Foreign Direct Investment and the Domestic Capital Stock: The Good-Bad Role of Higher Institutional Quality

Michael S. Delgado^{*} Department of Agricultural Economics Purdue University Nadine McCloud[†] Department of Economics University of the West Indies at Mona

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Abstract

We investigate heterogeneity between foreign direct investment (FDI) and domestic investment induced by corruption and human capital. Controlling for corruption and human capital, inbound FDI has significant, heterogeneous complementarity effects on domestic investment; the effect of outbound FDI on domestic investment is *fluid*: substitution and complementarity exist, and change direction over time. The *fluid* effects of outbound FDI oppose the popular dollar-fordollar hypothesis. Lower corruption and higher human capital strengthen, weaken, or do not change the degree of these FDI effects; this role of higher institutional quality appears consistent with the prediction of the General Theory of Second Best.

Keywords: Domestic Investment; Foreign Direct Investment; Corruption; Schooling; Heterogeneity; Second Best; Generalized Method of Moments; Semiparametric Estimation.

JEL Codes: C14; C26; E02; F21; O11.

^{*}Michael S. Delgado, Department of Agricultural Economics, Purdue University, West Lafayette, IN 47907-2056. Phone: 765-494-4211, Fax: 765-494-9176, Email: delgado2@purdue.edu.

[†]Correspondence to: Nadine McCloud, Department of Economics, University of the West Indies at Mona, Kingston 7, Jamaica. Phone: 876-977-1188, Fax: 876-977-1483, Email: nadine.mccloud02@uwimona.edu.jm.

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1 Introduction

It is widely accepted that tangible and intangible interactions between domestic and foreign resources is an important way in which both inbound and outbound foreign direct investment (FDI) can effect change in a country's domestic capital stock. In theory, the nature of the relationship between inbound FDI and domestic investment is ambiguous. On the one hand, if foreign investors use domestic creditors to finance their investment needs, this puts an upward pressure on domestic interest rates, which in turn may discourage local firms from undertaking investment projects; that is, inbound FDI may substitute for domestic investment. Also, inbound FDI may fuel competition to the extent that this competitive climate displaces some domestic firms. On the other hand, inbound FDI may complement domestic investment through the creation of downstream or upstream ventures. Similar theoretically conflicting arguments have also been advanced on the nexus between outbound FDI and domestic investment. One argument is that outbound FDI transfers domestic activities abroad and thus reduces domestic production; that is, outbound FDI and domestic investment are substitutes. A counter-argument is that outbound FDI allows investors to combine domestic production with foreign production in a manner that reduces costs and raises the private returns to domestic production, which consequently increases domestic output and domestic investment; that is, outbound FDI is complementary to domestic investment (Desai, Foley & Hines 2005). Insignificant effects of inbound and outbound FDI on domestic investment are also possible within countries where, for example, there is no meaningful interaction between domestic and foreign resources.

A few studies have analyzed empirically the aggregate macroeconomic effects of inbound and outbound FDI on domestic investment (Feldstein 1995, Desai et al. 2005); their cross-country results are that inbound FDI does not significantly impact domestic investment, while outbound FDI crowds out domestic investment nearly dollar for dollar. Desai et al. (2005), however, found some empirical evidence to suggest outbound FDI may be heterogeneously associated with domestic investment and state that "It is possible that foreign and domestic investment are complements in the American economy, whereas they are substitutes in other OECD economies" (p. 36). Indeed, countries can differ in their ability to exploit interactions between domestic and foreign resources. A *natural yet unexplored* question therefore is what factors influence the *existence*, *nature*, and *degree* of the heterogeneous interactions between the elements of inbound *and* outbound FDI and those of domestic investment. Anecdotal evidence points to corruption and human capital as important candidate factors.

In 1996, a World Bank survey of 3,685 firms in 69 countries reveals that (of 15 obstacles) corruption ranks as the *second* most important obstacle to business worldwide (Brunetti, Kisunko & Weder 1997, pg. 59). In fact, more recent anecdotal evidence suggests that this sentiment still exists among foreign investors. In 2007, the Worldwide Survey of Foreign Affiliates, conducted jointly by UNCTAD and the World Association of Investment Promotion Agencies, involving 96 chief executive officers of foreign affiliates around the world were asked to indicate the policy area that governments should improve upon to render their locations more attractive to FDI; the most important policy area was the regulatory and institutional environment - which includes anticorruption measures and skilled-labor supply and improvements in the education system were also viewed as important (UNCTAD 2007).

It is quite plausible that these institutional factors that foreign investors view as obstacles to conducting business worldwide may also be factors that impinge on the interactions between domestic and foreign resources within an economy. In fact, it is well documented in theoretical and empirical literatures that low institutional quality is associated with multiple economic distortions - various factors that obstruct the free flow of resources towards optimal output combinations - which affect the productivity of a country.¹ The General Theory of Second Best advanced by Lipsey & Lancaster (1956) suggests that in the presence of multiple distortions no definitive statement can be made a priori on the nature of changes in any distortion and the economic relationship of interest. In the present context, therefore, the effect of corruption and schooling on the interaction between domestic investment and FDI may not be simple and strictly monotonic.² A high level of, say, corruption can induce distortions that may not translate into, for example, weak linkages between domestic investment and FDI across all countries. Argentina, Brazil, China, Mexico and Thailand, for example, receive sizeable amounts of inbound FDI and have a high level of domestic investment, although they all have a high level of corruption. Moreover, reducing corruption from its prevailing level may come at the expense of over-regulation or under-regulation that does not impact the interaction between domestic investment and FDI in the same way in all countries. That is, reducing corruption from its prevailing level may induce added distortions that may weaken, strengthen or produce no change in the effects of FDI on domestic investment. To this end, empirically, the nature of changes in corruption and human capital on the association between domestic investment and inbound and outbound FDI may be consistent with the prediction General Theory of Second Best.

In this paper, we initiate filling a void in the literature by delving empirically into the *existence*, *nature*, and *degree* of heterogeneity across and within developed and developing economies in the relationships between inbound *and* outbound FDI and domestic investment. To proceed, our *first* hypothesis is that corruption and schooling enrollment are sources of parameter heterogeneity. Our *second* hypothesis is that nonlinear forms of this parameter heterogeneity exist in empirical domestic investment models, and specifically in the effects of inbound and outbound FDI on domestic investment. These workable hypotheses are precursors to detecting, from the data, whether the nature of the corruption and human capital as sources of parameter heterogeneity in these effects is consistent with the General Theory of Second Best. For developing countries, the presence of institutions-induced second-best traits in the association between domestic investment and FDI provides empirical support for the argument that changes in their "institutional landscape" warrants a second-best rather than a first-best "mindset" (Rodrik 2008).

To simultaneously incorporate these important dimensions that are fundamental to proper identification of the effects of inbound and outbound FDI on domestic investment, we veer from the conventional parametric modeling and propose a suitable semiparametric regression model. Recent theoretical econometric research (e.g., Cai & Li 2008, Tran & Tsionas 2009) has developed tools for estimating semiparametric models with parameter heterogeneities of unknown form. In our semiparametric framework, we represent the coefficients on all regressors as unknown smooth functions of corruption, schooling enrollment or literacy rate, and unobserved country- and year-specific factors

¹See, for example, Mauro (1995, 1998), North (1990), Shleifer & Vishny (1993), Hall & Jones (1999), and Acemoglu, Johnson & Robinson, (2001, 2002, 2005).

²Corruption and human capital are two measures of institutional quality that have been shown to be relevant in the macroeconomic empirical literature on FDI (see, e.g., Wei 2000*a*, Wei 2000*b*, Egger & Winner 2005, Busse & Hefeker 2007, Barassi & Zhou 2012) and domestic investment (Mauro 1995, Borensztein, De Gregorio & Lee 1998). More generally, Papaioannou (2009) shows that institutional quality is important for foreign investment flows. In addition, Borensztein et al. (1998) investigate whether human capital plays an important role in facilitating the interactive effects between inbound FDI and domestic investment but conclude that their empirical results "do not appear to be robust" (pg. 118).

(fixed effects).³ Thus, unlike standard panel models, we abstract from the use of neutral ("proper" or additively separable) fixed effects and incorporate non-neutral fixed effects to reflect the presence of unobserved parameter heterogeneities, stemming from unobservable country-specific or time-specific effects, which may effect change in the domestic investment function in many ways beyond a simple translation. For example, changes in a firm's inbound and (or) outbound FDI may lead to changes in input composition of its production process and organizational structure, which are likely to be associated with changes in the level of domestic investment.

Our work differs in other ways from some in the existing macroeconomic empirical literature on the determinants of domestic investment. Our simultaneous use of inbound *and* outbound FDI as variables of interest reflects the fact that many countries have trade agreements with other countries, which can induce a mechanical correlation between inbound FDI and outbound FDI. Thus, empirical studies that use only inbound FDI *or* outbound FDI in their analysis of the nexus between domestic investment and FDI (see, e.g., Borensztein et al. 1998, Bosworth & Collins 1999, Agosin & Machado 2005, Wang 2010) might yield biased results.

We fit our semiparametric regression model to a panel data of 137 developed and developing countries over the period 1984 to 2010. Our evidence lends empirical validity to our first hypothesis that corruption and human capital are sources of parameter heterogeneity in the relationships between domestic investment and inbound and outbound FDI. Our empirical results reveal that the nature and degree of such relationships differ markedly from existing studies. Controlling for the prevailing levels of corruption or human capital, we find that across developed and developing countries, inbound FDI has significant, heterogeneous complementarity effects on domestic investment. These complementarity effects are larger in some developing countries. Thus, our results temper previous findings that inbound FDI does not boost domestic investment. We find that the effect of outbound FDI on domestic investment is quite *fluid*: across developed and developing countries, substitution and complementarity exist between outbound FDI and domestic investment, and within some countries these effects change direction over different time horizons. This *fluid* effect of outbound FDI is not a unique characteristic of only developing or developed countries - it is a characteristic of some developed and developing countries. The complementarity effects of outbound FDI are substantially smaller than the absolute values of their substitution counterparts. In countries for which outbound FDI and domestic investment are substitutes, we do not find evidence in favor of the Feldstein (1995) dollar-for-dollar hypothesis; the substitution effects are significantly smaller than unity. In essence, previous findings disappear when focusing concurrently on larger groups of countries and sources of heterogeneity.

In strong support of our second hypothesis, we find that improvements in corruption and schooling may strengthen, weaken, or have no effect on the relationship between FDI and domestic investment within a particular country. In other words, reducing corruption or increasing human capital can be good *and* bad for the effects of FDI on domestic investment. Additional analyses of this characterization of higher institutional quality reveal the presence of multiple modes in the joint densities of the estimated FDI effects and measures of institutional quality. Therefore, this good-bad role of higher institutional quality that is exhibited by the data appears consistent with the prediction of the General Theory of Second Best.

 $^{^{3}}$ In essence, we do not simply lump corruption and schooling into our standard set of control variables; rather, we allow both variables to have both a *direct* effect on domestic investment, and an *indirect* effect on domestic investment by influencing the manner in which FDI, as well as other control variables, impact domestic investment.

Local conditions that affect domestic investment may influence a multinational corporation investment decision on the movement or distribution of its capital and other resources across its subsidiaries, which in turn may render FDI endogenous in the domestic investment equation. Our semiparametric approach allows us to assess the possible incidence of endogeneity of inbound and outbound FDI with instrumental variables. Economic conditions within a country's major trading partners can be potential sources of exogenous variation for inbound and outbound FDI in the domestic investment equation. We use four separate instrumental variables for FDI: the economic growth rate, savings rate, interest rate, and exchange rate for the top five major trading partners of each country. These variables are not likely to be influenced by the domestic investment in any particular country, yet are correlated with both inbound and outbound FDI for the country. We do not find any evidence that endogeneity bias drives any of our baseline regression results. In fact, various auxiliary estimation techniques with and without these external instruments strongly suggest that controlling for fixed effects and corruption or schooling in a flexible manner significantly discounts the occurrence of endogeneity in our framework.

We find substantial heterogeneities between domestic investment and the other covariates. The *nature* and *degree* of these heterogeneities appear to be influenced by differences in corruption and schooling across countries. Indeed, a formal nonparametric model specification test favors our semiparametric domestic investment model - with significant nonlinear effects from corruption and schooling - over its parametric counterpart that allows for homogeneous parameters. In addition, estimates of the smoothing parameters for corruption and schooling, and unobserved country- and year-specific factors do substantiate our claim that these three factors induce nonlinear forms of parameter heterogeneities in our semiparametric model, and are important in the relationship between domestic investment and inbound *and* outbound FDI. In particular, we find empirical support for our use of non-neutral, rather than neutral, fixed effects. Overall, our empirical results accord with our new-fangled semiparametric analysis of the domestic investment equation.

The concept of incorporating corruption and schooling, parameter heterogeneity, and endogeneity in our model of domestic investment is related to several important hypotheses and burgeoning research strands in the wider macroeconomic literature. First, the findings of this present paper has implications for the theory of irreversible investments (Dixit & Pindyck 1994) and the perfect capital mobility hypothesis (Feldstein & Horioka 1980). Second, it is widely cited that parameter heterogeneity across countries tends to severely influence the results from any empirical exercise.⁴ Third, endogeneity has been labeled as an important source of bias driving the results of many early empirical macroeconomic studies. Durlauf (2001), for example, argues that most aggregate macroeconomic variables are potentially endogenous in an economic growth specification; many empirical investigations focusing on growth effects of FDI have explored instrumental variables techniques to mitigate this potential source of bias (e.g., Borensztein et al. 1998, Bosworth & Collins 1999, Alfaro, Chanda, Kalemli-Ozcan & Sayek 2004, Delgado et al. 2014). While our focus is not on the economic growth rate, it is possible that similar unobservable correlations exist in a macroeconomic model of domestic investment leading to a potential source of endogeneity bias (Bosworth & Collins 1999).

