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Sovereign Debt Default: Are Countries Trapped by Their Own Default History?

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Abstract

Why are sovereign debt defaults so persistent in some EMEs, even at relatively low levels of external debt? The empirical literature has argued that the country's record of defaults is the main determinant of the future default risk. However, there are two factors generating the effect from history on the probability of default: state dependence and unobserved heterogeneity. Is a country more likely to default because it has experienced a default in the past (state dependence) or does the country have some previous specific characteristics that make it more prone to default (unobserved heterogeneity)? Results indicate that state dependence effects are large. Nevertheless, this paper presents evidence indicating that the omission of unobserved heterogeneity -which accounts for both unobserved and observed time invariant characteristics- has drastic consequences when assessing countries' risk of default. When unobserved heterogeneity is accounted for there are countries with high risk of default even if negligible levels of debt are assigned to them. Conversely, other countries show a low probability of default even with assigned levels of indebtedness higher than those observed in the sample. Finally, this paper presents evidence suggesting that unobserved heterogeneity could be associated to a set of different historical, political, and cultural factors that have deeply and persistently shaped institutions.

JEL Codes: C23; E60; F34; G28; H63

Keywords: Serial defaulters, debt intolerance, non-linear panel, bias correction.

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1 Introduction

A sovereign default occurs when either the central government fails to pay scheduled debt service on the due date (interest or principal) or when rescheduling of principal/interest is agreed at less-favorable terms than the original loan (see Beers *et al.*, 2007). There are three main stylized facts on the history of sovereign external debt defaults in Emerging Market Economies (EMEs). First, most EMEs display a history of multiple sovereign debt defaults episodes, behaving like serial defaulters.¹ Secondly, these economies are prone to default at relatively low levels of external debt, thus, showing *debt intolerance*.² Thirdly, default episodes are highly persistent in these countries. That is, once an EME enters the state of default, it remains there for an average of 9 years.³ When taking into account the length (persistence) and the high frequency (the serial defaulter feature) of default episodes, data shows that, in the last 200 years, some EMEs have been in state of default as much as 50%of the time.⁴ Why are sovereign debt defaults so persistent in EMEs, even at relatively low levels of debt? This paper starts from the existing idea that "history" is the main factor determining the probability of default (See Reinhart et al., 2003, Reinhart and Rogoff, 2009). This is done by disentangling the relative contribution of state dependence and unobserved heterogeneity in explaining the observed persistence of sovereign debt defaults.

Why is the study of this phenomenon important? The costs of sovereign defaults are numerous, not only for the country involved, but also for the world (systemic impacts through globalized markets). First, a sovereign debt default carries reputational costs (Eaton and Gersovitz, 1981; Tomz, 2007) that negatively affect the access to financial markets and borrowing terms. Secondly, it brings direct sanctions like trade embargoes or trade disruptions (Bulow and Rogoff, 1989), which generate direct loss of output (Krugman, 1988; Jorgensen and Sachs, 1989). Thirdly, defaults entail renegotiation processes that are highly time-consuming and costly in terms of coordination between borrowers and multiple lenders. Finally, debt crisis could evolve into domestic banking crisis (Reinhart and Rogoff, 2011). All of the above creates political instability and uncertainty.⁵ Consequently, it is critical to understand what determines sovereign debt default in EMEs and what is behind its persistence and debt intolerance to design economic policies that prevent debt crises.

State dependence means that the fact that a country experienced a default in the past makes it more likely to default again. For example, a default might lead to political instabil-

¹Advanced economies were also characterized by this phenomenon in the past.

²The terms *serial defaulter* and *debt intolerance* were coined by Reinhart and Rogoff (2003). The first reflects a high record of sovereign debt defaults. The second term refers to the incapacity some countries have to sustain levels of debt that are manageable in advanced economies. Therefore, according to the authors, the safe debt thresholds that *debt intolerant* countries can sustain without running into a default are extremely low.

³This average covers the last 200 years.

⁴One advanced economy that presents features of an EME, with multiple and persistent defaults, is Greece. The last time Greece defaulted (before the 2012 episode) was during the Great Depression, staying 33 years in that state. Greece has spent 48% of the time in state of default in the last 200 years (see Table A1.1).

⁵See Borensztein and Panizza (2008) for an empirical assessment of the importance of the different type of costs mentioned.

ity and uncertainty that will change the future probability of default. In addition, a default carries a punishment by the markets, i.e. a country in default will normally face worsened borrowing terms, which increases the cost of repayment, thus raising the likelihood of future defaults (Catão *et al.*, 2009). In this context state dependence is *Markovian, i.e.* the likelihood of a default event in the next period depends on whether the country is currently in default or not. This type of state dependence is associated with the persistence (length) of a default episode and it is mainly related with the benefits and costs involved in the decision of whether to remain or to exit the default.

Another kind of state dependence is the occurrence dependence, which captures the number of times a country has defaulted, and therefore, is connected with the serial defaulters concept. Occurrence dependence can be linked to frameworks that introduce government reputation (see Cole and Kehoe, 1997). In a scenario of incomplete information about each country's ability to repay debt, past defaults will affect lenders' decisions because governments' actions signal their type through those decisions. Conversely, "in models with full information and no political uncertainty, debt and output are sufficient statistics for the default probability, so there is no role for the history of default" (D'Erasmo, 2008). In these cases, past defaults have an authentic impact on the behavior of the country. In other words, state dependence means that a country who did not experience a default would behave differently in the future than a country which -otherwise identical- has experienced a default. This is true state dependence, i.e. the pure effect of a past default in the current probability of default.

Unobserved heterogeneity, reflects unmeasured time invariant factors, in which countries differ, that affect the probability of default, regardless of past defaults. These are country-specific characteristics, which are unobserved by the econometrician, such as different historical, political, cultural and ideological factors that affect policy decisions, and have shaped institutions and economic development of countries. For instance, unobserved heterogeneity could be associated with deep institutional features, such as protection of property rights or history of macroeconomic instability (Kraay and Nehru, 2006).

Why is the distinction between state dependence and unobserved heterogeneity important and why is it important to account for the two components of persistence when assessing the default risk? First, since state dependence gives the long-run impact of policies that affect the current default status, measuring it accurately is important. Secondly, it is crucial to identify the true magnitude of the parameters in a model of sovereign default in order to prevent a debt crisis, since it would help to better determine safe thresholds of debt that a country could target to avoid a default, or to better assess the risks in a scenario of economic shocks. These objectives cannot be achieved if unobserved heterogeneity is omitted. In the first case, since unobserved heterogeneity is correlated over time, the failure to account for it could give a spurious degree of state dependence or at least an overstated one. In the second case, if the same unobserved heterogeneity that is determining the probability of default is also influencing any other explanatory variable, endogeneity might arise. Thus, accounting for unobserved heterogeneity might affect the predicted outcomes. However, there are no applications of nonlinear panel models⁶ that introduce unobserved heterogeneity and dynamics in the literature of sovereign debt default since the econometric methodologies that deal with these features have been recently developed.

This paper implements a dynamic probit fixed effect panel data model to estimate the probability of sovereign debt default. Since the introduction of unobserved heterogeneity in a non-linear model gives rise to the incidental parameter problem,⁷ recent bias-correction methodologies are employed to tackle this issue.⁸

Results indicate that if a country runs into a default, the probability of defaulting again increases by 25%. In this sense, defaults are like a "trap".⁹ Once a country defaults, the probability it will default again is higher compared to another country with identical fundamentals, but with no default in the previous period. However, the most striking result is that -after controlling for state dependence and other determinants of sovereign risk-the main factor behind the differences across countries' propensities to default is the variation in country-specific effects. Furthermore, evidence suggest that there are countries with significantly high risk of default even if negligible levels of debt are assigned to them. Conversely, other countries show a low probability of default even with assigned levels of indebtedness far higher than those in the sample. Finally, this paper empirically explores the extent to which unobserved heterogeneity could be associated to a set of different historical, political, and cultural factors that have deeply and persistently shaped institutions. Results suggest that countries with French legal origin are more prone to default, while countries with higher levels of democracy in their first year of independence are less likely to default. Additionally, results suggests that higher economic volatility and lower government stability increase the likelihood of a sovereign debt default. Therefore, the interpretation of these results is that country fixed effects are accounting for deep-rooted and persistent features in institutions.

The rest of the paper is organized as follows. Section 2 offers a review of the related literature. Section 3 introduces the empirical implementation. Section 4 reports results. Section 5 presents a brief policy discussion and section 6 concludes.

2 Related Literature

Theoretical papers that have extended the seminal paper by Eaton and Gersovitz (1981), such as Aguiar and Gopinath (2006), Aguiar and M. Amador (2013), Arellano (2008) and Mendoza and Yue (2009), among others, explain default as a mechanism that provides par-

⁶The nonlinearity arises from the fact that the dependent variable is binary. That is, it takes the value of 1 if the country is experiencing a default, 0 otherwise.

⁷This bias arises because the specific effects are replaced by estimates, as in non-linear panel models, the specific effects cannot be separated from the estimation of the parameters of main interest. Therefore, the error of the individual effects contaminates the parameter estimates.

⁸See Arellano and Hahn (2006) for a survey of this literature.

