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Does FDI Promote Entrepreneurial Activities? A Meta-Analysis

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Abstract: This study uses meta-analysis to analyze 557 estimates from 35 studies that estimate the effect of inward FDI on entrepreneurial activity. We address two questions: (i) Does FDI lead to greater entrepreneurial activity in host countries? (ii) What factors are responsible for the different estimates across studies? In addressing these questions, we make two methodological contributions. We extend the new Andrews-Kasy meta-analysis estimators (Andrews & Kasy, 2019) to allow for explanatory variables, and we develop a nested framework of multiple meta-analysis models that allows for testing between models and model selection. We estimate that, across all studies, the average estimated effect of FDI on entrepreneurship is positive but small in size, and statistically insignificant. In contrast, the average effect from studies that control for endogeneity is negative and statistically significant.

Keywords: Meta-analysis, FDI, Entrepreneurship

JEL Classifications: L26, F21, C10

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I. INTRODUCTION

The flow of capital, technology, knowledge and skills across national boundaries through FDI can have substantial positive external (spillover) effects on the economic development of host economies (De Vita & Kyaw, 2009; Doucouliagos, 2011; Hermes & Lensink, 2003; Iamsiraroj, & Ulubaşoğlu, 2015; Iršová & Havránek, 2013; Li & Liu, 2005). Similarly, entrepreneurship plays a major role in countries' growth and development. Many studies have shown that new firms generally trend to be more efficient, create more job opportunities and enhance productivity and economic growth (Ayyagari, Demirgüç-Kunt, & Vojislav, 2011; Djankov et al., 2002; Haltiwanger, Jarmin, & Miranda, 2013; Klapper, Laeven, & Rajan, 2006). Given these two strands of literature, a number of studies have investigated the relationship between FDI and entrepreneurship. In particular, there is interest in determining whether FDI positively impacts entrepreneurial activity in the host country.

The literature on the subject has grown substantially, with some studies finding a positive relationship (Herrera-Echeverri, Haar, & Estévez-Bretón, 2014; Kim & Li, 2014; Munemo, 2017); some a negative relationship (Danakol et al., 2017; Goel, 2018); and some reporting mixed results (Angulo-Guerrero, Pérez-Moreno, & Abad-Guerrero, 2017). It is difficult to synthesize this literature because many of the studies use different definitions of FDI and entrepreneurship, study different time periods and countries, and apply different estimation procedures to generate their results. We address these difficulties and use meta-analysis to analyze the empirical literature on the impact of FDI on entrepreneurship.

Our study focuses on two questions: (i) Does FDI lead to greater entrepreneurial activity in host countries? (ii) What factors are responsible for the different estimates across studies? In addressing these questions, we make two methodological contributions. We extend the new Andrews-Kasy meta-analysis estimators (Andrews & Kasy, 2019) to allow for explanatory variables, and we develop a nested framework of multiple meta-analysis models that allows for

testing between models and model selection. Our main conclusion is that FDI has, at best, a small, positive effect on entrepreneurial activity. Further, we find that even this small effect disappears when studies correct for endogeneity using instrumental variable procedures.

Our study proceeds as follows. Section II discusses how we selected estimates for our meta-analysis. Section III describes the data, including the different measures that studies have used for FDI and entrepreneurship. Section IV presents our estimation strategy and demonstrates how the recently developed Andrews-Kasy estimators can be used to create a nestable framework of models that allows for testing and model selection. Section V presents results that addresses our first question regarding the overall effect of FDI on entrepreneurial activity. Section VI addresses the second question regarding factors associated with different estimates across studies. Section VII concludes.

II. SELECTION OF STUDIES

In selecting studies for our meta-analysis, we followed the MAER-Net protocol presented in Stanley et al. (2013). A preliminary search was done using combinations of the following keywords: “FDI”, “entrepreneurship”, “Start a business”, and “foreign direct investment.” We used the following search engines: EconLit, JSTOR, EBSCO, Google Scholar, RePEc, ProQuest, Social Science Citation Index (SSCI), Wiley-Blackwell, SAGE, SpiScholar, Emerald, ScienceDirect (Elsevier), Taylor & Francis, Bing, SpecialSciDBS, NBER, China National Knowledge Infrastructure (CNKI), Open Access Library, Global Entrepreneurship Monitor (GEM), as well as various working paper, books, doctoral dissertations, and master theses collections.

Our initial search produced over 400 studies. We narrowed this down to empirical studies where the dependent variable was a measure of entrepreneurship and the independent variable was a measure of FDI. We only included country-level studies, because we wanted to measure economy-wide impacts of FDI on entrepreneurship. It was our judgment that effects of FDI on

entrepreneurship at the firm level measure a sufficiently different effect, so that it would be inappropriate to combine them with country-level studies.¹

To be included in our meta-analysis, a study had to have both a numerical estimate for the effect of FDI on entrepreneurship, and either a corresponding standard error or *t*-statistic. We only included single-effect estimates. This eliminated VAR studies, because these generally focused on impulse response functions and did not report a cumulative, long-run impact with corresponding standard error (Zhao & Du, 2007). A similar difficulty arose with Granger causality studies (Liu, Burridge, & Sinclair, 2002). We eliminated studies using interaction terms and quadratic specifications of the FDI variable because of the difficulty of calculating a single effect with corresponding standard error.

Our final sample consisted of 35 studies with a total of 557 individual coefficient estimates. The respective studies are reported in TABLE 2. Our study is somewhat unique in that it includes Chinese language studies. Four of the studies were published in Chinese-language journals. Twenty-five were published in English-language journals. And six came from student theses or working papers, some of which are also in Chinese. The number of estimates per study varied widely, from 1 to 187. The majority of studies included a relatively large number of countries that were a mix of OECD and non-OECD countries. We emphasize that all the estimates in our meta-analysis focused on the effect of FDI on entrepreneurship, they were all based on country-level data to capture the full effects of FDI, and they are all legitimate effect estimates (not based on interaction terms, VARs etc.).

¹ For example, Desai (2017) writes, “There is also a disconnect between firm-level and country-level data. Country-level data is helpful to understand the overall trend and to track major changes over time. Firm-level data provide the richness and granularity necessary to identify the drivers, nature, trend, and outcomes of entrepreneurship. This information is useful when targeting specific types of entrepreneurship, such as female or growth entrepreneurship, or for targeting particular outcomes like job creation or export growth.”

III. DATA

The measurement of FDI. We focus on studies that estimate the effect of FDI on entrepreneurship. However, studies differ with respect to how they measure these two key variables. By far the most common measure of FDI for country-level studies is the ratio of FDI to GDP. Examples of studies that employ this measure are Chowdhury, Terjesen, & Audretsch (2015); Tian et al. (2018); and Yay, Yay, & Aksoy (2018). Less common measures include the log of FDI (Chatmi and Elasri, 2018), the growth rate of FDI (Herrera-Echeverri et al., 2014), and foreign capital as a share of total investment (Tian & Wu, 2014).

The measurement of entrepreneurship. The most common measure of entrepreneurship in our sample of studies is Total early-stage Entrepreneurial Activity (TEA). This is defined as the percentage of individuals aged 18-64 who are either starting new businesses, or currently run a business that is less than 42 months old. The data for this measure come from cross-country survey data collected by the Global Entrepreneurship Monitor (GEM).² Studies in our sample that use this measure include Albulescu & Tămășilă (2014); Danakol et al. (2017); Pathak, Xavier-Oliveira, & Laplume (2013); Pathak, Laplume, & Xavier-Oliveira (2015); etc.