⁴Now classic research documenting these findings include Durlauf & Johnson (1995), Liu & Stengos (1999), and Durlauf, Kourtellos & Minkin (2001). More recent contributions documenting the importance of parameter heterogeneity and model flexibility include Maasoumi, Racine & Stengos (2007), Minier (2007), Henderson, Papageorgiou & Parmeter (2012), McCloud & Kumbhakar (2012), and Delgado, McCloud & Kumbhakar (2014). In particular, Minier (2007) and McCloud & Kumbhakar (2012) document institutional quality as an important source of parameter heterogeneity in cross-country empirical growth models.

Our present analysis of the FDI and domestic investment nexus therefore adds to important aspects of the empirical macroeconomic literature.

The remainder of our paper is outlined as follows. Section 2 details our proposed empirical semiparametric framework, econometric estimation and identification procedures, and model specification test for the null hypothesis of homogeneous parameters. We present a description of our data in Section 3, and turn to our main set of results in Section 4. We carefully consider endogeneity, and the general robustness of our results, in Section 5, and we provide our conclusions in Section 6.

2 Empirical Model

2.1 A Smooth Varying-Coefficient Model of Domestic Investment

We let I_{it} denote domestic investment, define $F_{1,it}$ and $F_{2,it}$ to respectively be inbound and outbound FDI, and let the indices i = 1, 2, ..., n and t = 1, 2, ..., T denote country and time, respectively. We model empirically the relationship between domestic investment and FDI as

$$I_{it} = \beta_0(Z_{it}) + F_{1,it}\beta_1(Z_{it}) + F_{2,it}\beta_2(Z_{it}) + Controls'_{it}\beta_3(Z_{it}) + \epsilon_{it},$$
(1)

in which $Controls_{it}$ is a *l*-dimensioned vector of control variables that vary both across countries and over time, and ϵ_{it} is a zero mean error term. We model the effects of FDI and the control variables on domestic investment as functions of a *p*-dimensioned vector of environmental variables, Z_{it} , through the coefficient functions $\beta_j(Z_{it})$, j = 0, 1, 2, 3, and $\beta_j(Z_{it}) : \mathbb{R}^p \to \mathbb{R}$ for j = 0, 1, 2 but $\beta_j(Z_{it}) :$ $\mathbb{R}^p \to \mathbb{R}^l$ for j = 3. Z_{it} can, in general, include any variable that may be a source of heterogeneity within the I_{it} and $\{F_{1,it}, F_{2,it}, Controls_{it}\}$ relationship. Therefore, this flexible framework in (1) is a straightforward generalization of the standard homogeneous parameters specification in which the coefficient functions $\beta_j(\cdot)$ are assumed to be constant parameter(s) across country and time, β_j , and the environmental variables Z_{it} may be subsumed into the vector of control variables. The specification in (1) thus confers an advantage over the homogeneous model of allowing us to model the heterogeneous effects of $F_{1,it}$, $F_{2,it}$ and $Controls_{it}$ on I_{it} induced by the variables Z_{it} , rather than simply trying to control for confounding effects.

In general, there are a variety of ways to incorporate heterogeneity into the coefficient functions by making use of Z_{it} . One approach is to assume a particular form of heterogeneity, by imposing a parametric structure on the coefficient functions so that $\beta(Z_{it}) = \beta(Z_{it}; \phi)$, for some parameter vector ϕ , and where $\beta(Z_{it}) = [\beta_0(Z_{it}), \beta_1(Z_{it}), \beta_2(Z_{it}), \beta_3(Z_{it})']'$. For instance, we can assume that $\beta(Z_{it}; \phi)$ are linear functions of Z_{it} with homogeneous parameter vector ϕ , or we can adopt a more specialized form and assume that $\beta(Z_{it}; \phi)$ captures some nonlinear (e.g., transition) effect based on Z_{it} . We, however, adopt the most general approach of an unspecified $\beta_j(\cdot)$. The assumption of an unspecified $\beta_j(\cdot)$ paves the way for us to use the data to select the appropriate form of heterogeneity; a data-driven approach to modeling heterogeneity ensures that we do not bias our empirical results by erroneously imposing a parametric form of heterogeneity that is at odds with the data.⁵

 $^{^{5}}$ Our only general requirement for this data-driven approach is that our coefficient functions are twice continuously differentiable, so that our kernel estimation approach is theoretically valid for estimating the coefficient functions. Given that this assumption can be maintained in many different forms of nonlinear models, this requirement seems fairly innocuous.

2.2 Econometric Identification and Estimation

Under the assumption that the coefficient functions are unspecified, smooth functions of Z_{it} , our empirical model is an applied specification of the smooth varying-coefficient regression model that has received much theoretical attention in recent years (Hastie & Tibshirani 1993, Li, Huang, Li & Fu 2002, Cai & Li 2008). We maintain the assumption that the $\beta_j(\cdot)$'s are twice continuously differentiable functions and adopt a local-linear semiparametric approach to estimate these functions and their first order partial derivatives with respect to a point z in Z_{it} : $\partial \beta_j(\cdot)/\partial z$. In particular, we derive the local-linear estimator from a first order Taylor approximation of $\beta_j(Z_{it})$ around an interior point z^c - for the continuous variables Z_{it}^c in Z_{it} - yielding $\beta_j(Z_{it}) \approx \beta_j(z) + \delta_j(z^c)'(Z_{it}^c - z^c)$ for $\delta_j(z^c) = \partial \beta_j(Z_{it}^c)/\partial z^c$.⁶ Given Z_{it} , we can obtain an estimate of $\beta_j(z)$ and $\delta_j(z^c)$ in a single step using semiparametric kernel methods (Li & Racine 2007).

An important assumption, which has been the subject of burgeoning research in the smooth varying-coefficient literature (Cai, Das, Xiong & Wu 2006, Cai & Li 2008), is the exogeneity of the explanatory variables in the smooth coefficient specification. Undoubtedly, our general account of parameter heterogeneity in (1) removes much of the correlation between the explanatory variables and ϵ_{it} , and thus reduces the potential for endogeneity. Nevertheless, when formulating a model such as (1), it is important to consider instrumental variables estimators that can assess the incidence of endogeneity bias induced by any remnants of uncontrolled correlation between the explanatory variables and ϵ_{it} .

To formally address this important issue of endogeneity, we adopt the semiparametric estimator proposed by Cai & Li (2008) and recently deployed in an empirical macroeconomic context by Delgado et al. (2014). Cai & Li (2008) derive a nonparametric generalized method of moments (GMM) estimator that is a single-step instrumental variables estimator of a standard smooth coefficient regression model, capable of recovering consistent estimates of both the $\beta_j(\cdot)$'s and $\delta_j(\cdot)$'s in the presence of endogeneity of *all* explanatory variables (the environmental variables are assumed to be exogenous). Other nonparametric instrumental variables estimators for the smooth varyingcoefficient model are designed to mitigate the endogeneity with respect to a *single* variable (Cai et al. 2006). At a minimum, we allow for both inbound FDI *and* outbound FDI to be endogenous to domestic investment. Consequently, the Cai & Li (2008) estimator is fitting for our empirical analysis.

For ease of notation, we re-write (1) as

$$I_{it} = X'_{it}\beta(Z_{it}) + \epsilon_{it},\tag{2}$$

where $X_{it} = [1, F_{1,it}, F_{2,it}, Controls'_{it}]'$, and make the assumption that the variables in X_{it} are endogenous, whereas Z_{it} is exogenous; that is, $E[\epsilon_{it}|X_{it}] \neq E[\epsilon_{it}|Z_{it}] = 0$. We denote the dimension of X_{it} with d. Then, the nonparametric GMM estimator proposed by Cai & Li (2008) is based on the conditional moment restriction

$$E[Q(\Omega_{it})\epsilon_{it}|\Omega_{it}] = E[Q(\Omega_{it})\{I_{it} - X'_{it}\beta(Z_{it})\}] = 0,$$
(3)

in which $\Omega_{it} = (W'_{it}, Z'_{it})'$ for a *m*-dimensioned vector of instrumental variables W_{it} that satisfy

⁶The partial effects of the coefficient functions with respect to any discrete variable can be calculated in a second step as the difference in the estimated coefficient as the discrete variable changes from one value to another.

the condition $E[\epsilon_{it}|W_{it}] = 0$, $m \ge d$, and for any function $Q(\cdot)$ for which (3) is satisfied. We follow Cai & Li (2008) and define $Q(\Omega_{it}) = [W'_{it}, W'_{it} \otimes (Z^c_{it} - z^c)'/h_c]'$, in which h_c is a smoothing parameter for the continuous variables in Z_{it} and \otimes is the Kronecker product operator. Letting $U_{it} = [X'_{it}, X'_{it} \otimes (Z^c_{it} - z^c)']'$ and $\alpha = [\beta(z)', \delta(z^c)']'$ be the vector of coefficient functions and their first order partial derivatives, where $\delta(z^c) = [\delta_0(z^c), \delta_1(z^c), \delta_2(z^c), \delta_3(z^c)']'$, we can define the locally weighted orthogonality condition

$$\sum_{i=1}^{n} \sum_{t=1}^{T} Q(\Omega_{it}) (I_{it} - U'_{it}\alpha) K(Z_{it}) = 0$$
(4)

for generalized product kernel $K(\cdot)$ that is of dimension p and admits a mix of continuous and discrete variables (Racine & Li 2004). In particular,

$$K(Z_{it}) = \prod_{c=1}^{p_c} k^c \left(\frac{Z_{it}^c - z^c}{h_c}\right) \prod_{u=1}^{p_u} l^u (Z_{it}^u - z^u; \lambda_u) \prod_{o=1}^{p_o} l^o (Z_{it}^o - z^o; \lambda_o),$$
(5)

in which

$$k^{c}\left(\frac{Z_{it}^{c}-z^{c}}{h_{c}}\right) = \frac{1}{\sqrt{2\pi}} \exp\left[\frac{1}{2}\left(\frac{Z_{it}^{c}-z^{c}}{h_{c}}\right)^{2}\right]$$
(6)

is a univariate Gaussian kernel function used for each of the p_c continuous variables, Z_{it}^c , in Z_{it} ,

$$l^{u}(Z_{it}^{u} - z^{u}; \lambda_{u}) = \begin{cases} 1 & \text{if } Z_{it}^{u} - z^{u} = 0\\ \lambda_{u} & \text{if } Z_{it}^{u} - z^{u} \neq 0 \end{cases}$$
(7)

is a univariate discrete kernel function used for each of the p_u unordered discrete variables, Z_{it}^u , in Z_{it} , and

$$l^{o}(Z_{it}^{o} - z^{o}; \lambda_{o}) = \begin{cases} 1 & \text{if } Z_{it}^{o} - z^{o} = 0\\ \lambda_{o}^{|Z_{it}^{o} - z^{o}|} & \text{if } Z_{it}^{o} - z^{o} \neq 0 \end{cases}$$
(8)

is a univariate discrete kernel function used for each of the p_o ordered discrete variables, Z_{it}^o , in Z_{it} . In the above product kernel setup, h_c is a p_c -dimensioned vector of bandwidths for the continuous variables and λ_u and λ_o are p_u - and p_o -dimensioned vectors of unordered and ordered discrete variable bandwidths.

Then, the local-linear GMM estimator of α is given by

$$\widehat{\alpha} = (S'_n S_n)^{-1} (S'_n T_n), \tag{9}$$

for

$$S_n = (nT)^{-1} \sum_{i=1}^n \sum_{t=1}^T Q(\Omega_{it}) U'_{it} K(Z_{it})$$
(10)

and

$$T_n = (nT)^{-1} \sum_{i=1}^n \sum_{t=1}^T Q(\Omega_{it}) K(Z_{it}) I_{it}.$$
(11)

Hence, $\hat{\alpha}$ is simply a weighted version of a standard parametric GMM regression estimator. Note that like parametric GMM estimation, this semiparametric specification allows for over-identification of parameters by allowing the dimension of W to be larger than that of X. Standard errors for

our estimate of α are obtained from a wild-bootstrap based on 399 replications, which corrects for autocorrelation and heteroscedasticity of unknown form.

2.2.1 Selecting and Interpreting Bandwidth

We follow Delgado et al. (2014) and select the optimal bandwidths, $\{h_c, \lambda_u, \lambda_o\}$, using the method of least squares cross validation. The method of least squares cross validation selects $\{h_c, \lambda_u, \lambda_o\}$ by minimizing the following criterion function

$$\min_{\{h_c,\lambda_u,\lambda_o\}} (nT)^{-1} \sum_{i=1}^n \sum_{t=1}^T \left[I_{it} - X'_{-it} \widehat{\beta}(Z_{-it}) \right]^2,$$
(12)

in which $X'_{-it}\hat{\beta}(Z_{-it})$ is the leave-one-out nonparametric GMM estimate of $X'_{it}\beta(Z_{it})$. It is common to employ a cross validation procedure to select bandwidths in applied research as regression estimates are typically sensitive to choice of bandwidth parameter. Further, the least squares cross validation procedure has been shown to asymptotically select the optimal bandwidth, and has been shown to have impressive finite sample performance that includes the ability to detect nonlinearities in the data (Li & Racine 2007).

