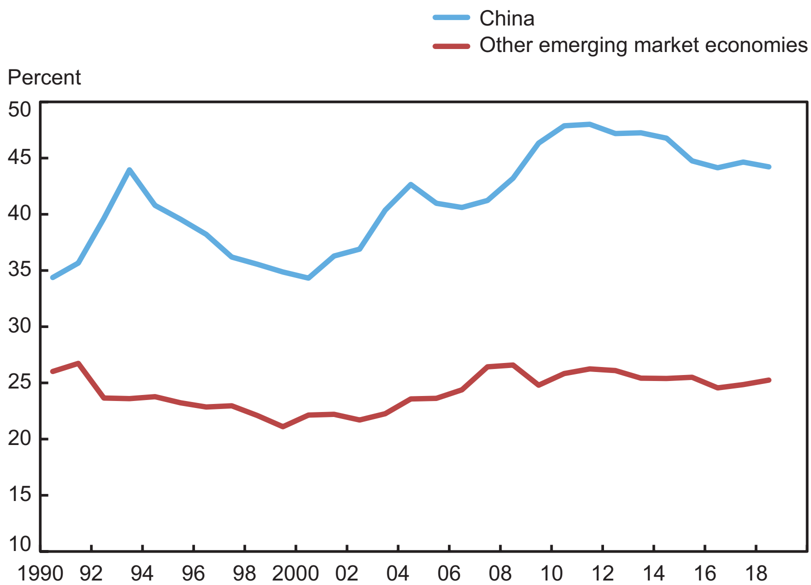
- China's governance quality will rise over time, either through deliberate reform efforts or endogenously with the country's level of income, allowing it to achieve high-income status.
- China will fail to achieve adequate governance improvements, leaving it caught in the middle-income trap.
- China will prove a unique case, attaining high-income status while retaining governance features unlike those of all current high-income economies.[16]

Chinese authorities have been clear about their plans to proceed with market-oriented reforms. But authorities have been equally clear that the Communist Party will retain control over the commanding heights of the economy and over political life. And in this connection, policy is currently moving in the wrong direction, toward greater state and party control of the economy. (Lardy [2019] provides a comprehensive account of the policy shift.) In short, we face a test of the third possibility above.[17]

We close by briefly taking note of some additional obstacles to continued rapid growth.

China faces a daunting rebalancing challenge. The share of capital expenditure in GDP has been close to or above 45 percent since 2009 and above 30 percent since the late 1970s (Chart 9). This represents a lopsided expenditure profile even by the standards of China's high-income East Asian neighbors. Japan, Taiwan, and Hong Kong never saw capital

Chart 9
Capital Spending as a Share of GDP



Sources: IMF, World Economic Outlook database; author's calculations.

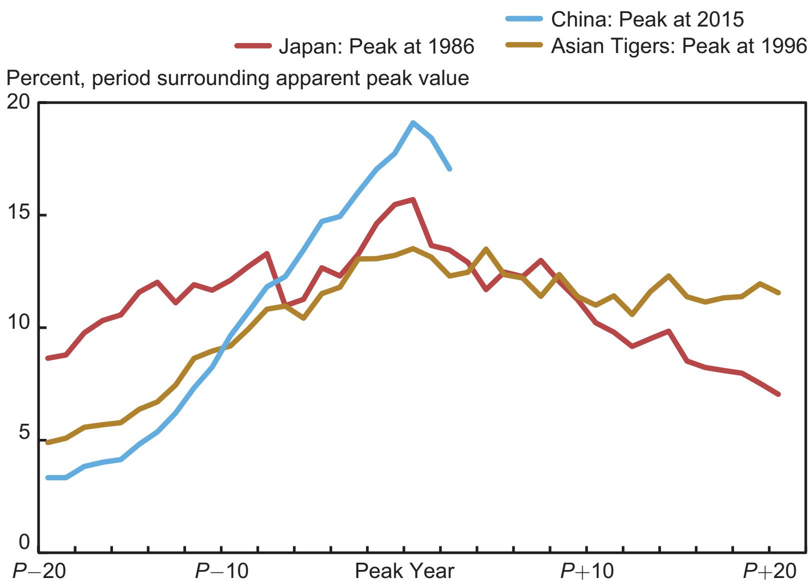
expenditure reach 40 percent of GDP during their high-growth periods; South Korea reached that level only once. None of these economies sustained capital expenditure shares above 30 percent for much more than twenty years; China is approaching 50 percent. Only tiny Singapore devoted a comparable share of national income to capital accumulation during its high-growth period.

The need to rebalance China's growth model away from excessive reliance on investment spending, and toward greater reliance on consumption, has been widely discussed for at least two decades. Rebalancing has been an official goal of economic policy since the implementation of the Eleventh Five-Year Plan in 2004, with capital expenditure as a share of GDP falling by almost 3½ percentage points over the past five years. Yet, at that pace of decline, China's capital expenditure share would remain above 30 percent until the early 2040s. Faster progress will be essential for a successful transition from resource-led to innovation-led growth.

China's credit-centered growth model has pushed credit to the private nonfinancial sector relative to GDP to the highest in the world (except for a few financial entrepôts), resulting in significant legacy financial problems. The need to restrain credit growth weighs on growth prospects in two ways. Most immediately, it limits authorities' ability or willingness to employ a primary macroeconomic support tool when growth falters. Less immediately, to the extent that the credit tool is employed, the odds of an eventual growth-crimping credit shakeout mount that much higher.

A final headwind for growth comes from the external side. China's fast-growth neighbors reached China's current income level during a period in which global trade growth was running well ahead of global production growth, underwriting export-oriented

Chart 10
Shares of Global Manufacturing Exports



Sources: IMF, *World Trade Statistics*; World Bank, World Development Indicators database.

Note: The "Asian Tigers" are Hong Kong, Singapore, South Korea, and Taiwan.

development strategies. Global trade volumes grew more than twice as fast as production volumes from 1991 to 2001, the decade after the newly industrialized economies (NIEs; Hong Kong, Singapore, South Korea, and Taiwan) reached China's income level. Global trade volumes grew roughly 1½ times as fast as production volumes from 1976 to 1986, the decade after Japan reached China's income level. This support for growth is apparently a thing of the past. Since 2011, global trade volumes have grown no faster than production volumes.

Moreover, China's already high penetration of foreign markets will make it difficult to expand exports via gains in market share (Chart 10). Indeed, China's share of global manufacturing exports has apparently already peaked, mirroring developments in Japan and the NIEs from similar income levels. Last but not least, external support for growth will remain scarce absent a resolution of the current trade dispute with the United States.

