Unbalanced credit distribution in emerging economies and FDI

Damien Cubizol

GATE LYON SAINT-ÉTIENNE
UMR 5824

93, chemin des Mouilles
69130 Ecully - France

Maison de l'Université, Bâtiment B
10, rue Tréfilerie
42023 Saint-Etienne cedex 02 - France

http://www.gate.cnrs.fr
gate@gate.cnrs.fr

WP 1532 – December 2015, revised February 2017

Unbalanced credit distribution in emerging economies and FDI

Damien Cubizol

Abstract:

This empirical study shows that an increasing credit distribution to State-Owned Enterprises (SOEs), to the detriment of private firms, slows the increase in inward FDI in emerging economies. The first approach is global and dynamic; it relies on GMM and Bayesian techniques, utilizing a sample of 40 emerging countries over the period 1988-2008. Then, a sectoral approach is implemented for 1992-2012 and strengthens the negative effect on inward FDI (but the difference of financial dependence between sectors does not have clear effects). Finally, certain policy actions can improve the allocation of domestic and foreign capital in emerging economies.

Keywords:

Financial intermediation; Foreign Direct Investment; emerging economies; privatization

JEL codes:

F21, G20, L30, O10

Unbalanced credit distribution in emerging economies and FDI*

Damien Cubizol†

First version: December 2015
This version: February 2017

Abstract

This empirical study shows that an increasing credit distribution to State-Owned Enterprises (SOEs), to the detriment of private firms, slows the increase in inward FDI in emerging economies. The first approach is global and dynamic; it relies on GMM and Bayesian techniques, utilizing a sample of 40 emerging countries over the period 1988-2008. Then, a sectoral approach is implemented for 1992-2012 and strengthens the negative effect on inward FDI (but the difference of financial dependence between sectors does not have clear effects). Finally, certain policy actions can improve the allocation of domestic and foreign capital in emerging economies.

JEL Classification: F21, G20, L30, O10

Keywords: Financial intermediation; Foreign Direct Investment; emerging economies; privatization.

*I would like to thank Céline Gimet for her continual help. I am also very grateful to Sylvie Démurger, Gilles Dufrénot, Aurélien Eyquem, Jérôme Héricourt and Sandra Poncet for advices, and to Jesus Gonzalez-Garcia and Francesco Grigoli for data access. I also thank seminar participants and Tavis Barr, Emmanuel Bougna, Olivier Brossard, Christian de Peretti, Carl Grekou, Jie Jiang, Carl Lin, Alexis Penot and Stefano Ugolini for additional help and comments. This work has been partly carried out within financial support from Région Rhônes-Alpes (Explo'ra Doc) and during a visit at Beijing Normal University (I thank Sylvie Démurger and Li Shi for having given me this opportunity). I also gratefully acknowledge three years doctoral grant. All remaining errors are mine.

†Sciences Po Toulouse, 2 Ter Rue des Puits Creuses, 31000 Toulouse. Also Univ Lyon, Université Lumière Lyon 2, GATE L-SE UMR 5824, F-69130 Ecully, France. Email: cubizol@gate.cnrs.fr

Highlights

- In most emerging economies, credit has been distributed more to State-Owned Enterprises than to private firms during some periods of their development.
- First, a global and dynamic approach studies the effect of this capital misallocation on FDI: it slows the increase in inward FDI.
- Second, a sectoral analysis strengthens the negative effect on inward FDI.
- This study leads to two types of policy implications: reducing the credit bias at its source or limiting the negative consequences for investment.

1 Introduction

In the majority of emerging economies, the share of SOEs decreased at different speeds or remained constant (first stylized fact) during the last thirty years. However, the share of credit to SOEs over credit to all firms increased during some periods of their liberalization (second stylized fact[1]); therefore, the banking system favored SOEs to the detriment of private firms at a certain stage of the development or transition process of some countries. By financing more SOEs, this credit bias has created some distortions in the access to credit between public and private firms.

This phenomenon has been well developed for former Soviet countries in Perotti (1993), Anderson et al. (1998), Kornai et al. (2003) and Megginson (2005); and for China in Boyreau-Debray (2003), Dollar and Wei (2007), Héricourt and Poncet (2009) and Song et al. (2011).[2] Our study extends the presence of the credit bias in favor of SOEs to other emerging economies and analyzes its effect on inward FDI. Indeed, although private firms can also use alternative access to credit in emerging economies[3], their formal access to credit remains constrained *compared to* SOEs during some periods of their development. Moreover, according to Harrison and McMillan (2003), Du and Girma (2007), Alfaro et al. (2009), and Desbordes and Wei (2014), FDI are also financed by the *local* country and not only by the parent country. Thus, by financing more SOEs to the detriment of private firms, local financial intermediation can modify the decision of a foreign private investor to expatriate production, acquire shares of a company, or conduct a

[1] Table 1 gives some examples from the data.
[2] For China see also Boyreau-Debray and Wei (2005) and Poncet et al. (2010).
[3] See Krugman (2011), Claessens et al. (2012), Acharya et al. (2013), Li (2014) and Funke et al. (2015).

merger or joint venture.[4]

The paper uses two databases with two different methodologies to study this effect of the credit bias toward SOEs on FDI entries. First, a global and dynamic study with 40 emerging countries; second, a sectoral analysis based on the work of Rajan and Zingales (1998) that gives more accurate results and links them to financial dependence. The conclusion is a slowdown of the increase in inward FDI when the credit bias toward SOEs rises. Given the heterogeneity in the degree of increase in inward FDI between emerging economies (see Figure 1), some factors may have slowed the increase in FDI entries in some countries; the results claim that the increase in inward FDI could have been higher in the countries where the credit bias in favor of SOEs was strong. Thus, the paper particularly deepens the analysis of the causal impact of local financial development on inward FDI (Harrison and McMillan, 2003; Alfaro et al., 2009; Desbordes and Wei, 2014). These two empirical studies also complete the literature on the soft budget constraints of SOEs described above and extend it to emerging economies.

Concerning the origins of the credit bias in favor of SOEs, the literature provides different explanations. In former Soviet states that experienced a transition process, the bias largely came from an incentive of State-Owned Banks (SOBs) to fund former debtors (SOEs) for future repayments (Perotti, 1993). Another explanation is the distortions of the lending rate in the credit market. Indeed, in China, the household savings deposit rate remains low to provide cheap credit to SOEs, whereas private firms face a higher lending rate (Aglietta and Bai, 2012; Song et al., 2014; Funke et al., 2015). High bank concentration by SOBs and lending policies determined by the government to support SOEs also play a significant role in the credit misallocation (Anderson et al., 1998; Boyreau-Debray, 2003; Dobson and Kashyap, 2006; Cull et al., 2007; Firth et al., 2008). La Porta et al. (2002), Sapienza (2004) and Khwaja and Mian (2005) note a link to corruption because SOBs remain controlled by politicians, with personal and political incentives (e.g., hiring political partners and bailing out low-performing firms, see Firth et al., 2008). Finally, another explanation is a method for the government to ensure tax revenues through SOEs, particularly during fiscal decentralization and privatization in emerging economies (for China, see Gordon and Li, 2005).

The first empirical study is detailed in Section 2, and Section 3 develops the sectoral analysis. The last section suggests policy actions to reduce the credit bias toward SOEs and its negative effects.

[4] Figure 6 in Appendix A illustrates the mechanism.

2 A global approach

2.1 Data and main variables

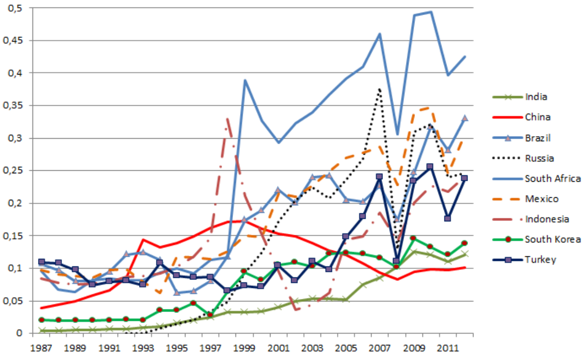
Before adopting a sectoral approach, the first model comprises a dynamic yearly study (which also captures the agglomeration effect of inward FDI, see Cheng and Kwan, 2000, and Kinoshita and Campos, 2003) of the 40 main emerging countries. It covers the period 1988-2008 to include the privatization of former Soviet states, some ASEAN and South American countries, and China.[5] None of these countries experienced a nationalization of the economy: the share of SOEs decreased significantly in the transition economies, more slowly in other emerging economies, or remained constant.

Inward FDI:

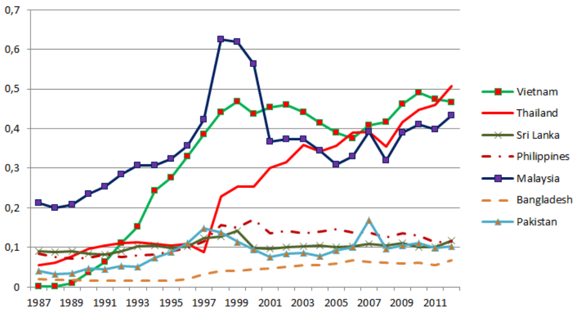
Inward FDI have been a strong factor of growth in emerging economies (Borensztein et al., 1998; De Mello, 1999). The increase in inward FDI started more than thirty years ago with the opening of the capital account of emerging economies, and the speed and magnitude of the entries varied across regions and countries (Figure 1 below). The variable FDI in the first global and dynamic study represents the stocks of inward FDI in percentage of GDP, and the data source is UNCTAD Statistics. A lag of the dependent variable is included in the first dynamic model (see Subsection 2.2) to capture the agglomeration effect of inward FDI (Cheng and Kwan, 2000; Kinoshita and Campos, 2003). Our study analyzes the effect of a credit distortion in favor of SOEs on inward FDI. Indeed, according to Harrison and McMillan (2003), Du and Girma (2007), Alfaro et al. (2009), and Desbordes and Wei (2014), FDI are also financed by the *local* country and not only by the parent country. Thus, by financing more SOEs to the detriment of private firms, local financial intermediation can modify the decision of a foreign private investor to expatriate production, acquire shares of a company, or conduct a merger or joint venture.[6] Note that there is a strong heterogeneity in the degree of increase in inward FDI between emerging countries in the sample (see Figure 1). Some factors may thus have slowed the increase in FDI entries in some countries, and the results of both global/dynamic and sectoral approaches claim that the increase in inward FDI could have been higher in the countries where the credit bias in favor of SOEs was strong.