In the local-linear least squares context, a continuous nonparametric variable that has nonlinear interactions with other variables is assigned a relatively small bandwidth when chosen with the least squares cross validation criterion. Li & Racine (2004) and Hall, Li & Racine (2007) show that an effective finite sample threshold for interpretation of nonlinear effects is approximately two standard deviations of the data. Variables whose cross validated bandwidth exceeds this threshold are interpreted to have linear interactions with the other nonparametric variables. Hence, examination of the cross validated bandwidths yields important insight into the data driven specification of heterogeneity within the model.⁷

2.2.2 Goodness of Fit Measures

We provide three separate measures of the goodness of fit - an in-sample R^2 , an out-of-sample R^2 , and an out-of-sample average squared prediction error (ASPE) - for our semiparametric domestic investment model. It is important to consider both in-sample and out-of-sample measures of fit because in-sample measures can often be inflated by over-fitting the model; in this case, the insample measures do not necessarily provide a reliable measure of model performance or reliability. We calculate the in-sample and out-of-sample R^2 as cor $\left[I_{it}, X_{it}\hat{\beta}(Z_{it})\right]^2$, the square of the correlation between observed domestic investment and our estimate (fitted values of domestic investment). The ASPE is calculated as $(nT)^{-1}\sum_{i=1}^{n}\sum_{t=1}^{T}\left[I_{it} - X_{it}\hat{\beta}(Z_{it})\right]^2$. To conduct the out-of-sample measures of fit, we first randomly sample 80 percent of the data without replacement, and fit our model. We then use the coefficient estimates to predict on the remaining 20 percent of the data, calculating both an R^2 and ASPE. To avoid any biases induced by our choice of sample split, we repeat this procedure 1000 times and report the average out-of-sample R^2 and ASPE.⁸

 $^{^7{\}rm Formal}$ statistical tests can be used to choose between linear parametric and potentially nonlinear semiparametric models.

 $^{{}^{8}}$ See Racine & Parmeter (2013) for further details, including adjustment to the bandwidth parameter to account for different sample sizes arising from the sample splits.

2.3 Model Specification Testing

In principle, the existence of significant heterogeneities in the relationships between inbound and outbound FDI and domestic investment should engender substantive differences in the estimates from the standard homogeneous-parameter model and our semiparametric model in (1). To formally test whether our semiparametric coefficient estimates are statistically different from a standard, homogeneous-parameter domestic investment model, we adopt the consistent semiparametric model specification testing procedure of Cai, Fan & Yao (2000).⁹ To implement the test, we define the null hypothesis to be

$$H_0: \beta(Z_{it}) - \beta(Z_{it}; \phi) = 0,$$
(13)

and the alternative hypothesis to be

$$H_1: \beta(Z_{it}) - \beta(Z_{it}; \phi) \neq 0.$$
(14)

Notice that for the testing procedure, $\beta(Z_{it}; \phi)$ can be any linear or nonlinear parametric form of $\beta(Z_{it})$. For our purpose, we assume $\beta(Z_{it}; \phi) = \beta$ - a constant, homogeneous parameter vector.

To derive the test statistic, define RSS_0 and RSS_1 to be the residual sum of squares under the null and alternative hypotheses, respectively. That is, from (2), we define RSS_0 to be

$$RSS_0 = (nT)^{-1} \sum_{i=1}^{n} \sum_{t=1}^{T} \left[I_{it} - X'_{it} \hat{\beta} \right]^2$$
(15)

in which $\widehat{\beta}$ is our parametric estimate of β from the homogeneous-parameter domestic investment model, and

$$RSS_1 = (nT)^{-1} \sum_{i=1}^n \sum_{t=1}^T \left[I_{it} - X'_{it} \widehat{\beta}(Z_{it}) \right]^2$$
(16)

in which $\hat{\beta}(Z_{it})$ is our semiparametric estimate of $\beta(Z_{it})$ from the flexible domestic investment model in (1). The test statistic is then defined as

$$T_n = \frac{RSS_0 - RSS_1}{RSS_1}.$$
(17)

It is clear that $T_n = 0$ under the null hypothesis, but that $T_n > 0$ under the alternative hypothesis. Hence, T_n provides a way to test for correct specification of a parametric restriction on the coefficient functions. We follow Cai et al. (2000) and approximate the distribution of T_n under the null hypothesis using a wild bootstrap procedure in which we resample the residuals from the semiparametric specification and construct our bootstrap sample using standardized residuals. We obtain a *p*-value from this test by calculating the frequency of $\{T_n^* \ge T_n\}$, where T_n^* is the bootstrapped test statistic, and reject H_0 at the 5 percent level if the *p*-value is less than or equal to 0.05.

If this Cai et al. (2000) test leads us to reject the homogeneous parameter model in favor of our semiparametric model, we have statistical evidence that any results obtained from the former model are biased - as a result of significant heterogeneities in the relationship between FDI and domestic investment - and consequently should not be used for statistical inference or policy analysis.

 $^{^{9}}$ See Ullah (1985) and Li & Racine (2007) for more general discussions on this test.

3 Data

3.1 Overview

Our data primarily come from the 2012 World Development Indicators (WDI) database published by the World Bank. Our sample is an unbalanced panel of 137 developed and developing countries over the period 1984-2010, which is substantially larger in country-level scope and contains more recent data than the samples used in previous studies. For example, the samples used by Feldstein (1995) and Desai et al. (2005) were restricted to OECD nations; the former sample contains about 18 OECD countries and covers the 1970 and 1980 decades, whereas the latter sample contains about 26 OECD countries and covers the 1980 and 1990 decades. Our expansion of this dataset to include both developed and developing countries constitutes a substantial departure from previous research, and allows us to ascertain whether there are differences in the effects of inbound and outbound FDI both within and across developed and developing nations. If there exists heterogeneous relationships between FDI and domestic investment, then the implied policy prescriptions from studies on developed countries may not be useful to developing nations, and vice versa. Moreover, from a developmental perspective, it is more important to understand the relationship between FDI and domestic investment in developing countries.

It is well known that parameter estimates from contemporaneous panels can be plagued by serial correlation and the effects of outliers induced by business cycles and other annual fluctuations. We therefore average the annual data into a 3-year panel. We also create a 9-year time-averaged panel to render a more direct comparison between our analysis and those of Feldstein (1995) and Desai et al. (2005). Note that the 3-year and 9-year averaged panels permit an equal number of years to be allotted to each of the new time dimensions. The 3-year and 9-year averaged panels should capture relationships between FDI and domestic investment over shorter and longer horizons, respectively.

Averaging the panel over 3-year periods provides a sample size of 727 observations, whereas the 9-year panel has 272 observations. The effective sample size used for each regression, however, is further reduced because of data limitations for different sets of control variables. Nevertheless, our use of a wild bootstrap to compute the standard errors mitigates, among other things, the lack of precision of the estimates that is usually a by-product of small sample estimation.

3.2 Outcome and Explanatory Variables

Domestic investment - our outcome variable - is defined as gross capital formation as a percentage of GDP. Gross capital formation includes net changes in inventories as well as fixed capital formation that includes land developments, plants and machinery investments, infrastructural development, and public, private, and commercial construction. Both Feldstein (1995) and Desai et al. (2005) use an identically defined measure of domestic investment (their data, however, come from the OECD; we address potential differences across data sources in Subsection 5.2).

Inbound FDI and outbound FDI - our key explanatory variables - are respectively defined as the net inflows and net outflows of FDI as a percentage of GDP. Our supplementary explanatory variables should control for additional factors that are correlated with both FDI and domestic investment, to mitigate omitted variable bias in the estimated effects of FDI on domestic investment. We follow Feldstein & Horioka (1980), Feldstein (1995) and Desai et al. (2005) and include gross national savings, the growth rate of GDP, the inflation rate, the log of the population, and the real interest

rate as control variables. Gross savings is calculated as gross national income less total national consumption, plus net transfers. GDP growth is the annual percentage change in real GDP, and the inflation rate is the annual percentage change in the consumer price index. The log of the population - a proxy for the size of the country - is the natural logarithm of the total population, and the real interest rate is defined as the lending interest rate adjusted for inflation.

3.3 Environmental Variables

Recall that environmental variables are the coefficient variables (Z_{it}) , and are assumed to induce heterogeneity in the effects of all the explanatory variables on the outcome variable. In light of existing research (see, e.g., Borensztein et al. 1998, Durlauf 2001, McCloud & Kumbhakar 2012, Delgado et al. 2014), our perspective is that corruption, schooling, and unobservable country and time effects are important environmental factors in understanding macroeconomic relationships. The index of corruption comes from the International Country Risk Guide published by Political Risk Services, and is defined as "actual or potential corruption in the form of excessive patronage, nepotism, job reservations, 'favor-for-favors', secret party funding, and suspiciously close ties between politics and business."¹⁰ This index ranges from 0 to 6, with 0 representing most corrupt and 6 representing the least corrupt.¹¹ To provide some perspective, the average level of corruption from 1984-2010 in Denmark is 5.81. The same measure for the United States is 4.54, whereas average corruption in Sierra Leone is 2.02. In Table 1 we document the average level of corruption for each country in our sample. In addition, this corruption index has inter- and intra-country variation, which aids in identifying the role of corruption in any relationship between domestic investment and FDI.

We use two measures of human capital: enrollment rates and the literacy rate. We explore both primary and secondary enrollment rates, and both are defined as the total number of students who are enrolled in primary (or secondary) school and are of primary (or secondary) school age, as a percent of the total population of the same age cohort. Both measures exclude enrollment of over- or under-aged students. The literacy rate is the percentage of the population aged 15 and above who possess basic reading and writing skills.

Examples of unobservable country effects are productivity shocks and FDI-related government policies. It is well documented that the governments of many host countries, particular developing countries, try to attract FDI by offering tax credits, infrastructure subsidies and import duty exemptions to foreign investors (see, e.g., World Bank 1997*a*, World Bank 1997*b*, UNCTAD 2000). These incentives are predicated on the governments' presumption that more inbound FDI engenders, among other things, increase in productive domestic activities. Thus, FDI-related government policies can influence the relationship between domestic investment and FDI. We use an unordered country variable and ordered year categorical variable to control for unobserved country- and timespecific heterogeneity in *all* the coefficient functions. Thus, we control for country and time-varying effects - i.e., fixed effects - in a non-neutral fashion. That is, in contrast to the orthodox case of a homogeneous coefficient fixed effects panel specification, we do not assume that the country and year effects have a neutral effect on the model by influencing the intercept only.¹² Our country and

¹⁰This corruption index is available for 1984 and onwards, hence restricting the beginning year of our dataset.

¹¹This measure of corruption was used previously in an macroeconomic growth context by Mauro (1995), McCloud & Kumbhakar (2012), and Delgado et al. (2014), to name only a few.

 $^{^{12}}$ Moreover, the Racine & Li (2004) kernels allow for interaction of unknown form between both fixed effects and variables that vary both across country and over time, so that our control of country- and year-specific effects is not restricted to additively separable effects.

year indicators are therefore capable of capturing *any* country and time-varying factors that induce heterogeneity in the intercept *and* slope coefficients across countries and time.¹³ Consequently, innumerable time-invariant measures of institutional quality and country-specific government policies are subsumed in our fixed effects in Z_{it} .

3.4 Basic Data Analysis

We begin with a cursory bivariate analysis of the main variables of interest in our data. Figure 1 shows unconditional correlations between domestic investment and inbound and outbound FDI, for a cross-section of 113 developed and developing countries, averaged over the period 1984-2010. For the full sample, inbound and outbound FDI have a positive and significant correlation with domestic investment. However, the correlation between outbound FDI and domestic investment seems quite sensitive to sample and/or outliers, which may be a symptom of parameter heterogeneity. For the subsamples of OECD and non-OECD countries, inbound FDI also has a positive and significant association with domestic investment, whereas the association between outbound FDI and domestic investment depends heavily on the sample. Thus, Figure 1 suggests that the *nature* of the relationship between inbound FDI and domestic investment may be quite different from its outbound FDI counterpart.

We present an alternative inspection of the general relationship between domestic investment and both inbound and outbound FDI in Figure 2. We consider the average level of domestic investment for countries above and below the median levels of inbound and outbound FDI (this results in four separate groups). Figure 2 clearly shows that countries that have higher inbound FDI, regardless of high or low outbound FDI, have relatively high domestic investment. Countries with low inbound FDI, but relatively high outbound FDI have relatively lower domestic investment rates than countries with low levels of both inbound and outbound FDI. However, it is prominently clear that countries with relatively high levels of inbound and outbound FDI have the highest levels of domestic investment. In essence, maintaining outbound FDI - either above or below its median value - and increasing inbound FDI from below to above the median is associated with an increase in domestic investment. Taken as a whole, Figure 2 seems to concur with Figure 1 that inbound FDI is beneficial for domestic investment (Bosworth & Collins 1999). In addition, Figure 2 implies an existence of a heterogeneous complementarity relationship between domestic investment and inbound FDI across many countries. Figure 2, however, reveals a different *nature* of the relationship between domestic investment and outbound FDI. On the one hand, maintaining inbound FDI above its median value and increasing outbound FDI from below to above the median, is associated with an increase in domestic investment suggesting possible net complimentary effects of outbound FDI in some countries. On the other hand, maintaining inbound FDI below its median value and increasing outbound FDI from below to above the median, is associated with a decrease in domestic investment suggesting possible substitution effects of outbound FDI in some countries.¹⁴ Thus, these average cross-country patterns in Figure 2 may be manifestations of a significantly *fluid* relationship - existence of substitution and complementarity - between outbound FDI and domestic investment.

In Figure 3, we present time series plots of average domestic investment as well as both average

¹³With exception of the country and year indicators, we require the variables in Z_{it} to vary across both *i* and *t*, thus allowing our country and year indicators to absorb all country or time-varying factors that may lead to heterogeneity in the coefficient functions.

