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Abstract

Negative foreign direct investment (divestment) between countries has received little attention in international macroeconomics. This is the first country-level study to investigate whether conventional drivers of bilateral foreign direct investment (FDI) have a reverse, but symmetric, impact on foreign direct divestment (FDD). Using bilateral negative and positive FDI data between 126 countries or territories, from 2005 to 2018, we find that conventional gravity variables that have statistically significant effects on FDI, such as host and source country GDP, distance, and source-country remoteness, have similar-signed effects on FDD, rather than opposite-signed effects. Formal testing of whether coefficients on the determinants of the absolute value of divestment are equal but opposite signed to those for investment rejects this hypothesis. The view that what deters FDI encourages FDD, and vice versa, is not supported by our empirical findings.

Keywords Foreign direct divestment, negative FDI, gravity modelling, Poisson pseudo-maximum likelihood

JEL Classification F21, F23, C51

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1 Introduction

To date, the literature on determinants of country-level foreign direct investment (FDI) has focused on positive investment. Foreign direct *divestment* (FDD) in the form of *negative* FDI flows, i.e., disinvestment, has received limited attention but only at the firm (micro) level. Arguments for ignoring FDD at the country-level are either that such flows are negligible in size at the macroeconomic level or that the determinants are the same as for FDI, just with opposite, but otherwise symmetric, effects. In the latter case, FDD can be included with positive FDI and treated as negative FDI flows in the analysis of foreign direct investment at the country level.

However, the OECD's FDI database,[1] which reports positive and negative foreign direct investment flows between OECD countries and the rest of the world, shows that total FDD flows increased from around 567 billion US dollars in 2013 to 854 billion US dollars in 2017, roughly equal to a quarter of annual FDI.[2] In addition, a database of 62,000 affiliates worldwide shows that 34% of all assets of foreign-owned firms in 2007 had been divested by 2014 (Borga et al. 2020). A global survey by EY (2019) also finds that 87% of firms planned to divest within the next two years, and 75% of them within the next 12 months. As well as an increase in divestment, there is a decrease in new investment. Xia and Liu (2021), for example, show that Chinese investors seem to be less willing to start new investments in Germany during the pandemic. In its Investment Trends Monitor, the United Nations Conference on Trade and Development (UNCTAD) (2021) reports a weak outlook for global FDI, reflected in a 42% decline from $1.5 trillion in 2019 to an estimated $859 billion in 2020, the latter being more than 30% below the trough after the Global Financial Crisis. Moreover, FDI flows to Europe turned negative to –4 billion US dollars, with several countries showing large negative flows.

[1] https://stats.oecd.org/Index.aspx?DataSetCode=FDI_FLOW_CTRY

[2] For an analysis of the concentration of FDI across various country groupings, see Bickenbach et al. (2018).

Therefore, discarding negative FDI flows from empirical analyses is inadvisable. On the other hand, pooling observations on negative and positive FDI flows in the same regression model may lead to misleading results if the determinants of positive and negative FDI flows have asymmetric effects.

Existing micro-level empirical studies of foreign divestment generally focus on the probability of complete exit of subsidiaries of multinational enterprises from the host country (e.g., Norbäck et al. 2015). These studies emphasise the role of firm-level and industry-specific factors, including size, age, host-country experience, ownership, entry modes, and performance; country-level macroeconomic factors are either omitted or included as controls but not analysed in much detail (e.g., Engel et al. 2013; Song and Lee 2017). Of the micro-level studies that consider macroeconomic variables, Belderbos (2003), for example, finds that host-country market growth does not have a statistically significant impact on Japanese affiliates' probability of exit, a result that conflicts with the findings of Berry (2013) for US subsidiaries' divestment decisions and of Chung et al. (2013) for Korean multinational enterprise foreign affiliates. Instead, Berry (2013) finds significant influences of labour costs, political stability, and GDP growth of the host country. Chung et al. (2013) also show that both home and host countries' GDP growth and GDP per capita have a negative effect on the probability of exit.

Firm-level and aggregate macro-level studies complement each other but have generally different goals. Micro-level studies analyse what motivates specific firms in their FDI decisions, whereas macro-level research examines the effects of country-level factors on aggregate flows and how government policies can influence FDI flows in general. That is not to say that individual firms do not care about country-level factors; however, some macro factors may matter to some firms and not to others. Country-level studies try to pin down what factors have the most effect on aggregate FDI flows overall, and hence cannot account for firm- or industry-specific characteristics. The large literature on macro and micro studies of FDI bear out the importance of each category. Our study adopts a macro-level approach but we consider both negative FDI and positive FDI at the bilateral, country level. As is common for studies of positive bilateral FDI, we use data on net flows of funds of all firms from source country A to host country B, and vice versa. However, we consider negative net flows (FDD) as well as positive net flows (FDI). The focus on net flows in our empirical analysis is a consequence of the lack of available data on bilateral gross flows but, as discussed in the next section, this still allows a meaningful test of the null hypothesis of symmetric coefficients for FDI and FDD.

Theories of (positive) FDI, such as the knowledge-capital model (Markusen, 2002) and the structural gravity model (Anderson et al. 2019), provide a basis for empirical specifications to study the determinants of FDI at the bilateral, country level. For a country to attract foreign investment and guide its economic policies, it is important to know what factors significantly influence foreign direct investment flows into a country. Equally important is to know what keeps FDI in the country, i.e., what macroeconomic factors lessen the outflow of FDI. Theories of FDD, however, are much less developed.

Boddewyn (1983) proposes a micro-level theory of FDD at the firm level that is the reverse of FDI theory, whereby drivers of FDI should have a symmetric impact on FDD. Furthermore, Blonigen and Piger (2014) survey the empirical macro-level FDI literature and note that empirical studies on bilateral FDI show little agreement on the variables to include in regressions. They use Bayesian model-averaging methods that allow them to select from a large set of potential candidate variables to choose the most likely determinants of FDI.[3] They find that traditional gravity variables, cultural distance factors, relative labour endowments and trade agreements are the most relevant. On the other hand, they uncover low inclusion probabilities for multilateral trade openness, most host-country business costs, host-country infrastructure

[3] See also Behera and Mishra (2020) for an application of model-averaging techniques to determine inclusion probabilities for a large set of potential determinants of bilateral FDI that originates in emerging economies, which is not our focus. Their findings are similar to Blonigen and Piger's (2014) but they show that FDI determinants differ based on the destination of FDI to developed, emerging or other developing host countries.