TEA can be divided into necessity-driven entrepreneurs (NDE) and opportunity-driven entrepreneurs (ODE) (Desai, 2017). NDE is the percentage of entrepreneurs involved in TEA who have no other option for work. ODE is the percentage of entrepreneurs involved in TEA in order to improve or maintain their income or increase their independence (Desai, 2017). Categorization into the two categories is based on survey participants' self-responses. Studies on FDI and entrepreneurship sometimes employ more than one measure of entrepreneurship. For example, Albulescu & Tămășilă (2014), and Zhang (2015; 2016) use all three measures, TEA, ODE, and NDE, as measures of entrepreneurship in separate regressions.

² GEM (No date) describes itself on its website as follows: "The Global Entrepreneurship Monitor is the world's foremost study of entrepreneurship. Through a vast, centrally coordinated, internationally executed data collection effort, GEM is able to provide high quality information, comprehensive reports and interesting stories, which greatly enhance the understanding of the entrepreneurial phenomenon."

TEA and its sub-categories ODE and NDE are attractive as measures of entrepreneurship because they do not rely on official government statistics. This is an advantage in cross-country studies because it facilitates standardization, since governments have varying definitions of entrepreneurship. Another advantage of the GEM survey data is that it is expected to be less vulnerable to biases in coverage across countries. For example, entrepreneurs in low-income countries may be underrepresented in official statistics because data collection is less thorough, or because the economic and regulatory environments discourage entrepreneurs from formally registering their activities (Desai, 2017).

To be sure, survey responses have their own shortcomings, so that some studies opt for the official government measures. The World Bank (WB) collects government statistics on new firm formation at the country level. However, differences in definitions constrain the WB to limit reporting to limited liability companies. While this facilitates comparability across countries, it restricts coverage to this one type of business enterprise, likely underestimating the extent of new firm formations.

Examples of studies that base their measure on WB statistics are Kim & Li (2014) and Tian & Chen (2017). They use annual number of newly registered limited-liability firms. Similarly, Doytch & Epperson (2011); Dutta, Roy, & Sobel (2011) and Herrera-Echeverri, Haar, & Estévez-Bretón (2014) measure entrepreneurship by the number of newly registered limited liability companies per 1,000 working-age people (ages 15-64).

There are other measurements of entrepreneurship. For instance, self-employment is sometimes employed as a proxy for entrepreneurship (Chowdhury, Terjesen, & Audretsch, 2015). Other studies are interested in particular types of entrepreneurship. For example, Terjesen & Hessel (2009), Tian & Wu (2014), and Tian et al. (2018) use another sub-category of TEA that measures the percent of entrepreneurs with overseas customers, in order to focus on “international” entrepreneurship. Danakol (2015) and Danakol, et al. (2017) use gross entry

rates in high-tech manufacturing as a proxy for “high quality” entrepreneurship.

The different measures of entrepreneurship naturally sort themselves into separate categories in the context of sensitivity to FDI. One expects NDE to be the least sensitive to FDI because this type of entrepreneurial activity is, by definition, not driven by choice. FDI will only affect this type of entrepreneurship if it is able to influence the conditions that determine “necessity”. ODE and specialized types of entrepreneurship such as “international” and “high-quality” entrepreneurship are expected to be more sensitive to FDI because FDI can lead to opportunities that make entrepreneurship more attractive (Albulescu & Tămășilă, 2014). Because TEA combines both ODE and NDE entrepreneurial activity, not distinguishing these two types in its measure, it should be categorized separately from these. Likewise, measures that don’t fit within any of the above categories should also be classified separately.

In the second half of our empirical analysis, we will investigate the factors that are associated with differences in estimated effects. We will pay particular attention to whether measures of entrepreneurship are systematically related to these differences.

IV. METHODOLOGY

How to accommodate the fact that estimates of the effect of FDI on entrepreneurship are based on different measures of these variables? We can think of the empirical literature on FDI and entrepreneurship as consisting of studies that estimate a linear regression model like the one below:

$$(1) \text{Entrepreneurship}_{in} = \alpha_i + \beta_i FDI_{in} + \sum_{k=1}^{K_i} \gamma_{ki} X_{k,in} + \text{error}_{in}, \quad n = 1, 2, \dots, N_i,$$

where i indicates a specific study. Studies differ not just in their measures of *Entrepreneurship* and *FDI*, but in the number (K_i) and composition of control variables (X_k), and nature and number of observations (N_i) used in the study. As a result, they obtain different estimated effects, $\hat{\beta}_i$. Meta-analysis aggregates and analyzes the respective estimated effects.

How to deal with different measures for *FDI* and *Entrepreneurship*? A common problem in meta-analysis is how to aggregate estimated effects when studies measure the key variables differently. For example, the studies in our sample use different measures for *FDI* and *Entrepreneurship*. There is a standard solution: convert estimates to Partial Correlation Coefficients (*PCCs*).

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

where t_i and df_i are the t -statistic and degrees of freedom associated with the respective estimated effect. The corresponding standard error is given by:

$$(2.b) \quad se(PCC_i) = \sqrt{\frac{1 - PCC_i^2}{df_i}}.$$

A useful relationship of *PCCs* is that

$$(3) \quad \frac{PCC_i}{se(PCC_i)} = t_i.$$

PCCs have the advantage of allowing one to compare otherwise noncomparable estimates. Like any correlation, they take values between -1 and 1. The main disadvantage of *PCCs* is that it can be challenging to interpret the sizes of the transformed effect estimates. A number of guidelines have been proposed.

Cohen (1988) recommends the values of 0.10, 0.30, and 0.50 be used to categorize correlations into small, medium, and large effects, respectively. His prescription is widely followed. However, Cohen's guidelines are intended for zero-order correlations. To better enable the interpretation of partial correlations, Doucouliagos (2011) canvassed the economics literature and collected over 22,000 estimates across a broad range of disciplines (labor economics, development economics, industrial organization, etc.).

He rank-ordered the absolute value of the associated *PCCs* and categorized effect sizes based upon their place in the ordered distribution. *PCC* values that corresponded to the 25th,

50th, and 75th percentiles were identified as “small”, “medium”, and “large” effects. For the full sample of 22,141 estimates, the corresponding *PCC* values were 0.07, 0.17, and 0.33. He also calculated percentile values for subfields of economics. For “FDI and economic growth”, the 25th, 50th, and 75th percentile values were 0.10, 0.21, and 0.34, based on 876 estimates. We will use these two sets of values to interpret the *PCC* values from our collection of estimates gleaned from the literature on FDI and entrepreneurship.³

Estimation. Our meta-analysis is concerned with two main questions: (1) What is the effect of FDI on entrepreneurship?, and (2) What factors account for differences in estimated effects across studies? Both questions can be addressed within the following estimation framework:

$$(4) PCC_i = \mu + \sum_{j=1}^J \delta_j C_{ji} + \varepsilon_i = \mu + \mathbf{C}_i \boldsymbol{\delta} + \varepsilon_i, \quad i = 1, 2, \dots, M,$$

where $\mathbf{C}_i$ is an $(1 \times J)$ vector of data, estimation, and study characteristics hypothesized to moderate the estimated effects of *FDI* on *Entrepreneurship*, and M is the total number of estimates from all studies.

