Heterogeneous Symbiosis and Commensalism between Foreign Direct Investment and Economic Growth: A Semiparametric System of Simultaneous Equations Analysis with Instrumental Variables

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Abstract

We characterize the types of interactions between foreign direct investment (FDI) and economic growth, and analyze the effect of institutional quality on such interactions. To do this analysis, we develop a class of instrument-based semiparametric system of simultaneous equations estimators for panel data and prove that our estimators are consistent and asymptotically normal. Our new methodological tool suggests that across developed and developing economies, causal, heterogeneous *symbiosis* and *commensalism* are the most dominant types of interactions between FDI and economic growth. Higher institutional quality facilitates, impedes, or has no effect on the interactions between FDI and economic growth.

Keywords: Foreign direct investment; economic growth; institutional quality; parameter heterogeneity; semiparametric system of equations model; nonparametric method of moments; instrumental variables.

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1 Introduction

In theory, FDI can provide an important source of capital, technology, and other productivity elements that are important for economic growth, but are otherwise lacking because of insufficient domestic investment (Borensztein, De Gregorio & Lee 1998).[1] In theory, also, FDI can reduce or have no effect on economic growth. Consequently, a large strand of literature has been devoted to analyzing the nature of the effect of FDI on economic growth across countries; see, for example, Balasubramanyam, Salisu & Sapsford (1996), Borensztein et al. (1998), Alfaro, Chanda, Kalemli-Ozcan & Sayek (2004), Durham (2004), Carkovic & Levine (2005), Kottaridi & Stengos (2010), Delgado, McCloud & Kumbhakar (2012) and McCloud & Kumbhakar (2012), and the relevant references cited therein.[2] However, knowledge of *only* the effect of FDI on growth may be *insufficient* to derive useful policy prescriptions on the relationship between these two variables. Useful policy prescriptions may be better derived from analyses on the (joint) interaction between FDI and growth; such general analyses lend themselves to answering questions such as whether countries experience (i) growth-FDI *symbiosis* - a *positive* effect of FDI on growth *and* a *positive* effect of growth on FDI, or (ii) *FDI-commensalism* - a *positive* effect of FDI on growth *but no* effect of growth on FDI. More important, the type of interaction between FDI and economic growth can shed light on the existence of direct multiplier benefits stemming from increases in either FDI or economic growth.

In principle, a study of the (joint) interaction between FDI and growth is unwarranted if FDI is exogenous to economic growth so that FDI affects growth *but* growth does not affect FDI. Existing evidence, however, does not lend support to exogeneity of FDI, at least not in all countries. Foreign investors may be attracted by, among other important factors, high or stable growth rates within host countries, which act as a signal of high or stable potentially private investment returns (Culem 1988, Blonigen 1997). Indeed, in the FDI empirical literature, some studies have found the economic growth rate to be a significant factor in explaining cross-country variations in FDI, using different subsets of countries (see, for e.g., Schneider & Frey 1985, Culem 1988, Mohamed & Sidiropoulos 2010, Thangamani, Xu & Zhong 2010). Some single-equation studies have tried to extract the exogenous component of FDI that engenders economic growth (see, for e.g., Carkovic & Levine 2005, Delgado et al. 2012). Nevertheless, a positive (negative or no effect) of FDI on economic growth is neither a necessary nor sufficient condition for a positive (negative or no effect) of economic growth on FDI, and *vice versa*.

The type of interaction between FDI and growth can help policymakers to ascertain if, for example, FDI-promoting strategies for fostering and sustaining economic growth (or growth-promoting strategies for attracting more inflows of FDI) have direct multiplier benefits. Indeed, these strategies are commonplace in many countries. Various sources allege that the governments of many host countries, particularly developing countries, try to attract FDI by offering tax credits, infrastructure subsidies, import duty exemptions and other dispensations to foreign investors (see, e.g., World Bank 1997*b*, World Bank 1997*a*, UNCTAD 2000, Hanson 2001). In general, these dispensations amount to sizable revenues that governments forgo predicated on their presumption that more FDI inflows engender higher economic growth rates. In 1997, for example, the state government of Rio Grande do Sul in Brazil persuaded General Motors to build a new $600 million automobile

[1] Insufficient domestic investment may occur because of weak institutions, because capital is relatively expensive in developing countries, or because developing countries have a history of default. See Prasad, Rajan & Subramanian (2007) for a brief review.

[2] See, also, Alfaro & Johnson (2013) for an excellent review.

assembly plant in that state - rather than a more developed state - by offering a dispensation package in which "the subsidies were reported to amount to $250 million, and the tax breaks appeared to have the potential to equal $1.5 billion over a 15-year period" (Hanson 2001, page 19). These dispensations may therefore be justifiable in the presence of interactions between FDI and economic growth that have direct multiplier benefits.

In this paper, we characterize the types of interactions between FDI and economic growth, *and* analyze the effect of institutional quality on such interactions. To do this analysis, we propose a semiparametric panel model of a system of simultaneous equations that allows FDI and economic growth to be modeled simultaneously *and* uses instrumental variables to identify causal effects. Our model is semiparametric - that is, we represent the coefficients on all regressors in all equations as unknown smooth functions of a measure of institutional quality, and unobserved country- and year-specific factors (fixed effects) - for a few reasons. *One*, we adopt the view that substantial linear and nonlinear forms of parameter heterogeneity that stem from, among other sources, cross-country differences in institutional quality, exist in empirical growth models (see, for e.g., Durlauf 2001, Minier 2007, Durlauf, Kourtellos & Tan 2008, Huynh & Jacho-Chávez 2009*a*, Huynh & Jacho-Chávez 2009*b*), and in particular in the effect of FDI on economic growth (see, for e.g., Borensztein et al. 1998, Alfaro et al. 2004, Durham 2004, Papaioannou 2009, Kottaridi & Stengos 2010, Delgado et al. 2012, McCloud & Kumbhakar 2012). Thus, we do not assume a priori that all countries use identical technologies to produce goods and services. In a recent review of the FDI literature, Alfaro & Johnson (2013) emphasize the importance of incorporating measures of institutional quality into empirical models of FDI and growth. Moreover, and although highly possible, the existence of parameter heterogeneity in empirical FDI models has not been considered in the literature. *Two*, 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 that may influence the FDI and growth equations in many ways beyond a simple translation of each equation. For example, changes in FDI inflows within a firm may lead to changes in input composition of the production process and organizational structure, which are likely to be associated with changes in economic growth.[3]

Semiparametric system of equations estimation is still in its infancy (Welsh & Yee 2006), and has not been used in any empirical economic studies of which we are aware. In the absence of a conditional distributional assumption on the response vector given the set of covariates, we opt to use the generalized method of moments (GMM) approach by Hansen (1982) to estimate our system of equations. The general unspecified form of our coefficient functions precludes estimation of our system with parametric GMM estimation. The estimators of the unknown coefficient functions, however, can be obtained using nonparametric GMM methods. In comparison to the literature on GMM and parametric systems of simultaneous equations, relatively little is known about using the GMM approach to estimate semiparametric systems of simultaneous equations and the asymptotic properties of the resultant estimators. To fill this gap in the literature, we therefore derive a broad

[3]In essence, our empirical specification can be viewed as a mixture of the standard parametric system of equations model of FDI and growth used by Li & Liu (2005), and the semiparametric smooth varying coefficient growth model used by Delgado et al. (2012). Note that the system model of Li & Liu (2005) was fully parametric, and, more important, (i) assumed that, by virtue of parameter homogeneity, the interaction between economic growth is the same across countries and (ii) did not control for country- and time-specific effects. The model used by Delgado et al. (2012) was restricted to a single equation specification of the effects of FDI on growth rates. The model considered here is therefore substantially more general than either of those empirical specifications.

class of local-linear GMM estimators - by coupling the GMM approach with local-linear estimation (see, e.g., Fan & Gijbels 1996) and the nonparametric system of equations symmetrical kernel-weighting approach in Welsh & Yee (2006) - for in-depth theoretical analysis. We establish the consistency and asymptotic normality of our class of system estimators. We propose a standard two-step estimation procedure that potentially yields more efficient estimates than a one-step systems estimator in the case that the errors across equations are indeed correlated. Our use of *non-neutral* fixed effects - in lieu of their neutral counterparts - circumvents the need to remove the fixed effects via some type of weighting or first difference transformation prior to estimation, to avoid biased and inconsistent estimates of, in particular, the marginal effects. Further, our use of generalized product kernels (Racine & Li 2004) allows us to avoid the incidental parameters problem associated with many parametric panel models that include dummy variables to account for unobserved effects.

Our theoretical framework can be seen as a generalization of both the *single* equation models proposed by Li, Huang, Li & Fu (2002), Das (2005), Cai, Das, Xiong & Wu (2006), Cai & Li (2008), Tran & Tsionas (2009), and Cai & Xiong (2012), as well as the *multivariate* response models of Welsh & Yee (2006). One important difference between our class of system estimators and those of Welsh & Yee (2006) is that we allow for correlation between any of the conditioning variables and the error term. Such an important distinction, among other attributes, renders our theoretical analysis a nontrivial extension of these aforementioned studies; we, however, show the numerical and asymptotic links between our estimators and some of these studies. Our model and estimators can be used to empirically analyze a wide range of economic and non-economic phenomena. Moreover, the theoretical contributions of this paper are of independent interest and complement the relevant existing theoretical works.

In our empirical model, the host country's total land area offers a potential source of exogenous variation in FDI within the growth equation, whereas fertility and life expectancy rates offer potential sources of exogenous variation in economic growth within the FDI equation. Implementation of our new methodological tool and its application to a panel of 114 developed and developing countries over the period 1984 to 2010 yield several important empirical conclusions regarding types of interactions that exist between FDI and economic growth, and the indirect effects of institutions on such interactions. We observe that across developed and developing economies, causal, heterogeneous *symbiosis* and *FDI-commensalism* are the most dominant types of interactions between FDI and economic growth. The latter interaction suggests that in some countries there is no direct multiplier benefit between FDI and economic growth. We further find a significant, nonlinear, and *non-neutral* relationship between our measure of institutional quality (corruption) and the different interactions that exist between growth rates and FDI inflows. Specifically, higher institutional quality facilitates, impedes, or has no effect on the interactions between FDI and economic growth.

Estimates of the smoothing parameters for our measure of institutional quality, and unobserved country- and year-specific factors substantiate our claim that these three factors induce nonlinear forms of parameter heterogeneity in our simultaneous equation model, and are important in the growth-FDI nexus. In particular, we find empirical support for the use of *non-neutral* - rather than neutral - fixed effects.

We begin in Section 2 with a brief review of several relevant strands of the empirical literatures on economic growth, FDI, and institutional quality that are unified by our empirical model. Section 3 formally sets up our semiparametric system of simultaneous equations model - through which we will

examine the FDI-growth nexus - and presents the derivation of our proposed class of semiparametric systems estimators. We present the large sample theory for the estimators in Section 4. We provide our empirical model and a description of our data, including the instrumental variables, in Section 5. We present our empirical results in Section 6, and Section 7 provides our conclusions. We provide detailed proofs for our large sample theory in the technical appendix to this paper.

2 A Brief Review of the Literature

Before presenting the econometric setup of our system of semiparametric equations, we first provide a brief review of the main points of overlap among the existing empirical research on growth, FDI, and institutions. The focus of our review is threefold: (i) to highlight several empirical growth determinants that are generally known to be robust *and* are relevant to the FDI-growth relationship; (ii) to summarize the widely used determinants of FDI; and (iii) to underscore the importance of incorporating both institutional factors and parameter heterogeneity into empirical macroeconomic specifications.[4] Thus, the contribution of this section is to provide a foundation for our empirical model specification, not to provide an exhaustive review of the related literatures. We defer our discussion of endogeneity and instrumental variables to Section 5.

2.1 Determinants of Economic Growth

There is a reasonably well-developed literature that documents the effects of FDI on economic growth rates, with notable contributions including Balasubramanyam et al. (1996), Borensztein et al. (1998), Alfaro et al. (2004), Durham (2004), Carkovic & Levine (2005), Kottaridi & Stengos (2010), Delgado et al. (2012) and McCloud & Kumbhakar (2012), and the relevant references cited therein. Our conditioning set of regressors for our growth equation must be standard in terms of the empirical growth literature, as a whole, as well as be adequate controls and measures for the important interactions identified in the literature on FDI and growth. Consequently, the specification of our growth equation incorporates factors from the following two growth ideologies: neoclassical, and macroeconomic policy.

The neoclassical growth specification is often referenced to Mankiw, Romer & Weil (1992) for the theoretical derivations and empirical specification, and includes initial income, the rate of physical capital investment, and population growth as traditional 'Solow' regressors. Inclusion of initial income provides the impetus for growth rate convergence, and the inclusion of the rate of physical capital investment and population growth are derived from an aggregate production function specification with productivity inputs capital and labor. Recent focus on model uncertainty through the use of linear model averaging (Durlauf et al. 2008) and nonparametric techniques that are immune to functional form misspecification (Henderson, Papageorgiou & Parmeter 2012, Delgado, Henderson & Parmeter 2014) have identified each of these 'Solow' variables as robust and important determinants of economic growth.

The macroeconomic policy growth ideology maintains that sound macroeconomic policies are prerequisite for economic growth. Macroeconomic policy is typically measured by trade openness, the inflation rate, and government consumption (Barro 1996, Durlauf et al. 2008), and there is

[4] The literature investigating the determinants of FDI has focused both on macroeconomic and microeconomic (i.e., firm specific) measures of FDI. The focus of our review is primarily on the macroeconomic research, as this relates closest to the focus of our current investigation.

strong empirical support for these variables as correlates of economic growth. Barro (1996) finds that trade openness has a positive and significant effect on growth rates, whereas government consumption has a negative and significant effect on growth rates. Henderson, Papageorgiou & Parmeter (2012), however, find evidence that trade openness is robust *but* has nonlinear effects on economic growth. In addition, Durlauf et al. (2008) and Henderson, Papageorgiou & Parmeter (2012) find evidence that the growth effects of the inflation rate and government consumption are robust to varying forms of model uncertainty.

In essence, these sets of determinants emanate from the general consensus within the empirical and theoretical spheres that - amid the myriad potential growth factors and sources of model uncertainty - the neoclassical and macroeconomic policy variables are generally robust. In addition, FDI has been found to be directly associated with growth-related macroeconomic factors within host countries (Alfaro & Johnson 2013); hence, the omission of such variables from the growth equation may induce a sizeable bias in the estimated relation between growth and FDI.

2.2 Determinants of FDI

The empirical literature investigating determinants of FDI is disproportionately smaller than the empirical growth literature, and is typically motivated by concerns over the locational determinants that can explain the variations in FDI flowing into *particular groups* of countries. The main purported correlates of FDI are the size of the host country, and several macroeconomic policy factors that influence the stability of the host economy as well as the expected risk and return of investment.

The macroeconomic policy factors are typically measured by the joint inclusion of the economic growth rate, the inflation rate, openness to trade, and the foreign exchange rate (see, e.g., Wheeler & Mody 1992). In particular, the economic growth rate is shown to be a statistically significant factor of FDI in the context of developing countries (Schneider & Frey 1985, Culem 1988), Middle Eastern and North African countries (Mohamed & Sidiropoulos 2010), and a sample of South Asian countries (Thangamani et al. 2010). The size of the host country is typically measured by GDP, and is generally found to be robust (Wheeler & Mody 1992, Chakrabarti 2001). Using a *linear* Extreme Bounds Analysis, however, Chakrabarti (2001) finds that the significant effects of the macroeconomic policy factors depend on model specification.

Nevertheless, the size of the host country, the economic growth rate, the inflation rate, openness to trade, and the foreign exchange rate, form a standard set of conditioning variables in the FDI literature (Lim 2001); a larger set of countries, and a more general and flexible model specification than those used by the existing literature, may help to resolve the conflicting findings on the importance of each factor in explaining cross-country variations in FDI levels.

2.3 Institutions and Parameter Heterogeneity

North (1990) defines institutions as "the rules of the game in a society" or "the humanly devised constraints that shape human interaction." The concept of institutions is quite general, reflecting the existence of its many different measures and hence its complexity.[5] In general, because of high collinearity between different measures of institutions, each measure is perhaps more appropriately

[5] In the literature, measures of institutions include, for example, the general level of corruption; the degree of enforcement of property rights, human rights, and the legal system; establishments of banking institutions and financial markets; or constraints on executive branches of government.

interpreted as "a measure of institutional quality", rather than measurement of a specific type of institutional quality, such as corruption (Shleifer 2000).