(including credit markets) and host-country institutions. An emphasis on gravity variables is consistent with the widespread use of a gravity approach in macro-level FDI studies (Bergstrand and Egger 2007; Kleinert and Toubal 2010; Fally 2015; Anderson et al. 2019; Mistura and Roulet 2019; Nguyen 2019; Nguyen et al. 2020; Bruno et al. 2021). This motivates us to estimate an empirical model for aggregate-level FDD containing gravity-type drivers of FDI and examine whether these are also determinants of (the absolute value of) FDD, but with the opposite signs. Given that FDD flows are of sizeable magnitudes, this paper tries to answer the question of whether or not the effects of the determinants of FDI and FDD at the country level are symmetric.

To the best of our knowledge, ours is the first study to analyse the determinants of bilateral FDD at the macroeconomic level. Moreover, we test empirically the symmetry between FDI and FDD. We employ a basic gravity-type model for foreign direct investment flows for this purpose, using bilateral data between 126 countries or territories over the period 2005 to 2018.

The remainder of the article is organised as follows. Section 2 discusses the empirical model and data. Section 3 presents the methodology and regression results. Section 4 concludes.

2 Empirical model and data

Bilateral FDI flows, whether positive or negative, are reported on a net basis in official databases. Studies on FDI often ignore negative FDI flows; however, these negative values are instances of divestment, or to be more precise net divestment, at the country level. In that sense, net divestment is the mirror image of the positive net FDI flows examined in numerous bilateral country-level studies. In our empirical analysis, we estimate separate models for positive bilateral directional country-level net flows of foreign direct investment and for negative bilateral directional country-level net flows.

To clarify, let $GFDI^{+}_{sh}$ represent the gross positive flows of FDI from source country *s* to host country *h*, and $\left|GFDI^{-}_{sh}\right|$ the absolute value of gross negative flows from the source country to the host country (divestment). In any given year, some firms located in source country A add new investment in host country B $(GFDI^{+}_{AB})$, while other firms located in country A pull out of investments that they made in country B $(GFDI^{-}_{AB})$. Net FDI from the source country to the host country, $NFDI_{sh}$, is defined as:

$$NFDI_{sh} \equiv GFDI^{+}_{sh} - \left|GFDI^{-}_{sh}\right| \tag{1}$$

It is the net of these two gross flows ($NFDI_{AB}$) that our data capture when we refer to net flows of foreign direct investment from firms in (source) country A to (host) country B. There may be corresponding flows from firms located in (source) country B that invest in (host) country A ($GFDI^{+}_{BA}$ and $GFDI^{-}_{BA}$), and again we consider the net value of these flows ($NFDI_{BA}$). In other words, between countries A and B there are four gross flows and two net flows.[4] We consider one-way net flows for pairs of countries: net flows from source A to host B ($NFDI_{AB}$) and, separately, net flows from source B to host A ($NFDI_{BA}$).

To examine whether the determinants of positive FDI have a reverse, but symmetric, effect on (the absolute value of) FDD, we would ideally estimate separate models for $GFDI^{+}_{sh}$ and $\left|GFDI^{-}_{sh}\right|$ and test the relevant parameter restrictions. For example, the following models relate $GFDI^{+}_{sh}$ and $\left|GFDI^{-}_{sh}\right|$ to a common set of explanatory variables, represented here for simplicity by *X*, but with potentially different coefficients:

$$GFDI^{+}_{sh} = \alpha_1 + \beta_1 X + u_{sh} \tag{2}$$

$$\left|GFDI^{-}_{sh}\right| = \alpha_2 + \beta_2 X + v_{sh} \tag{3}$$

[4] We are grateful to an anonymous referee for encouraging us to spell out the implications of testing models estimated using net flows for the underlying positive and negative gross investment flows.

where u_{sh} and v_{sh} are random error terms. To examine whether the determinants of positive FDI have a reverse, but symmetric, effect on (the absolute value of) FDD, we could, in principle, estimate models similar to equations (2) and (3) and test the null hypothesis H_0: $\beta_1 = -\beta_2$. However, data on the bilateral gross flows required to estimate equations (2) and (3) are not available.

Instead, we use available data on bilateral net flows. Substituting equations (2) and (3) in equation (1):

$$NFDI_{sh} = (\alpha_1 - \alpha_2) + (\beta_1 - \beta_2)X + (u_{sh} - v_{sh})$$

In addition, we distinguish between cases where bilateral net flows are positive, $NFDI_{sh}^{+}$, and cases where these net flows are negative, $NFDI_{sh}^{-}$. We model these separately with potentially different coefficients:

$$NFDI_{sh}^{+} = (\alpha_1 - \alpha_2) + (\beta_1 - \beta_2)X + (u_{sh} - v_{sh}) = \delta_0 + \delta_1 X + \omega_{sh} \quad (4)$$

$$\left| NFDI_{sh}^{-} \right| = -(\alpha_1' - \alpha_2') - (\beta_1' - \beta_2')X - (u_{sh}' - v_{sh}') = \gamma_0 + \gamma_1 X + \eta_{sh} \quad (5)$$

Equations (2) and (3) assume that the β_1 and β_2 parameters are constant through the full range of values of X and, hence, of $NFDI$; this would imply that the corresponding coefficients in equations (4) and (5) would be equal, i.e., $(\beta_1 - \beta_2) = (\beta_1' - \beta_2')$, so we test the null hypothesis H_0: $\delta_1 = -\gamma_1$. Note that this restriction does not require $\beta_1 = -\beta_2$ in equations (2) and (3). However, *if* $\beta_1 = -\beta_2$, then $(\beta_1 - \beta_2) = 2\beta_1$, $(\beta_1' - \beta_2') = 2\beta_1'$, thus defining a more restrictive subset of values for β_1 and β_2 that are consistent with $\delta_1 = -\gamma_1$. In other words, the restriction $\beta_1 = -\beta_2$ for the gross flows constitutes a special case of the restriction $\delta_1 = -\gamma_1$ that we test on the net flows.

However, if $\delta_1 \neq -\gamma_1$, the marginal effects of varying X are different for $NFDI^{+}_{sh}$ and $NFDI^{-}_{sh}$. This implies rejection of constant slope parameters through the full range of values of X and *NFDI*, including for the special case in which $\beta_1 = -\beta_2$. Therefore, even though we are unable to estimate equations (2) and (3) directly, rejection of H_0: $\delta_1 = -\gamma_1$ is not consistent with equations (2) and (3) with $\beta_1 = -\beta_2$, and therefore implies rejection of symmetric effects on gross flows $GFDI^{+}_{sh}$ and $\left|GFDI^{-}_{sh}\right|$.