⁹ "Default trap" is a term coined by Catão et al. (2009) to express the concept that the ocurrence of a default might "throw an otherwise solvent country on the path of serial default."

tial insurance against negative output shocks under asset incompleteness.¹⁰ In these models the probability of default is mainly explained by the level of debt and output shocks. Why some countries default considerably more often than others, despite having similar levels of debt and facing similar shocks, is still an open question in the literature. In answering this, a growing literature introduces the role of institutions in explaining sovereign debt default. Cuadra and Sapriza (2008) incorporate political uncertainty and polarization in a dynamic stochastic model of sovereign default and find that these factors increase the frequency of default episodes. D'Erasmo (2008) includes government reputation and renegotiation, finding that reputation has an important role because governments transit to different political states that are not directly observed by lenders. In addition, the inclusion of renegotiation generates endogenous periods of financial autarky. Benjamin and Wright (2009) propose a theory in which delays in negotiations to restructure sovereign debt arise as an optimal decision, where the debtor and the creditor wait until the risk of default is low.

In the empirical literature,¹¹ Reinhart and Rogoff (2009) found evidence of a phenomenon that they call "debt intolerance", in which EMEs with relatively low external debt ratios are perceived to be riskier than developed economies that hold significantly higher net debt burdens. Mendoza and Ostry (2008) also find evidence for the debt intolerance phenomenon in EMEs. These authors find that the primary balance reacts more to increments in public debt in EMEs than in advanced economies. This implies that emerging countries converge to lower mean debt ratios than advanced economies. To conciliate the notions of "debt intolerance" and "serial defaulters", Reinhart and Rogoff (2003) invoke history. Since EMEs have defaulted in the past, they are more likely to do so again. The authors estimate a cross-country regression for 53 industrial and developing economies, and find that ratings¹² -that could be interpreted as the market's perception of a country's probability of defaultare explained by three variables: gross external debt relative to GNP (this include total private and public debt), inflation and default history. The measure of history they use is the percentage of years each country has spent in default since 1824. The authors find that one percentage point increase in the country's historical record of default decreases the Institutional Investor Rating (IIR) by 0.17 percentage points, while the same increment in the ratio of external debt to GDP and in the number of periods with high inflation reduces the IIR by 0.34 and by 0.16 percentage points, thus increasing the perceived risk of default. The authors calculate country-specific debt thresholds using the estimated coefficients and, together with actual values of the regressors, they predict ratings for different ratios of external debt to GNP for a given country. They find that debt thresholds of countries with default history are lower than countries with no default history. In other words, given the same ratio of debt-to-GNP, a country with history of default will face lower ratings; which

 $^{^{10}}$ Aguiar and M. Amador (2013) also provide a review on empirical facts on the sovereign debt default history, and discuss different theoretical models and their implications.

¹¹See Tomz and Wright (2013) for a recent survey of the empirical literature.

¹²Measured by the Institutional Investor rating (IIR). This is an indicator of the creditworthiness of a country. The higher the IIR, the lower the risk of default. The authors use the average of the IIR for the period 1979-2000 as dependent variable.

is interpreted as a higher probability of default. The authors conclude that, instead of the variation in debt, is the country's record of default (history) the main determinant of the risk of default. However, the shortcoming of a cross-section estimation is that it does not allow assessing the two possible sources of default persistence. Namely, unobserved heterogeneity and state dependence that are entangled in this measure of "history".

Catão, et al. (2009) introduces the role of history in a theoretical model of sovereign debt default and providing empirical evidence for their propositions. It rationalizes a history dependent probability of default in a framework that combines asymmetry of information, persistence and volatility of output shocks; and the existence of pessimistic lenders. The informational asymmetry occurs between lenders and borrowers regarding the nature of output realizations. In this sense, a past default matters because it signals a negative output shock. Theoretically, the mechanism works as follows. Once the sovereign defaults, lenders learn the realization of a negative output shock. Since these shocks are assumed to have a permanent component, pessimistic lenders expect the worst about the future output path. In this context, new borrowing is only possible at higher spreads. Thus, the cost of future repayments increases beyond what is justified by other fundamentals and, consequently, the probability of future defaults increases too. The presence of this history-dependent "default premium" generates a "default trap". In other words, a sovereign that defaults on its debt will be more likely to default in the next period. To present evidence that supports this notion, the authors estimate pooled OLS regressions of countries' sovereign spreads on default history, the persistence and volatility of output shocks, and traditional control variables. The measure of default history is the share of years in default since the beginning of the sample and is highly significant. Regional dummies are included to capture some specific effects, but no country-fixed effects are included. Therefore, this might result in the failure to account for deep and structural characteristics that are persistent and specific to the country.

Borensztein and Panizza (2008) also investigates the impact of the country's record of default. The authors empirically assess the importance of reputation on bond spreads, and do not find evidence that suggests it has a significant effect on the default premium. Instead, they observe that only the default status from the previous year is significant, concluding that markets have short memory.¹³ This conclusion contrasts with that of Reinhart and Rogoff (2003). Although these two studies differ in terms of the default through bond spreads, while Reinhart and Rogoff (2003) do it through ratings- both measures represent the market's perception of the risk of default. The most important difference comes from the methodology. Borensztein and Panizza (2008) estimate the risk of default with a linear panel fixed effects, while Reinhart and Rogoff (2003) do it with a cross-section. As mentioned earlier, in a cross-section estimation "history" might be just reflecting the effect of country-specific characteristics that influence creditworthiness and increase the likelihood

¹³Same results are found by Flandreau and Zumer (2004).

of a default, rather than the "pure" effect of past defaults. In this context, the significance of history could be spurious.

McFadden *et al.* (1985) and Kraay and Nehru (2006) examine the impact of unobserved heterogeneity and state dependence on the probability of default, reaching completely opposite results. McFadden *et al.* (1985) estimate a dynamic probit random effect model. They find an important amount of state dependence and unobserved heterogeneity, with 40,4% of the variance underlying default due to the specific country effect. The other two variables that are found to be significant in explaining the probability of default are external debt relative to exports and the ratio of reserves to imports.

Kraay and Nehru (2006) estimate a dynamic probit model including country dummies, and implementing Wooldridge's initial condition correction. The country effect is imposed to be a linear function of the initial value of the dependent variable and the average of all the explanatory variables. Therefore, the method basically consists in estimating a correlated random effect probit, including the initial value of the dependent variable and the average of all the determinants among the explanatory variables. The authors do not find evidence of state dependence. The point estimates of pooling without state dependence and unobserved heterogeneity are similar to the ones obtained with the dynamic probit. Thus, they conclude that a pooled probit with no dynamics is a satisfactory approach (similar to Catão and Sutton, 2002; Detragiache *et al.*, 2001; Cohen *et al.*, 2010). They find that three variables explain the probability of default: external debt relative to exports, GDP growth and a governance indicator.¹⁴

These two studies differ from the present paper in at least three features. The definition of the dependent variable, the sample, and the empirical methodology. Kraay and Nehru (2006) define a binary dependent variable that takes the value of 1 if there is a debt distress event, focusing only on the beginning of a default, thus excluding all the subsequent observations which reflects its continuation, and ending up with an unbalanced panel with irregularly spaced observations. In this set-up, by construction, markovian state dependence is eliminated. Therefore, persistence is more related to occurrence dependence. In addition, they define a "normal period" as three consecutive years without debt distress, making the dependent variable to take the value of zero only in those cases. Kraay and Nehru (2006) focus on defaults with private and multilateral creditors, implying that the countries included are not only EMEs, but also low income countries with no access to capital markets. Finally, in terms of methodology, the authors implement a dynamic correlated random effect model, since country specific effects are not estimated, instead they are assumed to be a linear function of the explanatory variables and the initial value of the dependent variable. In the case of McFadden *et al.* (1985), the main difference is that they estimate a random effect model. The issue with this is that random effects provide inconsistent estimators when unobserved heterogeneity is correlated with the observed variables.

 $^{^{14}}$ One percentage point increase in each of these variables (at a time) changes the probability of default by 0.6, -5 and -0.6% , respectively.

3 Empirical Implementation

3.1 Sovereign debt default and its features

Sovereign defaults are taken from Reinhart and Rogoff (2011), which contains a list of defaults identified by Standard & Poor's, supplemented with other sources (see Suter, 1992; Tomz, 2007; Lindert and Morton, 1989). A sovereign default occurs when either the central government fails to pay scheduled debt service on the due date or when rescheduling of principal/interest is agreed at less-favorable terms than the original loan (see Beers *et al.*, 2007). Each year a country is in state of default, it accumulates arrears on either principal, interests, or both. To exit the state of default, the country has to go through a debt re-negotiation process.¹⁵

The high frequency and persistence of defaults on sovereign debt are not new phenomena. In the past, advanced economies were also characterized by these features (see Reinhart and Rogoff, 2009). Table 1 presents the list of advanced economies that used to behave like serial defaulters. For instance, Spain defaulted on its sovereign debt thirteen times during 1500-1900; while France, Austria and Germany failed to pay debt between seven and eight times during the same period. Greece, on the other hand, has spent 48% of the time in state of default in the last 200 years. The last time Greece defaulted (before the 2012 episode) was during the Great Depression, staying 33 years in that state.