Good institutions have long been thought to be fundamental factors requisite for economic development. Substantial empirical effort has been devoted to establishing the importance of institutions for economic growth. While criticism exists on the direction of causation between institutions and growth (Glaeser, La Porta, Lopez-de Silanes & Shleifer 2004), taken as a whole, this institutions-growth literature has presented compelling evidence that institutions are fundamental causal factors of growth. See, for example, Acemoglu, Johnson & Robinson (2001, 2002, 2005*a*, 2005*b*), or Alesina, Devleeschauwer, Easterly, Kurlat & Wacziarg (2003) for an excellent review of the evidence.

Different strands of the empirical literature have documented different interactions between measures of institutional quality and economic growth. Corruption has been shown to adversely impact many correlates of economic growth such as domestic investment (Mauro 1995) and government expenditure (Mauro 1998), as well as FDI (Wei 2000) and the composition of capital flows (Wei & Wu 2002). Other measures of institutional quality are also shown to be significant in explaining variations in FDI (Schneider & Frey 1985, Kahai 2004).

It has also been documented that institutions is a source of parameter heterogeneity. Durlauf (2001) argues that 'states of development', which can be thought of generally as institutional quality, induces heterogeneity into growth regression parameters. Minier (2007) parametrically models this hypothesis, and provides compelling evidence of support. Huynh & Jacho-Chávez (2009*a*, 2009*b*) find evidence of significant heterogeneity in the effects of institutions on economic growth using robust nonparametric estimation methods. Through their model averaging exercises, Durlauf et al. (2008) find evidence that institutions may impact growth indirectly through their effects on other regressors. Substantial evidence exists that financial institutions (Hermes & Lensink 2003, Alfaro et al. 2004, Durham 2004) are crucial for identifying a significant link between FDI and growth rates, and McCloud & Kumbhakar (2012) and Delgado et al. (2012) find evidence that corruption induces nontrivial sources of heterogeneity into the growth-enhancing effect of FDI. Further, McCloud & Kumbhakar (2012) identify heterogeneity in the growth effects of FDI using a wide array of institutional measures. These papers argue that for FDI to significantly improve growth rates, host countries must have at least some threshold level of institutional quality, which reflects the absorptive capabilities of the host economy.

Economic growth rates are also influenced by a host of other nontrivial sources of parameter heterogeneity; see, for example, Durlauf & Johnson (1995) for an important early contribution. There exists a host of important empirical papers that employ a wide array of flexible econometric methods and have identified important sources of nonlinearities in growth rates across countries (Liu & Stengos 1999, Durlauf, Kourtellos & Minkin 2001, Maasoumi, Racine & Stengos 2007, Henderson, Papageorgiou & Parmeter 2012). Others provide evidence that failure to model such nonlinearities and heterogeneity leads to inconsistent estimation, and hence erroneous identification of statistically significant growth factors (Temple 2001, Henderson, Papageorgiou & Parmeter 2012, Delgado et al. 2014). In essence, consideration of this research has important implications for the general robustness of econometric growth models, and is perhaps best addressed by modeling parameters as functional coefficients (Brock & Durlauf 2001, Durlauf 2001). Economic policy informed via econometric models that account for such heterogeneity is likely to be more effective at improving growth rates (Burnside & Dollar 2000).

In light of the preceding discussion, we need an empirical model that is a generalization of the standard linear-in-parameters (fully parametric) model of simultaneous equations, and allows us to unify and empirically assess the aforementioned important themes in the empirical macroeconomic and econometric literatures. *First*, we seek to model the types of (joint) interactions between economic growth and FDI. *Second*, we seek to use instrumental variables to mitigate any potential endogeneity embedded in any of the conditioning variables. *Third*, we seek to explore the impact of economic institutions as direct and indirect fundamental sources of heterogeneity in the coefficient functions in the growth and FDI models. Unlike the growth literature, there appears to be no meaningful analysis on the existence, nature, and sources of parameter heterogeneity in explaining variations in FDI across developed and developing countries. We therefore fill this gap in the FDI literature by allowing for nontrivial sources of parameter heterogeneity in our FDI equation. *Fourth*, we seek to allow for unrestricted (nonparametric) functional form of heterogeneity on the coefficient functions to avoid a potential source of model misspecification.

3 Semiparametric System of Simultaneous Equations Estimation

To unveil empirical evidence on the types of interactions between economic growth and FDI, and the effect of institutional quality on such interactions, we propose a very general semiparametric simultaneous system of equations model. We develop a novel class of semiparametric estimators suited for obtaining consistent estimates from different formulations of our semiparametric simultaneous system of equations model. We stress that our estimation strategy is fully general in that it is in no way tied to our particular empirical growth and FDI specification; it is capable of estimating any semiparametric system of simultaneous equations of the form below, with any number of equations in the system, and therefore has obvious and immediate application to economic and non-economic data. In this and the proceeding section, we provide a general derivation of our estimators and state their asymptotic properties. We provide rigorous proof of the asymptotic properties of our estimators in the technical appendix to this paper. From henceforth, we use the term *vector* to mean a *column* vector, unless otherwise stated.

To begin, consider in general form a J-variate semiparametric system of simultaneous equations

$$\begin{aligned} y_{1,it} &= Y'_{-1,it}\lambda_1(Z_{1,it}) + X'_{1,it}\gamma_1(Z_{1,it}) + \epsilon_{1,it} \\ &\vdots \qquad\qquad\qquad\qquad \vdots \\ y_{J,it} &= Y'_{-J,it}\lambda_J(Z_{J,it}) + X'_{J,it}\gamma_J(Z_{J,it}) + \epsilon_{J,it} \end{aligned} \tag{3.1}$$

where the j-th equation is

$$y_{j,it} = Y'_{-j,it}\lambda_j(Z_{j,it}) + X'_{j,it}\gamma_j(Z_{j,it}) + \epsilon_{j,it}, \tag{3.2}$$

for $j = 1, \ldots, J$, $i = 1, \ldots, N$, and $t = 1, \ldots, T$. In equation j for cross-sectional unit i in time period t, $y_{j,it}$ is a scalar response variable, $Y_{-j,it}$ is a p_j-dimensional vector of endogenous variables that includes at least one $y_{j_1,it}$ with $j_1 \neq j$; hence, the presence of $Y_{j,it}$ in each equation renders the system non-triangular. In addition, $X_{j,it}$ is a k_j-dimensional vector of exogenous variables in which the first entry is equal to 1, $Z_{j,it} \in \mathbb{R}^{d_j}$ is a vector of exogenous variables, $\lambda_j(\cdot)$ and $\gamma_j(\cdot)$ are unknown Borel measurable functions of conformable dimensions, and $\epsilon_{j,it}$ is the idiosyncratic error

term.[6] Notice that, for the general derivation, we assume that the elements of $Z_{j,it}$ are continuously distributed; in practice, this assumption is easily relaxed to accommodate mixed categorical and continuous data using the methods developed by Racine & Li (2004).

Our maintained conditional moment assumptions are that

$$E[\epsilon_{it}|Z_{it}] = 0,\ E[\epsilon_{it}|\widetilde{X}_{it}] \neq 0 \text{ and } E[\epsilon_{j,it}\epsilon_{k,it}|Z'_{it}, \widetilde{X}'_{it}] \neq 0, \tag{3.3}$$

where $\epsilon_{it} = (\epsilon_{1,it}, \ldots, \epsilon_{J,it})'$, $Z_{it} = (Z'_{1,it}, \ldots, Z'_{J,it})'$, $\widetilde{X}_{it} = (\widetilde{X}'_{1,it}, \ldots, \widetilde{X}'_{J,it})'$, and $\widetilde{X}'_{j,it} := (Y'_{-j,it}, X'_{j,it})$.

Our main interest is in the set of unknown coefficient functions $\{\lambda_j(\cdot)\}$, which clearly captures the types of interactions between the pairs y_j and y_{j_1} with $j_1 \neq j$. To characterize all interactions between any pair y_j and y_{j_1} with $j_1 \neq j$, we adopt the following taxonomy from the biological literature:

Definition 3.1. Let $l_j \in \{1, \ldots, J\}$ and $\lambda_j(\cdot) = \{\lambda_{j,l_j}(\cdot) : \mathbb{R}^{d_j} \to \mathbb{R},\ l_j \neq j\}$. Assume that for cross-sectional unit i in time period t the effect of y_j and y_{j_1} with $j_1 \neq j$ can be *positive*, *negative*, or *zero*, and *vice versa*. Between the pair of variables $(y_{j,it}, y_{j_1,it})$ we say there exists:

(a) *symbiosis* if $\lambda_{j,j_1}(\cdot), \lambda_{j_1,j}(\cdot) > 0$;

(b) $y_{j_1,it}$-*commensalism* if $\lambda_{j,j_1}(\cdot) > 0$ and $\lambda_{j_1,j}(\cdot) = 0$;

(c) *synnecrosis* if $\lambda_{j,j_1}(\cdot), \lambda_{j_1,j}(\cdot) < 0$;

(d) $y_{j_1,it}$-*antagonistic symbiosis* if $\lambda_{j,j_1}(\cdot) > 0$ and $\lambda_{j_1,j}(\cdot) < 0$;

(e) $y_{j,it}$-*ammensalism* if $\lambda_{j,j_1}(\cdot) < 0$ and $\lambda_{j_1,j}(\cdot) = 0$;

(f) *non-symbiosis* if $\lambda_{j,j_1}(\cdot) = \lambda_{j_1,j}(\cdot) = 0$.

Remark 3.2. As mentioned in the preamble of this paper, plausible theoretical predictions are that the effect of FDI on economic growth *and* the effect of economic growth on FDI can be *positive*, *negative*, or *zero*. Moreover, within a country there can be *symbiosis* between FDI and growth in one time period, but *growth-commensalism* in another time period as a result of, say, certain country-specific policies. Thus, this general taxonomy seems quite fitting for characterizing all possible theoretical interactions between FDI and growth. In other empirical applications, however, only a subset of this taxonomy may be applicable due to theoretical constraints of the signs of several $\{\lambda_j(\cdot)\}$ coefficient functions.

To proceed with estimation, we reformulate (3.2) as

$$y_{j,it} = \widetilde{X}'_{j,it} g_j(Z_{j,it}) + \epsilon_{j,it}, \tag{3.4}$$

where $g_j(Z_{j,it}) := (\lambda'_j(Z_{j,it}), \gamma'_j(Z_{j,it}))'$ and $m_j := p_j + k_j$.[7] In the absence of a distributional assumption on $\epsilon_{j,it}$, we opt to use the generalized method of moments (GMM) approach to estimate

[6] It is common in panel data models to define a one- or two-way error component specification for the idiosyncratic noise. We follow the panel nonparametric GMM models of Cai & Li (2008) and Tran & Tsionas (2009) in our theoretical specification, and in addition, deploy interactive discrete country and time indicators in our empirical application using the generalized product kernels of Racine & Li (2004) to more generally account for unobservable effects without imposing the restriction that the unobserved effects are linearly separable from the conditional mean.

[7] In general, $Z_{j,it}$ is required to be the same across $g_j(\cdot)$ for any j because of substantial econometric difficulties that arise in estimation of a semiparametric varying coefficient model in which the coefficient variables differ across coefficients.

our system of equations. The general unspecified form of our coefficient functions $g_j(\cdot)$ in (3.4) precludes estimation of our system with parametric GMM estimation. The estimators of $g_j(\cdot)$, however, can be obtained using nonparametric GMM methods. For our economic analysis, we are interested in estimating these unknown coefficient functions *and* their derivatives in all equations. Consequently, we first linearize the $g_j(\cdot)$ in each equation using local-linear approximation (Fan & Gijbels 1996); we apply this method to our system of equations as follows. We assume each g_j is sufficiently smooth and consider a first-order Taylor series expansion of $g_j(Z_{j,it})$ around a fixed point z_j in a neighborhood of $\{Z_{j,it}\}$, so that the sth component of this expansion is

$$g_j^s(Z_{j,it}) \approx a_j^s + (b_j^s)'(Z_{j,it} - z_j), \;\; s = 1, \ldots, m_j, \tag{3.5}$$

where $b_j^s := \partial g_j^s(z_j)/\partial z_j$, a $d_j \times 1$ vector of first-order derivatives. Note that for the j-th equation, the remainder term of the second-order Taylor series expansion of the s-th component of $g_j(Z_{j,it})$, $g_j^s(Z_{j,it})$, is

$$R_j^s(Z_{j,it}, z_j) = g_j^s(Z_{j,it}) - a_j^s - (b_j^s)'(Z_{j,it} - z_j) - \frac{1}{2}(Z_{j,it} - z_j)'\nabla^2 g_j^s(z_j)(Z_{j,it} - z_j), \tag{3.6}$$

and $R_j(Z_{j,it}, z_j) = (R_j^1(Z_{j,it}, z_j), R_j^2(Z_{j,it}, z_j), \ldots, R_j^{m_j}(Z_{j,it}, z_j))'$ is a m_j-dimensional vector. Define $\bar{R}_j^s(Z_{j,it}, z_j) := \frac{1}{2}(Z_{j,it} - z_j)'\nabla^2 g_j^s(z_j)(Z_{j,it} - z_j)$ to be the second order term in the expansion, and $\bar{R}_j(Z_{j,it}, z_j) = (\bar{R}_j^1(Z_{j,it}, z_j), \bar{R}_j^2(Z_{j,it}, z_j), \ldots, \bar{R}_j^{m_j}(Z_{j,it}, z_j))'$.

Combining (3.4) and the first-order approximation in (3.5) we obtain

$$y_{j,it} \approx U_{j,it}'\alpha_j + \epsilon_{j,it}, \tag{3.7}$$

where $U_{j,it} := \begin{pmatrix} \widetilde{X}_{j,it} \\ \widetilde{X}_{j,it} \otimes (Z_{j,it} - z_j) \end{pmatrix}$ is a vector of dimension $m_j(d_j + 1)$, $\otimes$ is the Kronecker product operator, and the corresponding coefficient vector is $\alpha_j := (a_j^1, \ldots, a_j^{m_j}, (b_j^1)', \ldots, (b_j^{m_j})')'$. Now stacking observations by T, then by N, and then by J gives the compact system formulation

$$y \approx U\alpha + \epsilon, \tag{3.8}$$

where $y = (y_1', \ldots, y_J')'$, $U = \textit{block diag}(U_1, \ldots, U_J)$ so that for each j, U_j is a matrix of $NT \times m_j(d_j + 1)$ observations on all right-hand side variables, $\alpha = (\alpha_1', \ldots, \alpha_J')'$, and $\epsilon = (\epsilon_1', \ldots, \epsilon_J')'$ with $\epsilon_j = (\epsilon_{j,11}, \ldots, \epsilon_{j,1T}, \ldots, \epsilon_{j,21}, \ldots, \epsilon_{j,2T}, \ldots, \epsilon_{j,N1}, \ldots, \epsilon_{j,NT})'$.

We now assume the existence of additional information in the form of instruments, W, to ensure the identification of the α parameter in the system in (3.8). For the population moment conditions, let $V_{j,it} := (W_{j,it}', Z_{j,it}')'$ and $V_{it} = (V_{1,it}', \ldots, V_{J,it}')'$. Thus,

$$E(\epsilon_{it}|V_{it}) = 0. \tag{3.9}$$

In light of our moment equality in (3.9), by the *equivalence principle* (see Theorem 16.10 in Billingsley 1995), for any measurable function $Q(V_{it})$,

$$E(\epsilon_{it}|V_{it}) = 0 \iff E(Q(V_{it})\epsilon_{it}|V_{it}) = 0. \tag{3.10}$$

In essence, a plethora of conditional and unconditional moment equations can be generated from (3.10) using different specifications of $Q(V_{it})$. In the spirit of Cai & Li (2008), we choose for each equation j, $Q_{j,it} := Q(V_{j,it}) = \begin{pmatrix} W_{j,it} \\ W_{j,it} \otimes (Z_{j,it} - z_j)/h_j \end{pmatrix}$, which is a low-order polynomial vector of dimension $l_j(d_j + 1)$ in $W_{j,it}$ and $Z_{j,it}$, l_j is the dimension of $W_{j,it}$, and $l_j \geq m_j$ for identification. In addition, the first entry of the vector $W_{j,it}$ is equal to one. Clearly, this simple form of $Q_{j,it}$ may not be the optimal form of the instruments for our model of interest. Newey (1990), for example, provides a mechanism for obtaining optimal instruments. However, deriving the functional form of optimal instruments for our model is beyond the scope of this paper.[8]

In comparison to the literature on GMM estimation for parametric systems of simultaneous equations, relatively little is known about using the GMM approach to estimate semiparametric systems of simultaneous equations and the asymptotic properties of the resultant estimators. To fill this gap in the literature, we therefore consider two types of local-linear GMM estimators for theoretical analysis. We draw on insights from the work of Welsh & Yee (2006) to guide us in constructing such estimators. Using a nonparametric exogenous system of seemingly unrelated regressions (SUR) - in which the regressor differs across equations - Welsh & Yee (2006) document that (i) consistency of the local-linear estimator via weighted least squares hinges on the position of the kernel weights in the unconditional moment equations, and (ii) under a homoscedasticity assumption, there is no gain in asymptotic efficiency from accounting for the correlation across errors - that is, there is no gain in smoothing jointly over smoothing marginally.