As a framework for testing, our analysis uses a variant of Nguyen's (2019) empirical model of FDI, which draws on the structural gravity model of bilateral FDI of Anderson et al. (2019) and includes country-specific and bilateral factors:

$$\begin{aligned} FDI \text{ or } FDD = \mathrm{f}(&Lgdp\_s, Lgdp\_h, Patentshare\_s, Patentshare\_h, Remoteness\_s,\\ &Remoteness\_h, Startcost\_Diff, BIT, Currency, Legal, Religion,\\ &Language, Colony, Border, Ldistance, Volatility, Crisis \times Lgdp\_h,\\ &Crisis \times Lgdp\_s, Crisis \times Volatility) \qquad (6)\end{aligned}$$

where suffix *s* denotes the source country and *h* the host country. Variables with no *s* or *h* suffix are pair-specific.

FDI (*FDD*), corresponding to $NFDI^{+}_{sh}$ ($\left|NFDI^{-}_{sh}\right|$), is the annual real net FDI flow invested (divested) in (from) host country *h* by source country *s*. We use FDI flow data from the OECD database. For countries that report only FDI stocks, we use the perpetual inventory method to calculate the FDI flows:

$$Flow_t = Stock_t - (1 - \delta_t)\, Stock_{t-1}$$

where δ is the host-country capital depreciation rate, and $Flow_t$ and $Stock_t$ are real FDI flows and stocks in constant 2010 US dollars in year *t*. The perpetual inventory method is also applied in, for example, Bitzer and Görg (2009), Hajzler (2012), and Feenstra et al. (2015).

Approximately 10% of the flow observations in our regressions are calculated using the perpetual inventory method; all other flow observations are directly available from the OECD database.

Theoretically, inward flows reported by host countries should be equal to outward flows reported by source countries. However, due to discrepancies in data collection and methodology, FDI values reported by host and source countries rarely match.[5] For our main results, we exclude observations when the data reported by source and host countries differ by more than 100 million USD.[6] In order to construct the final FDI flow series for our regressions, for each country pair, when either the inward or the outward series is missing, we choose the available series (inward or outward) in order to maximise the number of observations.

From the aggregate flow data, we derive series for divestment flows (*FDD*) and investment flows (*FDI*). *FDD* includes the absolute value of negative net FDI flow observations (corresponding to $|NFDI_{sh}^{-}|$); *FDI* includes the positive net FDI flow observations (corresponding to $NFDI_{sh}^{+}$). When there is no positive net investment flow, *FDI* is set equal to zero; similarly, when there is no net divestment, *FDD* is set equal to zero.

The logarithms of real GDP (*Lgdp_s* and *Lgdp_h*) are used to proxy for the source country's expenditure and host country's income. Source and host countries' shares in the global number of patent applications by residents, *Patentshare_s* and *Patentshare_h*, are included to proxy technology capital. The remoteness measures (*Remoteness_s* and *Remoteness_h*), following Baldwin and Harrigan (2011), are defined as $Remoteness_i = (\Sigma_j (Y_j / distance_{ij}))^{-1}$ $(i \neq j)$, where Y is income, and are used to proxy for multilateral resistance.

A number of explanatory variables represent bilateral factors. These include (the logarithm of) physical distance, *Ldistance*, and real exchange rate volatility, *Volatility*, measured by the

[5] See Nguyen's (2019) online appendix for a detailed description of inconsistencies in global bilateral FDI data.
[6] Applying this criterion, 239 observations are excluded.

ratio of the standard deviation of the relevant real exchange rate divided by its mean over a five-year period (Belderbos and Zou 2009). *Startcost_Diff* is the difference between start-up costs in the host country and start-up costs in the source country. Each country's start-up costs are estimated as 100 minus the starting business distance-to-frontier scores from the World Bank's Doing Business Database (World Bank 2020). While *FDI* is expected to be negatively related to physical distance, start-up cost differences, and exchange rate volatility, other bilateral variables are expected to positively affect *FDI*. These are represented by dummy variables for a bilateral investment treaty (*BIT*), common currency (*Currency*), common legal origin (*Legal*), common spoken language (*Language*), colonial relationship (*Colony*), and a common border (*Border*). A common religion index (*Religion*) is calculated from the population percentages of each country pair that share the same religion:

$$Religion = [\Sigma_k \text{ (\% religion } k \text{ in source country} \times \text{\% religion } k \text{ in host country)}]/1000$$

Since our period of analysis includes years of the global financial crisis (2007-2008) and the European debt crisis (2008-2012), we also include interaction terms between a crisis variable and time-varying macro variables to allow for the possibility of varying effects of these variables on *FDD* and *FDI* during these crises. The interaction terms are *Crisis* × *Lgdp_h*, *Crisis* × *Lgdp_s*, and *Crisis* × *Volatility*, where *Crisis* takes the value of 1 for years between 2007 and 2012 inclusive and 0 otherwise.[7]

A full listing of variables and sources is presented in Table A1 in the Appendix; descriptive statistics are reported in Table A2. The final dataset employed in the regression analysis includes 126 source and 126 host countries or territories (listed in the Note to Table A2 in the Appendix), from 2005 to 2018. Note that these data do not include FDI between non-OECD countries.

[7] We include a full set of year dummies in all the estimated models; so to avoid perfect multicollinearity we do not include the *Crisis* dummy separately.

3 Methodology and results

Separate models are specified for *FDI* and *FDD* with the same explanatory variables. If positive and negative observations on FDI are poolable, then the same coefficients would be relevant for both. In that case, the parameters in the equation for (the absolute value of) *FDD* would have the same values but the reverse signs compared to the *FDI* equation.

Since both investment and divestment flows contain extensive zero observations, we employ Poisson pseudo-maximum-likelihood (PPML) estimation (Santos Silva and Tenreyro 2006, 2011).[8] PPML is frequently employed to deal with corner solution outcomes for a continuous dependent variable. It helps address problems due to heteroskedasticity-induced dependence between the error terms and the explanatory variables, which causes ordinary least squares (OLS) estimates to be biased and inconsistent. Empirical results from applying PPML to the *FDD* and *FDI* equations separately are reported in Table 1. The PPML estimator is based on the assumption that the conditional variance is proportional to the conditional mean of the (non-logged) flows. Even if this assumption is not valid, the estimator is still consistent provided the conditional mean is correctly specified. Results from RESET tests, following the test procedure outlined in Santos Silva and Tenreyro (2006), do not reject the null of no functional form misspecification, using a standardised alpha value, as discussed below.

