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Biased FDI spillovers in incomplete datasets: An empirical examination

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Abstract

We examine biases in foreign direct investment (FDI) productivity spillovers that can arise when using incomplete datasets, by comparing estimates for Indonesia from the World Bank Enterprise Survey (WBES)—an incomplete dataset example—with estimates from the Indonesian Manufacturing Survey (MS). Furthermore, we conduct estimations on samples drawn from MS, following the sampling methodology of WBES. We find that estimates with this sampling framework are inaccurate, due to measurement error in industry-level horizontal and vertical FDI, strong presence of small firms, and small sample size. Relaxing the WBES sampling criteria and using FDI variables from MS produces substantially more reliable findings.

KEYWORDS

foreign direct investment, incomplete datasets, Indonesia, productivity spillovers

1 | INTRODUCTION

Many governments try to attract foreign direct investment (FDI) into their economies, motivated by the expectation that domestic firms benefit from FDI presence via positive spillovers. Through demonstration effects, labor turnover, and inter-firm linkages, FDI firms may disseminate new technologies, resulting into productivity spillovers among domestic firms (Blomström & Kokko, 1998; Görg & Greenaway, 2004; Smeets, 2008). However, despite the popular belief that positive FDI spillovers are prevalent, empirical evidence is mixed and inconclusive (Hanousek et al., 2011; Havranek & Irsova, 2011; Irsova & Havranek, 2013). Whereas some studies present evidence of positive FDI spillovers in developed or developing countries (Blalock & Gertler, 2008; Girma et al., 2015; Keller & Yeaple, 2009), others report negative or insignificant associations between FDI presence and domestic firm productivity (Aitken & Harrison, 1999; Javorcik & Spatareanu, 2008; Konings, 2001).

The FDI spillovers literature has explored several reasons for the heterogeneity of the evidence. First, findings of positive spillovers from early studies using cross-sectional industry-level data have been challenged, as estimated FDI spillovers may be biased upward when FDI firms gravitate toward high-productivity industries (Aitken & Harrison, 1999; Görg & Greenaway, 2004; Jordaan, 2011). Later studies, based on firm-level panel data, that control for time-invariant firm-level fixed effects, present mixed evidence (Javorcik, 2004; Meyer & Sinani, 2009). More recently, several studies explore direct approaches to address the endogeneity of industry FDI and identify spillovers more fully (e.g., Girma et al., 2015; Lu et al., 2017). Second, not all studies distinguish between FDI participation within and between industries. Studies that capture inter-industry links between input-producing domestic firms and FDI client firms show that these links may generate positive spillovers (Blalock & Gertler, 2008; Javorcik & Spatareanu, 2008). Third, a growing literature on FDI spillovers is examining conditions that influence the occurrence of these externalities. One approach in this research strand is theoretically driven (Eapen, 2012; Spencer, 2008), whereas another approach conducts empirical estimations that relate productivity spillovers to firm-level heterogeneity. This involves linking FDI spillovers to characteristics of FDI and domestic firms, including firm size, technology gap, human capital, and export status (Abraham et al., 2010; Blalock & Gertler, 2009; Damijan et al., 2013; Jordaan, 2017).

In comparison, the question whether dataset characteristics affect FDI spillovers estimations has received much less attention. The primary concern of researchers is to use a firm-level dataset containing information on inputs, output, and type of ownership that allows for the estimation of productivity spillovers from the presence of FDI. However, using incomplete datasets to estimate FDI productivity effects may contribute to the varied nature of the existing evidence. Through Monte Carlo simulations, Eapen (2013) shows that FDI spillovers estimated with incomplete datasets are potentially biased, due to problems surrounding the measurement of FDI industry participation and the presence of a selection bias, where firms of particular size classes are over- or underrepresented. The issue of the degree of incompleteness of firm-level datasets is important, as datasets are often derived from manufacturing surveys that omit small firms. Secondary datasets like Compustat only contain publicly listed firms. Datasets from ORBIS/AMADEUS are more representative of country firm populations. However, these datasets only contain firms that file financial and balance sheet information to national registers and countries differ in the extent to which firms are obliged to do so, indicating that these datasets may also suffer from incompleteness (Kalemli-Ozcan et al., 2015).[1]

Horizontal FDI spillovers are estimated by relating industry-level FDI—measured as the share of FDI in industry employment or output—to the productivity level of domestic firms in the same industry. Incomplete datasets are characterized by the omission of segments of the firm population from which samples are drawn. Therefore, industry-FDI indicators calculated with such datasets are error-prone, as they are not calculated with information from the full population of firms. Indicators of inter-industry (vertical) FDI are similarly affected. For a given industry, vertical FDI is usually calculated as a weighted average of intra-industry FDI in the other industries, using input–output table coefficients of the host economy as weights (see, e.g., Blalock & Gertler, 2008; Javorcik, 2004). Consequently, measurement errors of horizontal FDI are incorporated into measures of vertical FDI. Thus, the use of incomplete datasets may affect estimates of both horizontal and vertical FDI spillovers.

In this paper, we conduct an empirical examination to identify the causes and severity of possible biases from using incomplete datasets to estimate FDI spillovers. Our results provide important indications of the issues that researchers need to consider to obtain more accurate findings when using incomplete datasets. Our paper differs from Eapen (2013) in three ways. First, Eapen (2013) presents a

Monte Carlo–based assessment of biases that arise when FDI industry participation contains a specified measurement error and when small firms are underrepresented in the dataset. We examine biases from a concrete case of an incomplete dataset from the World Bank Enterprise Survey (WBES). The World Bank conducts firm-level surveys in developing and emerging countries, creating rich datasets of firm-level characteristics (see, e.g., Dethier et al., 2011). Several studies use these datasets to estimate FDI spillovers (e.g., Farole & Winkler, 2012; Gorodnichenko et al., 2014; Monastiriotis, 2014). As ownership type is not a sampling stratification criterion, it is unclear whether FDI participation can be measured accurately with these datasets, suggesting that measurement error may impact estimated FDI spillovers.