To yield a local-linear GMM estimator that is consistent, the nonparametric and multivariate nature of our model in (3.8) and our use of kernel smoothing therefore suggest careful consideration of our functional form for the system-based unconditional moment equation that is implied by (3.10). For ease of exposition, we let $Q = block\ diag(Q_1, \ldots, Q_J)$ so that for each j, Q_j is a matrix of $NT \times l_j(d_j + 1)$ observations on the variables in $Q_{j,it}$. Also, let the system kernel matrix $K = block\ diag(K_1, \ldots, K_J)$ where $K_j = diag(K_{h_j}(Z_{j,11} - z_j), \ldots, K_{h_j}(Z_{j,NT} - z_j))$ with $K_{h_j}(\cdot) := h_j^{-d_j} K_j(\cdot/h_j)$, a kernel function in $\mathbb{R}^{d_j}$ for equation j. Define $\tilde{m}_j := m_j(d_j + 1)$, $\tilde{m} := \sum_{j=1}^{J} \tilde{m}_j$, and similarly, $\tilde{l}_j := l_j(d_j + 1)$, $\tilde{l} := \sum_{j=1}^{J} \tilde{l}_j$.

For our *first* local-linear GMM estimator, we assume that $A := Var(\epsilon\epsilon'|V)$ is a known $NT \times NT$ positive definite weighting matrix, and seek the nonparametric GMM system estimator $\widehat{\alpha}$ such that the following unconditional moment requirement is satisfied

$$Q' K^{1/2} A^{-1} K^{1/2} (y - U\alpha) = 0. \tag{3.11}$$

[8] Is is well known that a set of conditional moment restrictions, such as those implied by (3.9) and by extension (3.10), is the staple component of many statistical strategies for identification, estimation, and testing. Indeed, several candidate functional forms for $Q(\cdot)$ have been used in the GMM single-equation literature on consistent parameter estimation in linear and nonlinear models. For example, Domínguez & Lobato (2004) use indicator functions as instruments to guarantee parameter identification in the estimation of endogenous nonlinear conditional mean models for time-series data; in nonlinear models, the use of indicator-based instrument functions leads to a continuum of unconditional moments and therefore precludes the use of an ad-hoc and finite number of instruments in estimation, which can lead to identification problems and hence engender parameter estimator inconsistency. As Carrasco & Florens (2000) demonstrate, continuum-of-moments approaches give rise to GMM estimators that are more efficient than their finite-moments counterparts. Recently, and as an alternative approach to Domínguez & Lobato (2004), Hsu & Kuan (2011) use a generically comprehensive revealing function - in spirit of Stinchcombe & White (1998) - to generate a continuum of unconditional moments that can guarantee parameter identifiability. In the context of specification testing, other choices of $Q(\cdot)$ - which allow for a continuum of moments - have been posited by Bierens (1982, 1990), Stinchcombe & White (1998), and Bierens & Ploberger (1997). Consequently, different choices for $Q(\cdot)$ can generate different classes of system estimators.

This moment condition corresponds to a local-linear GMM generalized least squares (GLS) estimator. In (3.11), we adopt the system of equations kernel weighting structure of Welsh & Yee (2006) that guarantees consistency of $\widehat{\alpha}$. Intuitively, the use and position of $K^{1/2}$ in (3.11) ensures that the cross-product of residuals, which are in the off-diagonal entries, are weighed symmetrically. This moment condition, however, represents an inconsistent system of $\widetilde{l}$ equations in $\widetilde{m}$ unknowns, which will not yield a unique estimator of α. We can premultiply (3.11) by a suitable scaling matrix to ensure we have a consistent system of equations for uniquely identifying the local-linear GMM-GLS estimator $\widehat{\alpha}$. In spirit of Cai & Li (2008), we choose $U'K^{1/2}A^{-1}K^{1/2}Q$ as the $\widetilde{m} \times \widetilde{l}$ scaling matrix so that (3.11) becomes

$$U'K^{1/2}A^{-1}K^{1/2}Q \cdot Q'K^{1/2}A^{-1}K^{1/2}(y - U\alpha) = 0. \tag{3.12}$$

Then solving (3.12) gives

$$\widehat{\alpha} = [U'(K^{1/2}A^{-1}K^{1/2})QQ'(K^{1/2}A^{-1}K^{1/2})U]^{-1}[U'(K^{1/2}A^{-1}K^{1/2})QQ'(K^{1/2}A^{-1}K^{1/2})y]. \tag{3.13}$$

Remark 3.3. Note that $\widehat{\alpha}$, as defined by (3.13), does not take into account the variance-covariance moment matrix $Var(Q'K^{1/2}A^{-1}K^{1/2}\epsilon)$, and is therefore not the fully-efficient GMM estimator of α. Deriving a formula for the fully-efficient GMM estimator of α that is predicated on (3.11) will yield a very long expression that will provide no additional insights beyond what can be extracted from the asymptotic theory of $\widehat{\alpha}$.

Using a nonparametric exogenous vector measurement error model (a nonparametric system of SUR that has identical covariates across equations), Welsh & Yee (2006) also document that (i) the position of the kernel weights in the unconditional moment equations is immaterial for consistency of the local linear estimator via weighted least squares, and (ii) in some instances, and even under the homoscedasticity assumption, ignoring the correlations in errors across equations can result in a large loss in efficiency - that is, there can be gains in smoothing jointly over smoothing marginally. A semiparametric system of simultaneous equations in which the coefficient covariates are identical across equations is the model we use in our empirical application; moreover, and in light of the findings in Welsh & Yee (2006), a local-linear GMM estimator for such a model has different asymptotic properties from those of $\widehat{\alpha}$.

Thus, for our *second* local-linear GMM estimator, we consider another GMM-based local-linear system estimator but for the system model with $Z_{1,it} = Z_{2,it} = \cdots = Z_{J,it} = Z_{it}$. For this model, we also assume $h_1 = h_2 = \cdots = h_J = h$, and $K_1 = K_2 = \cdots = K_J = K$ to carry out local-linear estimation. Also, we assume that Γ^{-1} is a known $\tilde{l} \times \tilde{l}$ positive definite weighting matrix and seek the local-linear GMM system estimator $\widehat{\alpha}_{GMM}$ such that

$$\widehat{\alpha}_{GMM} = \arg\min_{\alpha} \ (y - U\alpha)'\widetilde{K}Q\Gamma^{-1}Q'\widetilde{K}(y - U\alpha), \tag{3.14}$$

where $\widetilde{K} = K \otimes I_J$, and Q and U are as previously defined but with Z_{it} in lieu of $Z_{j,it}, \forall\ j$. Then

$$\widehat{\alpha}_{GMM} = \Big[U'\widetilde{K}Q\Gamma^{-1}Q'\widetilde{K}U\Big]^{-1}\Big[U'\widetilde{K}Q\Gamma^{-1}Q'\widetilde{K}y\Big]. \tag{3.15}$$

Our proposed estimators - $\widehat{\alpha}$ and $\widehat{\alpha}_{GMM}$ - are relatively simple to implement. Moreover, and

as previously mentioned, our estimators are generalizations of several existing estimators, including the parametric generalized method of moments estimator (Hansen 1982), the single equation nonparametric generalized method of moments estimator (Cai & Li 2008, Tran & Tsionas 2009), the standard single equation smooth coefficient model with exogenous variables (Li et al. 2002), the two-step smooth coefficient instrumental variables estimators developed for both continuous (Cai et al. 2006, Cai & Xiong 2012) and discrete (Das 2005) endogenous regressors, and several nonparametric estimators for system of equations models that assume the regressors are exogenous (Welsh & Yee 2006). Indeed, the advantage of our estimators over these other estimators is that we can simultaneously model unknown forms of parameter heterogeneity, endogeneity, and under specific model assumptions, cross-equation correlation of the errors to obtain more efficient estimates. In the middle part of the next section, we show the numerical and asymptotic links between the estimator $\widehat{\alpha}$ and some of those in the existing literature.

4 Asymptotic Properties

To establish the asymptotic properties of our class of estimators, $\widehat{\alpha}$ and $\widehat{\alpha}_{GMM}$, we adopt the scaling approach in Cai & Li (2008) by defining $H := \textit{block diag}(H_1, \ldots, H_J)$ so that for each j, $H_j := \textit{diag}(I_{m_j}, h_j I_{d_j m_j})$ where I_{m_j} represents an identity matrix of size m_j. We develop and discuss the asymptotic properties of $\widehat{\alpha}$, and then state the corresponding properties for $\widehat{\alpha}_{GMM}$, in that order.

For ease of exposition, we define $\widehat{\alpha} := [S_n' S_n]^{-1} S_n' T_n$, where $n := NT$, and

$$S_n = \frac{1}{n} Q'(K^{1/2} A^{-1} K^{1/2}) U, \quad \text{and} \quad T_n = \frac{1}{n} Q'(K^{1/2} A^{-1} K^{1/2}) y.$$

We define $\widetilde{U}_{j,it} := H_j^{-1} U_{j,it} = \begin{pmatrix} \widetilde{X}_{j,it} \\ \widetilde{X}_{j,it} \otimes (Z_{j,it} - z_j)/h_j \end{pmatrix}$, so that

$$H\widehat{\alpha} = [\widetilde{S}_n' \widetilde{S}_n]^{-1} \widetilde{S}_n' T_n,$$

where

$$\widetilde{S}_n = S_n H^{-1} = \frac{1}{n} Q'(K^{1/2} A^{-1} K^{1/2}) U H^{-1} = \frac{1}{n} Q'(K^{1/2} A^{-1} K^{1/2}) \widetilde{U},$$

with $\widetilde{U} := U H^{-1}$. Then, we decompose T_n as follows:

$$T_n = \widetilde{S}_n H \alpha + T_n^* + B_n + R_n,$$

in which $T_n^* = \frac{1}{n} Q'(K^{1/2} A^{-1} K^{1/2}) \epsilon$, $B_n = \frac{1}{n} Q'(K^{1/2} A^{-1} K^{1/2}) \widetilde{X} \bar{R}$, $R_n = \frac{1}{n} Q'(K^{1/2} A^{-1} K^{1/2}) \widetilde{X} R$, and $\widetilde{X} := \textit{block diag}\ (\widetilde{X}_1, \ldots, \widetilde{X}_J)$, $\widetilde{X}_j$ is a $n \times m_j$ matrix of observations on $\widetilde{X}_{j,it}$, and $\bar{R} := (\bar{R}_1', \ldots, \bar{R}_J')'$ and $R := (R_1', \ldots, R_J')'$ are vectors of dimension $\sum_{j=1}^{J} m_j$. We seek to establish the asymptotic properties of a properly normalized variant of $H(\widehat{\alpha} - \alpha)$, which we express as

$$H(\widehat{\alpha} - \alpha) - (\widetilde{S}_n' \widetilde{S}_n)^{-1} (\widetilde{S}_n' B_n) - (\widetilde{S}_n' \widetilde{S}_n)^{-1} (\widetilde{S}_n' R_n) = (\widetilde{S}_n' \widetilde{S}_n)^{-1} (\widetilde{S}_n' T_n^*). \tag{4.1}$$

On the left-hand side of (4.1), the second term will determine the asymptotic bias, whereas the third term will be shown to be asymptotically negligible. The term on the right-hand side of (4.1)

will be shown to be asymptotically normal.

Without loss of generality, and in light of our empirical analysis of interest, from henceforth we restrict our theoretical developments to a *bivariate* semiparametric system of simultaneous equations. Some additional notations are in order. We define

$$\mu_{j,2}(K_j) := \int u_j u_j' K_j(u_j) du_j, \text{ and } \nu_{j,0} := \int K_j^2(u_j) du_j,$$
$$\Omega_j = \Omega_j(z_j) = E[W_{j,it}\widetilde{X}_{j,it}' | Z_{j,it} = z_j],$$
$$\Omega_j^* = \Omega_j^*(z_j) = Var[W_{j,it}\epsilon_{j,it} | Z_{j,it} = z_j],$$
$$\Omega_{jk}^{lm}(z_1, z_2) := E\{W_{j,it}W_{k,it}'\epsilon_{l,it}\epsilon_{m,it} | Z_{1,it} = z_1, Z_{2,it} = z_2\}, \text{ for } j, k, l, m = \{1, 2\},$$
$$\Omega_{jk} = \Omega_{jk}(z_1, z_2) = E[W_{j,it}\widetilde{X}_{k,it}' | Z_{1,it} = z_1, Z_{2,it} = z_2], \text{ for } j \neq k = \{1, 2\},$$
$$S_j = S_j(z_j) := \begin{pmatrix} \Omega_j & \mathbf{0} \\ \mathbf{0}' & \Omega_j \otimes \mu_{j,2}(K_j) \end{pmatrix}, \text{ and } S = block\ diag(S_1, S_2),$$
$$S_j^* = S_j^*(z_j) := \begin{pmatrix} \Omega_j^* \nu_{j,0} & \mathbf{0} \\ \mathbf{0}' & \Omega_j^* \otimes \mu_{j,2}(K_j^2) \end{pmatrix}, \text{ and } S^* = block\ diag(S_1^*, S_2^*),$$
$$B_j(z_j) = \int \begin{pmatrix} \Omega_j A_j(u_j, z_j) \\ \{\Omega_j A_j(u_j, z_j)\} \otimes u_j \end{pmatrix} K_j(u_j) du_j, \text{ and } A_j(u_j, z_j) = \begin{pmatrix} u_j' \nabla^2 g_j^1(z_j) u_j \\ \vdots \\ u_j' \nabla^2 g_j^{m_j}(z_j) u_j \end{pmatrix},$$

with $\nabla^2 g_j^s(z_j) := \partial g_j^s(z_j)/\partial z_j \partial z_j'$, and $B(z) = \big(B_1(z_1)', B_2(z_2)'\big)'$, and the dimension of $\mathbf{0}$, the *zero* matrix, differs according to context in which it is used. In addition, define

$$G_{1t}^{(jk,lm)}(z_1, z_2) := E\{W_{j,i1}W_{k,it}'\epsilon_{l,i1}\epsilon_{m,it} | Z_{i1} = z_1, Z_{it} = z_2\}.$$

The following assumptions are needed to establish the asymptotic properties of $\widehat{\alpha}$, our local-linear GMM-GLS estimator, in the case of large N and small T. Note that we will use the vector notation ϵ_{it} to mean $(\epsilon_{1,it}, \epsilon_{2,it})'$, and similar notations for $W_{it}, X_{it}, Y_{it}, Z_{it}$, etc.

Assumption A.1. (i) $\{(W_{it}, X_{it}, Y_{it}, Z_{it}, \epsilon_{it})\}$ are *i.i.d.* across the i index for each fixed t and strictly stationary over t for each fixed i, $E|\epsilon_{j,it}|^2 < \infty$, and $E\|W_{j,it}\tilde{X}_{k,it}'\|^2 < \infty$, $E\|W_{j,it}W_{k,it}'\|^2 < \infty$, where $\|A\|$ is the Frobenius norm for a finite-dimensional matrix A; this norm reduces to the usual Euclidean norm if A is a column vector.
(ii) The conditional variance of ϵ_{it} is Σ a bivariate positive definite matrix defined as

$$\Sigma(v) := Var(\epsilon_{it} | V_{it} = v) = \begin{pmatrix} \sigma_1^2 & \sigma_1\sigma_2\rho \\ \sigma_1\sigma_2\rho & \sigma_2^2 \end{pmatrix}.$$

Assumption A.2. For each $t \geq 1$, $G_{1t}^{(jk,lm)}(z_1, z_2)$ and $f_{1t}(z_1, z_2)$, the joint density of Z_{i1} and Z_{it}, are continuous at (z_1, z_2). Also, for each z_j, $\Omega_j(z_j)$, $\Omega_{jk}(z_1, z_2)$, and $f_j(z_j)$ are bounded away from zero, where $f_j(z_j)$ is the marginal density function of $Z_{j,it}$. Further, $\sup_{t\geq 1} |G_{1t}^{(jk,lm)}(z_1, z_2) f_{1t}(z_1, z_2)| \leq M(z_1, z_2) < \infty$ for some arbitrary function $M(z_1, z_2)$. In addition, $g_j(z_j)$ and $f_j(z_j)$ are both twice continuously differentiable at $z_j \in \mathbb{R}^{d_j}$. The joint density of $Z_{it} = (Z_{1,it}', Z_{2,it}')'$ is $f(z) = f(z_1, z_2)$, and the partial derivatives $f^{(j)}(z) = \partial f(z)/\partial z_j$ and $f^{(j,k)}(z) = \partial^2 f(z)/\partial z_j \partial z_k'$ exist and are continuous.