[5]The sample includes Argentina, Bangladesh, Brazil, Bulgaria, Chile, China, Colombia, the Czech Republic, Egypt, Estonia, Greece, Hong Kong, Hungary, India, Indonesia, Iran, Latvia, Lithuania, Malaysia, Mexico, Morocco, Nigeria, Pakistan, Peru, the Philippines, Poland, Romania, Russia, Singapore, Slovakia, Slovenia, South Africa, South Korea, Sri Lanka, Thailand, Turkey, Ukraine, the United Arab Emirates, Venezuela and Vietnam. These countries are or were classified by international institutions as emerging markets during the sample period; Hong Kong, Singapore and South Korea were considered emerging markets at the beginning of the sample period but were then classified as developed countries. The Commonwealth of Independent States (CIS) is not included in this sample because insufficient data are available for privatization. In all of the countries in the sample, the share of SOEs decreased, at different speeds, or remained constant. There was no nationalization across time, and a credit bias toward SOEs appeared within certain periods of time (an increasing ratio of credit to SOEs over credit to SOEs and the private sector).

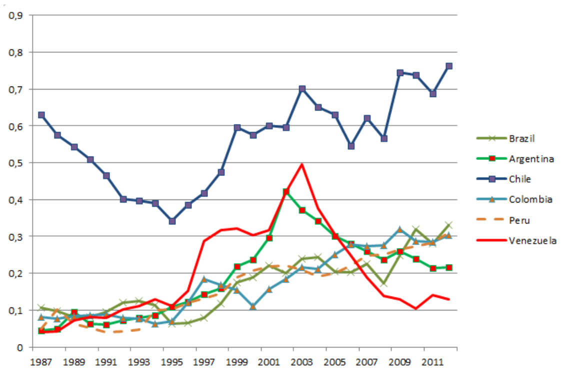
[6]Figure 6 in Appendix A illustrates the mechanism.



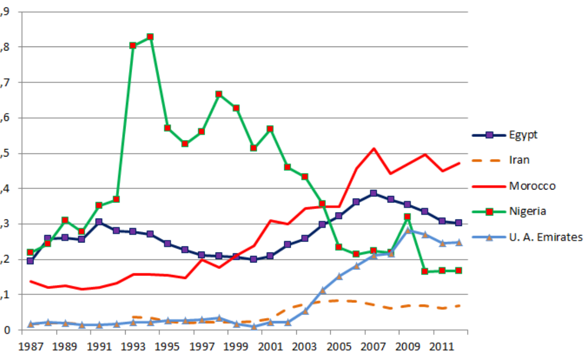
Inward FDI - BRICMS, Indonesia, South Korea and Turkey (a) (Stocks in % GDP)



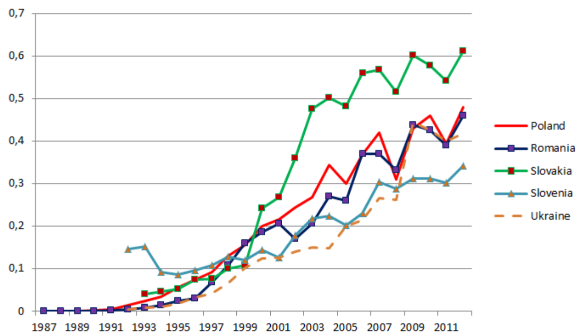
Inward FDI - Asian countries (b) (Stocks in % GDP)



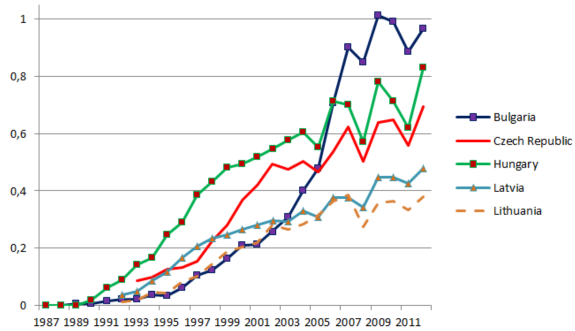
Inward FDI - South America countries (c) (Stocks in % GDP)



Inward FDI - African and Middle East countries (d) (Stocks in % GDP)



Inward FDI - Eastern Europe countries (1) (e) (Stocks in % GDP)



Inward FDI - Eastern Europe countries (2) (f) (Stocks in % GDP)

Figure 1: Inward FDI stocks

The misallocation of capital and privatization:

Because it is the crucial issue of the study, the regressor for the misallocation of capital is added (variable *crpubpriv*, see Table 3). It is the share of credit to SOEs against the total credits to the private sector and SOEs (Source: International Financial Statistics, 2013, IMF). We consider that there is a credit bias toward SOEs when this ratio increases *whereas* the share of SOEs in GDP decreases or remains constant. For all countries in the sample, the share of SOEs decreases at different speeds or remains constant, but there is no nationalization across time. The *crpubpriv* variable increases during some periods, meaning that a credit bias toward SOEs appears. All the factors at the origin of this credit bias are described at the end of the introduction; and Table 1 gives some examples of its presence in some countries of the sample.

Country	**Period**	**Ratio of credit to SOEs[1] over credit to the private sector and SOEs** (%)	**Country**	**Period**	**Ratio of credit to SOEs[1] over credit to the private sector and SOEs** (%)
Brazil	1994-1998	4.88 up to 6.01	Chile	1988-1990	1.58 up to 6.52
Russia	2006-2009	0.95 up to 1.01		2002-2005	0.17 up to 0.43
South Africa	2003-2007	0.16 up to 0.73	Colombia	1995-2001	3.54 up to 6.11
Mexico	1999-2004	0.95 up to 3.31	United Arab	1989-1994	1.67 up to 8.41
Indonesia	1997-1999	2.81 up to 4.97	Emirates	2001-2005	3.87 up to 7.87
	2004-2007	2.24 up to 3.82	Philippines	1996-2003	1.51 up to 10.07
Turkey	2002-2008	0.19 up to 1.31	Thailand	1997-2001	2.41 up to 6.32
Bulgaria	1988-1992	2.86 up to 98.19	Ukraine	1998-2000	20.09 up to 29.39

This table presents some examples of the credit bias toward SOEs in the sample. It appears when the ratio of credit to SOEs over credit to SOEs and the private sector increases, *whereas* the share of SOEs decreases or remains constant.
[1] In the data, SOEs are "public non-financial corporations" (Source: International Financial Statistics, 2013, IMF), that is, when a state, a government or a public authority holds more than 50.01% of the firms' shares.

Table 1: Some data on the credit bias toward SOEs

It is initially assumed that the decision to lend more to SOEs is a strategy by the government, as in Boyreau-Debray (2003), Boyreau-Debray and Wei (2005), and Gonzalez-Garcia and Grigoli (2013). Thus, the first estimations consider that *crpubpriv* is exogenous. This assumption is not realistic for all emerging countries but corresponds to the situation of credit distortions in China now and in former Soviet states in the late 1990s. In these cases, it is a choice by the government or SOB governance to favor SOEs.[7]

Then, estimations are performed with instruments for *crpubpriv*, which are the lags of the share of SOEs. Indeed, if there were no credit bias toward SOEs, *crpubpriv* would follow the past privatization process of firms (and the latter is unlikely to be correlated to the entries of FDI). In the sources from which the data are extracted, firms are considered SOEs when a state, a government or a public authority holds

[7] According to Boyreau-Debray (2003, p. 4), "the state banks have been asked to channel savings to the loss-making state-owned enterprises".

more than 50.01% of the firms' shares.

Some estimations are also performed with an interaction term to include privatization: *crpubpriv*$\times$*soe* is added to *crpubpriv*. The share of SOEs (variable *soe*, see Table 3) is also instrumented to ensure the exogenous process of privatization in the estimations.[8] The low correlation between *crpubpriv* and *soe* is checked to avoid biases in the estimations with the interaction term (Figures 2 and 3). This low correlation confirms the existence of soft budget constraints for SOEs: otherwise, *crpubpriv* would follow *soe*. The presence of the credit bias can also be confirmed by a significant correlation between *crpubpriv* and the share of SOBs. As explained in the literature (see the introduction), SOBs can provide more credit to SOEs, either for rational or political incentives.

Variables	crpubpriv	soe	sob
crpubpriv	1.000		
soe	0.093	1.000	
	(0.152)		
sob	0.344	0.225	1.000
	(0.000)	(0.003)	

Figure 2: Correlation table

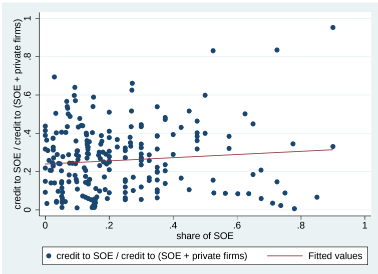


Figure 3: Credit to SOEs over total credit (to SOEs and private sector) and the share of SOEs

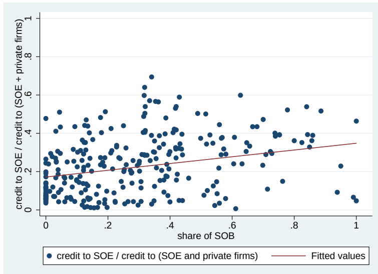


Figure 4: Credit to SOEs over total credit (to SOEs and private sector) and the share of SOBs

Explanatory and control variables for FDI:

The usual macroeconomic control variables are used as regressors for the estimations of FDI, i.e., GDP and the real exchange rate. Then, because there are many potential explanatory variables for FDI in the literature, their correct determinants are chosen with Bayesian model averaging. By generating additional estimations, this method determines the probability that a variable explains the dependent variable of a specific database. This technique is described in Appendix B, and we present only the results in this section.