COUNTRY	NUMBER O	F DEFAULTS	YEARS IN DEFAULT (%) ¹	EXTERNAL DEBT TO GDP (%) ²
PERIOD	(1501-1813)	(1814-2010)		(1990-2010)
Spain	6	7	24	84
France	8	0	1	107
Austria	1	6	17	132
Germany	4	3	16	99
Greece	n.a	5	48	85
Portugal	n.a	6	11	128
Netherlands	1	1	6	185
Italy	n.a	1	3	79
Japan	n.a	1	5	34
United Kingdom	n.a	1	4	252
Average	4	3.1	13	119

Table 1: Advanced e	economies that	used to be	serial defaulters
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1. Percentage of years in default since independence year.

2. Gross external debt.

Source: Author's calculation from data in Reinhart and Rogoff (2011).

EMEs show heterogeneity in their sovereign default history, with four groups that can be broadly identified according to their default frequency and persistence. The first group comprises EMEs that tend to behave like serial defaulters, with default episodes that are highly persistent. A second group includes EMEs that present few default episodes and exit them quickly, while a third group spend a high amount of time in one or two default episodes. Finally, a small number of EMEs have never defaulted.

¹⁵According to Standard & Poor's, "sovereign defaults often trigger a debt workout process, usually involving negotiations with creditors, that culminates in the exchange of newly issued debt for old debt. When such a settlement occurs and Standard & Poor's concludes that no further near-term resolution of creditors' claims is likely, the sovereign is regarded as having emerged from default" (see Beers et. al., 2007).

Table 2 reports EMEs belonging to the first group, that is, countries which have defaulted at least six times in the last two centuries. The first and second columns present the number of default episodes and the percentage of years a country has been in default since its independence year (or 1800, if independence occurred before). The third column presents the average ratio of external debt to GDP,¹⁶ considering only the last 40 years of history. With the exception of Ecuador and Nicaragua, all these countries held an average ratio of external debt relative to GDP lower than 55% prior to defaulting, which is lower than the ratio considered sustainable in advanced economies.¹⁷

In the past two centuries, the average length of a default episode is 8 years for EMEs in this group. Combining the length (persistence) and the frequency of the default episodes (the serial defaulter feature), the percentage of years some countries have spent in state of default can be as high as 50%. Some striking cases are Ecuador, Nicaragua and Mexico, countries that have spent 58, 48, and 44% of the time in state of default, respectively. Extreme cases are Honduras and Nicaragua that have never left the state of default since 1981 and 1979, respectively; and Côte d'Ivoire which -with the exception of one year- has been in default since 1983. Default episodes with particularly high persistence are observed during the financial crisis that started in the early 1980's.¹⁸

10	Table 2. Serial defaulters							
COUNTRY	NUMBER OF DEFAULTS	YEARS IN DEFAULT (%) ¹	EXTERNAL DEBT/GDP (%) ²					
PERIOD	(1800-2010)	(1800-2010)	(1970-2010)					
Argentina	6	32	47					
Brazil	9	27	30					
Chile	9	27	54					
Colombia ³	6	35	32					
Costa Rica	8	35	53					
Dominican Republic	7	28	30					
Ecuador	9	57	60					
Guatemala	7	31	25					
Mexico	8	44	35					
Nicaragua	6	47	253					
Paraguay	7	23	33					
Peru	8	40	49					
Turkey/Ottoman Empire	9	15	35					
Uruguay	9	13	40					
Venezuela	9	36	42					
Average	8	33	54					

abl	e	2:	Ser	ial	de	fau	lte	rs

1. Percentage of years in default since independence year or 1800, whichever comes later.

2. Gross external debt.

3. Colombia did not have a default episode between 1970-2010. Source: Author's calculation from data in Reinhart and Rogoff (2011).

Source: Author's calculation from data in Reinhart and Rogott (2011).

Table 3 reports EMEs belonging to the second and third group. Countries that present few

¹⁸Some examples are Argentina, Bolivia, Brazil, Côte d'Ivoire, Dominican Republic, Ecuador, Nicaragua, Nigeria, Panama, Peru, and Zambia, among others, spending between 11 to 17 years in state of default.

¹⁶Gross external debt comprises external obligations of public and private debtors. This measure of indebtedness is only used in this section for the purpose of comparison across countries since it is available for both advanced economies and EMEs. The data is from Reinhart and Rogoff (2011). Another measure of indebtedness, which reflects better the debt burden of a sovereign, will be introduced in the estimation of the probability of default.

 $^{^{17}}$ According to the Maastricht Treaty, that defines the euro convergence criteria, the ratio of gross government debt to GDP has to be lower than 60%.

default episodes and exit them quickly (second group) are mainly Asian, like China, India, Indonesia and Philippines, plus a few North African countries like Egypt and Tunisia. These economies have sustained an average debt to GDP ratio of 45% in the past 40 years. EMEs with low number of default episodes but a high level of persistence (third group) are mostly from Sub-Saharan Africa (SSA), and have sustained an average debt to GDP ratio of 93% in the past 40 years.

Table 2: Countries that default less often

Table 3: Countries that default less often							
	NUMBER OF	YEARS IN	EXTERNAL DEBT				
COUNTRY	DEFAULTS	DEFAULT (%) ¹	TO GDP (%) ²				
PERIOD	(1800-2010)	(1800-2010)	(1970-2010)				
Africa							
Côte d'Ivoire	2	53	101				
Zimbabwe	2	44	55				
Zambia	1	27	149				
Kenya	2	21	66				
Tunisia	1	13	56				
Egypt	2	3	47				
Average	1.7	27	79				
Asia							
China	2	13	12				
India	3	11	20				
Indonesia	4	15	54				
Myanmar	1	14	63				
Philippines	1	19	59				
Sri Lanka	2	6	48				
Average 2.2 13 43							
1. Percentage of years in default since independence year.							
2. Gross external							
Source: Author's calculation from data in Reinhart and Rogoff (2011).							

Finally, in the fourth group, there are 6 EMEs -mainly Asian countries- which have never defaulted.¹⁹ These countries -with the exception of Singapore- have sustained an average debt to GDP ratio of 34% in the past 40 years (see Table 4).

Table 4: Countries with no default					
COUNTRY	NUMBER OF DEFAULTS	EXTERNAL DEBT TO GDP (%)*			
PERIOD	(1800-2010)	(1970-2010)			
Emerging market e	economies				
Korea	0	31			
Malaysia	0	41			
Mauritius	0	27			
Singapore	0	95			
Taiwan	0	16			
Thailand	0	36			
Average	0	41			

(*) Gross external debt.

Source: Author's calculation from data in Reinhart and Rogoff (2011).

Although these country groups show -on average- differences in terms of their debt burden, there is evidence that suggests that sovereign debt defaults cannot be fully explained by observed variables. For example, in 2008 Ecuador had a relatively low ratio of external debt to GDP and a relatively high GDP growth, at 19% and 7% respectively (see Table A2), but

¹⁹These countries are: Korea, Malaysia, Mauritius, Singapore, Taiwan, and Thailand. This is very interesting considering that all of them were affected by the Asian financial crisis in the nineties, which was particularly severe in Malaysia and Thailand.

defaulted on two bonds because the authorities claimed that those securities were "illegal" and "illegitimate". According to Moody's (2011), this default represented more a problem of "willingness to pay" rather than "capacity to pay", as the government's decision to default was apparently based on ideological and political grounds, and it was not related to immediate liquidity and solvency issues. In this regard, unobserved heterogeneity could be linked to countries' deep institutional characteristics, which also determines the government willingness or ability to service its debt.

Figure 1 plots the net total external debt to GDP against the Institutional Investor Ratings,²⁰ splitting the sample into defaulters and non-defaulters. We can observe that countries that have defaulted in the past are perceived by the market to be riskier than countries that have never defaulted, even if they sustain the same level of debt.²¹

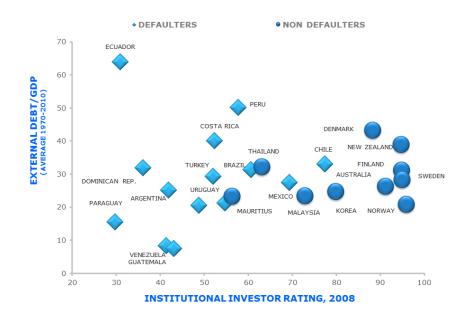


Figure 1: Ratings and net external debt to GDP

Source: Author's calculation from data in Reinhart and Rogoff (2011) and Institutional Investor Ratings.

A first look at the data suggests that a country's level of indebtedness might not be sufficient to explain its default risk, or at least the market's perception of its probability of default. However, this does not shed light into what is behind the observed persistence: the country's default history or its specific characteristics.

 $^{^{20}}$ See footnote 10.

²¹One exception among serial defaulters is Chile, which shows similar ratings of creditworthiness as nondefaulters countries. Chile has decreased its ratios of PPG external debt to GDP from 80% in 1985 to around 7% in the last 17 years. Its median GDP growth and political risk indicator are 5.5% and 75.5 respectively, both in the top 5% of the sample distribution. In this sense, the main factors behind Chile's low probability of default (or high ratings) are its macroeconomic and governance indicators.