Second, we also examine whether the strong presence of small firms and the sample size of WBES datasets affect estimated spillovers. Not only may the large presence of small firms influence the measurement of industry FDI, it may also affect the size and/or significance of spillovers, as firm size is a determinant factor of these externalities (Aitken & Harrison, 1999; Keller & Yeaple, 2009). This relation between firm size and FDI spillovers may affect estimated FDI spillovers when particular firm size classes are strongly represented in the datasets.

Third, whereas Eapen (2013) focuses specifically on biases in estimated horizontal FDI spillovers, we also examine whether incomplete datasets influence estimated vertical spillovers (specifically through backward linkages to domestic suppliers), as measurement errors that affect horizontal FDI are by construction carried over into vertical FDI indicators.

To examine these issues we use Indonesia as a case study. Indonesia offers a fruitful setting to study FDI spillovers, as existing evidence suggests that FDI firms create positive spillovers in this economy (Blalock & Gertler, 2008; Sjöholm & Blomström, 1999; Takii, 2005). In our analysis, we first estimate horizontal and vertical FDI spillovers using a 2009 firm-level dataset from the WBES. We then compare the findings with results from a much larger firm-level dataset from the annual Indonesian Manufacturing Survey for the years 2008 and 2009.[2]

Next, we conduct estimations on many random samples drawn from MS, using the WBES sampling criteria. We treat the findings from the larger MS dataset as representing FDI spillovers among the population of manufacturing firms in Indonesia, against which we can compare findings from the simulated incomplete datasets. This allows us to assess to what extent measurement error in industry FDI, strong representation of small firms, and limited sample size create biases in estimated FDI spillovers. Furthermore, by relaxing the WBES sampling criteria and combining information from WBES and MS, we can identify which characteristics of incomplete datasets are instrumental in obtaining results that approach those obtained with the full MS dataset.

The remainder of the paper is constructed as follows. Section 2 discusses the research problem in more detail. Section 3 describes the research setting, datasets, and regression model specifications. Section 4 presents our findings, which can be summarized as follows. First, we find no evidence of horizontal or backward FDI spillovers with the WBES dataset. In contrast, the MS dataset produces significant positive backward FDI spillovers, indicating that dataset incompleteness does affect the estimations. Second, findings from the simulated incomplete datasets show that small sample size, strong presence of small firms, and measurement error of industry FDI all contribute to the unreliability of the estimated effects. Third, only by using horizontal and vertical FDI indicators from MS in our estimations with the simulated incomplete datasets, and weakening the effects of small sample size and strong presence of small firms, do we obtain similar results to those from the full population of firms. In combination, these findings indicate that researchers who use incomplete datasets to estimate FDI spillovers need to try to obtain information on the level of industry FDI among a country's firm population and carefully consider sample size and the extent of over- or underrepresentation of particular firm size classes. Section 5 summarizes and concludes.

2 | RESEARCH PROBLEM

2.1 | Introduction

WBES datasets are frequently used to estimate FDI spillovers in developing and emerging economies. Overall, evidence on spillovers with these datasets is very heterogeneous. Gorodnichenko et al. (2014) use WBES data for 17 transition economies and find positive backward FDI spillovers, but no evidence of horizontal spillovers. In contrast, Monastiriotis (2014), using data for 28 transition economies, focuses specifically on horizontal FDI spillovers and presents evidence that FDI firms generate significant negative productivity effects. Dunne and Masiyandima (2016) use data from sub-Saharan African countries and find that positive horizontal spillovers materialize in only a few of them. Farole and Winkler (2012) estimate FDI spillovers in 78 low- and middle-income countries and find that FDI firms generate negative horizontal spillovers; in a few of these countries the spillover effect turns positive among domestic firms with sufficient absorptive capacity. Finally, Waldkirch (2014) uses WBES data for 114 countries and finds no evidence of horizontal spillovers.[3]

The variability of findings from WBES datasets is in line with the heterogeneous nature of the general body of evidence on FDI spillovers. It is likely that this heterogeneity in findings from WBES datasets is caused by measurement error of the degree of FDI industry participation. Such measurement error is likely to affect most studies on FDI spillovers, as datasets usually omit parts of the underlying population of firms of a host economy (Eapen, 2013). As FDI industry participation is calculated with information from the firms that are included in these datasets, it will probably incorporate a measurement error. Given their small sample size and their definition of size categories, the WBES datasets are especially prone to be affected by this issue.

2.2 | Measurement error, small firms, and sample size

To understand the issues from estimating FDI spillovers with incomplete datasets such as the WBES, we need to consider their sampling procedure. WBES datasets are based on a cross-country uniform stratified sampling methodology (Enterprise Surveys, 2009). Sampling is performed by randomly selecting firms from previously separated, non-overlapping groups of elements in a country's firm population. Such stratification is preferred, as it provides unbiased estimates for the population of firms as a whole, as well as for the different subsets. It also ensures a weighted representation of the entire firm population. Compared to non-stratified random sampling, stratified sampling achieves lower standard errors and higher significance levels (Lohr, 2009).

Stratification is done by a main sector of activity, firm size, and geographical location. Type of ownership (domestic or foreign-owned) is not part of the stratification criteria. There is therefore no guarantee that the selected sample captures the industry distribution of foreign-owned firms in the population. Researchers use information from domestic and foreign-owned firms in the sample to measure horizontal FDI by calculating the share of FDI in industry employment or output. Therefore, it is likely that these indicators incorporate measurement error, resulting in biased estimates of horizontal and, by design, vertical FDI spillovers.

