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Does FDI Promote Entrepreneurial Activities? A Meta-Analysis

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Sanghyun Hong
W. Robert Reed
Bifei Tian
Tingting Wu
Gen Chen

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Department of Economics and Finance
School of Business
University of Canterbury
Private Bag 4800, Christchurch
New Zealand

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Does FDI Promote Entrepreneurial Activities? A Meta-Analysis

Sanghyun Hong[1]
W. Robert Reed[1]
Bifei Tian[2†]
Tingting Wu[2]
Gen Chen[2]

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Abstract: Researchers have long identified both FDI and entrepreneurship as potentially important determinants of economic development. Accordingly, a literature has grown to investigate whether FDI stimulates entrepreneurial activity in host countries. It is difficult to synthesize these empirical findings 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. In order to better understand this literature, we collect 675 estimates from 47 studies that estimate the relationship between FDI and entrepreneurial activity using country-level data. We use meta-analysis to address two questions: (1) What is the overall, mean effect of FDI on entrepreneurship?, and (2) What factors account for differences in estimated effects across studies? An innovation of our study is that it develops a nested testing framework to select among a number of competing meta-analytic models. It also extends the new Andrews-Kasy meta-analytic estimators to allow for explanatory variables. We find that the overall, mean effect of FDI on entrepreneurial activity is close to zero and statistically insignificant. While FDI and entrepreneurial activity may each play an important role in economic development, our results indicate that FDI does not generally stimulate entrepreneurship. This suggests that public policy efforts to encourage entrepreneurship through FDI are unlikely to be successful. All the files necessary to reproduce the results in this paper are available online at *Harvard Dataverse*.

Keywords: Meta-analysis, FDI, Entrepreneurship

JEL Classifications: L26, F21, C10

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[1] Department of Economics and Finance, University of Canterbury, Christchurch, NEW ZEALAND

[2] School of Business Administration, Zhongnan University of Economics and Law, Wuhan, CHINA

† Corresponding author: Bifei Tian. Email: tianbifei@zuel.edu.cn

1. INTRODUCTION

It is generally acknowledged that FDI can have positive 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). It is also widely recognized that entrepreneurship plays a major role in countries' growth and development (Ayyagari, Demirguc-Kunt, & Maksimovic, 2011; Djankov, La Porta, Lopez-de-Silanes, & Shleifer, 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.

Since Grossman (1984), the literature on the relationship between FDI and entrepreneurship has grown substantially. Some studies find a positive relationship (Apostolov, 2017; Herrera-Echeverri, Haar, & Estévez-Bretón, 2014; Kim & Li, 2014); others report a negative relationship (Danakol, Estrin, Reynolds, and Weitzel, 2017; Goel, 2018; Pathak, Laplume, & Xavier-Oliveira, 2015); and still others report mixed findings (Albulescu & Tămăsilă, 2016; Lee, Hong, & Sun, 2014; Munemo, 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. It is unclear to what extent these differences are responsible for the different outcomes reported in the literature.

Our study focuses on two questions: (i) Does FDI generally lead to greater entrepreneurial activity in host countries? (ii) What factors are responsible for the different estimates across studies? The answers to these questions are important for improving our understanding of the relationship between FDI and entrepreneurship. They are also important from a public policy perspective: the success of government efforts to encourage entrepreneurship through FDI is conditioned on them. Our study also makes 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 competing models and estimators.

We proceed as follows. Section 2 provides the theoretical framework for our analysis. Section 3 discusses how we selected estimates for our meta-analysis. Section 4 describes the data, including the different measures that studies have used for FDI and entrepreneurship. Section 5 presents our estimation strategy and demonstrates how the recently developed Andrews-Kasy estimators can be used to create a nested framework of models that allows for testing and model selection. Section 6 presents results that addresses our first question regarding the overall effect of FDI on entrepreneurial activity. Section 7 addresses the second question regarding factors associated with different estimates across studies. The last section concludes. All the files necessary to reproduce the results in this paper are available online at *Harvard Dataverse*: https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/VZLM35.

2. THEORETICAL FRAMEWORK

Two strands of theory provide the framework for understanding the relationship between FDI and entrepreneurship. Occupational choice theory argues that individuals choose careers based on the relative attractiveness of those careers (Shane, 1996). According to occupational choice theory, FDI affects entrepreneurial behavior primarily by impacting the prospective earnings of entrepreneurs.

The knowledge spillover theory of entrepreneurship (KSTE) focuses on the roles of firms, knowledge organizations (such as universities and research institutes), and government in producing and disseminating knowledge. Collectively, they affect the opportunities for individuals to obtain knowledge and convert it into commercial gain (Acs, Audretsch, & Lehmann, 2013). According to KSTE, FDI generates spillovers that lead to more entrepreneurship.

Research on KTSE can be roughly grouped into two categories: theories of “crowding-in” (Apostolov, 2017; Ayyagari & Kosová, 2010; Bayar, Gavriletea, & Ucar, 2018; Fu, 2012; Görg & Strobl, 2005; Herrera-Echeverri, Haar, & Benavides, 2014; Kim & Li, 2014; Wach & Wojciechowski, 2016), and theories of “crowding-out” (Angulo-Guerrero, Pérez-Moreno, & Abad-Guerrero, 2017; Danakol, Estrin, Reynolds, & Weitzel, 2017; De Backer & Sleuwaegen, 2003; Goel, 2018; Leitao & Baptista, 2011; Pathak, Laplume, & Xavier-Oliveira, 2015; Rusu & Roman, 2017; Tian & Wu, 2014).

Crowding-in theories emphasize the positive impact of FDI on entrepreneurship via three major avenues. The linkage effect of FDI on entrepreneurship occurs when the demand pull of FDI on both suppliers and customers generates opportunities that encourage entrepreneurial activity (Ayyagari & Kosová, 2010). The demonstration effect of FDI (Pitelis & Teece, 2010) arises when foreign-funded enterprises bring new technologies and organizational forms. Potential entrepreneurs can observe these and be motivated to initiate new economic activities based on what they see. The labor mobility effect of FDI (Fu, 2012) is actualized when local staffs working at multinational corporations leave to start new businesses based on the skills they have acquired. Less mentioned, but also related to crowding-in, is the impact that FDI can have on entrepreneurship via its role on improving the host country’s business environment. Foreign business interest groups can work with local governments and regulatory bodies to reduce market instability and operational risks (Tian & Chen, 2016). This creates conditions favorable to doing business that can stimulate entrepreneurial activity.

Countering these positive impacts are a number of other factors that collectively contribute to a crowding−out effect. On the supply side, foreign-funded enterprises can raise technology standards and prefer to work with larger, more established firms, making it more difficult for new ventures to succeed. Foreign-funded enterprises may receive preferential tax treatment, providing a competitive advantage over host country firms and adversely affecting the commercial opportunities of new businesses (Haddad & Harrison, 1993). Further, because they tend to be higher-paying, foreign-funded enterprises may attract highly skilled workers, drawing them away from starting businesses of their own. On the demand side, foreign-funded enterprises intensify market competition, lowering product prices and shrinking the profitability of competitors, including entrepreneurial companies. Further, their entry into the local marketplace raises local wages, increasing labor costs and making it more difficult for entrepreneurial ventures to turn a profit (De Backer & Sleuwaegen, 2003).