In Table 1, we also report results from pooled OLS estimation of the model, with the dependent variables transformed using the inverse hyperbolic sine transformation, $\sinh^{-1}(y) = \ln(y+\sqrt{y^2+1})$, where y is *FDD* or *FDI*. The IHS transformation is monotonic, approximates the natural log when the variable is sufficiently large, but permits transformation of non-positive values (Burbidge et al. 1988; Pence 2006; Bellemare and Wichman 2020). This approach has therefore been used in several studies of FDI as a way of including zero flows, which would be precluded if using a log transformation (e.g., Busse and Hefeker 2007; Baker 2014;

[8] A recent application of PPML to FDI in a gravity-type model is, for example, the study by Camarero et al. (2020).

Akhtaruzzaman et al. 2018; Kristjánsdóttir and Óskarsdóttir 2021). Although PPML is our preferred estimator, we consider the pooled OLS estimates to gauge whether the results of testing for symmetric effects on *FDD* and *FDI* are sensitive to the choice of estimation method.

In order to test whether the explanatory variables' effects are equal but opposite-signed for *FDI* and *FDD*, we use seemingly unrelated estimation of the two models. This approach, using the same overlapping data, yields the same parameter estimates as in Table 1, but allows us to estimate cross-model covariances using cluster-robust sandwich estimators and construct Wald tests of the implied cross-model restrictions (Weesie 1999; Mize et al. 2019).

For the models with the IHS-transformed dependent variables estimated using pooled OLS, we fit the models for *FDI* and *FDD* separately and then combine the results, using the 'suest' command for seemingly unrelated estimation in Stata version 16.1. For the models estimated using PPML, we instead stack the data for *FDI* and *FDD*, doubling the number of observations, and fit the stacked model using Santos Silva and Tenreyro's (2006) 'ppml' Stata routine.[9] In both cases, final standard errors are clustered by country pairs.

The number of bilateral observations is large (N = 25,871). To compensate for the increasing tendency to reject any null hypothesis as the sample size increases, assessment of statistical significance is based on a reduced alpha level (Type I error probability). For individual regressors, we use an asymptotic version of Leamer's (1978, p. 114) suggested rule to reject the null of a zero coefficient (against a two-sided alternative) if $|t| > [N(N^{1/N} - 1)]^{0.5}$. For N = 25,871, the implied critical t-value of approximately 3.188 corresponds to a (two-sided) alpha of approximately 0.0014; consequently, our assessment of statistically significant coefficients and test statistic values is more conservative than implied by conventional alpha values of 0.05 or 0.01.

[9] The format for stacking the data for the two models is similar to the example in StataCorp (2019, p. 2594). Using Stata's 'suest' command is not feasible with the 'ppml' routine because, initially, 'suest' needs to estimate the separate models without robust or clustered estimation of the covariances of the estimates, which is not feasible with the 'ppml' command.

For tests of equal but opposite-signed coefficients for each individual variable, or joint tests of sets of such parameter restrictions, we use a standardised alpha, $\alpha_{st} = \alpha/[(N/100)]^{0.5}$ (Lakens 2018). For tests based on estimates from the combined *FDI* and *FDD* models, taking N as 51,742, the α_{st} values corresponding to conventional 0.05 and 0.01 values of α are approximately 0.0022 and 0.0004, respectively. Qualitatively similar conclusions are obtained if, instead, we standardise the p-values of the test and use $p_{st} = \min(0.5, p[N/100]^{0.5})$ (Good 1988).

Tables 1 and 2 report regression and test results, respectively. We address whether the determinants of FDI and FDD have similar effects in two ways. First, we explore whether the determinants of FDI have a reverse impact on (the absolute value of) FDD by examining the signs of the estimated coefficients in both equations. Second, we test whether the size of the impact of the explanatory variables on *FDD* is equal to the size of the impact of these variables on *FDI*, but with the opposite sign.

Table 1 shows that the drivers of investment do not have a reverse impact on the absolute value of divestment. In other words, judging by the PPML-estimated coefficient signs, FDD is not the mirror image of FDI. Indeed, the majority of determinants of the absolute value of divestment flows (16 out of 19) have point estimates with the *same direction* of impact on investment flows. In particular, host and source countries' log of GDP have a positive and (using the Leamer rule) statistically significant impact on both divestment and investment, for both estimation methods. Similarly, remoteness of the source country has a significant deterrence effect on both *FDI* and *FDD*. For both estimation methods, the coefficients of log of GDP are approximately half the size for *FDD* as compared to *FDI*. For remoteness of the source country, the PPML estimates imply negative effects that, in absolute terms, are about double for *FDD* compared to *FDI*, suggesting that source-country remoteness is quantitatively more important in preventing loss of investment than it is in discouraging investment. The coefficients for common pair characteristics tend to be imprecisely estimated (based on our criterion for statistical significance). For variables that are statistically significant, again using the Leamer rule, in one of the two equations in the PPML estimates, we find that host country remoteness, BIT and log of distance have negative estimated effects on *FDD*.[10]

The pattern of individually significant coefficients is somewhat different for the pooled OLS results. However, in general, key gravity variables associated with more (less) FDI are also associated with more (less) divestment, with statistically significant same-sign coefficient estimates on host and source countries' log of GDP, source-country remoteness, *Religion*, and *Language*. In all these cases, the expected signs for *FDD* (noted in the second column in Table 1) are different from those estimated. *BIT* has the expected negative sign for *FDD* but not the expected positive sign for *FDI*, *Volatility* has a negative influence on FDI, as expected, but also discourages *FDD*. The only statistically significant crisis interaction term is for the effect of source-country log of GDP on *FDI*. Overall, pooled OLS results lead us to the same conclusion that FDD appears not to be the mirror image of FDI.