The strong presence of small firms in WBES datasets may also problematize the estimation of FDI spillovers. The economies covered by WBES are characterized by a large presence of (very) small firms. Therefore, the firm size stratification criterion leads to samples with a high ratio of small firms to medium and large firms. This increases the possibility that FDI industry measures contain errors. On the one hand, as small firms are less likely to be foreign-owned (Altomonte & Pennings, 2009), the strong presence of small firms in the dataset is likely to result in FDI industry shares that are too low, as the dataset would contain a low number of foreign-owned firms. On the other hand, supposing that the sample contains a representative number of FDI firms, their calculated level of industry participation may be too high. Due to the presence of a large number of small domestic firms with low levels of output and number of employees, the share of FDI firms in industry output or employment may be overestimated. Therefore, estimates of FDI spillovers may be affected by errors in the indicators of FDI industry participation caused by the strong presence of small firms in the sample.

Furthermore, even in the case that the measurement error itself is limited, a large presence of small firms in the sample may influence the estimated magnitude and sign of FDI spillovers. Several studies present evidence that small domestic firms are either subject to negative FDI spillovers or are less able to benefit from positive spillovers. Small firms are less likely to be able to compete with FDI firms, which can result in negative externalities due to a market-stealing effect (Aitken & Harrison, 1999). Small firms may also be less likely to benefit from positive spillovers (Zhang et al., 2010) as they are less able to absorb new technologies from FDI firms. Therefore, the strong presence of small firms (5–10 employees) in WBES datasets increases the possibility that the estimated spillover effects are insignificant or negative, in contrast to estimates from larger datasets that usually do not include firms with fewer than 20 (or even 50) employees.

Finally, it may be the case that the limited sample size of WBES amplifies the problems of measurement error and strong sample presence of small firms. The sample size of WBES is based on the estimated size of an economy's firm population, with the target of achieving a 7.5% precision level at the 90% confidence level for estimates of variables such as the logarithm of firm-level sales and of variables expressed as population proportions at the industry level (Enterprise Surveys, 2009). As WBES uses stratified sampling, this level of precision should be obtained for each industry stratum. Assuming the highest variance for proportion estimates, WBES aims to sample 120 firms per industry. For a large economy, nine main industries are distinguished, resulting in a total sample size of 1,080 firms. As the WBES relies on the voluntary participation by firms, item non-response is a major concern. Therefore, the sample size for large economies is usually increased by 25%, to 160 firms per industry.

However, the non-response rate for key variables such as number of employees, cost of labor, and especially the value of assets is considerably higher than 25%, resulting in a reduction in the effective sample size. Depending on the severity of the decrease in sample size, the margin of error of the estimated FDI spillover effect and the overall power of the regression estimation will be affected. Furthermore, the decrease in the number of observations is likely to increase the previously discussed measurement error in horizontal and vertical FDI. Also, if particular firm size classes are overrepresented in the sample that remains after removing observations with missing values, estimated FDI spillovers may be influenced by a change in the relative sample shares of small, medium, and large firms.

In summary, dataset suitability does not feature strongly in the FDI spillover literature as a possible reason for the heterogeneity of empirical findings. However, as most datasets used to estimate FDI spillovers are characterized by varying degrees of incompleteness, biases resulting from the use of such datasets may contribute to the variability of reported spillover effects. Given its characteristics, WBES constitutes a good case to examine the effects of using incomplete datasets to identify FDI spillovers. In particular, biases are likely to arise due to errors in the measurement of horizontal and vertical FDI, strong sample participation of small firms, and limited sample size.

3 | DATA AND MODEL SPECIFICATION

Indonesia provides a good setting to estimate FDI spillovers and examine the issue of incomplete datasets. Starting in the late 1970s, the country has undergone important economic reforms, gradually removing requirements and limitations on inward FDI (Blalock & Gertler, 2008). In recent years, Indonesia has persistently ranked among the top 15 FDI destination countries (UNCTAD, 2014). Several studies provide evidence of significant FDI spillovers during the 1990s. Sjöholm and Blomström, (1999) use cross-sectional firm-level data for 1991 from MS and identify positive horizontal FDI spillovers. These findings are corroborated by a firm-level panel data study by Takii (2005), using data from MS for the period 1990–1995. Blalock and Gertler (2008, 2009) use firm-level panel data from the same source for the period 1988–1996 and distinguish between horizontal and vertical (backward) FDI spillovers. Whereas they find clear evidence of positive FDI spillovers among Indonesian firms in input-supplying industries, they do not find evidence of significant horizontal spillovers.

3.1 | Data

We use the 2009 WBES dataset for Indonesia and the MS dataset for 2008–2009 by the Indonesian Statistics Office. The original WBES sample contains 1,444 observations from the nine most industrialized provinces in Indonesia. After removing firms in services and firms with missing values, the remaining number of observations is 1,164 firms, operating in seven 2-digit ISIC Rev.4 manufacturing industries. In comparison, the MS dataset is much more comprehensive in coverage. It contains over 20,000 observations in 2008 and 2009, with firms operating in 337 5-digit ISIC Rev.4 manufacturing industries. To conduct estimations at the same level of industry aggregation, we reclassify the firms in the MS dataset into the seven 2-digit manufacturing industries of WBES.