3.2 Explanatory variables

Regarding the determinants of the probability of a sovereign default, theoretical and empirical papers consider mainly four sets of variables. The first set are different measures of indebtedness scaled to a certain amount of repayment (GDP, exports or revenues), since the higher the debt burden the more likely the country is to default. The second set are indicators of the quality of institutions, as a country with a strong institutional background is less prone to default. The third set includes diverse types of output shocks to account for the idea that defaults tend to occur as a mechanism that provides partial insurance against negative output shocks. The fourth set are indicators of the level of development in a country, given that more developed countries could be associated to more developed domestic credit markets, relying far less on external financing and lowering the risk of external default. Bearing in mind that the aim of this paper is to study sovereign default on external debt, it would be sensible to have a measure of indebtedness on public and external debt in a country. Unfortunately, only total public debt, which includes domestic and external debt, or total external debt, which includes private and public debt, is available. However, in line with Reinhart and Rogoff (2011), this paper considers plausible that private debt may become public in periods of debt crisis, particularly if it is publicly-guaranteed. Therefore, the measure of indebtedness used in this paper is a subcategory of the external debt that only includes the portion of private debt that is guaranteed for repayment by a public entity. This is known as the external public and publicly-guaranteed (PPG) debt.²² Debt stock and debt service flow are included, scaled by measures of repayment capacity. GDP growth is included as a measure of output shocks. Political uncertainty is measured by the governance indicator known as the Political Risk Rating (source: Political Risk Services (2010)),²³ which is higher the lower is the potential political risk (the lowest number (0) indicates the highest potential risk and 100 represents no risk at all). Therefore, the political risk rating is expected to be negatively correlated with the probability of default. The GDP per-capita is included as a measure of the ability of a government to repay $debt^{24}$ and as an indicator of development. Other variables that have been also considered in the empirical literature are: (i) liquidity indicators like reserves and short-term debt, since countries choosing to rely excessively on short-term borrowing to fund growing debt levels are particularly vulnerable to crises in confidence that can lead to very sudden financial crises (Reinhart and Rogoff, 2010); (ii) openness, since the more open a country is, the higher the cost of default that comes from trade disruptions and the less willing to default its government becomes (See Milesi-Ferretti and Razin (1996)); (iii) inflation, since a high rate of inflation points to struc-

²²PPG external debt stands for: public and publicly guaranteed debt. It "comprises long-term external obligations of public debtors, including the national government, political subdivisions (or an agency of either), and autonomous public bodies, and external obligations of private debtors that are guaranteed for repayment by a public entity." World Bank, International Debt Statistics.

²³The components of the The Political Risk Rating are the following: Government Stability, Socioeconomic Conditions, Investment Profile, Internal Conflict, External Conflict, Corruption, Military in Politics, Religious Tensions, Law and Order, Ethnic Tensions, Democratic Accountability, Bureaucracy Quality.

²⁴Reflecting the greater potential tax base of the borrowing country.

VARIABLE	1 YEAR PRIOR VARIABLE TO DEFAULT		DEFAULT		NON-DEFAULT	
	Mean	Mean	Std. Dev.	Mean	Std. Dev.	
External debt-to-GDP	32.1	63.4	80.0	23.4	19.1	
PV external debt-to-EXP	333	685	3527	197	1157	
Debt service-to-EXP	30.0	61.5	294.0	23.0	19.1	
Political Risk Index	54.7	54.2	9.4	62.7	10.7	
GDP growth (real)	0.3	2.1	5.2	4.6	4.3	
Log GDP per-capita	6.8	6.9	0.8	7.0	1.0	
Share of short-term debt	20.2	13.7	8.5	16.5	10.7	
Reserves/imports	34.3	96.0	727.0	37.0	53.0	
Inflation rate	209	210	1417	20	175	
Observations		274		6	62	

Table 3: Summary Statistics (%), 1985-2010

Source: Author's calculation from data in Reinhart and Rogoff (2011) and World Bank (WDI).

tural problems in a government's finances. Table 3 shows summary statistics of the sample dividing the observations into three categories: one year before default, during default and non-default periods. The explanatory variables change dramatically between the state of default and non-default. During a default episode, the three ratios of external debt reported are roughly three times the levels of debt sustained during non-default times. However, standard deviations suggest a considerable degree of heterogeneity.

The Political Risk Indicator is lower during default and one year before default; while inflation increases severely in these periods, both reflecting the political instability that accompanies a debt default episode. Real GDP growth drops, on average, from 4.6% in "normal times" to 2% during default episodes. Nevertheless, the standard deviation is 5.2 percentage points, showing that there is considerable heterogeneity across countries. The decline in GDP is sharper the year before the default starts, averaging only 0.3% and reflecting that defaults tend to occur as a mechanism that provides partial insurance against negative output shocks.²⁵ The share of short-term debt is higher the year before the default starts, which is in line with the evidence found by Rodrik and Velasco (1999) that countries with high share of short-term liabilities are more vulnerable to a crisis in confidence and a reversal of capital flows. Nevertheless, the share of short-term debt decreases during the episode of default, probably showing the difficulty to roll-over debt due to constraints in access to financial markets. Reserve coverage -that is, the ratio of non-gold reserves to

²⁵However, there are some countries that performed very well during default episodes. For example, Dominican Republic averaged a GDP growth of 9% during the 2005 default, while Venezuela had a GDP growth of 14% during the 2004-06 default (see Appendix A for data on each country's default). These countries were in recession before the default, but during the period they were in default, their GDP growth recovered very fast. These examples seem to contradict the theoretical literature that assumes that output falls once a country defaults. One plausible explanation could be related to some evidence that indicates that currency devaluation could boost growth by making the export sector more competitive internationally (Rodrik, 2008). For these particular period, high commodity prices were boosting growth in some EMEs. However, they stayed in state of default.

imports- is lower the year before the default starts, suggesting that some liquidity issues might be driving the crisis. This might also reflect that, before the default episode, the country attempts to avoid a suspension of debt service payments, by running down its reserves (Eichengreen, 2003).

3.3 Modeling the probability of sovereign debt default

The event of a sovereign debt default can be represented as a function of the latent variable d_{it}^* :

$$d_{it}^{*} = \tau d_{i,t-1} + X_{it}^{'}\beta + \alpha_{i} + \delta_{t} + v_{it}$$
(3.1)

However, it is only possible to observe whether the country experiences a default or not. Therefore, the dependent variable d_{it} is binary, taking the value of 1 if the country experiences a default and zero otherwise.

$$d_{it} = 1\left\{\tau d_{i,t-1} + X'_{it}\beta + \alpha_i + \delta_t + v_{it} > 0\right\}$$
(3.2)

where,

 τ is the coefficient that indicates the degree of state dependence.

 β is a Kx1 vector of parameter (k=1,..,K).

 α_i is the specific country fixed effect, allowed to be correlated with X_{it} .

 δ_t is a time dummy to account for common shocks that countries face.

 $d_{i,t-1}$ is the lagged dependent variable.

 X_{it} is the set of explanatory variables.

 v_{it} represent the errors that are assumed to be normally distributed and uncorrelated with X_{it} .

The parameters $\theta = (\tau, \beta, \delta_t)$ and α_i are unknown.

The inclusion of the lagged dependent variable $(d_{i,t-1})$ allows to disentangle the role of state dependence from both observed and unobserved time invariant factors (α_i) .

A fixed effect approach is preferred over a random effect or a pooled model, since no restrictions are imposed regarding the distribution of the unobserved heterogeneity and its correlation with the observed variables, thus controlling for the endogeneity coming from the time invariant effects. This is important if the same unobserved heterogeneity that is determining the probability of default is also influencing any other explanatory variable. For example, even though it is simple to find a negative correlation between economic growth and the probability of default, it is not straightforward to find the magnitude of the impact of an economic recession on the default risk if there are unobserved factors that are causing both. That is because it is plausible that the same history that has given shape to institutions in a particular country could be also determining the economic and financial development of that country, combined with its political factors. Therefore, the unobserved heterogeneity could be also correlated to some covariates like the GDP per capita, political risk indicators and/or the level of external debt. Despite recognizing that persistent

unobserved heterogeneity cannot be separated from other specific observed time invariant characteristics, a fixed effect approach is still operative in accounting for both. Furthermore, an approach that favors the inclusion of time invariant explanatory variables over fixed effects could also result in statistical significance only because the former is proxying the latter (See Fernandez-Val, *et al.*, 2013).

Equation 3.2 is estimated by a probit fixed effects model. Thus, the corresponding loglikelihood function is:

$$L = \sum_{t=1}^{T} \sum_{i=1}^{N} d_{it} \log \Phi(\tau d_{i,t-1} + x'_{it}\beta + \alpha_i + \delta_t) + \sum_{t=1}^{T} \sum_{i=1}^{N} (1 - d_{it}) \log \left[1 - \Phi(\tau d_{i,t-1} + x'_{it}\beta + \alpha_i + \delta_t) \right]$$

where Φ is the cumulative distribution function (cdf) of a standard normal distribution.

In a non-linear model the vector of index coefficients θ is not informative about the impact of a variation in a regressor on the conditional probability of defaulting (y=1). Then, it is more meaningful to look at the marginal effects. For a continuous variable j, the marginal effect is:

$$m_{it}^{k}(z_{it};\theta,\alpha_{i}(\theta)) = \frac{\partial P(y_{it}=1|x_{it})}{\partial X_{it}^{k}} = \phi(\tau d_{i,t-1} + x_{it}^{'}\beta + \alpha_{i} + \delta_{t})\beta_{k}$$

where $z_{it} = (y_{it}, x'_{it})'$.

