ASSESSING THE GLOBAL IMPACT OF THE CHINESE ECONOMY*

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We study the global impact of the Chinese economy indirectly with a forecast error model. The novel application of this model type builds on the discovery of an equivalence between causal influence and the channel from data revisions of the causing variable to forecast errors of the caused variable. Empirical findings using the real-time World Economic Outlook dataset over the period 2004–15 indicate that real GDP growth spillover from China to other countries was primarily negative in the short to mid-term perspective. However, the estimations furthermore reveal a changing pattern of spillover across countries and time. While negative spillover was prevalent during the global financial crisis, spillover was mostly positive during the rest of the sample period.

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I. Introduction

The present paper contributes quantitative estimates of the effect of real GDP growth in China on that of other countries. The global financial crisis brought to focus the importance of international spillovers for economic policy. Recently, the global impact of the ongoing economic transformation of China, the largest goods exporter, has been of significant concern.[2] The discussion about spillover from the large and dynamic Asian economy is sharply divided, broadly along the lines of findings from the main alternative empirical approaches. The view that economic growth in China tends to benefit other economies is consistent with much of the previous econometric evidence that builds on country level data (Dizioli et al 2016; Feldkircher and Korhonen 2014; Arora and Vamvakidis 2011). At the same time, however, concerns that the Chinese economy grows at the cost of jobs especially in the developed world find support from studies using micro (firm level) data (Pierce and Schott 2016; Bloom et al 2016).

The divergence in views is, in part, symptomatic of the difficult identification and aggregation issues that challenge empirical work on spillover. Micro data holds the promise of strong identification with quasi experimental designs that utilize cross sectional variation across agents. Due to the scarcity of suitable data, however, aggregation of the results to the global or even national levels can pose a difficult challenge. Aggregation is less of an issue in work that utilizes widely available country level time series, but significant concerns have been voiced about the strength of identification in the context of the global economy, where the number of causal relationships is large and, realistically, partly unknown to

[2] Wall Street Journal (31.1.2019) China’s Slowdown Hits Growth Around the Globe; Financial Times (14.1.2019) The Impact of China’s Economic Slowdown is Spreading; BBC News (4.1.2019) China’s Economic Slowdown: How Worried Should We Be?; Scott R Mokhiber Z (2018) The China Toll Deepens, Economic Policy Institute.

the econometrician. Standard regression techniques including the Global Vector Autoregressive model (GVAR, Pesaran et al. 2004) are therefore susceptible to both degrees-of-freedom problems and omitted variable bias (Bai et al 2016). The factor augmented VAR (FAVAR, Bernanke et al. 2005) can in principle resolve these issues, but only under strong assumptions about the structure of the global economy.

To achieve strong aggregation and identification, we propose a novel empirical strategy where spillover is quantified from real-time GDP data indirectly, using a forecast error model. In the model, the endogenous variable is the error in the forecasts by the International Monetary Fund (IMF) regarding the real GDP growth rate of the countries that are target to spillover from China. The main explanatory variable is the (lagged) Chinese real GDP growth rate data revision. This novel application of a forecast error model builds on what we for further benefit refer to as 'Denton–Kuiper equivalence' ('*D–K equivalence*'). They find (Denton and Kuiper 1965)[3] that the impact of a data revision of a causing variable on the forecast error of the caused variable is equal to the strength of the causal interaction (see Trivellato and Rettore 1986 for a restatement in a systemic context).

The novel empirical approach integrates Denton and Kuiper's (1965) finding with two main recent strands of literature. Suarez Serranto and Wingender (SS&W, 2016) and Chodorow-Reich et al (C-R et al, 2019) use data revisions of the causing variable as shocks to identify causal effects. They show that if the data revisions are random identification can be achieved with a regression model of the caused variable which uses the data revision as a shock variable. We contribute to this work by showing that identification may be further strengthened if in the empirical model the caused variable is replaced by its forecast error.

[3] This is eq 14.of their paper.

Under *D–K equivalence*, the replacement of the caused variable with its forecast error does not change the interpretation of the estimated causal parameter. In the forecast error model the parameter estimate is unbiased if data revisions are random (as in SS&W 2016 and C-R et al 2019) or if the forecaster successfully controls for other contributing factors except the causal factor of interest in its forecast of the caused variable.

The paper furthermore integrates Denton and Kuiper's (1965) result with the innovative analysis by Blanchard and Leigh (2013). The latter use a forecast error model to make inference about a causal parameter (the fiscal multiplier), namely whether the parameter is smaller or larger than what the forecaster is using in her model. They are, however, not able to quantify the causal effect. We show that, under *D–K equivalence,* the causal effect can be quantified by including the data revision of the causing variable as an additional explanatory variable in the forecast error model. The conditions to identify the causal effect are less stringent than those that are needed to identify forecast bias.

The proposed indirect forecast error approach to estimate causal effects is therefore well suited for situations, where omitted variable bias is difficult to avoid under traditional regression analysis due, for example, to a large number of or unknown causal factors. Forecasts of the caused variable by well-informed professionals and the real-time data of the causing variable are also needed. Such is the case when studying GDP spillovers. The World Economic Outlook database records the GDP growth forecasts of the IMF along with the real time data for over 170 countries. We use this data for the estimations of GDP spillover from China to these countries over the period 2004–15.

The estimations yield the finding that, overall, GDP spillover from China was negative in most countries. However, the estimations furthermore reveal a fluid pattern of spillover across countries and time. While negative spillover was prevalent during the global financial crisis, spillover was mostly positive during the rest of the sample period. The finding of significant across country variation in spillover is consistent with earlier empirical work, such as Dedola et al (2017).

While our estimations do not reveal the spillover channels, we speculate that negative spillover may be indicative of supply side shocks to Chinese GDP. Such shocks could have been generated by policy-induced changes in the speed of technological catch-up of China with the developing world, and macro policies such as foreign exchange policy that favored Chinese firms over their global competition. This view is in particular supported by the apparent sharp strengthening of the negative spillover during the global financial crisis when macro policies in China were very accommodative. It has previously been shown (Cwik et al 2011; Deuven and Pieters 1998) that expansionary monetary and fiscal policies have the potential to cause negative spillover in other countries.

Below we formalize the empirical approach, and then present the estimation results. A discussion of our views on future work concludes.

II. The empirical approach

A. The Estimable Equation

Consider the model

$$Y_{t+1} = \alpha_1 + \alpha_2 China_t + \alpha_3 Other_t + \epsilon_{t+1} \quad (1)$$

, where Y indicates the real GDP growth rate of some country of interest; $China$ indicates the real GDP growth rate of China; $Other$ captures all other systematic factors that cause Y; ϵ is white noise; and α are unknown parameters. The focus of interest is the parameter α_2 which indicates the causal influence of $China$ on Y, the GDP spillover from China.