The *potential* explanatory variables from the literature are the lending rate (Gastanaga et al., 1998), wages (Blonigen, 2005; Braconier et al., 2005; Dooley et al., 2005), TFP growth (Wei and Liu, 2006; Bénassy-Quéré et al., 2007), FDI costs (trade, administrative and business costs; see Gastanaga et al.,

[8]Indeed, although *soe* can be considered exogenous in most cases because it is the direct result of the government's privatization policy to change ownership or sell shares, an endogenous bias can also appear (Megginson, 2005). Thus, in the literature, we can find studies that both control and do not control for these issues (Estrin et al., 2009). Therefore, the lags of *soe* are used as instruments for *soe*, as is true in the literature (Andreyeva, 2003; Hanousek et al., 2007 and 2009). Note that the general context of liberalization and deregulation also seems to be a quite good instrument for *soe*, however, it is correlated with the entries of FDI.

1998 and Bénassy-Quéré et al., 2007), capital controls, corruption (Bénassy-Quéré et al., 2007) and an index for the legal system and the level of property rights (Bénassy-Quéré et al., 2007). We also add the share of capital in production and savings (variables in Table 2).
According to the first results of Bayesian model averaging (in Appendix B) , TFP *growth* is not selected as an explanatory variable for this specific sample but TFP *level* is selected. Moreover, capital controls (*cp*), FDI costs (*fdicsts*) and the index for the legal system and the level of property rights (*lleg*) are also not selected by Bayesian simulations as explanatory variables for this sample.[9] However, in some GMM estimations, the *lleg* and *fdicsts* variables are significant.

Estimations with and without correlated variables (such as GDP or savings) are performed to reduce multicollinearity, and the GMM estimator reduces endogeneity issues (particularly for corruption) with internal instruments. As described above, we only use external instruments for the variables linked to privatization (*soe*) and the credit bias toward SOEs (*crpubpriv*). Finally, in this study, adding too many dummies considerably raises the number of instruments, and some dummies are often dropped due to collinearity. Thus, for some estimations, time dummies are only set for the 2007-2008 contagion of the U.S. financial collapse.

Observations:

The *soe* and *lleg* variables have considerable data gaps. Indeed, no studies include a yearly ratio of SOEs in the period 1988-2008 for the main emerging countries, and the few databases with information are limited to the most recent seven years (e.g., Bankscope). Therefore, for the *soe* variable, the sample has been completed by taking values from various studies and sources (see Table 3), and interpolation is necessary to have enough observations. Different interpolation techniques are used (linear, log-linear, Catmull-Rom Spline or Cardinal Spline interpolations), and errors are limited because, apart from the former Soviet states, the privatization process was gradual and linear in the countries in the sample. Concerning *lleg*, the Fraser Institute is the only source that gives a time dimension (1985, 1990, 1995, 2000, 2005 and 2010). Hence, interpolations are also performed for *lleg* to increase the sample size.[10] The variables, data and statistics are summarized in Tables 2, 3 and 8. Only the two variables *soe* and *lleg* are interpolated.

[9] The variable of capital controls *cp* is the Chinn-Ito index, which is a broad index of financial liberalization including many types of capital flows. Thus, this index can not explain the specific pattern of inward FDI.

[10] The other variables have observations for nearly each period and country, except wages and corruption (available for 1992-2008), FDI costs and the real effective exchange rate (available for 1994-2008). Countries such as Brazil, Bulgaria, Iran, Romania, Russia, Ukraine, the United Arab Emirates, Venezuela and Vietnam have sizeable data gaps.

2.2 The model

The first approach is global with a dynamic model. In the first stage, because there are many potential explanatory variables for inward FDI in the literature, their correct determinants are chosen with Bayesian model averaging (see Appendix B). This method allows for additional estimations to determinate the probability that a variable is included in the model. Then, to avoid the endogenous biases on the key variable *crpubpriv* explained above, the GMM estimator from Arellano and Bond (1991) is used, with the addition of external instruments. The number of countries is sufficient to have more robust results with the Arellano and Bond GMM estimator than with the usual OLS or panel regression (Bond et al., 2001; Soto, 2009). Because the GMM estimator needs a small period of time compared to the number of countries N (to avoid instrument proliferation, see Roodman, 2009), a variable value at one period is the average of the value of two years (thus, T=10).

A difference GMM is more convenient for an analysis with a small number of countries (Mileva, 2007) because System GMM uses more instruments than the difference GMM does (the instruments are the levels and first differences in the lags of explanatory variables for System GMM, whereas the instruments are only the levels for difference GMM). Indeed, with this number of countries (N=40), there would be more instruments than countries with a System GMM, which would generate invalid results, overfit the endogenous variables and weaken the Hansen test (Roodman, 2009). Another advantage of the first difference is in addressing the problem of omitted variables with panel data. However, although a difference GMM removes the unit root and individual specific/unobserved effects, it considerably reduces the size of the sample by magnifying gaps in unbalanced panels, which is why a GMM with Forward Orthogonal Deviation (GMM FOD) is applied to overcome this issue. The latter is "an alternative to differencing proposed by Arellano and Bover (1995) that preserves the sample size in panels with gaps" (Roodman, 2006, p. 1). Instead of subtracting the observation at *t-1* from that at *t*, it subtracts the average of all future available observations for a variable. Only the last observation for each individual is not computed, thus minimizing data loss. Via the Helmert transformation, the observations at time t become the following:

$$X^*_{i,t} = c_t \left[X_{i,t} - \frac{1}{T-t}(X_{i,t+1} + ... + X_{i,T}) \right], t = 1, ..., T-1, \tag{1}$$

with $c_t = \sqrt{\frac{T-t}{T-t+1}}$ introduced by Arellano and Bover to equalize the variances. In GMM FOD, unlike in difference GMM, lagged observations are valid as instruments because they do not enter the formula. The good performance of this estimator is detailed in the literature (Arellano and Bover, 1995; Bond et al., 2001; Roodman, 2006; Hayakawa, 2009). Indeed, all GMM estimators remain invariant for any transformation that removes individual effects, provided that the transformation matrix is upper triangular and with the use of available instruments, as is true for forward orthogonal deviation (Arellano and

Bover, 1995).[11] The model can be written as follows:

$$y_{i,t} = \alpha y_{i,t-1} + \beta \sum_{t=0}^{n} X_{i,t-n} + \varphi crpubpriv_{i,t,\substack{\wedge instru.L.soe_{i,t} \\ \backslash instru.L.soe_{i,t}}} + \gamma crpubpriv_{i,t} \times soe_{i,t,instru.L.soe_{i,t}} + u_i + v_t \quad (2)$$

with countries $i = 1, ..., 40$ and periods $t = 1, ..., 10$. A variable's value at one period is the average of the value of two years ($X(i,1) = \frac{X(i,1988)+X(i,1989)}{2}, X(i,2) = \frac{X(i,1990)+X(i,1991)}{2}, ..., X(i,10) = \frac{X(i,2007)+X(i,2008)}{2}$). $y_{i,t}$ ($y_{i,t-1}$) represents the dependent (lagged) variable for each country at each period t (the stock of inward FDI), which also captures the agglomeration effect of inward FDI (Cheng and Kwan, 2000; Kinoshita and Campos, 2003). $X_{i,t-n}$ the set of explanatory lagged variables, u_i the specific individual effect for each country and v_t time dummies. $E[x_{i,t-n}(u_i + v_{i,t})] = 0$ is valid for each country, and the Roodman hypotheses (2006) for the application of Arellano and Bond estimator are verified. The misallocation of capital is captured by *crpubpriv* (instrumented or not by $instru.L.soe_{i,t}$), which also interacts with privatization ($crpubpriv_{i,t} \times soe$). The key variables are described above, summarized in Tables 2 and 3, and the descriptive statistics are in Table 8 in Appendix C.

[11] In addition, forward orthogonal deviation preserves the orthogonality among the transformed errors; indeed, if the original individual specific effects are not autocorrelated and have constant variance, then the same is true for the transformed errors (Arellano and Bover, 1995). With this choice of c_t in Equation 1, it is assured that $X_{i,t}$ are not only independent but also identically distributed, both before and after the transformation.

name	definition	sources
dependent variable:		
fdiin	Inward FDI stock (/GDP)	UNCTAD Statistics
explanatory variables:		
gdpr	Real GDP (billions U.S. $, divided by deflator (index 2005=100))	World Bank
reer	Real effective exchange rate base 2010=100	Bank of International Settlements, World Bank, and author's calculations
r	Interest rate (%, lending rate)	International Monetary Fund and World Bank
rw	Word interest rate (mean of U.S. short- and long-term interest rates)	OECD
w	Wages (U.S.$, monthly average)	ILOSTAT Database (International Labour Organisation)
ky	Share of capital in production	World Bank
s	Gross savings (/GDP)	World Bank
tfpg	TFP growth (%)	The Conference Board Data and World Bank
tfpl	TFP level (U.S. index = 1)	Penn World Table
cp	Capital controls (financial openness)	The Chinn-Ito index (KAOPEN, Chinn and Ito, 2006), revised and updated to 2012
fdicsts	Trade costs, and administrative and business fees (/GDP)	World Development Indicators (Trade costs Dataset, the World Bank) and author's calculations on bilateral data
corru	Corruption index 0 (high corruption) to 10 (low corruption)	The Corruption Perceptions Index of Transparency International
lleg	Legal system and property rights 0 (low quality) to 10 (high quality)	The Fraser Institute Database

Table 2: Variables

name	definition	sources
privatization and the misallocation of capital:		
soe	Share of SOEs[1] in GDP	Kowalski et al. (2013, Source: Bureau Van Dijk Databases) Estrin et al. (2009, Source: European Bank for Reconstruction and Development Transition Reports), Ramamurti (1999), and China Statistical Yearbook.
sob (only in the correlation table, see Figures 2 and 4)	Share of SOBs[1] (share of assets and liabilities owned by the government)	Barth et al. (2001, Source: versions 2000 and 2003 of the Bank Regulation and Supervision Survey of the World Bank), La Porta et al. (2002, various sources), Gonzalez-Garcia and Grigoli (2013, Source: Bank Regulation and Supervision Survey of the World Bank), and Almanac of China's Finance and Banking.
crpriv	Domestic credit to the private sector (/GDP)	International Financial Statistics (2013, IMF, line "claims on private sector")
crpub	Domestic credit to SOEs (/GDP):	International Financial Statistics (2013, IMF, line "claims on public non-financial corporations"); when the latter is not available for a country: "credit to SOEs and government" (World Bank and St. Louis Fed Stats) - "credit to government" (IFS).
crpubpriv	crpub/(crpub+crpriv) Ratio of credit to SOEs over credit to SOEs and the private sector	

[1] In the sources where the data is extracted, firms and banks are considered SOEs and SOBs respectively when a state, a government or a public authority holds more than 50.01% of the firms or banks' shares.