Of course there is no guarantee that the competing forces of crowding−in and crowding−out will lead to a monotonic relationship between FDI and entrepreneurship. It is possible that these forces interact in complex, nonlinear ways that are influenced by local conditions (Barbosa & Eiriz, 2009; Lee, Hong, & Sun, 2014; Munemo, 2017; Tian & Chen, 2016). Moreover, elements of the local business environment may moderate the capacity for FDI to stimulate entrepreneurial activity. For example, environments where intellectual property rights receive strong protections may make it more difficult for FDI to generate technology spillovers (Pathak, Xavier-Oliveira, & Laplume, 2013). Further, jurisdictions where corruption is pervasive can stifle entrepreneurial activity, and thus the capacity for FDI to stimulate that activity (Bologna & Ross, 2015).

The discussion above sets the context for our empirical synthesis of the literature. In particular, it highlights two types of potential moderators of the relationship between FDI and entrepreneurship. First, we know that market conditions and institutional and regulatory environments differ across economic and political regions. To capture their influence on the relationship between FDI and entrepreneurship, we record whether the primary study included business environment variables such as Doing Business and World Governance indicators. We also identify whether the countries included in a given study were OECD members, outside the

OECD, or a mix of each. To the extent these variables successfully proxy for market, institutional, and regulatory differences that affect the FDI-entrepreneurship relationship, the associated estimates should provide a measure of their importance for moderating empirical estimates of the effect of FDI.

Second, theory makes clear that there are many potential influences of the relationship of FDI and entrepreneurial activity, and that many of these are difficult to measure. For example, whether FDI raises or lowers the profitability of host country firms depends on whether the associated foreign-owned enterprises are customers or competitors of local firms. Further, foreign-owned business may choose to locate in areas where there is already much economic activity, and thus economic opportunity, for entrepreneurs. As these variables are difficult to observe and measure, it is inevitable that many important determinants of entrepreneurial activity will be omitted from the analysis. If these, in turn, are correlated with the presence of FDI in a region or country, the associated estimates in the primary studies will be biased due to endogeneity. Some studies try to address this bias by using instrumental variable, econometric procedures such as Two Stage Least Squares (2SLS) or Generalized Method of Moments (GMM) estimators. As a result, our analysis will record whether the primary studies used these procedures, and whether there is any evidence that they are successful in correcting bias.

3. SELECTION OF STUDIES

In selecting studies for our meta-analysis, we followed the MAER-Net guidelines presented in Havránek et al. (2020). Our search procedure used three strategies to identify studies of potential interest. The first strategy used keywords in conjunction with search engines and databases to identify relevant studies. The keywords “FDI”, “foreign direct investment”, “entrepreneurship”, “entrepreneurial activity”, “start a business”, “start-up”, “new venture”, “new business”, and “new firm” were used with the following search engines and databases: Google Scholar, Bing, EconLit, JSTOR, EBSCO, RePEc, ProQuest, Social Science Citation Index, Wiley-Blackwell, SAGE, SpiScholar, Emerald, ScienceDirect, Taylor & Francis, SpecialSciDBS, NBER, Open Access Library, and Global Entrepreneurship Monitor.

The second strategy intensively searched seven journals noted for their coverage of entrepreneurship: *Journal of International Business Studies*, *Journal of Business Venturing, Entrepreneurship Theory and Practice*, *Small Business Economics*, *Entrepreneurship and Regional Development*, *Journal of Management Studies*, *Journal of Business Research*. We inspected every issue of the journals published between 1984 (the year Grossman's article appeared) and the present (2020). The final strategy consisted of forward and backward citation searching of selected studies to uncover any research works not identified by our first two strategies. These search efforts were conducted over two time periods: May to August 2019, and July to October 2020.

All together, these search strategies identified 715 studies of potential interest. From this initial group, we excluded 237 studies because they did not include statistical analyses. Another 314 empirical articles were eliminated because they did not provide a direct estimate of the effect of FDI on entrepreneurship. The remainder were read carefully to determine if they met our inclusion criteria. To be included, a study needed to conduct an empirical analysis in which (i) the dependent variable was a measure of entrepreneurship, and (ii) the explanatory variables included a measure of FDI. The statistical information reported by the study had to either directly report a *t*-statistic for the estimated FDI coefficient, or allow one to be computed.

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 also 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/*t*-statistic. Finally, we only included country-level studies because we wanted to measure the economy-wide impacts of FDI on entrepreneurship.[1]

Once these criteria were imposed, we were left with 47 studies containing a total of 679 individual coefficient estimates. Among these, four estimates were eliminated because the *t*-statistics were unrealistically large or the associated degrees of freedom were negative.[2] This left 675 estimates. Table 1 reports the respective studies. Most of the studies that we found were published in the last five years. They generally included a mix of OECD and non-OECD countries. The number of estimates per study varied widely, from 1 to 187.

The studies were then read carefully to transfer the information into a coding sheet. In the first phase, pairs of postgraduate students independently coded each paper. Differences were first reconciled among themselves, and then by a senior member of our research team (Tian). In the second phase, a senior member of our research team (Tian) and a postgraduate student independently coded the additional studies, and then met to compare results and resolve differences. In summary, our final sample consisted of 47 studies and 675 estimates of the relationship between FDI and entrepreneurship. In the analyses that follow, we combine these estimates to get an overall estimate of the FDI-entrepreneurship relationship, and try to identify if there are any data, estimation, and study characterisitics that can account for the differences in these estimates.

Table 1. *Studies*

ID	Article	Sample Period	# Countries	Country Composition	# Estimates
1	Fogel, Hawk, Morck, and Yeung (2006)	2003-03	34	Mixed	2
2	Van Stel, Storey, and Thurik (2006)	2002-05	47	Mixed	3
3	Van Stel, Storey, Thurik, and Wennekers (2006)	2002-04	44	Mixed	2
4	Terjesen and Hessels (2009)	2006-07	51	Mixed	4
5	Doytch and Epperson (2011)	2004-08	80	Mixed	24
6	Dutta, Roy, and Sobel (2011)	2000-05	95	Mixed	16
7	Vaaler (2011)	2002-07	45	Mixed	8
8	Herrera-Echeverri, Haar, and Estévez-Bretón (2013)	2004-09	19	Mixed	4
9	Herrera-Echeverri, Haar, and Estévez-Bretón (2014)	2004-09	35	Mixed	7
10	Kim and Li (2014)	2000-09	104	Mixed	8
11	Salman (2014)	2004-08	49	Mixed	2
12	Chowdhury, Terjesen, and Audretsch (2015)	2001-05	44	Mixed	24
13	Danakol (2015)	2000-09	70	Mixed	187
14	Hanusch and Vaaler (2015)	2002-07	47	Mixed	4
15	Pathak, Laplume, and Xavier-Oliveira (2015)	2001-08	38	Mixed	40
16	Yousafzai, Saeed, and Muffatto (2015)	2002-12	92	Mixed	2
17	Albulescu and Tămăşilă (2016)	2005-12	16	Mixed	24
18	Doytch (2016)	2004-12	90	Mixed	3
19	Goel (2016)	2015-15	128	Mixed	26
20	Angulo-Guerrero, Pérez-Moreno, and Abad-Guerrero (2017)	2001-12	29	OECD	12
21	Danakol, Estrin, Reynolds, and Weitzel (2017)	2000-09	70	Mixed	12