An answer to the first question can be obtained by estimating equation (4) without any explanatory variables, $\mathbf{C}$. In that case, an estimate of the overall mean value of PCC_i is given by the estimate of μ . Adding the explanatory variables $\mathbf{C}$ then allows one to observe how the overall mean is affected by various data, estimation, and study characteristics. Two issues need to be addressed.

The first issue is which estimator to use to estimate equation (4). The two most common meta-analysis estimators are the *Fixed Effects (FE)* and the *Random Effects (RE)* estimators (Hedges & Vevea, 1998). These make different assumptions about the behavior of the error term, ε .

³ Doucouliagos (2011) also reports values for another subfield, “FDI spillovers”, with corresponding *PCC* values of 0.02, 0.15, and 0.24. However, these were based on only 24 estimates so we don’t consider these reliable for our purposes.

The *FE* estimator assumes that there is a unique, homogeneous effect of *FDI* on *Entrepreneurship*. The only reason that studies produce different estimates is due to sampling error. Some studies, say, due to larger sample sizes, produce estimates with smaller sampling errors. *FE* models the associated heterogeneity by assuming the error term is distributed normally with variance equal to the square of the respective *PCC* standard errors, $\varepsilon \sim N(0, se(PCC_i)^2)$. The associated probability density function for the *i*th observation, $f_{FE,i}$, and log likelihood function, ℓ_{FE} , are given by

$$(5.a) \quad f_{FE,i} = p(PCC_i | C_i, se(PCC_i)^2; \mu, \delta) = \frac{1}{\sqrt{2\pi \cdot se(PCC_i)^2}} e^{-\frac{(PCC_i - \mu - C_i \delta)^2}{2 \cdot se(PCC_i)^2}}$$

and

$$(5.b) \quad \ell_{FE} = \sum_{i=1}^M \log[p(PCC_i | C_i, se(PCC_i)^2; \mu, \delta)].$$

The *FE* model is unrealistic for a number of reasons. Even if all studies use identical measures for *Entrepreneurship* and *FDI*, and have the same estimated effects, $\hat{\beta}_i$, in equation (1), different sample sizes alone would cause the corresponding *PCC* and $se(PCC)$ values to be heterogeneous.

To account for heterogeneity of estimated effects across studies, the *RE* model adds a second term to the variance of ε , $\varepsilon \sim N(0, se(PCC_i)^2 + \tau^2)$. τ^2 is a constant term that accommodates the fact that estimated effects differ across studies for reasons beyond simple sampling error. The associated probability density and log likelihood functions are given by

$$(6.a) \quad f_{RE,i} = p(PCC_i | C_i, se(PCC_i)^2; \mu, \delta, \tau^2) = \frac{1}{\sqrt{2\pi(se(PCC_i)^2 + \tau^2)}} e^{-\frac{(PCC_i - \mu - C_i \delta)^2}{2(se(PCC_i)^2 + \tau^2)}}$$

and

$$(6.b) \quad \ell_{RE} = \sum_{i=1}^M \log([p(PCC_i | C_i, se(PCC_i)^2; \mu, \delta, \tau^2)]).$$

Note that the *FE* estimator is nested within the *RE* estimator, so that a test of the *FE* model against the alternative *RE* model consists of testing $H_0: \tau^2 = 0$. This can be done, for example, via a likelihood ratio test.

Publication bias. Publication bias is the distortion that arises in the academic literature when researchers and/or journals report an unrepresentative sample of estimates. This can occur when researchers and/or journals prefer to publish statistically significant estimates, and discriminate against publishing estimates that are insignificant. It can also occur when theory or ideology leads researchers and/or journals to omit estimates that are inconsistent with that theory or ideology (Gunby, Jin, & Reed, 2017). If the estimates in the literature are distorted, the corresponding meta-analysis will be as well.

Many procedures have been proposed to correct for publication bias. In economics, the most common approach is to include the $se(PCC)$ variable as an explanatory variable in equation (4). This compensates for the distortion due to publication bias, similarly to how the inverse Mills ratio compensates for sample selection (Stanley and Doucouliagos, 2012).

The inclusion of the $se(PCC)$ variable has an additional benefit. It allows one to test for publication bias. Rejection of $H_0: \delta_{se(PCC)} = 0$ indicates the existence of publication bias. Most commonly, this test is performed when there are no explanatory variables included in the specification of equation (4). The resulting test is known as the FAT, for Funnel Asymmetry Test; or alternatively, as Egger's regression test (Sterne & Egger, 2005).

A recent paper in the *American Economic Review* by Andrews and Kasy (2019) provides an alternative procedure for dealing with publication bias. They pre-multiply the *RE* model by a function that accounts for different probabilities of publication depending on the statistical significance of the estimated effect in the original study. We work with two of their models here, which we denote *AK1* and *AK2*.

AK1 assigns observations to two categories, those that are significant at the 5% level and those that are not. It normalizes the probability of publication for significant estimates at 1, setting the publication probability for insignificant estimates, ρ , as an estimable parameter:

$$(7.a) \quad \varphi\left(t_i = \frac{PCC_i}{se(PCC_i)}\right) = \begin{cases} 1 & \text{if } |t_i| \geq 1.96 \\ \rho & \text{if } |t_i| < 1.96 \end{cases}.$$

The associated log likelihood function is:

$$(7.b) \quad \ell_{AK1} = \sum_{i=1}^M \log \left(\frac{\varphi(Z_i)}{E[\varphi(Z_i)|\mu, \delta, \tau^2, \rho]} \cdot p(PCC_i | \mathbf{C}_i, se(PCC_i)^2; \mu, \delta, \tau^2) \right)^4$$

Note that when $\rho = 1$, the *AK1* model reduces to the *RE* model, so that a test of *RE* against the alternative of *AK1* consists of testing $H_0: \rho = 1$. Rejection also provides evidence for the presence of publication bias.

AK2 is similar, except that it allows the probability of publication to be affected not only by the estimate's statistical significance, but also its sign. The resulting publication probability function has four categories, with positive and significant estimates normalized at 1.

$$(8.a) \quad \varphi(t_i) = \begin{cases} \rho_1 & t_i < -1.96 \\ \rho_2 & -1.96 \leq t_i < 0 \\ \rho_3 & 0 \leq t_i < 1.96 \\ 1 & t_i > 1.96 \end{cases}.$$

The corresponding log likelihood function is

$$(8.b) \quad \ell_{AK2} = \sum_{i=1}^M \log \left(\frac{\varphi(Z_i)}{E[\varphi(Z_i)|\mu, \delta, \tau^2, \rho_1, \rho_2, \rho_3]} \cdot p(PCC_i | \mathbf{C}_i, se(PCC_i)^2; \mu, \delta, \tau^2) \right).$$

Note that *AK1* can be tested against the alternative *AK2* model by jointly testing (i) $H_0: \rho_1 = 1$ and (ii) $H_0: \rho_2 = \rho_3$. A test for publication bias is given by $H_0: \rho_1 = \rho_2 = \rho_3 = 1$, with rejection indicating the presence of publication sample selection. We note that in a recent simulation exercise, Hong & Reed (2019) demonstrate that *AK1* and *AK2* generally have superior efficiency properties relative to *FE* and *RE*, with the best model in a given context depending on the nature of the publication sample selection.

