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Did FDI Really Cause Chinese Economic Growth? A Meta-Analysis

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Abstract: This study performs a meta-analysis of research that estimates the relationship between FDI and Chinese economic growth. Our sample includes 37 studies and a total of 280 estimates. We include both English- and Chinese-language studies. Our initial “raw” finding is that FDI has had a substantial, positive impact on Chinese economic growth. Furthermore, our results suggest that the effect is not inflated by endogeneity, nor impacted by publication bias. However, the positive effect is found to be smaller for more recent and better designed studies. When we adjust for preferred study and sample characteristics, we find that the estimated economic effect of FDI on Chinese economic growth is much smaller than indicated by the overall literature, and statistically insignificant. This suggests that the cause(s) of the Chinese “economic miracle” likely lie elsewhere.

Keywords: Meta-analysis, FDI, China, economic growth

JEL Classifications: O11, O53, F20

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I. INTRODUCTION

In 1978, Chinese was a developing country with a GDP of \$148 billion, 6.3 percent of U.S. GDP. By 2014, Chinese was a newly industrialized country with a GDP of \$10.360 trillion, virtually half that of U.S. GDP.¹ If GDP was measured at purchasing power parity (PPP), then the Chinese economy was bigger than the U.S. in 2014. Equally impressive is the scale of the increase in Chinese per capita GDP. Using PPP, Chinese per capita GDP is now a quarter of that of the U.S. with hundreds of millions of Chinese escaping poverty.² By the standard of Robert Lucas (1993), the growth of the Chinese economy could be described as a ‘miracle’.

The crucial question to answer is what has caused the Chinese economic miracle? If we know the answer to this question, then other developing countries could learn and benefit from China’s experience. Many reasons have been given for the sustained Chinese economic growth, see for example Jefferson, Hu and Su (2006), Prasad and Rajan (2006), Huang (2012), and Zhu (2012) for summaries of work in this area. Some of these are specific to China and therefore not applicable to other countries, such as the one-child policy or major cities close to important international sea routes. Some are also difficult to implement, such as establishing the rule of law or reducing corruption. What is left are several more general, orthodox and simpler policies such as reducing trade barriers, or privatising government businesses. One of these orthodox policies, which is the focus of this paper, is allowing foreign direct investment (FDI).

Why focus on FDI? Because changing a policy from prohibiting to allowing FDI applies to all countries and is relatively easy one to implement, and importantly, it is a policy that the Chinese did implement and saw as crucial in trying to achieve economic growth. As part of the reform process in the late 1970s, China used preferential and super-preferential

¹ These and the following figures are from the World Bank’s World Development Indicators unless otherwise indicated.

² Using the World Bank’s Poverty and Equity Database.

treatments (Ran, Voon and Li, 2007) with the expressed aim of attracting large amounts of FDI. We also know that it worked. For example, in 1982, FDI into China was \$430 million (0.21 percent of GDP), about 3.5 percent of U.S. FDI. By 2013, FDI into China was \$347.8 billion (3.7 percent of GDP) and was 121 percent of U.S. FDI. FDI also became far more important in the formation of fixed capital over this time. Further, Chinese FDI relative to the U.S. mirrored that of Chinese GDP so it seems a potential causal factor. Even more, there are plausible reasons why FDI might cause economic growth.

Findlay (1978) shows in a simple growth model that FDI can transfer technology and better management practices from advanced to developing countries. Coe and Helpman (1995) demonstrate the possibility of and find evidence for international R&D spillovers which De Mello (1997) claims occurs with FDI. Other claimed potential beneficial effects of FDI include increased training and skill acquisition (De Mello, 1999), and more disciplined macroeconomic policies and fewer policy errors (Bosworth and Collins, 1999).

Do these beneficial effects occur in practice? Some evidence suggests yes. One of the first empirical studies detecting that FDI can increase growth rates is a cross country study by Papnek (1973). Papnek's finding was subsequently supported by Alfaro et al (2004) and Doucouliagos, Lamsiraroj, and Ulubasoglu (2010) who find that FDI causes significantly higher growth rates. Blomström, Lipsey, and Zejan (1992) find that technology transfers are why FDI causes economic growth. This result is also found by Borensztein, De Gregorio, and Lee (1998) who report that FDI is important in transferring technologies across countries and contributes more to economic growth than domestic investment. These results are supported by the firm-level meta-analyses of Havránek and Iršová (2011, 2012) which conclude that FDI has positive spillovers. Other studies observing positive impacts of FDI are Bosworth and Collins (1999) who notice that FDI benefits domestic investment one-for-one, and Aitken and Harrison (1999) who find that that FDI increases domestic firm-level productivity.

The evidence as presented suggests that FDI has an unambiguously positive impact on economic growth. Unfortunately, it is not so clear cut. Alfaro et al's results hold true only if financial markets are well developed in a country. Equally, Borensztein, De Gregorio, and Lee conclude that FDI technology transfers only occur if the workforce of a country has a minimum level of human capital. This is consistent with Blomström, Lipsey, and Zejan's result that technology transfer from FDI only occurs in high-income developing countries. Durham (2004), De Mello (1997), De Mello (1999) and the meta-analysis of Iršová and Havránek (2013) all find that the positive impact of FDI on economic growth depends on the ability of an economy to absorb new technology and more modern capital. Aitken (1999) and Kosová (2010) both report that FDI actually has a negative effect on domestically owned firms. Temple (1999) argues that FDI is not causing economic growth, but in fact economic growth is at least in part leading to more FDI, thus any estimates of the positive impact of FDI on economic growth will be overstated. Finally, FDI might lead to economic inefficiencies because of distortionary policies such as FDI being required of foreign firms who want to export to the host country, or preferential tax treatment of foreign as opposed to domestic investment, or governments crowding out domestic investment because they need to invest in infrastructure to attract FDI.

Taken collectively, this means that while in principle FDI can have a positive impact on economic growth, in practice it might not because specific features have to be present for it to occur. This is problematic. If we want to learn from the Chinese experience with FDI to apply it to other developing countries, notably if policies designed to attract FDI actually led to high rates of economic growth, then we need to know that the policy actually 'worked' as intended. There is evidence that FDI has had a positive impact on Chinese economic growth (Sun and Parikh, 2001; Ljungwall and Tingvall, 2010; Zhang and Felmingham, 2002). Equally, there is evidence that such effects might be weak (Doucouliagos, Lamsiraroj, and

Ulubasoglu, 2010) if present at all (Yalta, 2013), or potentially not cause productivity spillovers but just improve financial performances of domestic firms (Wang and Wang, 2015). There is also the possibility that economic growth caused FDI to occur in China (Mah, 2010), or that FDI only affected economic growth if key factors were present (Batten and Vo, 2009).

The trick to solving this problem is to survey the many existing studies in a rigorous quantitative, and systematic way, to first determine the sign and magnitude of any impact of FDI on Chinese economic growth, and second to determine which factors are needed for FDI to affect economic growth, if such an effect exists. We use the method of meta-analysis as detailed by Stanley and Doucouliagos (2012) and Ringquist (2013) to do this. This method allows us to tease out more details about the impact of FDI on economic growth than can be considered by any one primary study, for example is any result the product of publication bias or do findings change over time. A novel feature of this meta-analysis as opposed to others studying Chinese FDI is its use of aggregate-level as opposed to firm-level or industry-level data. This means we can look at the overall effect of FDI on economic growth across many different specifications and check to see how the results have changed over time, or if any effect holds nationally or only for some regions. Another novel feature is that we are one of the few to include Chinese-language studies in our data set.

Our main finding is that the effect of FDI on Chinese economic growth is much smaller than one would expect from a reading of the literature once one adjusts for “preferred” study characteristics. We emphasize that this result is not due to publication bias. Secondary findings are that more recent studies find a noticeably smaller impact of FDI on Chinese economic growth than earlier studies, and that there is no evidence that endogeneity is responsible for inflated estimates of the effect of FDI.

The rest of the paper is organized as follows. Section II describes the procedure for selecting the studies. Section III explains the meta-analysis method and publication bias test used in this paper. Section IV presents and discusses our empirical results, and section V concludes.

II. SELECTION OF STUDIES

Our search for studies followed the MAER-Net protocols as outlined in Stanley et al. (2013). A preliminary search was done using the combination of keywords: “FDI,” “economic growth”, “China”, “growth”, “economic performance”, and “foreign direct investment.” The search was conducted using the English search engines EconLit, JSTOR, EBSCO, Google Scholar, RePEc, SSRN, Social Science Citation Index (SSCI), and Scopus. We also searched on the Chinese search engines China National Knowledge Infrastructure (CNKI), CQVIP, Wangfang data, and Science Paper Online. In addition to peer-reviewed, journal articles, we also searched working papers, books, doctoral dissertations, master theses, and government reports.

Our initial search produced over 400 studies. We narrowed this down using the criteria (i) dependent variable is economic growth, (ii) level of analysis is aggregate as opposed to firm- or industry-level; and (iii) analysis focuses solely on China. There is a balance between having more observations, and restricting the studies to those measuring “the same” effect. For example, most researchers would not consider estimates of the effect of FDI on exports as measuring the same thing as estimates of the effect of FDI on economic growth, though they may be related.

The reason for eliminating studies that use a dependent variable other than economic growth – say that estimate the association between FDI and the level of income – is that exogenous growth theory predicts that variables that affect the level of income may not affect

the growth of income.³ It is the latter relationship that we are interested in studying. For related reasons, we are interested in analyses at the aggregate level, since firm- and even industry-level data may miss some of the multiplier and spillover effects identified above. And finally we recognize that countries differ in institutions, regulatory frameworks, and economic processes that are only crudely modelled by the inclusion of country-specific dummy variables. By focussing solely on China, we aim to minimize unobserved heterogeneity across studies and concentrate on the “true effect” between FDI and Chinese economic growth.

