Web Appendix for paper:

The IMF, Domestic Public Sector Banks and Currency Crises in Developing States;

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In this web appendix, we first discuss the results from the probit model in which the dependent variable is *currency crash* (the *currency crash* measure is the second alternative measure of *currency crisis* –our main dependent variable – which is described in the paper). We then provide a brief description of the Spatial Autorefressive Error (SAE)-bivariate probit model that (employed for some of our robustness tests) and formally define the log likelihood function of this model. This is followed by a presentation of the main results from the SAE-bivariate probit model. Finally, we present some basic results obtained from evaluating the relationship between the level of compliance with banking sector reform conditions in IMF programs by program-recipient developing states and a 0 to 1 Hirschman-Herfindahl index of the market concentration of public banks across these states.

I. Additional Results

A.The results from the Probit model in which the dependent variable is currency crash is reported below in model a in Table A. This model shows that the estimated effect of *IMF* x *concentration* on *currency crash* is positive and statistically significant which corroborates our hypothesis. The results from the outcome equation of the bivariate probit model in which the concentration measure is included in the selection equation is reported in Table A; the selection equation results for this model is reported in Table B. The outcome equation results in this case shows that the estimated effect of *IMF* x *concentration* on currency crisis is positive and statistically significant which supports our hypothesis.

B. Formal Description of SAE-bivariate probit model

B.1. The SAE-bivariate probit model

Apart from selection bias, an additional econometric challenge that scholars may face when ascertaining the IMF's effect on currency crisis' is spatial dependence. Specifically, some scholars suggest that currency crises are influenced by contagion in that they can spread from one country to other geographically neighboring countries (Ito and Hashimoto 2002; Glick and Rose 1999). For instance, the currency crises that occurred across neighboring states in South-East and East Asia (in the 1990s) and Latin America (in the 1990s) indicates that geographic (i.e. spatial) proximity may have influenced the probability of currency crises across countries (Ito and Hashimoto 2002). In fact, tests reveal the presence of spatial dependence in our main dependent variable – *currency crisis* – across the countries in our sample. Thus we need to account for spatial dependence in our model.[1] Second, tests conducted on our data indicate that country participation in IMF programs exhibits clustering—a common form of spatial dependence—in which several countries within a region participate in IMF programs during the

[1] Kelejian and Prucha's (2001) modified Moran-I test for spatial autocorrelation in discrete choice models rejects the null of *no* spatial autocorrelation for *currency crisis* in our sample.

same time period.[2] Many Latin American nations, for example, participated in IMF programs in the mid-1980s and 1990s. Many Southeast Asian countries also participated in IMF programs in the late 1990s. Since participation of countries in IMF programs is characterized by clustering, we should control for this possibility as well to avoid bias.

To address these challenges, we estimate a spatial autoregressive error bivariate probit model (hereafter SAE bivariate probit model) that specifies spatially autocorrelated disturbances in *both* the selection and outcome equations. This model, developed by Wang, Iglesias and Wooldridge (2009), is defined (after dropping subscript *t* for time for notational convenience) as:

$$y_{i1}^{*} = X_{i1}\beta_1 + \varepsilon_{i1}, \quad \varepsilon_{i1} = \lambda \sum_{j \neq i} w_{ij}\varepsilon_{j1} + u_{i1} \tag{A.1}$$

$$y_{i2}^{*} = X_{i2}\beta_2 + \varepsilon_{i2}, \quad \varepsilon_{i2} = \lambda \sum_{j \neq i} w_{ij}\varepsilon_{j2} + u_{i2} \tag{A.2}$$

where w_{ij} are elements of the spatial weights matrix $\mathbf{W}$ and λ is the spatial autoregressive error coefficient.[3] Equation A.1 is the selection equation in which the binary dependent variable $y_{i1} = 1$ indicates participation in an IMF stabilization program and takes the value of zero otherwise. Equation A.2 is the outcome equation in which the binary variable y_{i2} is equal to 1 when a *currency crisis* occurs, and is zero otherwise.

Numerous measures can be used to operationalize elements of the spatial weights matrix (w_{ij}) in spatial econometric models (see, e.g., Franzese and Hays 2006). Since currency crises usually start spreading across countries in the same region, it is plausible that geographic proximity may influence the spread of currency crises across countries. Thus we operationalize

[2] Kelejian and Prucha's (2001) test *also* rejects the null of no spatial autocorrelation in IMF program participation.