A framework of nestable models. The set of models described above provides a (mostly) nestable set of models that facilitates model selection. In particular

$$(9.a) \quad FE \in RE \in AK1 \in AK2;$$

⁴ See the Appendix for equations for $E(\varphi(Z_i)| \cdot)$ for the *AK1* and *AK2* models.

(9.b) $FE(with\ SE) \in RE(with\ SE) \in AK1(with\ SE) \in AK2(with\ SE)$;

(9.c) $Model \in Model(with\ SE)$, where $Model = FE, RE, AK1, AK2$.

This allows one to test the respective restrictions built into the different model relationships. We estimate all eight models, employing a pairwise testing regime to select the most appropriate model given the data. TABLE 1 summarizes testable restrictions for respective pairs of nested models.

Methodological contribution. We note that our study is the first to generalize the Andrews-Kasy estimators to include data, estimation, and study characteristics. To do that, we extended the programming code they made available with their paper to include explanatory variables. In addition, it is the first study to identify and exploit the nested relationships between the FE , RE , $AK1$, and $AK2$ models to enable model testing and selection.

V. DATA ANALYSIS: Estimating the Mean Overall Effect of FDI on Entrepreneurship

Distribution of t -statistics and PCC values. The top panel of FIGURE 1 presents a histogram of the distribution of t -statistics for the 557 estimates in our study. Aside from a few, large positive outliers, the great majority of t -statistics are clustered around 0, with approximately half lying below and half lying above zero.

Beneath the histogram is a table that reports the percent of estimates that are statistically significant/insignificant in the original studies. Given that these studies all focused on the effect of FDI on entrepreneurship, and conventional wisdom is that it is difficult to publish insignificant estimates, it is surprising that approximately three-fourths of the estimates are statistically insignificant at the 5-percent level (two-tailed) level. This provides the first indication that FDI does not have a large effect on entrepreneurship. The bottom panel of FIGURE 1 presents the corresponding histogram for the PCC values. It reinforces the top panel, with the distribution of PCC values largely mirroring that of the t -statistics.

TABLE 3 provides further detail about the distribution of t -statistics and PCC values.

Both the mean and median *PCC* values are very close to zero (-0.004 and -0.003). Recall that Doucouliagos (2011)’s division of *PCC* effect sizes into “small”, “medium” and “large” are (i) 0.07, 0.17, and 0.33; and (ii) 0.10, 0.21, and 0.34. By either standard, roughly 80-90% of the distribution of *PCC* values is less than “medium”-sized.

FIGURE 2 presents a forest plot, which provides a study-level look at the distribution of *PCC* values. 95% confidence intervals are calculated around the respective *RE* estimates. While heterogeneity is evident across the studies, only two studies contain effects that could be classified as large (Studies 1 and 8). Most studies produce estimates that are tightly clustered around 0. The bottom of the figure reports *I-squared*, which measures the share of *PCC* variance due to between-study heterogeneity, as opposed to sampling error. For our sample, *I-squared* is 81.0%. The null of no between-study heterogeneity ($\tau^2 = 0$) is rejected with a *p*-value of 0.000. Finally, the rightmost column reports the weight each study receives in calculating the overall mean.⁵ The weights are relatively balanced across studies, ranging from a low of 0.80% (Study 8) to a high of 4.24% (Study 33).

As noted above, it is widely acknowledged that publication bias represents the biggest threat to meta-analysis validity (Rothstein, Sutton, & Borenstein, 2005). A particular form of publication bias is “accumulation bias” (ter Schure & Grünwald, 2019). This occurs when an initial study or studies reports a large effect and subsequent studies are undertaken to confirm the initial study. This generates a positive bias to the meta-analysis sample, because subsequent studies are conducted conditional on the initial study(studies) being significant and large in size. Evidence of accumulation bias is provided by a time series regression of effect size on publication date.

The two panels of FIGURE 3 report scatter plots of *PCC* values over time (measured by publication date). The top panel reports individual estimates, while the bottom panel reports

⁵ Individual study weights are increasing in (i) effect size precision and (ii) number of estimates per study.

median study values. Overlaid on both scatter plots is a regression line of the relationship of *PCC* and publication date. Both regression lines are virtually perfectly horizontal. As a result, we conclude that accumulation bias is not a problem for our sample of estimates.

What is the effect of FDI on entrepreneurship? TABLE 4 reports estimates to address our first question about the effect of FDI on entrepreneurship. The table displays the estimated, mean overall effect, $\hat{\mu}$, for six of the eight models discussed in Section III. It omits the versions of *AK1* and *AK2* that include the $se(PCC)$ variable.

In the *FE* and *RE* models, $se(PCC)$ is included as a kind of sample selection correction for publication bias. Its inclusion enables an unbiased estimate of μ , at least in theory. The *AK1* and *AK2* models correct for publication bias using a different procedure. Thus there is no rationale for including $se(PCC)$ for the purpose of correcting publication bias. On the other hand, some authors have conjectured that the standard error of the estimated effect is correlated with omitted study characteristics (Zigraiova & Havranek, 2016). Therefore, when it comes time to estimate the specification with data, estimation, and study characteristics, we will include $se(PCC)$ as an additional “moderator” variable. However, as TABLE 4 omits data, estimation, and study characteristics, we do not include $se(PCC)$ in the *AK1* and *AK2* specifications there.

The estimates of the mean overall effect of FDI on entrepreneurship range from -0.0032 to 0.0788 across the six models. All of the estimates are statistically insignificant at the 5% level.

Pairwise testing of models leads to the following ordering: $FE < RE < AK1 < AK2$; $FE(w/SE) < RE(w/SE)$; and $FE < FE(w/SE)$. For example, the *FE* model is rejected against the alternative *RE* model with a p-value of 0.000. The *RE* model is rejected against the alternative *AK1* model with a p-value of 0.001, and the *AK1* model is rejected against the alternative *AK2* model with a p-value of 0.000. The only case where the more restrictive model was not rejected against its paired, less restrictive alternative was $RE <> RE(w/SE)$, with a p-value of 0.157. In

three of the four cases, we reject the null of no publication bias.

A difficulty in using the pairwise testing of models is that all six models do not lie within one, nested framework. However, if we are willing to accept the null of RE against the alternative of $RE(w/SE)$, then pairwise testing leads us to the $AK2$ model as “best”, because (i) $FE < FE(w/SE) < RE(w/SE)$, (ii) RE is accepted against the alternative of $RE(w/SE)$, and (iii) $RE < AK1 < AK2$. Further evidence in favor of the $AK2$ model is provided by the two information criteria: $AK2$ has the lowest AIC and BIC values of all six models, indicating the best fit, even after being penalizing for having more parameters. Accordingly, we focus on the $AK2$ estimate.

The $AK2$ model produces a mean, overall effect estimate of 0.0359. The associated 95% confidence interval is (-0.0363, 0.2203). We can compare this to the two sets of benchmark values from Doucouliagos (2011) corresponding to “small”, “medium”, and “large”: (i) 0.07, 0.17, and 0.33; and (ii) 0, 0.21, and 0.34. The upper limit of the 95% confidence interval would classify FDI as having a positive, medium-sized effect on entrepreneurship. The lower limit sees FDI having a negative, small-sized effect. However, we cannot reject the hypothesis that FDI has no effect on entrepreneurship.