¹⁴Considering only developing countries does not change the general correlations shown in Figure 2.

inbound and outbound FDI to provide a glimpse into the temporal evolution of these variables over the last several decades. We plot the average time series for all countries, as well as averages for OECD and non-OECD countries. While the figure shows some temporal fluctuations in domestic investment over the past several decades, there does not appear to exist much difference in average domestic investment across OECD and non-OECD countries. We see clear downward trends in domestic investment in the late 1990's and late 2000's, no doubt a reflection of the Asian Financial Crisis and the Great Recession. However, for both inbound and outbound FDI, prior to the mid-1990's the level of FDI flows was relatively low, and there was relatively little temporal fluctuations or divergence between OECD and non-OECD countries. After the mid-1990's, and particularly post-2000, we clearly see relatively large temporal fluctuations (also because of the Asian Financial Crisis and the Great Recession) as well as heterogeneity across OECD and non-OECD countries. For outbound FDI, most of the fluctuations occur in OECD countries, indicating a clear divergence in outbound FDI between OECD and non-OECD countries. While these time series plots further reveal the existence of heterogeneity in FDI flows across countries as illustrated in Figures 1 and 2, they more importantly provide preliminary insight into the volatility in FDI flows over time, particularly in the post-2000 period.

Overall, our basic data analysis hints at the existence of relationships between FDI and domestic investment that are not found in existing studies. Further, many past studies are based on pre-2000 data; Figure 3 clearly indicates evolution in FDI flows post-2000, perhaps because of changes in investment climate following the Asian Financial Crisis, which is likely to effect change in the interactions between domestic investment and FDI. Therefore, the raw data strongly suggest a need to adjust for non-neutral time-specific effects in analyzing corruption- or schooling-induced heterogeneity in the relationship between FDI and domestic investment. In the ensuing sections, we use our semiparametric model in (1) to investigate empirically the *existence*, *nature*, and *degree* of heterogeneity across developed and developing economies in the relationships between inbound and outbound FDI and domestic investment.

4 Baseline Results

If all the conditioning variables in model (1) are assumed to be exogenous, the Cai & Li (2008) nonparametric GMM estimator collapses to the semiparametric estimator for the standard smooth varying-coefficient model. In this section, we estimate various standard smooth varying-coefficient models that rely on the aforementioned continuous controls - which are assumed to be exogenous - and fixed effects for identification. Our general, flexible control of heterogeneity across countries and time leads to a decrease in the possibility of unobservables being captured in the error causing a correlation between our regression error and conditioning variables. In the subsequent section, we compare these results to nonparametric GMM estimates from model (1) with endogenous regressors.

For all model specifications, we obtain observation-specific coefficient estimates; however, we tabulate these results by reporting only the coefficient estimate and its corresponding observation-specific standard error at the 25th, 50th (median), and 75th percentiles; reporting the estimates at these quantiles allows for a concise summary of the interquartile range of magnitudes for the estimated coefficients, as well as an analysis of statistical significance. We report bootstrapped standard errors directly below each estimate, and highlight in bold the estimates that are statistically significant at the 5 percent level.

4.1 Existence of Heterogeneous Parameter Estimates

To examine empirically the *existence* of heterogeneous estimates in the nexus between domestic investment and FDI that vary non-neutrally across country-year observations, we consider the smooth coefficient model in (1) with *only* country and year indicators as discrete environmental variables; we semiparametrically fit this model with the full set of control variables to the 3-year and 9-year averaged panel datasets.¹⁵ The 3-year panel has 562 total country-year observations, whereas the 9-year panel has 220 country-year observations. Table 2 contains results for our semiparametric (local-constant) estimates of this specific smooth coefficient model.

In Table 2, there is a clear absence of statistical parity among the reported percentiles for both inbound and outbound FDI; for example, the 95 percent confidence interval for the estimated 25th percentile associated with inbound FDI comfortably excludes the other corresponding percentiles. We display the distribution and statistical significance of each point estimate in Figure 4 for the 3-year panel, to provide more detailed distributional insight into our estimates.¹⁶ Figure 4 shows that *nearly all* of the point estimates for inbound and outbound FDI are statistically significant, and there is no clustering of these estimates. These results therefore establish the *existence* of substantial heterogeneities across developed and developing countries in the associations between domestic investment and inbound and outbound FDI. The signs of the reported percentiles signals that inbound FDI has a significant complementarity effect and outbound FDI has significant substitution effect on domestic investment. We, however, err on the side of caution in using these results to draw conclusive inferences on the *nature* and *degree* of heterogeneity because the model does not incorporate corruption or schooling.

Turning to the other control variables, Table 2 shows that there is also an absence of statistical parity among the reported percentiles for each of these controls, which suggests added parameter heterogeneities in the domestic investment function. Distributional summaries in Figure 4 for the 3-year panel, and those for the 9-year panel (which we omit), confirm that sizable heterogeneities exist in these point estimates.

Overall, the statistical significance of nearly all of the reported coefficient estimates, regardless of which panel is used, is a noteworthy departure from the cross-section parametric model counterparts with homogeneous parameters in Feldstein (1995) and Desai et al. (2005). This statistical significance suggests that country- and time-specific effects, as well as FDI and the control variables, are important

$$\widehat{\beta}(z) = (X'K(Z)X)^{-1}X'K(Z)I$$

for the discrete product kernel function

$$K(Z) = \prod_{u=1}^{p_u} l^u (Z_{it}^u - z^u; \lambda_u) \prod_{o=1}^{p_o} l^o (Z_{it}^o - z^o; \lambda_o).$$

The only difference between a standard (parametric) linear estimator and the local-constant smooth coefficient estimator is the kernel weight function. Hence, the local-constant estimator nests the ordinary least squares estimator as a special case. See Li et al. (2002) or Li & Racine (2007) for details.

¹⁶For each variable, the plots in Figure 4 show the observation-specific point estimates on the 45 degree line, with observation-specific bootstrapped confidence bounds placed above and below each point. Location of the point estimate relative to the vertical axis identifies the sign of the estimate, and the range of the estimates can be seen from their position relative to the horizontal axis. Statistical significance is shown for each observation if the horizontal axis lies outside of each confidence interval, and the density of the observations can been seen based on their proximity to each other. See Henderson, Kumbhakar & Parmeter (2012) for further information.

¹⁵The absence of any continuous variables in Z reduces our local-linear least squares smooth coefficient estimator to a local-constant least squares smooth coefficient estimator. In particular, we no longer obtain a vector of coefficient functions and partial effects simultaneously; rather, the local-constant estimator provides only an estimate of $\beta(z)$ via

in explaining variation in domestic investment over shorter and longer time horizons. Our goodness of fit measures show a high in-sample R^2 for both panel regressions, suggesting that semiparametric modeling of observation specific heterogeneous coefficients leads to in-sample over-fitting. However, the out-of-sample R^2 is of appropriate magnitude in both 3-year and 9-year panels: 0.5497 in the 3-year panel and 0.3226 in the 9-year panel. The ASPE is quite small in both models. Both of these latter measures suggest that our heterogeneous semiparametric models provide a good out-of-sample fit to the data. Moreover, the Cai et al. (2000) model specification test has a *p*-value of 0.0000 for both the 3-year and 9-year models, which suggests a strong rejection of the null hypothesis of a constantparameter model specification for the domestic investment function. Hence, at a minimum, we find empirical support in favor of our semiparametric model, which allows for parameter heterogeneity in the domestic investment function.

4.2 The Role of Corruption and Schooling Enrollment

To reiterate, our above-mentioned discrete semiparametric specification does not allow for analyses of the *nature* and *degree* of corruption- or schooling-induced heterogeneity in the FDI and domestic investment relationship; this specification merely models general parameter heterogeneity across countries and time. We therefore estimate our expanded semiparametric regressions that include corruption or schooling and the country and year indicators as environmental variables; we present these results in Tables 3 to 6. To present concise summaries, we only report quartile results for inbound and outbound FDI, and savings, as well as the partial effect of corruption and schooling on each of the coefficients for these three variables. The results for all other conditioning variables can be furnished on request.

4.2.1 Corruption

Table 3 reports a summary of the estimates from the models that include our index of corruption in the Z vector.

Inbound FDI We find that across quartiles of estimates, inbound FDI continues to have a heterogeneous and significantly positive association with domestic investment for both the 3-year and 9-year averaged panels. Thus, in *many* countries, the *nature* of the relationship between inbound FDI and domestic investment is one of complementarity, over shorter and longer time periods. This complementarity finding lends strong empirical support for the use of pro-FDI policies in, particularly, developing countries that struggle to parlay their natural comparative advantage to foster domestic investment, and hence economic development. In comparison to the results in Table 2, however, we find that *all* the reported percentiles for the complementarity effects are now substantially smaller for both panels. For example, the 25th percentile decreases by about 98 percent - from 0.2609 to 0.0046 - for the 3-year panel, and by about 88 percent - from 0.2737 to 0.0322 - for the 9-year panel. Hence, the omission of corruption from the discrete semiparametric model leads to a sizable overestimation of the complementarity association between inbound FDI and domestic investment for *many* observations in our sample. More important, these results lend credence to our view that corruption matters to the extent that it induces heterogeneity in the relationship between inbound FDI and domestic investment for both developed and developing countries.

Our results on the relationship between inbound FDI and domestic investment are different - in

nature and *degree* - from past results. First, we find that the heterogeneous complementarity effect of inbound FDI is generally significant over shorter and longer time periods and across both developed and developing countries, whereas previous research finds an insignificant effect for OECD countries (Feldstein 1995, Desai et al. 2005), an unstable complementarity effect for developing countries (Borensztein et al. 1998), and a short-run homogeneous substitution effect but long-run neutral effect for developed countries and short-run neutral effect but long-run homogeneous complementarity effect for developing countries (Wang 2010). Second, we find that the degrees of the complementarity effects of inbound FDI are substantially smaller - and in particular significantly different from *unity* - than previously identified (see, e.g., Bosworth & Collins 1999). In our 3-year averaged panel, for example, the estimates suggest that a one percent increase in inbound FDI is associated with about a 0.22 percent increase in domestic investment, at the median. Hence, we do not find that a dollar of inbound FDI translates into a dollar of domestic investment; rather, we observe a more modest translation from inbound FDI to domestic investment.

To get a better understanding of the role of corruption in the heterogeneous complementarity association between inbound FDI and domestic investment, we examine our estimates of the partial derivative of $\beta(Z_{it})$ with respect to corruption. To proceed, recall that an increase in the corruption index is interpreted as a *decrease* in the level of corruption. For the 3-year panel, the partial effect of a reduction in the level of corruption on the inbound FDI coefficient is negative and significant in the 3-year panel at the 25th and 50th percentiles, and is insignificant at the 75th percentile. In particular, we find that a one unit decrease in the level of corruption is associated with approximately 0.26 and 0.06 percent decrease at the 25th and 50th percentile, respectively, in the complementarity association between inbound FDI and domestic investment. In essence, over a shorter time period, a reduction in corruption leads to a decrease in the complementarity effects of inbound FDI on domestic investment for *many* countries but has no effect on such complementarity that exists in other countries. Over a longer time period, a reduction in the level of corruption leads to a decrease, or no change in the complementarity effects of inbound FDI on domestic investment for *many* countries but has no effect on such complementarity that exists in other countries. Over a longer time period, a reduction in the level of corruption leads to a decrease, increase, or no change in the complementarity effects of inbound FDI on domestic investment. These partial estimates also indicate that the resultant bias induced by omitting corruption from the coefficient function differs across countries and time periods, and is either positive, negative, or zero.

A simple yet informative way to determine whether the effects of corruption on the complementary effects of inbound FDI are consistent with the prediction of the General Theorem of Second Best is through the use of joint kernel density of the inbound FDI estimated coefficients and partials and corruption as in Figure 5. Several features of these densities point to second-best traits: (1) imposing *a priori* parametric structure on $\beta(Z_{it})$ would more likely lead to erroneous results; (2) there is an absence of a unique global optimum. Therefore, the policy of introducing or strengthening anticorruption measures - as implied by recent UNCTAD surveys - will not increase the complementary effects of inbound FDI on domestic investment in *all* countries. Hence, while curbing corruption is generally considered to be important in forging positive linkages between domestic investment and inbound FDI, our results signal a complex interaction between corruption and domestic investment, which further points towards country-specific, second-best, institutional policies.

Outbound FDI We find that in the 3-year panel, outbound FDI has a negative and significant association with domestic investment at the 25th and 50th percentiles, but a positive and significant association at the 75th percentile. In comparison to the results in Table 2, the estimates reflect a shift in the interquartile range of coefficients in the positive direction, with the magnitude of the

25th and 50th percentile substitution effects substantially increasing from -0.7291 and -0.4013 to -0.5912 and -0.1208, respectively. We find a generally insignificant association between outbound FDI and domestic investment in the 9-year panel, with a positive and significant association at the 75th percentile. Thus, controlling for corruption induces a significant reversal in the substitution effect of outbound FDI within some countries and over different time periods. These results lend credence to our view that corruption matters to the extent that it induces heterogeneity in the relationship between outbound FDI and domestic investment for both developed and developing countries.

Our results therefore suggest a *fluid* relationship between outbound FDI and domestic investment: across developed and developing countries, substitution and complementarity effects of outbound FDI exist, and depends on the level of corruption, and within some countries these effects change direction over different time horizons. The substitution effects are disproportionately larger in absolute value than the complementarity effects. Our finding of a *fluid* relationship between outbound FDI and domestic investment is not unique to our sample of non-OECD countries - it exists also in OECD countries. Hence, our finding on the *nature* of the relationship between outbound FDI and domestic investment differs markedly from the result of comparable studies. Feldstein (1995) and Desai et al. (2005) have found that one dollar of outbound FDI substitutes for one dollar of domestic investment in OECD countries. We find that in OECD countries for which outbound FDI substitutes for domestic investment, the Feldstein (1995) dollar-for-dollar hypothesis does not hold. In fact, our estimates of the substitution effects of outbound FDI are significantly smaller than unity.