We also imposed several other requirements: the original studies had to include both a coefficient estimate for the effect of FDI on economic growth, and either a corresponding standard error or a t-statistic. We required a single effect estimate. This eliminated VAR studies, because the empirical analysis in those studies was often constructed for the purpose of developing impulse response functions. They did not report a cumulative, long-run impact with corresponding standard error (Zhao and Du, 2007). A similar difficulty arose with Granger causality studies (Liu, Burrige and Sinclair, 2002).

For the same reason, we also eliminated studies using interaction terms and quadratic specifications of the FDI variable. Given the specifications $\Delta Y = \beta_0 + \beta_1 FDI + \beta_2 FDI \cdot Z + \beta_3 Z$ and $\Delta Y = \beta_0 + \beta_1 FDI + \beta_2 FDI^2$, where ΔY represents economic growth, the associated marginal effects are given by (i) $\partial \Delta Y / \partial FDI = \beta_1 + (\beta_2 \cdot FDI)$ and (ii) $\partial \Delta Y / \partial FDI = \beta_1 + (2 \cdot \beta_2 \cdot FDI)$. Some meta-analyses include estimates of β_1 and β_2 as separate effect estimates (Gechert, 2015). This is incorrect, as the individual coefficient estimates provide incomplete, and likely misleading, information about FDI’s marginal effect on economic

³ We do, however, include studies that have the level of income as a dependent variable if they also include a lagged dependent variable on the right hand side of the equation. Assuming the specification also includes other explanatory variables, it is straightforward to show that this specification produces identical coefficient estimates and standard errors for the other explanatory variables as a specification with growth as the dependent variable and lagged income included as an explanatory variable. We thank Chris Doucouliagos for pointing this out.

growth. It is easy to construct examples where the marginal effect is negative for all observations in the sample, but the coefficient on β_1 is positive and significant. Or the marginal effect is positive for all observations in the sample, but the coefficient on β_2 is negative and significant.⁴

Our search produced 37 studies with a total of 280 individual coefficient estimates. These are reported in TABLE 1. Our study is somewhat unique in that it includes Chinese-language studies.⁵ Eleven of the studies were published in Chinese-language journals. Fifteen were published in English-language journals. And 11 come from other sources such as student theses, book chapters, or working papers. Some of the latter are also in Chinese. The earliest study was published in 2001 and the most recent study was published in 2015. The number of estimates per study varies widely, from 1 to 40. We emphasise that all the estimates in our meta-analysis focus on the effect of FDI on Chinese economic growth, they are all based on aggregate-level data to capture the full effects of FDI, and they are all legitimate effect estimates (not based on interaction terms, VARs etc.).

III. METHOD OF ANALYSIS

Estimation procedure. Consider a study i that estimates the effect of FDI on economic growth using the following regression specification:

$$(1) \quad \Delta Y = \beta_0 + \beta_1 FDI + \sum_{k=2}^K \beta_k Z_k + error,$$

where the Z_k 's are various control variables. The estimated effect for study i is represented as $\hat{\beta}_{1i}$. One possible way of summarizing the empirical literature is to calculate the arithmetic

⁴ It is possible to combine coefficients associated with nonlinear effects to calculate a single, marginal effect, but the requisite information is usually not provided in the original studies. Zigraiova and Havránek (2015) calculate marginal effects from quadratic specifications but that requires (i) the variances of the respective linear and quadratic forms of the variable, (ii) the mean value of the variable, and (iii) the covariance between the linear and quadratic forms of the variable. They omit the latter in their calculation of standard error of the marginal effect. Whether this is a serviceable approximation is not clear.

⁵ The only other meta-analysis that we are aware of that includes Chinese-language studies is Fidrmuc and Korhonen (2015).

mean of the $\hat{\beta}_{1i}$ values across the different studies. This is equivalent to using OLS to estimate α_0 in the equation below:

$$(2) \quad \hat{\beta}_{1i} = \alpha_0 + \varepsilon_i, i = 1, 2, \dots, M,$$

where M is the number of estimates in the meta-analyst's sample, and α_0 is the measure of mean, "true" effect of FDI on growth. A test of whether FDI significantly affects economic growth thus consists of a test of the significance of α_0 .

While OLS is unbiased, it is inefficient, because the different $\hat{\beta}_{1i}$ have different standard errors, which induce heteroskedasticity in ε_i . Weighted Least Squares (WLS) is one way to obtain efficient estimates of α_0 . This is equivalent to dividing through Equation (2) by SE_i , the estimated standard error of $\hat{\beta}_{1i}$, and then using OLS to estimate the resulting equation:

$$(3) \quad \frac{\hat{\beta}_{1i}}{SE_i} = \alpha_0 \cdot \left(\frac{1}{SE_i} \right) + \frac{\varepsilon_i}{SE_i}, i = 1, 2, \dots, M.$$

Note that this procedure gives greater weight to the more precisely estimated effects. We shall refer to this WLS estimator as the "Fixed Effects" (FE) estimator, though we note that the meta-analysis literature typically uses a slightly different version of this estimator.⁶ This estimator is not to be confused with the fixed effects estimator associated with panel data. While the terminology can be confusing, we choose to stick with the terminology that is commonly employed in the meta-analysis literature.

The FE estimator implicitly assumes that the only reason the $\hat{\beta}_{1i}$ values differ is because of sampling error. In contrast, the "Random Effects" (RE) procedure assumes that an additional source of differences is heterogeneity in the underlying population parameter. Let this heterogeneity be represented by an error term with standard deviation τ . If this error component is independent of sampling error, then the s.e. ($\hat{\beta}_i$) = $\sqrt{(SE_i)^2 + \tau^2} = \omega_i$. In this

⁶ In the meta-analysis literature, it is common to have the FE estimator standardize the residuals so that their sample variance equals one.

case, WLS estimates can be obtained by dividing through Equation (2) by ω_i , and estimating the resulting equation by OLS:

$$(4) \quad \frac{\hat{\beta}_{i1}}{\omega_i} = \alpha_0 \cdot \left(\frac{1}{\omega_i} \right) + \frac{\varepsilon_i}{\omega_i}, \quad i = 1, 2, \dots, M,$$

This Random Effects estimator is not to be confused with the estimator of the same name that is associated with panel data models. While the terminology can be confusing to economics readers unfamiliar with the meta-analysis literature, the terms are too well-entrenched in that literature to attempt to develop an alternative nomenclature.

If all effects were estimated with equal precisions, the FE and RE estimators would give equal weight to every (respectively standardized) estimate. Suppose there are two studies. Study A reports one estimate, and Study B reports ten estimates. A consequence of giving equal weights to the observations is that Study B will be weighted ten times as much as Study A. An alternative is to give equal weights to each study (Havránek and Irsova, 2015). In this case, the standardized estimates are further weighted by the inverse of the number of estimates reported by that study. Each standardized estimate from Study B would thus receive one-tenth the weight as its counterpart from Study A. In the subsequent analysis, these weighting schemes are identified as *Weight1* (equal observations) and *Weight2* (equal studies).

Another issue has to do with differences in the specification of the economic growth and FDI variables in the original studies. Our collection of studies includes multiple measures of economic growth, including (i) growth rate of nominal GDP, (ii) growth rate of real GDP, and (iii) growth rate of real, per capita GDP. With respect to FDI, some of the studies use the ratio of FDI to GDP, while others use variables such as the growth rate of FDI, $\ln(\text{FDI})$, or FDI measured as a share of total investment. So even though our analysis restricts itself to studies that are trying to measure “the same effect” – the effect of FDI on Chinese economic growth – there is substantial heterogeneity in how the variables are measured.

This is a common problem in meta-analyses, and there is a widely adopted solution: in place of the estimated coefficient, one calculates the “partial correlation coefficient” (PCC). Define the PCC associated with an estimate $\hat{\beta}_i$ as:

$$(5) \quad PCC_i = \frac{t_i}{\sqrt{t_i^2 + df_i}},$$

where t_i and df_i are the t -statistic and degrees of freedom associated with the respective estimated effect, and $-1 \leq PCC_i \leq 1$. The standard error of PCC is given by:

$$(6) \quad \text{s.e.}(PCC_i) = \sqrt{\frac{1 - PCC_i^2}{df_i}}.$$

PCC_i and $\text{s.e.}(PCC_i)$ then replace $\hat{\beta}_{1i}$ and SE_i in Equation (2) and the subsequent analysis.

FIGURE 1 gives a histogram of the t -values and PCC values used in this study. The upper panel displays a wide range of t -statistics in the original studies. The distribution is well-behaved and displays a familiar bell shape. While there are a few large outliers, the weight of the distribution is centered between t -values from 0 to 5. The bottom panel shows how these t -values transform into PCC values. Again, the distribution of PCC values is well-behaved. None come close to either -1 or 1, so that there is no need to transform the data to Fisher z values (Steel, 2014).

The top panel of TABLE 2 reports further information about the distribution of t -stat and PCC values in our sample. The mean t -value in our sample of 280 estimates is 2.46. The mean PCC value is 0.228. Like any correlation, the PCC values are bounded by -1 and 1. PCCs are difficult to interpret in terms of economic significance. In a very useful analysis, Doucouliagos (2011) evaluated over 22,000 partial correlations from a diverse group of economics fields. The median absolute PCC was 0.174. He categorized the size of PCCs as “small,” “moderate,” or “large” depending on where they sat relative to the 25th, 50th, and 75th percentile values of the full sample of ordered PCC values. The corresponding PCC values

were 0.070, 0.174, and 0.327. By this standard, the majority of estimates in our sample can be characterized as “moderate” to “large.” Thus, a first impression of the data suggests that the relationship between FDI and Chinese economic growth is statistically and economically significant.