VI. DATA ANALYSIS: Identifying Factors Associated with Differences in Estimates Across Studies

What factors account for differences in estimated effects across studies? In this section we undertake exploratory analysis to determine if there are any data, estimation, or study characteristics that can account for systematic differences in estimated effects across studies. TABLE 5 reports the characteristics we include in our meta-regression analysis. To determine whether the measure of FDI influences the estimate of FDI’s effect on Entrepreneurship, we distinguish three types of FDI measures. The most common FDI measure is the ratio of FDI to a country’s GDP ($FDIGDP$). 75.9% of the estimates in our study use this measure for FDI. The

second most common measure is *FDIlog*, the log of a country's FDI (20.1%). The residual category, *FDIOther*, collects the remaining measures. In the subsequent empirical analysis, *FDIGDP* is excluded from the estimation, so that this category becomes the reference group for comparisons involving measures of FDI.

Entrepreneurship is measured by three categories plus "other". The largest category of estimated effects is *EntreType3* which is based on "opportunity-driven entrepreneurship" (41.5%). Next largest is *EntreType1* which uses the TEA measure of entrepreneurship (37.2%). The category hypothesized to be least affected by FDI, *EntreType2*, only includes 7.9% of the estimated effects. All other entrepreneurial measures account for 13.5%.

As this study focuses on country-level data, it provides an opportunity to explore whether FDI has different effects across countries. While most studies include a mix of OECD and non-OECD countries, 9.0% of the estimated effects are from studies that exclusively study OECD countries; 7.9% come from studies that exclusively study non-OECD countries.

Another feature that may contribute to different estimates across studies is the nature of the data that are used. A disadvantage of cross-sectional data is that omitted variables may bias estimates of included variables. For this reason, many researchers prefer panel data with fixed effects. If the omitted variables are time invariant, the inclusion of country-level fixed effects will eliminate omitted variable bias. However, panel fixed effects also have their disadvantages. If the key variables do not change much over time, then panel fixed effects will exacerbate measurement error bias.⁶ Our analysis sets estimates that use panel data without fixed effects as the reference group (62.3%). To see if the nature of the data matters for the estimated effects, we include variables to indicate cross-sectional (9.3%) and panel fixed effects (28.4%).

We also include a dummy variable to indicate whether a lagged dependent variable was included in the original regression (9.9%). When this variable is included, the FDI effect will

⁶ See Zhou (2001) for a nice example illustrating how cross-sectional estimates can be more reliable than panel fixed effects estimates.

only capture the short-run effect of FDI on entrepreneurship. If the effect accumulates over time, estimated FDI effects should be smaller when a lagged dependent variable is included. We also include a dummy variable to indicate whether the original effect was estimated with 2SLS or GMM (22.6%). If entrepreneurship simultaneously encourages FDI, then estimation which corrects this endogeneity bias should produce smaller estimates.

Lastly, we include variables to indicate whether Chinese-language studies report systematically different effects than English-language studies, and whether studies that appear in academic, peer-reviewed journals are systematically different from studies in other outlets (books, theses, working papers). 9.5% of the estimates comes from Chinese-language studies. 56.9% of the estimates in our study are taken from academic, peer-reviewed journals.

TABLE 6 reports the results of exploring whether data, estimation, and study characteristics can explain why studies obtain different estimates of FDI effects on entrepreneurship. A total of eight models are estimated. In determining which model is “best”, we turn to the pairwise tests of nested models at the bottom of the table.

Accordingly, we can order the respective pairs of models as follows:

- (i) $FE < RE < AK1 < AK2$, and
- (ii) $FE(w/SE) < RE(w/SE) < AK1(w/SE) < AK2(w/SE)$.

For example, when the FE model is tested against the RE model, we reject the restricted FE model with a p-value of 0.000. When the RE model is tested against the $AK1$ model, we reject the restricted RE model with a p-value of 0.001. And so on. This leaves us with $AK2$ being “best” in the first set of models, and $AK2(w/SE)$ “best” among the second set of models.

We can go further. When we test $H_0: \delta_{se(PCC)} = 0$ in $AK2(w/SE)$, we fail to reject the null with a p-value of 0.456. Accepting the null leads to the ordering that $AK2(w/SE) < AK2$, so that we can declare $AK2$ the “best” model over the full set of eight models. This conclusion is reinforced by the two information criteria, as both the AIC and BIC values for the $AK2$ model

(-711.5 and -633.7, respectively) are smaller than any of its competitors. Accordingly, we focus on the *AK2* model, noting that the effects do not differ greatly across the other models.

We first note that none of the $se(PCC)$ coefficients are significant in any of the models. This has a different interpretation depending on whether the models are *FE/RE* or *AK1/AK2*. In the *FE* and *RE* models, $se(PCC)$ is included to control for publication bias. The fact that it is statistically insignificant in these specifications suggests that publication bias is not a serious problem in our data. In the *AK1/AK2* models, publication bias is addressed in another way. For these models, $se(PCC)$ should be interpreted as picking up the effects of any omitted data, estimation, and study characteristics that may be correlated with the estimated effects of FDI on entrepreneurship. The fact that $se(PCC)$ is insignificant in the *AK1/AK2* models indicates that this kind of omitted variable bias is not a major concern for our sample of estimates.

Of the various data, estimation, and study characteristics, only three are significant at the 5-percent level in the *AK2* model. The estimate for *EntreOther* (-0.1616) suggests that the measure of entrepreneurship a study uses can have a significant effect on the estimates a study obtains. In particular, studies that use a measure of entrepreneurship different from TEA will produce lower estimates. Unfortunately, since this category includes a mix of different measures, it is difficult to attach an explanation for this result. Further, since relatively few estimates belong to this category (13.5%), there is little value in dividing this category further to identify the source of the lower estimated effects.

It is noteworthy that we do not see statistically significant differences between estimates based on either of the sub-categories of TEA (NDE and ODE – *EntreType2* and *EntreType3*, respectively), and those based on the general TEA category. Our expectation was that opportunity-driven entrepreneurship (ODE) was most likely to be affected by FDI. However, there is no statistical evidence to support this in our meta-regression analysis.

TABLE 6 also indicates that cross-sectional studies tend to produce larger estimates

than studies that rely on panel data but do not include fixed effects (0.1272). Pooled OLS is a weighted average of within- and between-OLS estimates. However, the cross-sectional estimate does not appear to be related to this distinction, because studies that use panel data with fixed effects are insignificantly different from those without fixed effects (0.0302). Therefore, there must be something else about the cross-sectional studies in our sample that is responsible for the larger FDI estimates.

Lastly, the results of TABLE 6 indicate that studies that control for endogeneity generally produce lower estimates than those that don't. The estimated coefficient (-0.1577) is sufficiently large that it reverses the finding of a positive FDI effect on entrepreneurship. Not controlling for anything else, studies that use 2SLS or GMM estimate, on average, a negative effect of FDI on entrepreneurship.⁷

Other than the characteristics identified above, we find that most data, estimation, and study characteristics are not systematically related to estimated effects of FDI on entrepreneurship. There is no evidence of substantial differences in estimated effects across countries. Nor that differences in FDI measures make a difference. Nor that Chinese studies differ from English-language studies; or that estimates in academic, peer-reviewed journals are different from those in other outlets.