We turn next to the second question, i.e., whether the determinants of *FDI* and *FDD* have quantitatively the same effects but with opposite signs. Table 2 presents the results of formal hypothesis tests that coefficients on the explanatory variables in the *FDD* regression are equal but opposite-signed to those in the *FDI* regression. Even using the adjusted 0.0022 or 0.0004 alpha values, the restrictions of equality with opposite signs are rejected for *Lgdp_s*, *Lgdp_h*, *Remoteness_s*, *BIT*, *Ldistance* and *Volatility* for both sets of estimates. The restrictions are also rejected for *Startcost_Diff*, *Currency*, *Religion*, *Language*, *Border* and *Crisis* × *Lgdp_s* for the pooled OLS estimates. At these more stringent alpha levels, some pairwise restrictions are not rejected, but this mainly reflects imprecision in estimation of the point estimates for one or both

10 Bilateral investment treaties (BIT) are estimated to have a counter-intuitive statistically significant negative impact on investment, similar to the PPML results for the intensive margin of FDI (without country fixed effects) reported by Nguyen (2019).

of the relevant coefficients in Table 1. The joint null hypothesis for all the coefficient pairs is clearly rejected for both sets of estimates, as are the joint coefficient restrictions for the year dummies.

The results in Tables 1 and 2 are based on models that include year dummies but not host- or source-country fixed effects. It is relatively common to include host- and source-country fixed effects (plus time fixed effects) in empirical trade and FDI models to control for multilateral resistance (Fally 2015), although these can absorb much of the explanatory power of the measured variables (Carr et al. 2001, 2003). Hence, we also estimate the models with host and source fixed effects. Results for the joint tests of equal and opposite coefficients are reported in Table 3, rows (1) and (2). As in Table 2, using a more stringent alpha level for the tests, the hypothesis of equal and opposite signs is rejected for the main explanatory variables as a group, the set of individual year dummies (for PPML), the set of country dummies, and the set of all variables (including all year and country fixed effects dummies).

The remainder of Table 3 reports the results of jointly testing equal and opposite coefficients for alternative coverage of the countries in our sample. The main results are for a sample that excludes observations for which the data reported by source and host countries differ by more than 100 million US dollars. We also estimate the models using all the available data, without imposing this arbitrary cut-off; the test results, reported in rows (3)-(6), continue to reject the corresponding symmetry restrictions.

One drawback of using aggregate FDI data arises from the existence of offshore financial centres and round-tripping. Round-tripping involves channelling outward FDI from an economy via “investment into empty corporate shells with no substance and no real links to the local economy” (Damgaard et al. 2019, p.26) in a foreign country back to the original economy; such ‘phantom’ FDI is often motivated by tax avoidance. Damgaard et al. (2019) identify several relatively small economies, in terms of GDP, that have a disproportionately large role in hosting global FDI, involving large but approximately balancing equal inward and outward investment flows. Because such phantom FDI is not randomly distributed across countries, reliance on conventionally reported, aggregate-level FDI data may lead to biased results, including for our tests of parameter restrictions. Damgaard et al. (2019, Figure 7) identify 10 economies that account for more than 85% of such phantom FDI in 2017, with Luxembourg and the Netherlands accounting for nearly 50% of the total. Of these 10 economies, our main sample includes Luxembourg, the Netherlands, Hong Kong SAR, Singapore, Switzerland, Ireland, and Mauritius. As a robustness check, we therefore estimate our models excluding data for these and report the corresponding test results in Table 3, rows (7)-(10); again, the parameter restrictions are resoundingly rejected, further supporting the conclusion that the determinants of investment do not have equal but opposite-signed effects on divestment.

Our sample of 126 source and host countries or territories includes 53 high-income countries, 63 middle-income countries and 10 low-income countries, according to the World Bank's classification of countries by income group.[11] The flows (in or out) are therefore dominated by high- and middle-income countries. Nevertheless, in order to check that the test results are not driven by heterogeneity within the sample, we consider two groups of countries: high-income countries (which we label 'High') and a combined group of low-income and middle-income countries (which we label 'Other'). We estimate the models using PPML for three directions of flows: High to High, High to Other, and Other to High. Coefficient estimates are reported in Table A3 in the Appendix and the associated tests of the restrictions of equal but opposite signed coefficients are reported in Table 3. Individual coefficient estimates vary between groups in terms of size and statistical significance, but all but one of the statistically significant coefficients, based on the more stringent Leamer *t*-threshold, exhibit the same sign

[11] https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups, accessed on 1st July 2021.

as in the main results in Table 1.[12] A pairwise comparison reveals a clear majority of coefficients with the same signs in the *FDD* and *FDI* equations (14/19 for the High to High flows, 15/18 for High to Other, and 13/18 for Other to High). More importantly, there is strong evidence of rejection of the joint hypothesis of equal and opposite signs in the *FDD* and *FDI* equations in Table 3, rows (11)-(16), regardless of whether country fixed effects are included or not.

Overall, these results are more consistent with Benito and Welch's (1997, p. 11) claim that "what serves as an entry deterrent, also deters exit ex post". However, the rejection of the symmetry restrictions tested in our framework calls into question the validity, in general, of the widespread practice of using net FDI flows, which combine both gross positive and gross negative FDI, as the dependent variable. This is why we focus primarily on the results of testing the symmetry restrictions rather than interpretation of individual estimated coefficient values.

4 Conclusion

Foreign direct divestment has been examined in the international business and management literature since the 1970s, but has received relatively little attention in country-level empirical analyses in international economics, despite the large literature on positive FDI flows in this area. To our knowledge, ours is the first study that utilises bilateral country-level divestment data to explore the determinants of negative foreign direct investment flows, which have become a particular concern in recent times. We study bilateral negative and positive foreign direct investment flows for 126 host and 126 source countries or territories over the period from 2005 to 2018.

Our results suggest that conventional gravity variables, such as host and source country GDP, distance and source-country remoteness, that have statistically significant effects on FDI have similar-signed effects on divestment, not opposite-signed effects. Moreover, formal

[12] *Legal* has a significant and positive effect on *FDI* in the High to Other results, whereas this is negative but not significant (even at conventional levels) in Table 1.

testing of whether coefficients for the absolute value of divestment are equal but opposite signed to those for investment rejects this hypothesis. Although constraints on data availability mean that we rely on models estimated using net bilateral positive and negative flows of FDI, rejection of the parameter restrictions on the net-flow models also imply rejection of the corresponding restrictions for inward and outward gross flows. Our results, therefore, indicate that the relevant macro-level theory for FDD is not simply the reverse theory of FDI with symmetric effects. The view that what deters FDI encourages FDD and vice versa, as proposed by Boddewyn (1983), is not supported based on bilateral country-level net flows of positive (FDI) and negative foreign direct investment (FDD). Rejection of the symmetry restrictions tested suggests that pooling observations on negative and positive net flows of FDI in the same regression model could lead to misleading results. Even focusing on only positive net flows of FDI, as in many existing studies, may be questionable, as net flows, whether positive or negative, combine both investment and divestment activities. However, our tests do not allow us to analyse directly the responses to the determinants of FDI (FDD) as the mix of inflows and outflows varies while still maintaining positive (negative) net flows. Availability of data on gross positive and gross negative bilateral flows would be desirable to explore further the determinants of gross foreign direct investment and gross foreign direct divestment separately.