FIGURE 2 presents a “forest plot” which reports the range of effect sizes (ES) for each of the studies. In this plot, the PCC values are weighted by their standard errors, in accordance with the FE model. The studies are arranged in the same order as TABLE 1.⁷ The first 11 studies are studies that appear in Chinese-language journals. The next 15 are studies that appear in English-language journals. And the last 11 are book chapters, student theses, and a working paper. Within each category, the studies are organized by publication date and author, with the oldest studies listed first. Each study is represented by a marker indicating the weighted mean of the estimates from that study, along with a 95% confidence interval around that mean. The forest plot also reports a test of the FE model using the statistic I^2 , which is equivalent to testing whether $\tau^2 = 0$. As is almost always the case in meta-analyses, the FE model is rejected in favour of the RE model. However, as we discuss below, that does not imply that the RE model should be preferred over FE in the subsequent estimation.

It is evident that there is a diversity of estimates both within and across the three groups of studies. These weighted PCC values indicate that Chinese-language journals report larger estimated FDI effects than English-language journals, and English-language journals report larger estimates, on average, than studies from non-journal sources. Further, there is some evidence to indicate that estimates are decreasing over time.

These patterns are not always evident in the unweighted data. The bottom panel of TABLE 2 reports the distribution of (unweighted) PCC values conditional on different sample characteristics. As suggested by the forest plot, older studies (those published before

⁷ FE weights are used to calculate ES’s in TABLE 2.

2006), reported larger FDI effects than more recent studies. Interestingly, the unweighted PCC values suggest that FDI effects are largest for English, rather than Chinese language journals. Other differences are also evident. There are differences by the type of data. FDI effects appear to be larger for cross-sectional data than panel data, and largest for time series. However, we should be wary of the latter result given the relatively small number of time series estimates. Finally, estimation method appears to be related to the size of the estimated FDI effect, with GMM, which is designed to correct for endogeneity, associated with the smallest estimated effects, on average.

There are several reasons why these preliminary assessments should be viewed with caution. TABLE 2 treats all estimates equally. In contrast, efficiency implies that estimates should be weighted by their respective standard errors and, as we have already seen, this can make a difference. Further, a multivariate analysis is required to identify the effects of individual variables. And, finally, we need to investigate the possibility that our estimates are influenced by “publication bias.”

Publication bias. Publication bias refers to the fact that the set of observed estimated effects may suffer from sample selection. This sample selection can arise from a number of reasons: it can arise because studies that don’t produce statistically significant estimates may find it harder to get published. Alternatively, it can arise because researchers give up on a project when the estimated effects are not significant, or keep trying alternative variable specifications until they find one or more that produce statistically significant estimates. It can also arise when there is a strong presumption that the estimate should take a certain sign (e.g., a price elasticity, or the value of a statistical life) so that estimated effects that violate the expectation are never written up, or never accepted for publication.

An informal test of publication selection bias is given by a “funnel plot.” A funnel plot graphs estimated effects (here PCCs) against the standard error of the PCC, with the

most precise estimates at the top. If estimated effects are all drawn from the same normal distribution, then the most precise estimates should be closely clustered around the mean of that distribution, with less precise estimates fanning out, producing a funnel formation. If the funnel plot is “lopsided”, with estimates favoring one side or the other, especially for less precise PCC values, that is evidence of publication selection bias.

FIGURE 3 produces funnel plots of the estimated effects in this study. The top panel of FIGURE 3 produces a funnel plot for the full sample of 280 estimates. In the bottom panel, each point represents one of the 37 studies, with the individual PCC/s.e.(PCC) points being the simple average of that study’s estimates. The dispersion at the top of the funnel, with the most precise estimates, is evidence of differences in “true” effects across studies, suggesting that the effect of FDI on Chinese economic growth is substantially moderated by sample and study characteristics. Both funnel plots show possible evidence of publication bias, as the scatter of estimates lies disproportionately to the right of the mean for estimates with larger standard errors. On the other hand, this pattern could be caused by study characteristics if study characteristics are correlated with standard errors.

A commonly employed statistical test of publication bias is given by the Funnel Asymmetry Test (FAT). The FAT consists of adding the standard error of the estimated effect to the regression specification of Equation (2) and testing for its significance:

$$(7) \quad PCC_{ij} = \alpha_0 + \alpha_1 se(PCC)_{ij} + \varepsilon_{ij}.$$

A test of publication bias is $H_0: \alpha_1 = 0$ (Stanley and Doucouliagos, 2012, page 62). Rejection of this hypothesis is evidence that the studies in the meta-analyst’s sample are affected by publication bias. A widely used correction for publication bias is to estimate α_0 with $se(PCC)$ included in the equation (or its square). As such, the $se(PCC)$ term serves a role analogous to the inverse Mills ratio in a Heckman-type correction for sample selection (Stanley and Doucouliagos, 2012, pages 117f).

A remaining estimation issue is the non-independence of estimates from the same study. As is evident in TABLE 1, many studies report multiple estimates. It seems likely that these estimates share a common component in their error terms, perhaps due to a common study design, similar estimation procedure, or common variable definitions. Non-independence in the error terms biases the estimation of standard errors. To address this, we follow best practice and calculate cluster robust standard errors.

The FE and RE estimators are the most commonly employed procedures in meta-analyses. While it is commonly acknowledged (and virtually always confirmed) that heterogeneity in estimated effects is best represented by the RE model, some authors (Doucouliagos and Paldam, 2013, p.586; Stanley and Doucouliagos, 2012, p.83) argue that the FE produces less biased estimates in the presence of publication bias. Others, such as Reed (2015), argue that while this is generally true, the RE estimator can be more efficient in some settings. As the jury is still out on which estimator is best, this study reports both, along with the two different weighting schemes (*Weight1* and *Weight2*). This yields four different estimation procedures. These can be compared as a robustness check.

IV. RESULTS

The first four columns of TABLE 3 report the results of testing for publication bias using the FAT. The FAT coefficients in the first row correspond to the coefficient on the $se(PCC)$ variable in Equation (7), along with its corresponding t -statistic, using each of the four estimation procedures described above. The FE estimates in Columns (1) and (2) indicate that publication bias is not an issue. In contrast, the RE estimators present conflicting results. The FAT coefficient is large and significant in Column (3), but statistically insignificant in Column (4).

In Equation (7) the constant term α_0 represents the mean effect in the absence of publication bias. Here again, there are differences within and across the different estimators,

with one of the FE estimates being significantly positive (Column 2), and one of the RE estimates being significantly negative (Column 3). The last two columns report the estimated mean effect using the FE estimator when the $se(PCC)$ term is dropped from Equation (7). As one would expect in the presence of positive publication bias, the (FE) mean effects are somewhat larger when the FAT term is omitted from the equation. However, the difference is not great. The main consequence of dropping the FAT term is that the estimated mean effect is now significant at the 1 percent level. The size of the mean effects indicate that the estimated FDI effects on economic growth are between “moderate” and “large.”

The results from TABLE 3 indicate that publication bias is likely not an issue for our data, but should be further investigated. They also indicate that the estimation method used can make a difference, so we will continue to analyse the data using a variety of procedures. Given the many different possibilities, the subsequent exposition focuses on the FE estimates. However, we will show that our main findings are robust across different specifications and estimators.

Estimates of the overall mean effect can be misleading because they can mask differences that are systematically related to study characteristics. For example, it may be that studies that correct for endogeneity have systematically lower estimates than those that don't. Understanding how study and sample characteristics affect the distribution of estimated effects can be insightful.

TABLE 4 reports the study characteristics that we include in our analysis. A number of authors have noted that a common feature of meta-analyses across many subject fields is that estimates tend to get smaller in absolute value over time. *PUBYEAR* is designed to pick up these time effects if they exist. *DATAYEAR* measures the age of the data used in the original study. The purpose of its inclusion is to determine if the relationship between FDI and Chinese economic growth has changed over time. *SPAN* measures the length of the

sample period covered in the original study. Longer time horizons can better capture temporal spillover effects to the extent that FDI values are correlated over time. China has 34 provinces and administrative regions. Most academic studies exclude the administrative regions of Hong Kong, Macao, and Taiwan. Many also exclude Tibet, Qinghai, Ningxia, and/or Chongqing for data reasons. As the latter generally have lower growth rates than other provinces/regions, especially the coastal provinces/regions, their omission may be associated with larger estimated FDI effects. Accordingly, *SUBSET* takes the value 1 if the study includes less than 27 provinces/regions.

As noted above, studies of Chinese economic growth have measured both the FDI and economic growth variables in a variety of ways. Most commonly, FDI is measured as the ratio of FDI to GDP. In this case, the variable *FDIGDP* takes the value 1. But growth studies have also specified the FDI variable as the growth rate of FDI, the natural log of FDI, and the share of total investment comprised of FDI, among others. In these cases, *FDIGDP* equals 0. Economic growth is most commonly measured by the growth rate of real, per capita GDP (*DVTYPE2* = 1). But it is also measured by the growth rate of nominal GDP (*DVTYPE 1* = 1), along with other variants, such as nominal GDP per capita. These latter are indicated by *DVTYPE_OTHERS*=1. The corresponding omitted category is the growth rate of real GDP.

The variable *INITIAL* indicates whether the growth specification includes the value of GDP at the start of the period, as suggested by convergence theory. *ENDO* takes the value 1 if the original study attempted to correct for endogeneity bias by using 2SLS or GMM. *SE_NOTOLS* takes the value 1 if the original studies calculated standard errors assuming that the errors were nonspherical (e.g., characterized by heteroskedasticity or serial correlation). Given that coefficient standard errors are used to weight the estimates in both FE and RE estimation, estimates that systematically under- (over-) state true standard errors could cause PCCs to be larger (smaller) solely as a result of how the standard errors were calculated.

Studies also differ in the form of the data they choose to work with. The study characteristics *PANEL_FE* and *PANEL_NOFE* take the value 1 when the studies used panel data with and without provincial level dummy variables, respectively. *TS = 1* when the data were time series. The omitted category was cross-sectional data.

Finally, we included variables to indicate whether the study appeared in a Chinese-language journal, or came from a source other than an academic journal (*CJOURNAL* and *NOTJOURNAL*). The omitted category was studies published in English-language journals.