7. Conclusion

China's growth record has been remarkable, lifting the country from poverty to middle-income status in the span of a few decades. Analysis based on the neoclassical growth model reveals that China's rise has come from high, sustained productivity growth, alongside an outsized contribution from capital accumulation given the country's high investment rate. The question for the future is whether this growth recipe will be enough to propel China to high-income status. To address it, we develop a set of projections informed by the experience of other countries at China's income level. The results are stark. Given growing drags from an aging population and diminishing returns to capital, China can attain high-income status in the coming decades only through productivity gains at the top end of the observed historical range. In short, reaching the income frontier depends on a successful transition from resource-led to innovation-led growth.

To succeed, China will almost certainly need to make large strides in institutional development, putting in place the legal, regulatory, and informal frameworks that support high-income status elsewhere. The apparent turn back toward a more state-directed development strategy leaves ample room for skepticism about China's growth prospects. But we shouldn't be too sure. China's growth performance has surprised the skeptics thus far.

Appendix: Data Sources and Projection Methods

Our projections are benchmarked to the latest vintage of the Penn World Table (Version 9.1, 2019). Feenstra, Inklaar, and Timmer (2015) provide a comprehensive treatment of the conceptual and measurement issues involved in constructing the data set. This source provides data or estimates over 1950-2017 for 182 countries on the following key variables: real GDP, real capital stock, employment, average hours worked (most countries), labor quality (most countries), the labor income share, the depreciation rate of the capital stock, and total factor productivity.

For real GDP, there are three important series: one with real expenditure measured at constant national prices (RGDPN), another with real expenditure measured at current purchasing power parities (CGDPE), and a third with real expenditure measured at constant purchasing power parities (RGDPE). The first is suited to measurement of growth rates over time in a given country; the second is suited to the comparison of living standards at a given time; and the third is designed for comparing living standards across countries and over time. Figures cited in the text and charts conform to this breakdown.

The Penn Table relies on the work of the Income Comparisons Project (ICP). The ICP is a World Bank initiative under the auspices of the United Nations and represents a multi-decade effort to place countries' national accounts on a comparable basis. The project involves periodic, highly detailed surveys of prices and expenditure patterns for a large number of countries. The World Bank statisticians then use this information to restate national GDP figures in purchasing power parity terms, that is, with reference to a standard consumption basket. The IMF's WEO Database and the Penn World Table also rely on the results of the ICP to construct cross-country databases on GDP at purchasing power parity. Also, all of these sources supplement the ICP data with more frequent surveys conducted by Eurostat and the Organisation for Economic Co-operation and Development (OECD) for member countries.

Purchasing power parity estimates are subject to error. Countries differ widely in their consumption and production baskets at a given time, and consumption and production baskets change widely over time. Data construction inevitably involves imputations and, at times, judgmental adjustments. Comparisons of real income levels across countries—and especially, across countries and over time—should be regarded as approximate.

The data in the Penn Table go only through 2017. To fill in data for 2018, we take data from Chinese official sources and, for some variables, the Conference Board's Total Economy Database. Also, as noted in the text, our projections assume that the GDP growth rates in the Chinese official data are accurate after 2011, the date of the last ICP benchmark survey. In certain places in the text, however, we make comparisons between official and "Penn Table" values for 2018. These Penn Table values are also derived from the Total Economy Database, since it also incorporates downward adjustments to Chinese official growth rates based on the work of Wu and his coauthors.

Three variables are missing for a few countries involved in our analysis: average hours per worker, human capital per worker, and the input to GDP from capital services. (The number of countries without these series is, respectively, two, one, and three.) Where average hours and human capital levels are not reported, we treat them as constant. Where the input from capital services is not reported, we set growth in this variable equal to growth in the real capital stock.

Appendix (Continued)

For countries where both variables are available, this relationship tends to hold quite closely, especially over spans of more than a few years. A regression of services growth on stock growth over non-overlapping ten-year periods yields the following: $\hat{\beta} = 0.99$, $t - stat. = 40.8$, $\overline{R}^2 = 0.75$, $N = 591$.

Our projections for China also assume that future growth in capital services is equal to growth in the real capital stock, with the latter derived in the usual manner from the perpetual inventory method. Finally, it should be noted that our projections implicitly assume that relative prices and the composition of capital expenditure across types of goods remain at their current values. Large departures from these assumptions could have a meaningful impact on our results, though in a direction that would depend on their precise character.

Notes

[1] The Penn Table and official sources such as the IMF and World Bank report similar figures for real GDP at purchasing power parity in 2011, based on the latest multi-country price and expenditure survey conducted for the United Nations' Income Comparisons Project. Outside of 2011, figures for China diverge. The IMF and the World Bank derive figures for other years via extrapolation at official growth rates; the Penn Table relies on its own growth estimates. Figures for other countries also diverge outside, albeit less dramatically, with the Penn Table data adjusted to align with the results of earlier ICP surveys. See the Appendix for details.

[2] Chinese real per capita income at purchasing power parity ranks 43rd out of 106 countries in 2018 using the IMF or World Bank data. China ranks 45th among the same 106 countries in the Penn Table.

[3] Growth has averaged 5.1 percent since 2011 in the Penn Table, a decline of 5.2 percentage points from the previous seven-year period. Growth has averaged 7.1 percent since 2011 in the official data, a decline of 4.0 percent from the earlier period.

[4] With a constant savings rate s^*, a capital depreciation rate δ, and labor force growth at the rate $\widehat{N}^*$, the long-run capital-output ratio is given by: $k^* = s^* \left\{ \left(1+\widehat{N}^*\right)\left(1+\hat{A}\right)^{1/1-\alpha} - (1-\delta) \right\}^{-1}$ The contribution of capital accumulation to growth in the steady state is given by: $\frac{\alpha}{1-\alpha}\hat{A} + \alpha\widehat{N}^*$.

[5] See Inklaar, Woltjer, and Gallardo Albarrán (2019) for details on the theoretical background and data construction.

[6] In particular, per capita income growth will be given by: $\hat{Y}^* - \widehat{N}^* = \hat{A}^* / (1-\alpha) + \widehat{hc}^*$, where the * denotes long-run values. Of course, population growth and human capital upgrading—especially if the latter is based on average years of schooling—could settle at zero in the long run.

[7] This limitation spawned a large literature featuring endogenous technological change beginning in the mid-1980s under the banner of the "new growth theory." But this effort petered out by the late 1990s without reaching a clear consensus, and with little impact on subsequent growth accounting studies. See Romer (2015).