[3] u_{i1} and u_{i2} are *i.i.d* $N(\mathbf{0}, \Sigma)$. Klaauw and Koning's (2006) likelihood ratio test for the distributional assumption of bivariate normality between the selection and outcome equation in the SAE bivariate probit model fails to reject the null of bivariate normality between the selection and outcome equation.

spatial contiguity in the spatial weights matrix as the inverse distance between states *i* and *j*, where $w_{ij} = 1/d_{ij}$. As the distance between *i* and *j* increases (decreases), w_{ij} decreases (increases), giving less (more) spatial weight to the state pair when $i \neq j$. We use a "minimum distance database" of the shortest distance between the two closest physical locations for every pair of independent polities in the world.[4] The log likelihood function of the SAE bivariate probit model and the procedure employed to estimate this model are briefly described formally below.

B.2. Estimation of SAE Bivariate Probit Model

The log-likelihood function of the SAE bivariate probit selection model is, according to Wang, Iglesias and Wooldridge (2009: 11) , defined (after dropping the parameter *t* for time for notational convenience) as

$$L = \sum_{i=1}^{N} \{ y_{i1} y_{i2} \log \Pr(y_{i1} = 1, y_{i2} = 1 | X_i) + y_{i1}(1 - y_{i2}) \log \Pr(y_{i1} = 1, y_{i2} = 0 | X_i) \\ + (1 - y_{i1}) y_{i2} \log \Pr(y_{i1} = 0, y_{i2} = 1 | X_i) + (1 - y_{i1})(1 - y_{i2}) \log \Pr(y_{i1} = 0, y_{i2} = 0 | X_i) \} \quad \text{(A.3)}$$

Each constituent term in the log-likelihood in (A.4) -- $\Pr(y_{i1} = 1, y_{i2} = 1 | X_i)$, $\Pr(y_{i1} = 0, y_{i2} = 1 | X_i)$, $\Pr(y_{i1} = 1, y_{i2} = 0 | X_i)$ and $\Pr(y_{i1} = 0, y_{i2} = 1 | X_i)$ -- is formally derived by Wang *et al* (2009: 9-11) in their paper. They show that $\Pr(y_{i1} = 1, y_{i2} = 1 | X_i) = \int_{-X_{i2}\beta_2}^{\infty} \Phi(\frac{X_{i1}\beta_1 + \delta_{i1}\varepsilon_{i2}}{\sqrt{Var(e_{i1})}}) \phi(\frac{\varepsilon_{i2}}{\sqrt{Var(\varepsilon_{i2})}}) d\varepsilon_{i2}$ where $Var(e_{i1}) = Var(\varepsilon_{i1}) - \delta_{i1}^2 Var(\varepsilon_{i2}) = Var(\varepsilon_{i1})(1 - \rho_i^2) = 1/1 + \lambda^2 w_{ij}^2$ because $(\varepsilon_{i1}, \varepsilon_{i2})$ has a joint normal distribution and where $\delta_{i1} = \frac{Cov(\varepsilon_{i1}, \varepsilon_{i2})}{\sqrt{Var(\varepsilon_{i1})}\sqrt{Var(\varepsilon_{i2})}} = \frac{2\lambda w_{ij}}{(1 + \lambda w_{ij}^2)} = \rho_i$. Note that ρ_i is the covariance between the two error

[4] Gleditsch and Ward (2006). The database records the shortest distance in kilometers between points on the outer boundaries for two polities, regardless of whether the states are separated by land or sea. We update their database for the countries in our sample until 2008. For robustness tests, we use directed trade-flow shares of country *j* in country *i's* total as an alternative measure of spatial contiguity since studies suggest that trade links can also be a channel for contagion in currency crises (Glick and Rose 1999).

terms and w_{ij} the elements in the spatial weights matrix. Since y_{i1} is a binary variable, it follows that $\Pr(y_{i1}=0, y_{i2}=1 | X_i) = 1 - \Pr(y_{i1}=1, y_{i2}=1 | X_i)$. This implies that

$$\Pr(y_{i1}=0, y_{i2}=1 | X_i) = \Phi(\frac{X_{i1}\beta_1}{\sqrt{Var(\varepsilon_{i2})}}) - \int_{-X_{i2}\beta}^{\infty} \Phi(\frac{X_{i1}\beta_1 + \delta_{i1}\varepsilon_{i2}}{\sqrt{Var(e_{i1})}})\phi(\frac{\varepsilon_{i2}}{\sqrt{Var(\varepsilon_{i2})}})d\varepsilon_{i2} \tag{A.4}$$

Thus $\Pr(y_{i1}=1, y_{i2}=0 | X_i) = \int_{\infty}^{X_{i2}\beta_2} \Phi(\frac{X_{i1}\beta_1 + \delta_{i1}\varepsilon_{i2}}{\sqrt{Var(e_{i1})}})\phi(\frac{\varepsilon_{i2}}{\sqrt{Var(\varepsilon_{i2})}})d\varepsilon_{i2}$ which, in turn, implies that