In principle, estimation of α_2 is straightforward linear regression. However, construction of the vector $Other$ is a difficult challenge, as it encompasses a potentially large number of controls, some of which may be unknown. Since we aim to estimate α_2 for over 170 countries, the construction task seems in practice impossible.

As it is well known (Clarke 2016, 2005), regression analysis using (1) may therefore lead to poor results, because un-modeled correlation between $China$ and $Other$ may bias the estimate $\widehat{\alpha_2}$. The omitted variable bias is:

(2) $$\widehat{\alpha_2} - \alpha_2 = \alpha_3 * corr(China_t, Other_t)\sqrt{\frac{var(Other)}{var(China)}}$$

, where $corr$ indicates correlation and var variance. Since $China$ and $Other$ are contemporaneous and thereby affected by common economic events, they are likely to be correlated. Since $Other$ is not observed, the size or direction of the omitted variable bias is, in this case, unknown.

While therefore lacking the information to credibly estimate α_2 via (1), we note that the IMF seems to be in a much better position informationally. It actively monitors the countries of interest, and has access to a wide range of both public and private information about them. Furthermore, since its country analysis has evolved under independent audition and public scrutiny for decades, substantial 'institutional knowledge' may be embedded in its processes. The IMF publishes regularly GDP forecasts of its member countries. Might it be possible to somehow extract from its GDP forecasts the information needed to estimate α_2?

To investigate this issue, we need to make assumptions about the IMF forecast process. It would be tempting to assume that IMF forecasts are rational, but that might be too strong. For what follows a necessary assumption is '*linearity*', namely that the IMF forecast process can be approximated by a linear function:

(3) $$F_t^{IMF} Y_{t+1} = \alpha_1^{IMF} + \alpha_2^{IMF} China_{t|t} + \alpha_3^{IMF} Other_{t|t}$$

, where F_t^{IMF} indicates a forecast based on information possessed by the IMF at t; $China_{t|t}$ and $Other_{t|t}$ are real-time data of $China$ and $Other$ available to the IMF at t; and $\alpha^{IMF}$are the (unknown) parameters embedded in the IMF forecast process which may or may not correspond with the correct parameters. We omit random noise from the right hand side of (3) for simplicity. Another subtle point is that since (3) is an approximation of the forecasting process of the IMF, which involves both judgement and models, rather than a statement about a specific econometric model, it may not be transparent even within the IMF.

By subtracting (3) from (1) we get the error of IMF forecasts:

$$\text{(4)} \qquad \begin{aligned} Y_{t+1} - F_t^{IMF} Y_{t+1} = \alpha_1 - \alpha_1^{IMF} \\ +\alpha_2 China_t - \alpha_2^{IMF} China_{t|t} \\ +\alpha_3 Other_t - \alpha_3^{IMF} Other_{t|t} + \epsilon_{t+1} \end{aligned}$$

The forecast error equation (4) can be further rephrased by simple algebra in a useful way:

$$\text{(5)} \qquad \begin{aligned} Y_{t+1} - F_t^{IMF} Y_{t+1} = \alpha_1 - \alpha_1^{IMF} \\ +\alpha_2\left(China_t - China_{t|t}\right) \\ +(\alpha_2 - \alpha_2^{IMF}) China_{t|t} \\ +\alpha_3 \left(Other_t - \frac{\alpha_3^{IMF}}{\alpha_3} Other_{t|t} \right) + \epsilon_{t+1} \end{aligned}$$

The rephrased forecast error equation (5) shows that, under the *linearity* assumption, access to IMF forecasts and real time data affords the possibility to approach the estimation of α_2 from an alternative point of view. Rather than studying the influence of the Chinese economy on other countries directly via (1), we can approach the problem indirectly by studying IMF forecast errors. Part of that error is caused by data revisions regarding $China$. The spillover parameter α_2 can alternatively be interpreted as the strength of this channel. This result is a special case of the result by Denton and Kuiper (1965) as discussed in the introduction.

However, Eq. (5) still includes the unobserved variable ‘modelling error of the IMF’ regarding other factors except spillover ($Other_t - \frac{\alpha_3^{IMF}}{\alpha_3} Other_{t|t}$). Does this mean that the indirect forecast error approach (5) is as affected by missing variable bias as the direct approach (1)?

If the unobserved IMF modelling error is omitted from (5) in empirical estimations, the resulting estimate $\widehat{\alpha_2}$ may, indeed, be biased. Based on Clarke (2005), the bias is in this case:

$$\widehat{\alpha_2} - \alpha_2 = \alpha_3 * \sqrt{\frac{var\left(Other_t - \frac{\alpha_3^{IMF}}{\alpha_3} Other_{t|t}\right)}{var\left(China_t - China_{t|t}\right)}} * \left\{ \frac{corr\left(China_t - China_{t|t}, Other_t - \frac{\alpha_3^{IMF}}{\alpha_3} Other_{t|t}\right)}{1 - corr\left(China_{t|t}, China_t - China_{t|t}\right)^2} - \frac{corr\left(China_{t|t}, China_t - China_{t|t}\right) * corr\left(China_{t|t}, Other_t - \frac{\alpha_3^{IMF}}{\alpha_3} Other_{t|t}\right)}{1 - corr\left(China_{t|t}, China_t - China_{t|t}\right)^2} \right\} \tag{6}$$

We note from (6), however, that the bias is negligible if data revisions and IMF modelling errors are uncorrelated with each other and either one of them is uncorrelated with the real time variable. Under this ‘*uncorrelated*’ -assumption, the last two terms on the right of (6) (in line brackets) vanish and take the omitted variable bias with them.

For the remainder of the paper, we assume that the ‘*uncorrelated*’ assumption regarding data revisions or IMF modelling errors holds as a reasonable approximation. Accordingly, we estimate for each country the following regression model:

(7) $Y_{t+1} - F_t^{IMF} Y_{t+1} = \beta_1 + \alpha_2\left(China_t - China_{t|t}\right) + \beta_2 China_{t|t} + \varepsilon_{t+1}$

, where β are parameters and $\varepsilon_t = \alpha_3\left(Other_t - \frac{\alpha_3^{IMF}}{\alpha_3} Other_{t|t}\right) + \epsilon_{t+1}$. Equation (7) is obtained from (5) by moving the unobserved modelling error of the IMF $\left(Other_t - \frac{\alpha_3^{IMF}}{\alpha_3} Other_{t|t}\right)$ into the residual. Under the *linear* and *uncorrelated* assumptions, regression analysis of (7) yields an unbiased estimate of α_2.