Horizontal FDI is calculated as the ratio of output in industry j produced by FDI firms over total industry output (Blalock & Gertler, 2008):

$$\text{Horizontal FDI}_j = \frac{\sum_{i \in j} \text{Foreign output}_i}{\sum_{i \in j} \text{Output}_i}$$

Following Javorcik (2004) and Blalock and Gertler (2008), we define backward FDI as the share of an industry's output that is sold to foreign buyers across all other industries. Therefore, backward FDI of industry j is constructed as a weighted sum of horizontal FDI of the other industries. The weights—labeled a_{jk}—are shares of industry j's output purchased by the other industries, which we take from the 2005 Indonesian input–output table from the OECD STAN database:

$$\text{Backward FDI}_j = \sum_k a_{jk} \text{Horizontal FDI}_k$$

Table 1 presents the levels of horizontal and vertical FDI by sector and their correlations across the WBES and MS samples. The Kolmogorov–Smirnov equality of distributions test shows that there is no significant difference between the datasets in their horizontal and vertical FDI distributions. Furthermore, indicators of both FDI measures are highly correlated across samples. Both samples indicate that the Chemicals industry has the highest level of horizontal FDI, followed by the umbrella category "Other Manufacturing." For both industries, WBES overestimates horizontal FDI, compared to MS. The ordering for the other industries is mixed. WBES produces higher levels of horizontal FDI for Plastics & Rubber; for the other industries WBES provides horizontal FDI indicators below those of MS. Differences are more uniform for vertical FDI. In both samples Textiles, Garments, and Chemicals industries have the highest levels of backward FDI, but the indicators are substantially

TABLE 1 Horizontal and backward FDI: WBES and MS samples

ISIC2 category	Industry	Dataset	Observations	Horizontal FDI	Vertical FDI
15	Food	WBES	392	0.076	0.019
		MS	5,507	0.309	0.079
17	Textiles	WBES	133	0.252	0.298
		MS	2,441	0.332	0.717
18	Garments	WBES	139	0.293	0.272
		MS	1,999	0.407	0.669
24	Chemicals	WBES	107	0.864	0.111
		MS	1,015	0.646	0.322
25	Plastics & Rubber	WBES	108	0.445	0.032
		MS	1,545	0.303	0.203
26	Non-metallic mineral products	WBES	144	0.164	0.009
		MS	1,595	0.384	0.038
3	Other manufacturing	WBES	141	0.814	0.038
		MS	7,865	0.537	0.059
Correlation (FDI_{WBES}; FDI_{MS})				0.86	0.986
Kolmogorov-Smirnov equality of distributions test (H_0: Equal distributions)				0.212	0.575

Note: Values are for 2009 for both samples.

lower in WBES. Although the ordering of the other industries is more varied, WBES consistently shows vertical FDI levels below MS. Therefore, although the distribution of the FDI measures is similar between the datasets, the differences in their levels indicate that the sample composition of WBES is giving too much weight to parts of the firm population with low foreign output share, which may be less likely to generate positive and significant spillovers.

3.2 | Model specification

To compare the estimated effects of horizontal and backward FDI between WBES and MS, we estimate regression models following two empirical specifications. The first specification adopts the regression model from Blalock and Gertler (2008), allowing us to compare the results of our two samples with their findings. The drawback of the WBES data is its cross-sectional nature, not allowing us to control for time-invariant firm-level fixed effects. This may pose an endogeneity problem, as FDI spillovers are biased upward when FDI firms gravitate toward industries with high-productivity firms (Aitken & Harrison, 1999; Jordaan, 2011). However, as we estimate FDI spillovers with WBES and with the 2009 observations from MS, both estimations are subject to the same potential bias, allowing us to compare the estimated effects between the two samples.

Following Blalock and Gertler (2008), we specify a flexible trans-log production function, relating firm-level output to labor, capital, raw materials, energy expenses, their squared terms and interactions, industry dummies, industry market concentration, and horizontal and backward FDI. We estimate the following model on the full set of firms and on a subsample of domestic firms for firm *i* in industry *j*:

$$
\begin{aligned}
\ln Y_{ij} = {} & \beta_0 + \beta_1 \text{Horizontal FDI}_{ij} + \beta_2 \text{Backward FDI}_{ij} + \beta_3 \ln K_{ij} + \beta_4 \ln L_{ij} + \beta_5 \ln M_{ij} \\
& + \beta_6 \ln E_{ij} + \beta_7 \ln^2 K_{ij} + \beta_8 \ln^2 L_{ij} + \beta_9 \ln^2 M_{ij} + \beta_{10} \ln^2 E_{ij} + \beta_{11} \ln K_{ij} \ln L_{ij} \\
& + \beta_{12} \ln K_{ij} \ln M_{ij} + \beta_{13} \ln K_{ij} \ln E_{ij} + \beta_{14} \ln L_{ij} \ln M_{ij} + \beta_{15} \ln L_{ij} \ln E_{ij} \\
& + \beta_{16} \ln M_{ij} \ln E_{ij} + \text{Herfindahl}_j + \text{Foreign}_i + \text{Industry}_j + \varepsilon_{ij}
\end{aligned} \tag{1}
$$

where $\ln Y$ is the natural logarithm of the total value of sales and $\ln L$, $\ln K$, $\ln M$, and $\ln E$ are the natural logarithms of the total number of permanent employees, book value of total assets, total value of raw materials, and total expenses on electricity and fuels, respectively. The Herfindahl index captures market competition and is measured as the sum of the squared market shares of each firm in its industry. Foreign is a dummy variable equal to one when at least 20% of a firm's equity is foreign-owned; Industry captures 2-digit industry fixed effects.