TABLE 5 reports the results of estimating the following specification:

$$(8) \quad PCC_{ij} = \alpha_0 + \sum_{k=1}^K \alpha_k \cdot W_{k,ij} + \varepsilon_{ij},$$

where $W_{k,ij}$ is the value of the k th study characteristic corresponding to the j th estimate from study i . As noted above, we focus on the FE estimates and try a variety of specifications to give a sense of robustness. The first two columns report FE estimates from specifications using the *Weight1* weighting scheme, with one specification including the publication bias term, and the other omitting it. The next two columns report estimates using the *Weight2* weighting scheme.

The final two columns use Bayesian Model Averaging (BMA) and report posterior inclusion probabilities (PIP). PIPs are the cumulative (posterior) probability of all specifications that contain a given variable. For example, we see from Columns (5) and (6) that virtually all models with substantial explanatory power contain the variable *PUBYEAR*. In contrast, the cumulative posterior probabilities associated with models containing the variable *DATAYEAR* are only 0.14 and 0.398. While BMA is useful for identifying important variables, it is also sensitive to the particular weighting scheme that is used. The BMA procedure underlying TABLE 5 is described in Zeugner (2011). Further details are given in Appendices 2-5.

The first thing to note from TABLE 5 is that the publication bias variable (*SE*) continues to be statistically insignificant once explanatory variables are included in the equation. Further, a comparison of Column (2) with Column (1), and Column (4) with Column (3) reveals that dropping the *SE* variable from the specification has relatively little effect on the other estimated coefficients. These results indicate that publication bias is not an issue for the literature on FDI and Chinese economic growth.

In evaluating the coefficient of the explanatory variables in TABLE 5, we make a distinction between continuous and dummy variables. The variables *PUBYEAR*, *DATAYEAR*, and *SPAN* are continuous, with the remaining variables being binary. This distinction is valuable in identifying which variables are economically significant. Given that the dependent variable is a correlation, binary variables having coefficients less than 0.05 in absolute value are economically unimportant. Binary variables having coefficient values in excess of 0.10 in absolute value are economically significant.

Using this as our yardstick, in combination with the PIPs from Columns (5) and (6), we judge the dummy variables *INITIAL* and *DVTYPE2* to be both statistically and economically significant. Growth studies that include initial level of income (*INITIAL*) report substantially lower estimates of the effect of FDI on Chinese economic growth. This may be because FDI is correlated with provincial income. Or it may be because studies that include initial income are better designed and executed since good practice calls for including initial income to address convergence. Studies that measure growth in real, per capita GDP (*DVTYPE2*) are associated with larger estimates of FDI effects, perhaps because this measure is less influenced by noise from non-FDI related changes in prices and population.

In contrast, the dummy variables *PANEL_NOFE* and *PANEL_FE* are sometimes economically and statistically significant, depending on how the variables are weighted.

Growth studies that use panel data, whether they employ fixed effects or not, produce lower estimated FDI effects on growth than studies that use cross-sectional data.

The continuous variables *PUBYEAR*, *DATAYEAR*, and *SPAN* are all measured in years. A rough measure of economic significance for these variables is given by multiplying the respective coefficients by 10. This compares results from studies published a decade apart. Using this yardstick, only *PUBYEAR* is both statistically and economically significant. The results indicate that the estimated effects of FDI are smaller for more recent studies.

In summary, the variables *INITIAL*, *DVTYPE2*, and *PUBYEAR* are consistently both economically and statistically significant across the different specifications. Further there is some evidence that the variables *PANEL_NOFE* and *PANEL_FE* are also economically and statistically significant, depending on the weighting scheme used. The RE estimates in APPENDIX 1 confirm these results.

Interestingly, studies that correct for endogeneity (*ENDOG*) using 2SLS or GMM obtain estimates that are not appreciably different from studies that do not address endogeneity. This may be because FDI is not endogenous to economic growth in China, or it may be because the respective instrumental variables are insufficient to correct endogeneity. It is somewhat reassuring to know that alternative measures of coefficient standard errors (*SE_NOTOLS*) are not systematically related to estimated effect sizes. Nor does it matter how the FDI variable is measured (*FDIGDP*). It appears that the relationship between FDI and economic growth does not depend on the time period analysed (*DATAYEAR*). Finally, there is little evidence that studies published in Chinese journals or that come from non-journal sources, are associated with different estimated effects than studies published in English-language journals.

As noted above, TABLE 5 only reports FE estimates. However, the RE estimates are very similar (see APPENDIX 1). In particular, the publication bias variable (*SE*) is again

statistically insignificant. This confirms our previous conclusion that publication bias is not an issue for the literature on FDI and Chinese economic growth.

Estimated effect for preferred study and sample characteristics. The previous analysis has established that estimated effects differ widely across studies, and according to study and sample characteristics. In this section, we want to estimate the FDI effect for a study with “preferred characteristics.” These are the study and sample characteristics that are in our opinion most likely to produce a reliable, representative estimate of the effect of FDI on economic growth in China.

To start with, we set $PUBYEAR = 2010$, since more recent estimates are likely to have access to more reliable data and use better procedures. We set $DATAYEAR = 1997.5$ and $SPAN = 25$, implicitly setting our sample ranges from 1985-2010. This allows both the use of recent data, and a sufficiently long span of data so that noisy data from a given year, or a yet-to-be revised GDP figure do not distort the results. Because we are interested in the effect of FDI on all of China, we set $SUBSET = 0$.

A good specification should measure FDI as the ratio of FDI to GDP ($FDIGDP = 1$), should include initial income as an explanatory variable to hold constant the effect of convergence, and should correct for any possible endogeneity ($ENDOG$). As it is now common practice to adjust coefficient standard errors for nonspherical behavior in the error terms, we set $SE_NOTOLS = 1$. With respect to the appropriate form of the dependent variable, we believe, as most of the literature does, that the best measure of economic growth is real GDP per capita ($DVTYPE1 = 0$, $DVTYPE2 = 1$, $DVTYPE_OTHER = 0$). Given provincial level data and an extended sample period, we believe that panel data with fixed effects is preferred so that it can control for omitted variable bias due to time-invariant, unobserved provincial characteristics ($PANEL_NOFE = 0$, $PANEL_FE = 1$, $TS = 0$). And lastly, we think that studies that appear in English-language journals are more likely to

undergo a comprehensive review process and thus represent more reliable estimates ($CJOURNAL = NOTJOURNAL = 0$).

For our predictions, we use the (i) estimated FE models in Columns (2) and (4) from TABLE 5, and (ii) estimated RE models from the same columns in Appendix 1. TABLE 6 presents the predicted FDI effects for our “preferred study,” along with a 2-standard deviation confidence interval. The predictions range from 0.044 to 0.107. These predictions are much smaller than would be surmised from the histograms of FIGURE 1 and the sample PCC values in TABLE 2. Whereas the raw PCC values indicate that the effect of FDI on Chinese economic growth is “moderate” to “large”, the predicted values in TABLE 6 are “small” using Doucouliagos’ classification scheme. Furthermore, all four confidence intervals encompass zero, so that we cannot eliminate the possibility that the effect of FDI on Chinese economic growth is zero for our “preferred study.”

What explains this result? While the predictions are the result of the accumulated effects from many study characteristics, it is clear from TABLE 5 that three study characteristics exert a disproportionate influence: *PUBYEAR*, *INITIAL*, and *DVTYPE2*, with the first and last of these exerting a substantial downward influence on the estimated FDI effect. More recent studies, that include initial income in the growth specification, and that measure economic growth using per capita real GDP will produce lower estimates than the literature as a whole. If one agrees that these are desirable study characteristics for estimating the effect of FDI on Chinese economic growth, then one should prefer these predictions to sample averages derived from the literature as a whole.

V. CONCLUSION

A widely held belief is that FDI is an important factor causing Chinese economic growth. Our initial analysis of the literature confirms this belief. Estimates of the effect of FDI on aggregate Chinese economic growth are, on average, “moderate” to “large.”

Furthermore, our results suggest that the estimated effects are not inflated by endogeneity, nor impacted by publication bias. The latter result indicates that the estimates in the literature can be taken as representative of the population of research estimates, undistorted by sample selection.

One potential problem with simply looking for an “average effect” of the wide range of differently specified studies is that the average study may have study and data characteristics that are less preferred. We take this possibility seriously and estimate the effect of FDI on economic growth using study and sample characteristics that are in our opinion most likely to produce a reliable, representative estimate. We find that the body of existing estimates likely overstate the effect of FDI on Chinese economic growth. Based on the size classifications presented by Doucouliagos (2011), the effects of FDI on growth, once adjusted, are “small” to “very small”. None are significantly different from zero. This is not because of publication bias. But because much of the literature is characterized by poorer quality study design and data characteristics. Reinforcing this possibility is our finding that more recent studies, which have access to more data and better estimation procedures, produce significantly smaller effects than earlier studies.

FDI has long been viewed as a policy variable for stimulating economic growth. The extraordinary growth of the Chinese economy, accompanied as it was by a conscious decision by the Chinese government to encourage foreign investment, seemingly provided evidence for this position. Our overall findings dispute this view. Our study suggests that further efforts by the Chinese government to stimulate the economy by encouraging FDI are unlikely to be successful because there is no significant evidence of spillovers from FDI at the aggregate level. Furthermore, this suggests that transplanting Chinese style policies that favour FDI to other developing countries to further their development on the basis of this belief will likely have little impact on their economic growth.