Notice that, since these two assumptions do not guarantee that the real time variable and the unobserved IMF modelling error variable are orthogonal, the estimate of β_2 may be subject to omitted variable bias ($\beta_2 \neq \alpha_2 - \alpha_2^{IMF}$). We shall therefore focus the discussion on α_2 and not discuss the estimate of β_2 in any detail. The conditions under which β_2 is identified in the context of a forecast error model are discussed by Blanchard and Leigh (2013). A priori, it is not clear whether and in which way the inclusion of the real time variable ($China_{t|t}$) in (7) contributes to the estimation of the spillover parameter. We shall investigate this issue empirically.

B. Finite sample properties

By transferring $F_t^{IMF} Y_{t+1}$ from the left to the right hand side of (7) the endogenous variable of the empirical model becomes the caused variable itself:

(8) $Y_{t+1} = \beta_1 + \alpha_2\left(China_t - China_{t|t}\right) + \beta_2 China_{t|t} + F_t^{IMF} Y_{t+1} + \varepsilon_{t+1}$

The restatement (8) of our empirical model (7) is equivalent to the model used by SS&W (2016)[4] except that they omit $F_t^{IMF} Y_{t+1}$ and $\beta_2 China_{t|t}$ on the right hand side. The finite sample properties of their approach are therefore similar to those of the present approach, except for the two additional missing variables. This link between the two models can be exploited to compare the finite sample properties of the two approaches.

[4] See equation (6) of their paper. Apart from the subject matter, the other differences are that they 'clean' the data revisions from any systematic elements, and they do not include the real time variable in the model.

For simplicity, we abstract in the discussion from the presence of the real time variable ($China_{t|t}$) in (8) which only has a second order influence on the issue.[5] Therefore, based on (2), the missing variable bias in the spillover parameter estimate obtained from our empirical model (8) (which omits $\alpha_3\left(Other_t - \frac{\alpha_3^{IMF}}{\alpha_3} Other_{t|t}\right)$) is equal or smaller than under the approach by SS&W (2016) (which omits $\alpha_3\left(Other_t - \frac{\alpha_3^{IMF}}{\alpha_3} Other_{t|t}\right) + F_t^{IMF} Y_{t+1}$) if:

(9)
$$abs\left[corr\left(China_t - China_{t|t}, \alpha_3(Other_t - \frac{\alpha_3^{IMF}}{\alpha_3} Other_{t|t})\right)\right] \leq abs\left[\sqrt{\frac{var\left(\alpha_3(Other_t - \frac{\alpha_3^{IMF}}{\alpha_3} Other_{t|t}) + F_t^{IMF} Y_{t+1}\right)}{var\left(\alpha_3(Other_t - \frac{\alpha_3^{IMF}}{\alpha_3} Other_{t|t})\right)}} * corr(China_t - China_{t|t}, \alpha_3(Other_t - \frac{\alpha_3^{IMF}}{\alpha_3} Other_{t|t}) + F_t^{IMF} Y_{t+1})\right]$$

, where *abs* gives the absolute value. Based on (9) the present approach (8) is preferable to the alternative approach if data revisions are not white noise but IMF modelling errors are white noise. In that case, omitted variable bias is negligible under (7) but not under the SS&W (2016) approach. The present approach and the SS&W (2016) approach are on even footing if data revisions are white noise. In that case, both approaches yield unbiased estimates of spillover.

If the *independence* assumption is violated so that neither data revisions nor IMF forecast errors are white noise, then the relative merits of the two approaches depend essentially on whether the data revisions correlate more strongly with IMF modelling errors (the present approach) or the sum of IMF modeling errors and its GDP forecasts (SS&W 2016 approach). While this is in general unknown, we

[5] Under the presence of the real time variable, the right hand side of (9) also includes the negative of the correlation between the data revision and the real time variable, multiplied by the covariance differential between the direct and the indirect model of the real time variable.

speculate that the present approach is preferable in the present context. Namely, since variation in $\alpha_3(Other_t - \frac{\alpha_3^{IMF}}{\alpha_3} Other_{t|t}) + F_t^{IMF} Y_{t+1}$ is most likely dominated by the latter term, the comparison (9) is in essence between correlation of data revisions and IMF modeling errors on the left (under the present approach) and correlation of data revisions and IMF forecasts on the right (under the SS&W 2016 approach). In case data revisions of Chinese real GDP growth are not white noise but, rather, influenced by economic fundamentals, then the former seems a far safer bet.

The previous empirical literature is not in contrast with the view that the novel indirect forecast error approach may be preferable in finite samples compared to the other approaches. Some related empirical evidence on the issue is provided by Aruoba (2008) and Faust et al (2005) who show that, while GDP data revisions are not necessarily white noise, their correlation with economic variables tends to be low– i.e. mostly auto-correlation as opposed to cross correlation. As regards GDP statistics in China, in particular, Holz (2014) finds in his careful study no significant evidence of falsification or bias regarding the period of interest. Furthermore, IMF forecasts tend to earn relatively high marks as regards unbiasedness by the auditors (IEO 2014).

III. Empirical analysis

A. The data

The estimation data is from the World Economic Outlook (WEO) database of the IMF, which provides access to forecasts and real time data. The start year of the estimation sample (2004) is the first year for which the necessary data are available for a large number of countries. The end year (2015) is selected so that, realistically, sufficient time has elapsed for the statistical authorities to provide a reasonable estimate of real GDP growth by 2018, which we use as the final data year. The length of time needed between the last real time data year and the final data year was selected based on the dynamics of squared data revisions in the WEO. For the relevant estimation years, the median squared data revision is no longer increasing after three years from the first real time data has passed.

For the benchmark model, the final data is taken from the April 2018 data vintage and April vintages are also used for the real time data. We use the term ‘observation year’ to indicate the year when the WEO came out. Since the April WEO is prepared at the start of the year, we use as the dependent variable ($Y_{t+1} - F_t^{IMF}Y_{t+1}$) the IMF forecast error of real GDP growth during the observation year. For example, the forecast error for the observation year 2014 is computed by diluting from the real GDP growth rates given in the April 2018 WEO regarding year 2014 the forecast of real GDP growth given for the year 2014 in the April 2014 WEO. The data revision variable ($China_t - China_{t|t}$) indicates the year that precedes the observation year. For example, the data revision for observation year 2014 is computed by diluting from the real GDP growth rate of year 2013 given in the April 2018 WEO the real time estimate of real GDP growth in 2013 given in the April 2014 WEO. Real time GDP growth ($China_{t|t}$) is measured correspondingly: for example the real time GDP growth rate for the observation year 2014 is the real GDP growth rate of year 2013 given in the April 2014 WEO.