Table 3: Variables (2)

2.3 Results

The results of the first approach are summarized in Table 4. Some elements are verified to attest to the robustness of the estimations. First, the stationarity of each variable is checked even if it is not a crucial issue with a *xtabond2* procedure. To tackle multicollinearity, correlation tests are performed, and other estimations are conducted without correlated variables such as GDP (as in Bénassy-Quéré et al., 2007). Then, to avoid biased estimations, the coefficient value of the dependent variable lag is, for most of the estimations, between the coefficient value in OLS and fixed effects estimations (Arellano and Bond, 1991).[12] Moreover, the Arellano and Bond test ensures that there is no second-order autocorrelation of residuals' first difference. To ensure the robustness of the coefficients, their standard deviations are often largely below the coefficients' values (approximately 20-40 %). Regarding instruments, their number is always less than N, and their exogeneity is controlled by Hansen statistics.[13] Finally, the results are strengthened by other robustness checks: bootstrapping, quantile estimations (given the heterogeneity in inward FDI between emerging economies), estimations for different periods, and the addition of explanatory variables or interaction terms; see Table 4 and the end of this subsection.

	Results			**Robustness checks**	
	Significance	Coefficient		Significance	Coefficient
crpubpriv (considered exogenous) (GMM FOD)	* up to ***	-0.082 down to -0.294	OLS	** up to ***	-0.108 down to -0.159
crpubpriv instrumented (GMM FOD)	** up to ***	-0.175 down to-0.421	Fixed effects	* up to **	-0.079 down to -0.22
with *crpubpriv* interacting with privatization (GMM FOD)	* up to ***	-0.072 down to -0.079	Bootstrapping on OLS and fixed effects (when possible) and robust standard errors	* up to **	-0.079 down to -0.22
			Shorter period of time (T=5) (GMM FOD, OLS and within)	Reduced for OLS and within	-0.088 down to -0.193
			Other data: *crpubpriv* extended to other SOEs (GMM FOD, OLS and within)	* up to ***	-0.042 down to -0.23
			Different interpolations techniques: (for variables soe and lleg)		
			-linear interpolation	* up to ***	-0.082 down to -0.421
			-log-linear interpolation	* up to ***	-0.082 down to -0.421

Note: This table contains results for additional combinations of explanatory variables, therefore, variances of coefficients are larger compared to the results in Table 5.

Table 4: The effect of the credit bias on inward FDI and robustness checks

[12]When the ordinary least squares estimator is used, there is some correlation between the explanatory variables and the error term due to individual effects, creating an upward bias. Concerning the within estimator, when the number of periods is limited, the dependent lagged variable is correlated with the fixed effects in the error term, leading to a downward bias (Arellano and Bond, 1991).

[13]Most of the estimations verify that the values of the Hansen test are neither too high nor too low and are not biased by too many instruments, although there is no precise rule (Ruud, 2000, p. 515; Roodman, 2009). Moreover, it is preferable to reduce the number of instruments as much as possible when the latter is close to the number of individuals because doing so considerably lowers the average bias in the two-step estimate of the parameters (Windmeijer, 2005). In the literature and in the STATA *xtabond2* procedure, the number of instruments becomes critical when it is equal to or greater than the number of individuals in the panel (which could be true in these estimations if the System GMM was applied because it has more instruments than GMM FOD or difference GMM).

	GMM *fod* (1) fdiin	GMM *fod* (2) fdiin	GMM *fod* (3) fdiin	GMM *fod* (4) fdiin	GMM *fod* (5) fdiin	GMM *fod* (6) fdiin	GMM *fod* (7) fdiin
L.fdiin	0.798***	0.590***	0.750***	0.533***	0.632***	0.603***	0.417*
	[0.046]	[0.055]	[0.058]	[0.077]	[0.041]	[0.056]	[0.244]
gdpr			-0.226**	0.096	0.274*	0.227*	
			[0.106]	[0.091]	[0.144]	[0.116]	
reer			0.120	0.411***	-0.455*	-0.595**	
			[0.234]	[0.142]	[0.255]	[0.257]	
ky	-0.319	-1.965**	-1.760**	-5.681***	-4.597***	-3.857***	-2.382
	[0.851]	[0.801]	[0.830]	[0.923]	[1.266]	[1.163]	[1.702]
r	0.002	0.002	0.001	-0.002	-0.007**	-0.006*	-0.002
	[0.002]	[0.001]	[0.002]	[0.002]	[0.003]	[0.003]	[0.007]
w	-0.113**	-0.232					-0.550***
	[0.053]	[0.141]					[0.176]
crpubpriv	-0.082**	-0.204*	-0.155***	-0.294***			
	[0.041]	[0.112]	[0.053]	[0.072]			
crpubpriv×soe$_{instru.L.soe}$		-0.079***		-0.072*			
		[0.027]		[0.036]			
crpubpriv$_{\mathbf{instru.L.soe}}$					-0.175**	-0.391***	-0.654***
					[0.071]	[0.091]	[0.213]
lleg	-0.204	0.222	0.558**	0.647**	1.032***	0.246	0.979
	[0.283]	[0.230]	[0.244]	[0.241]	[0.310]	[0.216]	[0.659]
tfpl						1.029**	2.330***
						[0.394]	[0.830]
fdicsts	0.006	-0.007	0.002	-0.029**	-0.022	-0.006	-0.035
	[0.007]	[0.015]	[0.013]	[0.011]	[0.015]	[0.018]	[0.022]
L.corru	0.084	0.039	0.041	-0.203***	0.087	0.263**	0.142
	[0.057]	[0.041]	[0.039]	[0.044]	[0.053]	[0.108]	[0.087]
time dummies	yes	yes	yes	yes	yes	yes	yes
Observations	168	112	202	134	104	102	91
Number of countries	35	32	38	36	29	28	26
Sargan statistic	22.25	15.06	12	12.26	16.65	19.53	14.31
p-value of Sargan statistic	0.0348	0.238	0.151	0.907	0.276	0.242	0.575
Hansen statistic	16.58	20.34	10.15	17.75	18.84	19.19	8.353
p-value of Hansen statistic	0.166	0.0610	0.255	0.604	0.171	0.259	0.938
Arellano-Bond test for AR(1)	-2.858	-2.556	-2.242	-2.619	-1.346	-1.621	-2.448
p-value AR1	0.00427	0.0106	0.0249	0.00882	0.178	0.105	0.0144
Arellano-Bond test for AR(2)	-1.618	-1.451	-0.965	-1.675	-0.991	-0.966	-0.152
p-value AR2	0.106	0.147	0.335	0.0939	0.321	0.334	0.880

Standard errors in brackets
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5: The effect on inward FDI - GMM with Forward Orthogonal Deviation

The effect on inward FDI:

It is initially assumed that the share of credit to SOEs (variable *crpubpriv*) is exogenous.[14] *crpubpriv* is quite significant, whether some variables are added or removed (e.g., wages, FDI costs, the share of capital in production, GDP, TFP and the real effective exchange rate; see Table 5). The coefficient of *crpubpriv* is negative: although there is likely endogeneity, there is a clear negative effect of the credit bias toward SOEs on inward FDI (estimations 1 to 4 in Table 5).

Then, *crpubpriv* is instrumented by lags of the share of SOEs. The negative effect of the credit bias is still significant when endogeneity is more controlled (estimations (5), (6) and (7) in Table 5). An interaction with *soe* is also added to include privatization in some estimations. As explained in Subsection 2.1, there is no correlation between *crpubpriv* and *soe* that could bias the estimations. There is an underlying

[14]See Subsection 2.1 for justifications.

first step in which *crpubpriv* and *soe* are estimated by the external instruments, whose predicted values are substituted for *crpubpriv* and *soe* in the next GMM, OLS and fixed effects. This first estimation is equivalent to the first step of the *ivreg* STATA procedure. In the new estimations with the interaction term, $crpubpriv \times soe$, *crpubpriv* is also significant with a negative coefficient, regardless of whether other explanatory variables are removed (estimations (2) and (4)) in Table 5). Regarding the tests, the instruments used in the model are validated by Hansen's test of overidentifying restrictions, and there is no second-order autocorrelation with the residuals (Arellano-Bond test). Moreover, the value of *crpubpriv*'s coefficient is close to the OLS and fixed effects values; see Table 4, and more complete robustness checks are available upon request.

Considering the low number of countries, bootstrap estimations ensure that the error margins are robust. Some other estimations are performed with SOEs directly affiliated with local governments accounted for in credit amounts to the public sector; the negative effect on inward FDI is still present with these new values (Table 4). This effect is consolidated by estimations with T=5 instead of T=10, which yield quite similar results.