$\Pr(y_{i1}=0, y_{i2}=0 | X_i) = [1 - \Phi(\frac{X_{i2}\beta_2}{\sqrt{Var(\varepsilon_{i2})}})] - \int_{-\infty}^{X_{i2}\beta_2} \Phi(\frac{X_{i1}\beta_1 + \delta_{i1}\varepsilon_{i2}}{\sqrt{Var(e_{i1})}})\phi(\frac{\varepsilon_{i2}}{\sqrt{Var(\varepsilon_{i2})}})d\varepsilon_{i2}$. We estimate the log likelihood function in (A.4) via full-information maximum likelihood. We obtain similar results if we estimate the log likelihood in (A.4) via partial maximum likelihood estimation (PMLE). The outcome equation results from the SAE-bivariate probit model are reported in models b,c and d respectively in Table A. The selection equation results for this model are reported below in columns a and b in table B.

C. Results in tables A and B

Table A: Probit and SAE-Bivariate Probit outcome equation results

Dependent variable:	*currency crash*	*currency crisis*		
	Probit	Bivariate probit	SAE-biv-probit	SAE-biv-probit
	Full	outcome eq	outcome eq	outcome eq
	Model a	**Model b**	**Model c**	**Model d**
			$w_{ij} = 1/d_{ij}$	$w_{ij} = 1/d_{ij}$
lag dependent variable	0.109	-1.312***	0.6491**	0.6277**
	(0.133)	(0.397)	(0.3120)	(0.3083)
log GDP per capita	0.0512	0.0743**	0.0175***	0.0164***
	(0.0355)	(0.0367)	(0.0037)	(0.0032)
external debt	-2.33e-05	0.000310	0.000203**	0.000184**
	(0.000442)	(0.000448)	(0.000101)	(0.00092)
current acct	0.0243***	0.0251***	-0.0519	-0.0277
	(0.00444)	(0.00466)	(0.0647)	(0.0850)
IMF	0.0135	-0.258*	0.0012	0.0011
	(0.110)	(0.152)	(0.0031)	(0.0064)
IMF x concentration	0.728**	0.929**	0.679***	
	(0.363)	(0.383)	(0.151)	
IMF x bank index				0.543***
				(0.110)
Concentration	0.283	0.875***	0.321	
	(0.195)	(0.250)	(0.483)	
Bank Index				0.1489
				(0.3022)
Reer	-1.25e-07	-9.38e-09	-1.34e-08	-2.04e-06
	(2.37e-07)	(2.06e-07)	(2.79e-07)	(3.77e-08)
bank crisis	0.583***	0.602***	0.212**	0.207**
	(0.157)	(0.165)	(0.106)	(0.101)
cap acct open	-0.103***	-0.102***	0.059	0.044
	(0.0331)	(0.0344)	(0.104)	(0.163)
M2/reserves	8.10e-08	6.46e-08	.0023	.0021
	(2.25e-07)	(2.58e-07)	(.0057)	(.0064)
budget balance	-0.0833***	-0.0811***	-0.0641*	-0.0583
	(0.0104)	(0.0110)	(0.0381)	(0.0375)
export growth	-0.00399*	-0.00554**	0.00226	0.00216

	(0.00226)	(0.00242)	(0.00673)	(0.00675)
credit growth	-0.000253	-0.000221	-0.00010	-0.00011
	(0.000348)	(0.000373)	(0.00089)	(0.00085)
LIEC	0.0354*	0.0360*	0.0295	0.0274
	(0.0196)	(0.0209)	(0.0306)	(0.0316)
Turnover	0.317***	0.267**	0.116*	0.114**
	(0.110)	(0.116)	(0.058)	(0.057)
divided gov	-0.00200	0.0122	0.0211**	0.0188**
	(0.0830)	(0.0888)	(0.0105)	(0.0091)
Fixed exchange rate				-0.0662**
				(0.0341)
Constant	-2.723***		-1.073**	-1.119***
	(0.275)		(0.414)	(0.215)
$\hat{\lambda}_i$			.031**	.020**
			(.015)	(.009)
ρ			.110**	0.307**
			(.052)	(0.048)
N	3,842		3,842	3,842
log likelihood	-695.6		-1259	-2234

Notes: ***, **, *: 1%, 5% and 10% levels of significance. Numbers in parentheses are robust standard errors. For robustness tests, As a robustness test, we use an alternative measure for the market concentration of public banks which is taken from Bikker (2004). Defined as the comprehensive bank concentration index (hereafter *bank index*), this alternative measure is operationalized for each country-year as,

$$bank\ index = s_1 + \sum_{i=1}^{n} s_i^2 (1 + (1 - s_i))$$

The aforementioned expression is equal to the sum of the market share of the largest public sector bank (s_1) in the economy plus the sum of the squared market shares of public banks (s_i^2), weighted by a multiplier reflecting the proportional market size of the rest of the banking industry.