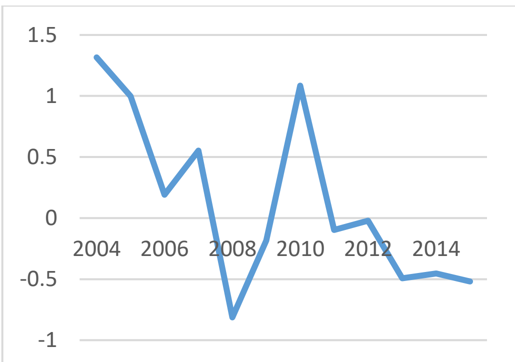
The IMF forecast errors and data revisions tended to be positive during the observation period (Table 1): the former by 0.14 pp, and the latter by 0.5 pp on average. The biases are not very large in relative terms: the median forecast error is less than 4 percent of the median forecast, and Chinese GDP data revision is about 5 percent of the average Chinese (real time) GDP growth rate during the sample period. In any case, since the empirical model has a constant term, identification is not sensitive to a positive or negative overall bias in forecasts or data revisions.

TABLE 1—DATA DESCRIPTION

	median	N
IMF forecast error of real GDP growth at t	0.14	2113
Data revision of Chinese real GDP growth at t-1	0.51	12
Real-time Chinese real GDP growth at t-1	9.1	12
Real GDP growth at t	4.0	2119

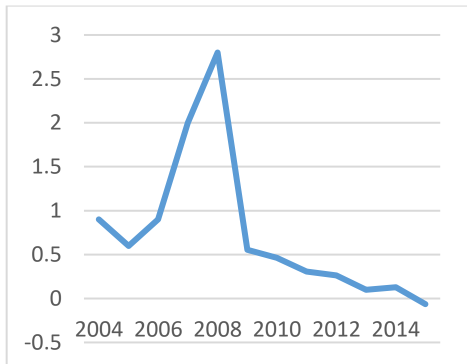
Notes: The first row of the second col indicates in pp the median error in the IMF forecasts of real GDP growth in 177 countries published in April WEOs of years 2004-2015 regarding the publication year; The second row of the second col indicates the median data revision in pp of Chinese real GDP growth across years 2003-2014; The third row of the second col is the median real GDP growth rate of China in percent during years 2003-20114; The fourth row of the second col is the median growth rate in percent of real GDP during years 2004-2015 for 177 countries; The third col gives the related numbers of observations. Data Source: IMF world economic outlook database..

FIGURE 1. AVERAGE REAL GDP GROWTH FORECAST ERROR BY THE IMF



Notes: Average error in real GDP growth forecasts across countries given in the April WEO of the forecast year. Real GDP growth given in the April 2018 WEO is used as the correct data; Units: pp; Data source IMF WEO

FIGURE 2. REVISIONS OF CHINESE REAL GDP GROWTH RATES



Notes: Data revision of real GDP growth in China. Real GDP growth given in the April 2018 WEO is used as the correct data. The real time data is from the April vintage of each observation year; Units: pp; Data source IMF WEO

More worryingly, forecast errors (Figure 1) and the data revisions (Figure 2) show significant variation in time that appears non-random. Namely, average forecast errors show signs of positive autocorrelation and data revisions show both clustering and a significant downward trend especially during the final part of the sample.

From the pow of the identification assumptions of the empirical model (7), the possible non-random dynamics of the endogenous variable may not be a major concern. Positive autocorrelation could be generated, for example, if IMF forecasts build on a biased constant term and spillover parameter, neither of which affects identification. However, non-random dynamics of the endogenous variable might also be indicative of systematic IMF modelling errors regarding the other contributing factors except spillover. Such errors may affect identification, if at the same time data revisions are also not random. We explore the robustness of our estimation results to these issues empirically based on de-trending techniques and by exploiting variation in data revisions across the April and October data vintages.

B. Estimation results

Estimation with the benchmark model yields the main result (Model 1 in Table 1, col 2) that spillover from China was, in median terms, negative during the observation period at about -0.09. The estimated 177 country level models explain on average just under a third of the variation in GDP growth rates across countries. The fourth column of Table 1 gives the sum of p -values across the country models as an indication of how many countries experienced significant spillover from China. In the benchmark model the number is 87 countries, or just under a half. The reduced model where the real time variable has been dropped, yields very similar results.

TABLE 2—MAIN ESTIMATION RESULTS

	$\widehat{\alpha_2}$	R^2	sum(p)
Model 1 benchmark	-0.09	0.29	87
Model 2: reduced, omits real time variable	-0.07	0.29	85
Model 3: subsample 2004-7 & 2014-15	0.52	0.24	34
Model 4: subsample 2008-13	-0.3	0.16	41

Notes: Estimations based on Eq. 7 by OLS at country level for 177 countries 2004-15 unless otherwise stated. All models builds on Eq. (7). In Models 2, 3 and 4, the real time variable is omitted. The second column gives the median spillover estimate and the third column the median R^2 across countries. The fourth column is the sum of p values of the spillover parameter across countries. Data Source: WEO April vintages.

While we therefore conclude that, overall, spillover was negative on average, sub-sample estimations reveal a more nuanced picture (Models 3 and 4). To explore how spillover changed during the observation period, we divide the sample in two roughly along the lines of the global financial crisis. Each subsample only has six observations per country, so we omit the real time variable from these models to save degrees of freedom. The sub-sample estimations indicate that negative spillover was prevalent, in particular, during the global financial crisis period 2008–13 (Model 5). During the rest of the sample, spillover from China was predominantly positive (Model 4).

The country level spillover estimates are reported in Table A1 (Annex) for Models 1, 3 and 4, and Figure 3 displays the spillover estimates from Model 1. As regards the country level results, the main finding is that the analysis does not produce a stable spillover pattern. Rather, a complex picture of spillover emerges which varies both across countries and time. For example, the spillover estimates from the ‘non-crisis’ subsample (Model 4) are broadly uncorrelated with the estimates regarding the sample that covers the global financial crisis (Model 5). We leave further analysis of this issue for future efforts.