ID	Article	Sample Period	# Countries	Country Composition	# Estimates
22	Ghosh (2017)	2001-16	79	Mixed	4
23	Jimenez, Matos, Palmero-Cámara, and Ragland (2017)	2000-07	9	Mixed	16
24	Jiménez, Puche-Regaliza, Jiménez-Eguizábal, and Alon (2017)	2002-07	93	Mixed	8
25	Mohamadi, Peltonen, and Wincent (2017)	2008-15	59	Mixed	4
26	Munemo (2017)	2004-12	92	Mixed	3
27	Rusu and Roman (2017)	2002-15	18	Mixed	1
28	Abubakar, Mitra, Modupe (2018)	2005-09	66	Mixed	6
29	Atiase, Mahmood, Wang, and Botchie (2018)	2017-17	35	Non-OECD	2
30	Canare (2018)	2004-12	123	Mixed	28
31	Chatmi and Elasri (2018)	2004-12	17	Mixed	12
32	Dvouletý (2018)	2001-15	11	OECD	4
33	Goel (2018)	2015-15	125	Mixed	24
34	Jiménez and Alon (2018)	2002-07	93	Mixed	6
35	Lecuna and Chávez (2018)	2002-14	18	Mixed	3
36	Munemo (2018)	2004-14	28	Non-OECD	10
37	Roman, Bilan and Ciumaș (2018)	2003-15	18	Mixed	18
38	Tomak (2018)	2007-17	1	OECD	1
39	Yay, Yay, and Aksoy (2018)	2004-12	54	Mixed	34
40	Zheng and Musteen (2018)	2001-09	30	Mixed	4
41	Arif and Khan (2019)	2006-16	11	Mixed	2
42	Bermpei, Kalyvas, Neri, and Russo (2019)	2005-13	83	Mixed	27
43	Cummings and Gamlen (2019)	2001-10	35	Mixed	13
44	Ajide (2020)	2006-18	20	Non-OECD	18

ID	Article	Sample Period	# Countries	Country Composition	# Estimates
45	Berrill, O'Hagan-Luff and Van Stel (2020)	2002-15	75	Mixed	2
46	Moore, Dau, and Doh (2020)	2002-15	49	Mixed	10
47	Peter and Pierk (2020)	2006-18	139	Mixed	1

Note: References for the studies in Table 1 are available in a supplementary, online file.

4. 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); and Yay, Yay, & Aksoy (2018). Less common measures include the log of FDI (Chatmi & Elasri, 2018), the growth rate of FDI (Herrera-Echeverri, Haar, & Estévez-Bretón, 2014), and measures of the relative importance of FDI as a contributor of new technology (Terjesen and Hessels, 2009).

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).[3] Studies in our sample that use this measure include Albulescu & Tămăşilă (2016); Danakol, Estrin, Reynolds, & Weitzel (2017); Mohamadi, Peltonen, & Wincent, 2017; and Pathak, Laplume, & Xavier-Oliveira (2015).

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 & Tămăşilă (2016) and Pathak, Laplume, & Xavier-Oliveira (2015) use all three measures, TEA, ODE, and NDE, as measures of entrepreneurship in separate regressions.

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 Cummings & Gamlen (2019). They use annual numbers 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 used as a proxy for entrepreneurship (Chowdhury, Terjesen, & Audretsch, 2015). Other studies are interested in particular types of entrepreneurship. For example, Terjesen & Hessel (2009) employ another sub-category of TEA that measures the percent of entrepreneurs with overseas customers in order to focus on "international" entrepreneurship. Moreover, Danakol (2015) and Danakol, Estrin, Reynolds, & Weitzel (2017) use gross entry rates in high-tech manufacturing as a proxy for "high quality" entrepreneurship. In addition, both Jiménez, Puche-Regaliza, Jiménez-Eguizábal, & Alon (2017) and Yay, Yay, & Aksoy (2018) categorize entrepreneurship into "formal" and "informal".

The different measures of entrepreneurship naturally sort themselves into separate categories in the context of sensitivity to FDI. One expects NDE or "informal" 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 "formal", "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 & Tămăşilă, 2016). Because TEA includes both nascent entrepreneurship and new business ownership rates, which combine 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.

5. METHODOLOGY

<u>How to accommodate estimates of the effect of FDI on entrepreneurship that are based on different measures</u>? One 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) $Entrepreneurship_{in} = \alpha_i + \beta_i FDI_{in} + \sum_{k=1}^{K_i} \gamma_{ki} X_{k,in} + error_{in}, \quad n = 1,2, \dots, N_i,$

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.

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. This is a common problem in the meta-analysis literature and there is a standard solution: convert estimates to Partial Correlation Coefficients (*PCCs*).[4]

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

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

A useful relationship of *PCCs* is that

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

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.[5]

Estimation. Our meta-analysis is concerned with two main questions: (1) What is the overall mean 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) $PCC_i = \mu + \sum_{j=1}^{J} \delta_j C_{ji} + \varepsilon_i = \mu + \boldsymbol{C_i \delta} + \varepsilon_i, \quad i = 1,2,\ldots,M,$

where $\boldsymbol{C_i}$ 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, $\boldsymbol{C}$. In that case, an estimate of the overall mean value of PCC_i is given by the estimate of μ. Adding the explanatory variables $\boldsymbol{C}$ 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). It needs to be noted that these estimators are not related to the panel data estimators of the same name. In the meta-analytic literature, and as we discuss below, the *FE* and *RE* estimators refer to whether the underyling effect being estimated is homogenous or heterogeneous across studies. While this nomenclature is confusing, given its ubiquitousness in the meta-analysis literature, we will use "Fixed Effects" and "Random Effects" in their meta-analytic sense.

The *FE* estimator assumes that there is a unique, homogeneous effect of FDI on Entrepreneurship. Accordingly, 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, $\varepsilon \sim N(0, se(PCC_i)^2)$. Most researchers consider the *FE* model, with its assumption of homogeneity, to be unrealistic.

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. 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 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).

The *FE* and *RE* estimators are themselves nested within a family of estimators known as selection models. These models essentially take the *RE* model and pre-multiply it with a truncated probability function that imposes a normal distribution of *t*-statistics. This accommodates the fact that some *t*-values are more likely than others due to publication selection bias. There are a large number of possible selection models. Two models common in the psychology literature are the Three-Parameter Selection Model (3PSM) and Four-Parameter Selection Models (4PSM) (Iyengar & Greenhouse, 1988; Vevea & Hedges, 1995; Vevea & Woods, 2005). In a recent *American Economic Review* paper, Andrews & Kasy (2019) proposed two alternative selection models, which we will refer to as *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:

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

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.

(6) $$\varphi(t_i) = \begin{cases} \rho_1 & t_i < -1.96 \\ \rho_2 & -1.96 \le t_i < 0 \\ \rho_3 & 0 \le t_i < 1.96 \\ 1 & t_i \ge 1.96 \end{cases}.$$

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. In a recent simulation exercise, Hong & Reed (2020) demonstrate that *AK1* and *AK2* generally perform quite well, often dominating other meta-analytic estimators, including other selection models. For that reason, we chose these two models to complement the *FE* and *RE* estimators, along with their *SE* variants, in forming our estimation strategy. Further details about the *FE, RE, AK1,* and *AK2* estimators are presented in the Appendix.

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

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

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

(7.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 2 summarizes testable restrictions for the respective pairs of nested models.

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*, and selection model estimators for model testing and selection. The latter is important for resolving differences when competing estimators produce conflicting estimates. When this happens, it is common in the literature to count up estimates on either side and go with the "voting majority". However, there is no statistical basis for this. In their massive simulation exercise, Carter et al. (2019) strongly recommend against this procedure. In contrast, the nested framework that we employ provides a way of selecting between conflicting findings when they occur.