[8] The official transcript of Premier Li's remarks is at: http://www.npc.gov.cn/zgrdw/englishnpc/Speeches/2016-03/18/content_1985677.htm. See also Li's remarks in the Netherlands in 2018, at: http://english.gov.cn/premier/speeches/2018/10/18/content_281476350372342.htm. Former Finance Minister Lou's comments on the risk of a middle-income trap were covered extensively in the press, including at: https://www.scmp.com/news/china/economy/article/2116295/has-china-really-avoided-middle-income-trap. Lou has since said that recent reforms have substantially diminished that risk.

[9] The IMF offers no precise definition for its high-income grouping, but membership has conformed quite closely to the "greater than 50 percent of U.S." metric since that organization introduced income categories in the May 1980 *World Economic Outlook*. (The high-income group is now referred to as "advanced economies" but originally went by the moniker "industrial countries.") The World Bank's classification scheme is defined in U.S. dollar terms, with income thresholds adjusted upward over time based on inflation in special drawing rights countries to preserve a link with real purchasing power. But these thresholds seem unreasonably low. The upper-income category includes countries with per capita incomes as low as $12,056, just 19 percent of the current U.S. level. The upper-middle-income category extends down to $3,896, just 6 percent of the U.S. level.

[10] Our selection algorithm in fact requires at least seven years of growth history before and after passing this threshold. (Growth rates are annualized.) In addition, we eliminate cases in which countries slip back below the income threshold within three years.

[11] Consider regression to mean from the standpoint of a simple linear model. Given the data in Chart 3, we can estimate $After = \alpha + \beta * Before + \varepsilon$. We derive the estimate $\hat{\beta} = 0.31$, with a t-statistic of 2.89. The change in growth rates is simply, $After - Before$ with an implied coefficient of $\hat{\beta} - 1 = -0.69(t - \text{statistic} = -6.35.)$ A country that grows 1 percentage point faster in the "before" period tends to grow roughly 0.3 percentage point faster in the "after" period, or equivalently, to slow by roughly 0.7 percentage point more than the norm.

[12] The "Tukey industry standard" calls for excluding observations that reside more than 1.5 times the length of the interquartile range outside of it. Under a normal distribution, such outliers would include roughly the lower and upper 0.3 percent of outcomes.

Notes (Continued)

[13] Lee (2017) considers convergence in the context of China's growth experience.

[14] See the plan draft at: https://en.ndrc.gov.cn/newsrelease_8232/201612/P020191101481868235378.pdf. A natural counterpart to urbanization is a shift in the composition of employment, out of agriculture and into the industrial and service sectors. Agricultural employment remains at 27 percent of the labor force, compared with an average of 12 percent for countries reaching China's income level, and an average of 3 percent for advanced economies. The ongoing shift of labor from agriculture to higher-productivity sectors should add to productivity growth in the coming decades. However, "shift-share" analysis reveals that productivity gains from labor reallocation are past their high point. (We rely on data on real output and employment in agriculture, industry, and services.) Over the past five years, labor reallocation has added an average of 1.2 percentage points to growth in output per worker, down from a five-year average of 1.8 percentage points five years ago, and a peak of 2.6 percentage points ten years ago. The key reason is that labor has now begun to shift out of the industry and into services, a sector with an intermediate level of productivity.

[15] China scores above Israel in Political Stability and Control of Violence, a category that also encompasses the incidence of terrorism.

[16] A comparison with Singapore is instructive, since Chinese officials often cite that country as a model for their own: Singapore has attained exceptional institutional effectiveness and high-income status despite having political institutions that are well short of fully democratic. Singapore is the lowest-rated high-income country in the most relevant category, Voice and Accountability, at -0.11, slightly below the average for all countries. China has a long way to go to match its putative model, scoring -1.48.

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The Impact of Foreign Slowdown on the U.S. Economy: An Open Economy DSGE Perspective

Ozge Akinci, Gianluca Benigno, and Paolo Pesenti

OVERVIEW

- Global economic activity decelerated noticeably over the course of 2018, owing to various factors that affected major economies—including those of China and the euro area.

- At the same time, foreign growth projections for 2019 and 2020 were lowered, signaling potentially large headwinds for the U.S. economy.

- The authors use a multi-country dynamic stochastic general equilibrium (DSGE) model to study the role of financial integration in the global transmission of demand shocks—examining the impact of economic spillovers to the United States from slowdowns originating in the euro area and China.

- In a scenario with unrestricted policy space and rates above the zero lower bound, they find that the impact is sizable if the shock originates in Europe rather than in Asia, mainly because of greater financial integration between Europe and the United States.

- Policy space limitations in Europe amplify the effects of higher financial integration, and the economic contraction in the U.S. economy becomes more severe.

Over the course of 2018, economic activity in major advanced foreign economies and emerging markets—including the euro area and China—decelerated noticeably. In parallel, foreign growth projections for 2019 and 2020 were revised down, signaling potentially large headwinds for the U.S. economy over the medium term. In this article we use a multi-country simulation model to quantify economic spillovers to the United States from a slowdown originating in the euro area. Next, we compare these results with spillovers from a slowdown originating in China. We find that spillovers to the U.S. economy from a slowdown in the euro area are sizable, mainly because of a lack of monetary policy space in the region along with greater financial integration between Europe and the United States. Standard trade-related spillovers to the United States from a slowdown in China, instead, are quantitatively limited.

The pace of global economic activity slowed down in the second half of 2018 owing to a variety of factors affecting the major economies, in particular, China and the euro area. Moreover, global growth forecasts for 2019 were revised down markedly. For example, the consensus forecast for annual euro-area GDP growth in 2019 dropped

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from 1.9 percent in mid-2018 to 1.1 percent at the beginning of 2019. Although U.S. domestic fundamentals were not projected to weaken at a similar pace, market participants promptly recognized that a global slowdown was bound to represent a significant source of macroeconomic headwinds for the U.S. economy. In this article, we provide a quantitative assessment of the extent to which these external developments could affect the U.S. macroeconomic outlook.

As a first pass to gauge the quantitative implications of foreign spillovers, we consider a number of model-based simulations adopting the SIGMA model, a multi-country dynamic stochastic general equilibrium (DSGE) model developed at the Federal Reserve Board for policy evaluation and scenario analysis. SIGMA offers a rich benchmark framework for the analysis of cross-border spillovers and trade interdependencies among countries. The model reflects current state of the art in terms of open economy modeling, and it serves our purpose of examining alternative scenarios in terms of different degrees of international financial markets integration among different economies and the possibility that economies might be constrained in terms of monetary policy space.[1]

Specifically, in our simulations we use a three-country version of SIGMA calibrated to a U.S. bloc, an advanced foreign economy (AFE) bloc, and an emerging market economy (EME) bloc. Given the three-bloc structure of the model economy, we assume that a slowdown in the GDP growth of the euro area or China leads to a decline in AFE or EME GDP growth by the same magnitude, respectively. Compared to the EME bloc, the AFE bloc is characterized by a relatively higher degree of trade and financial integration with respect to the United States. In the different regions covered in the simulations, monetary policies are assumed to follow inertial Taylor rules in which the nominal interest rate responds to the deviation of domestic inflation from the central bank's inflation target and to the deviation of output from potential output, subject to a zero-lower bound (ZLB) constraint.