And for the lagged dependent variable, which is binary, the marginal effect is:

$$m_{it}(z_{it};\theta,\alpha_i(\theta)) = \Phi(\tau + x'_{it}\beta + \alpha_i + \delta_t) - \Phi(x'_{it}\beta + \alpha_i + \delta_t)$$

where ϕ is the probability density function (pdf) of a standard normal distribution.

Let μ represents the average marginal effects:

$$\hat{\mu}(\theta) \equiv \frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} m_{it}(\hat{\theta}, \hat{\alpha}_i(\theta))$$

The incidental parameter bias arises in both the index coefficients and the average marginal effects, because in the estimation of the parameters of main interest, the specific effects are replaced by estimates. That is, the estimation error of $\hat{\alpha}_i(\theta)$ contaminates the estimation of θ . In order to tackle this issue, the bias-correction methodology proposed by Hahn and Kuersteiner (2011) is implemented.²⁶ See Appendix B for a characterization of the incidental parameter problem and the construction of the analytical expression for the bias.

The inclusion of specific-country effects in a dynamic panel data model also gives raise to the initial condition problem (Nickell, 1981). That is, the estimates will be inconsistent since the initial value of the dependent variable cannot be truly exogenous, meaning that it is highly unlikely that its distribution does not depend on the country's fixed effect. The

²⁶Two other methodologies that yield very similar results were also implemented. The first is the methodology carried out by Fernandez-Val (2009), which, like Hahn and Kuersteiner (2011), provides analytical expressions of the bias. In particular, it proposes score-corrected estimators. The second one is developed by Dhaene and Jochmans (2012), which reduces the bias of the profile loglikelihood through a jackknife method.

bias-correction in Hahn and Kuersteiner (2011) removes this dynamic panel bias in addition to the incidental parameter bias.

The sample is circumscribed to economies with access to international markets, since this paper studies sovereign debt defaults on public external debt with private creditors.²⁷ Thus, the sample consists of 36 EMEs for the period 1985-2010, covering default episodes from the debt crisis in the 1980's, those that took place during the Asian crisis in the 1990's, and more recent ones in the 2000's decade.²⁸

In this sample, there are 44 defaults episodes, lasting 6 years on average (see Table A2 for a list of defaults).²⁹ The total number of observations in default status is 274, while 662 observations are not in default status.

4 Results

4.1 Estimation Results

Table 4 reports the estimations of the probability of default with a dynamic FE probit model. In general, results show -as expected- that the probability of default increases with the level of indebtedness, it decreases with political stability,³⁰ and decreases when the country achieves better macroeconomic performance (higher GDP growth and higher GDP per-capita).³¹

Table 4. Dependent Variable: delaart danning, 1969 2010							
	INC	DEX COEFFICIE	NTS				
VARIABLE	Pooled MLE	FE MLE	BC MLE				
Default (t-1)	2.633***	1.685***	1.866***				
	(0.158)	(0.199)	(0.204)				
		[0.347]	[0.350]				
PPG external debt-to-GDP, % (t-1)	0.012***	0.015	0.015				
	(0.003)	(0.008)	(0.008)				
		[0.013]	[0.013]				
GDP growth, % (t-1)	-0.061***	-0.059*	-0.061*				
	(0.019)	(0.024)	(0.025)				
		[0.033]	[0.034]				
Political Risk Indicator	-0.026***	-0.077***	-0.075***				
	(0.009)	(0.016)	(0.017)				
		[0.028]	[0.028]				
Log GDP per capita	0.208*	-0.620	-0.538				
	(0.120)	(0.537)	(0.545)				
		[0.817]	[0.816]				
Observations	936	650	650				

Table 4: Dependent variable: default dummy, 1985-2010

Note: Asymptotic standard errors in parenthesis, bootstrap standard errors in brackets (999 replications). Country and year dummies included. Sample size: N=36, T=26. *** p<0.01, ** p<0.05, * p<0.1 (using bootstrap standard errors)

²⁷Countries with no international market access can only borrow from multilateral institutions. ²⁸This sample allows to have a completely balanced panel.

²⁹This represents a reduction with respect to the 9-years length in the sample that starts in 1814. ³⁰Remember that the higher the rating the lower is the potential political risk.

³¹Time-dummies are also included, as a measure of common shocks that countries might face.

The coefficients on the lagged default indicate an important degree of state dependence. The first column presents the pooled probit estimates, where the estimation of the parameters does not distinguish between the cross and within variation. Thus, the unobserved heterogeneity, captured by α_i in equation 3.3, is not included, and every country share the same constant, α . The second column shows the unadjusted FE probit estimates, thus eliminating the endogeneity operating through country-specific effects and allowing for different intercepts. The number of observations is lower than when all countries are pooled, because in order to identify parameters a change in status is required in the sample. Therefore, when fixed effects are included, all the countries that either never defaulted or were always in state of default are dropped from the sample.³² In this context, the resulting estimates would be consistent under the assumption that sample selection operates through fixed effects. Meaning that the unobserved factor determining whether a country enters the sample or not, is time-invariant. The third column reports the bias-corrected results.

Asymptotic standard errors are reported in parenthesis and bootstrap standard errors are reported in brackets. Given that asymptotic standard errors are valid in large samples, cross-sectional bootstrap standard errors are also estimated. The bootstrap was done by re-sampling randomly countries with 999 replications. See Kapetianos (2008) for more details. In the first column, asymptotic standard errors are clustered at the country level.³³

The consequences of choosing a FE approach over a pooled model are the following. First, the pooled estimates present a significantly larger coefficient for the lagged dependent variable than the unadjusted and adjusted fixed effect estimates, suggesting that state dependence is overstated in the pooled model due to uncontrolled time invariant unobserved heterogeneity. This is suggested by ratios of the coefficients of default lag with respect to any other coefficient in the model (given that pooled and FE estimators use different normalizations). Secondly, the country fixed effects are statistically significant, showing a high degree of heterogeneity (results are not reported). Thirdly, once the specific-country effects are included, the ratio of debt to GDP is not statistically significant anymore, suggesting that what is really driving the risk of default are idiosyncratic country-specific factors. In other words, the impact of debt is overstated if unobserved heterogeneity is omitted since the explanatory power of the latter would be captured by the former. The other coefficient that loses statistical significance is that for GDP per capita, consistent with the fact that the GDP per capita has relatively higher between variation than within variation.

The main interest lies in identifying the effects of changing an explanatory variable on the conditional probability of defaulting P(Y=1|X), which in binary choice models is captured by the marginal effects. Table 5 reports the average marginal effects (AMEs)

³²Of the 36 countries included in the study, 9 countries never defaulted in the sample, 2 of which have never defaulted in history (Malaysia and Thailand). Two countries were all the time in default in the sample: Honduras and Nicaragua. Côte d'Ivoire was not dropped from the sample because it did not default in one year.

³³To control for the possibility that the dependent variable y_{it} is conditionally correlated over time for a given country and conditionally heteroskedastic.

	AVERAGE MARGINAL EFFECTS					
VARIABLE	Pooled MLE	FE MLE	BC MLE			
Default (t-1)	0.663***	0.219***	0.247***			
	(0.013)	[0.055]	[0.072]			
PPG external debt-to-GDP, %	0.001***	0.001	0.001			
	(0.000)	[0.001]	[0.001]			
GDP growth, % (t-1)	-0.007***	-0.005*	-0.005*			
	(0.002)	[0.003]	[0.003]			
Political Risk Indicator	-0.003***	-0.006***	-0.006***			
	(0.001)	[0.002]	[0.002]			
Log GDP per capita	0.023*	-0.051	-0.042			
	(0.013)	[0.058]	[0.053]			

Table 5: Dependent variable: default dummy, 1985-2010

Note: Asymptotic standard errors in parenthesis, bootstrap standard errors in brackets (999 replications). Country and year dummies included. Sample size: N=36, T=26. *** p<0.01, ** p<0.05, * p<0.1 (using bootstrap standard errors)

Results show that the pooled estimate of state dependence is significantly overstated when unobserved heterogeneity is not accounted for (66% compared to 22%). Nevertheless, state dependence is large and significant even after taking into account unobserved heterogeneity. Bias-corrected results (column 3) show that a country which experienced a default in the previous period will be, on average, 25% more likely to default in the next period than a country which -otherwise identical- has not experienced a default. The average marginal effects for the other explanatory variables show almost no difference between the bias-corrected and the unadjusted FE estimator with the exception of the GDP per capita. However, pooled estimates are larger -in absolute terms- compared to the adjusted estimates (with the exception of the political risk index). Thus, emphasizing the consequences of dismissing unobserved heterogeneity.

Regarding the effect of the level of indebtedness on the probability of default, biascorrected estimates indicate that one percentage point increase in the PPG of external debtto-GDP raises the probability of default in 0.1%. In terms of the GDP growth, one percentage point increase reduces the probability of default by 0.5%. One percentage point increase in the political risk index -which means higher political stability-³⁴ decreases the probability of default by 0.6%. Finally, one percentage point increase in the GDP per capita decreases the probability of default in 0.04%.

4.2 Analyzing the impact of unobserved heterogeneity

If the sovereign's decision to whether default or not on its debt is influenced by persistent unobserved factors -such as the country's history, sociocultural heritage, ideologies and politics-, then it is plausible that these factors would be reflected in the country's fixed effects estimates. Although unobserved heterogeneity cannot be separated from other specific observed time invariant characteristics, a fixed effect approach is still operative in accounting for both. For instance, it is possible to observe whether a country was colonized or not,

 $^{^{34}}$ Remember that the index is constructed in a way that 0 would mean the highest risk and 100 the lowest risk.

while it is not possible to measure the sociocultural heritage of a country. However, these two persistent factors can be captured by a fixed effect. In this context, it is interesting to analyze the impact of varying the amount of the fixed effects on the default risk.