VI. CONCLUSION

This study uses meta-analysis to analyze the empirical literature on FDI and entrepreneurship. It collects 557 estimates from 35 studies. Because the studies vary in their measurement of FDI and entrepreneurship, we transform the respective coefficient estimates to partial correlation coefficients (*PCCs*) to enable aggregation and analysis. We estimate that the mean, overall effect of FDI on entrepreneurship across all the estimates in our sample is small in economic size and

⁷ The mean PCC value for studies that use 2SLS or GMM is -0.076 with a 95% confidence interval of (-.103, -0.050).

statistically insignificant. Further, estimates from studies that control for endogeneity suggest that FDI discourages entrepreneurial activities.

This study also makes two methodological contributions. First, we extend the estimation framework of Andrews & Kasy (2019) to show how their estimators can be generalized to include data, estimation, and study characteristics. Furthermore, we develop a nestable framework that allows one to test alternative meta-analysis models for the purpose of model selection. Thus, our study of FDI and entrepreneurship also provides a useful empirical application of the newly developed Andrews-Kasy estimators.

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TABLE 1
Testable Hypotheses for Assessing Nested Model Restrictions and Publication Bias

		<u><i>Restricted Model</i></u>							
		<i>FE</i>	<i>FE(w/SE)</i>	<i>RE</i>	<i>RE(w/SE)</i>	<i>AK1</i>	<i>AK1(w/SE)</i>	<i>AK2</i>	<i>AK2(w/SE)</i>
<u><i>Unrestricted Model</i></u>	<i>FE</i>								
	<i>FE(w/SE)</i>	$\delta_{se(PCC)} = 0$							
	<i>RE</i>	$\tau^2 = 0$	Not Nested						
	<i>RE(w/SE)</i>		$\tau^2 = 0$	$\delta_{se(PCC)} = 0$					
	<i>AK1</i>			$\rho = 1$	Not Nested				
	<i>AK1(w/SE)</i>				$\rho = 1$	$\delta_{se(PCC)} = 0$			
	<i>AK2</i>					$\rho_1 = 1$ $\rho_2 = \rho_3$	Not Nested		
	<i>AK2(w/SE)</i>						$\rho_1 = 1$ $\rho_2 = \rho_3$	$\delta_{se(PCC)} = 0$	
<i>Null Hypotheses for Tests of Publication Bias</i>		----	$\delta_{se(PCC)} = 0$	----	$\delta_{se(PCC)} = 0$	$\rho = 1$	$\rho = 1$	$\rho_1 = 1$ $\rho_2 = 1$ $\rho_3 = 1$	$\rho_1 = 1$ $\rho_2 = 1$ $\rho_3 = 1$

TABLE 2
Studies

ID	Article	Language	Period	# Countries	Country	# Estimates
1	Tian and Wu (2014)	Chinese	2001-11	39	Mixed	6
2	Zhang (2015)	Chinese	2005-13	25	OECD	15
3	Tian and Chen (2017)	Chinese	2004-12	79	Mixed	12
4	Tian, Mei, Du, and Wang (2018)	Chinese	2003-13	52	Mixed	5
5	Terjesen and Hessels (2009)	English	2006-07	51	Mixed	4
6	Doytch and Epperson (2011)	English	2004-08	80	Mixed	24
7	Dutta, Roy, and Sobel (2011)	English	2000-05	95	Mixed	12
8	Pathak , Xavier-Oliveira, and Laplume (2013)	English	2002-08	20	Mixed	1
9	Herrera-Echeverri, Haar, and Estévez-Bretón (2014)	English	2004-09	35	Mixed	7
10	Chowdhury, Terjesen, and Audretsch (2015)	English	2001-05	44	Mixed	24
11	Kim and Li (2014)	English	2000-09	104	Mixed	8
12	Pathak, Laplume, and Xavier-Oliveira (2015)	English	2001-08	38	Mixed	40
13	Albulescu and Tămășilă (2014)	English	2005-12	16	Mixed	18
14	Yousafzai, Saeed, and Muffatto (2015)	English	2002-12	92	Mixed	2
15	Ghosh (2017)	English	2001-16	79	Mixed	4
16	Angulo-Guerrero, Pérez-Moreno, and Abad-Guerrero (2017)	English	2001-12	29	OECD	12
17	Jiménez, Puche-Regaliza, Jiménez-Eguizábal, and Alon (2017)	English	2002-07	93	Mixed	8

ID	Article	Language	Period	# Countries	Country	# Estimates
18	Danakol, Estrin, Reynolds, Weitzel (2017)	English	2000-09	70	Mixed	12
19	Munemo (2017)	English	2004-12	92	Mixed	3
20	Rusu and Roman (2017)	English	2002-15	18	OECD	1
21	Mohamadi, Peltonen, and Wincent (2017)	English	2008-15	59	Mixed	4
22	Atiase, Mahmood, Wang, and Botchie (2018)	English	2017-17	35	Non-OECD	2
23	Munemo (2018)	English	2004-14	28	Non-OECD	10
24	Jiménez and Alon (2018)	English	2002-07	93	Mixed	6
25	Lecuna and Chávez (2018)	English	2002-14	18	Mixed	3
26	Goel (2018)	English	2015-15	125	Mixed	24
27	Yay, Yay, and Aksoy (2018)	English	2004-12	54	Mixed	34
28	Dvouletý (2018)	English	2001-15	11	OECD	4
29	Chatmi and Elasri (2018)	English	2004-12	17	Mixed	12
30	Van Stel, Storey, and Thurik (2006)	English	2002-05	47	Mixed	3
31	Herrera-Echeverri, Haar, and Estévez-Bretón (2013)	English	2004-09	19	Mixed	4
32	Danakol, Estrin, Reynolds, and Weitzel (2014)	English	1999-08	70	Mixed	5
33	Danakol (2015)	English	2000-09	70	Mixed	187
34	Zhang (2016)	Chinese	2005-14	38	Mixed	15
35	Goel (2016)	English	2015-15	128	Mixed	26

TABLE 3
Descriptive Statistics for Effect Size Variables

	<i>t-Statistics</i>	<i>df</i>	<i>PCC Values</i>
<i>Mean</i>	0.008	205	-0.004
<i>Median</i>	-0.025	188	-0.003
<i>Minimum</i>	-4.39	20	-0.384
<i>Maximum</i>	20.10	670	0.854
<i>Std. Dev.</i>	2.38	111.1	0.148
<i>1%</i>	-4.09	39	-0.306
<i>5%</i>	-3.28	69	-0.204
<i>10%</i>	-2.71	74	-0.183
<i>90%</i>	2.05	338	0.141
<i>95%</i>	2.74	390	0.190
<i>99%</i>	7.38	662	0.611
<i>Studies</i>	35	35	35
<i>Obs</i>	557	557	557