Assumption A.3. The kernel functions $K_j(\cdot)$ are even, nonnegative, bounded density functions with compact support.

Assumption A.4. The instrumental variable W_{it} satisfies the conditions that $E(\epsilon_{it}|W_{it}, Z_{it}) = 0$ and $E[\pi(V_{it})\pi(V_{it})'|Z_{it} = z]$ is of full rank for all z, where $\pi(V_{it}) = E(\widetilde{X}_{it}|V_{it})$.

Assumption A.5. For $j = 1, 2$, (i) $h_j \to 0$, (ii) $Nh_j^{d_j} \to \infty$, and (iii) $Nh_j^{d_j}h_k^{d_k} \to \infty$ as $N \to \infty$, and $h_j^{d_j}/h_k^{d_k} \to 1$ for $j \neq k$.

Assumption A.6. There exists some arbitrary $\delta > 0$ such that $E\{|\epsilon_{j,it}W_{k,it}|^{(2+\delta)}|Z_j = u_j, Z_k = u_k\}$ is continuous at $u_j = z_j$ and $u_k = z_k$.

Remark 4.1. These assumptions contain some standard regularity conditions in the GMM and nonparametric literatures for panel data models with large N and small T. Moreover, these conditions represent generalizations to those in Welsh & Yee (2006) and Cai & Li (2008). Assumption A.1 extends the orthodox assumptions in the single-equation panel data models to a two-equation case. Note that $E|\epsilon_{j,it}\epsilon_{k,it}| < \infty$, an assumption that we omit, follows from $E|\epsilon_{j,it}|^2 < \infty$ and an application of the Cauchy-Schwarz inequality. Assumption A.2 provides bounds and smoothness conditions on the functionals in the proofs. The twice differentiability condition on the marginal distributions and functions is slightly stronger than warranted because it is possible to impose a Lipschitz condition on the first derivative of these marginals in lieu of the assumption of existence and continuity of the second derivative. The use of such general substitution, however, would lead to more cumbersome notations. Assumption A.3 renders $K_j(\cdot)$ a member of the class of second-order kernels. The nonnegativity and boundedness of $K_j(\cdot)$ are used several times in the proofs. Assumption A.4 is the identification condition. Assumption A.5 states that the each bandwidth is a null sequence of positive integers, and provides minimal conditions on the bandwidths to ensure consistency of the corresponding kernel estimators. Also, Assumption A.5 requires that the two bandwidths have the same order of magnitude. Assumption A.6 provides a Liapounov's condition, which we use in establishing asymptotic normality.

Define $\theta := \{\sigma_1^2(1-\rho^2)\}^{-1}$, $\beta := -\rho\{\sigma_1\sigma_2(1-\rho^2)\}^{-1}$, and $\gamma := \{\sigma_2^2(1-\rho^2)\}^{-1}$ with $|\rho| < 1$. By virtue of Assumption A.1, we can express the matrices $\Upsilon := \Sigma^{-1}$ and A^{-1} as follows:

$$\Upsilon = \begin{pmatrix} \theta & \beta \\ \beta & \gamma \end{pmatrix}, \quad A^{-1} = \Upsilon \otimes I_{NT} := \begin{pmatrix} D_\theta & \vdots & D_\beta \\ \dots & \dots & \dots \\ D_\beta & \vdots & D_\gamma \end{pmatrix}. \tag{4.2}$$

Finally, we define $D_{\theta\gamma} := block\ diag(\theta I_{\tilde{l}_1}, \gamma I_{\tilde{l}_2})$, $\tilde{D}_j := h_j^{d_j} I_{\tilde{m}_j}$, $\tilde{D} := block\ diag(\tilde{D}_1, \tilde{D}_2)$, and $\iota_{\tilde{m}_j}$ is an $\tilde{m}_j$-dimensional unit vector so that

$$\tilde{h}_{\tilde{m}}^2 := \big(h_1^2\iota'_{\tilde{m}_1}, h_2^2\iota'_{\tilde{m}_2}\big)',\ \tilde{h}_{\tilde{l}}^2 := \big(h_1^2\iota'_{\tilde{l}_1}, h_2^2\iota'_{\tilde{l}_2}\big)',$$
$$\tilde{I}_{\tilde{m}}^2 := block\ diag\big(h_1^2 I_{\tilde{m}_1}, h_2^2 I_{\tilde{m}_2}\big),\ \tilde{I}_{\tilde{l}}^2 := block\ diag\big(h_1^2 I_{\tilde{l}_1}, h_2^2 I_{\tilde{l}_2}\big)$$
$$\tilde{f}_{\tilde{m}}(z) := block\ diag\big(f_1(z_1)I_{\tilde{m}_1}, f_2(z_2)I_{\tilde{m}_2}\big),\ \tilde{f}_{\tilde{l}}(z) := block\ diag\big(f_1(z_1)I_{\tilde{l}_1}, f_2(z_2)I_{\tilde{l}_2}\big).$$

The following results establish consistency and asymptotic normality of $\widehat{\alpha}$.

Proposition 4.2. *If Assumptions A.1 to A.5 hold, then*

(i) $\widetilde{S}_n = \tilde{f}_{\tilde{l}}(z) D_{\theta\gamma} S\{1 + o_{\mathbb{P}}(1)\}$,

(ii) $B_n = \frac{1}{2}\tilde{I}_{\tilde{l}}^2 \tilde{f}_{\tilde{l}}(z) D_{\theta\gamma} B(z) + o_{\mathbb{P}}(\tilde{h}_{\tilde{l}}^2)$, *and*

(iii) $R_n = o_{\mathbb{P}}(\tilde{h}_{\tilde{l}}^2)$.

Proposition 4.3. *If Assumptions A.1 to A.5 hold, then*

$$n\tilde{\mathcal{D}} Var(T_n^*) = \tilde{f}_{\tilde{l}}(z) D_{\theta\gamma}^2 S^*, \tag{4.3}$$

where $\tilde{\mathcal{D}} :=$ *block diag*$(\tilde{\mathcal{D}}_1, \tilde{\mathcal{D}}_2)$ *with* $\tilde{\mathcal{D}}_j := h_j^{d_j} I_{\tilde{l}_j}$, *for* $j = 1, 2$.

Theorem 4.4. *(i) If Assumptions A.1 to A.5 hold, then*

$$H(\widehat{\alpha} - \alpha) - \frac{\tilde{I}_{\tilde{m}}^2}{2} B^*(z) = o_{\mathbb{P}}(\tilde{h}_{\tilde{m}}^2) + O_{\mathbb{P}}\big(n^{-1/2}\tilde{D}^{-1/2}\iota_{\tilde{m}}\big), \tag{4.4}$$

where $B^*(z) := \big(S'S\big)^{-1}\big(S'B(z)\big)$.

(ii) If Assumptions A.1 to A.6 hold, then

$$\big(n^{1/2}\tilde{D}^{1/2}\big)\left[H(\widehat{\alpha} - \alpha) - \frac{\tilde{I}_{\tilde{m}}^2}{2} B^*(z) + o_{\mathbb{P}}(\tilde{h}_{\tilde{m}}^2)\right] \xrightarrow{d} N\big(\mathbf{0}, \tilde{f}_{\tilde{m}}^{-1}(z)\Delta\big), \tag{4.5}$$

where $\Delta := (S'S)^{-1}S'S^*S(S'S)^{-1}$.

Remark 4.5. The block-diagonal nature of the matrices S and S^* implies that the estimators of the coefficient functions and their derivatives are asymptotically uncorrelated across equations. This result is equivalent to assuming the errors across equations are conditionally uncorrelated, that is $\rho = 0$. Thus, under specific conditions, $\widehat{\alpha}$ - the local-linear GMM-GLS estimator - does not yield any gain in smoothing jointly over smoothing marginally. Indeed, decomposing $B^*(z)$ and Δ reveals that

$$B^*(z) = \Big(B_{1,g}(z_2)'|\mathbf{0}'|B_{2,g}(z_2)'|\mathbf{0}'\Big)',$$

with

$$B_{j,g}(z_j) = \int A_j(u_j, z_j) K_j(u_j) du_j = \Big[tr\big(\nabla^2 g_j^s(z_j)\mu_{j,2}(K_j)\big)\Big]_{m_j \times 1},$$

and $\Delta :=$ *block diag*(Δ_1, Δ_2), and $\Delta_j = diag\Big\{\nu_{j,0}\Omega_{j,g}, \Omega_{j,g} \otimes [\mu_{j,2}^{-1}(K_j)\mu_{j,2}(K_j^2)\mu_{j,2}^{-1}(K_j)]\Big\}$ with $\Omega_{j,g} = (\Omega_j'\Omega_j)^{-1}\Omega_j'\Omega_j^*\Omega_j(\Omega_j'\Omega_j)^{-1}$, which are identical to the asymptotic bias and variance terms from a bivariate variant of the main results of Cai & Li (2008). Note that these results also demonstrate the parallels between certain properties of GMM estimators for parametric and nonparametric system models.

As previously mentioned, the results in Theorem 4.4 are quite general and therefore nest the asymptotic properties of several other estimators including, for example, a few in Welsh & Yee (2006). We now demonstrate the links between our $\widehat{\alpha}$ and some estimator in the existing literature. The comparable estimators in Welsh & Yee (2006) are derived from a set of nonparametric SUR models. We first consider a semiparametric estimator of the Welsh & Yee (2006) econometric

modeling framework that is predicated on the assumption of $E[\epsilon_{j,it}|\widetilde{X}'_{j,it}] = 0$. To begin, we suppose $W_{j,it} = \widetilde{X}_{j,it},\ \forall\ i,j,t$, and define $\widetilde{Q}_{j,it} := \begin{pmatrix} \widetilde{X}_{j,it} \\ \widetilde{X}_{j,it} \otimes (Z_{j,it} - z_j)/h_j \end{pmatrix}$. We define the system estimator in this case as $\tilde{\alpha}$, where

$$\tilde{\alpha} = [\widetilde{Q}'(K^{1/2}A^{-1}K^{1/2})U]^{-1}[\widetilde{Q}'(K^{1/2}A^{-1}K^{1/2})y]. \tag{4.6}$$

To derive the asymptotic properties, we simply put $W_{j,it}$ in lieu of $\widetilde{X}_{j,it}$ in all relevant expressions on page 13 and relabel, for example, in the following way:

$$\begin{aligned}
\widetilde{\Omega}_j &:= E[\widetilde{X}_{j,it}\tilde{X}'_{j,it}|Z_{j,it} = z_j], \\
\widetilde{\Omega}^*_j &:= Var[\widetilde{X}_{j,it}\epsilon_{j,it}|Z_{j,it} = z_j], \\
\widetilde{\Omega}^{lm}_{jk}(z_1, z_2) &:= E\{\widetilde{X}_{j,it}\widetilde{X}'_{k,it}\epsilon_{l,it}\epsilon_{m,it}|Z_{1,it} = z_1, Z_{2,it} = z_2\},\ \text{for } j,k,l,m = \{1,2\}, \\
\widetilde{\Omega}_{jk} &:= \Omega_{jk}(z_1, z_2) = E[\widetilde{X}_{j,it}\tilde{X}'_{k,it}|Z_{1,it} = z_1, Z_{2,it} = z_2],\ \text{for } j \neq k = \{1,2\}.
\end{aligned}$$

We relabel $\widetilde{S}_j$, $\widetilde{B}_j(z_j)$, $\widetilde{B}(z)$, $\widetilde{S}$, $\widetilde{S}^*$, and $\widetilde{G}^{(jk,lm)}_{1t}$ in a similar manner. To this end, the results of Propositions 4.2 and 4.3 continue to hold but with $\widetilde{\widetilde{S}}_n$, $\widetilde{S}$, $\widetilde{B}_n$, $\widetilde{R}_n$, $\widetilde{T}^*_n$ and $\widetilde{S}^*$ respectively in lieu of $\widetilde{S}_n$, S, B_n, R_n, T^*_n and S^*. The following theorem establishes consistency and asymptotic normality of the GMM estimator $\tilde{\alpha}$ from the semiparametric system of SUR model.

Theorem 4.6. *Suppose $E[\epsilon_{j,it}|\widetilde{X}'_{j,it}] = 0$.*

(i) If Assumptions A.1 to A.5 hold, then

$$H(\tilde{\alpha} - \alpha) - \frac{\tilde{I}^2_{\tilde{m}}}{2}\tilde{B}^*(z) = o_{\mathbb{P}}(\tilde{h}^2_{\tilde{m}}) + O_{\mathbb{P}}\big(n^{-1/2}\tilde{D}^{-1/2}\iota_{\tilde{m}}\big), \tag{4.7}$$

where $\tilde{B}^*(z) := \tilde{S}^{-1}\tilde{B}(z)$.

(ii) If Assumptions A.1 to A.6 hold, then

$$\big(n^{1/2}\tilde{D}^{1/2}\big)\left[H(\tilde{\alpha} - \alpha) - \frac{\tilde{I}^2_{\tilde{m}}}{2}\tilde{B}^*(z) + o_{\mathbb{P}}(\tilde{h}^2_{\tilde{m}})\right] \xrightarrow{d} N\big(\mathbf{0}, \tilde{f}^{-1}_{\tilde{m}}(z)\tilde{\Delta}\big), \tag{4.8}$$

where $\tilde{\Delta} := \tilde{S}^{-1}\tilde{S}^*\tilde{S}^{-1}$.

We can use our preceding results to obtain an estimator for a purely nonparametric SUR model characterized by

$$y_{j,it} = g_j(Z_{j,it}) + \epsilon_{j,it},\ g_j(\cdot) : \mathbb{R}^{d_j} \to \mathbb{R},\ \text{for } j = 1, 2. \tag{4.9}$$

To begin, we set $W_{j,it} = \widetilde{X}_{j,it} = 1$, $\breve{Q}_{j,it} := \begin{pmatrix} 1 \\ (Z_{j,it} - z_j)/h_j \end{pmatrix}$, and $\breve{U}_{j,it} := \begin{pmatrix} 1 \\ (Z_{j,it} - z_j) \end{pmatrix}$. We define the system estimator in this case as $\breve{\alpha}$, where

$$\breve{\alpha} = [\breve{Q}'(K^{1/2}A^{-1}K^{1/2})\breve{U}]^{-1}[\breve{Q}'(K^{1/2}A^{-1}K^{1/2})y]. \tag{4.10}$$

The results of Propositions 4.2 and 4.3 continue to hold but with $\breve{\widetilde{S}}_n$, $\breve{S}$, $\breve{B}_n$, $\breve{R}_n$, $\breve{T}^*_n$ and $\breve{S}^*$ respectively in lieu of $\widetilde{S}_n$, S, B_n, R_n, T^*_n and S^*. The following corollary establishes consistency and asymptotic normality of $\breve{\alpha}$.

Corollary 4.7. *Suppose in 3.4* $\widetilde{X}_{j,it} = 1,\ \forall\ i, j, t$. *That is, suppose the purely nonparametric SUR in (4.9) is the model of interest.*

(i) If Assumptions A.1 to A.5 hold, then

$$H(\breve{\alpha} - \alpha) - \frac{\tilde{I}^2_{\tilde{m}}}{2}\breve{B}^*(z) = o_{\mathbb{P}}(\tilde{h}^2_{\tilde{m}}) + O_{\mathbb{P}}\big(n^{-1/2}\tilde{D}^{-1/2}\iota_{\tilde{m}}\big), \tag{4.11}$$

where $\breve{B}^*(z) := \breve{S}^{-1}\breve{B}(z)$.

(ii) If Assumptions A.1 to A.6 hold, then

$$\big(n^{1/2}\tilde{D}^{1/2}\big)\left[H(\breve{\alpha} - \alpha) - \frac{\tilde{I}^2_{\tilde{m}}}{2}\breve{B}^*(z) + o_{\mathbb{P}}(\tilde{h}^2_{\tilde{m}})\right] \xrightarrow{d} N\big(\mathbf{0}, \tilde{f}^{-1}_{\tilde{m}}(z)\breve{\Delta}\big), \tag{4.12}$$

where $\breve{\Delta} := \breve{S}^{-1}\breve{S}^*\breve{S}^{-1}$.