To understand the magnitude of the impact of the fixed effects on the probability of default, an exercise presented by Fernández-Val, *et al. (2013)* is replicated. This consists in computing predicted probabilities by moving the fixed effects along its empirical distribution, while keeping each country's observed characteristics. Namely, the index $\tilde{\tau}d_{i,t-1} + \tilde{\beta}'X_{it}$ is calculated for each country *i* at every point in time *t*, and then augmented by the amount of the fixed effects $\tilde{\alpha}_{pth}$ at the pth percentile of its distribution. Thus, a country's probability of default evaluated at its observed characteristics and at a fixed effect quantity corresponding to the pth percentile of its distribution would be:

$$\hat{p}_{i}^{\tilde{\alpha}_{pth}} = \frac{1}{T} \sum_{t=1}^{T} \Phi(\tilde{\tau}d_{i,t-1} + \tilde{\beta}' X_{it} + \tilde{\alpha}_{pth})$$

$$(4.1)$$

where $\tilde{\tau}$ is its bias-corrected coefficient of the lagged dependent variable, $\tilde{\beta}$ is the vector of bias-corrected coefficients for the explanatory variables included in X, and $d_{i,t-1}$ is the default status in the previous year (which is assumed for now to be equal to zero, $d_{i,t-1} = 0$). Probabilities are computed for all countries, i = 1, ..., N, moving the amount of the fixed effect from the 5th to the 95th percentile of its distribution. Then, the average probability of default at each percentile (p_{th}) of the fixed effects is:

$$\hat{p}^{\tilde{\alpha}_{pth}} = \frac{1}{N} \sum_{i=1}^{N} \hat{p}_{i}^{\tilde{\alpha}_{pth}}$$
(4.2)

The same exercise is done for each of the explanatory variables contained in X. Thus, for the variable k the index $\tilde{\tau}d_{i,t-1} + \tilde{\beta}_k * x_{pth}^k + \tilde{\beta}'_{-k}X_{it}^{-k} + \tilde{\alpha}_i$ is computed. Where only the variable x^k is moved throughout its distribution, while the other variables comprised in X_{it}^{-k} are assigned at each country's own values.³⁵ Accordingly, each country is assigned its own fixed effect, $\tilde{\alpha}_i$. Therefore, the country's probability of default would be the following in this case:

$$\hat{p}_{i}^{x_{pth}^{k}} = \frac{1}{T} \sum_{t=1}^{T} \Phi(\tilde{\tau}d_{i,t-1} + \tilde{\beta}_{k} * x_{pth}^{k} + \tilde{\beta}_{-k}' X_{it}^{-k} + \tilde{\alpha}_{i})$$
(4.3)

And the average probability of default at each percentile (p_{th}) of x^k is:

$$\hat{p}^{x_{pth}^{k}} = \frac{1}{N} \sum_{i=1}^{N} \hat{p}_{i}^{x_{pth}^{k}}$$
(4.4)

To see how the impact of each variable on the probability of default changes with the default status in the previous year, equations 4.1 to 4.4 are computed, first, assuming there was no default in the previous period $(d_{i,t-1} = 0)$ and then, assuming there was default in the

 $[\]overline{{}^{35}X_{it}^{-k}}$ excludes only the variable that is changing across its distribution, x_{pth}^k . Correspondingly, $\tilde{\beta}_{-k}$ contains the bias-corrected coefficients in $\tilde{\beta}$, but excluding $\tilde{\beta}^k$.

previous year $(d_{i,t-1} = 1)$. This allows computing different probabilities for the onset of a default and the persistence of a default. In other words, the probability a sovereign defaults on its debt the current year conditional on having not defaulted the previous year; and the current default risk conditional on having defaulted the previous year. Table 6a reports the average probabilities at each percentile for $\hat{P}^{\tilde{\alpha}_{pth}}$ and $\hat{P}^{x_{pth}^{k}}$ setting the previous default status as $d_{i,t-1} = 0$. The first column in Table 6a (FE) presents the probabilities for each percentile of the fixed effect distribution $(\hat{P}^{\tilde{\alpha}_{pth}})$ and the subsequent columns show the same for each explanatory variable $(\hat{P}^{x_{pth}^k})$. Table 6a shows that varying the fixed effect from its 25th percentile to its 75th percentile increases the probability of default from 9.5% to 35.1%. Then, at the 95th percentile of the fixed effect, the probability raises to 50.5%. Similarly, increasing the ratio of the external debt to GDP from its 25th to its 75th percentile raises the default risk from 7.8% to 12.8%. That is, moving the value of the fixed effect from the first to the third quartile raises the probability of default by 26 percentage points, while doing the same with the amount of debt raises the default probability only by 5 percentage points. This is a striking result specially knowing that -between these two locations in the debt distribution- the level of indebtedness is increasing by 36 percentage points, from 19%of GDP to 55% of GDP.

	CONDTIONAL PROBABILITY OF DEFAULT (d _{t-1} =0) (MEAN OVER COUNTRIES)							
PERCENTILES	FE	PPG external debt-to-GDP	GDP growth	Political Risk Indicator	Log GDP per capita			
5th	4.3	6.5	17.2	31.6	22.3			
10th	4.8	6.9	15.4	26.9	20.9			
15th	6.2	7.2	14.8	23.8	18.8			
20th	8.4	7.5	14.0	19.9	17.2			
25th	9.5	7.8	13.5	16.2	16.5			
30th	10.1	8.0	13.1	14.0	15.7			
35th	14.4	8.3	12.9	12.7	14.8			
40th	15.1	8.7	12.5	11.4	14.1			
45th	16.2	9.1	12.3	10.3	13.4			
50th	25.2	9.6	12.1	9.4	12.4			
55th	27.7	10.2	11.9	8.6	11.6			
60th	30.8	10.8	11.7	8.0	10.9			
65th	31.7	11.5	11.5	7.3	10.3			
70th	33.3	12.0	11.2	6.8	9.7			
75th	35.1	12.8	11.0	6.3	9.2			
80th	36.2	13.7	10.6	5.4	8.5			
85th	37.2	15.1	10.3	4.7	7.9			
90th	38.8	18.5	9.8	4.0	7.1			
95th	50.5	24.0	9.1	3.3	5.9			

Table 6a: Probability of default evaluated at different FE and Xs percentiles

Note: Each country's conditional probability of default is computed with the average of tis respective observed variables (X_1) and different levels of FE.

Regarding the political risk indicator, moving it from its 25th percentile to its 75th percentile decreases the probability of default from 16.2% to 6.3%. That is, an improvement of the index by 13 percentage points lowers the probability of default by about 10 percentage points. On the other hand, changing the GDP growth and the GDP per capita (one at a time) from the 25th percentile to the 75th percentile lowers the probability of default from 13.5% to

11% and from 16.5% to 9.2%; respectively.

Table 6b shows results for $\hat{P}^{\tilde{\alpha}_{pth}}$ and $\hat{P}^{x_{pth}^{k}}$, setting the previous default status as $d_{i,t-1} = 1$. This exercise indicates that the influence of all the explanatory variables is amplified under the presence of state dependence. For instance, moving the amount of the fixed effect from its 5th percentile to its 50th percentile increases the probability of default by 20.9 percentage points when $d_{t-1} = 0$, and by 38 percentage points when $d_{t-1} = 1$. Doing the same with the amount of debt increases the default risk by 3 percentage points when $d_{t-1} = 0$ and, by 6 percentage points when $d_{t-1} = 1$.

	CONDTIONAL PROBABILITY OF DEFAULT (d _{t-1} =1) (MEAN OVER COUNTRIES)							
PERCENTILES	FE	PPG external debt-to-GDP	GDP growth	Political Risk Indicator	Log GDP per capita			
5th	20.0	29.2	44.2	58.4	50.0			
10th	21.5	30.1	41.9	55.5	48.7			
15th	25.5	30.7	41.1	53.2	46.6			
20th	30.8	31.2	40.0	49.9	44.8			
25th	33.2	31.8	39.3	46.1	43.9			
30th	34.2	32.3	38.7	43.3	42.9			
35th	42.2	33.0	38.3	41.5	41.8			
40th	43.4	33.6	37.8	39.5	40.8			
45th	45.2	34.4	37.5	37.6	39.8			
50th	58.1	35.2	37.2	36.1	38.3			
55th	61.2	36.2	36.8	34.6	37.0			
60th	64.9	37.2	36.5	33.3	35.9			
65th	65.8	38.3	36.2	31.9	34.9			
70th	67.6	39.1	35.7	30.7	33.8			
75th	69.5	40.2	35.4	29.4	32.8			
80th	70.6	41.5	34.8	27.2	31.4			
85th	71.6	43.2	34.2	24.9	30.1			
90th	73.1	47.0	33.3	22.7	28.5			
95th	82.7	51.9	32.0	20.3	25.5			

Table 6b: P	robability of	f default	evaluated	at	different	Xs and	FE percentiles

Note: Each country's conditional probability of default is computed with the average of its respective observed variables (X,) and different levels of FE.