REFERENCES

- Aitken, B., and Harrison, A. (1999). Do domestic firms benefit from direct foreign investment? Evidence from Venezuela. *American Economic Review*, 89(3), 605-618.
- Alfaro, L., Chanda, A., Kalemli-Ozcan, S., and Sayek, S. (2004). FDI and economic growth: the role of local financial markets. *Journal of International Economics*, 64(1), 89-112.
- Batten, J., and Vo, . (2009). An analysis of the relationship between foreign direct investment and economic growth. *Applied Economics*, 41(3), 1621-1641.
- Blomström, M., Lipsey, R., and Zejan, M. (1992). Is fixed investment the key to economic growth? *Quarterly Journal of Economics*, 111(1), 269-276.
- Borensztein, E., De Gregorio, J., and Lee, J. (1998). How does foreign direct investment affect economic growth? *Journal of International Economics*, 45(1), 115-135.
- Bosworth, B., and Collins, S. (1999). Capital flows to developing countries: implications for saving and investment. *Brookings Papers on Economic Activity*, 1, 143-180.
- Brun, J., Combes, J., and Renard, M. (2002). Are there spillover effects between coastal and noncoastal regions in China? *China Economic Review*, 13, 161-169.
- Buckley, P., Clegg, J., Wang, C., and Cross, A. (2002). FDI, regional differences and economic growth: panel data evidence from China. *Transnational Corporations*, 11(1), 1-28.
- Cao, W. (2005). An empirical analysis of FDI's role in economic growth in China. *World Economy Study*, 8, 39-43 (in Chinese).
- Chartas, V. (2011). *The impact of foreign direct investment on economic growth in China*. Unpublished Masters dissertation. Erasmus University Rotterdam.
- Chaudhry, N., Mehmood, A., and Mehmood, M. (2013). Empirical relationship between foreign direct investment and economic growth: an ARDL co-integration approach for China. *China Finance Review International*, 3(1), 26-41.
- Chen, N. (2015). An empirical test of FDI, international trade and economic growth. *Statistics and Decision*, 8, 135-138. (in Chinese)
- Coe, D., and Helpman, E. (1995). International R&D spillovers. *European Economic Review* 39(5), 859-887.
- De Mello, L. (1997). Foreign direct investment in developing countries and growth: a selective survey. *Journal of Development Studies*, 34(1), 1-34.
- De Mello, L. (1999). Foreign direct investment-led growth: evidence from time series and panel data. *Oxford Economic Papers*, 51(1), 133-151.
- Demurger, S. (2001). Infrastructure development and economic growth: an explanation for regional disparities in China? *Journal of Comparative Economics*, 29(1), 95-117.

Doucouliaagos, H., Iamsiraroj, S., and Ulubasoglu, M. (2010). Foreign direct investment and economic growth: a real relationship or wishful thinking? School of Accounting, Economics and Finance Working Paper SWP 2010/14, Deakin University.

Doucouliaagos, H. (2011). How large is large? Preliminary and relative guidelines for interpreting partial correlations in economics. School of Accounting, Economics and Finance Working Paper SWP 2015/9, Deakin University.

Doucouliaagos, H., and Paldam, M. (2013). The robust result in meta-analysis of aid effectiveness: a response to Mekasha and Tarp. *Journal of Development Studies*, 49(4), 584-587.

Durham, J. (2004). Absorptive capacity and the effects of foreign direct investment and equity foreign portfolio investment on economic growth. *European Economic Review*, 48(2), 285-306.

Ek, A. (2007). *The impact of FDI on economic growth: the case of China*. Unpublished Bachelors thesis. Jönköping University.

Fidrmuch, J. and Korhonen, I. (2015). Meta-analysis of Chinese business cycle correlation. Institute for Economies in Transition Discussion Paper 6/2015, Bank of Finland.

Findlay, R. (1978). Relative backwardness, direct foreign investment, and the transfer of technology: a simple dynamic model. *Quarterly Journal of Economics*, 92(1), 1-16.

Gechert, S. (2015). What fiscal policy is most effective? A meta-regression analysis. *Oxford Economic Papers*, 67(3), 553-580.

Guo, Z., and Yang, X. (2008). Different impacts of foreign direct investment on economic growth among China's Eastern, Middle and Western regions: an empirical test of the provincial data from 1990 to 2004. *Nankai Economic Studies*, 1, 75-86. (in Chinese)

Guariglia, A., and Poncet, S. (2008). Could financial distortions be no impediment to economic growth after all? Evidence from China. *Journal of Comparative Economics*, 36(4), 633-657.

Hao, H. (2006). The Relation among the human capital, FDI and economic growth: the case of China. *East China Economic Management*, 20(11), 133-151. (in Chinese)

Havránek, T., and Iršová, Z. (2011). Estimating vertical spillovers from FDI: why results vary and what the true effect is. *Journal of International Economics*, 85(2), 234-244.

Havránek, T., and Iršová, Z. (2012). Survey article: publication bias in the literature on foreign direct investment spillovers. *Journal of Development Studies*, 48(10), 1375-1396.

Havránek, T., and Iršová, Z. (2015). Do borders really slash trade? A meta-analysis. *William Davidson Institute Working Papers Series*, WP1088, University of Michigan.

- Huang, Y. (2012). How did China take-off? *Journal of Economic Perspectives*, 26(4), 147-170.
- Iršová, Z., and Havránek, T. (2013). Determinants of horizontal spillovers from FDI: evidence from a large meta-analysis. *World Development*, 42(C), 1-15.
- Jefferson, G., Hu, A., and Su, J. (2006). The sources and sustainability of China's economic growth. *Brookings Papers on Economic Activity*, 37(2), 1-60.
- Jin, F., Lee, K., and Kim, Y. (2008). Changing engines of growth in China: from exports, FDI and marketization to innovation and exports. *China and World Economy*, 16(2), 31-49.
- Jones, D., Li, C., and Owen, A. (2003). Growth and regional inequality in China during the reform era. *China Economic Review*, 14(2), 186-200.
- Knight, J., and Ding, S. (2012). The role of physical and human capital formation. In: J. Knight and S. Ding, eds., *China's remarkable economic growth*, Oxford: Oxford University Press, pp. 112-130.
- Kosová, R. (2010). Do foreign firms crowd out domestic firms? Evidence from the Czech Republic. *Review of Economics and Statistics*, 92(4), 861-881.
- Lai, M., Bao Q., and Yang, X. (2002). FDI absorptive capacity: theory and evidence from China. *Shanghai Economic Review*, 6, 9-17. (in Chinese)
- Ljungwall, C., and Tingvall, P. (2010). Is China different? A meta-analysis of the effects of foreign direct investment on domestic firms. *Journal of Chinese Economics and Business Studies*, 8(4), 353-371.
- Liu, W., and Jiang, R. (2006). The impact of FDI on economic growth, an empirical analysis and policy implication. *Economic Theory and Business Management*, 4, 21-26. (in Chinese)
- Liu, X., Burridge, P., and Sinclair, P. (2002). Relationships between economic growth, foreign direct investment and trade: evidence from China. *Applied Economics*, 34, 1433-1440.
- Liu, X., Luo, Y., Qiu, Z., and Zhang, R. (2014). FDI and economic development: evidence from China's regional growth. *Emerging Markets Finance & Trade*, 50(6), 87-106.
- Ljungwall, C., and Tingvall, P. (2010). Is China different? A meta-analysis of the effects of foreign direct investment on domestic firms. *Journal of Chinese Economic and Business Studies*, 8(4), 353-371.
- Lucas, R. (1993). Making a miracle. *Econometrica*, 61(2), 251-272.
- Luo, C. (2006). FDI, domestic capital and economic growth: evidence from Chinese provincial panel data during 1987-2001. *World Economic Papers*, 4, 27-43. (in Chinese)
- Mah, J. (2010). Foreign direct investment inflows and economic growth of China. *Journal of Policy Modeling*, 32(1), 155-158.

- Papanek, G. (1973). Aid, foreign private investment, savings, and growth in less developed countries. *Journal of Political Economy*, 81(1), 120-130.
- Prasad, E., and Rajan, R. (2006). Modernizing China's growth paradigm. *AEA Papers and Proceedings*, 96(2), 331-336.
- Ran, J., Voo, J., and Li, G. (2007). How does FDI affect China? Evidence from industries and provinces. *Journal of Comparative Economics*, 35(4), 774-799.
- Reed, W.R. (2015). A monte carlo analysis of alternative meta-analysis estimators in the presence of publication bias. *Economics: The Open-Access, Open-Assessment E-Journal*, 9(2015-30), 1-40. Available from: <http://dx.doi.org/10.5018/economics-ejournal.ja.2015-30>. [Accessed: 6 November 2015].
- Ren, J. (2012). *Determinants and impact of foreign direct investment in China: a national and regional analysis*. Unpublished doctoral dissertation. Loughborough University.
- Ringquist, E. (2013). *Meta-analysis for public management and policy*. San Francisco: Jossey-Bass.
- Stanley, T., and Doucouliagos, H. (2012). *Meta-regression analysis in economics and business*. London: Routledge.
- Stanley, T., Doucouliagos, H., Giles, M., Heckemeyer, J., Johnston, R., Laroche, P., Nelson, J., Paldam, M., Poot, J., Pugh, G., Rosenberger, R., Rost, K. (2013). Meta-Analysis of economics research reporting guidelines. *Journal of Economic Surveys*, 27(2), 390-394.
- Steel, P. (2014). Converting between meta-analytic variance estimates based on correlations and Fisher z. Unpublished paper, Haskayne School of Business, University of Calgary.
- Stohldreier, M. (2009). *The Impact of Foreign Direct Investments on Economic Growth in China during the Era 1979-2009*. Unpublished Bachelor's thesis. University of Zurich.
- Su, S., and Deng, J. (2007). FDI, R&D and economic growth-pool data of provinces in China. *Journal of Chongqing University*, 30(8), 145-148. (in Chinese)
- Sun, H., and Parikh, A. (2001). Exports, inward foreign direct investment (FDI) and regional economic growth in China. *Regional Studies*, 35(3), 187-196.
- Temple, J. (1999). The new growth evidence. *Journal of Economic Literature*, 37(1), 112-156.
- Tian, X., Lin, S., and Lo, V. (2004). Foreign direct investment and economic performance in transition economies: evidence from China. *Post-Communist Economies*, 16(4), 497-510.
- Wang, Y. (2006). *Openness, openness policy and economic growth: a case study of China*. Unpublished doctoral dissertation, University of Missouri-Columbia.