Table B: Selection equation results for models in Table A

	Column a	Column b	Column c
	selection eq results for model b in table A	*selection eq results for model c in table A*	*Selection eq results for model d in table A*
veto players	0.0113	0.00643	0.00639
	(0.0174)	(0.0235)	(0.0237)
log reserves	-0.0202	-0.0165**	-0.0162**
	(0.0144)	(0.0082)	(0.0080)
log inflation	0.236***	0.314***	0.305***
	(0.0698)	(0.0135)	(0.0130)
ln GDP per capita	0.0303	0.0045	0.0038
	(0.0254)	(0.0139)	(0.0164)
current account	0.000985	0.00279	0.000254
	(0.00331)	(0.00642)	(0.00612)
output loss	0.000274	0.0163***	0.0145***
	(0.000255)	(0.00434)	(0.00412)
trade shock	0.000143	0.0106**	0.0102**
	(0.000711)	(0.00502)	(0.00481)
bank crisis	0.405**	0.231**	0.225**
	(0.168)	(0.117)	(0.110)
lag IMF	2.034***	1.831***	1.741***
	(0.0552)	(0.0211)	(0.0202)
concentration	0.392**		
$\hat{\lambda}_i$	(0.161)	.045**	.036**
		(.021)	(.017)
Constant	-2.477***	-1.036***	-1.129***
	(0.467)	(0.322)	(0.311)

Notes: ***, **, *: 1%, 5% and 10% levels of significance. Numbers in parentheses are robust standard errors.

II. Public Bank Concentration and Compliance with Banking Sector Program conditions

Scholars at the Fund have developed an index called the Index of Fund Program Implementation (Mercer-Blackman and Unigovskaya 2001). We label this index as FPI. This index operationalizes the extent to which some program-recipient developing states have complied with various banking sector reform measures incorporated in stabilization programs approved by the Fund between 1993 and 2005. These banking sector reform measures include, for example, public bank privatization, banking sector liberalization, and reduction of non-performing loans of public banks. More formally, the FPI index mentioned above has been developed in three main steps.

First, note that there are *n* "performance criteria" in each stabilization program approved by the Fund during the 1990s (details about the number and types of performance criteria is limited to the programs for which the Fund has released information). The *n* "performance criteria" refers to the number of policy actions – associated with the banking sector reform measures mentioned above – that the borrowing country has to implement to receive the IMF's assistance. Second, as emphasized by the IMF, there are *T* test dates in each program. The *T* test dates refer to the number of times the Fund's staff has checked (and recorded) the extent to which the borrowing country in question has complied with the *n* "performance criteria" in its program. Third, given *n* and *T*, the Index of Fund Program Implementation (labeled as FPI) is calculated by for each country-program as follows:

$$FPI = \frac{\sum_{t=1}^{T}\sum_{i=1}^{n} pc_{it}}{10Tn} \qquad \text{(A.5)}$$

where pc_{it} refers to the result value for performance criteria i in test date t and takes values determined by compliance (as recorded and evaluated by the Fund's staff) as follows:

- Met = 10
- Waived = 5
- Met after modification = 5
- Waived after modification = 3
- Not met after modification = 0
- Not Met = 0

The FPI index is operationalized on a continuous 0 to 100 scale. The index takes a value of 0 if $all \;\; pc_{it}$ at all test dates are not met or not met after modification. Converse, the index takes a value of 100 if $all \;\; pc_{it}$ at all test dates are met. We used the data from the FPI index for the 21 program-recipient developing states (for which data is available) to broadly evaluate our claim that program-recipient countries with concentrated public banks tend to renege from their commitment to implement structural banking sector program conditions. To this end, we conducted some difference-of-means test to asses the relationship between the level of compliance with banking sector program conditions (listed earlier) by these 21 program-recipient states in the FPI database and each decile of a 0 to 1 continuous Hirschman-Herfindahl index of the market concentration of public banks across these 21 states.

Results from the difference of means test provides two important insights. The first is that the mean compliance level with the banking sector program conditions (we focus on) by program-participating countries observed in the highest range of the Herfindahl pubic bank concentration index (i.e. between 0.65 and 1) is 12.31 on the 0 (no compliance) to 100 (highest compliance level) FPI scale. Second, the mean score of 12.31 is substantively 77.49% lower than the mean compliance level by program-participating states observed in the following ranges of the Herfindahl public concentration index: between 0 and 0.40 (mean compliance level =54.7). This provides – at best – some preliminary support for the claim that borrowing countries with concentrated public banks are more likely to renege from implementing structural banking sector reform measures in IMF programs.

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