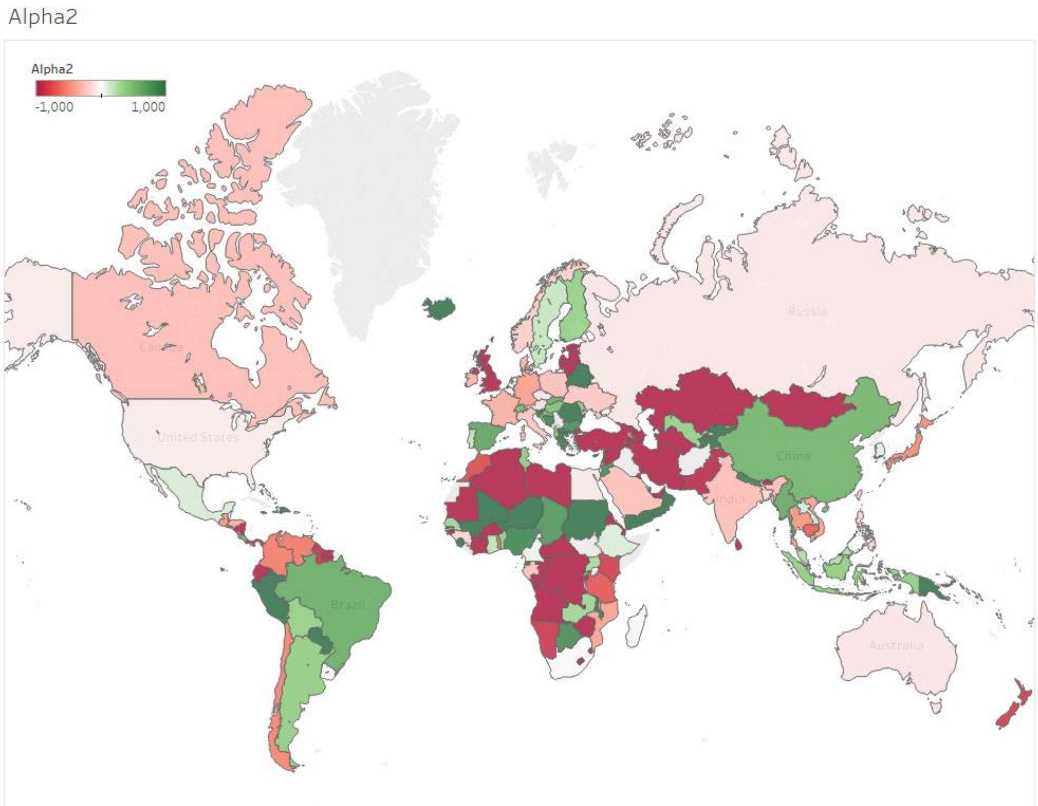


FIGURE 3. ESTIMATES OF α_2 INDICATING GDP SPILLOVER FROM CHINA

Notes: Estimation based on Eq. (7); Negative spillover in red and positive spillover in green. Strength of spillover is indicated by the shade of the color, except that all spillover estimates in excess of 1 and below -1 are shown in the darkest color category. Data source: Own calculations. We thank Jonna Elonen-Kulmala for drawing the Chart.

C. Further robustness tests

To explore the robustness of these findings to possible irregularities in the data revisions, we estimate a model with de-trended and de-meaned data revisions (Model 5). This model does not challenge our main estimation result that spillover was negative overall.

We furthermore study the issue by exploiting variation in real time data within the revision period (from the initial data and the final data). The approach builds on a decomposition of the data revision into two components, namely the ‘late revision’ that occurred after the October vintage of the observation year

$(China_t - China_{t|t\ Oct})$, and the ‘early revision’ that occurred between the April and October vintages of WEO during the observation year $(China_{t|t\ Oct} - China_{t|t\ Apr})$:

$$China_t - China_{t|t\ Apr} = China_t - China_{t|t\ Oct} + China_{t|t\ Oct} - China_{t|t\ Apr} \tag{10}$$

The two components of the data revision may have different statistical properties reflecting the process by which GDP data is compiled (see Holz 2014 for an analysis of the Chinese case). The early estimate of real GDP growth included in the April WEO is based on incomplete data. The early data revision is therefore white noise if the statistical authority of China manages to correctly predict the systematic component of the still partly missing data already in its early release. By the October WEO, the underlying data is more complete, and the statistical authority has also had more time to remove the systematic components from the still missing data. Correspondingly, confidence that the data revision is white noise is stronger for the late release than for the early release. In Model 6, we therefore use the ‘late data revision’ variable (de-trended and de-meaned) as the shock variable

The overall finding of negative spillover is robust to the change in the shock variable. However, we note that both Model 5 and Model 6 yield significantly larger (in absolute terms) negative spillover estimates relative to the benchmark Model (1). This suggests that the possible issues with the independence of data revisions might lead to underestimation of the strength of negative spillover from China in Models 1-4.

To assess the robustness of the results to data vintage and forecast window, we estimate alternative models based on the October vintages of WEO, rather than the April vintages. The correct data regarding years 2004–15 is taken from the October 2018 data vintage. The dependent variable is the GDP forecast error during the single year that follows the observation year, and the explanatory variable is the data revision during the year that precedes the observation year. From the models that build on October vintages, we omit the real-time GDP growth rate ($China_{t|t}$).

The models (Model 7, 8 and 9) based on October vintages do not challenge the main findings. However, they tend to show stronger positive and negative spillover compared to the models that build on the April vintages. This finding might be indicative that spillover takes some time to 'build up' so that it is stronger during the second year than the first year after the shock. Also, the divergence in results may reflect the stronger independence of the October (late) data revision relative to earlier releases relative to omitted variables.

TABLE 3—SELECTED ROBUSTNESS TESTS

	$\widehat{\alpha_2}$	R^2	sum(p)
Model 5: de-trended	-0.49	0.15	76
Model 6: late revision as shock	-0.54	0.26	77
Model 7 Oct vintages, overall	-0.36	0.29	87
Model 8: Oct vintages, subsample 2004-7, 14-5	.4	0.23	40
Model 9: Oct vintages, subsample 2008-13	-1.76	0.42	26
Model 10: SS&W benchmark	0.72		
Model 11: SS&W de-trended	-0.58		

Notes: Estimations based on Eq. 7 by OLS at country level for 177 countries 2004-15 unless otherwise stated. The second column gives the median spillover estimate and the third column the median R^2 across countries. The fourth column is the sum of p values of the spillover parameter across countries.

For comparison, we also study spillover along the lines of SS&W (2016), using as the endogenous variable GDP growth and as the sole exogenous variable the data revision. As discussed above, this model type is sensitive to non-random elements in the data revision, which also shows in the results. The 'plain vanilla' variant of this model type, corresponding with our benchmark Model 1, indicates strong positive spillover. The de-trended model (corresponding with our Model 5) yields strong negative spillover estimates.

Finally, we estimated Eq. (7) using the IMF forecast errors of the World real GDP growth as the left hand side variable (Table 1). The analysis is based on a longer event window: as the endogenous variable we use the average forecast error over the two years starting with the forecast year. As the independent variable we use the average data revision of the two years preceding the observation year. The resulting spillover estimate from the benchmark model is -0.8 thereby confirming that our overall finding of negative spillover is robust to possible aggregation error and the lengthening of the forecast window. The negative correlation between the forecasts errors and the data revisions in this model is clearly visible in the data (Figure 4).