- Wang, Z., and O'Brien, R. (2001). The coastal-inland income gap in China from 1991 to 1999: the role of geography and policy. Department of Economics Working Paper 0301, University of Southampton.
- Wang, C., Zhang, J., and An, H. (2002). FDI, regional disparity and economic growth. *The Journal of World Economy*, 4, 15-23. (in Chinese)
- Wang, Z., and Li, Z. (2004). FDI, spillover effect and endogenous economic growth. *World Economic Papers*, 3, 23-33. (in Chinese)
- Wang, J., and Wang, X. (forthcoming). Benefits of foreign ownership: evidence from foreign direct investment in China. *Journal of International Economics*.
- Wei, Y., and Liu, X. (2001). *Foreign direct investment in China: determinants and impact*. Cheltenham: Edward Elgar, pp. 112-132.
- Wei, K., Yao, S., and Liu, A. (2009). Foreign direct investment and regional inequality in China. *Review of Development Economics*, 13(4), 778-791.
- Xu, G., and Wang, R. (2007). The effect of foreign direct investment on domestic capital formation, trade, and economic growth in a transition economy: evidence from China. *Global Economy Journal*, 7(2), 1-21.
- Yalta, A. (2013). Revisiting the FDI-led growth hypothesis: the case of China. *Economic Modelling*, 31(1), 335-343
- Yan, L. (2011). *Quality of foreign direct investment and China's economic growth*. Unpublished Masters dissertation, Nanjing University of Finance and Economics. (in Chinese)
- Ye, Y. (2010). *FDI and economic growth in China*. Unpublished doctoral dissertation, University of Texas at Dallas.
- Zeng, H. (2009). *FDI and economic growth in China: a statistical and empirical study based on absorptive capabilities*. Unpublished doctoral dissertation, Zhejiang Gongshang University. (in Chinese)
- Zeugner, S. (2011). Bayesian model averaging with BMS. [pdf] Available at <http://bms.zeugner.eu/> [Accessed 15 Oct. 2015].
- Zhang, K. (2001). How does foreign direct investment affect economic growth in China? *Economics of Transition*, 9(3), 679-693.
- Zhang, K. (2001). Roads to prosperity: assessing the impact of foreign direct investment on economic growth in China. *Economia Internazionale*, 54(1), 113-125.
- Zhang, Q., and Fellingham, B. (2002). The role of FDI, exports and spillover effects in the regional development of China. *Journal of Development Studies*, 38(4), 157-178.
- Zhang, T. (2004). An empirical analysis of FDI's impact on economic growth in China. *World Economy Study*, 10, 73-78. (in Chinese)

Zhang, W. (2001). Rethinking regional disparity in China. *Economics of Planning*, 34(1), 113-138.

Zhao, C., and Du, J. (2007). Causality between FDI and economic growth in China. *The Chinese Economy*, 40(6), 68-82.

Zhu, X. (2012). Understanding China's growth: past, present, and future. *Journal of Economic Perspectives*, 26(4), 103-124.

Zigraiova, D., and Havránek, T. (2015) "Bank competition and financial stability: much ado about nothing?" Institute of Economic Studies Working Paper 7/2015, Charles University.

TABLE 1
Description of Studies

<i>ID</i>	<i>Study</i>	<i>Publication Type</i>	<i>Language</i>	<i>Number of Estimates</i>
1	Lai, Bao and Yang (2002)	Journal	Chinese	1
2	Wang, Zhang, and An (2002)	Journal	Chinese	17
3	Wang and Li (2004)	Journal	Chinese	3
4	Zhang, T. (2004)	Journal	Chinese	1
5	Cao (2005)	Journal	Chinese	1
6	Hao (2006)	Journal	Chinese	1
7	Liu and Jiang (2006)	Journal	Chinese	1
8	Luo (2006)	Journal	Chinese	16
9	Su and Deng (2007)	Journal	Chinese	5
10	Guo and Yang (2008)	Journal	Chinese	6
11	Chen (2015)	Journal	Chinese	1
12	Demurger (2001)	Journal	English	7
13	Sun and Parikh (2001)	Journal	English	16
14	Zhang, K.H. (2001)	Journal	English	4
15	Zhang, K.H. (2001)	Journal	English	4
16	Zhang, W. (2001)	Journal	English	2
17	Brun, Combes, and Renard (2002)	Journal	English	1
18	Buckley, Clegg, Wang, and Cross (2002)	Journal	English	17
19	Jones, Li, and Owen (2003)	Journal	English	12
20	Tian, Lin, and Lo (2004)	Journal	English	4
21	Xu and Wang ((2007)	Journal	English	3
22	Guariglia and Poncet (2008)	Journal	English	9
23	Jin, Lee, and Kim (2008)	Journal	English	6
24	Wei, Yao, and Liu (2009)	Journal	English	10
25	Chaudhry, Mehmood and Mehmood (2013)	Journal	English	3
26	Liu, Luo, Qiu, and Zhang (2014)	Journal	English	18
27	Wei and Liu (2001)	Book Chapter	English	7
28	Wang and O'Brien (2003)	Working paper	English	2

<i>ID</i>	<i>Study</i>	<i>Publication Type</i>	<i>Language</i>	<i>Number of Estimates</i>
29	Wang (2006)	PhD Thesis	English	40
30	Ek (2007)	Bachelor Thesis	English	2
31	Stohldreier (2009)	Bachelor Thesis	English	12
32	Zeng (2009)	PhD Thesis	Chinese	8
33	Ye (2010)	PhD Thesis	English	6
34	Chartas (2011)	Master Thesis	English	13
35	Yan (2011)	Master Thesis	Chinese	7
36	Knight and Ding (2012)	Book Chapter	English	2
37	Ren (2012)	PhD Thesis	English	12

TABLE 2
Selected Sample Characteristics

A. Selected Characteristics of the Data

<i>Characteristics</i>	<i>OBS</i>	<i>MEAN</i>	<i>MIN</i>	<i>MAX</i>
<i>t-stat</i>	280	2.449	-9.32	14.12
<i>PCC</i>	280	0.231	-0.377	0.805
<i>Year of publication</i>	280	2006.4	2001	2015
<i>Mid-point of sample years</i>	280	1995.0	1985	2004.5
<i>Span of sample years</i>	280	13.80	4	33
<i>Growth specification includes initial income</i>	280	0.611	0	1

B. Distribution of PCC Values by Variable Values

<i>CONDITIONING VALUES</i>	<i>OBS</i>	<i>MEAN</i>	<i>MIN</i>	<i>MAX</i>
<i>Older studies</i>	99	0.308	0.055	0.805
<i>More recent studies</i>	181	0.188	-0.377	0.723
<i>Chinese-language journals</i>	53	0.205	-0.128	0.772
<i>English-language journals</i>	116	0.257	-0.377	0.805
<i>Not journal</i>	111	0.215	-0.316	0.611
<i>Cross-sectional data</i>	62	0.381	0.016	0.805
<i>Panel data (no fixed effects)</i>	66	0.180	-0.377	0.710
<i>Panel data (fixed effects)</i>	137	0.167	-0.316	0.675
<i>Time series data</i>	15	0.417	-0.149	0.772
<i>OLS</i>	204	0.241	-0.377	0.805
<i>GLS</i>	14	0.242	-0.096	0.439
<i>2SLS</i>	27	0.270	-0.128	0.577
<i>GMM</i>	35	0.115	-0.316	0.458

NOTE: Values in the table report the mean, minimum, and maximum values of the PCC variable for those observations satisfying the condition in the leftmost column.

TABLE 3
Funnel Asymmetry Test (FAT)

	<i>Fixed Effects (Weight1) (1)</i>	<i>Fixed Effects (Weight2) (2)</i>	<i>Random Effects (Weight1) (3)</i>	<i>Random Effects (Weight2) (4)</i>	<i>Fixed Effects (Weight1) (5)</i>	<i>Fixed Effects (Weight2) (6)</i>
<i>(1) FAT</i>	1.844 (1.55)	0.770 (0.62)	3.477** (2.64)	2.044 (1.61)	---	---
<i>(2) Mean Effect</i>	0.073 (0.71)	0.217* (1.79)	-0.539** (-1.82)	-0.166 (-0.56)	0.181*** (4.30)	0.266*** (5.12)
<i>Observations</i>	280	280	280	280	280	280

NOTE: Values in Row (1) come from estimating α_1 in Equation (7) in the text. Values in Row (2) come from estimating α_0 in Equation (2) in the text. In both cases, the top value is the coefficient estimate, and the bottom value in parentheses is the associated t -statistic. All four of the estimation procedures calculate cluster robust standard errors.