Over a shorter time period, a reduction in the level of corruption leads to a significant decrease in the effect of outbound FDI on domestic investment in a few countries and a significant increase in many countries. Over a longer time period, a reduction in the level of corruption leads to no change in the effect of inbound FDI on domestic investment in a few countries and a significant increase in many countries. These results do indicate a nonlinear effect of corruption on the outbound FDI and domestic investment relationship. As in the case of inbound FDI, the joint kernel densities of the outbound FDI estimated coefficients and partials and corruption in Figure 6 show features that are consistent with the prediction of the General Theorem of Second best.

Our empirical finding of a *fluid* relationship between outbound FDI and domestic investment, coupled with the added result that a reduction in the level of corruption induces nonlinear effects on the interactions between domestic investment and outbound FDI, has an important implication. Small variations in outbound FDI can induce large variations in domestic investment, and hence be a source of macroeconomic instability within the domestic economy. Considerable thought should therefore be given to appropriate second-best institutional policies that can smooth the deleterious effects of outbound FDI on domestic investment.

Controls Our empirical results show that the savings retention coefficient has a heterogeneously positive and significant association with domestic investment in many countries. Thus, the savings rate appears to be a main determinant of domestic investment within both developed and developing countries, although the size of its impact on domestic investment differs substantially across countries. However, even over a longer time horizon, the estimated savings retention coefficients are significantly smaller than those reported by previous results, which include the popular Feldstein-Horioka finding that the amount of OECD savings invested domestically ranges from 80 to 90 percent. Our estimates suggest that at most 30 percent of a country's savings rate contributes to domestic investment in that country. Thus, our present finding reveals that a major portion of the savings of both developed

and developing countries seems to be invested in other countries, and not in the country of origin. A plausible rationale is that investors have become increasingly adept at devising ways of overcoming the natural and manufactured barriers to the movement of international capital that existed in the latter half of the Bretton-Woods era.¹⁷ In essence, this present paper provides empirical evidence that is more consistent with the more nuanced hypothesis that international capital mobility is skewed toward perfect than imperfect.

The estimated percentiles of the savings retention coefficient are similar to those from the discrete semiparametric models, which suggests that corruption may not be a main source of heterogeneity in the relationship between savings and domestic investment. Indeed, our partial estimates show that the savings retention coefficient exhibits either little or no sensitivity to changes in the level of corruption. For example, we find that a 1 point reduction in the level of corruption is associated with a statistically significant increase in the savings retention coefficient of approximately 0.04 percent at the median for the 3-year panel. We find an insignificant positive effect of a reduction in corruption on the savings retention coefficient at the median for the 9-year panel. In general, our results suggest that for some countries the positive link between savings and domestic investment strengthens with reductions in corruption; this result may be because with lower corruption, savings are more efficiently transformed into investments in some countries. For other countries, however, a reduction in corruption either weakens or renders no change to the positive effect on savings on domestic investment.

Model Assessment Overall, the statistical significance of many coefficient estimates and their corresponding partials, including the estimates omitted from Table 3, strongly supports our hypothesis that corruption is a crucial factor that induces heterogeneity in the relationship between FDI and domestic investment. More important, we find corroborative evidence in both 3-year and 9-year models that the bandwidth on our corruption index is less than twice the standard deviation of the corruption index for each sample, confirming our view that corruption has a nontrivial and nonlinear interaction with the other conditioning variables. In addition, we obtain a *p*-value of 0.0000 for the model specification test of parameter constancy for both 3-year and 9-year corruption models. Rejection of the null hypothesis of a constant parameter setup is not surprising given our statistically significant heterogeneous estimates, and the magnitudes of our cross validated bandwidths suggest nonlinear interactions between our environmental variables and the conditioning variables. In terms of model performance, we find that the in-sample R^2 for the 3-year and 9-year panel specifications is slightly lower than its counterparts in the previous discrete specification, which suggests that less over-fitting is exhibited by the corruption model.

4.2.2 School Enrollment

Turning now to the role of human capital in the FDI and domestic investment relationship, we first measure human capital using both the primary and secondary school enrollment rates. Tables 4 and 5 present a summary of these results. Using the primary (secondary) school enrollment rates reduces our 3-year and 9-year samples to 415 (312) and 186 (158) observations, respectively.

Inbound FDI For both primary and secondary school enrollment rates, we continue to find significant and heterogeneous complementarity association between inbound FDI and domestic investment

¹⁷Recall that the popular Feldstein-Horioka finding is based on the sample period 1960 to 1974.

across developed and developing countries. In comparison to the results in Table 2, we find for both measures of human capital that the interquartile range in the 3-year panel is substantially smaller - by approximately 80 percent in one case - and has shifted towards zero; specifically, the interquartile range in the 3-year panel when using the primary enrollment rate is 0.0718 with a median value of 0.0520, whereas the range for the secondary enrollment rate is 0.1136 with a median value of 0.0995. We find this range is also approximately 80 percent smaller in the 9-year panel associated with primary enrollment rate. These results bolster our hypothesis that human capital is important in the association between inbound FDI and domestic investment. In addition, ignoring the role of human capital renders a sizable upward bias in the complementarity relationship between inbound FDI and domestic investment. We find mostly negative effects of an increase in primary enrollment rates on the inbound FDI coefficient, indicating that countries with higher primary enrollment rates have a lower dependence on inbound FDI for spillovers into domestic investment. The joint kernel densities of the inbound FDI estimated coefficients and partials and primary and secondary school enrollment rates, which we omit, show features that are consistent with the prediction of the General Theorem of Second Best.

Outbound FDI We find *fluid* effects of outbound FDI on domestic investment across both measures of enrollment rates for both panel specifications. In particular, using primary enrollment rates, we find a generally complementary association between outbound FDI and domestic investment in the 3-year panel, but a strong substitution association in the 9-year panel. Using secondary enrollment rates, we find mostly insignificant associations between outbound FDI and domestic investment with only a few countries realizing complementary (substitution) effects for the 3-year (9-year) panel. In all cases, we find mixed effects of a marginal increase in enrollment rates on the outbound FDI and domestic investment relationship, suggesting that in some countries, increases in enrollment rates have the opposite or neutral effect. In general, these results lend support to our second hypothesis that human capital has a nonlinear role in the relationship between outbound FDI, the joint kernel densities of the outbound FDI and domestic investment. As in the case of inbound FDI, the joint kernel densities of the outbound FDI estimated coefficients and partials and primary and secondary school enrollment rates, which we omit, display patterns that are most consistent with a second-best interpretation for the effect of human capital on the outbound FDI and domestic investment relationship.

Controls As identified in the corruption models, we find that the savings retention coefficient has a robustly positive and significant association with domestic investment across developed and developing countries. The interquartile range on the savings coefficient is slightly smaller than in the corruption models, but the qualitative effects are consistent. At almost all reported percentiles, a marginal increase in the enrollment rate is associated with a significant decrease in the savings and domestic investment relationship.

Model Assessment We find that despite the reduction in sample size, the performance of our enrollment rate models is commensurate with our corruption specification. In contrast to our model with the index of corruption, the cross validated bandwidths indicate that enrollment rates have a generally linear interaction with the other variables in the model. This interpretation, however, does not necessarily point towards a particular parameterization of such a specification. In each enrollment

rate model, we reject the null hypothesis of the baseline parametric specification with a p-value of 0.0000 except for the 9-year primary school semiparametric specification. In this latter model, the p-value from our specification test is 0.1479, which suggests that the semiparametric specification is not necessarily statistically preferred to the homogeneous parameter model. A p-value that exceeds conventional levels of significance is not surprising given the statistical parity among the estimated 25th, 50th and 75th percentiles that correspond to each of the inbound and outbound FDI and savings variables.¹⁸ Note that this p-value does not necessarily imply that the baseline parametric model is correctly specified; the implication of this test is that the semiparametric specification does not provide a statistically better fit to the 9-year panel data.¹⁹

4.2.3 Literacy

We next use the literacy rate as an alternative measure of human capital and report the corresponding empirical results in Table 6. Deployment of the literacy rate considerably reduces our 3-year and 9-year samples to 150 and 131 observations, respectively. The reduced samples render the literacy rate less preferred to enrollment rates as our measure of human capital, but is nevertheless useful as an alternative proxy to enable qualitative comparisons.

Using the literacy rate, we continue to find inbound FDI has a positive association with domestic investment. However, unlike the enrollment rate models, we now find that the marginal effect of an increase in human capital on the inbound FDI coefficient is mixed in both sign and significance. We again find evidence of a *fluid* relationship between outbound FDI and domestic investment: a negative relationship in the 3-year panel, but a positive relationship in the 9-year panel. For many countries, an increase in the literacy rate has a negative effect on the outbound FDI coefficient across the panel specifications. Overall, our results indicate human capital induces nonlinear heterogeneity in the FDI-domestic investment relationship. Thus, these finds confirm the empirical validity of our two hypotheses. All the joint kernel densities of the FDI estimated coefficients and partials and literacy rate, which we omit, display second-best traits.

Also, we continue to find the savings rate has a positive association with domestic investment and a negative marginal effect of an increase in human capital on the savings coefficient. Our goodness-offit measures are commensurate with those from previous semiparametric models, and that we reject the null hypothesis of a homogeneous parameter model with a *p*-value of 0.0576 and 0.0000 for the 3-year and 9-year panel specifications, respectively.

4.3 Developed versus Developing Countries

As previously mentioned, existing studies analyze the association between FDI and domestic investment using data from developing countries (Borensztein et al. 1998), developed countries (Feldstein 1995, Desai et al. 2005), or both developed and developing countries (Wang 2010). To ensure better comparability with these studies, we analyze estimates across OECD countries and non-OECD coun-

¹⁸The 95 percent confidence interval for the 75th percentile estimate that is associated with inbound FDI, outbound FDI and savings is [0.1606, 0.3271], [-0.2885, -0.1137], and [0.0551, 0.1403], respectively. Notice that each of these confidence intervals contains the estimates of their 25th and 50th percentile counterparts.

¹⁹Thus, certain parameter restrictions may improve the fit of our semiparametric model to the data that include human capital. Note however that although some reported percentiles, and hence specific observation units, are statistically insignificant, our flexible semiparametric model does not allow for restrictions on estimates that correspond to a particular country within a particular year. Therefore, imposing certain parameter restrictions in our present framework can be a nontrivial and taxing undertaking.

tries from each of our regression models; this exercise should allow us to see if there are fundamental differences between OECD and non-OECD countries in the effects of inbound and outbound FDI on domestic investment. Existing studies use subsamples of OECD and non-OECD countries to estimate the relationship between FDI and domestic investment. However, the observation-specific estimates generated from our semiparametric models preclude the use of such pre-estimation sample-splitting, which reduces degrees of freedom and can lower precision of estimates. To provide a concise representation of these differences, we use boxplots for each set of coefficient functions across OECD and non-OECD countries.

Figure 7 shows juxtaposed OECD and non-OECD boxplots for the estimated inbound FDI coefficient from (i) the discrete model (top panel) and (ii) the model with corruption as the main heterogeneity variable (bottom panel). Both plots are for the dataset averaged over 3-year periods. The top panel suggests that there are not substantial differences between developed and developing countries in the effect of inbound FDI on domestic investment. However, the bottom panel with the estimates from the corruption model shows substantial differences between the distribution of estimated inbound FDI coefficients from developed and developing countries. In particular, while both developed and developing countries have generally positive coefficients, a larger fraction of developing countries enjoy much larger complementarity effects. These results strongly suggest that some developing countries are better at extracting and transforming benefits from inbound FDI.²⁰

We provide a similar analysis of the outbound FDI coefficients in Figure 8 for the discrete (see top panel) and corruption (bottom panel) models. The story is largely the same. The top panel shows no substantial differences in the outbound FDI estimates across developed and developing countries in the discrete coefficient model. For the corruption model, however, we find that the impact of outbound FDI on domestic investment is much smaller in developed countries. We see that the median is higher in absolute value and the interquartile range is wider for developing countries, indicating that any crowding out effects of outbound FDI on domestic investment are particularly severe in some developing countries; this is intuitive because resources are relatively more scarce in developing countries, so any resources invested abroad are more likely to come at the expense of reducing resources invested domestically.²¹

In summary, these boxplots show that our two hypotheses on the nexus between FDI and domestic investment are empirically valid within both developed and developing countries. Moreover, these boxplots in Figures 7 and 8 point to fundamental, institution-induced differences between developed and developing countries in the effects of inbound and outbound FDI on domestic investment. In essence, these boxplots reveal another way in which results from domestic investment models that do not incorporate institutional quality as a source of parameter heterogeneity - such as our discrete model - can yield misleading inferences on developed versus developed countries.

5 Sensitivity Analysis

A few legitimate reservations regarding our baseline results are in order. *One*, it is well known that neglected parameter heterogeneity (from unobserved factors), and more generally the omission of factors that are correlated with both FDI and domestic investment, can introduce correlation between

²⁰Boxplots for each of our human capital proxies - primary schooling, secondary schooling, and literacy - tell a similar story as our corruption model, namely that inbound FDI boosts domestic investment by a larger amount in a higher percentage of developing than developed countries.

²¹Our findings are qualitatively similar for the models using secondary schooling and literacy.

explanatory variables and the error term. Other possible sources of bias in the domestic investment equation are reverse causality and measurement errors. For example, the existence or absence of economies of scale from domestic investment can attract or deter inbound and outbound FDI. Measurement errors in economic variables are inevitably commonplace in aggregate macroeconomic models due to the absence of a standard data collection system across countries. In addition, the subjective ilk of the ICRG corruption index renders it prone to mis-measuring the true level of corruption in a country and to corruption being endogenous in our specifications; in the latter case, the ICRG survey respondents may take into account certain macroeconomic factors and government policies that affect domestic investment of surveyed countries when answering corruption-related questions. Two, our baseline results are predicated on the assumption that all conditioning variables, including corruption and human capital, are exogenous. In addition, and by design, consistency of our semiparametric estimator hinges on exogeneity of all conditioning variables. Although our flexible semiparametric modeling framework, coupled with the inclusion of country and time fixed effects, has several inherent attributes that account for different sources of bias, it may not be an antidote for all dominant sources of bias in the domestic investment equation. Three, our set of X regressors is identical to that in Feldstein (1995) and Desai et al. (2005); nevertheless, our findings on the relationship between domestic investment and inbound and outbound FDI differ markedly from these two studies.