The results also indicate the need for more empirical and theoretical research on foreign divestment. From a theoretical perspective, country-level models explaining FDI, such as the knowledge-capital model developed by Markusen (2002), the knowledge and physical capital model of Bergstrand and Egger (2007), and the structural gravity model of FDI developed by Anderson et al. (2019) deal with only one aspect of the foreign direct investment landscape: invest or not invest. They do not explain foreign direct divestment. Therefore, constructing models that explain divestment or incorporating both investment and divestment decisions into one equilibrium model seem fruitful areas for future research.

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Table 1 OLS and PPML estimation results

		OLS		PPML	
	Expected sign for *FDD*	Divestment *FDD* (1)	Investment *FDI* (2)	Divestment *FDD* (3)	Investment *FDI* (4)
Lgdp_s	–	**0.066**	**0.188**	**0.218**	**0.452**
		(0.005)	(0.008)	(0.065)	(0.057)
Lgdp_h	–	**0.057**	**0.170**	**0.263**	**0.422**
		(0.004)	(0.008)	(0.054)	(0.048)
Patentshare_s	–	–3.384	**10.515**	4.957	16.504
		(1.108)	(2.770)	(11.443)	(5.423)
Patentshare_h	+	–2.589	2.672	–8.161	7.219
		(1.214)	(3.563)	(10.829)	(5.815)
Remoteness_s	+	**–1.694**	**–2.620**	**–15.342**	**–7.153**
		(0.256)	(0.518)	(3.871)	(1.880)
Remoteness_h	+	**–1.598**	–0.005	**–9.117**	2.355
		(0.259)	(0.609)	(2.766)	(2.302)
Startcost_Diff	+	0.003	**0.030**	–0.010	0.027
		(0.003)	(0.007)	(0.032)	(0.029)
BIT	–	**–0.103**	**–0.262**	–0.392	**–0.675**
		(0.017)	(0.032)	(0.175)	(0.143)
Currency	–	**0.160**	0.217	0.205	0.180
		(0.043)	(0.069)	(0.203)	(0.175)
Legal	–	–0.016	0.024	–0.379	–0.058
		(0.016)	(0.033)	(0.192)	(0.179)
Religion	–	**0.016**	**0.019**	0.058	0.009
		(0.003)	(0.006)	(0.025)	(0.024)
Language	–	**0.114**	**0.258**	0.406	0.174
		(0.034)	(0.073)	(0.182)	(0.167)
Colony	–	–0.020	0.229	0.224	0.567
		(0.050)	(0.117)	(0.281)	(0.253)
Border	–	0.054	**0.507**	0.033	0.211
		(0.066)	(0.129)	(0.290)	(0.242)
Ldistance	+	–0.032	**–0.143**	–0.182	**–0.428**
		(0.014)	(0.026)	(0.129)	(0.102)
Volatility	+	**–0.134**	**–0.182**	–4.005	–2.114
		(0.024)	(0.044)	(1.310)	(0.720)
Crisis × *Lgdp_h*	+	0.007	0.028	–0.008	–0.060
		(0.007)	(0.011)	(0.079)	(0.060)
Crisis × *Lgdp_s*	+	0.009	**0.060**	0.088	0.012
		(0.007)	(0.012)	(0.091)	(0.085)
Crisis × *Volatility*	+	0.043	0.042	2.288	0.121
		(0.025)	(0.050)	(1.291)	(1.001)
Constant		**–0.367**	**–1.378**	–0.258	**–3.348**
		(0.072)	(0.145)	(0.895)	(0.788)
Pseudo log-likelihood				–99845	–185698
RESET *p*-value				0.210	0.055
N		25871	25871	25871	25871

Standard errors, clustered by country pairs, reported in parentheses. Coefficients in bold denote rejection of a zero null based on Leamer's rule ($|t| > [N(N^{1/N} - 1)]^{0.5}$), where *N* is the sample size. Year dummies included. 'Expected sign' for *FDD* is the negative of the expected sign of the variable for *FDI*. RESET tests the correct specification of the conditional expectation.

Table 2 Testing symmetry restrictions

	(1) OLS	(2) PPML
Lgdp_s	601.22	40.62
	[0.0000]	[0.0000]
Lgdp_h	511.66	65.15
	[0.0000]	[0.0000]
Patentshare_s	5.45	2.25
	[0.0196]	[0.1336]
Patentshare_h	0.00	0.01
	[0.9821]	[0.9431]
Remoteness_s	46.32	20.16
	[0.0000]	[0.0000]
Remoteness_h	5.10	2.59
	[0.0239]	[0.1073]
Startcost_Diff	20.00	0.15
	[0.0000]	[0.6979]
BIT	76.61	14.10
	[0.0000]	[0.0002]
Currency	18.02	1.53
	[0.0000]	[0.2167]
Legal	0.03	1.83
	[0.8557]	[0.1763]
Religion	22.90	2.58
	[0.0000]	[0.1079]
Language	20.78	4.20
	[0.0000]	[0.0405]
Colony	2.36	3.49
	[0.1247]	[0.0619]
Border	15.92	0.29
	[0.0001]	[0.5899]
Ldistance	26.90	9.41
	[0.0000]	[0.0022]
Volatility	28.05	12.09
	[0.0000]	[0.0005]
Crisis × *Lgdp_h*	8.28	0.34
	[0.0040]	[0.5582]
Crisis × *Lgdp_s*	31.46	0.49
	[0.0000]	[0.4845]
Crisis × *Volatility*	1.78	1.74
	[0.1817]	[0.1875]
Joint test	1552.26 (19)	710.46 (19)
	[0.0000]	[0.0000]
Year dummies	182.68 (13)	51.59 (13)
	[0.0000]	[0.0000]
All variables	1650.13 (32)	963.11 (32)
	[0.0000]	[0.0000]

Asymptotic chi-squared test statistics of equality (with reverse signs) of the parameters in the equations for *FDI* and (the absolute value of) *FDD*. Degrees of freedom, equal to the number of restrictions, are in parentheses. *p*-values are reported in square brackets.