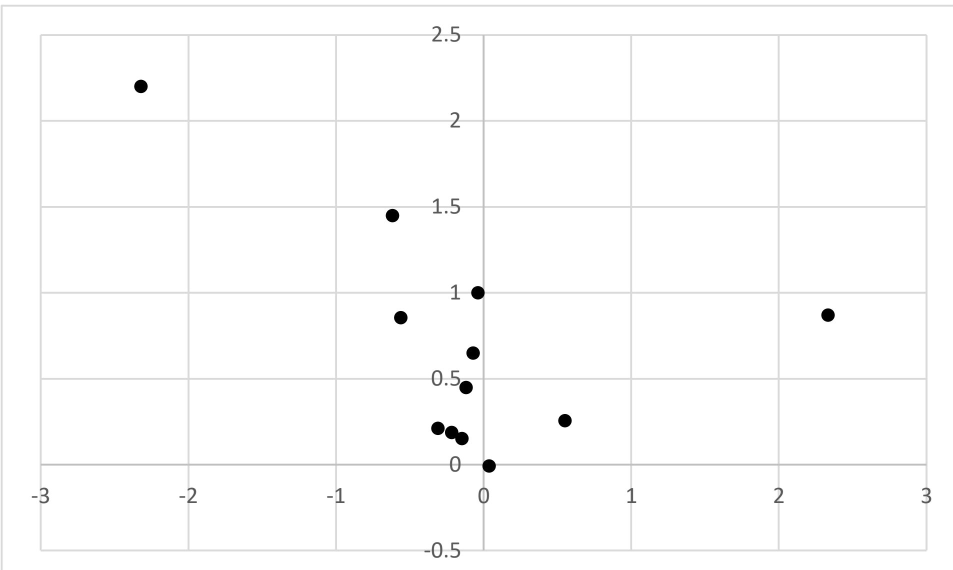


FIGURE 4. DATA REVISION IN CHINA (VERTICAL AXIS), AND THE IMF FORECAST ERROR REGARDING WORLD GDP GROWTH

Notes: The data is in percent; data revisions are computed as average over two years before the observation year; forecast errors are computed as average over the observation year and the following year; Data source WEO, April vintages.

IV Conclusions

We study real GDP spillover from China to other countries over the period 2004-15 based on novel, indirect approach. Estimations yield the main finding that spillover from China tended to be negative: a growth spurt in China was in most countries associated with a growth decline in the short to mid-term perspective. However, we also find strong variation is spillover across countries and in time. While negative spillover was prevalent during the global financial crisis period, positive spillover was more common during the other observation years.The estimation results raise a number of interesting questions, such as the nature of spillover. We leave the study of this issue for future efforts.

The novel empirical approach seems well suited to study spillover from other countries, and other types of spillovers and causal effects. The main estimation challenge is availability of suitable real time datasets. Our analysis therefore motivates the release of real time datasets by professional forecasters such as the IMF and the World Bank to promote understanding of the world economy.

REFERENCES

Arora V, Vamvakidis A (2011) China's economic growth: International spillovers, China & World Economy, Vol 19, Issue 5, 31– 46.

Aruoba S (2008) Data revisions are not well behaved. Journal of Money, Credit and Banking, 40(2–3): 319–340.

Bai j, Li K, Lu L (2016) Estimation and Inference of FAVAR models, Journal of Business & Economic Statistics, 620–641.

Bernanke B, Boivin J, Eliasz P (2005) Measuring the effects of monetary policy: a factor-augmented vector autoregressive (FAVAR) approach, Quarterly Journal of Economics,120, 387– 422.

Blanchard O, Leigh D (2013) Growth forecast errors and fiscal multipliers, American Economic Review, 103(3), 117−20.

Bloom N, Draca M (2016) Trade-induced technical change? The impact of Chinese imports on innovation, IT, and productivity, Review of Economic Studies, 83, 87−117.

Chodorow-Reich G, Coglianese J, Karabarbounis L (2019) The macro effects of unemployment benefit extensions: a measurement error approach, The Quarterly Journal of Economics, 227–279.

Clarke K, Kenkel B, Rueda M (2016) Omitted variables, countervailing effects, and the possibility of overadjustment. Political Science Research and Methods.

Clarke K (2005) The Phantom Menace: omitted variable bias in econometric research, Conflict Management and Peace Science, 22, 341–352.

Cwick T, Wieland V (2011) Keynesian government spending multipliers and spillovers in the euro area, Economic Policy July 2011, 493–549.

Dedola L, Rivolta G, Stracca L (2016) If FED sneezes, who catches a cold?, Journal of International Economics, 108, S1, 23–41.

Denton F, Kuiper J (1965) The effect of measurement errors on parameter estimates and forecasts: a case study based on the Canadian preliminary national accounts, The Review of Economics and Statistics, vol 47, No 2, 198–206.

Dizioli A, Guajardo J, Klyuev V, Mano R, Raissi M (2016) Spillovers from China's Growth Slowdown and Rebalancing to the ASEAN-5 Economies, IMF Working Paper WP/16/170.

Douven R, Peeters M (1998) GDP spillovers in multi-country models, Economic Modelling 15, 163–195.

Faust J, Rogers H, While J (2005) News and noise in G-7 GDP announcements, Journal of Money Credit and Banking, 37, 403–20.

Feldkircher M, Korhonen I (2014) The rise of China and its implications for the global economy: evidence from a global vector autoregressive model, Pacific Economic Review 19(1).

Holz C (2014) The quality of China's GDP statistics, China Economic Review, 30, 309–338.

IEO (2014) IMF forecasts process, quality and country perspectives, evaluation report. Technical report, IEO – Independent Evaluation Office of the International Monetary Fund.

Kose A, Lakatos C, Ohnsorge F, Stocker M (2017) The global role of the U.S. economy: linkage, policies, and spillovers, Kos University-TUSIAD economic research forum working papers 1706.

Kose A, Otrok C, Whiteman C (2003) International business cycles: world, region and country-specific factors, American Economic Review, Vol. 93, No. 4, 1216–1239.

Li G (1985) Robust regression, In Exploring Data Tables, Trends, and Shapes, ed. D. C. Hoaglin, F. Mosteller, and J. W. Tukey, Wiley.

Pesaran M, Schuermann T, Weiner S (2004) Modeling regional interdependencies using a global error-correcting macroeconometric model, Journal of Business & Economic statistics, Vol 22, Issue 2.

Pierce J, Schott P (2016) The surprisingly swift decline in US manufacturing employment, American Economic Review, 106(7), 1632–1662.

Ramey V (2016) Macroeconomic shocks and their propagation, Handbook of Macroeconomics Vol 2, Eds. Taylor J, Uhlig H, 71–162.

Suarez Serranto J, Wingender P (2016) Estimating local fiscal multipliers, manuscript.