TABLE 4
Description of Study Characteristics

<i>VARIABLE</i>	<i>DEFINITION</i>
<i>SE</i>	Standard error of estimated effect (PCC)
<i>PUBYEAR</i>	Year study was published
<i>DATAYEAR</i>	Midpoint year of data
<i>SPAN</i>	Length of data range
<i>SUBSET</i>	Takes the value 1 if the sample consists of less than 27 provinces and administrative regions; 0 otherwise
<i>FDIGDP</i>	Takes the value 1 if the FDI variable is the ratio of FDI to GDP; 0 otherwise (such as growth rate of FDI, $\ln(\text{FDI})$, or FDI as a share of total investment) comprised by FDI)
<i>INITIAL</i>	Takes the value 1 if the growth specification includes initial income; 0 otherwise
<i>ENDO</i>	Takes the value 1 if the estimation procedure is 2SLS or GMM; 0 if it is OLS or GLS
<i>SE_NOTOLS</i>	Takes the value 1 if coefficient standard error in original study is calculated as something other than an OLS standard error, such as White standard errors, Newey-West standard errors, GLS standard errors, etc.
<i>DVTYPE1</i>	Takes the value 1 if the dependent variable is the growth rate of nominal GDP; 0 otherwise (<i>Omitted category = DV is growth rate of real GDP</i>)
<i>DVTYPE2</i>	Takes the value 1 if the dependent variable is the growth rate of real GDP per capita; 0 otherwise (<i>Omitted category = DV is growth rate of real GDP</i>)
<i>DVTYPE_OTHER</i>	Takes the value 1 if the dependent variable is something other than growth rate of nominal GDP, real GDP, or real GDP per capita (such as nominal GDP per capita) (<i>Omitted category = DV is growth rate of real GDP</i>)

<i>VARIABLE</i>	<i>DEFINITION</i>
<i>PANEL_NOFE</i>	Takes the value 1 if analysis uses panel data without fixed effects; 0 otherwise (<i>Omitted category = Cross-sectional data</i>)
<i>PANEL_FE</i>	Takes the value 1 if analysis uses panel data with fixed effects; 0 otherwise (<i>Omitted category = Cross-sectional data</i>)
<i>TS</i>	Takes the value 1 if analysis uses time series data; 0 otherwise (<i>Omitted category = Cross-sectional data</i>)
<i>CJOURNAL</i>	Takes the value 1 if Chinese-language journal; 0 otherwise (<i>Omitted category = English-language journal</i>)
<i>NOTJOURNAL</i>	Takes the value 1 if book, thesis, or working paper; 0 otherwise (<i>Omitted category = English-language journal</i>)

TABLE 5
Multiple Meta-Regression Analysis: Fixed Effects

VARIABLE	<u>WLS</u>		<u>WLS</u>		<u>BMA – PIP^l</u>	
	Weight1 (1)	Weight1 (2)	Weight2 (3)	Weight2 (4)	Weight1 (5)	Weight2 (6)
Intercept	0.225 (1.08)	0.378*** (3.72)	0.580** (2.29)	0.525*** (4.97)	0.160	1.000
SE	1.354 (1.05)	----	-0.432 (-0.29)	----	----	----
PUBYEAR	-0.019** (-2.18)	-0.017** (-2.11)	-0.023* (-2.01)	-0.025** (-2.29)	1.000	0.974
DAYEAR	0.008 (0.87)	0.006 (0.74)	0.012 (0.99)	0.013 (1.11)	0.140	0.398
SPAN	-0.003 (-0.81)	-0.004 (-1.41)	0.002 (0.30)	0.002 (0.43)	0.053	0.458
SUBSET	0.039 (1.18)	0.068*** (3.08)	0.047 (1.16)	0.040 (1.19)	0.080	0.991
FDIGDP	-0.052 (-0.99)	-0.048 (-0.82)	-0.017 (-0.26)	-0.014 (-0.23)	0.083	0.092
INITIAL	-0.312*** (-6.41)	-0.296*** (-5.62)	-0.277*** (-3.66)	-0.282*** (-3.80)	1.000	1.000
ENDO	0.000 (0.01)	0.011 (0.24)	-0.029 (-0.58)	-0.035 (-0.73)	0.031	0.198
SE_NOTOLS	0.005 (0.08)	-0.009 (-0.16)	-0.072 (-0.97)	-0.069 (-0.95)	0.061	0.966
DVTYPE1	-0.042 (-1.01)	-0.046 (-0.99)	-0.072 (-1.19)	-0.070 (-1.13)	0.064	0.314
DVTYPE2	0.314*** (5.46)	0.289*** (4.66)	0.272*** (3.58)	0.284*** (3.65)	1.000	1.000
DVTYPE_OTHER	0.036 (0.75)	0.024 (0.47)	0.044 (0.42)	0.054 (0.49)	0.337	0.271
PANEL_NOFE	-0.034 (-0.26)	-0.113 (-1.30)	-0.307* (-1.96)	-0.280*** (-3.19)	0.080	1.000
PANEL_FE	-0.080 (-0.64)	-0.162* (-1.89)	-0.298* (-1.93)	-0.272*** (-3.06)	0.054	1.000
TS	-0.021** (-2.11)	-0.017 (-1.69)	-0.001 (0.09)	-0.002 (-0.15)	0.055	0.183
CJOURNAL	-0.131** (-2.17)	-0.122* (-1.92)	-0.013 (-0.15)	-0.017 (-0.19)	0.998	0.124
NOTJOURNAL	-0.020 (-0.51)	-0.011 (-0.28)	-0.031 (-0.59)	-0.033 (-0.63)	0.037	0.095

VARIABLE	<u>WLS</u>		<u>WLS</u>		<u>BMA – PIP¹</u>	
	Weight1 (1)	Weight1 (2)	Weight2 (3)	Weight2 (4)	Weight1 (5)	Weight2 (6)
Observations	280	280	280	280	280	280
Studies	37	37	37	37	37	37
R-Squared	0.477 ²	0.704 ²	0.639 ²	0.805 ²	n/a	n/a

¹ These two columns report the Posterior Inclusion Probabilities (PIP) associated with Bayesian Model Averaging (BMA) analysis of the variables. The dependent variable is the PCC variable, with weights identified by the column headings. The analysis employed the R package BMS, described in Zeugner (2011). Further details associated with the BMA analysis are given in the Appendix.

² Note that the R-squared values are not directly comparable across columns because the respective specifications weight the variables differently and/or differ with respect to the inclusion of a constant term.

NOTE: The values in the table come from estimating Equation (8) in the text. The top value in each row is the coefficient estimate, and the bottom value in parentheses is the associated *t*-statistic. All four of the estimation procedures calculate cluster robust standard errors. Variables are defined in TABLE 2. Note that the variables *PUBYEAR*, *DAYEAR*, and *SPAN* have been demeaned in order to facilitate comparison of the intercept term with the *Mean Effect* estimates in TABLE 3.

TABLE 6
Predictions for Alternative Samples and Models

<i>PROCEDURE</i>	<i>PREFERRED SPECIFICATION</i>
<i>FIXED EFFECTS</i> <i>(Weight1)</i>	0.066 <i>(-0.028,0.160)</i>
<i>FIXED EFFECTS</i> <i>(Weight2)</i>	0.107 <i>(-0.011,0.226)</i>
<i>RANDOM EFFECTS</i> <i>(Weight1)</i>	0.044 <i>(-0.083,0.172)</i>
<i>RANDOM EFFECTS</i> <i>(Weight2)</i>	0.094 <i>(-0.046,0.234)</i>

NOTE: Each cell contains three values on two lines. The top line is the prediction. The bottom line, in parentheses, reports a two, standard-deviation prediction interval. Predictions are obtained using the same four procedures employed in TABLE 4.

¹ The first three columns estimate the mean value of PCC for each of three sets of observations: PCC values obtained from (i) cross-sectional studies, (ii) time series studies, and (iii) panel data studies, respectively. The mean is estimated by the constant term in a regression specification where the constant term is the only term in the model. The different estimates and prediction intervals arise from using the four different WLS procedures to estimate the equation/constant term.

²The last column uses the full sample and the variable specification of TABLE 4 to predict the value of PCC when *PUBYEAR* = 2010, *DATAYEAR* = 1997, *SPAN* = 25, *SUBSET* = 0, *FDIGDP* = 1, *INITIAL* = 1, *ENDO* = 1, *SE_NOTOLS* = 1, *DVTYPE1* = 0, *DVTYPE2* = 1, *DVTYPE_OTHER* = 0, *PANEL_NOFE* = 0, *PANEL_FE* = 1, *TS* = 0, *CJOURNAL* = 0, and *NOTJOURNAL* = 0.

FIGURE 1
Histograms of t -stat and PCC Values

A. t -stat values

B. PCC values

FIGURE 2
Forest Plot of Studies

NOTE: Studies 1-11 were published in refereed Chinese journals. Studies 11-26 were published in refereed Western journals. And studies 27-37 are theses, books, and working papers. Within each category, studies are arranged by year and author. ID numbers correspond to the study ID numbers in TABLE 1.

FIGURE 3
Funnel Plot

A. All estimates

B. Mean of study estimates

APPENDIX

APPENDIX 1: Multiple Meta-Regression Analysis: Random Effects

APPENDIX 2: BMA Analysis Underlying TABLE 5, Column (5)

APPENDIX 3: BMA Analysis Underlying TABLE 5, Column (6)

APPENDIX 4: BMA Analysis Underlying APPENDIX 1, Column (5)

APPENDIX 5: BMA Analysis Underlying APPENDIX 1, Column (6)