To understand the interplay between limited policy space and higher financial integration within advanced economies, we proceed in two steps. We begin by considering a foreign slowdown (here, modeled as being due to a loss of consumer confidence that gives rise to a fall in consumption expenditure) when policy space in the AFE bloc is unrestricted and interest rates are above the ZLB. Next, we focus on the relevant case in which monetary policy in the AFE bloc is subject to the ZLB constraint. We consider two scenarios: In the first one, the global slowdown originates in the euro area (which is part of the AFE bloc); in the second one, the slowdown originates in China (which is part of the EME bloc). We find that the transmission of the China-led slowdown to the United States through trade and financial linkages is quantitatively limited, despite the fact that EMEs currently account for a large share of the global economy.[2]

The impact on the U.S. economy of a slowdown originating in the euro area is larger, mainly because of the greater financial integration within advanced economies. Intuitively, higher financial integration implies that the bulk of international adjustment occurs through a current account rebalancing: The contraction in total domestic demand in the AFE bloc generates larger capital outflows and more pronounced depreciation of the euro vis-à-vis the U.S. dollar. This translates into a bigger trade deficit in the United States and, hence, contributes to a more significant U.S. downturn compared with a similar slowdown originating in the EME bloc. When monetary policy space is limited in the AFE bloc, the effects of higher financial integration are amplified and the economic contraction in the U.S. economy becomes even more severe.

This article is organized as follows. Section 1 provides a brief overview of the model and characterizes the different regional blocs. Section 2 describes the recent performance of real GDP growth in major foreign economies. Section 3 outlines our quantitative experiments. Section 4 concludes.

1. Overview of the Model

The simulation exercises considered in this article are carried out by adopting SIGMA, the multi-country model used for international policy analysis at the Federal Reserve Board of Governors. Earlier vintages of the model are illustrated in detail in Erceg, Guerrieri, and Gust (2006), Erceg, Gust, and Lopez-Salido (2009), and Gust, Leduc, and Sheets (2009). The model adopts a medium-scale DSGE framework with financial frictions, where the latter are modeled à la Bernanke, Gertler, and Gilchrist (1999) by linking domestic credit spreads to entrepreneurs' net worth. The model includes numerous features that have been found to be critical for an empirically realistic response to a broad spectrum of domestic and international shocks (see, for example, Christiano, Eichenbaum, and Evans [2005], and Smets and Wouters [2007]): costs of changing the level of investment, habit persistence in consumption, and costs of adjusting trade flows. Final consumption and investment goods are produced using both domestically produced goods and imports. International financial markets are incomplete, in the sense that households' portfolio choices are restricted to borrowing or lending internationally a non-state contingent bond.

SIGMA features incomplete exchange rate pass-through from exchange rate changes to imported goods, consistent with the empirical evidence. This is because the model embeds demand curves with time-varying elasticities that induce strategic complementarity in price setting (see, for example, Kimball (1995) or Guerrieri, Gust, and Lopez-Salido (2010)). As a result, the desired markup in the model varies in response to fluctuations in the real exchange rate, which creates an incentive for firms to charge different prices in home and foreign markets (even under fully flexible prices). Prices and wages are set in staggered Calvo-style contracts, with prices set and invoiced in local currency in both domestic and foreign markets.

In each country bloc, monetary policy is assumed to follow an inertial Taylor rule in which the nominal interest rate responds to the deviation of domestic inflation from the central bank's inflation target and to the deviation of output from potential output. Nominal interest rates are subject to the ZLB constraint in the advanced economy bloc. There is an array of domestic and foreign shocks in the model, including shocks to permanent and temporary components of total factor productivity, markups, consumer confidence (implemented as shocks to the marginal utility of consumption of households), the foreign exchange risk premium, government expenditures, corporate spreads, and monetary policy.

The model is calibrated at a quarterly frequency. Most of the structural parameters are set at identical values for each of the three blocs, except for the parameters determining population size, the degree of trade openness, and the degree of financial integration. As discussed in Erceg, Guerrieri, and Gust (2006) in detail, the parameters governing the degree of openness are chosen such that U.S. imports are about 14 percent of GDP, and 55 percent of U.S. trade is with the EMEs in the simulations; both features are consistent with the data. The population levels are chosen such that the U.S. economy constitutes about 20 percent of world output, while the other advanced economies constitute 28 percent of world output.[3]

The model features incomplete international financial markets. Households in the AFE and EME blocs have access to a non-state contingent international bond, B_{Ft}, issued by the U.S. private sector and denominated in the U.S. currency. From the perspective of a generic economy, we assume that its households pay a cost when adjusting their holding of the foreign bond. By combining the log-linear version of the intertemporal Euler equations in the United States and the $j = AFE, EME$ countries, we obtain the modified uncovered interest parity equation, which is standard in incomplete market models:

$$e_t^{US-j} = E_t e_{t+1}^{US-j} + R_t^{nj} - R_t^n - \nu_F^j b_{Ft}^j,$$

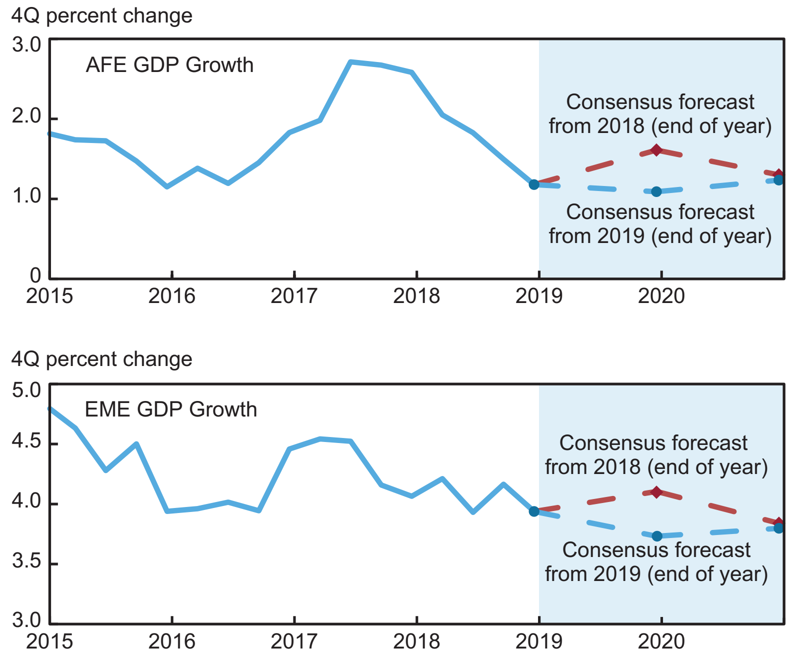
where ν_F^j captures the extent of financial markets' imperfection, since it governs the degree of the portfolio rebalancing cost paid by the households in region j. We assume that this cost depends on the ratio of economy-wide holdings of net foreign assets to nominal output, denoted by b_{Ft} in the model economy. The variable e_t^{US-j} denotes the bilateral nominal exchange rate between the United States and country *j* (that is, the price of a dollar in terms of country j's currency), R_t^n is the nominal policy rate in the U.S. economy, and and R_t^{nj} is the nominal policy rate in country *j*.