Quantile estimations:

Given the heterogeneity in the degree of increase in inward FDI between emerging economies (see Figure 1), the distributional impact of the credit bias in favor of SOEs on inward FDI is analyzed by using quantile regressions for panel data (Baker et al., 2016). In Figure 5, the quantile treatment effects estimates are clearly negative until close to the 85% of the FDI distribution, then slightly below zero, and again clearly negative at the end of the FDI distribution. The responses are quite heterogeneous along the distribution: (i) the lower 25% of the inward FDI distribution is generally highly responsive to credit market distortions that constrain private firms (variable *crpubpriv*) but with a wide confidence interval (ii) the magnitude of the negative effect of *crpubpriv* on FDI is generally lower for the upper part of the distribution (except above 92%) but the confidence interval is tighter.

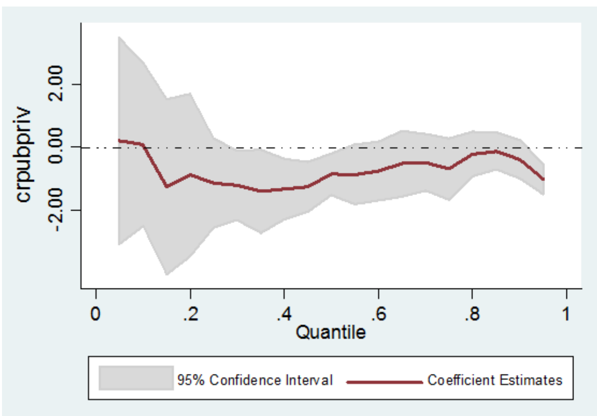


Figure 5: Quantile estimations - the effect of the credit bias (*crpubpriv*) on inward FDI

Given the results, this first global and dynamic approach extends the notion of credit bias in favor of SOEs (developed in the literature) to other emerging economies (not only former Soviet states and China) and shows that it slows the increase in inward FDI. Therefore, this result is also in line with Feldstein (2000), Harrison and McMillan (2003), Du and Girma (2007), Alfaro et al. (2009) and Desbordes and Wei (2014), who explain that the *local* financial system and its development are also determinants of inward FDI. Moreover, the analysis deepens the link between inward FDI and local credit constraints: the increase in inward FDI can also be slowed by an unbalanced local credit distribution between private and public firms, and is not only a means to overcome local credit constraints (Héricourt and Poncet, 2009; Ju and Wei, 2010; Poncet et al., 2010).

However, at this step and considering the error margins and the few observations, it is difficult to precisely quantify the slowdown of inward FDI due to the increase in *crpubpriv*. For this reason, the next analysis relies on a sectoral database and another estimator. The results strengthen the previous global and dynamic approach.

3 A sectoral approach and financial dependence

This sectoral approach makes it possible to capture more specific and richer firms' effects, knowing that the ownership structure and dependence on external finance widely vary between sectors. Moreover, by utilizing a sectoral database over the period 1992-2012, some estimations reach approximately 600 observations versus 200 in the global approach, providing more accuracy to the quantification of the effect of the credit bias on inward FDI.

3.1 The model and data

The model follows the methodology developed by Rajan and Zingales (1998), which enables correcting for country and industry characteristics and reduces omitted variables or endogeneity issues. This approach relies on the interaction of the key variable, the credit bias, with an index of sectoral financial dependence, which is *independent of time and country.* The estimated model is as follows:

$$\begin{aligned} FDI_{i,j,t} \quad &= \quad \alpha TB_{i,j,t} + \mu Z_{i,t} + \beta crpubpriv_{i,t,\substack{\wedge instru.L.soe_{i,t} \\ \backslash instru.L.soe_{i,t}}} + \varphi crpubpriv_{i,t} \times soe_{i,t,instru.L.soe_{i,t}} \\ &\quad + \gamma crpubpriv_{i,t} \times fidep_j + u_i + v_j + \eta_t + Cste \end{aligned} \tag{3}$$

with $Z_{i,t} = [gdpr; r; lleg; fdicsts]$ and u_i, v_j, η_t, dummies for dimensions i (country), j (sector) and t (time).

The estimations concern manufacturing sectors (ISIC revision 2 classification). $FDI_{i,j,t}$ is the dependent variable: the amount of inward FDI stock by *country, sector and time* (from CEIC database) relative to GDP (aggregated GDP by country and time). The trade balance $TB_{i,j,t}$ is a control variable by *country, sector and time* (from Nicita and Olarreaga, 2007). $Z_{i,t}$ are control and explanatory variables by *country and time*, which were previously described in Section 2 and Tables 2 and 3. $crpubpriv_{i,t}$ is the key variable proxy for the credit bias, i.e., the amount of credit afforded to SOEs relative to credit to SOEs and private firms, by *time and country.* $fidep_j$ represents financial dependence for each sector, *independent of time and country.*[15] The data (Table 6) come from Rajan and Zingales (1998); only financial dependence on external finance is considered because the study focuses on credit distribution.[15] Similar to the previous global study, the privatization of SOEs is also considered through an interaction between $crpubpriv_{i,t}$ and $soe_{i,t}$ (by country and time); $instru.L.soe_{i,t}$ is the external instrument, that is, lags of $soe_{i,t}$ (Andreyeva, 2003; Hanousek et al., 2007 and 2009). The external instrument is used or not

[15] Note that financial dependence is calculated by Rajan and Zingales (1998) and often used in the literature as a global sectoral index, independent of country and time. It is based on a large sample of U.S. firms (from the Compustat database). The key assumption is that the U.S. financial market is the most liquid in the world, thus, the measure of sectors financial dependence in the U.S. captures the specific needs of credit for each sector (so independently of countries). Moreover, the difference of financial dependence between sectors is the interesting point, but not the level of financial dependence of each sector. The authors also specify that the calculation of this index is based on the 1980s and corresponds to the emerging economies' product life cycle in the 1990s.

used with $crpubpriv_{i,t}$ and $soe_{i,t}$ to ensure exogeneity because the latter are considered either exogenous or endogenous in the literature (see Subsection 2.1). Finally, country, sector and time dummies control for omitted variables and characteristics for each dimension; in addition, the robustness is ensured by adding interactions between dummies (for example $time \times sector$ to correct for all sectoral effects). Estimations are performed on a panel of eight countries, restricted by sectoral data availability, that experienced in the last 25 years a credit bias toward SOEs within certain periods of time (China, Indonesia, Romania, Slovenia, South Africa, South Korea and Turkey).[16]

Manufacturing			
Sector	**Financial dependence**	**Sector**	**Financial dependence**
311 Food products	0.14	355 Rubber products	0.23
313 Beverages	0.08	356 Plastic products	1.14
314 Tobacco	−0.45	361 Pottery. china. earthenware	−0.15
321 Textile	0.4	362 Glass and products	0.53
322 Apparel	0.03	369 Other non-metallic mineral products	0.06
323 Leather products	−0.14		
324 Footwear	−0.08	371 Iron and steel	0.09
331 Wood products, except furniture	0.28	372 Non-ferrous metals	0.01
		381 Fabricated metal products	0.24
332 Furniture	0.24	382 Machinery	0.45
341 Paper and products	0.18	383 Electric machinery	0.77
342 Printing and publishing	0.2	384 Transport equipment	0.31
351 Industrial chemicals	0.21	385 Professional and scientific equipment	0.96
352 Other chemicals	0.22		
353 Petroleum refineries	0.04	390 Other manufactured products	0.47
354 Miscellaneous petroleum and coal products	0.33		

Table 6: Sectors' financial dependence -
Source: Rajan and Zingales (1998)

3.2 Results

We can observe that the *crpubpriv* variable is significant only when instrumented ($crpubpriv_{instru.L.soe}$ in Table 7); it emphasizes the endogeneity of *crpubpriv* for inward FDI (see Subsection 2.1). The key variables *crpubpriv* and $crpubpriv_{instru.L.soe}$ are also significant if other explanatory variables are added or removed (estimations (2), (3), (4) and (6)). When technically possible, bootstrap estimations are implemented and provide substantial robustness. Dummies do not appear in Table 7 but have a significant effect, particularly in 1999-2002 and 2007-2011 (during financial crises) in Central and Eastern Europe countries (that is, where privatization was the largest) and for some sectors (particularly for ISIC codes 332, 341, 342, 355, 369 and 381). An interesting point is that the effect of the key variable *crpubpriv* is robust to the addition of dummies by sector *and* time, which strengthens the causality link. However, the

[16]Brazil, India Russia, and some Central and Eastern Europe countries are not in the sample because of a lack of available sectoral data. South Korea was considered an emerging market at the beginning of the sample period but was then classified as a developed country.

interaction between financial dependence and the credit distortion ($crpubpriv_{i,t} \times fidep_j$) is not robust to changes of explanatory variables; it means that the difference of financial dependence between sectors has no effects.

These results are consistent with those of the first global approach. The negative effect of the credit bias on inward FDI is more accurate in the sectoral approach: a one percentage point increase in the credit afforded to SOEs to the detriment of private firms is associated with a slowdown of inward FDI by approximately 1.8% to 3.1%. Similar to the GMM results, these sectoral estimations deepen the causality between local credit constraints and FDI described the literature. They also emphasize local funding as a FDI determinant.