Remark 4.8. Consider the specific case of Corollary 4.7 in which $Z_{j,it}$ is a scalar - as in Welsh & Yee (2006). Then it is straightforward to show that $\breve{B}^*(z)$ simplifies to the 4-dimensional vector $\big(\mu_{1,2}(K_1)\nabla^2 g_1(z), 0, \mu_{2,2}(K_2)\nabla^2 g_2(z), 0\big)'$, whereas $\breve{\Delta}$ becomes the 4×4 matrix *block diag*$\big(\breve{\Delta}_1, \breve{\Delta}_2\big)$ with

$$\breve{\Delta}_j = \sigma^2_j(z)\begin{pmatrix} \nu_{j,0} & 0 \\ 0 & \mu_{j,2}(K^2_j)(\mu_{j,2}(K_j))^{-2} \end{pmatrix}.$$

This specific case captures the asymptotic properties of a scaled variant of the nonparametric SUR estimator in Welsh & Yee (2006), for panel data and under the assumption that the errors $\{\epsilon_{it}\}$ are *i.i.d.* across i for each fixed t. Note that, unlike the unscaled $\breve{\alpha}$ in Welsh & Yee (2006), scaling of our $\breve{\alpha}$ by the H matrix renders (i) the biases of the derivative estimators asymptotically zero and (ii) the estimators of $g_j(z_j)$ and $\nabla g_j(z_j)$ asymptotically uncorrelated. However, similar to Welsh & Yee (2006), the estimates of $\big(g_1(z_1), \nabla g_1(z_1)\big)'$ and $\big(g_2(z_2), \nabla g_2(z_2)\big)'$ are asymptotically uncorrelated. These observations also apply to $\widehat{\alpha}$ and $\tilde{\alpha}$.

For $\widehat{\alpha}_{GMM}$, our second estimator, we seek to establish the asymptotic properties of a properly normalized variant of $H(\widehat{\alpha}_{GMM} - \alpha)$, which we express as

$$H(\widehat{\alpha}_{GMM} - \alpha) - (\widetilde{S}'_n\Gamma^{-1}\widetilde{S}_n)^{-1}(\widetilde{S}'_n\Gamma^{-1}B_n) - (\widetilde{S}'_n\Gamma^{-1}\widetilde{S}_n)^{-1}(\widetilde{S}'_n\Gamma^{-1}R_n) = (\widetilde{S}'_n\Gamma^{-1}\widetilde{S}_n)^{-1}(\widetilde{S}'_n\Gamma^{-1}T^*_n), \tag{4.13}$$

where we redefine $\widetilde{S}_n, B_n, R_n$ and T^*_n respectively as

$$\widetilde{S}_n = \frac{1}{n}Q'\widetilde{K}\widetilde{U},\ B_n = \frac{1}{n}Q'\widetilde{K}\widetilde{X}\bar{R},\ R_n = \frac{1}{n}Q'\widetilde{K}\widetilde{X}R,\ T^*_n = \frac{1}{n}Q'\widetilde{K}\epsilon.$$

The following assumptions are needed to establish the asymptotic properties of $\widehat{\alpha}_{GMM}$ in the case of large N and small T.

Assumption B.1. For each $t \geq 1$, $G_{1t}(z_1, z_2)$ and $f_{1t}(z_1, z_2)$, the joint density of Z_{i1} and Z_{it}, are continuous at $(z_1 = z, z_2 = z)$. Also, for each z, $\Omega(z) > 0$ and $f(z) > 0$, where $f(z)$ is the marginal density function of Z_{it}. Further, $\sup_{t\geq 1}|G_{1t}(z, z)f_{1t}(z, z)| \leq M(z) < \infty$ for some function $M(z)$. Finally, $g(z)$ and $f(z)$ are both twice continuously differentiable at $z \in \mathbb{R}^d$.

Assumption B.2. The kernel function $K(\cdot)$ is an even, nonnegative, and bounded density function with compact support.

Assumption B.3. $h \to 0$ and $Nh^d \to \infty$ as $N \to \infty$.

Assumption B.4. There exists some $\delta > 0$ such that $E\{|\epsilon_{it}W_{it}|^{(2+\delta)}|Z = u\}$ is continuous at $u = z$.

Clearly, Assumptions B.1 to B.4 are simplifications of Assumptions A.2, A.3, A.5, A.6, respectively. We now state the asymptotic properties of $\widehat{\alpha}_{GMM}$.

Proposition 4.9. *Suppose $Z_{1,it} = Z_{2,it} = Z_{it}$, $h_1 = h_2 = h$, and $K_1 = K_2 = K$. If Assumptions A.1, A.4 and B.1 to B.3 hold, then*

(i) $\widetilde{S}_n = f(z)S\{1 + o_{\mathbb{P}}(1)\}$,

(ii) $B_n = \frac{1}{2}h^2 f(z)B(z) + o_{\mathbb{P}}(h^2)$,

(iii) $R_n = o_{\mathbb{P}}(h^2)$,

(iv) $nh^d Var(T_n^*) = f(z)S^{**}$, *where*

$$S^{**} := \begin{pmatrix} S_1^* & S_{12}^* \\ S_{21,}^* & S_2^* \end{pmatrix}, \; S_{12}^* := \begin{pmatrix} \Omega_{12}^{12}\nu_0 & \mathbf{0} \\ \mathbf{0}' & \Omega_{12}^{12} \otimes \mu_2(K^2) \end{pmatrix}, \; S_{21}^* = (S_{12}^*)'.$$

Remark 4.10. The result in Proposition 4.9 (iv) suggests that the diagonal and off-diagonal block terms in $Var(T_n^*)$ are of the same order of magnitude: an efficacy of the assumption of common Z's across equations; consequently, if we impose this assumption on our estimator $\widehat{\alpha}$, its asymptotic variance will not be a block diagonal matrix.

Theorem 4.11. *Suppose $Z_{1,it} = Z_{2,it} = Z_{it}$, $h_1 = h_2 = h$, and $K_1 = K_2 = K$.*

(i) If Assumptions A.1, A.4 and B.1 to B.3 hold, then

$$H(\widehat{\alpha}_{GMM} - \alpha) - \frac{h^2}{2}B^*(z) = o_{\mathbb{P}}(h^2) + O_{\mathbb{P}}\big(n^{1/2}h^{d/2}\big), \tag{4.14}$$

where $B^*(z) := \big(S'\Gamma^{-1}S\big)^{-1}\big(S'\Gamma^{-1}B(z)\big)$.

(ii) If Assumptions A.1, A.4 and B.1 to B.4 hold then

$$n^{1/2}h^{d/2}\left[H(\widehat{\alpha}_{GMM} - \alpha) - \frac{h^2}{2}B^*(z) + o_{\mathbb{P}}(h^2)\right] \xrightarrow{d} N\big(\mathbf{0}, f^{-1}(z)\Delta_{GMM}\big), \tag{4.15}$$

where $\Delta_{GMM} := (S'\Gamma^{-1}S)^{-1}S'\Gamma^{-1}S^{**}\Gamma^{-1}S(S'\Gamma^{-1}S)^{-1}$.

Remark 4.12. To estimate our empirical bivariate simultaneous model in the ensuing section, we use the $\widehat{\alpha}_{GMM}$ estimator and assume that the Z variables and the kernel density function are the same but allow for the bandwidths to differ across equations. The salient asymptotic properties of $\widehat{\alpha}_{GMM}$ are not eliminated by the assumption of different bandwidths across equations.

5 Empirical Model and Data

5.1 An Empirical Simultaneous Model of Growth and FDI

Our empirical bivariate semiparametric system of equations model allows for the economic growth rate and FDI to be modeled simultaneously. We measure economic growth rate, GRO_{it}, as the growth rate of real per capita GDP, and FDI_{it} as the share of FDI inflows to GDP. We let $i = 1, 2, \ldots, N$ denote country index, and $t = 1, 2, \ldots, T$ denote the time period. Our bivariate model takes the form

$$\begin{aligned} GRO_{it} &= FDI_{it}\lambda_1(Z_{it}) + X'_{1,it}\gamma_1(Z_{it}) + \epsilon_{1,it} \\ FDI_{it} &= GRO_{it}\lambda_2(Z_{it}) + X'_{2,it}\gamma_2(Z_{it}) + \epsilon_{2,it}. \end{aligned} \tag{5.1}$$

In our empirical model of (5.1), $X_{j,it}$ is a k_j-dimensioned vector of control variables for equations $j = 1, 2$, such that the first entry in the vector is equal to one; $X_{j,it}$ may share common elements across j. $\gamma_j(\cdot)$ and $\lambda_j(\cdot)$ are unknown smooth coefficient functions of conformable dimensions. We presume that Z_{it} is a d-dimensioned vector of environmental variables, which may include a mix of continuous and discrete regressors (Racine & Li 2004, Li & Racine 2010). We assume that Z_{it} is constant across both equations and across each of the m_j coefficient functions. That is, we maintain the hypothesis of the same sources of parameter heterogeneities in the growth and FDI equations. As in our general model in Section 4, the errors $\epsilon_{j,it}$ are assumed to be mean zero disturbances that are correlated across equations, and all other model assumptions are assumed to be satisfied.

5.2 Data Overview

Our data are primarily derived from the 2012 World Development Indicators database published by the World Bank, unless otherwise specified. Our sample contains an unbalanced panel of 114 developed and developing countries, spanning the period 1984-2010. We average our data into 9 non-overlapping 3-year panels to reduce the influence of serial correlation on our results. Also, using time-averaged data can partially mitigate the effect of purely random measurement error and provide more reliable estimates for our variables of interest. Due to time averaging and a dearth of data on some variables for some countries, our effective sample contains 463 total observations.

Although our data share some similarities with the data used in previous studies, we point out several important differences. First, our data are measured up until 2010, and are more recent than the data used in many previous studies. Second, our data form a panel, and cover both developed and developing countries. This is in contrast to many studies that have focused only on cross-sectional data (e.g., Alfaro et al. 2004) and/or a particular subset of countries, e.g., Latin American countries (e.g., Bengoa & Sanchez-Robles 2003). Using more countries and a wider time span should, among other things, increase the precision of our estimates and lend credence to the inferences drawn from our empirical results.

5.3 Environmental Variables

Recall that environmental variables are the coefficient variables, and are assumed to induce heterogeneity in the effects of all the explanatory variables on the outcome variables. Recall also that the induced heterogeneity in the $\lambda_j(\cdot)$ coefficients of FDI and economic growth is a particular focal

point of our paper. In light of our foregoing discussion on parameter heterogeneity, we include a mix of continuous and discrete environmental variables in our specification of Z_{it}. Specifically, we include an index of corruption in Z_{it}. The index of corruption comes from the International Country Risk Guide published by Political Risk Services. This measure of institutional quality 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." This measure of corruption is quite popular in empirical works and, particularly has been used to study the effects of corruption on economic growth (Mauro 1995), investment (Mauro 1998), and the intersection between economic growth and FDI (McCloud & Kumbhakar 2012, Delgado et al. 2012), to name only a few. The corruption index ranges continuously from 0 to 6, with 0 representing high levels of corruption and 6 representing low levels of corruption. For instance, over the 1984-2010 period, Sierra Leone has an average corruption measure of 2.02, Denmark has an average corruption index of 5.81, while the United States has an average measure of 4.54.

We further allow for unobserved heterogeneity in all the coefficient functions across both countries and time, through an unordered country variable and ordered year categorical variable. The advantage of including country and year indicators in each of our coefficients is that we can control for country and time invariant effects - i.e., fixed effects - in a *non-neutral* fashion. That is, the country and year indicators capture *any* country and time invariant factors that induce heterogeneity in the intercept *and* slope coefficients across countries and time, which are likely to be present in our empirical model. Hence, we are not restricted to assuming that the country and year effects have a neutral effect on the model by influencing the intercept only, as would be the case of a standard constant coefficient fixed effects simultaneous equations specification. Moreover, the Racine & Li (2004) kernels (see our discussion below) allow for interaction of unknown form between both fixed effects and corruption, so that our control of country and year specific effects is not restricted to additively separable effects. In essence, our use of panel data coupled with the inclusion of fixed effects aids in the mitigation of endogeneity that may bias our estimates.[9] Many time-invariant measures of institutional quality and country-specific growth-enhancing and FDI-attracting government policies are therefore subsumed in our country-specific effects in Z_{it}; consequently, the role of corruption in the relationship between growth and FDI is adjusted for these country-specific factors.

5.4 Explanatory Variables

Our choice of explanatory variables for both equations is predicated on our discussion in Section 2. The control variables we choose for the growth equation pertain to both the benchmark neoclassical growth specification and the macroeconomic policy ideology. The control variables we choose for the FDI equation are empirically and/or theoretically related to FDI.

5.4.1 The Growth Equation

We specify $X_{1,it}$ to contain initial income, the growth rate of the population, the rate of investment in physical capital, the inflation rate, government consumption, and openness. Initial income, population growth, and the rate of physical capital investment are the traditional neoclassical

[9] With 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 invariant factors that may lead to heterogeneity in the coefficient functions.

'Solow' growth variables and are defined as follows. Initial income is the log of GDP per capita at the beginning of each 3-year panel period; the growth rate of the population is the annual percentage change in the total population; and investment in physical capital is defined to be gross capital formation as a percentage of GDP. The inflation rate is the annual percentage change in the consumer price index. Government consumption is current period government expenditure on goods and services, excluding military spending on government capital formation. Openness is the sum of exports and imports as a percentage of GDP, and comes from the Penn World Table version 7.1 of Heston, Summers & Aten (2012).

Identification. Under our maintained assumption that economic growth and FDI are determined simultaneously, there is concern that FDI is endogenous in our growth equation. In the growth equation, a valid instrumental variable for FDI is one that is correlated with FDI, but uncorrelated with economic growth, conditional on both X_1 (i.e., 'Solow' and macroeconomic policy variables) and Z (i.e., institutional quality and unobservable country and year effects).

In general, the literature that has investigated single equation growth models with FDI as the key variable has failed to unearth a generally suitable instrumental variable for FDI. Notable contributions proposing a variety of instrumental variables for FDI - such as lagged values of FDI, some time-invariant measures of institutional quality, and total area of the country - include panel and cross-sectional growth studies by Borensztein et al. (1998), Alfaro et al. (2004), Durham (2004), and Delgado et al. (2012). Borensztein et al. (1998), Durham (2004) and Delgado et al. (2012) find evidence that lagged values of FDI perform well and mitigate at least part of the endogeneity of contemporaneously measured FDI.[10] However, after considering which instrumental variables are available for panel data (i.e., with country and year variation) and not internal to FDI (i.e., lagged measures), we are left with one other potential source of exogenous variation in FDI: the total area of the country to measure country size.[11] The general intuition for using the total land area as an instrument is that, all else equal, FDI is attracted to larger countries. Yet, there is no reason to believe that, given our set of control variables, economic growth is directly correlated with the size of the country. In addition, Borensztein et al. (1998) find empirical evidence to support the validity and strength of this instrumental variable. Hence, we consider the log of the total land area in square kilometers of a country as an instrumental variable for FDI in our growth equation. We assert that our use of an instrumental variable, in conjunction with our robust array of conditioning variables and generalized interactive fixed effects, are able to alleviate any concerns that endogeneity of FDI is driving any of our results.

5.4.2 The FDI Equation

In the FDI equation, we specify $X_{2,it}$ to contain schooling, trade openness, the inflation rate, the foreign exchange rate, and the log of total GDP. The level of schooling in the host economy may

[10] In the case that suitable instrumental variables cannot be identified, as is common in empirical macroeconomic studies and in a panel data context, researchers often turn to lagged values of the endogenous variable as lagged values are more likely to be correlated with the contemporaneous measure of the endogenous variable, but less likely to be correlated with the outcome (Temple 1999). Indeed, this strategy is widely used in the context of panel studies on growth and FDI to remedy the absence of suitable instrumental variables.