TABLE 4
Estimates of Overall Mean Effect

	<i>FE</i>	<i>FE(w/SE)</i>	<i>RE</i>	<i>RE(w/SE)</i>	<i>AK1</i>	<i>AK2</i>
μ	0.0054	0.0788	-0.0024	0.0304	-0.0032	0.0359
<i>95% CI</i>	(-0.0486, 0.0594)	(-0.1521, 0.3097)	(-0.0374, 0.0326)	(-0.1236, 0.1844)	(-0.0434, 0.0369)	(-0.0363, 0.2203)
<i>Observations</i>	557	557	557	557	557	557
<i>Parameters</i>	1	2	2	3	3	5
<i>LogLikelihood</i>	-633.9336	-610.8217	266.6321	267.6322	273.5297	286.0700
<i>AIC</i>	1269.8672	1225.6434	-529.2643	-529.2644	-541.0594	-562.1400
<i>BIC</i>	1274.1898	1234.2886	-520.6191	-516.2967	-528.0917	-540.5271
<i>Tests of Restrictive Model Against Alternative Model(s)</i>						
	<i>FE(w/SE)</i> <i>p</i> = 0.000	<i>RE(w/SE)</i> <i>p</i> = 0.000	<i>RE(w/SE)</i> <i>p</i> = 0.157	----	<i>AK2</i> <i>p</i> = 0.000	----
	<i>RE</i> <i>p</i> = 0.000	----	<i>AK1</i> <i>p</i> = 0.000	----		----
<i>Results of Testing the Null of No Publication Bias</i>						
	----	<i>Reject</i>	----	<i>Fail to Reject</i>	<i>Reject</i>	<i>Reject</i>

NOTE: *, **, and *** indicate statistical significance at the 10-, 5-, and 1-percent level, though none of the estimates of overall mean effect achieve significance at even the 10-percent level. Estimated standard errors used in calculating confidence intervals are robust to clustering at the study level.

TABLE 5
Description of Variables

<i>Variable</i>	<i>Description</i>	<i>Mean</i>	<i>Min</i>	<i>Max</i>
<i>FDI</i>				
<i>FDIGDP*</i>	= 1 if FDI measured as ratio of FDI to GDP	0.759	0	1
<i>FDIlog</i>	= 1 if FDI is measured as log of FDI	0.201	0	1
<i>FDIOther</i>	= 1 if another measure for FDI is used, such as growth rate of FDI, or the ratio of foreign capital to total investment	0.039	0	1
<i>ENTREPRENEURSHIP</i>				
<i>EntreType1*</i>	= 1 if entrepreneurship is measured by TEA	0.372	0	1
<i>EntreType2</i>	= 1 if entrepreneurship is measured by the TEA subcategory, NDE	0.079	0	1
<i>EntreType3</i>	= 1 if entrepreneurship is measured by TEA-subcategory, ODE, or related measures such as “international” entrepreneurship or “high-quality” entrepreneurship	0.415	0	1
<i>EntreOther</i>	= 1 if entrepreneurship variable is a measure not included in <i>EntreTypes1-3</i> .	0.135	0	1
<i>COUNTRIES</i>				
<i>OECD</i>	= 1 if sample is limited to OECD countries	0.090	0	1
<i>NonOECD</i>	= 1 if sample is limited to non-OECD countries	0.079	0	1
<i>MixedCountry*</i>	= 1 if sample consists of both OECD and non-OECD countries	0.831	0	1
<i>DATA AND ESTIMATION CHARACTERISTICS</i>				
<i>CrossSection</i>	= 1 if data is cross-sectional	0.093	0	1
<i>PanelFE</i>	= 1 if data is panel and fixed effects were included in the specification	0.284	0	1
<i>PanelNoFE*</i>	= 1 if data is panel and no fixed effects were included in the specification	0.623	0	1
<i>Lagged DV</i>	= 1 if the specification included a lagged dependent variable	0.099	0	1
<i>IV</i>	= 1 if estimation method corrected for endogeneity (e.g., 2SLS, GMM)	0.226	0	1

<i>Variable</i>	<i>Description</i>	<i>Mean</i>	<i>Min</i>	<i>Max</i>
<i>STUDY CHARACTERISTICS</i>				
<i>English*</i>	= 1 if study is written in English	0.905	0	1
<i>Chinese</i>	= 1 if study is written in Chinese	0.095	0	1
<i>Journal</i>	= 1 if study is an academic, peer-reviewed journal	0.569	0	1
<i>NotJournal*</i>	= 1 if study is a book, working paper, or thesis	0.431	0	1

NOTE: When the grouped variables include all possible categories, the categories omitted in the subsequent analysis (the benchmark categories) are indicated by an asterisk.

TABLE 6
Estimates of Model with Data, Estimation, and Study Characteristics

	<i>FE</i>	<i>FE(w/SE)</i>	<i>RE</i>	<i>RE(w/SE)</i>	<i>AKI</i>	<i>AKI(w/SE)</i>	<i>AK2</i>	<i>AK2(w/SE)</i>
<i>se(PCC)</i>	----	-0.1670 (1.1851)	----	-0.2809 (0.9505)	----	-0.3053 (0.8130)	----	-0.2917 (0.8011)
<i>FDIlog</i>	0.0051 (0.0347)	0.0046 (0.0357)	0.0013 (0.0401)	0.0014 (0.0406)	0.0000 (0.036)	0.0000 (0.0356)	-0.0050 (0.0354)	-0.0053 (0.0351)
<i>FDIOther</i>	0.1932 (0.0848)	0.1921 (0.086)	0.1111 (0.0846)	0.1124 (0.0851)	0.1133* (0.0661)	0.1147* (0.0646)	0.0973* (0.0542)	0.0982* (0.0526)
<i>EntreType2</i>	-0.1106* (0.0743)	-0.1098* (0.0776)	-0.1015 (0.0872)	-0.1002 (0.0901)	-0.1169 (0.0833)	-0.1153 (0.0837)	-0.1111 (0.0848)	-0.1097 (0.0852)
<i>EntreType3</i>	0.0241 (0.0615)	0.0232 (0.0606)	0.0188 (0.0551)	0.0180 (0.0557)	0.0226 (0.051)	0.0217 (0.0503)	0.0242 (0.0502)	0.0232 (0.0496)
<i>EntreOther</i>	-0.1809** (0.0832)	-0.1801** (0.0877)	-0.1433** (0.0618)	-0.1432** (0.0634)	-0.1637*** (0.0559)	-0.1633*** (0.0559)	-0.1616*** (0.0521)	-0.1610*** (0.052)
<i>OECD</i>	-0.0229 (0.0358)	-0.0206 (0.0423)	-0.0280 (0.0337)	-0.0240 (0.0394)	-0.0312 (0.0284)	-0.0269 (0.0319)	-0.0317 (0.03)	-0.0277 (0.0326)
<i>NonOECD</i>	0.0044 (0.0322)	0.0089 (0.0441)	-0.0099 (0.0388)	-0.0026 (0.0409)	-0.0125 (0.0358)	-0.0044 (0.0347)	-0.0103 (0.037)	-0.0027 (0.0355)
<i>CrossSection</i>	0.1630 (0.0677)	0.1678 (0.076)	0.1182 (0.0429)	0.1272 (0.0531)	0.1332*** (0.0403)	0.1428*** (0.0506)	0.1272*** (0.0402)	0.1360*** (0.0492)