We now undertake a variety of sensitivity analyses designed to address these concerns about our baseline results. In particular, we rigorously explore whether our results are robust to the different potential sources of bias in our estimates. We further explore differences in informational content of different data as a means of reconciling the divergences between our results and those of Feldstein (1995) and Desai et al. (2005). Results from these analyses are not shown, due to space considerations, but are available upon request.

5.1 Endogeneity

In this subsection, we address endogeneity and measurement error concerns by using three alternative strategies: initial-valued regressors, residual semiparametric regressions, and the Cai & Li (2008) nonparametric GMM approach coupled with external instrumental variables.

5.1.1 Initial Values

In theory, it is less likely that initial values of variables in each time-averaged panel period will be correlated with the error term, and hence endogenous in model specifications. Our first robustness check is to re-estimate each of our semiparametric regression models with corruption or schooling using the initial values - in lieu of averaged values - of inbound and outbound FDI and the economic growth rate. Indeed, domestic investment has been documented in the macroeconomic literature to be one of the most robust determinants of the economic growth rate. In addition, FDI has been shown to have first-order effects on economic growth rates in many countries (see, e.g., Delgado et al. 2014, McCloud & Kumbhakar 2012, and the references cited therein). Thus, unobserved determinants of domestic investment that are correlated with the economic growth rate could also be correlated with inbound and outbound FDI. We measure inbound FDI as the initial value of inbound FDI for that 3-year period - and not as the average of annual inbound FDI over the 3-year period. We measure outbound FDI and the growth rate in a similar manner but continue to measure domestic investment as the 3-year average.

In each of the initial value regressions, and regardless of whether corruption or schooling is used, we continue to find strong statistical significance for heterogeneous complementarity between inbound FDI and domestic investment. Hence, the heterogeneous *nature* of the relationship between inbound FDI and domestic investment is invariant to the use of initial values of inbound and outbound FDI, and the economic growth rate.²² Across each of these initial value specifications, we find that the partial effects of the corruption and human capital measures to be largely consistent qualitatively with our previous results.

The *fluid* relationship between outbound FDI and domestic investment that we identify in our baseline results is also evident in our initial value regressions, despite changes in the size and sign of the estimated percentiles in two human capital models.²³ In general, our partial effect estimates for the outbound FDI coefficient are qualitatively the same as with averaged data.

In terms of the control variables in the initial value models, across each model and 3-year or 9-year panel specification, we continue to find results that are qualitatively consistent with those from the averaged variables. We find that the cross validated bandwidths and the goodness-of-fit measures are generally qualitatively consistent with those from the averaged panel regressions.

In summary, we do not find convincing evidence to suggest that the qualitative implications of our main models are erroneously driven by reverse causality in our key variables of interest. Our semiparametric model with corruption appears to be less influenced by reverse causality.

5.1.2 Regression of Residuals

Our second robustness check is to explore regressions of the residuals from each of our semiparametric regression models on the conditioning variables in each regression, as a means of identifying any unexplained correlation between any of the conditioning variables - including corruption and human capital - and the residuals. In general, residual-type regressions are derived from conditional moment restrictions, which are a critical component in the construction of many seminal parametric and nonparametric specification tests for cross-sectional, time series and panel data. Depending on the type of estimation - parametric or nonparametric - residual-type regressions can identify many low-order and high-order forms of model misspecification. To facilitate comparability across our residual regressions, and between our baseline and residual regressions, we also use the semiparametric estimator for the residual regressions. Our semiparametric residual regressions can therefore detect nonlinear forms of misspecification in inbound and outbound FDI and the control variables, and neglected parameter heterogeneity induced by (and hence endogeneity of) corruption and human capital.

Using the 3-year panel, we estimate four residual semiparametric models: the corruption, primary enrollment, secondary enrollment, and literacy rate models. For each residual regression, we consider

 $^{^{22}}$ In some cases, however, the use of initial values engenders changes in the *degree* of the complementarity. In the initial value regressions with primary enrollment, we find the estimated percentiles of complementary effects are substantially smaller than reported previously. In the 9-year secondary enrollment rate specification, however, we find larger complementarity effects of inbound FDI on domestic investment, with more observation specific estimates being statistically significant.

²³Specifically, in the 9-year primary model, the regression using averaged regressors returns negative and significant outbound FDI coefficients (see Table 4), but deployment of initial values returns a generally positive and significant set of coefficient estimates. In the literacy rate specifications, the averaged data returns positive and significant effects in the 3-year specification but a negative and significant estimate when using initial measures, and a negative and insignificant effect in the 9-year averaged model but a positive and significant effect using 9-year initial values.

the following assessment criteria: (i) the distribution and mean values of the coefficient functions and their bootstrapped standard errors to assess statistical significance of each coefficient function estimate; (ii) the in-sample R^2 ; and (iii) the cross validated bandwidths for the environmental variables specific to each model. We interpret statistical insignificance of each conditioning variable in these residual regressions as evidence of no (statistically identifiable) correlation between our residuals and the conditioning variables - that is, no endogeneity.

We identify statistical significance at the mean for savings in the corruption model, inbound FDI and growth in the primary school enrollment model, and savings and inflation in the secondary school enrollment rate specification. However, added checks reveal that in these cases where there exists some significance at the mean, very few observations are statistically significant, suggesting that the significance at the mean is an artifact of our averaging of the estimates. Only for the inflation rate in the secondary school enrollment specification do we find a relatively large share of statistical significance in the coefficient function estimates. More important, *all* distributions for the corruption and school enrollment models are concentrated around zero. Hence, across each of the four residual semiparametric models, we do not find meaningful statistical significance in any of the coefficient functions. The distributions and mean values of the coefficient functions in the residual regressions therefore strongly suggest that our baseline results are not driven by endogeneity in either FDI, the controls, or the corruption or schooling variables.

Turning to the in-sample R^2 for each residual regression, we find that this measure is 0.0190, 0.2276, 0.2073, and 0.4058 for the corruption, primary enrollment, secondary enrollment, and literacy rate models, respectively. Most notably is the minute in-sample R^2 for the corruption residual regression: the conditioning variables explain 1.9% of the variation in residuals. Recall that in our baseline regressions the in-sample R^2 ranged from 0.5854 to 0.9926 across many of the models. Thus, in many cases, the in-sample R^2 in the residual regression is minuscule relative to its counterpart in the baseline regressions. Hence, once again, we do not find resounding evidence that the conditioning variables explain in the residuals from our baseline regressions.

Analysis of the cross validated bandwidths yields similar conclusions. In each residual specification, the country indicator has a bandwidth equal to its upper bound of unity, and hence is irrelevant (Li & Racine 2007). We find that the bandwidth on our year indicator is generally relatively large, but below its upper bound of unity. The corruption and primary enrollment variables are shown to have linear interactions with the conditioning variables, whereas the secondary enrollment and literacy rate potentially have nonlinear interactions; note that this does not imply statistical significance. Taken as a whole, these cross validated bandwidths imply that there is substantially less heterogeneity and interactions in these residual regressions, compared to both our baseline regressions and our expectations for a residual regression if there was significant endogeneity in our main regressions.

Therefore, there is no consequential evidence that our baseline regression specifications suffer from any significant endogeneity, measurement errors, or other forms of model misspecification that may engender appreciable bias in their corresponding estimates. More important, the residual regressions suggest that our semiparametric model with corruption may be particularly well specified.

5.1.3 Instrumental Variables

In the preceding initial-valued and residual semiparametric regressions, there is a lack of evidence that our model suffers from meaningful endogeneity biases. As a another robustness check, we consider several instrumental variables as exogenous sources of variation in inbound FDI and outbound FDI. Lagged values of FDI are usually good *internally* measured instruments due to their high correlation with their non-lagged counterparts. However, such lagged values of FDI are also likely to be correlated with the error term, thus rendering them invalid instruments. Economic conditions in the top five major trading partners (MTPs) of each country are unlikely to be influenced by domestic investment in any particular country, yet are correlated with both inbound and outbound FDI for the country. That is, economic conditions in the MTPs are valid and strong instruments for inbound and outbound FDI. We therefore use economic conditions in the MTPs as *externally* measured instrumental variables to causally identify the effects of inbound and outbound FDI on domestic investment. Specifically, we use the economic growth rate, savings rate, interest rate, and exchange rate, each defined as averages over the top five MTPs of each country in the first year of each panel period.²⁴ For example, in 2005, the top five MTPs for Costa Rica were the United States, Japan, Venezuela, Mexico and China. Our growth instrument for Costa Rica in 2005 is the average of the economic growth rate for each of these five countries. There is precedent on the use of external economic conditions as exogenous sources of variation in other related empirical contexts. For example, Frankel & Roubini (2003) demonstrate that macroeconomic conditions in economies that have been highly developed in the post-war period are forces behind capital flows in developing countries; also, Desai, Foley & Hines (2009) use the growth rate of foreign economies as exogenous source of variation for changes in foreign investment by American multinational firms.

We use the Cai & Li (2008) nonparametric GMM approach to fit our semiparametric model with instrumental variables to the data. Given the GMM nature of the Cai & Li (2008) estimator, we include all four instrumental variables in each regression. That is, our instrumental variables regressions are over-identified. Over-identified GMM estimators can have a sizable finite sample bias, which can exacerbate in nonparametric frameworks. The small sample size of the semiparametric models with human capital are likely to have a multiplier effect on the finite sample bias of the estimator. We therefore err on the side of caution in using these GMM results to draw causal inferences from the human capital models on the relationship between FDI and domestic investment.

In the instrumental variables regression with corruption, we continue to find that inbound FDI has significant and heterogeneous complementarity effects on domestic investment. Outbound FDI continues to exert *fluid* effects on domestic investment. We do not find much economic significance in the size of a reduction in corruption on the FDI and domestic investment relationship. In our instrumental variables models with human capital, we find that the effect of inbound FDI on domestic investment is mixed, and the effect of outbound FDI is generally negative. These results are inconsistent with our earlier findings but are not surprising and may be manifestations of sizable finite sample bias.

Unlike the existing parametric instrumental variable methods, an accompanying J-test of instrument validity for the Cai & Li (2008) nonparametric GMM estimator has not yet been developed. In theory, valid instruments should uncorrelated with the regression error. To acquire some knowledge about the validity of our external instruments, we exploit the formulation of the traditional J-test and estimate two-way fixed effects parametric regression of each vector of GMM residuals on *all* instruments in the corresponding GMM model. This type of residual regression, though not a

²⁴We use trade data from the Correlates of War database, to identify each country's top five MTPs. We define MTP as a country with the largest volume of exports to the host nation ($\mathbf{flow1}$) at beginning of each time period as per the *dyadic_trade_3.xls* file. Unlike averaging, this method was less sensitive to the distortions across time periods. *Note:* **flow1** variable here represents the flow into country 1 (host nation) from country 2 (trading partner). See http://www.correlatesofwar.org/.

formal check of instrument validity, is quite sensitive to the presence of any correlation between the GMM residuals and their underlying instruments. Given the parametric nature of all the residual regressions, we use the adjusted R^2 as a metric of the strength of the correlation between the GMM residuals and regressors. Thus, we interpret a very low adjusted R^2 as evidence for validity of our external instruments.

We find that the adjusted R^2 is 0.030, 0.080, 0.064, and 0.054 for the corruption, primary enrollment, secondary enrollment, and literacy rate two-way fixed effects parametric GMM-residual models, respectively. This is strong corroborative evidence that our external instruments are valid, particularly in the nonparametric GMM corruption model. In fact, it appears that the inclusion of corruption or schooling and country and time fixed effects in *all* smooth coefficient functions of the semiparametric model in (1) captures many sources of biases in the domestic investment equation. Therefore, the qualitative implications of our GMM model do not appear to be plagued by invalid instruments.

5.2 Unraveling Data Discrepancies

Two important conclusions identified by both Feldstein (1995) and Desai et al. (2005) in their crosssectional analysis of OECD countries are that outbound FDI reduces domestic investment nearly dollar-for-dollar, and that there is not a statistically significant relationship between inbound FDI and domestic investment. As we have shown, our results do not confirm these findings - not even for OECD countries - despite our deployment of identically defined measures of FDI and domestic investment.

FDI data used by Feldstein (1995) and Desai et al. (2005) come from the OECD, whereas our measures come from the World Bank. In addition, Feldstein (1995) and Desai et al. (2005) use data for the period 1970 to 1990 and 1980 to 2000, respectively, whereas our time span is from 1984 to 2010. FDI measures from different sources may contain systematically different information, which will lead to discrepancies in related conclusions drawn by different studies. Also, if there is a change over time in the nature of the relationship between domestic investment and FDI (see also Figure 3), then different time periods can give rise to a difference in empirical findings.

To reconcile the differences between our findings and those of Feldstein (1995) and Desai et al. (2005), we explore a series of regression models that use inbound and outbound FDI from both the OECD and World Bank sources. We consider parametric cross-sectional specifications, in the spirit of Feldstein (1995) and Desai et al. (2005), for samples of countries that vary or are held constant across both sources of data. These exercises should help to determine whether differences between our FDI results and those of Feldstein (1995) and Desai et al. (2005) are driven by differences in measurements (and hence in information) across data sources, time span, sample of countries, or regression model specification (i.e., cross-section vs panel).