Table 2. *Testable hypotheses for assessing nested model restrictions and publication bias*

		Restricted Model							
		FE	FE(w/SE)	RE	RE(w/SE)	AK1	AK1(w/SE)	AK2	AK2(w/SE)
Unrestricted Model	FE								
	FE(w/SE)	$\delta_{se(PCC)} = 0$							
	RE	$\tau^2 = 0$	Not Nested						
	RE(w/SE)		$\tau^2 = 0$	$\delta_{se(PCC)} = 0$					
	AK1			$\rho = 1$	Not Nested				
	AK1(w/SE)				$\rho = 1$	$\delta_{se(PCC)} = 0$			
	AK2					$\rho_1 = 1$ $\rho_2 = \rho_3$	Not Nested		
	AK2(w/SE)						$\rho_1 = 1$ $\rho_2 = \rho_3$	$\delta_{se(PCC)} = 0$	
Null hypotheses for tests of publication bias		----	$\delta_{se(PCC)} = 0$	----	$\delta_{se(PCC)} = 0$	$\rho = 1$	$\rho = 1$	$\rho_1 = 1$ $\rho_2 = 1$ $\rho_3 = 1$	$\rho_1 = 1$ $\rho_2 = 1$ $\rho_3 = 1$

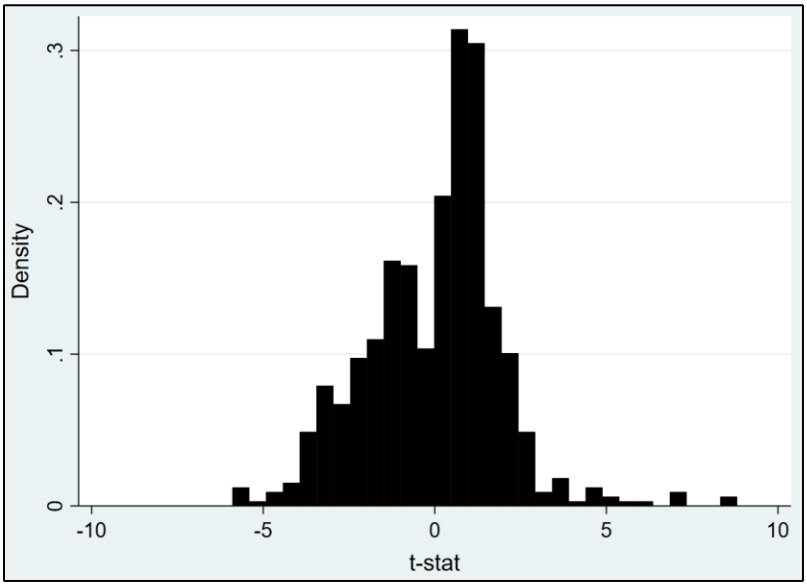
6. DATA ANALYSIS: Estimating the Mean Overall Effect of FDI on Entrepreneurship

Distribution of *t*-statistics and *PCC* values. The top panel of Figure 1 presents a histogram of the distribution of *t*-statistics for the 675 estimates in our study.[6] 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 the amount of research attention that the FDI-entrepreneurship relationship has attracted, it is perhaps 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 0.027). 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 in absolute value.

A. *t*-statistics values



Distribution of t-statistics	Percent
t < -2.00	15.1
-2.00 ≤ t ≤ 2.00	75.6
t > 2.00	9.3

B. PCC values

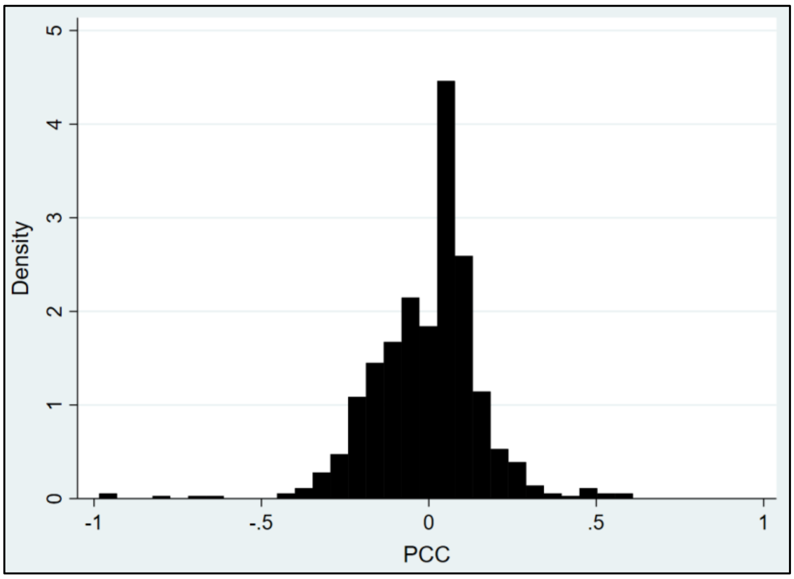
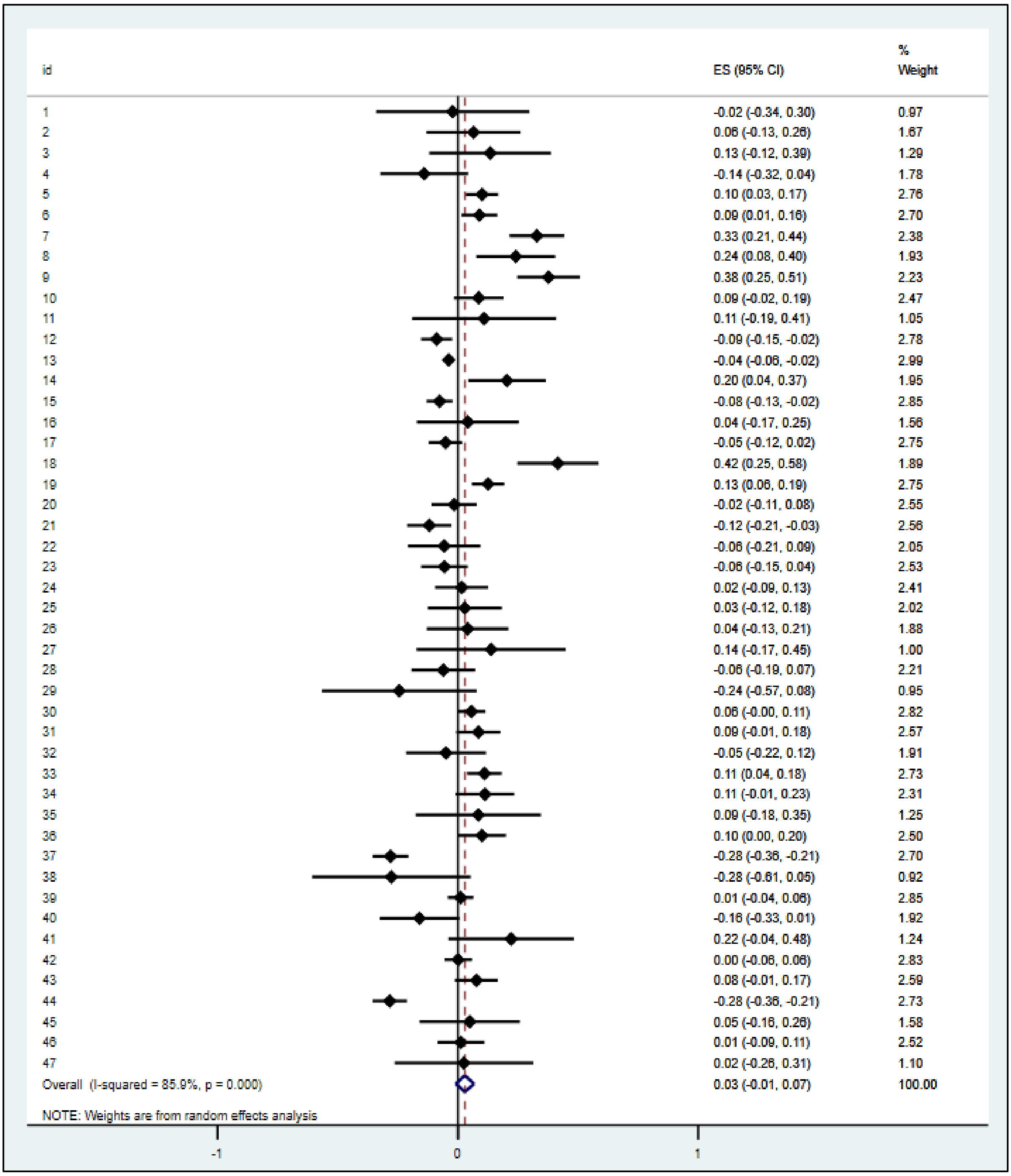