The second regression model takes advantage of the panel data nature of the MS sample for 2008–2009. To account for firm-specific time-invariant characteristics we control for firm fixed effects (a_i). We also control for year $\left(\vartheta_t\right)$, and region-year $\left(r_r * \vartheta_t\right)$ effects. Thus, the model for firm i in industry j in year t is:

$$
TFP_{ijt} = \gamma_0 + \gamma_1 \text{Horizontal FDI}_{jt} + \gamma_2 \text{Backward FDI}_{jt} + \text{Herfindahlindex}_{jt} + a_{ij} + \vartheta_t + r_r * \vartheta_t + \mu_{ijt} \tag{2}
$$

To estimate model (2) we first estimate firm-level TFP. One approach is to add firm-level inputs to regression model (2). The drawback of this approach is that input decisions are not treated as endogenous to the production process (Grilliches & Mairesse, 1995). Specifically, productivity shocks observed by the firm (but not by the econometrician) affect a firm's input choice, thereby biasing OLS coefficient estimates. Starting with Olley and Pakes (1996) and Levinsohn and Petrin (2003), the productivity literature has developed a two-step semi-parametric estimation method where a firm's level of investment or raw materials is used as a proxy for uncaptured productivity shocks. In the first step, they produce estimates for the shock; in the second step, input coefficients and the TFP residual are estimated. Ackerberg, Caves, and Frazer (2015) build upon these methods and correct for collinearity issues related to the timing of input decisions. While we cannot use either approach for estimations with the cross-sectional WBES data, we show results from both fixed effects and the ACF method for the estimations with MS panel data. However, TFP estimates from the latter are preferred to the fixed effects estimates, because they alleviate issues of input endogeneity and timing concerns. Therefore, we follow other studies in the FDI spillovers literature (e.g., Javorcik & Spatareanu, 2011; Lenaerts & Merlevede, 2015) and use the ACF method to estimate TFP with the full MS panel data and in our simulations. TFP is estimated separately for each industry as the second stage residual, using an inverse polynomial function of capital and raw materials as proxy for unobserved productivity shocks in the first stage. Subsequently, we regress estimated TFP on horizontal and vertical FDI, controlling for market competition and firm, year, and region-year fixed effects.

3.3 | Simulations

To assess whether and how FDI spillovers estimates are affected by the use of an incomplete dataset, we conduct a series of simulations. Using the WBES sampling criteria, we draw 1,000 random samples from MS for each simulation that we carry out, treating the MS dataset as the true population of firms. If the sampling methodology of WBES achieves its objective of being representative of the population of firms and estimating parameters with a 7.5% precision level at the 90% confidence level, the results from the simulations should converge to the results from the full MS sample.

Treating the MS sample as the true population of firms is only an approximation, as, similar to other samples based on manufacturing surveys, it does not contain the smallest types of firms. In the case of MS, firms with fewer than 20 employees are not included. Thus, MS is also an incomplete dataset. However, as Eapen (2013) also argues, given that a survey like the MS contains many more firms, it is less incomplete than the WBES sample. Therefore, although there may be a bias in the estimated effects with the MS sample, we can still assess whether the use of incomplete datasets biases estimated spillovers, by comparing the results obtained with a potentially strongly incomplete dataset (WBES) with the results from a weakly incomplete dataset (MS).

For stratification purposes, we redefine the firm-size classes used in the stratified sampling applied to MS. We define firms with fewer than 30 employees as small, firms with 30–100 employees as medium-sized, and firms with more than 100 employees as large. The main difference with WBES is that the category of small firms in MS contains slightly larger firms, as small firms in WBES have 5–20 employees. As small firms are less likely to be foreign-owned, our definition of small firms that incorporates slightly larger firms may, if anything, lower the measurement error of industry FDI, resulting in estimates of FDI spillovers closer to those obtained with the full MS sample.

4 | EMPIRICAL FINDINGS

4.1 | FDI spillovers: WBES and MS samples

Table 2 presents the findings from our estimations of regression models (1) and (2). Columns (1) and (2) contain the estimates of the flexible trans-log production function for all firms and for domestic firms with the WBES data. Both estimations show no significant effect of either horizontal or backward FDI. In contrast, and similar to the findings presented by Blalock and Gertler (2008, 2009), the results from the 2009 cross-sectional MS sample—columns (3) and (4)—show significant positive backward FDI spillovers. Horizontal FDI does not create significant spillovers, while the sign of the estimated effect differs from the results with WBES. The strong differences between the findings from the two samples suggest that the results from WBES may be affected by the incompleteness of the dataset.

Columns (5)–(8) report the results from the MS panel dataset. Columns (5) and (6) contain the results from estimating model (2) with firm-level inputs, market competition, year, industry-year, region-year, and firm-level fixed effects. The findings are similar to those from the cross-sectional estimations, with backward FDI carrying a significant and positive coefficient. The decrease in magnitude of the estimated backward coefficient reflects that we now control for firm-level fixed effects. Columns (7) and (8) contain the findings from our preferred model, with TFP as a dependent variable. After controlling for time-invariant characteristics and input endogeneity, we still find insignificant horizontal FDI spillovers and significant and positive backward FDI spillovers.

4.2 | FDI spillovers: Simulations

The results in the previous section show that whereas we obtain evidence of positive backward FDI spillovers with the MS dataset, the estimations with the WBES dataset do not produce significant FDI

TABLE 2 Horizontal and backward FDI spillovers: WBES and MS estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	WBES	**WBES**	**MS**	**MS**	**MS**	**MS**	**MS**	**MS**
Year	**2009**	**2009**	**2009**	**2009**	**2008–2009**	**2008–2009**	**2008–2009**	**2008–2009**
Firms	All	Domestic	All	Domestic	All	Domestic	All	Domestic
Dependent variable	ln$Y$	ln$Y$	ln$Y$	ln$Y$	ln$Y$	ln$Y$	TFP (ACF)	TFP (ACF)
Horizontal FDI	–0.288 (0.41)	–0.236 (0.428)	0.126 (0.11)	0.106 (0.112)	1.379 (1.233)	1.438 (1.279)	1.384 (1.938)	1.709 (2.054)
Backward FDI	4.587 (8.45)	4.155 (9.06)	3.212*** (0.37)	3.311*** (0.375)	0.272** (0.107)	0.246** (0.106)	0.969** (0.266)	1.062** (0.319)
ln$K$	0.05 (0.275)	0.0162 (0.31)	0.078*** (0.021)	0.075*** (0.023)	0.116** (0.04)	0.122** (0.04)		
ln$L$	0.565 (0.58)	0.444 (0.63)	0.683*** (0.055)	0.666*** (0.06)	0.942*** (0.04)	1.029*** (0.04)		
ln$M$	–1.132*** (0.22)	–1.197*** (0.234)	0.116*** (0.035)	0.051 (0.038)	0.192** (0.08)	0.128 (0.08)		
ln$E$	1.359*** (0.33)	1.522*** (0.38)	0.275*** (0.024)	0.305*** (0.027)	0.302*** (0.035)	0.319*** (0.02)		
Foreign	0.152 (0.116)		0.130*** (0.018)		0.032 (0.056)		0.08 (0.136)	
Herfindahl			–0.282** (0.128)	–0.390*** (0.136)	0.658 (0.38)	0.635 (0.378)	–1.00 (0.92)	–0.627 (1.03)
Constant	11.06*** (2.60)	10.77*** (2.564)	3.592*** (0.228)	3.957*** (0.244)	2.970*** (0.643)	3.016*** (0.697)	5.258*** (0.762)	5.058*** (0.793)
Nobs	699	637	12,541	11,661	25,246	23,528	26,333	24,496
adj. R^2	0.924	0.910	0.966	0.963	0.807	0.818	0.010	0.011
Nr of panels					15,031	15,583	15,583	14,532