Differently from Erceg, Guerrieri, and Gust (2006), we assume that the elasticity of the exchange rate with respect to the net foreign asset position in each bloc, ν_F^j, differs across countries, so that we can capture different degrees of financial integration of the AFEs and the EMEs compared with the United States. In particular, we set the coefficient ν_F^{AFE} to a very small number to reflect the fact that financial frictions in borrowing or lending between the AFEs and the United States are very limited and financial markets are well integrated. Instead, this coefficient is set to a non-negligible constant for the EMEs to capture various possible international financial frictions between the U.S. economy and the EMEs that are not explicitly modeled in our quantitative framework.

2. The Recent Global Slowdown: Stylized Facts

As shown in Chart 1, foreign GDP growth decelerated in 2018, led mainly by a slowdown in the advanced foreign economies, after strong growth in 2017. Consensus growth forecasts for 2019 in both AFEs and EMEs were markedly revised down as well. As of the summer of 2019, advanced foreign economies are projected to slow down further in 2019, compared with the corresponding consensus forecast for 2019 at the beginning of 2018. Similarly, emerging economies are projected to slow down from a pace of around 4 percent to around 3.7 percent.

Chart 1
Foreign GDP Growth



Sources: *Consensus Forecasts*, Consensus Economics Inc.; Haver Analytics.

For reference purposes, these economies were expected to continue to grow just above 4 percent in 2019 based on projections elaborated in early 2018.

Focusing on individual countries, as shown in Table 1, euro-area GDP growth slowed down from 2.7 percent (year-over-year) in 2017 to 1.8 percent (year-over-year) in 2018. Moreover, consensus forecasts for euro-area GDP growth in 2019 were marked down from 1.9 percent (as of March 2018) to 1.1 percent, while forecast revisions for 2020 were more limited. EME growth forecasts were also revised down for the majority of the countries, China included. These recent revisions for 2019 and 2020, relative to the forecasts produced around the first quarter of 2018, represent the quantitative underpinnings and the motivation for the experiments we consider in the next section.

3. Model-Based Simulation Results

This section presents our simulation results. We start by illustrating the effects on the U.S. economic outlook of a decline in foreign demand, when policy space in the AFE bloc is unrestricted. The objective here is to understand the role of higher financial integration for the transmission of foreign shocks to the U.S. economy. We next consider a foreign slowdown when policy space in the AFE bloc is restricted.

Table 1
Annual GDP Growth in Selected Countries

			2019		2020	
	2017	2018	Consensus Mar-18	Consensus Apr-19	Consensus Jan-19	Consensus Apr-19
Euro Area	2.7	1.8	1.9	1.1	1.4	1.3
Japan	1.9	0.8	1.1	0.6	0.4	0.5
U.K.	1.9	1.4	1.5	1.3	1.6	1.5
Canada	3.0	1.8	1.9	1.5	1.8	1.7
China	6.8	6.6	6.3	6.2	6.1	6.1
Taiwan	3.1	2.6	2.4	2.0	2.1	2.0
Korea	3.2	2.7	2.8	2.4	2.4	2.4
Mexico	2.4	2.0	2.2	1.6	1.9	1.8
Brazil	1.1	1.1	2.9	1.9	2.6	2.6
EMEs	4.3	4.1	4.1	3.7	3.8	3.8
AFEs	2.3	1.5	1.6	1.1	1.3	1.2

Sources: Country GDP data: Instituto Brasileiro de Geografia e Estatistica, Statistics Canada, National Bureau of Statistics (CHN), Statistical Office of the European Communities, Business Office of Japan, Bank of Korea, INEGI (MX), Directorate-General of Budget, Accounting, and Statistics (TA), Office for National Statistics (UK); consensus forecasts are from Consensus Economics.

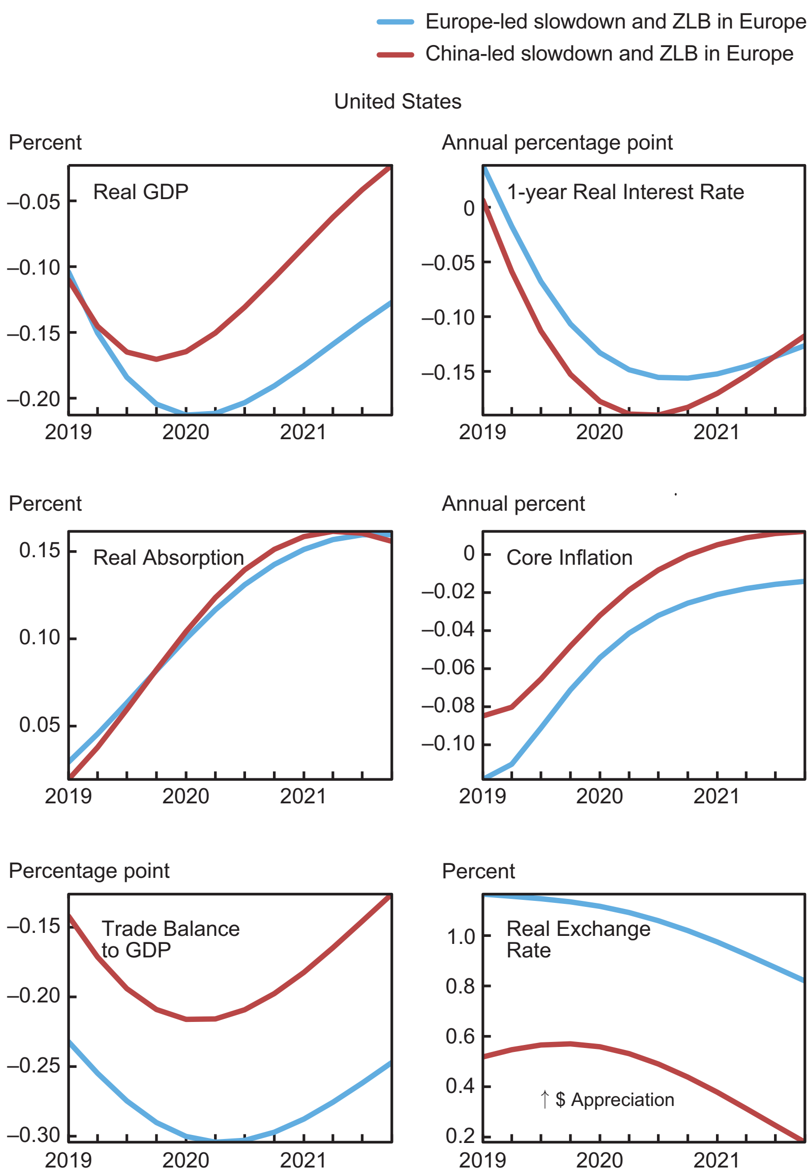
3.1 Effects of Slower Foreign Growth on the U.S. Economy