[11] For example, alternative instruments that are not already included in our conditioning set include indicators for country of legal origin (Durham 2004) or continental dummies (Borensztein et al. 1998), however these are time invariant and it is not clear that these measures have much reliability given that our endogenous variable is time variant. Further, our inclusion of country fixed effects in Z will render such time invariant measures redundant.

have explanatory power in the FDI equation. Often, foreign firms bring advanced technology into the host economy that requires a relatively more skilled labor force relative to that required by pre-existing technology. Hence, all else equal, a more highly educated labor force may be more inviting for FDI.[12] We define schooling to be the net enrollment rate in secondary school; and trade openness and inflation are the same as those measures in the growth equation. The foreign exchange rate comes from the Penn World Table version 7.1 of Heston et al. (2012), and is defined as the exchange rate to United States dollars. Each of these control variables are important correlates of FDI, measuring the relative attractiveness, macroeconomic conditions and policies, and ease of entry into the host country (foreign exchange, trade openness, and inflation), the size of the country (log of total GDP), and the degree of absorptive capacity (schooling).[13]

Identification. One important consideration that arises in our model is the endogeneity of the economic growth rate in the FDI equation. Endogeneity of the growth rate likely arises because foreign investors view strong economic growth as a favorable metric of financial returns, and as a general measure of economic and institutional stability. Appropriate instrumental variables for the growth rate in the FDI equation must be factors that are correlated with economic growth, but uncorrelated with FDI, conditional on both X_2 (i.e., macroeconomic stability and schooling variables) and Z (i.e., institutional quality and country and year effects). One important set of growth correlates that are unlikely to be correlated with FDI are demographic growth correlates - specifically, the fertility rate and life expectancy. Henderson, Papageorgiou & Parmeter (2012) find robust econometric evidence that the demographic growth variables have a nontrivial relationship with economic growth, using robust nonparametric estimators; hence, there is ample evidence that these demographic variables are correlated with growth. We argue that these variables are uncorrelated with FDI decisions, as FDI decisions are typically related to investment risk and private return. Of course, fertility and life expectancy may be correlated with economic or institutional factors that may also determine economic risk and return factors that influence FDI. However, *conditional* on the set of economic and institutional factors in X_2 and Z, we maintain that all potential indirect linkages between demographic variables and FDI have been accounted for. Hence, demographic growth variables are suitable instruments for economic growth in the FDI equation.

Therefore, given our rationale for using these variables as appropriate instruments for growth in the FDI equation, we consider several different regressions using the fertility rate and life expectancy as instrumental variables. The fertility rate is defined as the average number of births per woman, and life expectancy is defined as the life expectancy at birth measured in years.

5.5 Practical Implementation of our Estimator and Goodness of Fit Measures

With regards to the practical implementation of our proposed estimator in the context of the economic growth and FDI model in (5.1), a few clarifications are appropriate. Since Z_{it} is assumed to contain a mix of continuous variables and unordered and ordered discrete categorical variables, we adopt the generalized product kernel technique of Racine & Li (2004) and Li & Racine (2010).

[12] We exclude schooling from the growth equation following Delgado et al. (2014) who show that controlling for other factors mean years of schooling is not a robust and statistically relevant factor of economic growth rates using a wide array of nonparametric regression models and tests.

[13] Note that absorptive capacity and general macroeconomic stability are also controlled for through our set of environmental variables that measure institutional quality and unobservable country effects.

We define the product kernel function $K_{h_j}(\cdot) := h_j^{-d_j} K_j(\cdot/h_j)$ to be

$$K_j(\cdot) = \prod_{c=1}^{d_j^c} k^c\left(\frac{Z_{j,it}^c - z_j^c}{h_j^c}\right) \prod_{u=1}^{d_j^u} k^u(Z_{j,it}^u - z_j^u; h_j^u) \prod_{o=1}^{d_j^o} k^o(Z_{j,it}^o - z_j^o; h_j^o) \tag{5.2}$$

in which

$$k^c\left(\frac{Z_{j,it}^c - z_j^c}{h_j^c}\right) = \frac{1}{\sqrt{2\pi}} \exp\left[\frac{1}{2}\left(\frac{Z_{j,it}^c - z_j^c}{h_j^c}\right)^2\right] \tag{5.3}$$

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

$$k^u(Z_{j,it}^u - z_j^u; h_j^u) = \begin{cases} 1 & \text{if } Z_{j,it}^u - z_j^u = 0 \\ h_j^u & \text{if } Z_{j,it}^u - z_j^u \neq 0 \end{cases} \tag{5.4}$$

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

$$k^o(Z_{j,it}^o - z_j^o; h_j^o) = \begin{cases} 1 & \text{if } Z_{j,it}^o - z_j^o = 0 \\ h_j^{o\,|Z_{j,it}^o - z_j^o|} & \text{if } Z_{j,it}^o - z_j^o \neq 0 \end{cases} \tag{5.5}$$

is a univariate discrete kernel function used for each of the d_j^o ordered discrete variables in $Z_{j,it}$ (Li & Racine 2007). In the above product kernel setup, h_j^c is a d_j^c-dimensioned vector of bandwidths for the continuous variables, and h_j^u and h_j^o are d_j^u- and d_j^o-dimensioned vectors of unordered and ordered discrete variable bandwidths.[14]

We select the optimal smoothing parameters, $\{h_j^c, h_j^u, h_j^o\}$ using the method of least squares cross validation. The method of least squares cross validation selects $\{h_j^c, h_j^u, h_j^o\}$ by minimizing the following criterion function

$$\underset{\{h_j^c, h_j^u, h_j^o\}}{\arg\min} \sum_{j=1}^{J} \sum_{i=1}^{N} \sum_{t=1}^{T} \left[y_{j,it} - \widetilde{X}'_{-j,-it}\widehat{a}_j(Z_{-j,-it})\right]^2 \tag{5.6}$$

in which $\widetilde{X}'_{-j,-it}\widehat{a}_j(Z_{-j,-it})$ is the leave-one-out nonparametric generalized method of moments estimate of $\widetilde{X}'_{j,it}\widehat{a}_j(Z_{j,it})$. Although we have constructed our empirical model such that $Z_{j,it} = Z_{it}$ for each j, our cross validation procedure selects a set fixed bandwidths for each variable in Z_{it} in each equation; note that we do not restrict the bandwidths to be fixed across equations. Given our small number of cross-sectional units, we opt to not use our asymptotic distribution in computing the standard error of our estimate. We obtain standard error for our estimate of α from a wild bootstrap procedure based on 399 replications, which corrects for autocorrelation and heteroscedasticity of unknown form.

We provide three separate measures of the goodness of fit for each equation in our model. The first measure is the in-sample R^2 calculated as $R_j^2 = \text{cor}\left[y_{j,it}, \widetilde{X}'_{j,it}\widehat{a}_j(Z_{j,it})\right]^2$, the square of the correlation between the observed dependent variable in equation j and its estimated counterpart. The second measure is the out-of-sample R^2, and the third measure is the out-of-sample Average

[14] In our empirical model, $d_j^c = d_j^u = d_j^o = 1$. Note that the presence of discrete components in z_j has changed the interpretation of some of the regularity conditions in Sections 3 and 4. In particular, (i) $z_j \in \mathbb{R}^{d_j}$ should be interpreted as $(z_j^c, z_j^u, z_j^o) \in \mathbb{R} \times A^u \times A^o$, the product space where A^u and A^o denote the finite support of z_j^u and z_j^o, respectively, and (ii) the derivative with respect to z_j should be interpreted as the derivative with respect to z_j^c.

Squared Prediction Error ($ASPE$), calculated as $(NT)^{-1}\sum_{i=1}^{N}\sum_{t=1}^{T}\left[y_{j,it}-\widetilde{X}'_{j,it}\widehat{a}_j(Z_{j,it})\right]^2$ for each equation. The advantage of using out-of-sample measures of fit is that these measures are typically robust to over-fitting, which can sometimes inflate in-sample measures of fit.[15]

6 Empirical Results

We now turn to the results from applying our semiparametric instrumental variables systems estimator to our novel empirical model of economic growth and FDI in (5.1). We consider the log of the total area of the country as an instrumental variable for FDI inflows in our growth equation, and both the fertility rate and life expectancy as instruments for growth in our FDI equation. For each of these models, we consider estimates of (3.15) that use first stage estimates of A as our weighting matrix. We also explore non-instrumental variables estimates that rely solely on exclusion restrictions implied by the sets of controls X_1 and X_2, while accounting for institutional and non-neutral unobservable effects through Z, for identification. We do not report these non-instrumental variables estimates because (i) these estimates rely on identification assumptions that may not be satisfied and, more important, (ii) the nonparametric density equality test of Li, Maasoumi & Racine (2009) very strongly rejects (with p-value 0.0000) the null hypothesis that the density for each of our non-instrumental variables estimates is equal to that of its instrumental variables counterparts - which points to higher-order differences between the densities from the different estimation methods. We view the latter case as strong statistical evidence in favor of the instrumental variables results. We therefore focus exclusively on the instrumental variables results in our ensuing discussion. Our results for the non-instrumental variables systems model, however, can be furnished on request.

We first discuss our estimated coefficient functions for our bivariate growth-FDI system, and then analyze the marginal effects on these coefficients from a reduction in corruption. Since our semiparametric systems estimator provides observation-specific estimates and standard errors, we summarize these estimates using kernel density plots and 45 degree gradient plots that are depicted by Figures 1 and 2, and the 25th, 50th (median), and 75th percentiles that are in Tables 1 and 3. The 45 degree gradient plots found in the lower panels of the figures show the observation specific function estimates plotted on the 45 degree line, with 95 percent observation specific confidence intervals plotted above and below each point estimate. If the horizontal dotted line at zero lies outside of each observation specific confidence interval, then that point estimate is statistically significant.[16]

6.1 Coefficient Function Estimates

6.1.1 Effects of Economic Growth and FDI

Consider first the system of equations that uses the life expectancy rate as our instrument for the growth rate. It is clear from the kernel density of FDI coefficient estimates in Figure 1 that the

[15] To implement our out-of-sample goodness of fit measures, we sample 80 percent of our data without replacement and fit our model. We then use our estimates to predict on the 20 percent hold out sample and calculate both the R^2 and $ASPE$. We repeat this procedure 1,000 times, and report the mean R^2 and $ASPE$, in order to avoid any potential biases in our measures of fit induced by our choice of sample splits. We refer the reader to Racine & Parmeter (2014) for additional details on model evaluation, including adjustments to the optimal bandwidth parameter to account for different sample sizes arising from the out-of-sample splits.

[16] See Zhang, Sun, Delgado & Kumbhakar (2012) and Henderson, Kumbhakar & Parmeter (2012) for use of these plots to summarize semiparametric regression results and for more details.

effects of FDI on economic growth rates are heterogeneous yet largely positive. The corresponding 45 degree gradient plot in Figure 1 shows that the majority of these estimates are statistically significant at the 5 percent level. For the FDI equation, Figure 1 reveals that the distribution of growth coefficient estimates is generally positive, and the corresponding 45 degree plot reveals that many of these positive estimates are statistically significant.

We turn to Table 1 for a more detailed analysis of particular point estimates. We find that the effect of FDI on growth (see the growth equation) has an interquartile range of 0.5531, with a median effect of 0.2081. Our point estimates at the quartiles are statistically significant for both the median and upper quartile. More important, there is a clear absence of statistical parity among the estimated quartiles. For example, the 95 percent confidence interval for the estimated upper quartile comfortably excludes the estimated lower quartile and median estimates. These results confirm that for many countries FDI has a significantly positive, heterogeneous and causal effect on economic growth rates. Moreover, at the median a 10 percent increase in FDI inflows relative to GDP causes approximately a 2 percent increase in the economic growth rate.

Turning to the FDI equation, we see that the growth rate has a significantly causal effect on FDI inflows at each reported quartile. These coefficients have an interquartile range of 0.5584 with a median effect of 0.2114. These estimates imply that at the median, a 10 percent increase in the growth rate causes about a 2.1 percent increase in the ratio of FDI inflows to GDP. However, there is statistical parity between the median and upper quartile estimates in that the 95 percent confidence interval for the estimated upper quartile contains the median estimate. Nevertheless, we find strong evidence that for many countries economic growth has a significantly positive, heterogeneous and causal effect on FDI. This empirical evidence of heterogeneity in the effect of economic growth on FDI represents a salient distinction between our work and the existing FDI literature. Further, our goodness of fit measures show that our model has high predictive ability in-sample, and while relatively lower, the out-of-sample predictive ability is acceptable.

6.1.2 Characterizing the Types of Interactions between Economic Growth and FDI

Our results in Figure 1 and Table 1 yield an important observation - empirically, FDI has positive, negative or no effect on economic growth, and *vice versa*. This observation therefore parallels the theoretical predictions on the effect on FDI on growth *and* the effect on growth on FDI. Hence, our semiparametric system of simultaneous equations, coupled with the taxonomy in Definition 3.1, seems quite appropriate for our analysis of the types of interactions between growth and FDI.

To characterize the types of interactions between growth and FDI on the basis of the taxonomy in Definition 3.1, we use the following criterion: a country is placed in the category, for example, *symbiosis* if at least 50 percent of its estimated effects of FDI on growth *and* its estimated effects of growth on FDI is *positive* and *statistically significant*. This criterion, therefore, is not all-inclusive; for some countries, the estimated effect of, say, FDI on growth changes sign and/or statistical significance across time periods. That is, on the basis of this criterion a country can belong to two or no categories in Definition 3.1.[17]

Table 2 contains the number of countries that can be characterized according to our Definition 3.1 and criterion. In this table, we use the term *distinct* to refer to countries that fall in only one

[17]Countries that do not appear in any category are Botswana, Burkina Faso, Costa Rica, Denmark, El Salvador, Finland, Malaysia, New Zealand, Niger, Norway, Philippines, Portugal, United Kingdom, and United States.

category. We find that the *most dominant* relationships between FDI and growth are *symbiosis* and *FDI-commensalism*; that is, for a large number of countries either (i) FDI has a positive effect on growth *and* growth has a positive effect on FDI, or (ii) FDI has a positive effect on growth *but* growth has no effect on FDI, respectively. The number of countries that are in the *symbiosis* category is 63, of which 45 are *distinct*. To get an understanding of the economic significance of the nature of the growth-FDI interaction, consider two countries Australia and Turkey that fall into only the *symbiosis* category. For the period 1993 to 1995, for example, our estimates reveal that in Australia a 1 percent increase in FDI leads to a 0.987 percent increase in economic growth and a 1 percent increase in economic growth leads to a 0.097 percent increase in FDI; for this same period, in Turkey a 1 percent increase in FDI leads to a 0.228 percent increase in economic growth and a 1 percent increase in economic growth leads to a 0.062 percent increase in FDI. These *symbiosis* estimates imply that appreciable direct multiplier effects exist between FDI and growth in Australia and Turkey. These multiplier effects suggest that (at least some) resources in these two countries may devote to strengthening the effect of, say, FDI on economic growth can be reallocated to other correlates of economic growth.

The dominance of the *FDI-commensalism* category means that many more countries experience *FDI-commensalism* than those that experience *growth-commensalism* - FDI has no effect on growth *but* growth has a positive effect on FDI. Only 2 countries experience *non-symbiosis* - FDI has no effect on growth *and* growth has no effect on FDI - which suggests that at least a one-way relationship between growth and FDI exists in almost all countries. In addition, and in fact, only developing countries (very few) fall into this latter category, as well as the categories of *FDI-antagonistic symbiosis*, *synnecrosis* and *growth-commensalism*. In addition, there is no country that experiences *FDI-ammensalism* - FDI has no effect on growth *and* growth has a negative effect on FDI.

It is worth mentioning that relative to our non-instrumental variables regression results, the instrumental variables regression results reported here reveal slightly larger coefficient estimates of symbiosis between FDI and growth. At least in terms of the growth effects of FDI, these findings indicate that our instrumental variables are able to mitigate the endogeneity in our system.

6.1.3 Effects of the Control Variables

Turning to our other coefficient estimates in the growth equation, we see in Table 1 that the standard 'Solow' variables are generally significant at the reported quartiles. In particular, our results show that initial income, population growth, openness, and inflation have negative and significant effects on growth rates at the lower quartile and median, whereas the physical capital investment rate has positive and significant effects at the median and upper quartile. This initial income result is, of course, further evidence of the classic beta-convergence phenomenon that countries with relatively low initial levels of income have faster rates of growth in order to catch up to developed countries. Similarly, we find that government consumption has mixed effects on growth rates, with a negative and significant growth effect at the lower quartile, but a positive and significant growth effect at the upper quartile. That is, in the context of economic growth, government consumption is not productive in all countries. For all the standard 'Solow' variables, there is a clear absence of statistical parity among the corresponding estimated quartiles. These results therefore complement the existing nonlinear growth literature by providing added evidence of sizable heterogeneities within the effects of each of these variables on growth rates.

Considering the effects of our control variables in the FDI equation, we see that foreign exchange and the log of GDP have a significantly negative effect on FDI at the lower quartile, an insignificant effect at the median, and a positive and significant effect at the upper quartile. Schooling has an insignificant effect on FDI at all quartiles, trade openness has a positive and significant effect on FDI inflows at all quartiles, and inflation has a negative but insignificant effect on FDI flows at the lower and median quartiles. Taking the coefficients on inflation, trade openness, and growth jointly, our results indicate that for many countries the primary attractants of FDI inflows are economic growth and trade openness, but high rates of inflation deter foreign investment. We further emphasize that these findings mark important empirical results for research investigating factors related to macroeconomic factors of FDI flows. In particular, the nature of the heterogeneous effects in the FDI equation partially explains why the previous results from linear models were unable to unearth statistically robust correlates of FDI flows.