Trivellato U, Rettore E (1986) Preliminary data errors and their impact on forecast error in simultaneous-equation models, Journal of Buriness & Economic Statistics, Vol 4, No 4, 445–453.

TABLE A1. SPILLOVER ESTIMATES

Country		$\alpha_{2\ \text{benchmark}}$	$\alpha_{2\ \text{2004-7, 2014-5}}$	$\alpha_{2\ \text{2008-13}}$
Angola	AGO	-1.97923	-5.602613	-0.21526
Albania	ALB	0.439059	0.3068401	0.492464
United Arab Emirates	ARE	-2.06743	-2.101371	-1.93023
Argentina	ARG	0.378649	0.5128948	-0.8053
Armenia	ARM	-0.61367	0.9786255	-1.08162
Antigua and Barbuda	ATG	2.210691	1.244063	0.251759
Australia	AUS	-0.08912	0.9465986	-0.25649
Austria	AUT	-0.12237	0.6460843	-0.0941
Azerbaijan	AZE	-2.96816	-1.290781	-3.27005
Burundi	BDI	-1.78827	1.877329	-0.60203
Belgium	BEL	0.007767	0.6779686	-0.40794
Benin	BEN	0.387815	1.444831	-0.53538
Burkina Faso	BFA	-1.64594	-0.6538242	0.426258
Bangladesh	BGD	-0.13554	-0.2944826	-0.1006
Bulgaria	BGR	0.830856	0.0536838	0.411932
Bahrain	BHR	0.639207	0.6488526	-0.23882
Bahamas, The	BHS	-3.6629	0.9647348	-2.217
Bosnia and Herzegovina	BIH	0.900846	-0.01109	-0.11417
Belarus	BLR	2.332858	2.184625	1.137067
Belize	BLZ	0.055724	-1.9683	0.119083
Bolivia	BOL	0.365479	-0.1701111	0.20179
Brazil	BRA	0.627905	2.019042	0.12298
Barbados	BRB	-0.8837	-1.945015	-0.6308
Brunei Darussalam	BRN	-1.6263	0.6068524	-0.0627
Bhutan	BTN	-1.0192	-0.2539104	1.154928
Botswana	BWA	0.842867	3.403719	-0.73346
Central African Republic	CAF	-2.97917	0.5858141	4.105066
Canada	CAN	-0.27734	0.0870815	-0.23868
Switzerland	CHE	0.535546	0.8279124	0.149733
Chile	CHL	-0.55518	0.5877362	-0.36313
China	CHN	0.571097	1.977309	0.067113
Côte d'Ivoire	CIV	-1.81325	-0.6349523	-0.70403
Cameroon	CMR	0.045951	0.2067589	-0.5334
Congo, Democratic Republic of	COD	-1.02917	0.457799	-1.24432
Congo, Republic of	COG	-1.18258	-1.472113	-0.49184
Colombia	COL	-0.57483	0.7873871	-0.75725

		$\alpha_{2\ \mathrm{benchmark}}$	$\alpha_{2\ \mathrm{2004\text{-}7,\ 2014\text{-}5}}$	$\alpha_{2\ \mathrm{2008\text{-}13}}$
Comoros	COM	-1.36008	-0.141467	-0.34007
Cape Verde	CPV	0.781045	2.435373	0.748159
Costa Rica	CRI	0.626369	1.01756	0.357564
Cyprus	CYP	1.916875	-0.8057831	0.574998
Czech Republic	CZE	-0.09077	-0.664314	-0.42294
Germany	DEU	-0.42634	0.6633095	-0.49023
Djibouti	DJI	-1.11893	-0.0803325	-0.37024
Dominica	DMA	3.451133	2.846913	2.010393
Denmark	DNK	-0.31836	-0.7694495	-0.59949
Dominican Republic	DOM	1.071851	-0.8026231	-0.85976
Algeria	DZA	-1.01174	-0.7767755	-0.81706
Ecuador	ECU	-1.08723	0.4802401	0.637195
Egypt	EGY	-0.06998	-0.0307091	-0.27149
Eritrea	ERI	-3.53474	-1.280334	-4.6577
Spain	ESP	0.685229	-0.3485515	-0.00174
Estonia	EST	-5.1522	-1.075587	-3.6943
Ethiopia	ETH	0.09061	1.333124	-0.2384
Finland	FIN	0.367257	1.481789	-0.26154
Fiji	FJI	0.033611	-2.194461	-0.90011
France	FRA	-0.35295	0.3184069	-0.57955
Gabon	GAB	-0.25543	1.140138	-0.92454
United Kingdom	GBR	-1.11923	-0.2060115	-1.06407
Georgia	GEO	-2.30931	1.995578	-2.52113
Ghana	GHA	0.205515	-0.8234334	0.57997
Guinea	GIN	-0.17141	0.7810571	-0.38871
Gambia, The	GMB	2.263269	0.2052615	0.179247
Guinea-Bissau	GNB	-1.24867	-0.4673314	0.249689
Equatorial Guinea	GNQ	4.922713	2.550826	3.265217
Greece	GRC	2.050344	0.5806222	-0.55734
Grenada	GRD	-1.03219	-3.267722	-1.00296
Guatemala	GTM	-0.46669	0.675892	-0.74243
Guyana	GUY	-0.9216	1.253988	-1.18696
Hong Kong SAR	HKG	-0.39075	0.8025357	-0.93516
Honduras	HND	-0.35917	0.6366944	-0.22069
Croatia	HRV	0.539895	-0.4688908	-0.28569
Haiti	HTI	0.064996	0.730828	-0.36749
Hungary	HUN	0.47441	-1.746856	-0.3105
Indonesia	IDN	0.382326	0.3429893	0.534692