Table 3 Testing symmetry restrictions – robustness checks

	Main variables	Year dummies	Country FEs	All variables
Including country FEs				
(1) OLS	552.86 (19)	58.22 (13)	2400.97 (250)	5609.22 (282)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
(2) PPML	102.27 (19)	31.71 (13)	7104.25 (244)	44972.15 (276)
	[0.0000]	[0.0027]	[0.0000]	[0.0000]
No data excluded				
(3) OLS	1456.69 (19)	176.77 (13)		1543.31 (32)
	[0.0000]	[0.0000]		[0.0000]
(4) OLS, with country FEs	527.67 (19)	56.54 (13)	2347.61 (250)	5327.57 (282)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
(5) PPML	706.85 (19)	65.01 (13)		1008.35 (32)
	[0.0000]	[0.0000]		[0.0000]
(6) PPML, with country FEs	97.83 (19)	40.81 (13)	9766.16 (245)	69242.16 (277)
	[0.0000]	[0.0001]	[0.0000]	[0.0000]
Excluding countries with high levels of phantom investment				
(7) OLS	1310.93 (19)	164.18 (13)		1547.65 (32)
	[0.0000]	[0.0000]		[0.0000]
(8) OLS, with country FEs	421.30 (19)	77.55 (13)	1582.92 (236)	3720.36 (268)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
(9) PPML	1605.08 (19)	27.67 (13)		2131.01 (32)
	[0.0000]	[0.0101]		[0.0000]
(10) PPML with country FEs	188.50 (19)	29.61 (13)	4570.08 (230)	52989.47 (262)
	[0.0000]	[0.0054]	[0.0000]	[0.0000]
Disaggregated by income groups				
(11) PPML, High to High	398.67 (19)	60.06 (13)		583.89 (32)
	[0.0000]	[0.0000]		[0.0000]
(12) PPML, High to High,	90.38 (19)	34.16 (13)	2315.49 (102)	6820.66 (134)
with country FEs	[0.0000]	[0.0011]	[0.0000]	[0.0000]
(13) PPML, High to Other	505.72 (18)	93.05 (13)		724.28 (31)
	[0.0000]	[0.0000]		[0.0000]
(14) PPML, High to Other,	117.65 (18)	64.23 (13)	3023.61 (108)	3.0e+05 (138)
with country FEs	[0.0000]	[0.0000]	[0.0000]	[0.0000])
(15) PPML, Other to High	277.28 (18)	99.23 (13)		582.10 (31)
	[0.0000]	[0.0000]		[0.0000]
(16) PPML, Other to High,	59.30 (18)	27.88 (13)	6076.84 (105)	2.2e+05 (136)
with country FEs	[0.0000]	[0.0094]	[0.0000]	[0.0000]

Asymptotic chi-squared test statistics of equality (with reverse signs) of the parameters in the equations for *FDI* and (the absolute value of) *FDD*. Degrees of freedom, equal to the number of restrictions, are in parentheses. *p*-values are reported in square brackets.

Appendix

Table A1 Variables and data sources

Variable	Unit	Abbreviation	Data source
Investment & divestment flows	Million		OECD[a,b]
FDI stocks	2010 US$		
Source country GDP (log)	Billion	*Lgdp_s*	World Bank[c]
Host country GDP (log)	2010 US$	*Lgdp_h*	
Source country's technology capital share		*Patentshare_s*	
Host country's technology capital share		*Patentshare_h*	
Source country's remoteness		*Remoteness_s*	Own calculation
Host country's remoteness		*Remoteness_h*	
Difference in start-up costs		*Startcost_Diff*	World Bank[d]
Bilateral investment treaty, dummy	Dummy	*BIT*	UNCTAD[e]
Common currency	Dummy	*Currency*	De Sousa (2012)[f] & own updates
Common legal origin	Dummy	*Legal*	CIA World Factbook[g]
Common religion	Index	*Religion*	
Common spoken language	Dummy	*Language*	The Centre d'Études Prospectives et d'Informations Internationales (CEPII)[h]
Ever in a colonial relationship	Dummy	*Colony*	
Common border		*Border*	
Distance (log)	1000 km	*Ldistance*	
Real exchange rate volatility		*Volatility*	World Bank[c] & own calculation
Crisis dummy (= 1 for 2007 to 2012)	Dummy	*Crisis*	Own calculation
Interaction between crisis and log of host country GDP		*Crisis×Lgdp_h*	Own calculation
Interaction between crisis and log of source country GDP		*Crisis×Lgdp_s*	Own calculation
Interaction between crisis and exchange rate volatility		*Crisis×Volatility*	Own calculation

[a] Stocks: https://stats.oecd.org/Index.aspx?DataSetCode=FDI_POS_CTRY
[b] Flows: https://stats.oecd.org/Index.aspx?DataSetCode=FDI_FLOW_CTRY
[c] https://databank.worldbank.org/source/world-development-indicators
[d] https://www.doingbusiness.org/
[e] https://investmentpolicy.unctad.org/international-investment-agreements
[f] De Sousa (2012)
[g] https://www.cia.gov/library/publications/the-world-factbook/
[h] Mayer and Zignago (2011)

Table A2 Descriptive statistics

Variable	Mean	Std. Dev.	Minimum	Maximum
FDD	1.299	12.145	0	784.215
FDI	4.066	23.497	0	833.682
Lgdp_s	5.782	1.857	–0.415	9.790
Lgdp_h	5.573	1.861	–0.415	9.790
Patentshare_s	0.002	0.007	0	0.065
Patentshare_h	0.002	0.006	0	0.065
Remoteness_s	0.058	0.036	0.016	0.224
Remoteness_h	0.058	0.035	0.016	0.224
Startcost_Diff	0.049	1.395	–7.081	7.081
BIT	0.500	0.500	0	1
Currency	0.078	0.268	0	1
Legal	0.684	0.465	0	1
Religion	2.847	2.393	0	9.920
Language	0.090	0.286	0	1
Colony	0.037	0.188	0	1
Border	0.037	0.189	0	1
Ldistance	1.411	0.998	–2.820	2.977
Volatility	0.118	0.229	0.001	2.205
Crisis×Lgdp_h	1.171	2.435	0	9.653
Crisis×Lgdp_s	1.209	2.502	0	9.653
Crisis×Volatility	0.041	0.196	0	2.205