Notes: Estimations (1)–(4) also contain squared and interaction terms of the input variables and industry effects. Estimations (5)–(8) also control for firm, year, industry-year, and region-year effects. Robust standard errors (clustered at the industry level) reported in parentheses. TFP (ACF) uses TFP indicator estimated following Ackerberg et al. (2015). The Herfindahl index was dropped from estimations (1) and (2) due to multicollinearity.

**$p < 0.05$;

***$p < 0.01$.

spillovers. There may be several reasons for this, which we examine sequentially with sets of simulations based on the MS 2008-2009 panel dataset.

First, the results could be specific to the particular WBES sample. The sample constitutes one draw from the population of firms, and it may be that this sample does not produce significant backward spillovers. To test the validity of the WBES sampling methodology, we estimate model (2) on 1,000 stratified random samples drawn from MS, using the WBES sampling criteria.

Second, small sample size may affect the estimation power and the margin of error of the estimated spillovers with WBES. To examine the severity of this issue, in a second round of simulations we estimate the model on 1,000 random samples with twice the number of firms in each stratum, while keeping the stratification criteria the same.

Next, we address the issue of measurement error. We add a "foreign output share" stratification criterion to ensure accurate measures of foreign output shares in each industry. For this, we measure the share of foreign output in each industry in the MS dataset, and estimate how many foreign firms need to be sampled from each industry-region-size "cell" with WBES sampling to reach the same industry foreign output share in each simulation sample. This ensures that foreign firms are sampled from each cell where they are present in the population. As foreign firms tend to be larger, adding this criterion indirectly increases the number of large firms in the sample.

However, adding a foreign output share criterion does not completely solve measurement error of industry FDI. Due to the small size of the drawn samples, cells with small but non-zero foreign output shares in the population are rounded down to having zero foreign firms in the simulation samples. Therefore, while weakening selection bias by increasing the share of foreign firms in each industry, random samples drawn with this strategy still suffer from rounding errors that prevent a one-to-one reproduction of "population" FDI measures. To see the effect of introducing fully accurate FDI measures, we also run simulations with samples drawn according to the strategies above, but transplanting horizontal and backward FDI measures directly from the MS dataset.

Finally, we investigate the effect of the strong presence of small firms in the WBES sample. Comparing the two datasets, we find that the share of small firms in the WBES sample is significantly higher than in the MS sample. To assess whether the presence of small firms influences estimated spillovers, we remove firm size as stratification criterion. We keep the other sampling criteria and run two sets of simulations, one without and one with the additional foreign output share sampling criterion. By decreasing the number of small firms and increasing the number of medium-sized and large firms, the average share of each size category in the simulation samples is closer to their share in the population.[4]

Table 3 shows the results from the simulated sample draws. We report the mean coefficient estimate of horizontal and backward FDI from each set of 1,000 estimations. We also report the mean standard error and *t*-statistic of the hypothesis that the spillover coefficient is different from 0. Subsequently, we test for bias in the estimated coefficients by testing the hypothesis that the coefficients from the simulations are significantly different from the estimated "population" coefficients reported in column 8 in Table 2. Finally, for each set of simulations we report the percentage of estimated coefficients not significantly different from the coefficients obtained with the full MS sample.[5]

Column (1) presents the results from estimating model (2) on 1,000 randomly drawn samples following the WBES sampling methodology. As not all firms feature in both 2008 and 2009, the number of observations for each estimation falls below 2,238 (2 times 1,164). In addition, similar to WBES, the number of panels decreases further due to missing values. The results show that on average the estimated horizontal and backward FDI coefficients are smaller than population coefficients. Moreover, neither effect is significant, and the mean absolute values of the *t*-statistics are very low.

TABLE 3 Results from simulations with varying sample designs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	WBES sampling	**WBES sampling × 2**	**Foreign output share criterion**	**WBES sampling without firm-size criterion**	**Foreign output share, no size criterion, ×2**	**WBES sampling**	**WBES sampling × 2**	**Foreign output share criterion**	**WBES sampling without firm-size criterion**	**Foreign output share, no size criterion, ×2**
	FDI variables measured from random samples					**FDI variables taken from MS sample**				
Horizontal FDI										
Mean β estimate	–0.042	0.006	0.211	0.039	–0.056	1.674	1.823	1.569	1.139	0.888
Mean s.e.	0.597	0.580	0.627	0.544	0.645	2.887	2.729	3.077	2.587	2.353
Mean *t*-stat	–0.172	0.047	0.447	0.185	–0.274	0.739	0.777	0.612	0.560	0.532
Different from population β	YES (0.101)	NO (0.113)	NO (0.152)	YES (0.095)	NO (0.116)	NO (0.501)	NO (0.567)	NO (0.510)	NO (0.474)	NO (0.522)
% similar to population β	23.5	27.1	33.3	22.7	26.8	87.1	93.8	89.8	86.2	92.2
Backward FDI										
Mean β estimate	0.170	0.011	0.280	0.529	0.543	0.907	0.841	0.943	1.188	1.191
Mean s.e.	1.219	0.779	0.671	1.279	0.670	0.893	0.663	0.984	0.881	0.641
Mean *t*-stat	0.262	0.142	0.579	0.633	1.233	1.226	1.537	1.194	1.663	2.219
Different from population β	NO (0.285)	NO (0.257)	NO (0.258)	NO (0.351)	NO (0.326)	NO (0.436)	NO (0.474)	NO (0.464)	NO (0.437)	NO (0.487)
% similar to population β	58.6	54.7	52	67	67.3	78.8	86.1	83.8	81	86.7