		$\alpha_{2\ \text{benchmark}}$	$\alpha_{2\ \text{2004-7, 2014-5}}$	$\alpha_{2\ \text{2008-13}}$
India	IND	-0.26635	-0.083502	-1.63903
Ireland	IRL	-0.31985	-7.818513	-2.78559
Iran, Islamic Republic of	IRN	-1.49425	1.042681	-1.99305
Iceland	ISL	2.958935	4.432695	0.211448
Israel	ISR	0.074082	0.9288127	-0.41823
Italy	ITA	-0.23737	-0.0904416	-0.36472
Jamaica	JAM	-0.94697	-0.2726635	-0.984
Jordan	JOR	0.838314	1.618482	0.80926
Japan	JPN	-0.51975	-0.3020749	-1.02806
Kazakhstan	KAZ	-1.25802	0.5188184	-1.17627
Kenya	KEN	-0.85845	0.8413404	-1.11396
Kyrgyz Republic	KGZ	2.11627	0.8290462	0.398553
Cambodia	KHM	-0.70549	1.187396	-0.53895
Kiribati	KIR	-2.98634	-1.770041	-2.44432
St. Kitts and Nevis	KNA	0.647683	-3.045603	0.83784
Korea	KOR	0.055888	0.684304	-0.6326
Kuwait	KWT	-3.07223	2.658294	-1.39836
Lao People's Democratic Republic	LAO	0.117292	0.4095284	-0.17401
Lebanon	LBN	4.075306	4.532894	2.173164
Libya	LBY	-38.5431	15.12067	0.821963
St. Lucia	LCA	3.191314	-1.224777	1.104736
Sri Lanka	LKA	-1.66057	0.754507	-0.29195
Lesotho	LSO	-1.76012	0.8106892	-0.251
Lithuania	LTU	-1.38956	2.068665	-1.88345
Luxembourg	LUX	0.245028	0.8573903	-2.2935
Latvia	LVA	-4.27991	-0.0260724	-2.98366
Morocco	MAR	-0.79425	0.425271	-0.31033
Moldova	MDA	0.387512	-1.179501	-0.29817
Madagascar	MDG	0.014235	0.9379404	0.227516
Maldives	MDV	5.361639	2.351919	1.559763
Mexico	MEX	0.102924	-0.4869179	0.02183
Macedonia, Former Yugoslav Republic c	MKD	1.191957	0.8379858	0.422383
Mali	MLI	1.395404	-1.579218	1.344948
Malta	MLT	1.46745	-2.830551	-0.13214
Myanmar	MMR	0.645722	3.475566	-0.54671
Mongolia	MNG	-2.37665	2.31239	-0.045
Mozambique	MOZ	-0.41258	0.414289	-0.0011

		$\alpha_{2\ \mathrm{benchmark}}$	$\alpha_{2\ 2004\text{-}7,\ 2014\text{-}5}$	$\alpha_{2\ 2008\text{-}13}$
Mauritania	MRT	-2.63311	2.206284	-1.91895
Mauritius	MUS	0.2533	0.8323655	-0.52479
Malawi	MWI	1.678642	3.028649	0.454911
Malaysia	MYS	0.237447	0.2256122	-0.32688
Namibia	NAM	-0.89493	-1.046504	-1.39809
Niger	NER	2.085366	-0.890232	2.580976
Nigeria	NGA	0.885791	0.9745799	-0.52647
Nicaragua	NIC	-1.25996	0.2222333	-0.84361
Netherlands	NLD	0.050271	0.0891085	-0.22135
Norway	NOR	-0.19987	-0.5881247	-0.76323
Nepal	NPL	0.937743	0.2285592	0.596007
New Zealand	NZL	-0.85914	0.4536544	-1.0391
Oman	OMN	1.456487	-0.9507645	0.213394
Pakistan	PAK	-0.96156	-0.5416117	-0.43536
Panama	PAN	-0.92856	2.961877	0.140986
Peru	PER	1.138239	2.005814	0.947128
Philippines	PHL	-0.17415	0.7630496	-1.18338
Papua New Guinea	PNG	1.432254	5.00788	-1.67751
Poland	POL	-0.26224	0.4504477	-0.46426
Portugal	PRT	0.182822	0.4514626	-0.61573
Paraguay	PRY	1.962602	1.049666	0.397594
Qatar	QAT	5.751147	6.78863	2.428676
Romania	ROU	1.586124	-0.133978	1.125871
Russia	RUS	-0.08149	0.7897367	-0.36769
Rwanda	RWA	0.562585	0.7628297	2.051963
Saudi Arabia	SAU	-0.26082	-1.349064	0.599284
Sudan	SDN	2.363069	-2.638781	-0.29121
Senegal	SEN	0.300993	-0.7099699	-0.46836
Singapore	SGP	-0.93247	2.001326	-2.36287
Solomon Islands	SLB	-2.85887	2.092021	0.923697
Sierra Leone	SLE	2.502975	5.189317	0.972316
El Salvador	SLV	-0.74788	-0.0530891	-0.57962
São Tomé and Príncipe	STP	-0.77446	-2.591278	0.993676
Suriname	SUR	-1.37143	2.446546	-0.77129
Slovak Republic	SVK	0.634574	0.8409725	-0.1779
Slovenia	SVN	1.459707	0.5296515	0.030726
Sweden	SWE	0.168946	-0.363476	-1.06083

		$\alpha_{2\ benchmark}$	$\alpha_{2\ 2004\text{-}7,\ 2014\text{-}5}$	$\alpha_{2\ 2008\text{-}13}$
Swaziland	SWZ	-1.27716	1.264948	-1.2665
Seychelles	SYC	-4.49458	1.617996	-3.66808
Syrian Arab Republic	SYR	-2.07885	-0.4768421	-0.02792
Chad	TCD	0.782543	4.295421	0.40489
Togo	TGO	-0.56259	-2.059635	-0.47766
Thailand	THA	-0.47184	1.010861	-1.10584
Tajikistan	TJK	1.098614	-0.6582257	0.985471
Turkmenistan	TKM	-1.13477	1.936426	1.10176
Timor-Leste, Dem. Rep. of	TLS	-1.76048	-8.481219	4.727134
Tonga	TON	1.321039	-1.091614	1.049495
Trinidad and Tobago	TTO	0.279065	-0.4512694	-0.47145
Tunisia	TUN	0.404611	0.9376425	-0.02084
Turkey	TUR	-3.3003	-1.390658	-2.84709
Taiwan Province of China	TWN	-0.22209	1.889567	-1.152
Tanzania	TZA	-0.73672	0.7162762	-0.94241
Uganda	UGA	0.280998	1.15671	1.26088
Ukraine	UKR	-0.23066	3.970238	-0.32931
Uruguay	URY	-0.00455	1.129498	0.118542
United States	USA	-0.06491	-0.0945858	-0.17901
Uzbekistan	UZB	0.365361	0.2271692	-0.0216
St. Vincent and the Grenadines	VCT	-1.43581	-0.1278984	-1.88707
Venezuela	VEN	-0.58884	1.98749	-0.66139
Vietnam	VNM	-0.4093	-0.7239639	-0.73733
Vanuatu	VUT	2.412335	-1.017828	1.797249
Samoa	WSM	-2.15187	-0.852097	0.16678
Yemen, Republic of	YEM	1.630376	12.09604	0.96756
South Africa	ZAF	0.006938	0.6968623	-0.11581
Zambia	ZMB	0.316142	3.060131	0.612099
Zimbabwe	ZWE	-6.69258	2.200558	-6.4341

Notes: Estimations based on Eq. 7. The first three numeric columns indicate spillover estimates from Models 1, 3 and 4 respectively (see Table 2). Data source own calculations.