Figure 1. *Distribution of t-statistics and PCC values*

Table 3. *Descriptive statistics for effect size variables*

	t-statistics	df	PCC values
Mean	-0.247	208	0.004
Median	0.334	186	0.027
Minimum	-89.42	6	-0.985
Maximum	13.02	1174	0.609
Std. Dev.	4.92	127.8	0.163
1%	-5.78	31	-0.406
5%	-3.42	58	-0.261
10%	-2.81	70	-0.193
90%	2.00	354	0.154
95%	2.70	455	0.212
99%	6.97	663	0.471
Studies	47	47	47
Observations	675	675	675

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 three studies contain effects that could be classified as "large" (Studies 7, 9, and 18). 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 85.9%. The null of no between-study heterogeneity ($\tau^2 = 0$) is rejected with a p-value of 0.000. This amounts to a rejection of the assumption of effect homogeneity. Finally, the rightmost column reports the weight each study receives in calculating the overall mean.[7] The weights are relatively balanced across studies, ranging from a low of 0.92% (Study 38) to a high of 2.99% (Study 13).



Note: Studies are arranged by year and author, in ascending order. ID numbers correspond to the study ID numbers in Table 1.

Figure 2. *Forest plot: Study-level Random Effects estimates*

What is the effect of FDI on entrepreneurship? Table 4 reports estimates that 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 5. 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 & Havránek, 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 -0.5173 to -0.0046 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 0.000, and the *AK1* model is also 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 0.104. In three of the four cases, we reject the null of no publication bias.

Table 4. *Estimates of overall mean effect*

	FE	FE(w/SE)	RE	RE(w/SE)	AK1	AK2
μ	-0.0843	-0.5173	-0.0046	-0.0376	-0.0062	-0.0262
95% CI	(-0.2563, 0.0877)	(-1.1622, 0.1277)	(-0.0431, 0.0340)	(-0.1824, 0.1072)	(-0.0600, 0.0475)	(-0.1272, 0.0749)
Observations	675	675	675	675	675	675
Parameters	1	2	2	3	3	5
LogLikelihood	-6480.0	-4209.1	268.6	269.9	293.3	316.9
AIC	12961.9	8422.1	-533.1	-533.8	-580.6	-623.8
BIC	12966.4	8431.2	-524.1	-520.2	-567.1	-601.3
Tests of restrictive model against alternative model(s)						
	FE(w/SE) $p = 0.000$	*RE(w/SE)* $p = 0.000$	*RE(w/SE)* p = 0.104	----	*AK2* $p = 0.000$	----
	RE $p = 0.000$	----	*AK1* $p = 0.000$	----	----	----
Results of testing the null of no publication bias						
	----	Reject	----	Fail to Reject	Reject	Reject

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.

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 -0.03. The associated 95% confidence interval is (-0.13, 0.07). 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) 0.10, 0.21, and 0.34. The absolute values of the endpoints of the 95% confidence interval provide strong confidence that FDI has less than a "medium" effect on entrepreneurship. However, we cannot reject the hypothesis that FDI has no effect on entrepreneurship.

<u>A closer look at publication bias</u>. As noted above, publication bias can distort estimation of the mean overall effect. To identify if there is a problem, researchers have employed a variety of procedures to detect its presence. Table 4 reports two procedures, one based on the inclusion of the *se(PCC)* variable, and the other based on testing whether the respective selection probabilities (ρ_i) equal one. Based on these tests, our results indicate mixed evidence of publication bias.

Table 5 provides some additional tests. A potential criticism of using the *se(PCC)* variable as an indicator of publication bias is that the estimated coefficient may pick up the influence of omitted variables, causing bias. To address this, some researchers suggest instrumenting this variable with the square root of the respective regression's degrees of freedom (cf. Cazachevici, Havranek, & Horvath, 2020). Another approach is known as the caliper test (Gerber and Malhotra, 2008). It tests whether the distribution of t-statistics is equal in close bands (10%, 15%, 20%) on either side of some critical value, usually 1.96.[8] A third test is based on the p-uniform estimator. The logic behind this test is that the distribution of p-values should be uniformly distributed when the null hypothesis sets the effect size equal to its true value. The p-uniform tests whether the fixed effects estimate (which should be unbiased in the absence of publication bias) is uniformly distributed. The test statistic is gamma distributed with degrees of freedom equal to the number of significant estimated effects.

Table 5 reports the results of these tests. The null hypothesis in each case is that there is no publication bias. In contrast to the findings of Table 4, these additional tests suggest that there is no publication bias. However, it should be noted that these tests assess different aspects of publication bias. For example, if publication selection is directed towards the sign of the estimated effects without consideration of statistical significance, the selection tests of AK1 and AK2 would show evidence of publication bias, while, for example, the caliper test would not.

Table 5. *Additional tests for publication bias*

	Egger test/FAT: IV estimate		
Variable	Coefficient	Std. error	p-value
se(PCC)	-2.392	2.073	0.249
	Caliper test		
Test	p-value		
10% Caliper	0.121		
15% Caliper	0.244		
20% Caliper	0.536		
	p-uniform test		
Sample Statistic	p-value		
$L^{\hat{\mu}} = 424.02$	1.000		

Note: In each case, the reported p-value corresponds to a test of the null hypothesis that there is no publication bias. The respective tests are described in the text.

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

Frequentist analysis of variables associated with differences in estimated effects. 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 6 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*). 73.6% 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 (19.7%). 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" (44.0%). Next largest is *EntreType1* which uses the TEA measure of entrepreneurship (35.7%). The category hypothesized to be least affected by FDI, *EntreType2*, only includes 6.1% of the estimated effects. All other entrepreneurial measures account for 14.2%.

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, 5.2% of the estimated effects are from studies that exclusively study OECD countries; 9.8% come from studies that focus exclusively on non-OECD countries.