Explained variable: $fdiin_{indus}$	Level (1)	Level (2)	Level (3)	Level (4)	Bootstrap (5)	Level (6)	Level (7)	Bootstrap (8)	Level (9)
tb_{manuf}	-0.132***	-0.081	-0.013	0.002	0.002	0.311**	0.101	0.101	0.630***
	[0.046]	[0.113]	[0.127]	[0.128]	[0.131]	[0.154]	[0.115]	[0.107]	[0.163]
crpubpriv	-0.001	0.017							
	[0.006]	[0.014]							
$\mathbf{crpubpriv_{instru.L.soe}}$			-0.018**	-0.024***	-0.024***	-0.024***	-0.030***	-0.030***	-0.031***
			[0.009]	[0.009]	[0.007]	[0.009]	[0.008]	[0.009]	[0.007]
crpubpriv$\times fidep_{indus}$	-0.003	-0.040**	-0.015	0.007	0.007	0.009	0.042***	0.042***	0.042***
	[0.012]	[0.018]	[0.014]	[0.016]	[0.021]	[0.013]	[0.014]	[0.014]	[0.012]
crpubpriv$\times soe_{instru.L.soe}$		-0.057		-0.074***	-0.074***	-0.075***	-0.084***	-0.084***	-0.085***
		[0.058]		[0.023]	[0.024]	[0.019]	[0.013]	[0.015]	[0.012]
fdicsts		-0.001	-0.001	-0.001	-0.001	-0.001			
		[0.001]	[0.001]	[0.001]	[0.001]	[0.001]			
r		0.001**	-0.000	-0.000	-0.000	-0.000			
		[0.000]	[0.000]	[0.000]	[0.000]	[0.000]			
gdpr	-0.002***	-0.001	-0.001***	-0.002***	-0.002***	-0.002***			
	[0.000]	[0.001]	[0.000]	[0.000]	[0.001]	[0.000]			
lleg		-0.008	-0.010***						
		[0.005]	[0.002]						
Dummies									
time	yes	yes	yes	yes	yes	yes	yes	yes	yes
country	yes	yes	yes	yes	yes	yes	yes	yes	yes
sector	yes	yes	yes	yes	yes	yes	yes	yes	yes
time$\times$sector	no	no	no	no	no	yes	no	no	yes
Observations	605	345	345	345	345	345	373	373	373
R-squared	0.462	0.637	0.605	0.594	0.594	0.810	0.544	0.544	0.746

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Results: manufacturing sectors

4 Policy implications

This section proposes policy actions to reduce the credit bias toward SOEs and its negative effect on FDI.

First, the problem may obviously be solved at its source by directly reducing the over-financing of SOEs. The first option would be, in countries that experienced a transition process, to restructure SOEs' debts to reduce the incentive for SOBs to fund former debtors for future repayments (see the end of the introduction). Begg and Portes (1993) and Perotti (1993) mention that the government should write off banks' bad loans from SOEs. Indeed, such debt raises and concentrates financial risk and instability, in addition to hindering investment in private firms. Calvo and Frenkel (1991) argue that a substitution of these claims in the banks' balance sheets with long-term government bonds could be a solution. Furthermore, the scourge of corruption reduces inward FDI in some estimations in this work, and is above all one cause of the credit bias of SOBs (in favor of SOEs).[17] The fight against corruption is not a new element and is already in progress in these emerging economies, but this study adds a new important consequence if the issue of corruption is underestimated.

Second, because it has been demonstrated in the literature that inward FDI can improve the efficiency of the local credit market (Héricourt and Poncet, 2009; Ju and Wei, 2010; Poncet et al., 2010), administrative and business barriers must be reduced. It is even more important according to this paper's results in which the increase in inward FDI is already slowed by a better access to credit for SOEs compared to private firms. Thus, the loosening of protectionism measures that are already in place in specific sectors (for example in China; see Branstetter and Lardy, 2006) could both offset the negative consequences of the credit bias and support private firms to bypass domestic credit constraints.

Third, in addition to reducing the credit bias at its origin or alleviate administrative and business barriers, it is necessary to slow privatization. Indeed, although the over-financing of SOEs is high in China, the privatization catch-up was done step by step compared to other countries. That process allowed China to avoid or reduce many issues encountered by former Soviet states and others (e.g., underdevelopment of supporting institutions, huge capital flight, government favors, public and private indebtedness, and the Russian crisis; for more details see Roland, 1994, and Havrylyshyn and Mc Gettigan, 1999). Moreover, if the credit bias cannot be reduced and if SOBs still have an incentive to fund former debtors (SOEs) for future repayments, a gradual privatization will reduce the losses in credit distribution to private firms each year. This consequence will allow supplementary time for future SOE repayments and adjustments, thus providing more credit opportunities for future new private firms.

Finally, one approach for the government and some banks to lend more to certain types of firms is to control lending rates (Aglietta and Bai, 2012, Song et al., 2014, and Funke et al., 2015 for China). Hence,

[17] See Wei (2000), Wei and Wu (2001), Gelos and Wei (2002 and 2005), Papaioannou (2005), and Branstetter and Lardy (2006) for the link between corruption and capital flows; and La Porta et al. (2002), Sapienza (2004), Khwaja and Mian (2005), and Firth et al. (2008) for the effect of corruption on financial intermediation during privatization.

the necessity to liberalize interest rates, bearing in mind that doing so will most likely result in an increase in lending rate volatility (which could occur in China; see Feyzioglu et al., 2009).

5 Conclusion

Both global and sectoral approaches show that while the share of SOEs decreases or remains constant, an increasing credit distribution to SOEs compared to private firms slows the increase in inward FDI in emerging economies. This misallocation of capital is a crucial issue because the credit bias toward SOEs continues to occur in certain emerging economies, particularly in China, Russia, United Arab Emirates, Venezuela and Vietnam.[18]

The implications of this study are twofold. First, many policy actions can be established to improve capital allocation, either by reducing the over-financing of SOEs at its source or by limiting the negative consequences. Second, the analysis completes two fields of the literature. On the one hand, it extends the presence of the credit bias in favor of SOEs to other emerging economies (not only former Soviet states and China; see Perotti, 1993, Boyreau-Debray, 2003, Dollar and Wei, 2007, Poncet et al., 2010, and Song et al., 2011) and analyzes its effect on inward FDI. On the other hand, the paper strengthens the role of local financial intermediation as a determinant of inward FDI in the host country (Feldstein, 2000; Harrison and McMillan, 2003; Alfaro et al., 2009; Desbordes and Wei, 2014).

The two empirical studies in this article suggest future research directions. An interesting point would be, if the data are obtainable, to extend this study to Commonwealth of Independent States because these countries experience a substantial privatization program. Therefore, the magnitude and the consequences of the credit bias toward SOEs would be strong. Then, we can also expect a negative effect on outward FDI; such analysis would require another model including determinants of outward FDI in the foreign countries.

[18]Source: International Financial Statistics (2013, IMF).

References

Acharya, V. V., H. Khandwala, and T. S. Öncü (2013). The growth of a shadow banking system in emerging markets: Evidence from india. *Journal of International Money and Finance 39*, 207–230. 1

Aglietta, M. and G. Bai (2012). La voie chinoise, capitalisme et empire. *Odile Jacob*, 289–365. 2, 18

Alfaro, L., S. Kalemli-Ozcan, and S. Sayek (2009). Fdi, productivity and financial development. *The World Economy 32*(1), 111–135. 1, 2, 3, 14, 19, 22

Anderson, R. W., C. Kegels, et al. (1998). Transition banking: financial development of central and eastern europe. *OUP Catalogue*. 1, 2

Andreyeva, T. (2003). Company Performance in Ukraine: What Governs its Success. EERC Working Paper Series 03-01e, EERC Research Network, Russia and CIS. 6, 15

Arellano, M. and S. Bond (1991). Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations. *Review of Economic Studies 58*(2), 277–97. 8, 11

Arellano, M. and O. Bover (1995). Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics 68*(1), 29–51. 8, 9

Baker, M. et al. (2016). Qregpd: Stata module to perform quantile regression for panel data. *Statistical Software Components*. 13

Barth, J. R., G. Caprio Jr, and R. Levine (2001). The regulation and supervision of banks around the world - a new database. Policy Research Working Paper Series 2588, The World Bank. 10

Begg, D. and R. Portes (1993). Enterprise debt and economic transformation (Financial restructuring of the state sector in Central and Eastern Europe). *The Economics of Transition 1*(1), 116–117. 18

Bénassy-Quéré, A., M. Coupet, and T. Mayer (2007). Institutional Determinants of Foreign Direct Investment. *The World Economy 30*(5), 764–782. 6, 7, 11

Blonigen, B. A. (2005). A Review of the Empirical Literature on FDI Determinants. NBER Working Papers 11299, National Bureau of Economic Research, Inc. 6

Bond, S., A. Hoeffler, and J. Temple (2001). GMM Estimation of Empirical Growth Models. Economics Papers 2001-W21, Economics Group, Nuffield College, University of Oxford. 8

Borensztein, E., J. De Gregorio, and J.-W. Lee (1998). How does foreign direct investment affect economic growth? *Journal of international Economics 45*(1), 115–135. 3

Boyreau-Debray, G. (2003). Financial intermediation and growth - Chinese style. Policy Research Working Paper Series 3027, The World Bank. 1, 2, 5, 19

Boyreau-Debray, G. and S.-J. Wei (2005). Pitfalls of a State-Dominated Financial System: The Case of China. NBER Working Papers 11214, National Bureau of Economic Research, Inc. 1, 5

Braconier, H., P.-J. Norback, and D. Urban (2005). Multinational enterprises and wage costs: vertical FDI revisited. *Journal of International Economics 67*(2), 446–470. 6

Branstetter, L. and N. Lardy (2006). China's Embrace of Globalization. NBER Working Papers 12373, National Bureau of Economic Research, Inc. 18

Calvo, G. A. and J. A. Frenkel (1991). Credit Markets, Credibility, and Economic Transformation. *Journal of Economic Perspectives 5*(4), 139–148. 18

Cheng, L. K. and Y. K. Kwan (2000). What are the determinants of the location of foreign direct investment? the chinese experience. *Journal of international economics 51*(2), 379–400. 3, 9

Chinn, M. D. and H. Ito (2006). What matters for financial development? Capital controls, institutions, and interactions. *Journal of Development Economics 81*(1), 163–192. 10

Claessens, S., L. Ratnovski, and M. M. Singh (2012). *Shadow banking: economics and policy*. Number 12. International Monetary Fund. 1