(Continues)

TABLE 3 (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	WBES sampling	**WBES sampling × 2**	**Foreign output share criterion**	**WBES sampling without firm-size criterion**	**Foreign output share, no size criterion, ×2**	**WBES sampling**	**WBES sampling × 2**	**Foreign output share criterion**	**WBES sampling without firm-size criterion**	**Foreign output share, no size criterion, ×2**
	FDI variables measured from random samples					**FDI variables taken from MS sample**				
Mean nr. obs.	1,345.3	2,705.7	1,272.8	1,358.2	2,572.1	1,354.3	2,707.2	1,271.9	1,357.7	2,573.7
Mean nr. Panels	760.8	1,527.7	718.7	766.5	1,453.3	764.9	1,528.7	718.5	766	1,453.5
Mean overall adj. R^2	0.128	0.127	0.152	0.107	0.119	0.130	0.122	0.130	0.107	0.109

Notes: Values in parentheses are mean p-values from 1,000 tests whether the estimated coefficient in each drawn sample differs from the population estimate. WBES sampling: samples drawn according to WBES sampling criteria. WBES sampling × 2: WBES sampling + double sample size. Foreign output share: WBES sampling + representative foreign output share in each industry. No size criterion: firm-size stratification criterion removed.

Therefore, WBES sampling, in combination with small sample size, yields consistently biased results, as indicated especially by the insignificance of the estimated backward FDI effect. Moreover, with an average *p*-value of 0.1, the estimated horizontal FDI coefficients are significantly different from the population coefficient, further indicating the presence of bias. The estimated horizontal FDI coefficient does not differ significantly from the population coefficient in only 24% of the estimations; for backward FDI, this is close to 60%.

Column (2) shows the results from samples twice as large as the original WBES sample, to assess whether small sample size is the primary cause of the differences in the estimated effects. The findings suggest that this is not the case. Horizontal FDI estimates do not improve, and backward FDI estimates perform worse: the mean horizontal FDI estimate now carries the same sign as the population estimate and remains insignificant, while the backward FDI estimate is on average less significant. The percentage of biased horizontal FDI estimates is only slightly lower than in the first round of simulations. In the case of backward FDI, this share has increased. Therefore, simply increasing sample size does not alleviate the bias.

Column (3) shows the results from adding a stratification criterion to the WBES sampling methodology, requiring an accurate FDI output share for each stratum. On average, the estimated coefficients approach population estimates in magnitude and sign, but they remain insignificant. The improvement of the findings indicates that measurement error does bias WBES estimates. However, it is not the only source of bias, as the findings still differ from the population estimates. In terms of the mean *t*-statistics, there is a clear improvement compared to the previous columns. Finally, the share of biased coefficients decreases for horizontal FDI but not for backward FDI.

The last factor that we consider is the strong presence of small firms. To examine this, we remove firm size as a stratification criterion. The findings in column (4) show that dropping the size criterion improves the results. The mean backward FDI coefficient increases from 0.17 with the original WBES sample to 0.58, and its mean *t*-statistic also increases. However, the estimated coefficient remains on average insignificant. Also, removing the size criterion increases the share of non-biased backward FDI estimates, but the share of non-biased horizontal FDI estimates decreases.

So far, the analysis confirms our expectations that the WBES sampling design contributes to biased and unreliable FDI spillovers estimates. Moreover, we find that while horizontal FDI spillovers are affected mostly by a measurement error of industry FDI, this effect is less pronounced for backward FDI. Instead, for this type of FDI, the overrepresentation of small firms is more important. This could be because small firms are less able to absorb new technologies from foreign-owned client firms, but also because they are less likely to supply FDI firms, excluding them from potential inter-industry spillovers.

As an additional check, we combine all three modifications of columns (2)–(4). We run simulations on a stratified sample with foreign output share as additional stratification criterion, without the size stratum, and with double sample size. The results are shown in column (5). On average, the estimates for backward FDI have improved further, with an increase in significance (mean *t*-statistic = 1.233) and closer in magnitude to the population estimate. The findings for horizontal FDI are less clear; on average the estimated coefficients remain insignificant, and the share of unbiased estimates has not improved.

The second panel of findings in Table 3 shows the results when we exclude measurement error in industry FDI as a source of bias, by taking measures of industry horizontal and backward FDI participation directly from the population, that is, the MS sample. Using these indicators improves the results substantially. We find that the mean horizontal FDI estimate is larger and closer in size to the population coefficient. Its estimated effect remains insignificant, in line with the MS results. The estimates from our preferred specification—double sample size, foreign output share stratification, and no size stratification—as reported in column (10), outperform all other specifications in terms of *t*-statistics and share of unbiased estimates. Horizontal FDI estimates are similar to the population coefficient in more than 80% of the estimations.