Table 6. *Description of variables*

Variable	Description	Mean	Min	Max
	FDI			
FDIGDP*	= 1 if FDI measured as ratio of FDI to GDP	0.736	0	1
FDIlog	= 1 if FDI is measured as log of FDI	0.197	0	1
FDIOther	= 1 if another measure for FDI is used, such as growth rate of FDI, or the ratio of foreign capital to total investment	0.067	0	1
	Entrepreneurship			
EntreType1*	= 1 if entrepreneurship is measured by TEA including nascent and new businesses	0.357	0	1
EntreType2	= 1 if entrepreneurship is measured by the TEA subcategory, NDE or informal entrepreneurship	0.061	0	1
EntreType3	= 1 if entrepreneurship is measured by the TEA subcategory, ODE, or high-quality entrepreneurship such as formal entrepreneurship, international entrepreneurship, or newly registered limited-liability firm	0.440	0	1
EntreOther	= 1 if the entrepreneurship variable is a measure not included in EntreTypes1-3.	0.142	0	1
	Countries			
OECD	= 1 if sample is limited to OECD countries	0.052	0	1
NonOECD	= 1 if sample is limited to non-OECD countries	0.098	0	1
MixedCountry*	= 1 if sample consists of both OECD and non-OECD countries	0.850	0	1
	Data and estimation characteristics			
CrossSection	= 1 if data is cross-sectional	0.080	0	1
PanelFE	= 1 if data is panel and fixed effects were included in the specification	0.335	0	1
PanelNoFE*	= 1 if data is panel and no fixed effects were included in the specification	0.557	0	1
Lagged DV	= 1 if the specification included a lagged dependent variable	0.136	0	1

Variable	Description	Mean	Min	Max
BusEnviron	= 1 if the specification included business environment measures, such as Doing Business indicators and/or World Governance indicators	0.964	0	1
IV	= 1 if estimation method corrected for endogeneity (e.g., 2SLS, GMM)	0.262	0	1
	Study characteristics			
Journal	= 1 if study is an academic, peer-reviewed journal	0.625	0	1
NotJournal*	= 1 if study is a book, working paper, or thesis	0.375	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.

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.[9] Our analysis sets estimates that use panel data without fixed effects as the reference group (55.7%). To see if the nature of the data matters for the estimated effects, we include variables to indicate cross-sectional (8.0%) and panel fixed effects (33.5%).

We also include a dummy variable to indicate whether a lagged dependent variable was included in the original regression (13.6%). When this variable is included, the FDI effect will only capture the short-run effect of FDI on entrepreneurship. If the effect accumulates (decreases) over time, estimated FDI effects should be smaller (larger) when a lagged dependent variable is included. The dummy variable *BusEnviron* indicates whether Doing Business, World Governance, or related measures were included in the original study. Most of the estimates (96.4%) in our sample come from primary studies that included these variables. The effect of these variables on estimated FDI effects is uncertain. Some factors (e.g., low corruption) contribute to crowding-in, while other factors (e.g., protection of intellectual property rights) can contribute to crowding-out.

As noted above, simultaneity and omitted variables can bias estimates of FDI effects. We include a dummy variable to indicate whether the original effect was estimated with 2SLS or GMM (26.2%). If entrepreneurship, or the conditions that stimulate entrepreneurship, attract FDI, then estimation that corrects this endogeneity bias should produce smaller estimates.

Lastly, we include variables to indicate whether studies that appear in academic, peer-reviewed journals are systematically different from studies in other outlets (books, theses, working papers). 62.5% of the estimates in our study are taken from academic, peer-reviewed journals, with the remainder coming from unpublished working papers, books, and Master and PhD theses.

Table 7 reports the results of using frequentist analysis to explore 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 0.000. 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 0.411. The corresponding *se(PCC)* coefficient in the *AK2(w/SE)* specification has a *t*-value of -0.27. 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 (-780.4 and -699.1, respectively) are smaller than any of its competitors. Accordingly, we focus on the *AK2* model, noting that the effects do not differ greatly across other models.

Table 7. *Frequentist analysis of factors associated with estimated effects of FDI on entrepreneurship*

	FE	FE(w/SE)	RE	RE(w/SE)	AK1	AK1(w/SE)	AK2	AK2(w/SE)
se(PCC)	----	4.9548* (2.6731)	----	0.1131 (1.1954)	----	0.0226 (1.1223)	----	-0.3054 (1.1162)
FDIlog	0.1238 (0.0812)	0.0506 (0.0803)	0.0373 (0.0506)	0.0354 (0.0473)	0.0462 (0.0561)	0.0458 (0.0519)	0.0422 (0.0563)	0.0479 (0.0522)
FDIOther	0.0267 (0.0754)	0.0161 (0.0886)	0.0192 (0.0441)	0.0189 (0.0447)	0.0266 (0.0472)	0.0265 (0.0468)	0.0256 (0.0496)	0.0264 (0.0484)
EntreType2	-0.0388 (0.0918)	-0.0440 (0.1034)	0.0172 (0.0895)	0.0170 (0.0915)	0.0203 (0.1083)	0.0203 (0.1087)	0.0172 (0.1044)	0.0174 (0.1043)
EntreType3	0.0165 (0.0702)	0.0894 (0.0900)	0.0646 (0.0626)	0.0653 (0.0622)	0.0840 (0.0769)	0.0841 (0.0756)	0.0867 (0.0731)	0.0846 (0.0718)
EntreOther	-0.0256 (0.0774)	-0.0209 (0.0999)	-0.0349 (0.0566)	-0.0346 (0.0576)	-0.0539 (0.0592)	-0.0538 (0.0583)	-0.0466 (0.0549)	-0.0475 (0.0534
OECD	-0.0611** (0.0291)	-0.1276** (0.0483)	-0.0450 (0.0273)	-0.0464 (0.0323)	-0.0601** (0.0295)	-0.0604* (0.0357)	-0.0636** (0.0292)	-0.0601* (0.0352)
NonOECD	-0.5499*** (0.1824)	-0.4861*** (0.1277)	-0.1170 (0.0877)	-0.1186 (0.0996)	-0.1515 (0.0997)	-0.1519 (0.1090)	-0.1480* (0.0863)	-0.1438 (0.0983)
CrossSection	0.1876* (0.0939)	0.0093 (0.1417)	0.1586** (0.0647)	0.1545** (0.0748)	0.2168*** (0.0739)	0.2160*** (0.0713)	0.2138*** (0.0710)	0.2254*** (0.0675)
PanelFE	0.1011 (0.0957)	0.0882 (0.0885)	0.0231 (0.0598)	0.0237 (0.0634)	0.0300 (0.0683)	0.0301 (0.0710)	0.0345 (0.0683)	0.0331 (0.0704)

	FE	FE(w/SE)	RE	RE(w/SE)	AK1	AK1(w/SE)	AK2	AK2(w/SE)
LaggedDV	0.1538 (0.0918)	0.1104 (0.1017)	0.1785** (0.0688)	0.1772** (0.0722)	0.2319*** (0.0640)	0.2316*** (0.0620)	0.2161*** (0.0676)	0.2200*** (0.0676)
BusEnviron	-0.0111 (0.0538)	-0.0057 (0.0665)	0.0255 (0.0497)	0.0256 (0.0506)	0.0377 (0.0549)	0.0377 (0.0550)	0.0357 (0.0530)	0.0352 (0.0527)
IV	-0.1181** (0.0509)	-0.0908* (0.0525)	-0.1619*** (0.0478)	-0.1611*** (0.0494)	-0.2067*** (0.0425)	-0.2065*** (0.0392)	-0.1879*** (0.0449)	-0.1902*** (0.0437)
Journal	-0.0843* (0.0466)	-0.0497 (0.0452)	-0.0607* (0.0343)	-0.0604* (0.0340)	-0.0790* (0.0420)	-0.0790* (0.0412)	-0.0801* (0.0413)	-0.0809* (0.0409)
τ	----	----	0.1211	0.1210	0.1420	0.1420	0.1425	0.1429
Selection parameter(s)	----	----	----	----	$\rho = 2.237$	$\rho = 2.236$	$\rho_1 = 1.169$ $\rho_2 = 1.735$ $\rho_3 = 3.152$	$\rho_1 = 1.192$ $\rho_2 = 1.755$ $\rho_3 = 3.210$
Observations	675	675	675	675	675	675	675	675
Parameters	14	15	15	16	16	17	18	19
LogLikelihood	-2260.9	-1540.8	362.9	363.0	388.6	388.6	408.2	408.5
AIC	4549.7	3111.6	-695.8	-693.9	-745.2	-743.2	-780.4	-779.0
BIC	4612.9	3179.4	-628.1	-621.7	-673.0	-666.4	-699.1	-693.2

	FE	FE(w/SE)	RE	RE(w/SE)	AK1	AK1(w/SE)	AK2	AK2(w/SE)
Tests of restrictive model against alternative model(s)								
----	FE(w/SE) p = 0.000	RE(w/SE) p = 0.000	RE(w/SE) p = 0.695	AK1(w/SE) p = 0.000	AK1(w/SE) p = 0.950	AK2(w/SE) p = 0.000	AK2(w/SE) p = 0.411	----
----	RE p = 0.000	----	AK1 p = 0.000	----	AK2 p = 0.000	----	----	----
Results of testing the null of no publication bias								
	----	Fail to Reject	----	Fail to Reject	Reject	Reject	Reject	Reject

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.