Cull, R., L. C. Xu, and T. Zhu (2007). Formal finance and trade credit during China's transition. Policy Research Working Paper Series 4204, The World Bank. 2

De Mello, L. R. (1999). Foreign direct investment-led growth: evidence from time series and panel data. *Oxford economic papers 51*(1), 133–151. 3

Desbordes, R. and S.-J. Wei (2014). The effects of financial development on foreign direct investment. 1, 2, 3, 14, 19, 22

Dobson, W. and A. K. Kashyap (2006). The Contradiction in China's Gradualist Banking Reforms. *Brookings Papers on Economic Activity 37*(2), 103–162. 2

Dollar, D. and S.-J. Wei (2007). Das (Wasted) Kapital: Firm Ownership and Investment Efficiency in China. IMF Working Papers 07/9, International Monetary Fund. 1, 19

Dooley, M., D. Folkerts-Landau, and P. Garber (2005). Direct investment, rising real wages and the absorption of excess labor in the periphery. *Proceedings*. 6

Du, J. and S. Girma (2007). Finance and Firm Export in China. *Kyklos 60*(1), 37–54. 1, 3, 14, 22

Estrin, S., Hanousek, J. Kocenda, and J. Svejnar (2009). Effects of Privatization and Ownership in Transition Economies. Policy Research Working Paper Series 4811, The World Bank. 6, 10

Feldkircher, M. (2011). Bms and the fixed effects estimator - a tutorial. 23

Feldstein, M. (2000). Aspects of global economic intergration: Outlook for the future. Technical report, National Bureau of Economic Research. 14, 19, 22

Fernández, C., E. Ley, and M. F. J. Steel (2001). Model uncertainty in cross-country growth regressions. *Journal of Applied Econometrics*. 23

Feyzioglu, T., N. Porter, and E. Takats (2009). Interest Rate Liberalization in China. IMF Working Papers 09/171, International Monetary Fund. 19

Firth, M., C. Lin, and S. M. Wong (2008). Leverage and investment under a state-owned bank lending environment: Evidence from China. *Journal of Corporate Finance 14*(5), 642–653. 2, 18

Funke, M., P. Mihaylovski, and H. Zhu (2015). Monetary policy transmission in China: A DSGE model with parallel shadow banking and interest rate control. BOFIT Discussion Papers 9/2015, Bank of Finland, Institute for Economies in Transition. 1, 2, 18

Gastanaga, V. M., J. B. Nugent, and B. Pashamova (1998). Host Country Reforms and FDI Inflows: How Much Difference do they Make? *World Development 26*(7), 1299–1314. 6

Gelos, G. and S.-J. Wei (2002). Transparency and International Investor Behavior. IMF Working Papers 02/174, International Monetary Fund. 18

Gelos, R. G. and S.-J. Wei (2005). Transparency and International Portfolio Holdings. *Journal of Finance 60*(6), 2987–3020. 18

Gonzalez-Garcia, J. and F. Grigoli (2013). State-Owned Banks and Fiscal Discipline. IMF Working Papers 13/206, International Monetary Fund. 5, 10

Gordon, R. H. and W. Li (2005). Taxation and economic growth in china. *Critical Issues in Chinas Growth and Development, edited by Y. K. Kwan and E. S. H. Yu, 22 40. Burlington, VT: Ashgate*. 2

Hanousek, J., E. Kocenda, and J. Svejnar (2007). Origin and Concentration: Corporate Ownership, Control and Performance. *The Economics of Transition 15*(1), 1–31. 6, 15

Hanousek, J., E. Kocenda, and J. Svejnar (2009). Divestitures, privatization and corporate performance in emerging markets. *The Economics of Transition 17*(1), 43–73. 6, 15

Harrison, A. E. and M. S. McMillan (2003). Does direct foreign investment affect domestic credit constraints? *Journal of International Economics 61*(1), 73–100. 1, 2, 3, 14, 19, 22

Havrylyshyn, O. and D. Mc Gettigan (1999). Privatization in transition countries: Lessons of the first decade. *International Monetary Fund - Economic Issues No. 18*. 18

Hayakawa, K. (2009). First Difference or Forward Orthogonal Deviation- Which Transformation Should be Used in Dynamic Panel Data Models?: A Simulation Study. *Economics Bulletin 29*(3), 2008–2017. 8

Héricourt, J. and S. Poncet (2009). FDI and credit constraints: Firm-level evidence from China. *Economic Systems 33*(1), 1–21. 1, 14, 18, 22

Hoeting, J., D. Madigan, A. Raftery, and C. Volinsky (1999). Bayesian model averaging: a tutorial. *Statistical Science 14*, 382–401. 23

Ju, J. and S.-J. Wei (2010). Domestic Institutions and the Bypass Effect of Financial Globalization. *American Economic Journal: Economic Policy 2*(4), 173–204. 14, 18, 22

Khwaja, A. I. and A. Mian (2005). Do Lenders Favor Politically Connected Firms? Rent Provision in an Emerging Financial Market. *The Quarterly Journal of Economics 120*(4), 1371–1411. 2, 18

Kinoshita, Y. and N. F. Campos (2003). Why does fdi go where it goes? new evidence from the transition economies. 3, 9

Kornai, J., E. Maskin, and G. Roland (2003). Understanding the soft budget constraint. *Journal of economic literature 41*(4), 1095–1136. 1

Kowalski, P., M. Buge, M. Sztajerowska, and M. Egeland (2013). State-Owned Enterprises: Trade Effects and Policy Implications. OECD Trade Policy Papers 147, OECD Publishing. 10

Krugman, P. (2011). Will China break? *The New York Times*. 1

La Porta, R., F. Lopez-De-Silanes, and A. Shleifer (2002). Government ownership of banks. *Journal of Finance 57*(1), 265–301. 2, 10, 18

Li, T. (2014). Shadow banking in China: expanding scale, evolving structure. *Journal of Financial Economic Policy 6*(3), 198–211. 1

Megginson, W. L. (2005). The economics of bank privatization. *Journal of Banking & Finance 29*(8), 1931–1980. 1, 6

Mileva, E. (2007). Using Arellano Bond Dynamic Panel GMM Estimators in Stata. *Fordham University*. 8

Moral-Benito, E. (2012). Determinants of Economic Growth: A Bayesian Panel Data Approach. *The Review of Economics and Statistics 94*(2), 566–579. 23

Nicita, A. and M. Olarreaga (2007). Trade, Production, and Protection Database, 1976–2004. *World Bank Economic Review 21*(1), 165–171. 15

Papaioannou, E. (2005). What drives international bank flows? Politics, institutions and other determinants. Working Paper Series 0437, European Central Bank. 18

Perotti, E. C. (1993). Bank lending in transition economies. *Journal of Banking & Finance 17*(5), 1021–1032. 1, 2, 18, 19

Poncet, S., W. Steingress, and H. Vandenbussche (2010). Financial constraints in China: Firm-level evidence. *China Economic Review 21*(3), 411–422. 1, 14, 18, 19, 22

Rajan, R. G. and L. Zingales (1998). Financial Dependence and Growth. *American Economic Review 88*(3), 559–86. 2, 15, 16

Ramamurti, R. (1999). Why haven't developing countries privatized deeper and faster? *World Development 27*(1), 137–155. 10

Roland, G. (1994). On the Speed and Sequencing of Privatization and Restructuring. CEPR Discussion Papers 942, C.E.P.R. Discussion Papers. 18

Roodman, D. (2006). How to Do xtabond2: An Introduction to difference and system GMM in Stata. Working Papers 103, Center for Global Development. 8, 9

Roodman, D. (2009). A Note on the Theme of Too Many Instruments. *Oxford Bulletin of Economics and Statistics 71*(1), 135–158. 8, 11

Ruud, P. A. (2000). *An Introduction to Classical Econometric Theory*. Oxford University Press. 11

Sala-I-Martin, X., G. Doppelhofer, and R. I. Miller (2004). Determinants of Long-Term Growth: A Bayesian Averaging of Classical Estimates (BACE) Approach. *American Economic Review 94*(4), 813–835. 23

Sapienza, P. (2004). The effects of government ownership on bank lending. *Journal of Financial Economics 72*(2), 357–384. 2, 18

Song, Z., K. Storesletten, and F. Zilibotti (2011). Growing like china. *American Economic Review 101*(1), 196–233. 1, 19

Song, Z., K. Storesletten, and F. Zilibotti (2014). Growing (with Capital Controls) like China. *IMF Economic Review 62*(3), 327–370. 2, 18

Soto, M. (2009). System GMM Estimation With A Small Sample. UFAE and IAE Working Papers 780.09, Unitat de Fonaments de l'Anlisi Econmica (UAB) and Institut d'Anlisi Econmica (CSIC). 8

Wei, S.-J. (2000). How Taxing is Corruption on International Investors? *The Review of Economics and Statistics 82*(1), 1–11. 18

Wei, S.-J. and Y. Wu (2001). Negative Alchemy? Corruption, Composition of Capital Flows, and Currency Crises. NBER Working Papers 8187, National Bureau of Economic Research, Inc. 18

Wei, Y. and X. Liu (2006). Productivity spillovers from R&D, exports and FDI in China's manufacturing sector. *Journal of International Business Studies 37*(4), 544–557. 6

Windmeijer, F. (2005). A finite sample correction for the variance of linear efficient two-step GMM estimators. *Journal of Econometrics 126*(1), 25–51. 11

Zeugner, S. (2011). Bayesian Model Averaging with BMS. 23

Appendices

Appendix A: Inward FDI, local and foreign funding, and the credit bias toward SOEs.