Using FDI variables from the MS dataset also improves the reliability of backward FDI spillover estimates substantially. On average the estimated coefficients in columns (6)–(10) are much closer to the population coefficient. Our preferred specification in column (10) produces a statistically significant average coefficient with a *t*-statistic of 2.219. Moreover, the share of unbiased estimates is much higher in these estimations; on average, around 80% of the simulation sample estimates do not differ significantly from the population coefficient. Thus, by removing measurement error, correcting for the strong presence of small firms and increasing the sample size to improve estimation power, we obtain estimated FDI spillovers that approximate "population" coefficients obtained with the MS dataset.

These findings clearly indicate that the estimation of FDI spillovers with incomplete datasets requires careful consideration, and also point to some possible solutions to increase the accuracy of the estimations. In particular, industry FDI needs to be based on information from the underlying firm population, rather than calculated with information from incomplete datasets. Therefore, given a sufficiently large sample and accurate representation of firm-size classes, a possible way to keep using incomplete datasets to estimate FDI spillovers would be to obtain information on the degree of industry FDI participation in the underlying population of firms from national statistics offices.[6] However, depending on the severity of incompleteness, it is also necessary to assess to what extent sample size affects estimation power and whether firm-size class sample composition may affect estimated FDI spillovers.

5 | SUMMARY AND CONCLUSIONS

Despite popular belief that domestic firms in host economies benefit from FDI firms through positive productivity spillovers, the evidence on these externalities is mixed and inconclusive. Although the FDI spillovers literature discusses several reasons for the heterogeneous nature of the evidence, the question whether the use of incomplete datasets may affect estimated FDI spillovers has received limited attention. Incomplete datasets such as the WBES are commonly used to estimate FDI spillovers, as they contain the necessary firm-level information on inputs, output, and type of ownership. However, as their sampling methodology does not require an accurate representation of FDI industry participation, it is likely that indicators of horizontal and vertical FDI contain measurement errors. These measurement errors are reinforced in the case of strong sample presence of small firms and limited sample size. Furthermore, the strong presence of (very) small firms reduces the likelihood of positive spillovers. Lastly, the limited sample size increases the margin of error and lowers the overall power of the estimation to identify any significant spillovers.

Using Indonesia as a case study, we find no evidence of horizontal or vertical FDI spillovers with the WBES sample. In contrast, using the much larger MS sample produces evidence of significant and positive vertical FDI spillovers, suggesting that using incomplete datasets such as the WBES biases estimated FDI spillovers. To examine this, we conduct sets of estimations on simulated incomplete datasets, created by applying the sampling methodology of WBES to draw random samples from the MS dataset. The findings from these sets of estimations show that small sample size, strong sample presence of small firms, and measurement error in industry FDI participation all contribute to inaccurate estimates of horizontal and vertical FDI spillovers. When we weaken the effects of these factors by sequentially relaxing the WBES sampling criteria, we obtain estimates of FDI spillovers that are closer to those identified with the MS sample. However, the estimated effects do persist to differ. Only when we use indicators of horizontal and vertical FDI calculated directly with the MS sample, increase the sample size, and clear the samples from the strong presence of small firms, do we obtain results similar to those obtained for the underlying firm population.

In conclusion, our findings provide clear evidence that using incomplete datasets biases estimated FDI spillovers. Therefore, they indicate that the quality and completeness of the datasets used in FDI spillover studies constitute additional possible reasons for the considerable degree of inconclusiveness that characterizes the body of empirical evidence. Researchers who use incomplete datasets to estimate FDI spillovers should assess the degree of incompleteness of their datasets, examine how this may affect their findings and, if addressing the issue is not feasible with their data, at least discuss its possible effects when presenting their findings. Transplanting accurate indicators of FDI industry participation into a sufficiently large and representative incomplete dataset is likely to lower the bias caused by sampling imperfections and produce more reliable estimates of FDI spillovers.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the World Bank Enterprise Surveys and the Indonesian Statistics Office Annual Manufacturing Survey 2009. Restrictions apply to the availability of these data, which were used under license for this study. Enterprise Survey data are available upon registration at http://www.enterprisesurveys.org.

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ENDNOTES

[1] The degree of representativeness is further affected by whether researchers use several vintages of the database and by the type of license, affecting the coverage of smaller firms (Kalemli-Ozcan et al., 2015).

[2] To the best of our knowledge, our paper is the first to examine the effects of using incomplete datasets for FDI spillovers estimations in this way. Jefferson and Ouyang (2014) discuss the variability in findings from studies on FDI spillovers in China and argue that the use of various datasets that differ in their firm population coverage provides an explanation for this variability.

[3] For studies that use WBES data to estimate FDI spillovers in individual countries, see, for example, Bwalya (2006), Brambilla et al. (2009), Castillo et al. (2014), Sokty and Ung (2014), and Konara and Wei (2016).

[4] After removing firm size and introducing foreign output share as criteria, average firm size shares in the simulated samples are 32.4% small firms (MS sample 35%, original WBES sampling 47.3%), 38.2% medium-sized firms (MS 38.3%, original WBES sampling 29.7%) and 29.4% large firms (MS 26.5%, original WBES sampling 23.1%).

[5] For space considerations, we report the findings from samples containing only domestic firms. Findings for samples containing both domestic and foreign firms are similar to those presented in Table 3 and are available upon request.

[6] Eapen (2013) addresses both measurement error and selection bias of certain class sizes by instrumenting FDI with US sector TFP growth and R&D intensity and using the inverse of firm sales as sampling probability weights. We tried several variations of this estimation on the original WBES sample, instrumenting horizontal FDI with US sector TFP growth and R&D intensity, using the fitted values of the instrumented horizontal FDI to build backward FDI, and using the inverse of the firm's number of employees as weights. However, although the coefficient and ***t***-statistic for backward FDI did increase, the estimated coefficient remained insignificant. Therefore, using weighted IV does not fully alleviate the issues of incompleteness and small sample size of the WBES dataset.

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