We first note that none of the *se(PCC)* coefficients are significant at the 5% level 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 standard deviation of 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 four are significant at the 5-percent level. Cross-sectional studies tend to produce larger estimates than studies that rely on panel data but do not include fixed effects (0.2138). However, this is likely not due to omitted, time invariant effects because studies that use panel data with fixed effects are insignificantly different from those without fixed effects (0.0345). Therefore, there must be something else about the cross-sectional studies in our sample that is responsible for the larger FDI estimates.

Studies that include a lagged dependent variable as an explanatory variable tend to have larger estimates. The estimated coefficient on *LaggedDV* of 0.2161 indicates that the short-run effect of FDI is larger than the long-run effect. An interpretation consistent with this estimate is that FDI has an immediate, positive impact on entrepreneurial behavior, but over time that effect dissipates and settles into a smaller, long-run equilibrium. We also find that studies that focus on OECD countries estimate smaller FDI effects than other studies, however the effect is relatively small (-0.0636).

The last of the estimated coefficients to achieve significance corresponds to studies that control for endogeneity by using some form of an instrumental variables estimator (2SLS or GMM). The estimated coefficient of -0.1879 is consistent with an interpretation that omitted variables or simultaneity induce a positive bias to estimates of the effect of FDI on entrepreneurship. Correcting for that significantly mitigates that bias. In fact, not controlling for anything else, studies that use 2SLS or GMM estimate, on average, a negative effect of FDI on entrepreneurship, albeit the estimated effect is very small.[10]

It is noteworthy that none of variables distinguishing the various measures of entrepreneurship were estimated to have a significant effect. In particular, we do not find support for the expectation that opportunity-driven entrepreneurship (ODE) is most likely to be affected by FDI. The coefficient on *EntreType3*, while positive, is statistically insignificant. 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.

Bayesian Model Averaging. The preceding meta-regression analysis assumes that the full set of variables belongs in the "true model" relating data, estimation and study characteristics to estimated effects. Some researchers argue that regressions such as those reported in Table 7 do not take into account "model uncertainty"; that is, that the set of variables that belong in the "true model' is uncertain. Accordingly, they recommend estimation procedures that take this uncertainty into account. A common procedure is Bayesian Model Averaging, or BMA (Zeugner & Feldkircher, 2015). Essentially, BMA works by positing a prior distribution for the number of variables in the model, and a prior distribution on the size of the variable coefficients. It then forms all possible permutations of variable specifications. Not counting the *se(PCC)* variable, there are 2^{13} possible model specifications. As these are too many models to estimate all of them, Gibbs sampling is used to select a subsample of models. This subsample is weighted using the respective likelihood values to created weighted means of the parameters. The results are reported in Table 8.

Table 8. *Results of Bayesian Model Averaging analysis*

Variable	Posterior mean	Cond. pos. sign	Posterior inclusion probability (PIP)
IV	-0.164	0.00	1.00
LaggedDV	0.188	1.00	1.00
NonOECD	-0.122	0.00	1.00
CrossSection	0.123	1.00	1.00
EntreType3	0.074	1.00	1.00
Journal	-0.048	0.00	0.98
OECD	-0.007	0.00	0.16
FDIlog	0.004	1.00	0.15
EntreOther	-0.005	0.00	0.13
PanelFE	0.002	0.99	0.09
EntreType2	0.002	0.99	0.08
BusEnviron	0.001	1.00	0.06
FDIOther	0.000	0.99	0.04

Note: The results in the table report Bayesian Model Averaging (BMA) (weighted) estimates of the respective coefficient values ("Posterior mean"), the probability that the respective coefficient is positive ("Cond. pos. sign"), and the probability that the respective variable belongs in the true model ("Posterior inclusion probability (PIP)"). We don't report the posterior standard deviations because they are unable to accommodate the clustered nature of the estimates arising from having multiple estimates from the same study. Estimates were obtained using the R program BMS (Zeugner and Feldkircher), with options: "uniform" model prior; "UIP" g prior; burnins = 1,000,000; and interations = 2,000,000. While the individual models are estimated using OLS, the variables were pre-treated by multiplying them by the square of the inverse of ($se(PCC)^2+\tau^2$) so as to approximate a Random Effects model.

For each variable, BMA calculates a Posterior Inclusion Probability (PIP), which can be loosely thought of as the probability that the respective variable belongs in the true model. Table 8 sorts the variables in descending order of PIP, with the idea that the variables at the top of the table are the ones most likely to belong in the model. The takeaway from Table 8 is generally similar to that of Table 7. Six variables (*IV, LaggedDV, NonOECD, CrossSection, EntreType3,* and *Journal*) are determined to be virtually certain to belong in the true model. Five of these are statistically significant at the 10 percent level in the preferred AK2 specification of Table 7. Only OECD is statistically significant at the 5% level in Table 7 while having a small PIP (0.16) in Table 8. The four variables with the largest posterior mean coefficient estimates in Table 8 (*IV, LaggedDV, NonOECD,* and *CrossSection*), are also the four variables with the largest coefficients (in absolute value) in Table 7. All the coefficients have the same signs in Tables 7 and 8 and the sizes of the coefficients are generally close.

8. CONCLUSION

This study uses meta-analysis to examine the empirical literature on FDI and entrepreneurship. It analyzes 675 estimates from 47 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. Our research addressed two questions: (1) What is the overall, mean effect of FDI on entrepreneurship?, and (2) What factors account for differences in estimated effects across studies?

With respect to the first question, our estimates of the overall, mean effect are generally close to zero and statistically insignificant (cf. the estimates in the top row of Table 4). This is supported by the fact that approximately 3/4ths of the corresponding estimates in the literature are statistically insignificant (cf. Panel A of Figure 1). One might counter by noting that that also means that a fourth of the estimates are statistically significant: If the effect truly was zero across all studies, one would only expect 5% of the estimates to be significant. However, this ignores the impact of publication bias whereby statistically significant estimates are more likely to be published. In fact, there is some evidence to indicate that publication bias is present in this literature (cf. the last row of Tables 4 and 7). It also worth noting that our result is consistent with recent meta-analyses of the spillover effects of FDI on productivity (Havránek & Iršová, 2010; Iršová & Havránek, 2013; Iwasaki & Tokunaga; 2016) and on exports (Duan et al., 2020).

To investigate the second question, we regressed our measure of estimated FDI effects on thirteen study, data, and estimation characteristics. Only four of these were economically and statistically significant. Of these, the most interesting finding is that studies that used instrumental variable estimation procedures such as 2SLS and GMM were associated with smaller estimates. This is consistent with the fact that foreign businesses locate in areas where business conditions are also favorable for entrepreneurs. It suggests that future studies of the FDI-entrepreneurship relationship should address endogeneity.