Note: The number of bilateral observations is 25,871. Std. dev. refers to the standard deviation. The countries or territories included are: Albania, Algeria, Antigua and Barbuda, Armenia, Australia, Austria, Azerbaijan, Bahamas, Bahrain, Bangladesh, Barbados, Belgium, Bhutan, Bolivia, Bosnia and Herzegovina, Botswana, Brazil, Brunei Darussalam, Bulgaria, Burkina Faso, Cabo Verde, Cambodia, Canada, Chile, China, Colombia, Cote d'Ivoire, Costa Rica, Croatia, Cyprus, Czech Republic, Denmark, Dominican Republic, Ecuador, Egypt, El Salvador, Estonia, Ethiopia, Finland, France, Germany, Ghana, Greece, Guatemala, Guyana, Haiti, Honduras, Hong Kong, Hungary, Iceland, India, Indonesia, Iran, Iraq, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kazakhstan, Kenya, Korea (Republic), Kuwait, Kyrgyz Republic, Laos, Latvia, Lebanon, Lithuania, Luxembourg, Madagascar, Malawi, Malaysia, Malta, Mauritius, Mexico, Moldova, Mongolia, Morocco, Namibia, Nepal, Netherlands, New Zealand, Nicaragua, Nigeria, Norway, Oman, Pakistan, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Poland, Portugal, Qatar, Russia, Rwanda, Samoa, Saudi Arabia, Singapore, Slovak Republic, Slovenia, South Africa, Spain, Sri Lanka, St. Lucia, Sudan, Sweden, Switzerland, Tajikistan, Tanzania, Thailand, Trinidad and Tobago, Tunisia, Turkey, Uganda, Ukraine, United Arab Emirates, United Kingdom, United States of America, Uruguay, Venezuela, Vietnam, Yemen (Republic), and Zambia.

Table A3 PPML estimates by country groups

	High to High		High to Other		Other to High	
	Divestment	Investment	Divestment	Investment	Divestment	Investment
Lgdp_s	0.140	**0.329**	0.272	**0.578**	**0.941**	**0.991**
	(0.078)	(0.064)	(0.141)	(0.084)	(0.122)	(0.143)
Lgdp_h	0.170	**0.323**	**0.626**	**0.869**	0.233	0.291
	(0.064)	(0.055)	(0.082)	(0.062)	(0.117)	(0.146)
Patentshare_s	2.588	**43.832**	13.323	27.584	–16.184	–5.368
	(25.629)	(13.401)	(79.387)	(22.305)	(10.151)	(9.978)
Patentshare_h	2.091	17.937	**–28.140**	–9.657	53.743	–26.989
	(21.077)	(11.371)	(8.515)	(5.198)	(64.880)	(37.194)
Remoteness_s	–10.094	–5.553	–22.053	–9.600	0.829	4.471
	(4.126)	(2.566)	(19.434)	(5.926)	(5.926)	(4.279)
Remoteness_h	–7.406	2.547	8.770	13.290	–34.394	0.995
	(2.901)	(2.443)	(7.340)	(4.777)	(15.124)	(6.325)
Startcost_Diff	–0.020	–0.030	–0.132	–0.008	0.021	0.206
	(0.044)	(0.035)	(0.117)	(0.083)	(0.111)	(0.104)
BIT	–0.268	–0.539	0.149	–0.101	–0.043	–0.265
	(0.214)	(0.199)	(0.224)	(0.261)	(0.222)	(0.343)
Currency	0.042	0.168				
	(0.194)	(0.170)				
Legal	–0.336	–0.233	–0.308	**0.564**	–0.011	–0.022
	(0.213)	(0.209)	(0.267)	(0.188)	(0.268)	(0.264)
Religion	0.025	–0.036	0.039	0.051	**0.146**	0.067
	(0.034)	(0.036)	(0.050)	(0.047)	(0.047)	(0.044)
Language	0.504	0.278	–0.240	–0.080	0.546	0.215
	(0.204)	(0.186)	(0.467)	(0.200)	(0.303)	(0.320)
Colony	0.237	0.611	0.919	0.620	0.033	0.381
	(0.320)	(0.304)	(0.762)	(0.361)	(0.356)	(0.350)
Border	0.067	0.284	–0.666	–0.003	–0.709	–0.128
	(0.320)	(0.272)	(0.876)	(0.374)	(0.671)	(0.573)

Ldistance	–0.184	**–0.429**	–0.099	**–0.615**	–0.291	–0.187
	(0.144)	(0.117)	(0.257)	(0.127)	(0.216)	(0.206)
Volatility	–3.577	–1.911	–2.423	–2.390*	–0.798	–4.685
	(1.282)	(0.711)	(2.129)	(1.403)	(1.208)	(3.083)
Crisis × *Lgdp_h*	0.016	–0.059	–0.075	–0.021	–0.157	0.090
	(0.099)	(0.074)	(0.159)	(0.110)	(0.119)	(0.110)
Crisis × *Lgdp_s*	0.137	–0.024	0.350	0.141	–0.141	0.018
	(0.101)	(0.091)	(0.185)	(0.095)	(0.169)	(0.126)
Crisis × *Volatility*	1.653	–0.965	2.314	–0.530	–4.032	2.698
	(1.309)	(1.210)	(2.211)	(3.541)	(3.624)	(3.139)
Constant	0.916	–1.468	**–5.557**	**–8.938**	**–6.908**	**–8.692**
	(0.996)	(0.927)	(1.337)	(0.737)	(1.083)	(0.945)
Pseudo log-likelihood	–77614.9	–136740.7	–11094.2	–20807.9	–4835.9	–11437.9
N	12251	12251	6902	6902	6281	6281
RESET p-value	0.233	0.002	0.158	0.880	0.002	0.741
t-threshold	3.0687		2.9741		2.9583	

Standard errors, clustered by country pairs, reported in parentheses. Coefficients in bold denote rejection of a zero null based on Leamer's rule for the *t*-threshold ($|t| > [N(N^{1/N} - 1)]^{0.5}$). Year dummies included. RESET tests the correct specification of the conditional expectation.