In all, we interpret these significant effects in both equations to be robust evidence that our model is flexible enough to significantly capture heterogeneity across countries that might arise because of nonlinearities from interactions of these variables with respect to institutional quality or unobserved country and time effects.

6.2 Effect of Institutional Improvement

Recall that for this paper, an improvement in institutional quality means a reduction in the level of corruption. Turn now to Figure 2 for a set of the results of an improvement in institutional quality on the coefficients in the instrumental variables model. Both distributions are centered around zero, and the associated 45 degree plots show that many of these effects are significant in the FDI coefficient case, but that many of the growth coefficient partials are statistically insignificant. However, it is clear that there are subsets of growth coefficient partials that are negative and positive, and significant.

In Table 3, we find significance of the partial effect of corruption on the FDI coefficient at the lower and upper quartiles. Specifically, an improvement in institutional quality dampens the causal effect of FDI on growth at the lower quartile, but increases the effect at the upper quartile. These results are evidence that for some countries, an improvement in institutional quality weakens, strengthens or has no impact on the effect of FDI on growth. In terms of the effect of a reduction in corruption on the growth coefficient in the FDI equation, we find a significantly positive effect at the upper quartile, but insignificance at the lower and median quartiles. These results suggest that, in general, the effect of growth on FDI does not vary significantly with respect to institutional quality. Nevertheless, improvements in institutional quality reduce the impact of economic growth rates on FDI for some countries, and increase the impact for others.

More important, for each type of the FDI-growth interaction in Table 2, there is no evidence that countries that exhibit a specific type of interaction respond in the same direction to an improvement in institutional quality. Therefore, an improvement in institutional quality weakens, strengthens, or has no impact on the interactions between FDI and growth.

Turning towards the effects of a reduction in corruption on the rest of the coefficients in the growth equation, we see a reduction in corruption is associated with a weakening of the relationships between most control variables and the growth rate. In the FDI equation, however, we see that improvements in institutional quality is associated with a strengthening of mainly the relationships

between FDI inflows and the foreign exchange rate and trade openness. Overall, our results strongly suggest that corruption is a main source of parameter heterogeneity in the growth equation but not in the FDI equation.

6.3 Cross-Validated Bandwidths and Model Specification

One important way we glean additional insight from our model about the nature of parameter heterogeneity is to examine the cross-validated bandwidths used for regression estimation. It is becoming increasingly well known (e.g., Li & Racine 2007) that if a cross-validated bandwidth on a continuous regressor does not exceed its upper bound in a local linear regression, then that variable is chosen by the cross-validation procedure to enter nonlinearly into the regression model. For discrete variables, a bandwidth that is less than unity implies nonlinear, nontrivial interactions in the regression. An examination of the cross-validated bandwidths in our model shows that for each environmental variable - corruption, country effect and year effect - the best fit of our model to the data is one that incorporates nonlinear interactive effects. That is, we find that our bandwidths are less than their upper bounds, which is a signal that any ad hoc parametric linear restriction is not justified by the data.[18] Further, existence of nonlinear interactions does not provide insight into correct parametric specification; hence our bandwidth analysis signals that parametric restrictions on the functional form of heterogeneity within our model should be carefully considered and supported by appropriate model specification tests. We finally note that since the degree of smoothing varies across equations for each regressor, we conclude that the nature of these nontrivial interactions differs across equations as well.

6.4 Developed versus Developing Countries

Our foregoing empirical results strongly suggest that institutional quality can impinge on the growth-FDI interactions across countries. In addition, it is well known that developed countries, on average, have better institutional quality than their developing counterparts. On the basis of such difference in institutional quality, developed countries that experience *symbiosis* and *FDI-commensalism* may have a natural comparative advantage over their developing counterparts. On the surface, two empirical regularities - which are not necessarily mutually exclusive - may lend credence to such comparative advantage. *One*, there are two main types of FDI that flow to host countries: vertical FDI - investment that allows for different components of a final good to be produced in different countries with different factor intensities; and horizontal FDI - investment that allows for the entire production process of a final good to be replicated in a foreign country that is within close proximity to major foreign markets. On average, developed host countries receive mostly horizontal FDI, whereas developing host countries receive mostly vertical FDI. *Two*, differences in institutional quality is associated with, among other things, differences in investment climate, factor endowments and thus absorptive capacity, direct and indirect transaction costs, and organizational structure of firms and industries.

To investigate this concern, we examine whether the conditional densities of the growth and FDI effects differ between OECD and non-OECD countries using kernel densities and boxplots. In Figure 3, the top graph shows superimposed kernel density plots of FDI effects (from the growth

[18] See, also, Henderson, Papageorgiou & Parmeter (2012) for a detailed discussion of the implications of cross-validated bandwidths for model specification in an empirical growth context.

equation) for both OECD and non-OECD countries, whereas the bottom graph shows superimposed kernel density plots of growth effects (from the FDI equation) for both OECD and non-OECD countries. In Figure 4, the top graph shows boxplots across quartiles of FDI effects for both OECD and non-OECD countries, whereas the bottom graph shows boxplots across quartiles of growth effects for both OECD and non-OECD countries. A cursory glance at these graphs suggests a discernible difference in both sets of growth and FDI effects between OECD and non-OECD countries. However, a formal test of the difference in densities is warranted prior to drawing inferences from these graphs; we use the nonparametric kernel-based test for equality of distributions by Li et al. (2009) to test for statistical differences between the OECD and non-OECD distributions of FDI and growth effects. The application of this nonparametric kernel-based test to our estimated FDI and growth effects yields p-values of 0.0000 under the null hypothesis of equality of the OECD and non-OECD for both FDI and growth densities. Thus, we reject the null hypothesis of equality of OECD and non-OECD distributions for both sets of growth and FDI effects. Therefore, these formal statistical tests confirm our intuition that OECD and non-OECD countries have statistically different interactions between FDI and economic growth.

Looking specifically at Figure 3, it is clear that for both FDI and growth effects the distribution for OECD countries is generally centered at zero, but has a fat right-tail that indicates a subset of non-zero effects. Non-OECD countries, on the other hand, do not have a large mass at zero for either FDI or growth effects, and are distributed generally over positive, non-zero values. These differences suggest that the *symbiosis* and *FDI-commensalism* between growth and FDI are not substantial in many OECD countries. This finding is consistent with our earlier results that indicate an important interactive relationship between growth, FDI, and institutional quality: countries that have better institutions, on average, have smaller *symbiosis* and *FDI-commensalism* interactions between growth and FDI. Non-OECD countries, on the other hand, have sizeable *symbiosis* and *FDI-commensalism* interactions; for *symbiosis*, this indicates that in the absence of high quality institutions, FDI is an important component for economic growth *and* economic growth rates are important for attracting FDI.

These results have important implications, particularly for developing countries. First, it is clear that in many developing countries, FDI is a key factor for growth; yet, since growth is crucial for attracting FDI, it is clear that countries looking to improve growth rates through FDI may not be successful given that they are not relatively attractive to FDI investors. Improvements in institutional quality may be one way to circumvent this cycle. Our results also indicate that countries with high levels of institutional quality (e.g., OECD countries) may not gain much from improving growth rates by pursuing policies aimed at attracting FDI.

We turn to Figure 4 to focus on the distribution of FDI and growth effects across OECD and non-OECD countries within each quartile. These boxplots provide an alternative view into the differences in our estimates across developed and developing countries. The top panel in the figure shows the distribution of FDI effects in the growth equation across OECD and non-OECD countries; the bottom panel shows the distributions for the growth effects in the FDI equation. It is clear from the top panel that the distribution of estimates within the first and third percentile are generally wider for non-OECD countries, with a wider interquartile range and higher mean for non-OECD countries in each group. We do not see much difference in FDI effects at the second percentile across OECD and non-OECD countries, and we see a slightly wider interquartile range for OECD countries

at the highest quartile. Interestingly, we find that the interquartile range is higher, with higher mean estimate, within each quartile of growth effects (FDI equation) for non-OECD countries. Therefore, although developed countries may have a natural comparative advantage because of their higher level of institutional quality, the magnitudes of their *symbiosis* and *FDI-commensalism* interactions between FDI and economic growth are smaller than those of their developing counterparts.

6.5 An Alternative Instrumental Variables Specification

We also estimate a semiparametric system of simultaneous equations model that uses the fertility rate, which supplants life expectancy rate, as an instrument for growth in our FDI equation. These additional results are not reported for space considerations, but are available upon request. We find results that *parallel* the preceding reported results that are predicated on the life expectancy rate. That is, across developed and developing economies, causal, heterogeneous *symbiosis* and *FDI-commensalism* are the most dominant types of interactions between FDI and economic growth. Higher institutional quality facilitates, impedes, or has no effect on the interactions between FDI and economic growth. In addition, our out-of-sample goodness of fit measures for this alternative model are lower than their counterparts in the preceding model; this observation lends credence to the preceding model.

7 Conclusion

In theory, FDI inflows can have *positive*, *negative*, or *no* effect on economic growth, and *vice versa*. If within a country FDI has a *positive* effect on growth *and* growth has a *positive* effect on FDI - our concept of *symbiosis* - then FDI-promoting strategies for fostering and sustaining economic growth have added and direct multiplier benefits. In such a country, policymakers can therefore reallocate scarce resources to, for example, other correlates of economic development. To date, however, no study has analyzed empirically the types of interactions between economic growth and FDI that may exist within and across countries *and* the effect of institutional quality on such interactions.

In this paper, we characterize the types of interactions between FDI and economic growth, *and* analyze the effect of institutional quality on such interactions. To do so, we propose a novel semiparametric system of simultaneous equations model with the economic growth rate and FDI as a bivariate response. Our model unifies several important aspects of the empirical growth and FDI literatures, including (i) the joint determination of economic growth and FDI, (ii) nonlinear and nontrivial interactions of institutional quality with each of the conditioning variables, (iii) an instrumental variables approach for identification, (iv) unobserved heterogeneity (country- and time-specific effects) of unknown and *non-neutral* form, (v) and correlations in errors across equations. Only a few existing papers have explored a *subset* of these important model structures.

To estimate the coefficient functions and their derivatives for the proposed bivariate response growth-FDI model, we derive and establish the large sample properties of a class of semiparametric system of simultaneous equations estimators. We show using rigorous proof that our class of systems estimators is both consistent and asymptotically normal. We emphasize that our econometric model is fully generalizable to J separate equations, and is in no way restricted to the empirical growth-FDI context in which our model is framed. Our proposed class of systems estimators is a generalization of several important econometric models, including the fully parametric systems generalized method

of moments estimator, the single-equation nonparametric generalized method of moments estimator, and the nonparametric system of equations (i.e., without endogeneity) estimators. Our proposed class of estimators is relatively straightforward to implement and, more important, has a wide range of applicability to economic and non-economic data.

In light of the general scope of our paper, our empirical results reveal several important interactions in the growth-FDI-institutional quality nexus that have not been documented by the relevant existing literatures. Specifically, our proposed semiparametric system of equations model, and associated specification tools, suggests that across developed and developing economies, causal, heterogeneous (i) *symbiosis* and (ii) *FDI-commensalism* are the most dominant types of interactions between FDI and economic growth; that is, for a large number of countries either (i) FDI has a *positive* effect on growth *and* growth has a *positive* effect on FDI, or (ii) FDI has a *positive* effect on growth *but* growth has *no* effect on FDI, respectively. We further find that there is a significant, nonlinear, and *non-neutral* relationship between our measure of institutional quality (corruption) and the different interactions that exist between growth rates and FDI inflows. Specifically, higher institutional quality facilitates, impedes, or has no effect on the interactions between FDI and economic growth.

These findings are strong evidence in support of research advocating a more tailored, country-specific set of macroeconomic policies for the relationship between economic growth and FDI. Additionally, we uncover substantial heterogeneity in terms of interactions between our conditioning variables in each equation and institutional quality and country- and time-specific effects. Is it well-known that neglected heterogeneity can lead to misleading inferences on the parameters of interest. Thus, our findings underscore the importance of accounting for different sources of heterogeneities in a flexible - rather than the traditionally *ad hoc* parametric - manner to obtain consistent and generally reliable results.

An auxiliary non-instrumental variables semiparametric regression suggests that there is an appreciable downward bias in both the FDI (growth equation) and growth (FDI equation) effects that is mitigated by our instrumental variable strategy, which yields generally more robust estimates. To formally investigate this observation, we perform kernel density tests on our parameters of interest that determine the types of interactions that exist between growth and FDI. The tests show statistically significant higher-order differences between the estimates of these parameters from the non-instrumental variables and instrumental variables methods. In essence, our new-fangled semiparametric system of simultaneous equations model coupled with its instrument-based estimator seems appropriate for assessing empirically the types of interactions between growth and FDI.

Technical Appendix

Please contact the authors regarding technical proofs at this time.

Data Appendix

List of Countries: Albania, Algeria, Angola, Argentina, Armenia, Australia, Austria, Azerbaijan, Bahamas, Bahrain, Bangladesh, Belarus, Belgium, Bolivia, Botswana, Brunei, Bulgaria, Burkina Faso, Canada, Colombia, Congo, Costa Rica, Cote d'Ivoire, Croatia, Cyprus, Czech Republic, Denmark, Dominican Republic, Ecuador, Egypt, El Salvador, Estonia, Ethiopia, Finland, France, Gambia, Germany, Ghana, Greece, Guatemala, Guinea, Guinea-Bissau, Guyana, Honduras, Hong Kong, Hungary, Iceland, Indonesia, Iran, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kazakhstan, Kenya, Kuwait, Latvia, Lebanon, Lithuania, Luxembourg, Madagascar, Malawi, Malaysia, Mali, Malta, Mexico, Moldova, Mongolia, Morocco, Mozambique, Namibia, Netherlands, New Zealand, Nicaragua, Niger, Norway, Oman, Pakistan, Panama, Paraguay, Peru, Philippines, Poland, Portugal, Qatar, Romania, Saudi Arabia, Senegal, Slovenia, South Africa, Spain, Sri Lanka, Suriname, Sweden, Switzerland, Syria, Tanzania, Thailand, Togo, Trinidad & Tobago, Tunisia, Turkey, Uganda, Ukraine, United Kingdom, United States, Uruguay, Venezuela, Vietnam, Yemen, Zambia, Zimbabwe.

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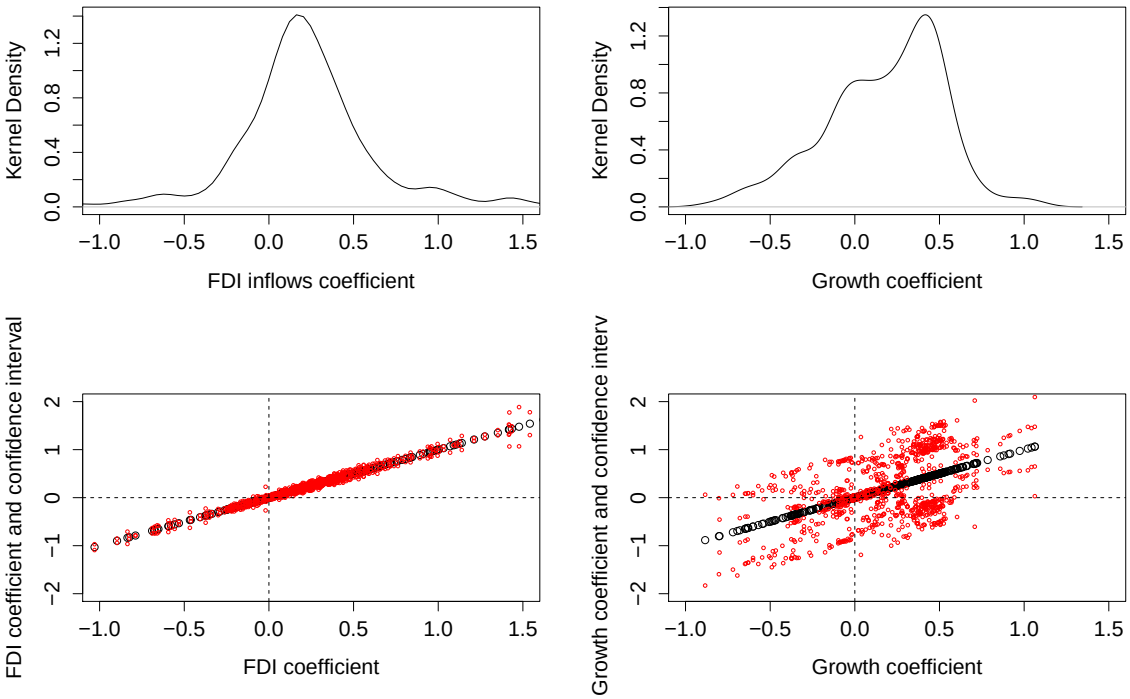

Figure 1: Kernel density plots and significance plots for FDI inflows and growth coefficient functions for the model with instrumental variables.