We consider two scenarios regarding the sources of slowdown in the global economy. In the first scenario, we examine a global slowdown that *originates* in the euro area and propagates to the whole AFE bloc, and we trace its spillovers to the U.S. economy and EMEs through standard trade linkages. Our second scenario entails a global slowdown that *originates* in China and affects symmetrically the other emerging market economies included in the EME bloc, before getting transmitted to the United States and AFE blocs. Under each scenario we consider a consumer confidence shock (defined as a shock to the marginal utility of consumption of households) that leads to a 1 percent decline in AFE or EME private consumption on impact.

As is briefly explained in Section 2, in the model economy, the United States is financially more integrated with the AFE countries than with the EME bloc. This happens because there are various possible international financial frictions between the U.S. economy and the EMEs, which are captured by deviations from the uncovered interest parity condition that are linked to the foreign asset position of the country in the model economy (that is, EMEs face a non-negligible and time-varying risk premium in their access to international financial markets, and this premium negatively co-moves with the net foreign asset position of the country).

Chart 2

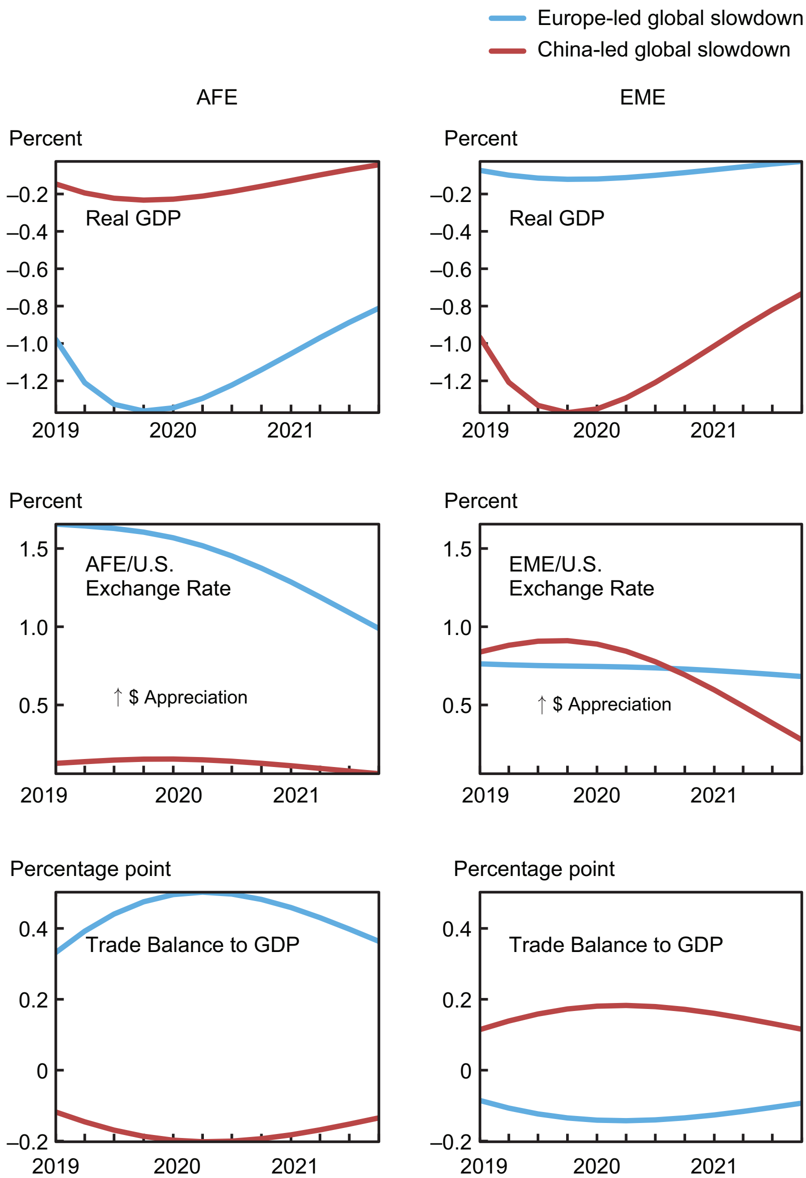
Lower Advanced Foreign Economy or Emerging Market Economy Demand (No-ZLB Case)



(Chart 2, continued on page 105)

The effects of the foreign slowdown on the U.S. economy and other foreign economies are shown in Chart 2. Blue lines correspond to the euro-area-led slowdown when policy rates in the AFE bloc are unrestricted. A shock is contractionary for the AFEs, leading to capital outflows from these countries to the United States and the EMEs, as reflected by their respective trade balance-to-output ratios shown in the chart. The trade balance improves in the AFE bloc and deteriorates in the United States and the EMEs. Capital outflows are associated with the

Chart 2 (Continued)



Source: Authors' calculations.

Notes: In the first six panels, the blue line (red line) shows the effects on the U.S. economy of a 1 percent decline in AFE (EME) consumption on impact when nominal interest rates are unconstrained. In the next six panels, the blue line (red line) shows the effects on the AFEs (the left column) and on the EMEs (the right column) of a 1 percent decline in AFE (EME) consumption on impact when nominal interest rates are unconstrained.

depreciation of the AFE currency vis-à-vis the U.S. dollar and EME currencies. Despite the fact that the weaker AFE currencies boost world demand for their firms' exports, real GDP in the AFEs declines on impact and continues to deteriorate through mid-2020. Lower total foreign demand (note that the AFE shock is contractionary for the EMEs as well) and a stronger U.S. dollar cause U.S. net exports to fall. U.S. real interest rates rise for a very short period of time before falling persistently below the steady-state level, leading to a slight increase in U.S. domestic absorption. On net, U.S. real GDP decreases by about 0.25 percent throughout mid-2020. Core inflation in the United States falls about 0.15 percentage point due to a combination of lower economic activity in the United States and lower import prices (owing to appreciation of the dollar).