5.2.1 Cross-sectional Regression Results for Identical OECD Economies

We address the issue of difference in FDI data by constructing a cross-section of identical observations across both sources of FDI for both the 1990's and 2000's (36 and 43 observations, respectively).²⁵

²⁵These data are constructed as 10-year averages over 1990-1999 (36 observations) and 2000-2009 (43 observations). We first consider unconditional correlations between both sources of FDI. Unconditional correlations between the inbound FDI across sources is 0.9771 for the 1990's cross-section, and 0.9254 for the 2000's cross-section. Outbound FDI correlations for the corresponding periods are 0.9736 and 0.7977, respectively. From unconditional correlations,

We fit the parsimonious cross-sectional regression of domestic investment on gross national savings and inbound and outbound FDI - following Feldstein (1995) and Desai et al. (2005) - to the data from the two 10-year cross-sections of countries that are consistent across both OECD and WDI FDI sources. We find for the 1990's cross-section that inbound FDI is positive but insignificant for both sources of FDI, whereas outbound FDI is negative and significant for both.²⁶ Our results from the 1990's cross-section, therefore, provide strong evidence that our use of WDI data - rather than OECD data - is not a source of discrepancy between the findings in this present paper and those of Feldstein (1995) and Desai et al. (2005).

Our 2000's cross-section specifications yield that both inbound and outbound FDI are insignificant, regardless of which source (OECD or WDI) is included. These results suggest that the relationship between outbound FDI and domestic investment has significantly changed over time for (and possibly within) OECD countries, for the period 1990 to 2009, perhaps being a result of the Asian Financial Crisis (as suggested in Subsection 3.4). That is, parameter heterogeneity, and more precisely a *fluid* relationship, may exist between outbound FDI and domestic investment. These findings lend credence to the use of country and time fixed effects in the smooth coefficient functions of our panel specifications.

5.2.2 Cross-sectional Regression Results for OECD and non-OECD Economies

We fit the parsimonious cross-sectional regression to data that do not restrict the sample of countries to be the same across sources of FDI. In light of our finding that the OECD and WDI FDI data have the same information, we use the WDI sample because it contains more countries than the OECD sample. This exercise yields interesting results about the role of sample in the nexus between FDI and domestic investment. For the 1990's regression using the full sample of 92 OECD and non-OECD countries in the WDI dataset, we no longer find a negative and significant effect of outbound FDI (which is the result from the 1990's restricted sample). Our estimate for outbound FDI is now positive and insignificant. This sign reversal that is induced by adding developing countries to the restricted sample strongly suggests that the relationship between outbound FDI and domestic investment differs across countries (as suggested in Subsection 3.4). Our estimate for the inbound FDI coefficient remains positive (although smaller than its counterpart from the 1990's restricted sample) and insignificant.

Focusing on 114 available OECD and non-OECD countries for the 2000's cross-section does not yield results that are qualitatively different from those from the restricted 2000's sample; our estimate for the outbound FDI coefficient continues to be negative and insignificant, whereas that for inbound FDI remains positive and insignificant. The sign reversal of the outbound FDI coefficient estimate moving from the 1990's to 2000's unrestricted sample indicates that the relationship between outbound FDI and domestic investment has significantly changed over time also for non-OECD countries.

Overall, the reassessment of these cross-sectional regressions reveal that it is *critical* to simultaneously consider both a large sample of countries, country- and time-specific effects, and a flexible

it does not appear that the OECD and WDI measures of FDI differ substantially across a cross-section of identical countries. Therefore, by and large, it appears that the OECD and WDI measures of FDI contain the same information.

 $^{^{26}}$ Specifically, the WDI measure of outbound FDI has a coefficient of -0.9396 and its OECD counterpart has a coefficient estimate of -0.6225. The OECD measures employed by Desai et al. (2005) for the 1990's cross-section yielded an estimate of the outbound FDI coefficient of -1.0767, which is more consistent with our WDI measure of outbound FDI.

regression model to accurately estimate the relationship between domestic investment and these variables. Hence, we have found added evidence in support of both our semiparametric modeling approach and the validity of our resultant empirical findings.

6 Conclusion

Few empirical papers have directly investigated the macroeconomic relationship between domestic investment and inbound *and* outbound FDI. These papers have considered relatively small crosssections of OECD countries, and all have deployed simple parametric models. The general conclusion from these papers has been that inbound FDI does not significantly impact domestic investment, while outbound FDI crowds out domestic investment nearly dollar for dollar (Feldstein 1995, Desai et al. 2005). These results are generally concerning from the perspective of any individual country, particularly less developed countries that struggle to parlay their natural comparative advantage to foster domestic investment, and hence economic development

Recent evidence hints at possible nontrivial interactions between corruption or schooling and the nexus between domestic investment and inbound and outbound FDI. We therefore add to this small literature by exploring possible differences in the effects of inbound *and* outbound FDI on domestic investment across and within developed and developing countries, and the role of corruption and schooling in these effects. We adopt flexible fixed-effects semiparametric estimation approaches for accommodating unknown forms of heterogeneity within and across countries, and instrumental variables.

Our results are contrary to existing literature. Controlling for corruption and human capital, we show that inbound FDI has significant heterogeneous complementary effects on domestic investment, whereas outbound FDI has *fluid* effects on domestic investment: across developed and developing countries, substitution and complementarity exist, and depend on whether we use corruption or schooling, and within some countries these effects change direction over different time horizons. We emphasize that the magnitudes of the substitution effects of outbound FDI on domestic investment depend on whether we use corruption or schooling, and the estimates are less than half the magnitude of previously estimated effects. That is, even when outbound FDI crowds out domestic investment, it is not dollar-for-dollar as previous research has suggested. Additionally, we find that the nature of these inbound and outbound FDI effects are present in both developed and developing countries. The *fluidity* of outbound FDI to domestic investment suggests that small variations in outbound FDI can have more deleterious effects - than inbound FDI - on macroeconomic stability, particularly in developing countries that have quite limited resources to buffer the effects of shocks. Rigorous robustness checks confirm that the qualitative implications of our main results are not driven by endogeneity bias, suggesting that our semiparametric strategy for modeling heterogeneity accounts for many unobservable factors that would otherwise be captured in the regression error.

Our empirical evidence also indicates that reducing corruption or increasing human capital from its prevailing level can be good *and* bad for the effects of FDI on domestic investment. In particular, a careful analysis of our estimates reveals that this characterization of the effect of higher institutional quality is consistent with the General Theory of Second Best. Thus, our empirical evidence suggests that the policy of introducing or strengthening anti-corruption measures and human capital deepening - as implied by recent UNCTAD surveys - will not, for example, increase the complementary effects of inbound FDI on domestic investment in *all* countries. Hence, while reductions in corruption and improvements in schooling are generally considered as best-practice reforms for economic development, our empirical results underscore the complexities of the interaction between these institutional variables and the relationships between domestic investment and inbound and outbound FDI, which further points towards country-specific institutional policies. In fact, parallel sentiments are echoed by, for example, Rodrik (2008) who espoused that "Best-practice institutions are, almost by definition, noncontextual and do not take into account these complications." In essence, "no single set of best practices will serve the needs of all countries".

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Figure 1: Cross-sectional correlations between domestic investment and inbound and outbound FDI. Sample includes 113 OECD and non-OECD countries averaged over the period 1984-2010.



Figure 2: Average investment for countries grouped according to relative levels of inbound and outbound FDI. Sample includes 113 countries, averaged over 1984-2010 period.

Average Domestic Investment Time Series



Figure 3: Average domestic investment and inbound and outbound FDI per year from 1984-2010 for the full sample, OECD, and non-OECD countries.



Figure 4: 45 degree gradient plots for each of the estimated coefficient functions in the discrete environmental variable model.



Figure 5: Joint kernel density of inbound FDI estimated coefficients and corruption.



Figure 6: Joint kernel density of outbound FDI estimated coefficients and corruption.



Figure 7: Boxplots of the inbound FDI coefficients for the discrete (top panel) and corruption (bottom panel) models across OECD and non-OECD countries.



Figure 8: Boxplots of the outbound FDI coefficients for the discrete (top panel) and corruption (bottom panel) models across OECD and non-OECD countries.

| hed by Political 0 to 6, with 0 | y Risk Guide publis index ranges from | cernational Country 984 to 2010. This | ion comes from the Int aged for the period 19 | index of corrupt ces, and is aver | Note: The Risk Servi |
|------------------------------------|--|--|--|--------------------------------------|---------------------------|
| | | Uruguay | | Libya | |
| | | Sri Lanka | Zambia | Latvia | |
| | | South Africa | Vietnam | Kuwait | |
| | | Slovenia | Venezuela | Kenya | |
| | | Slovakia | Uganda | Jamaica | |
| | | Poland | Tunisia | India | |
| | | Mozambique | Trinidad & Tobago | Honduras | |
| | | Mongolia | Thailand | Guatemala | |
| | | Malta | Sierra Leone | El Salvador | |
| | United States | Malaysia | Serbia-Montenegro | Egypt | |
| | United Kingdom | Jordan | Senegal | Croatia | |
| | Spain | Italy | Russia | Congo | |
| | Singapore | Hungary | Romania | $\operatorname{Colombia}$ | $\operatorname{Zimbabwe}$ |
| | Portugal | Greece | Philippines | China | Ukraine |
| Switzerland | Japan | $\operatorname{Estonia}$ | Peru | Cameroon | $\operatorname{Paraguay}$ |
| \mathbf{S} weden | Israel | Czech Republic | Papua New Guinea | Burkina Faso | $\operatorname{Pakistan}$ |
| Norway | Ireland | Cyprus | Oman | Bolivia | Moldova |
| New Zealand | Hong Kong | Costa Rica | Niger | Belarus | Lebanon |
| Netherlands | Germany | Bulgaria | Namibia | $\operatorname{Bahrain}$ | Indonesia |
| Iceland | France | Brunei | Morocco | $\operatorname{Bahamas}$ | Gabon |
| Finland | Belgium | Brazil | Mexico | Angola | Bangladesh |
| $\operatorname{Denmark}$ | Austria | Botswana | Malawi | Algeria | Azerbaijan |
| Canada | Australia | Argentina | Lithuania | Albania | $\operatorname{Armenia}$ |
| 5.01-6 | 4.01-5 | 3.01-4 | 2.01-3 | | 1.01-2 |
| | - | C | , | | |

representing most corrupt and 6 representing the least corrupt.

| | 3-year averaged panel | | | 9-year averaged panel | | |
|-------------------------------------|-----------------------|---------|---------|-----------------------|---------|---------|
| Variable | 25th | 50th | 75th | 25th | 50th | 75th |
| Intercept | 0.0612 | 0.1172 | 0.1701 | 0.1047 | 0.1377 | 0.1674 |
| | 0.0050 | 0.0093 | 0.0145 | 0.0103 | 0.0097 | 0.0139 |
| Inbound FDI | 0.2609 | 0.4255 | 0.6357 | 0.2737 | 0.3831 | 0.4825 |
| | 0.0427 | 0.0132 | 0.0356 | 0.0631 | 0.0609 | 0.0268 |
| Outbound FDI | -0.7291 | -0.4013 | -0.1837 | -0.6368 | -0.4742 | -0.3183 |
| | 0.0467 | 0.0164 | 0.0216 | 0.0483 | 0.0441 | 0.0335 |
| Savings | 0.0826 | 0.1791 | 0.3661 | 0.0666 | 0.1943 | 0.2472 |
| | 0.0131 | 0.0045 | 0.0151 | 0.0091 | 0.0143 | 0.0167 |
| Inflation | -0.0168 | -0.0014 | 0.0044 | -0.0032 | -0.0014 | -0.0002 |
| | 0.0012 | 0.0013 | 0.0007 | 0.0016 | 0.0004 | 0.0009 |
| Growth | 0.1300 | 0.3481 | 0.5369 | 0.2666 | 0.5089 | 0.7308 |
| | 0.0846 | 0.0389 | 0.1080 | 0.0494 | 0.0684 | 0.0483 |
| Interest | -0.1182 | -0.0530 | -0.0032 | -0.1379 | -0.1109 | -0.0920 |
| | 0.0118 | 0.0029 | 0.0039 | 0.0188 | 0.0043 | 0.0150 |
| Population | -0.0001 | 0.0031 | 0.0062 | 0.0010 | 0.0027 | 0.0046 |
| | 0.0008 | 0.0003 | 0.0003 | 0.0009 | 0.0011 | 0.0013 |
| Sample size | | 562 | | | 220 | |
| In-sample R^2 | | 0.9926 | | | 0.9592 | |
| Out-sample R^2 | | 0.5497 | | | 0.3226 | |
| Out-sample $ASPE$ | | 0.0017 | | | 0.0019 | |
| Specification test: <i>p</i> -value | | 0.0000 | | | 0.0000 | |

Table 2: Summary of results from the local-constant smooth coefficient models.

1. 25th, 50th, 75th refer to percentiles in the distribution of coefficient estimates.

2. Estimate specific standard errors are reported below each estimate.

3. Statistically significant estimates at the 5% level are highlighted in bold.

4. R^2 is calculated as the square of the correlation between (y, \hat{y}) .

5. ASPE is the average of the squared difference between (y, \hat{y}) .

6. Out-of-sample prediction measures are the mean of 1000 out-of-sample replication exercises (see text for details).

7. The p-value is for the consistent semiparametric model specification test for the null hypothesis of parameter constancy by Cai et al. (2000).