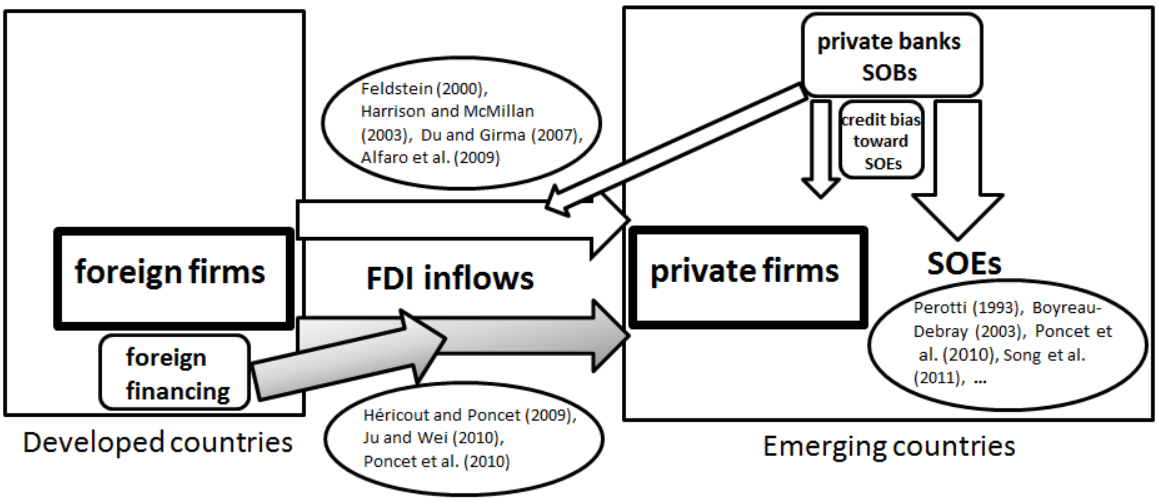


Figure 6: Inward FDI, local and foreign funding, and the credit bias toward SOEs.

The figure shows that: (i) inward FDI can be financed by the local credit market (Feldstein, 2000; Harrison and McMillan, 2003; Du and Girma, 2007; Alfaro et al., 2009; Desbordes and Wei, 2014); (ii) thus, inward FDI can be slowed if SOEs are more financed to the detriment of private firms (it is the focus of this article); (iii) inward FDI are also financed by the foreign country and are a means for private firms to bypass local credit constraints (Héricourt and Poncet, 2009; Ju and Wei, 2010; Poncet et al., 2010).

Appendix B: Bayesian meaning average and the determination of fundamentals

A problem appears when there are too many potential explanatory variables X_i for a dependent variable y, a situation that pertains to this study for the determinants of inward FDI. The models and combinations of explanatory variables from the literature are numerous (see Subsection 2.1), which can skew the study of a specific variable and causality. Bayesian Model Averaging (BMA) addresses model uncertainty and allows determining which variables $X_i \in X$ should be included in the model and their importance. This methodology is based on a linear model structure with all potential explanatory variables and a normal *iid* error term with variance σ^2 ($y = \alpha + \beta X + \epsilon$, $\epsilon \sim N(0, \sigma^2 I)$). Then, BMA creates a weighted average over estimated models for all combinations of X, meaning 2^K combinations of variables (inward FDI fundamentals) for K potential explanatory variables, i.e., 2^K models. Let $p(y|M_i, X)$ denote the marginal likelihood of the model (the probability of the data given the model M_i). The *posterior* model probability, $p(M_i|y, X)$, is proportional to $p(y|M_i, X)$ times a *prior* model probability $p(M_i)$:

$$p(M_i|y, X) = \frac{p(y|M_i, X)p(M_i)}{p(y|X)} = \frac{p(y|M_i, X)p(M_i)}{\sum_{s=1}^{2^K} p(y|M_s, X)p(M_s)} \tag{4}$$

For further details on the theoretical framework, see Hoeting et al. (1999) and Sala-I-Martin et al. (2004). In this paper, the study is based on panel data following the methodology of Feldkircher (2011) and Moral-Benito (2012). As is often true for BMA, and because of uncertainty among a variety of potential determinants, priors are set to be uniform. In other words, the prior expected model size is $K/2$ with a common prior model probability.[19] Markov Chain Monte Carlo (MCMC) sampling and birth-death methods are used, as in Fernández et al. (2001).[20] The number of "burn-ins" and draws (iterations) does not significantly change the results, but a minimum of 5000 "burn-ins" and 10000 draws is set.[21] The hyperparameter "g" is fixed at $g = max(N, K^2)$ as in Fernández et al. (2001).

13 potential explanatory variables are selected for inward FDI (*L.fdiin*, *gdpr*, *reer*, *r*, *ky*, *s*, *w*, *tfpl*, *corru*, *fdicsts*, *cp*, and *lleg*); thus, the BMA routine obtains 2^{12} models, i.e. 4096 models, each of them defined by a different combination of FDI fundamentals, and by a probability of being the "true" model (therefore, the prior expected model size is 6).

BMA results: The posterior inclusion probability of each variable is given by the "PIP" column in Figure 7. "Post Mean" is the coefficients averaged over all models (including a zero coefficient when the variable was not contained), "Post SD" the corresponding standard deviations and "Cond. Pos. Sign" the probability that the coefficient's sign is positive. All coefficients with a PIP above 0.5 are selected, as is usually true for uniform priors. In addition to the above, control variables just below the

[19]Indeed, for K potential explanatory variables, there are 2^K possible variable combinations. Therefore, the common prior model probability is $p(M_i) = 2^{-K}$ for a uniform prior model. Hence, a prior expected model size of $\sum_{k=0}^{K} \binom{K}{k} 2^{-K} = K/2$ is anticipated.

[20]MCMC is used when there are many covariates, and birth-death sampler is the standard model sampler used in most BMA routines. These methods are well developed in Zeugner (2011).

[21]The number of draws (iterations) limits the quality and duration of MCMC approximation to the actual posterior distribution. Because the first set of iterations does not draw models with high posterior model probabilities, this first set of iterations (the "burn-ins") is not included in the computation of results.

0.5 threshold in the PIP rank are selected, or the variables that, according to the literature, still seem crucial.[22] Therefore, GDP and the real effective exchange rate are included as control variables. Then, in addition to explanatory variables with a $PIP > 0.5$ (r, w and *corru*), the lag of inward FDI, savings, investments, GDP and the real exchange rate are also included as fundamentals. The legal environment, TFP level and FDI costs (*lleg*, *tfpl* and *fdicsts*) are included in some estimations because they can be significant despite the results below. Moreover, because the focus of the study is the bias toward public sector, all of the associated variables (*crpubpriv*, *crpubpriv*×*soe* and instrumentation (lags of *soe*)) are added to the previous fundamentals for each estimation. There is a quite good certainty concerning coefficients' signs (see "Cond. Pos. Sign" in Figure 7), which broadly corresponds to the literature, to the expected results and to the results.

Variable	PIP	Post Mean	Post SD	Cond. Pos.Sign
r	0.9989	−0.0869	0.0209	0.0000
w	0.9780	0.0026	0.0008	1.0000
corru	0.9725	−0.9955	0.3175	0.0000
L.fdiin	0.4757	0.7031	0.9154	0.9967
ky	0.3358	−3.3044	5.5008	0.0000
reer	0.2755	−0.0053	0.0104	0.0002
s	0.2431	−0.2570	0.5514	0.0000
gdpr	0.1759	−0.0054	0.0154	0.0277
tfpl	0.1502	0.0412	0.1271	1.0000
fdicsts	0.0804	−0.0022	0.0165	0.0000
lleg	0.0740	−0.0006	0.1041	0.5857
cp	0.0735	−0.0270	0.4656	0.3262

Figure 7: BMA results - inward FDI

[22] Indeed, the BMA regression from $y = \alpha + \beta X + \epsilon$ cannot fully reflect the GMM FOD estimations presented in this paper; primarily because of the addition of variables for the credit misallocation, privatization and instruments. Therefore, not to omit some determinants, variables with a PIP close to 0.5, or those that are often used in the literature, are also considered.

Appendix C: Descriptive statistics

Variable	Mean	Std. Dev.	Min.	Max.	Obs.	Variable	Mean	Std. Dev.	Min.	Max.	Obs.
Global database:											
fdiin	0.373	0.688	0	4.89	392	Linear interpolation:					
gdpr	4.59	14.193	0.07	101.568[1]	351	SOEs	0.259	0.239	0	0.9	256
reer	90.026	30.723	4.98	262.927	359	lleg	5.446	1.372	1.76	8.529	358
r	24.454	47.692	0.192	509.835[2]	361	Log-linear interpolation:					
w	508.725	552.146	20.607	2755.502	253	SOEs	0.263	0.24	0	0.9	251
ky	0.241	0.068	0.069	0.46	394	lleg	5.436	1.379	1.76	8.529	358
s	0.316	0.713	-1.868	8.529	388	Catmull-Rom Spline					
tfpl	0.573	0.225	0	1.139	359	interpolation:					
cp	0.163	1.485	-1.864	5.3	375	SOEs	0.322	0.257	0	0.9	180
fdicsts	3.937	5.827	0.049	47.144	286	lleg	5.451	1.394	1.76	8.529	351
rw	5.505	1.617	2.878	8.543	400						
crpriv	0.472	0.385	0.013	1.705	386						
crpub	0.142	0.164	0.006	0.982	386						
crpubpriv	0.235	0.163	0.006	0.982	381						
corru	3.998	1.705	0.4	9.35	319						
Sectoral database:[3]											
$fdiin_{indus}$	0.011	0.019	0	0.118	1062	$fdiin_{serv}$	0.038	0.099	0	1.004	1028
$trade_{indus}$	0	0.009	-0.052	0.05	2212	gdp_{serv}	0.063	0.065	0.001	0.327	1349

[1] Such differences between the minimum and maximum of the real GDP are due to large differences in terms of development and population size (the presence of very small countries in the first periods (like Estonia) and very large countries in the last periods (like China)).
[2] 509.835 is the mean of the lending rate on 1991-1992 during the war in Slovenia. The database has been cleaned of other more extreme values.
[3] All sectoral variables are divided by GDP; variables of the global database are also used as control and explanatory variables for the sectoral approach (see Subsection 3.1).

Table 8: Descriptive statistics