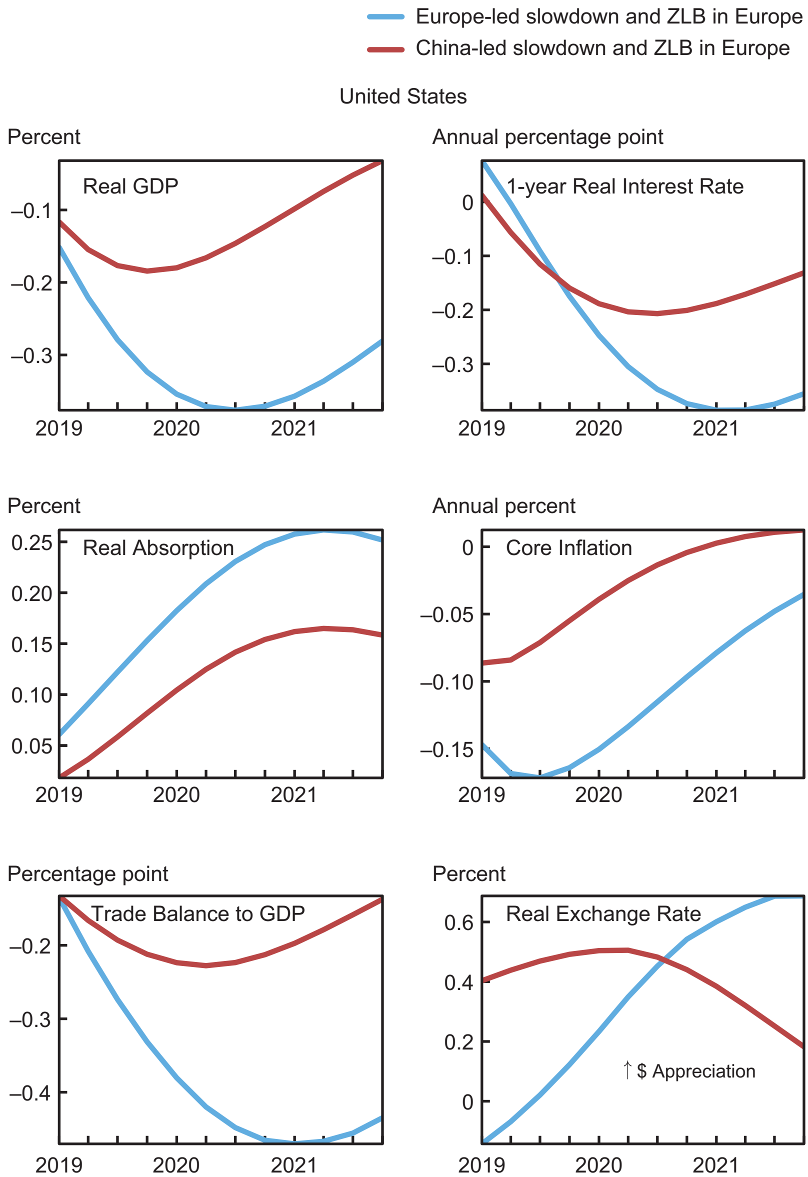
Our second scenario, which entails a steady slowdown in China, affects the U.S. economy through similar channels, but the overall size of spillovers is much smaller. The effects of the China-led EME slowdown on the United States are shown in Chart 2, with red lines for the case of unrestricted policy rates abroad. The shock is contractionary for the EMEs, leading to capital outflows from these countries to the United States, but as reflected in the smaller improvement in the trade balance-to-output ratios for the EMEs, capital outflows from EMEs are smaller under this scenario. As a result, the U.S. dollar appreciates less vis-à-vis the EME currencies, leading to a smaller contraction in U.S. net exports and GDP. Note that foreign demand decreases by a similar magnitude under both scenarios. However, in response to falling foreign demand and slower growth, the expenditure-switching effects on the U.S. economy are much smaller under this scenario. This is because U.S. goods are now less expensive from the vantage point of the foreign economies, reflecting the relatively moderate appreciation in the U.S. dollar. U.S. real interest rates fall, as in the previous scenario, and U.S. domestic absorption increases slightly. Note that domestic absorption improves less under this scenario owing to smaller decreases in import prices. For similar reasons, core inflation in the United States falls by less under this scenario compared with the one in which global slowdown originates in the euro area.

Overall, the impact of the shock on the United States is more pronounced under the scenario in which the foreign demand shock originates in the euro area compared with the scenario in which the shock originates in China. A key factor contributing to the stronger negative spillover is the fact that the U.S. economy is financially more integrated with the AFE countries than with the EME bloc.

3.2 Spillovers and Availability of Policy Space Abroad

Other things equal, the magnitude of the spillovers is crucially affected by the availability of policy space abroad, as summarized in Chart 3. In this section, we consider what happens when nominal interest rates are subject to the ZLB constraint in the AFE bloc (which is a more realistic case to consider given the fact that there is limited policy space in several advanced foreign economies). As before, the blue lines in the chart depict the global impact of the euro-area-led slowdown. Different from above, our simulation results now explicitly consider situations in which AFE policy rates are constrained by the ZLB. In the same chart, red lines plot the simulation results for the China-led EME slowdown under the assumption that the monetary authorities in the AFE countries are unable to cut their policy rates further down

Chart 3
Lower Advanced Foreign Economy or Emerging Market Demand (ZLB Case)