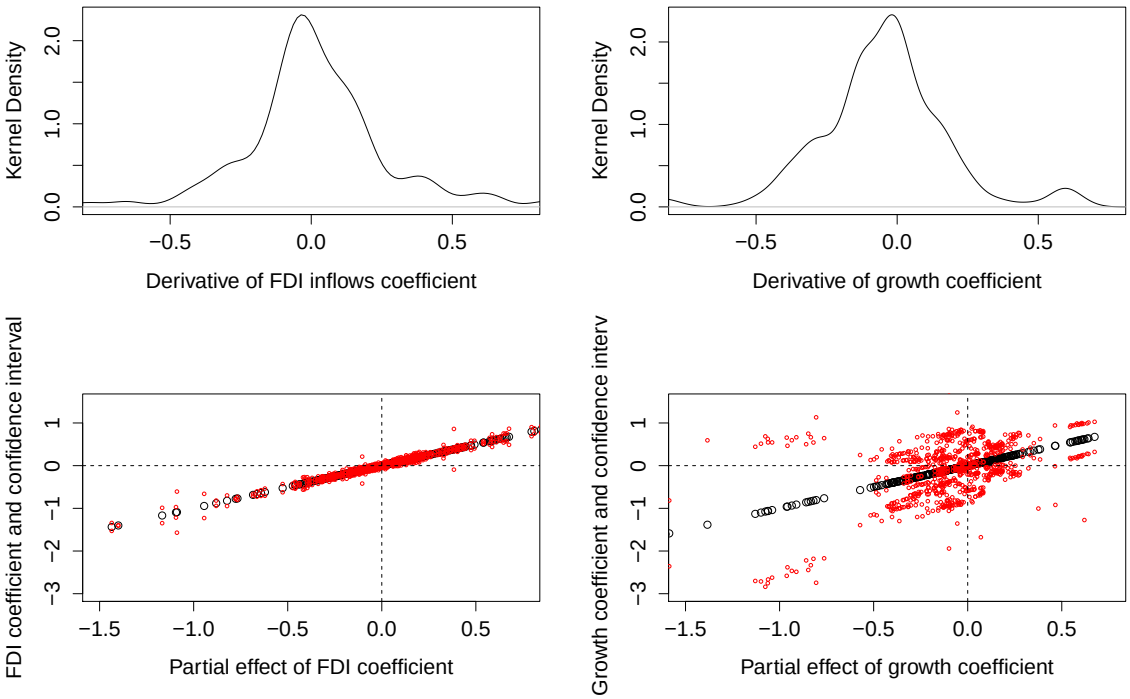

Figure 2: Kernel density plots and significance plots for the partial effect of FDI inflows and growth coefficient functions with respect to corruption for the model with instrumental variables.

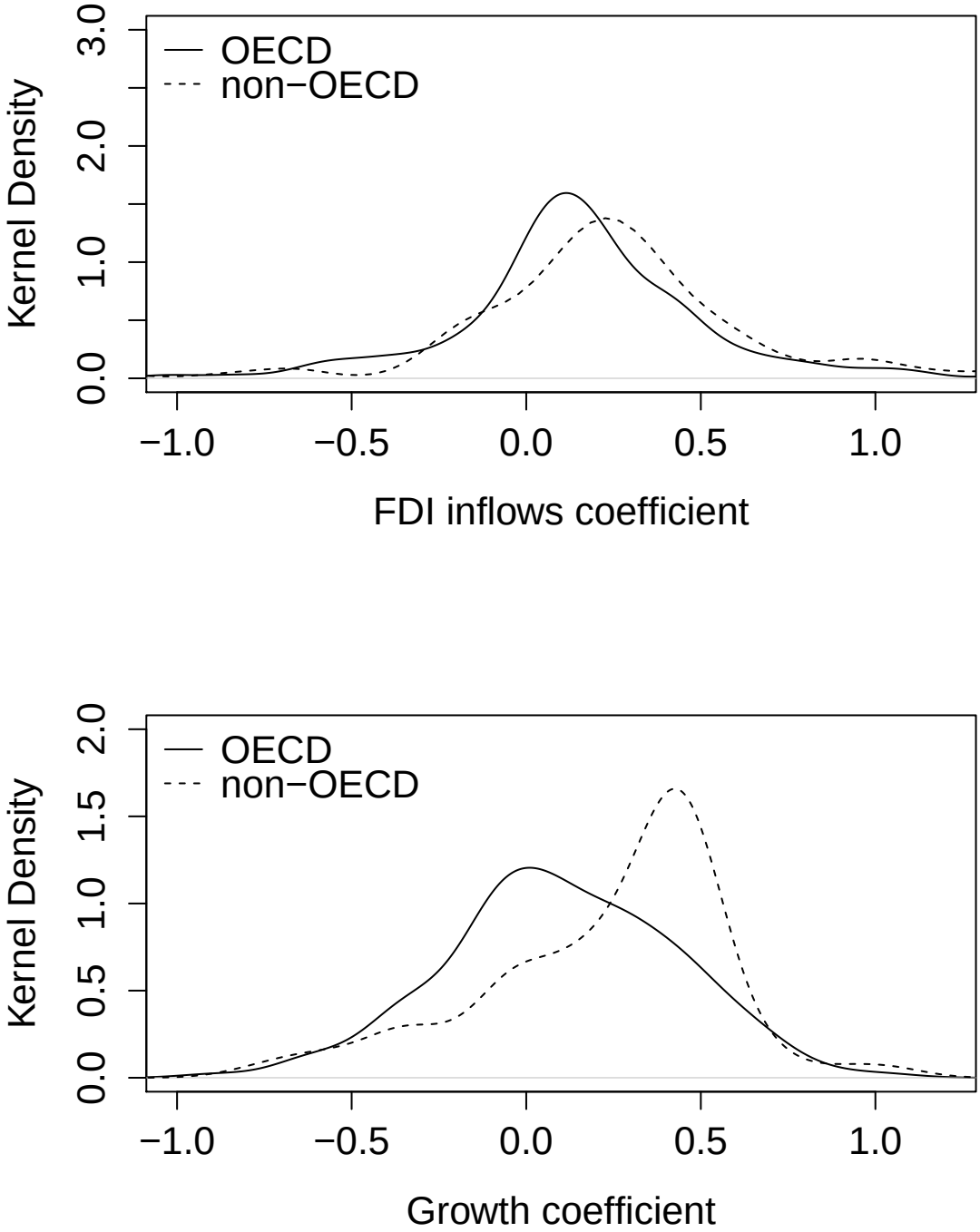

Figure 3: Kernel density plots of FDI inflows and growth coefficient function estimates for OECD and non-OECD countries based on the model with instrumental variables.

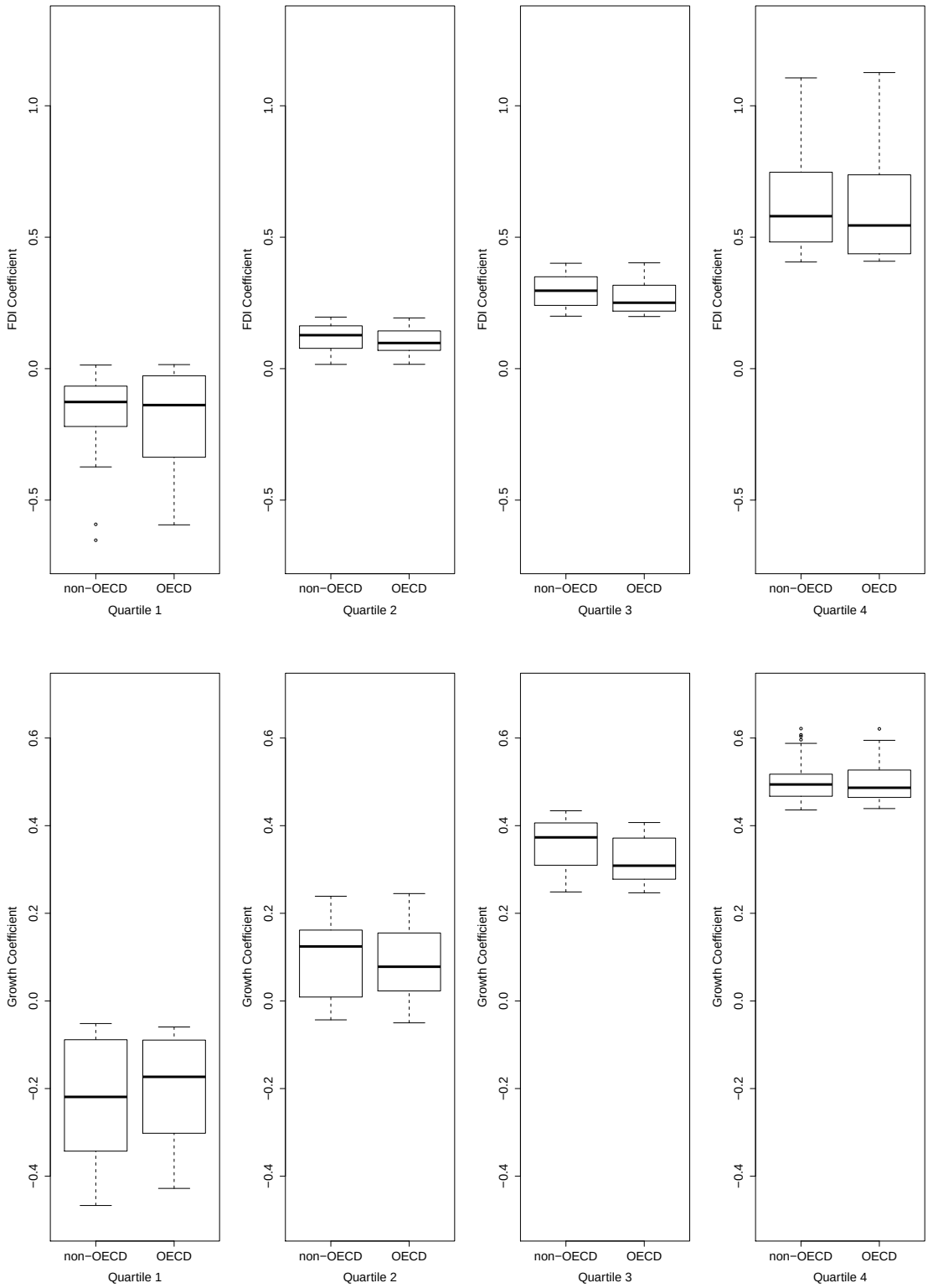

Figure 4: Box plots across quartiles of FDI inflows and growth coefficient function estimates for OECD and non-OECD countries based on the model with instrumental variables.

Table 1: Summary of estimated coefficients from the system of simultaneous equations model of economic growth and FDI for the instrumental variables model.

Growth Equation				FDI Equation			
Variable	25th	50th	75th	Variable	25th	50th	75th
Intercept	**-0.0362**	**0.0086**	**0.0779**	Intercept	**-0.0452**	0.0193	0.1324
	0.0009	0.0021	0.0183		0.0181	0.0232	0.0919
FDI inflows	0.0087	**0.2081**	**0.5618**	Growth	**0.0167**	**0.2114**	**0.5751**
	0.0210	0.0314	0.0067		0.0020	0.0733	0.2485
Initial income	**-0.0071**	**-0.0011**	**0.0034**	Foreign Exchange	**-0.0003**	-0.0001	**0.0006**
	0.0002	0.0001	0.0000		0.0001	0.0001	0.0003
Population growth	**-0.5209**	**-0.1068**	**0.0407**	Log GDP	**-0.0053**	-0.0005	**0.0018**
	0.0100	0.0020	0.0014		0.0025	0.0013	0.0004
Investment	**-0.0313**	**0.0936**	**0.2054**	Schooling	-0.0146	0.0107	0.0380
	0.0066	0.0049	0.0038		0.0185	0.0113	0.0270
Openness	**-0.0279**	**-0.0028**	**0.0162**	Openness	**0.0167**	**0.0313**	**0.0494**
	0.0007	0.0003	0.0005		0.0044	0.0100	0.0170
Inflation	**-0.0956**	**-0.0205**	**0.0675**	Inflation	**-0.0221**	**-0.0052**	0.0172
	0.0002	0.0025	0.0069		0.0045	0.0017	0.0115
Government consumption	**-0.1316**	-0.0063	**0.0758**				
	0.0022	0.0043	0.0095				
Sample size		463		Sample size		463	
In-sample R^2		0.9999		In-sample R^2		0.9322	
Out-sample R^2		0.1681		Out-sample R^2		0.2084	
Out-sample $ASPE$		0.0012		Out-sample $ASPE$		0.0059	

1. 25th, 50th, 75th refer to percentiles.
2. Estimate-specific bootstrapped standard errors are reported below each estimate. Coefficients in bold are significant at the 5% nominal significance level.
3. R^2 is calculated as the square of the correlation between $(y, \widehat{y})$.
4. $ASPE$ is the average of the squared difference between $(y, \widehat{y})$.
5. Out-of-sample prediction measures are the mean of 1000 out-of-sample replication exercises (see text for details).

Table 2: Characterizing the types of interactions between economic growth and FDI

		Growth Effect		
		Positive	Negative	Zero
FDI Effect	Positive	**Symbiosis**: 63 countries (45 distinct)	**FDI-Antagonistic Symbiosis**: 3 *countries*[d]	**FDI-Commensalism**: 37 countries (21 distinct)
	Negative	**Growth-Antagonistic Symbiosis**: 11 countries (5 distinct)	**Synnecrosis**: 3 *countries*[d] (1 distinct)	**Growth-Ammensalism**: 4 countries (3 distinct)
	Zero	**Growth-Commensalism**: 1 *country*[d] (not distinct)	**FDI-Ammensalism**: No countries	**Non-Symbiosis**: 2 *countries*[d]

1. To characterize the types of interactions between growth and FDI on the basis of the taxonomy in Definition 3.1, we use the following criterion: a country is placed in the category, for example, *symbiosis* if at least 50 percent of its estimated effects of FDI on growth *and* its estimated effects of growth on FDI is *positive* and *statistically significant* at least at the 5% level.
2. *d* are cells with *only* developing countries.
3. *distinct* refers to countries that exhibit *only* one type of interaction on the basis of our criterion.

Table 3: Summary of estimated partial effects of corruption on the coefficients from the system of simultaneous equations model of economic growth and FDI for the instrumental variables model.

Growth Equation				FDI Equation			
Variable	25th	50th	75th	Variable	25th	50th	75th
Intercept	**-0.0452**	-0.0010	**0.0660**	Intercept	-0.0388	0.0164	**0.0639**
	0.0020	0.0066	0.0023		0.0500	0.0238	0.0171
FDI inflows	**-0.1371**	0.0000	**0.1523**	Growth	-0.2242	0.0112	**0.1345**
	0.0073	0.0000	0.0151		0.2096	0.1681	0.0155
Initial income	**-0.0058**	0.0002	**0.0061**	Foreign Exchange	0.0000	**0.0002**	**0.0007**
	0.0003	0.0011	0.0003		0.0001	0.0001	0.0003
Population growth	**-0.0477**	**0.0207**	**0.1511**	Log GDP	-0.0024	-0.0005	0.0021
	0.0025	0.0043	0.0010		0.0021	0.0012	0.0013
Investment	**-0.1981**	**-0.0614**	**0.0477**	Schooling	**-0.0126**	0.0090	0.0239
	0.0166	0.0065	0.0061		0.0013	0.0143	0.0261
Openness	**-0.0272**	**-0.0009**	**0.0259**	Openness	-0.0086	**0.0138**	**0.0274**
	0.0009	0.0003	0.0008		0.0044	0.0037	0.0050
Inflation	**-0.0662**	**0.0230**	**0.0844**	Inflation	-0.0077	-0.0006	**0.0161**
	0.0146	0.0011	0.0078		0.0052	0.0006	0.0014
Government consumption	**-0.1029**	**0.0095**	**0.1087**				
	0.0019	0.0020	0.0124				

1. 25th, 50th, 75th refer to percentiles.
2. Estimate-specific bootstrapped standard errors are reported below each estimate.