The dependent variable is domestic investment, which is gross capital formation as a percentage of GDP. Inbound FDI and outbound FDI are respectively net inflows and net outflows of FDI as a percentage of GDP. Savings is calculated as gross national income less total national consumption, plus net transfers. Growth is the annual percentage change in real GDP, and inflation is the annual percentage change in the consumer price index. Population is the natural logarithm of the total population, and interest is the lending interest rate adjusted for inflation. All data are from the 2012 World Development Indicators database published by the World Bank. Our sample is drawn from an unbalanced panel of 137 developed and developing countries over the period 1984-2010.

| | 3-year averaged panel | | | 9-year averaged panel | | |
|-------------------------------------|-----------------------|---------|--------|-----------------------|---------|--------|
| Variable | 25th | 50th | 75th | 25th | 50th | 75th |
| Coefficients | | | | | | |
| Inbound FDI | 0.0046 | 0.2182 | 0.5951 | 0.0322 | 0.1104 | 0.3182 |
| | 0.0001 | 0.1068 | 0.0280 | 0.0025 | 0.0096 | 0.0925 |
| Outbound FDI | -0.5912 | -0.1208 | 0.0039 | -0.5078 | -0.0014 | 0.0163 |
| | 0.0225 | 0.0142 | 0.0004 | 0.3439 | 0.0009 | 0.0008 |
| Savings | 0.0586 | 0.1556 | 0.2843 | 0.0625 | 0.1917 | 0.2801 |
| | 0.0093 | 0.0137 | 0.0118 | 0.0242 | 0.0179 | 0.0231 |
| Corruption Partials | | | | | | |
| Inbound FDI | -0.2579 | -0.0639 | 0.0341 | -0.0277 | 0.0040 | 0.3440 |
| | 0.0276 | 0.0145 | 0.0332 | 0.0044 | 0.0043 | 0.1532 |
| Outbound FDI | -0.1731 | 0.0005 | 0.2430 | -0.4457 | 0.0005 | 0.0086 |
| | 0.0354 | 0.0000 | 0.0265 | 0.3515 | 0.0002 | 0.0010 |
| Savings | -0.0063 | 0.0368 | 0.0974 | -0.0109 | 0.0566 | 0.1653 |
| | 0.0003 | 0.0045 | 0.0071 | 0.0005 | 0.0580 | 0.0562 |
| Sample size | | 557 | | | 220 | |
| In-sample R^2 | | 0.9919 | | | 0.9342 | |
| Out-sample R^2 | | 0.5092 | | | 0.1131 | |
| Out-sample ASPE | | 0.0019 | | | 0.0034 | |
| Specification test: <i>p</i> -value | | 0.0000 | | | 0.0000 | |

Table 3: Summary of results from the local-linear smooth coefficient corruption models.

1. 25th, 50th, 75th refer to percentiles in the distribution of coefficient estimates.

2. Estimate specific standard errors are reported below each estimate.

3. Statistically significant estimates at the 5% level are highlighted in bold.

4. R^2 is calculated as the square of the correlation between (y, \hat{y}) .

5. ASPE is the average of the squared difference between (y, \hat{y}) .

6. Out-of-sample prediction measures are the mean of 1000 out-of-sample replication exercises (see text for details).

7. The p-value is for the consistent semiparametric model specification test for the null hypothesis of parameter constancy by Cai et al. (2000).

The dependent variable is domestic investment, which is gross capital formation as a percentage of GDP. Inbound FDI and outbound FDI are respectively net inflows and net outflows of FDI as a percentage of GDP. Savings is gross national income less total national consumption, plus net transfers. The controls that are omitted from the table are growth (annual percentage change in real GDP), inflation (annual percentage change in the consumer price index), population (natural logarithm of the total population), and interest rate (lending interest rate adjusted for inflation). All these data are from the 2012 World Development Indicators database published by the World Bank. Corruption is the ICRG corruption index, which ranges from 0 to 6 with higher values representing lower levels of corruption. Our sample is drawn from an unbalanced panel of 137 developed and developing countries over the period 1984-2010.

| | 3-year averaged panel 9-year averaged pa | | | panel | | |
|-------------------------------------|--|---------|--------|---------|---------|---------|
| Variable | 25th | 50th | 75th | 25th | 50th | 75th |
| Coefficients | | | | | | |
| Inbound FDI | 0.0162 | 0.0520 | 0.0888 | 0.2041 | 0.2214 | 0.2439 |
| | 0.0012 | 0.0062 | 0.0127 | 0.0374 | 0.0398 | 0.0416 |
| Outbound FDI | 0.0060 | 0.0196 | 0.0357 | -0.2416 | -0.2154 | -0.2011 |
| | 0.0049 | 0.0021 | 0.0014 | 0.0460 | 0.0425 | 0.0437 |
| Savings | 0.0759 | 0.1148 | 0.1607 | 0.0778 | 0.0862 | 0.0977 |
| | 0.0057 | 0.0099 | 0.0179 | 0.0222 | 0.0223 | 0.0213 |
| Primary Partials | | | | | | |
| Inbound FDI | -0.0027 | -0.0010 | 0.0003 | -0.0352 | -0.0247 | -0.0172 |
| | 0.0001 | 0.0005 | 0.0004 | 0.0044 | 0.0067 | 0.0031 |
| Outbound FDI | -0.0009 | -0.0004 | 0.0004 | -0.0168 | -0.0080 | 0.0004 |
| | 0.0004 | 0.0003 | 0.0002 | 0.0026 | 0.0011 | 0.0011 |
| Savings | -0.0073 | -0.0039 | 0.0001 | -0.0634 | -0.0570 | -0.0517 |
| | 0.0008 | 0.0009 | 0.0001 | 0.0109 | 0.0085 | 0.0074 |
| Sample size | | 415 | | | 186 | |
| In-sample R^2 | | 0.9391 | | | 0.6896 | |
| Out-sample R^2 | | 0.5343 | | | 0.2765 | |
| Out-sample ASPE | | 0.0015 | | | 0.0019 | |
| Specification test: <i>p</i> -value | | 0.0000 | | | 0.1479 | |
| × 1 | | | | | | |

Table 4: Summary of results from the local-linear smooth coefficient primary school models.

1. 25th, 50th, 75th refer to percentiles in the distribution of coefficient estimates.

2. Estimate specific standard errors are reported below each estimate.

3. Statistically significant estimates at the 5% level are highlighted in bold.

4. R^2 is calculated as the square of the correlation between (y, \hat{y}) .

5. ASPE is the average of the squared difference between (y, \hat{y}) .

6. Out-of-sample prediction measures are the mean of 1000 out-of-sample replication exercises (see text for details).

7. The p-value is for the consistent semiparametric model specification test for the null hypothesis of parameter constancy by Cai et al. (2000).

The dependent variable is domestic investment, which is gross capital formation as a percentage of GDP. Inbound FDI and outbound FDI are respectively net inflows and net outflows of FDI as a percentage of GDP. Savings is gross national income less total national consumption, plus net transfers. The controls that are omitted from the table are growth (annual percentage change in real GDP), inflation (annual percentage change in the consumer price index), population (natural logarithm of the total population), and interest rate (lending interest rate adjusted for inflation). Primary is the total number of students who are enrolled in primary school and are of primary school age, as a percent of the total population of the same age cohort; this measure excludes enrollment of over- or under-aged students. All these data are from the 2012 World Development Indicators database published by the World Bank. Our sample is drawn from an unbalanced panel of 137 developed and developing countries over the period 1984-2010.

| | 3-year averaged panel | | | 9-year averaged panel | | |
|-------------------------------------|-----------------------|---------|---------|-----------------------|---------|---------|
| Variable | 25th | 50th | 75th | 25th | 50th | 75th |
| Coefficients | | | | | | |
| Inbound FDI | 0.0422 | 0.0995 | 0.1558 | 0.0699 | 0.1002 | 0.3259 |
| | 0.0053 | 0.0228 | 0.0084 | 0.0384 | 0.0526 | 0.0554 |
| Outbound FDI | -0.0268 | 0.0008 | 0.0147 | -0.3380 | -0.0701 | -0.0292 |
| | 0.0146 | 0.0085 | 0.0018 | 0.0584 | 0.0555 | 0.0496 |
| Savings | 0.0344 | 0.0759 | 0.1225 | 0.0314 | 0.1148 | 0.1629 |
| | 0.0099 | 0.0246 | 0.0109 | 0.0316 | 0.0409 | 0.0559 |
| Secondary Partials | | | | | | |
| Inbound FDI | -0.0081 | -0.0005 | 0.0104 | -0.0253 | -0.0030 | 0.0278 |
| | 0.0006 | 0.0007 | 0.0010 | 0.0065 | 0.0129 | 0.0137 |
| Outbound FDI | -0.0025 | -0.0008 | 0.0014 | -0.0358 | -0.0193 | -0.0059 |
| | 0.0007 | 0.0001 | 0.0001 | 0.0081 | 0.0048 | 0.0071 |
| Savings | -0.0295 | -0.0164 | -0.0012 | -0.2347 | -0.2034 | -0.1547 |
| | 0.0038 | 0.0019 | 0.0025 | 0.1095 | 0.0679 | 0.0895 |
| Sample size | | 312 | | | 158 | |
| In-sample R^2 | | 0.9180 | | | 0.7105 | |
| Out-sample R^2 | | 0.3922 | | | 0.1396 | |
| Out-sample ASPE | | 0.0014 | | | 0.0020 | |
| Specification test: <i>p</i> -value | | 0.0000 | | | 0.0000 | |

Table 5: Summary of results from the local-linear smooth coefficient secondary school models.

1. 25th, 50th, 75th refer to percentiles in the distribution of coefficient estimates.

2. Estimate specific standard errors are reported below each estimate.

3. Statistically significant estimates at the 5% level are highlighted in bold.

4. R^2 is calculated as the square of the correlation between (y, \hat{y}) .

5. ASPE is the average of the squared difference between (y, \hat{y}) .

6. Out-of-sample prediction measures are the mean of 1000 out-of-sample replication exercises (see text for details).

7. The p-value is for the consistent semiparametric model specification test for the null hypothesis of parameter constancy by Cai et al. (2000).

The dependent variable is domestic investment, which is gross capital formation as a percentage of GDP. Inbound FDI and outbound FDI are respectively net inflows and net outflows of FDI as a percentage of GDP. Savings is gross national income less total national consumption, plus net transfers. The controls that are omitted from the table are growth (annual percentage change in real GDP), inflation (annual percentage change in the consumer price index), population (natural logarithm of the total population), and interest rate (lending interest rate adjusted for inflation). Secondary is the total number of students who are enrolled in secondary school and are of secondary school age, as a percent of the total population of the same age cohort; this measure excludes enrollment of overor under-aged students. All these data are from the 2012 World Development Indicators database published by the World Bank. Our sample is drawn from an unbalanced panel of 137 developed and developing countries over the period 1984-2010.

| | 3-year averaged panel 9-year averaged | | | panel | | |
|-------------------------------------|---------------------------------------|------------------|---------|---------|---------|---------|
| Variable | 25th | 50th | 75th | 25th | 50th | 75th |
| Coefficients | | | | | | |
| Inbound FDI | 0.5385 | 0.5633 | 0.5769 | 0.2405 | 0.2961 | 0.3244 |
| | 0.0960 | 0.0989 | 0.1000 | 0.0601 | 0.0658 | 0.0503 |
| Outbound FDI | -0.3482 | -0.3321 | -0.3178 | -0.0242 | 0.0022 | 0.0255 |
| | 0.0721 | 0.0698 | 0.0686 | 0.0287 | 0.0007 | 0.0063 |
| Savings | 0.0637 | 0.0974 | 0.1608 | 0.0480 | 0.1183 | 0.1543 |
| | 0.0290 | 0.0270 | 0.0245 | 0.0232 | 0.0230 | 0.0272 |
| Literacy Partials | | | | | | |
| Inbound FDI | -0.0296 | -0.0022 | 0.0411 | -0.0032 | 0.0105 | 0.0309 |
| | 0.0117 | 0.0140 | 0.0146 | 0.0095 | 0.0022 | 0.0091 |
| Outbound FDI | -0.0509 | -0.0170 | -0.0008 | -0.0053 | -0.0031 | -0.0009 |
| | 0.0075 | 0.0033 | 0.0050 | 0.0020 | 0.0013 | 0.0014 |
| Savings | -0.6697 | -0.6494 | -0.6218 | -0.2825 | -0.1885 | -0.1187 |
| | 0.1184 | 0.1197 | 0.1162 | 0.0665 | 0.0408 | 0.0272 |
| Sample size | | 150 | | | 131 | |
| In-sample B^2 | | 0 5854 | | | 0 7917 | |
| Out-sample R^2 | | 0.0001 0.2774 | | | 0.3193 | |
| Out-sample ASPE | | 0.0029 | | | 0.0035 | |
| Specification test: <i>n</i> -value | | 0.0576 | | | 0.0000 | |
| Specification tost. p value | | 5.0010 | | | 0.0000 | |

Table 6: Summary of results from the local-linear smooth coefficient literacy models.

1. 25th, 50th, 75th refer to percentiles in the distribution of coefficient estimates.

2. Estimate specific standard errors are reported below each estimate.

3. Statistically significant estimates at the 5% level are highlighted in bold.

4. R^2 is calculated as the square of the correlation between (y, \hat{y}) .

5. ASPE is the average of the squared difference between (y, \hat{y}) .

6. Out-of-sample prediction measures are the mean of 1000 out-of-sample replication exercises (see text for details).

7. The p-value is for the consistent semiparametric model specification test for the null hypothesis of parameter constancy by Cai et al. (2000).

The dependent variable is domestic investment, which is gross capital formation as a percentage of GDP. Inbound FDI and outbound FDI are respectively net inflows and net outflows of FDI as a percentage of GDP. Savings is gross national income less total national consumption, plus net transfers. The controls that are omitted from the table are growth (annual percentage change in real GDP), inflation (annual percentage change in the consumer price index), population (natural logarithm of the total population), and interest rate (lending interest rate adjusted for inflation). Literacy is the percentage of the population aged 15 and above who possess basic reading and writing skills. All these data are from the 2012 World Development Indicators database published by the World Bank. Our sample is drawn from an unbalanced panel of 137 developed and developing countries over the period 1984-2010.