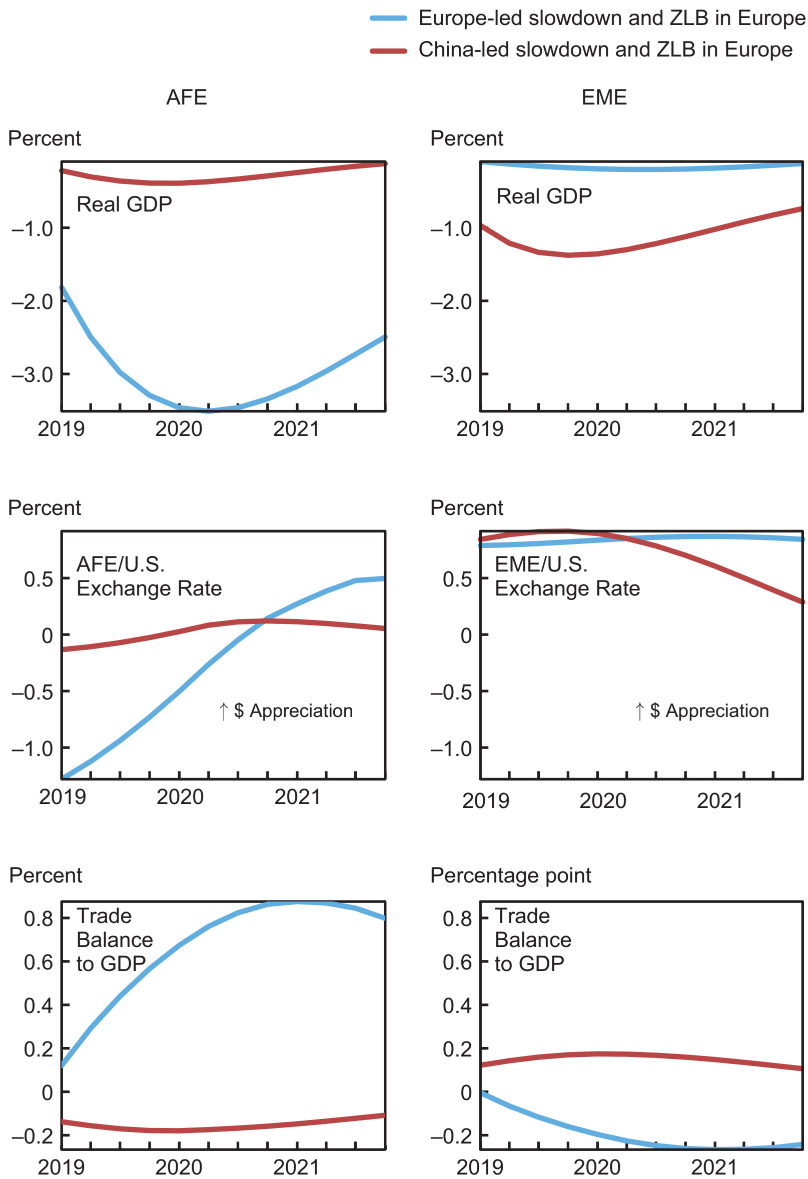


(Chart 3, continued on page 108)

below the baseline path. Under each scenario, we continue to consider a consumer confidence shock that leads on impact to a 1 percent decline in AFE or EME private consumption if nominal rates were not constrained.

Reduced policy space abroad has key implications for the transmission of the global slowdown to the U.S. economy through standard trade linkages, to the extent that the shock originates in the euro area. This shock is now severely contractionary in the AFEs, since the policy rate cannot

Chart 3 (Continued)



Source: Authors' calculations.

Notes: In the first six panels, the blue line (red line) shows the effects on the U.S. economy of a shock equivalent to a 1 percent decline in AFE (EME) consumption on impact if nominal rates were unconstrained. In this simulation we assume that AFE policy rates are constrained by the ZLB. In the next six panels, the blue line (red line) shows the effects on the AFEs (the left column) and on the EMEs (the right column) of a shock equivalent to a 1 percent decline in AFE (EME) consumption on impact if nominal rates were unconstrained. In this simulation we assume that AFE policy rates are constrained by the ZLB.

be cut below the effective lower bound to stimulate economic activity. As a result, net capital outflows are almost twice as large as the net outflows obtained under the unconstrained policy case (similarly, we have a larger improvement in the AFE trade balance-to-output ratio). A fall in AFE GDP causes the level of U.S. GDP to decrease through lower foreign demand (note that the AFE shock is contractionary for the EMEs as well). Unlike in the unrestricted monetary policy case, the real broad dollar slightly depreciates on impact, reflecting the greater divergence between the monetary policy rates in the United States (which can be reduced to stimulate the economy) and the AFEs (whose policy rates are stuck at the ZLB). In fact, AFE currencies vis-à-vis the U.S. dollar *appreciate* by around 1 percent on impact, while they *depreciated* around 1.5 percent in the unrestricted policy case. Conditional to a restricted AFE policy rate, the combination of an initial depreciation in the U.S. dollar and a much shallower path for the appreciation of the dollar thereafter tends to mitigate the drop in U.S. output. U.S. real interest rates now decline more, providing more stimulus for U.S. private absorption and aggregate demand. Nonetheless, the expenditure-reducing channel of lower foreign demand dominates, and U.S. real GDP decreases around 0.4 percent by mid-2020. U.S. core inflation decreases a bit more because of much lower economic activity, despite the fact that U.S. import prices fall less.

As above, the China slowdown has a relatively muted impact on the U.S. economy through standard trade linkages. The impact of the initial shock on the foreign economies is somewhat amplified under the scenario of a China-led slowdown owing to limited policy space in the AFEs. Yet, the overall size and the channels of spillovers to the United States from a slowdown in foreign economies are not very dissimilar across policy scenarios.

4. Conclusion

We have studied the impact of a foreign slowdown on the U.S. economy through the lens of a multi-country DSGE model developed at the Federal Reserve Board. In order to assess the role of financial integration in the global transmission of shocks, we have first considered a foreign slowdown scenario when policy space in the AFE bloc is unrestricted and interest rates are above the ZLB. We have considered two sources of global slowdown: In the first one, the source of slowdown originates in the euro area, which is financially more integrated with the U.S. economy; in the second one, a slowdown originates in China, which is less integrated with the U.S. economy. We assume that foreign demand decreases by a similar magnitude under both scenarios. Our simulations suggest that the impact on the United States of a global slowdown is stronger if the shock originates in Europe rather than in Asia, an intuitive result in light of the greater financial integration that characterizes the transatlantic economy. Under higher financial integration, in fact, international adjustment occurs through a current account rebalancing: The contraction in domestic demand in the AFE bloc translates into a bigger trade deficit in the United States, thus contributing to a more significant U.S. downturn compared with the scenario depicting an equivalent slowdown in the EME bloc. We next considered a scenario analysis where policy space in the AFE bloc is restricted in order to assess the role of limited policy space in the advanced economies outside the United States. When policy space is limited, the effects of higher financial integration are amplified, and the economic contraction in the U.S. economy becomes more severe.

Notes

[1] As any model, SIGMA has limitations: here we emphasize that the model tends to understate the importance of financial amplification effects across countries because of its simplified international financial market structure. To allow for a more realistic treatment of key financial frictions, the simulations need to include exogenous financial shocks. Similarly, it does not fully capture the complexity of the trade interaction among countries in terms of global value chain and currency- invoicing in firms' price-setting behavior.

[2] When measured in terms of purchasing parity power, the share of China's GDP in world GDP (19.18 percent) overtook that of the United States (15.01 percent) in 2014.

[3] The calibration of the two-country version of the model is presented in Erceg, Guerrieri, and Gust (2006).

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