Tables 6a and 6b illustrate how varying fixed effects can drastically modify the predicted probability of default. This exercise present evidence indicating that the distribution of country fixed effects is by far the dominant contributing factor behind the distribution of default responses, followed by the political risk indicator, the GDP per capita, the external debt relative to GDP and the GDP growth.

This finding has important consequences. , it differs in that it does not assign most of the explanatory power to past defaults per se, but to country specific characteristics. This implies that countries that are identical in terms of observed fundamentals and default history could still display different propensities to default on their debt. Furthermore, the amount of debt these "identical" countries can afford without running into a default would differ too. This would lead to cases where some countries could exhibit a considerably high risk of default even if their level of indebtedness is relatively low. Conversely, other countries may display low default probabilities even at levels of debt that are higher than those observed in the country's debt distribution.

One plausible interpretation of this result is that a sovereign default could be a manifestation or a response to deep-rooted structures. In this context, unobserved heterogeneity could be linked to persistent features that have shaped the institutional background of a country, which influences the government willingness or ability to service its debt. Thus, the main factors in explaining the variation of the probabilities to default across countries -the fixed effects and the political risk indicator- could be seen as two components of the institutional background of a country, the former accounting for the persistent component.

The following section explores what is behind unobserved heterogeneity.

4.3 What underlies unobserved heterogeneity?

The evidence in this paper suggests that time-invariant unobserved heterogeneity is by far the dominant contributing factor behind the variation of default risk across countries. This could be an indication that the main underlying forces could be associated to a set of different historical, political, and cultural factors that have deeply and persistently shaped institutions and economic development in countries. This section explores empirically the extent to which unobserved heterogeneity can be connected to these factors.

Among the literature that studies the causes of substantial differences in the level of economic development across countries, there is a very influential study suggesting that these differences are associated to persistent features in institutions. Accordingly et al. (2001) provide a theory in which variation across countries' institutional background can be explained by different colonial influences. This theory is based on three propositions. First, colonial powers implemented contrasting strategies of colonization that shaped different types of institutions; ranging from extractive structures to "Neo-Europes"³⁶ According to the authors, extractive institutions were created to exploit the existing resources in the colony, while "Neo-Europes" type of institutions were created to provide social order and political structure to Europeans who migrated to colonies. Therefore, the former type of institution was characterized by the lack of property rights or procedures to prevent governments from exerting excessive power; while the latter was characterized by the existence of formal mechanisms to protect property rights and constrain political power. Consequently, the viability of European settlement in a colony was a key factor in determining the choice of the institutional approach. Finally, early structures of governance arranged by colonial powers were inherited by countries after independence, and persisted over time setting the roots of existing institutions. This argument is based on the fact that building good institutions is costly (see Acemoglu and Verdier, 1998). Therefore, if the colonizer already incurred in the cost of setting them, the new ruling elites have incentives to perpetuate the inherited structure instead of shifting to an extractive type of institution. On the other hand, if the colonial power set an extractive institution the new ruler can reap the benefits from maintaining such

 $[\]overline{}^{36}$ As mentioned in Acemoglu *et al.* (2001), "Neo-Europes" is a term coined by the historian Alfred Crosby (1986) to express the attempt of reproducing the institutions prevailing in Europe.

a structure, instead of paying the cost of building a new one.

There is extensive literature that demonstrate how British common law were superior than French civil law in terms of providing protection to property rights, structures to enforce contracts, and checks to political rule-making (see F. A. von Hayek, 1960; Lipset, 1994; La Porta, et al., 1997; among others). These legal traditions were normally inherited by countries through colonization, and their features are associated with political and economic stability.

Table 7 reports regressions of the fixed effects estimates³⁷ on the following controls: (i) a dummy indicating whether the country's legal origin is French with a base case representing countries with British common law origin;³⁸ (ii) the country's level of democracy in its first year of independence;³⁹ (iii) economic growth volatility during the past 40 years; and (iv) political stability.

0							
VARIABLE	DEPENDENT VARIABLE: FE, α_i						
French legal origin dummy	1.734***		1.763***				
Democracy in first year of independence	(0.505)	-0.231**	(0.616) -0.163				
Economic growth volatility		(0.098)	(0.115) 0.450**				
Government stability			(0.163) -0.561*				
Constant	4.613*** (0.451)	6.397*** (0.279)	(0.320) 6.800** (2.470)				
Observations	25	25	25				
R-squared	0.34	0.20	0.55				

Table 7: Regression of Fixed Effects Estimates

Standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Tables 6a and 6b in Section 4.2 showed that increasing the amount of the fixed effects increases the probability of default. Therefore, results in Table 7 indicate that countries with French legal origin are more prone to default, while countries with higher levels of democracy in their first year of independence are less likely to default. Additionally, results suggests that higher economic volatility and lower government stability increase the likelihood of a sovereign debt default.

Although these findings are drawn from a regression with a small sample size,⁴⁰ they still provide noteworthy insight. First, results give some evidence to the hypothesis that what underlies unobserved heterogeneity is a set of country-specific characteristics such as different historical, political, and cultural factors. The interpretation of these results is that country

 $^{^{37}}$ The mean of the fixed effects estimates is 6.0, while the standard deviation is 1.2. The maximum value is 8.4 and the minimum 3.9.

 $^{^{38}}$ Although there are other legal traditions besides these two -like the German civil law and Scandinavian civil law-, countries in the sample have legal origins based on either British common law or French civil law. Data on country's legal origin is from La Porta *et al.* (1999).

³⁹Data on the level on democracy is from the Polity III data set, with scores ranging from 0 to 10 where increasing scores indicates higher degrees of democracy. This indicator is constructed by three subcomponents, which are competitiveness of political participation, competitiveness of executive recruitment, and constraints on chief executive.

⁴⁰Since the fixed effects are estimated at the country level it is difficult to avoid this limitation.

fixed effects are accounting for persistent features deep-rooted in institutions. Secondly, these results are in line with conclusions confirmed by extensive literature in the fields of law, history and political economy, indicating that a country's institutional background can be linked back to its colonial history. In other words, some structures of governance arranged by colonial powers were inherited by the independent nations and persist to the present.

5 Robustness checks

To assess the impact of *occurrence dependence*, a variable is constructed accounting for the percentage of years a country has been in default since its independence year (or 1800, if independence occurred before). This variable changes in percentage points over time when a new default takes place and it is seen as a sufficient statistic for government reputation. Table C.1 in Appendix C report the results of adding the countries' record of default to the estimation. Consistent with Borensztein and Panizza (2008), the effect of reputation on default risk do not appear to be statistically significant, and the point estimates of the coefficients on the other explanatory variables do not present any significant change. A plausible interpretation of this result is that reputation is already captured in the country-specific effect. That is, that the fixed effect accounts for the country's type.

To study if the type of debt matters when assessing the risk of default, two other measures of indebtedness are considered: the present value of external debt relative to GDP and total debt service relative to exports. The estimation of this paper uses as a measure of indebtedness the stock of external public and publicly-guaranteed (PPG) debt⁴¹ at *face value*. That is, it comprises the undiscounted sum of future debt payments. As Tomz and Wright (2013) point out, measuring the stock of debt at its *face value* has two shortcomings. First, future payments at different points in time are treated equally and, second, it only considers future repayments of the principal. To address these issues, external debt is incorporated at its rate of the debt.⁴²

Another measure of indebtedness considered is the total debt service relative to exports, which is a ratio that indicates the fraction of a repayment measure (in this case, exports) that has been already spent on debt payments. Results are reported in Table C.2 (Appendix C). The three different measures of indebtedness yield similar results, as the point estimates of the coefficients on the other explanatory variables do not present statistically significant changes.

Additionally, other variables such as the share of short term debt, reserves relative to imports, inflation rate and openness were considered. However, none of them turned out significant. It is plausible that their variation is already captured by the political risk indicator,

⁴¹It consists of long-term external debt of public borrowers and the fraction of private borrowers for which repayment is guaranteed by a public entity.

 $^{^{42}}$ Alternatively, future debt service obligations could be discounted at market interest rates. However, as Tomz and Wright (2013) highlight, it is more sensible to use the contractual interest rate of debt when the objective is to determine the debt burden of a sovereign, as market values could be misleading.

since liquidity and inflationary issues could be indications of political instability.

Finally, two different bias-correction methodologies, discussed in Appendix B, were also implemented. The first one, carried out by Fernandez-Val (2009), proposes analytical expressions of the bias as does the methodology of Hahn and Kuersteiner (2011). The second one developed by Dhaene and Jochmans (2014), reduces the bias through a jackknife method. All three methods produce very similar results (see Tables B.1 and B.2 in Appendix B).

6 Policy discussion

How much debt can a country afford? This is still an open question in the literature on sovereign debt default and in policy debates. The common wisdom is that the main determinant of the probability of default is a country's record of past defaults, and thus the suggested policy is that EMEs with a default history "may need to aim for far lower levels of external debt-to-GDP than what has been conventionally considered prudent" (see Reinhart and Rogoff, 2009). However, disentangling the factors that underlie the effect from default history on the probability of default is essential for understanding the process that drives a sovereign default decision. That is, knowing whether a country is more likely to default because it has experienced a default in the past or because the country has some previous specific characteristics that make it more prone to default. If the former is the case, then policies that aim to prevent EMEs from entering into a default are required. If the latter is the case, then policies that aim to build better institutions are necessary.