	<i>FE</i>	<i>FE(w/SE)</i>	<i>RE</i>	<i>RE(w/SE)</i>	<i>AKI</i>	<i>AKI(w/SE)</i>	<i>AK2</i>	<i>AK2(w/SE)</i>
<i>PanelFE</i>	0.0144 (0.0374)	0.0133 (0.0373)	0.0287 (0.0413)	0.0257 (0.0413)	0.0341 (0.0382)	0.0306 (0.0363)	0.0302 (0.0357)	0.0271 (0.0342)
<i>LaggedDV</i>	0.0774 (0.069)	0.0790 (0.0697)	0.0971 (0.0734)	0.1007 (0.075)	0.1099* (0.0617)	0.1136* (0.0629)	0.1110* (0.0632)	0.1141* (0.0645)
<i>IV</i>	-0.1278** (0.0595)	-0.1289** (0.0577)	-0.1316** (0.0638)	-0.1335** (0.0634)	-0.1504*** (0.0528)	-0.1524*** (0.0522)	-0.1577** (0.062)	-0.1589** (0.062)
<i>Chinese</i>	0.1007 (0.0542)	0.1000 (0.0551)	0.0696 (0.0572)	0.0675 (0.0578)	0.0755 (0.0475)	0.0732 (0.0466)	0.0691 (0.0428)	0.0673 (0.0424)
<i>Journal</i>	0.0585 (0.0405)	0.0588 (0.0414)	0.0373 (0.0386)	0.0385 (0.0395)	0.0426 (0.035)	0.0440 (0.0352)	0.0444 (0.0334)	0.0456 (0.0335)
τ	----	----	0.1034	0.1034	0.1135	0.1134	0.1124	0.1126
<i>Selection parameter(s)</i>	----	----	----	----	$\rho = 1.526$	$\rho = 1.524$	$\rho_1 = 8.171$ $\rho_2 = 5.747$ $\rho_3 = 3.526$	$\rho_1 = 8.135$ $\rho_2 = 5.713$ $\rho_3 = 3.551$
<i>Observations</i>	557	557	557	557	557	557	557	557
<i>Parameters</i>	14	15	15	16	16	17	18	19
<i>LogLikelihood</i>	-6.9193	-6.5939	354.2626	354.5861	359.739	360.0388	373.7348	374.013
<i>AIC</i>	41.8385	43.1878	-678.5251	-677.1722	-687.4779	-686.0776	-711.4697	-710.026
<i>BIC</i>	102.3544	108.0263	-613.6867	-608.0111	-618.3169	-612.594	-633.6635	-627.8973

	<i>FE</i>	<i>FE(w/SE)</i>	<i>RE</i>	<i>RE(w/SE)</i>	<i>AK1</i>	<i>AK1(w/SE)</i>	<i>AK2</i>	<i>AK2(w/SE)</i>
<i>Tests of Restrictive Model Against Alternative Model(s)</i>								
----	<i>FE(w/SE)</i> <i>p = 0.420</i>	<i>RE(w/SE)</i> <i>p = 0.000</i>	<i>RE(w/SE)</i> <i>p = 0.421</i>	<i>AK1(w/SE)</i> <i>p = 0.001</i>	<i>AK1(w/SE)</i> <i>p = 0.439</i>	<i>AK2(w/SE)</i> <i>p = 0.000</i>	<i>AK2(w/SE)</i> <i>p = 0.456</i>	----
----	<i>RE</i> <i>p = 0.000</i>	----	<i>AK1</i> <i>p = 0.001</i>	----	<i>AK2</i> <i>p = 0.000</i>	----	----	----
<i>Results of Testing the Null of No Publication Bias</i>								
	----	<i>Fail to Reject</i>	----	<i>Fail to Reject</i>	<i>Reject</i>	<i>Reject</i>	<i>Reject</i>	<i>Reject</i>

NOTE: The top value in each row is the coefficient estimate, and the bottom value in parentheses is the associated, cluster-robust standard error (clustered at the study level). *, **, and *** indicate statistical significance at the 10-, 5-, and 1-percent level. All specifications also include a constant term.

FIGURE 1
Distribution of t-and PCC Values

A. *t*-Statistics

<i>Distribution of t-statistics</i>	<i>Percent</i>
$t < -2.00$	14.4
$-2.00 \leq t \leq 2.00$	75.4
$t > 2.00$	10.2

B. PCC Values

FIGURE 2
Forest Plot: Study-Level Random Effects Estimates

NOTE: Studies 1–4 were published in refereed Chinese journals. Studies 5–29 were published in refereed western journals. And studies 30–35 are theses and working papers. Within each category, studies are arranged by year and author. ID numbers correspond to the study ID numbers in Table 2.

FIGURE 3
Relationship Between PCC and Year of Publication

A. Individual Estimates

B. Study Estimates (Median Value)

APPENDIX
Equations for $E(\varphi(Z_i)|\cdot)$ for the AK1 and AK2 Models

A. AK1 Model

$$\begin{aligned}
& E[\varphi(Z_i)|\mu, \boldsymbol{\delta}, \tau^2, \rho, se(PCC_i)] \\
&= \int_R \rho \times I\left(\left|\frac{PCC_i}{se(PCC_i)}\right| < 1.96\right) \times \frac{1}{\sqrt{2\pi(se(PCC_i)^2 + \tau^2)}} e^{-\frac{(PCC_i - \hat{\epsilon}_i)^2}{se(PCC_i)^2 + \tau^2}} dPCC_i \\
&+ \int_R 1 \times I\left(\left|\frac{PCC_i}{se(PCC_i)}\right| \geq 1.96\right) \times \frac{1}{\sqrt{2\pi(se(PCC_i)^2 + \tau^2)}} e^{-\frac{(PCC_i - \hat{\epsilon}_i)^2}{se(PCC_i)^2 + \tau^2}} dPCC_i.
\end{aligned}$$

B. AK2 Model

$$\begin{aligned}
& E[\varphi(Z_i)|\mu, \boldsymbol{\delta}, \tau^2, \rho, se(PCC_i)] \\
&= \int_R \rho_1 \times I\left(\frac{PCC_i}{se(PCC_i)} < -1.96\right) \times \frac{1}{\sqrt{2\pi(se(PCC_i)^2 + \tau^2)}} e^{-\frac{(PCC_i - \hat{\epsilon}_i)^2}{se(PCC_i)^2 + \tau^2}} dPCC_i \\
&+ \int_R \rho_2 \times I\left(-1.96 \leq \frac{PCC_i}{se(PCC_i)} < 0\right) \times \frac{1}{\sqrt{2\pi(se(PCC_i)^2 + \tau^2)}} e^{-\frac{(PCC_i - \hat{\epsilon}_i)^2}{se(PCC_i)^2 + \tau^2}} dPCC_i \\
&+ \int_R \rho_3 \times I\left(0 \leq \frac{PCC_i}{se(PCC_i)} < 1.96\right) \times \frac{1}{\sqrt{2\pi(se(PCC_i)^2 + \tau^2)}} e^{-\frac{(PCC_i - \hat{\epsilon}_i)^2}{se(PCC_i)^2 + \tau^2}} dPCC_i \\
&+ \int_R 1 \times I\left(\frac{PCC_i}{se(PCC_i)} > 1.96\right) \times \frac{1}{\sqrt{2\pi(se(PCC_i)^2 + \tau^2)}} e^{-\frac{(PCC_i - \hat{\epsilon}_i)^2}{se(PCC_i)^2 + \tau^2}} dPCC_i.
\end{aligned}$$