APPENDIX 1
Multiple Meta-Regression Analysis: Random Effects

VARIABLE	<u>WLS</u>		<u>WLS</u>		<u>BMA – PIP^l</u>	
	Weight1 (1)	Weight1 (2)	Weight2 (3)	Weight2 (4)	Weight1 (5)	Weight2 (6)
Intercept	0.401 (0.90)	0.446*** (6.05)	0.947** (2.37)	0.540*** (7.09)	0.202	1.000
SE	0.226 (0.11)	----	-1.983 (-1.11)	----	----	----
PUBYEAR	-0.017* (-1.88)	-0.016** (-2.17)	-0.018 (-1.62)	-0.025*** (-2.79)	0.996	1.000
DATAYEAR	0.004 (0.50)	0.004 (0.53)	0.008 (0.81)	0.012 (1.36)	0.288	0.135
SPAN	-0.002 (-0.62)	-0.002 (-0.69)	0.002 (0.49)	0.005 (0.99)	0.242	0.100
SUBSET	0.067** (2.08)	0.069** (2.34)	0.045 (1.00)	0.034 (0.79)	0.381	0.868
FDIGDP	-0.050 (-0.97)	-0.049 (-0.91)	-0.035 (-0.60)	-0.031 (-0.55)	0.310	0.095
INITIAL	-0.189*** (-3.68)	-0.189*** (-3.56)	-0.165** (-2.61)	-0.167*** (-2.77)	1.000	1.000
ENDOGEN	0.015 (0.33)	0.016 (0.39)	-0.028 (-0.52)	-0.048 (-0.95)	0.040	0.508
SE_NOTOLS	-0.047 (-0.79)	-0.050 (-0.91)	-0.126 (-1.65)	-0.115 (-1.56)	0.118	1.000
DVTYPE1	-0.061 (-1.29)	-0.061 (-1.28)	-0.083 (-1.34)	-0.094* (-1.73)	0.273	0.223
DVTYPE2	0.168*** (3.13)	0.166*** (2.83)	0.130* (1.99)	0.153** (2.26)	0.998	1.000
DVTYPE_OTHER	0.017 (0.33)	0.016 (0.30)	0.053 (0.47)	0.077 (0.66)	0.234	0.812
PANEL_NOFE	-0.154 (-01.30)	-0.164** (-2.70)	-0.337*** (-3.10)	-0.251*** (-3.89)	0.736	1.000
PANEL_FE	-0.211* (-1.76)	-0.221*** (-3.89)	-0.322*** (-2.78)	-0.234*** (-3.55)	0.994	1.000
TS	-0.011 (-1.01)	-0.011 (-0.88)	0.008 (0.68)	0.006 (0.47)	0.086	0.125
CJOURNAL	-0.082 (-1.34)	-0.081 (-1.32)	0.010 (0.13)	0.014 (0.18)	0.660	0.097
NOTJOURNAL	0.003 (0.06)	0.003 (0.07)	-0.050 (-0.82)	-0.046 (-0.80)	0.080	0.113

VARIABLE	<u>WLS</u>		<u>WLS</u>		<u>BMA – PIP¹</u>	
	Weight1 (1)	Weight1 (2)	Weight2 (3)	Weight2 (4)	Weight1 (5)	Weight2 (6)
Observations	280	280	280	280	280	280
Studies	37	37	37	37	37	37
R-Squared	0.403 ²	0.730 ²	0.549 ²	0.804 ²	n/a	n/a

¹ These two columns report the Posterior Inclusion Probabilities (PIP) associated with Bayesian Model Averaging (BMA) analysis of the variables. The dependent variable is the PCC variable, with weights identified by the column headings. The analysis employed the R package BMS, described in Zeugner (2011). Further details associated with the BMA analysis are given in the Appendix.

² Note that the R-squared values are not directly comparable across columns because the respective specifications weight the variables differently and/or differ with respect to the inclusion of a constant term.

NOTE: The values in the table come from estimating Equation (8) in the text. The top value in each row is the coefficient estimate, and the bottom value in parentheses is the associated *t*-statistic. All four of the estimation procedures calculate cluster robust standard errors. Variables are defined in TABLE 2. Note that the variables *PUBYEAR*, *DATAYEAR*, and *SPAN* have been demeaned in order to facilitate comparison of the intercept term with the *Mean Effect* estimates in TABLE 3.

APPENDIX 2: BMA Analysis Underlying Column (5), TABLE 5

NOTE: Each column represents a single model. Variables are listed in descending order of posterior inclusion probability (PIP) and have all been weighted according to the Fixed Effects – Weight 1 case. Blue (the darker colour in greyscale) indicates that the variable is included in that model and estimated to be positive. Red (lighter in greyscale) indicates the variable is included and estimated to be negative. No colour indicates the variable is not included in that model. Further details about this plot and the information reported below is given in Zeugner (2011).

<i>Variable</i>	<i>Posterior Inclusion Probability (PIP)</i>	<i>Posterior Mean</i>	<i>Posterior SD</i>	<i>Cond. Pos. Sign</i>
pubyear	1	-0.01915	0.003054	0
dvtype2	1	0.341735	0.034442	1
initial	1	-0.30526	0.030543	0
cjournal	0.99781	-0.11452	0.026298	0
dvtype_other	0.336779	0.033836	0.053363	1
intercept	0.159687	0.012743	0.035442	1
datayear	0.140156	0.001045	0.003031	1
subset	0.079568	0.002507	0.010564	1
panel_nofe	0.07666	0.002436	0.011447	0.979829
fdigdp	0.072719	-0.00246	0.011423	0
dvtype1	0.063967	-0.00278	0.014924	0.048732
se_notols	0.06136	0.001626	0.008403	1
ts	0.055036	-0.00086	0.004854	0
panel_fe	0.054417	-0.0014	0.00935	0.18531
span	0.052891	-0.00011	0.000694	0.07058
notjournal	0.037246	-0.00041	0.00557	0.331885
endog	0.031454	-0.0003	0.004854	0.046325
(Intercept)	1	2.718933	NA	NA

APPENDIX 3: BMA Analysis Underlying Column (6), TABLE 5

NOTE: Each column represents a single model. Variables are listed in descending order of posterior inclusion probability (PIP) and have all been weighted according to the Fixed Effects – Weight 2 case. Blue (the darker colour in greyscale) indicates that the variable is included in that model and estimated to be positive. Red (lighter in greyscale) indicates the variable is included and estimated to be negative. No colour indicates the variable is not included in that model. Further details about this plot and the information reported below is given in Zeugner (2011).

<i>Variable</i>	<i>Posterior Inclusion Probability (PIP)</i>	<i>Posterior Mean</i>	<i>Posterior SD</i>	<i>Cond. Pos. Sign</i>
panel_nofe	1	-0.333232034	0.036614128	0
panel_fe	1	-0.338205713	0.034170399	0
dvtype2	1	0.254761109	0.035126872	1
initial	1	-0.249093109	0.030414613	0
intercept	1	0.65090785	0.047810892	1
subset	0.99112073	0.098379386	0.027549308	1
pubyear	0.97403412	-0.015640482	0.005560795	0
se_notols	0.96631855	-0.083813632	0.029419497	0
span	0.45751903	-0.002084152	0.002780722	0.00042332
datayear	0.39844241	0.002892234	0.005155599	0.94283627
dvtype1	0.31383616	-0.021204027	0.038037084	0
dvtype_other	0.27082467	0.023929629	0.048419584	0.99958846
endog	0.19791651	-0.007259265	0.018911849	0
ts	0.18286037	-0.001824647	0.005125235	0
cjournal	0.12373964	-0.002840413	0.012473999	0.01863049
notjournal	0.09473093	-0.000576087	0.008186957	0.19774947
fdigdp	0.09184828	0.000241703	0.007141059	0.61708208
(Intercept)	1	-0.661115649	NA	NA

APPENDIX 4: BMA Analysis Underlying Column (5), APPENDIX 1

NOTE: Each column represents a single model. Variables are listed in descending order of posterior inclusion probability (PIP) and have all been weighted according to the Random Effects – Weight 1 case. Blue (the darker colour in greyscale) indicates that the variable is included in that model and estimated to be positive. Red (lighter in greyscale) indicates the variable is included and estimated to be negative. No colour indices the variable is not included in that model. Further details about this plot and the information reported below is given in Zeugner (2011).

<i>Variable</i>	<i>Posterior Inclusion Probability (PIP)</i>	<i>Posterior Mean</i>	<i>Posterior SD</i>	<i>Cond. Pos. Sign</i>
initial	1	-0.17647	0.032773	0
dvtype2	0.998001	0.166024	0.040728	1
pubyear	0.995932	-0.01822	0.004781	0
panel_fe	0.994311	-0.13109	0.049897	0
panel_nofe	0.735558	-0.07944	0.063708	0
cjournal	0.659613	-0.04987	0.042518	0
subset	0.381003	0.022044	0.032305	1
fdigdp	0.310395	-0.01567	0.026989	0
datayear	0.287767	0.002444	0.004602	0.987107
dvtype1	0.272931	-0.01921	0.03634	0
span	0.24153	-0.00103	0.00213	0.000575
dvtype_other	0.233966	0.02257	0.047749	0.997958
intercept	0.202409	0.054591	0.138797	0.92439
se_notols	0.117637	-0.00416	0.014382	0
ts	0.086012	-0.00139	0.006122	0.004138
notjournal	0.080443	0.002374	0.012024	0.880216
endog	0.039865	-0.00019	0.005916	0.330592
(Intercept)	1	1.697274	NA	NA

APPENDIX 5: BMA Analysis Underlying Column (6), APPENDIX 1

NOTE: Each column represents a single model. Variables are listed in descending order of posterior inclusion probability (PIP) and have all been weighted according to the Random Effects – Weight 2 case. Blue (the darker colour in greyscale) indicates that the variable is included in that model and estimated to be positive. Red (lighter in greyscale) indicates the variable is included and estimated to be negative. No colour indices the variable is not included in that model. Further details about this plot and the information reported below is given in Zeugner (2011).

<i>Variable</i>	<i>Posterior Inclusion Probability (PIP)</i>	<i>Posterior Mean</i>	<i>Posterior SD</i>	<i>Cond. Pos. Sign</i>
panel_nofe	1	-0.2338753	0.034809	0
panel_fe	1	-0.2481160	0.029702	0
initial	1	-0.1735454	0.029124	0
intercept	1	0.6142658	0.036061	1
dvtype2	0.999998	0.1963087	0.035579	1
se_notols	0.999932	-0.1305137	0.026526	0
pubyear	0.999668	-0.0162510	0.003017	0
subset	0.867568	0.0684379	0.036493	1
dvtype_other	0.812205	0.1334092	0.082275	1
endog	0.508489	-0.0334838	0.039045	0
dvtype1	0.223198	-0.0128950	0.03083	0
datayear	0.134734	0.0004731	0.001867	0.997539
ts	0.124796	-0.0007634	0.003401	0.002535
notjournal	0.113426	-0.0020886	0.011079	0.007076
span	0.099862	-0.0000400	0.000685	0.200783
cjournal	0.096632	-0.0008498	0.008665	0.107588
fdigdp	0.094608	-0.0000618	0.007101	0.596198
(Intercept)	1	-0.3354104	NA	NA