It is noteworthy that most variables in our analysis were statistically insignificant, providing little explanation for the differences in estimated effects across studies. The fact that models that allowed for effect heterogeneity (*RE, AK1,* and *AK2*) performed better than models that assumed effect homogeneity (*FE*) indicates that differences in estimates observed in the literature are not simply due to sampling error. There are real differences in the effects of FDI across time and place. However, we either do not have the right variables to explain those differences, or the measures that we have are not sufficiently constructed to pick up those effects. This is a subject that deserves further investigation.

NOTES

1. 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.”

2. Salman (2014) reported standard errors that implied t-statistics of 135; 58,000; and 2,571; and another regression where the degrees of freedom was negative.

3. 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.”

4. See Cazachevici, Havranek, & Horvath (2020) for an example of a recent paper that also uses *PCCs* to transform estimated effects to make them comparable for empirical analysis.

5. 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.

6. Figure 1 cuts off extreme outliers to facilitate readability.

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

8. Where 10% of 1.96 is approximately 0.20. Thus, the 10% caliper test tests whether the probability studies report t-statistics between 1.76 and 1.96 is the same as the probability they report t-statistics between 1.96 and 2.16.

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

10. The mean *PCC* value for studies that use 2SLS or GMM is -0.04 with a 95% confidence interval of (-.06, -.02).

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APPENDIX

Details Regarding the FE, RE, AK1, and AK2 Models

Given

(A1) $PCC_i = \mu + \sum_{j=1}^{J} \delta_j C_{ji} + \varepsilon_i = \mu + \boldsymbol{C_i \delta} + \varepsilon_i,\ i = 1,2,\ldots,M,$

where $\boldsymbol{C_i}$ 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.

A. <u>Fixed Effects (FE) Model</u>

The FE estimator assumes that there is a unique, homogeneous effect of FDI on entrepreneurship. 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 ith observation, $f_{FE,i}$, and log likelihood function, ℓ_{FE}, are given by

(A2) $$f_{FE,i} = \mathrm{p}(PCC_i \mid \boldsymbol{C_i}, se(PCC_i)^2; \mu, \boldsymbol{\delta}) = \frac{1}{\sqrt{2\pi \cdot se(PCC_i)^2}} e^{-\frac{(PCC_i - \mu - \boldsymbol{C_i \delta})}{2 \cdot se(PCC_i)^2}}$$

and

(A3) $$\ell_{FE} = \sum_{i=1}^{M} \log[\mathrm{p}(PCC_i \mid \boldsymbol{C_i}, se(PCC_i)^2; \mu, \boldsymbol{\delta})].$$

B. <u>Random Effects (RE) Model</u>

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

(A4) $$f_{RE,i} = \mathrm{p}(PCC_i \mid \boldsymbol{C_i}, se(PCC_i)^2; \mu, \boldsymbol{\delta}, \tau^2) = \frac{1}{\sqrt{2\pi(se(PCC_i)^2 + \tau^2)}} e^{-\frac{(PCC_i - \mu - \boldsymbol{C_i \delta})}{2(se(PCC_i)^2 + \tau^2)}}$$

and

(A5) $$\ell_{RE} = \sum_{i=1}^{M} \log([\mathrm{p}(PCC_i \mid \boldsymbol{C_i}, se(PCC_i)^2; \mu, \boldsymbol{\delta}, \tau^2)]).$$

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.

C. <u>AK1 Model</u>

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:

(A6) $$\varphi\left(t_i = \frac{PCC_i}{se(PCC_i)}\right) = \begin{cases} 1 & if\ |t_i| \geq 1.96 \\ \rho & if\ |t_i| < 1.96 \end{cases}.$$

The associated log likelihood function is:

(A7) $$\ell_{AK1} = \sum_{i=1}^{M} \log\left(\frac{\varphi(Z_i)}{E[\varphi(Z_i)|\mu,\boldsymbol{\delta},\tau^2,\rho]} \cdot \mathrm{p}(PCC_i \mid \boldsymbol{C_i}, se(PCC_i)^2; \mu, \boldsymbol{\delta}, \tau^2)\right).$$

where

(A8) $$E[\varphi(Z_i)|\mu,\boldsymbol{\delta},\tau^2,\rho,se(PCC_i)]$$

$$= \int_R \rho \times I\left(\left|\frac{PCC_i}{se(PCC_i)}\right| < 1.96\right) \times \frac{1}{\sqrt{2\pi(\mathrm{se(PCC_i)^2} + \tau^2)}} e^{-\frac{(PCC_i - \hat{\epsilon}_i)^2}{\mathrm{se(PCC_i)^2} + \tau^2}} dPCC_i$$

$$+ \int_R 1 \times I\left(\left|\frac{PCC_i}{se(PCC_i)}\right| \geq 1.96\right) \times \frac{1}{\sqrt{2\pi(\mathrm{se(PCC_i)^2} + \tau^2)}} e^{-\frac{(PCC_i - \hat{\epsilon}_i)^2}{\mathrm{se(PCC_i)}^2 + \tau^2}} dPCC_i.$$

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.

D. <u>AK2 Model</u>

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.

(A9) $$\varphi(t_i) = \begin{cases} \rho_1 & t_i < -1.96 \\ \rho_2 & -1.96 \leq t_i < 0 \\ \rho_3 & 0 \leq t_i < 1.96 \\ 1 & t_i \geq 1.96 \end{cases}.$$

The corresponding log likelihood function is

(A10) $$\ell_{AK2} = \sum_{i=1}^{M} \log\left(\frac{\varphi(Z_i)}{E[\varphi(Z_i)|\mu,\boldsymbol{\delta},\tau^2,\rho_{1,}\rho_{2,}\rho_3]} \cdot \mathrm{p}(PCC_i \mid \boldsymbol{C_i}, se(PCC_i)^2; \mu, \boldsymbol{\delta}, \tau^2)\right).$$

where

(A11) $E[\varphi(Z_i)|\mu, \boldsymbol{\delta}, \tau^2, \rho, se(PCC_i)]$

$$= \int_R \rho_1 \times I\left(\frac{PCC_i}{se(PCC_i)} < -1.96\right) \times \frac{1}{\sqrt{2\pi(\mathrm{se(PCC_i)}^2 + \tau^2)}} e^{-\frac{(PCC_i - \hat{\epsilon}_i)^2}{\mathrm{se(PCC_i)}^2 + \tau^2}} dPCC_i$$

$$+ \int_R \rho_2 \times I\left(-1.96 \leq \frac{PCC_i}{se(PCC_i)} < 0\right) \times \frac{1}{\sqrt{2\pi(\mathrm{se(PCC_i)}^2 + \tau^2)}} e^{-\frac{(PCC_i - \hat{\epsilon}_i)^2}{\mathrm{se(PCC_i)}^2 + \tau^2}} dPCC_i$$

$$+ \int_R \rho_3 \times I\left(0 \leq \frac{PCC_i}{se(PCC_i)} < 1.96\right) \times \frac{1}{\sqrt{2\pi(\mathrm{se(PCC_i)}^2 + \tau^2)}} e^{-\frac{(PCC_i - \hat{\epsilon}_i)^2}{\mathrm{se(PCC_i)}^2 + \tau^2}} dPCC_i$$

$$+ \int_R 1 \times I\left(\frac{PCC_i}{se(PCC_i)} \geq 1.96\right) \times \frac{1}{\sqrt{2\pi(\mathrm{se(PCC_i)}^2 + \tau^2)}} e^{-\frac{(PCC_i - \hat{\epsilon}_i)^2}{\mathrm{se(PCC_i)}^2 + \tau^2}} dPCC_i.$$

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.