This paper presents evidence suggesting the following. First, default risk differences across EMEs can be explained by some persistent specific characteristics that are associated to historical factors that have shaped deep institutional features, such as protection of property rights or history of macroeconomic instability. This implies that countries that are identical in terms of both fundamentals and default history could still display different propensities to default on their debt, and thus the amount of debt these countries can afford without running into a default would differ too. In this context, under a policy that dismisses these factors EMEs will be imposed to target "safe" debt thresholds that could end up being too restrictive or to loose. A debt threshold that is restrictive might have negative consequences in terms of growth, if, for example, public investment that could boost productivity is not carried out, while debt thresholds that are too loose will increase the risk of default. Secondly, results show a high degree of state dependence in sovereign debt defaults. This implies that policies that affect the current default status will have important dynamic effects. Finally, evidence indicates that countries with relatively better institutional background and lower political risk indicators are able to sustain higher ratios of debt to GDP without running into default risks. This highlights the relevance of structural reforms to institutions and policy frameworks.

7 Final remarks

This paper provides new empirical evidence about the persistence of sovereign debt defaults observed in Emerging Markets Economies (EMEs), by disentangling the relative contributions of both state dependence and unobserved heterogeneity. In the context of a sovereign debt default, unobserved heterogeneity is understood as a set of different historical, political, and cultural factors that have shaped deep and persistent features of institutions and economic development in countries.

Three are the main findings of this paper. First, the variation in the country-specific effects, which account for both unobserved and observed time invariant characteristics, is the main factor behind the differences across countries' propensities to default. Secondly, state dependence effects are large and significant, with results indicating that if a country runs into a default, the probability of defaulting again increases, on average, by 25%. Finally, in terms of the impact of debt on the probability of default, there are countries with significantly high risk of default even if negligible levels of debt are assigned to them. Conversely, other countries show a low probability of default even with assigned levels of indebtedness far higher than those in their sample.

The contributions of this paper are the following. First, it disentangles the relative contribution of state dependence and unobserved heterogeneity in explaining the observed persistence of sovereign debt defaults. Although this study concurs with Reinhart and Rogoff (2009) in that sovereign defaults are only loosely related to the country's debt level, it differs in that it does not assign most of the explanatory power to past defaults, by accounting for both unobserved and observed time invariant characteristics. This is in line with the notion that the omission of time-invariant factors -that influence the country's default likelihood- would make past defaults seem to explain the future probability of default due solely to uncontrolled heterogeneity. Secondly, unlike other studies introducing unobserved heterogeneity, that do not implement methodologies allowing for its consistent estimation, this paper provides a bias-corrected estimate of the time-invariant unobserved heterogeneity that operates as a sufficient statistic for the country's institutional background or country's unobserved type of borrower. This gives the possibility to incorporate this measure in the computation of the country's predicted probability of default, thus helping to explain why some countries may still have high default risk with relatively low levels of external debt and, conversely, why some countries show low probabilities of default even with relatively high levels of external debt. Thirdly, it allows unobserved heterogeneity to be correlated with the observed variables. This might explain the difference with other studies in terms of the impact of debt on the probability of default, since a random effect methodology does not account for the possibility that the same unobserved heterogeneity that is determining the probability of default is also affecting the level of debt a country can sustain. Finally, it presents evidence of the drastic consequences of dismissing unobserved heterogeneity when assessing the country's default risk and the implications this has in terms of policy advice.

References

- Acemoglu, D., Johnson, S., Robinson, J.A., 2001. Colonial origins of comparative development: an empirical investigation. American Economic Review 91, 1369–1401.
- Acemoglu, D., and Verdier, Thierry, 1998. Property Rights, Corruption and the Allocation of Talent: A General Equilibrium Approach." Economic Journal, September 1998, 108(450), pp. 1381-403.
- Aguiar, M., Gopinath, G., 2006. Defaultable debt, interest rates and the current account. Journal of International Economics 69, p. 64-83.
- Aguiar, M. and M. Amador. 2013. Sovereign Debt: A Review. NBER Working Papers 19388.
- Arellano, C., 2008. Default risk and income fluctuations in emerging markets. American Economic Review, 98(3), p. 690-712.
- Arellano, M. and J. Hahn. 2006. Understanding Bias in Nonlinear Panel Models: Some Recent Developments, Invited Lecture, Econometric Society World Congress, London.
- Beers, David T. and John Chambers. 2006. Default Study: Sovereign Defaults At 26-Year Low, To Show Little Change In 2007. Standard & Poor's CreditWeek, September 18.
- Benjamin, D. and M. L. J. Wright, 2009. Recovery Before Redemption: A Theory of Delays in Sovereign Debt Renegotiations. CAMA Working Papers 2009-15, Centre for Applied Macroeconomic Analysis, Crawford School of Public Policy, The Australian National University.
- Borensztein, Eduardo and Ugo Panizza. 2008. The Costs of Sovereign Default. IMF Staff Papers, 56(4): 683-741.
- Bulow, Jeremy & Rogoff, Kenneth, 1989. Sovereign Debt: Is to Forgive to Forget? American Economic Review, American Economic Association, vol. 79(1), pages 43-50, March.
- Catão, Luis A.V. & Bennett Sutton. 2002. Sovereign Defaults: The Role of Volatility. IMF Working Papers 02/149, International Monetary Fund.
- Catão, Luis A.V Fostel, Ana & Kapur, Sandeep, 2009. Persistent gaps and default traps, Journal of Development Economics, Elsevier, vol. 89(2), pages 271-284.
- Cole, H., and P. Kehoe. Reviving Reputation Models of International Debt. Federal Reserve Bank of Minneapolis Quarterly Review, 21(1), 1997, 2130.
- Crosby, Alfred. 1986. Ecological imperialism: The biological expansion of Europe 900-1900. New York: Cambridge University Press, 1986.
- Cuadra, G. and H. Sapriza, 2008. Sovereign default, interest rates and political uncertainty in emerging markets. Journal of International Economics, 76, p.78-88.

- Dhaene, G. and Jochmans, K. 2014. Split-Panel Jackknife Estimation of Fixed-Effect Models. Sciences Po Economics Discussion Papers 2014-03, Sciences Po Department of Economics.
- Detragiache, Enrica and Antonio Spilimbergo (2001). Crises and Liquidity: Evidence and Interpretation. IMF Working Paper No. 01/2.
- D'Erasmo, P., 2008. Government Reputation and Debt Repayment in Emerging Economies. 2008 Meeting Papers 1006, Society for Economic Dynamics.
- Eichengreen, Barry. 2003. Restructuring Sovereign Debt. The Journal of Economic Perspectives, Vol. 17, No. 4 (Autumn, 2003), pp. 75-98.
- Eaton, J. and M. Gersovitz. 1981. Debt with Potential Repudiation: Theoretical and Empirical Analysis. Review of Economic Studies, 48(2), 289-309.
- Flandreau, M. and F. Zumer, 2004, The Making of Global Finance 1880-1913, Paris: OECD.
- Fernandez-Val, I. 2009. Fixed effects estimation of structural parameters and marginal effects in panel probit models. Journal of Econometrics, 150:71-85.
- Fernández-Val, I., Y. Savchenko, and Vella, Francis, 2013. Evaluating the Role of Individual Specific Heterogeneity in the Relationship Between Subjective Health Assessments and Income. IZA Discussion Papers 7651, Institute for the Study of Labor (IZA).
- Hahn, Jinyong & Kuersteiner, Guido, 2011. Bias Reduction for Dynamic Nonlinear Panel Models with Fixed Effects. Econometric Theory, Cambridge University Press, vol. 27(06), pages 1152-1191, December.
- Jorgensen, Erika, and Jeffrey Sachs. 1989. Default and Renegotiation of Latin American Foreign Bonds in the Interwar Period. In The International Debt Crisis in Historical Perspective, ed. Barry Eichengreen and Peter H. Lindert, 48 85. Cambridge, MA. and London: MIT Press.
- Kapetanios, G. 2008. A bootstrap procedure for panel data sets with many crosssectional units. Econometrics Journal, 11:377-395.
- Kraay, Aart & Vikram Nehru, 2006. When Is External Debt Sustainable? World Bank Economic Review, Oxford University Press, vol. 20(3), pages 341-365.
- Krugman, Paul, 1989. Financing vs. forgiving a debt overhang. Journal of Development Economics, Elsevier, vol. 29(3), pages 253-268, November.
- La Porta, R., Lopez-de-Silanes, F., Shleifer, A., Vishny, R., 1997. Legal determinants of external finance. Journal of Finance 52, 1131-1150.
- Lindert, Peter H., and Peter J. Morton. 1989. How Sovereign Debt Has Worked. In Developing Country Debt and Economic Performance Volume 1 the International Financial System, ed. J. D. Sachs, 39106. Chicago: University of Chicago Press.

- McFadden, Daniel, Richard Eckaus, Gershon Feder, Vassilis Hajivassiliou and Stephen O'Connell (1985). "Is There Life After Debt? An Econometric Analysis of the 27 Creditworthiness Developing Countries", in Gordon Smith and John Cuddington, eds., International Debt and the Developing Countries. World Bank: Washington, DC.
- Mendoza, Enrique G. & Ostry, Jonathan D., 2008. International evidence on fiscal solvency: Is fiscal policy "responsible"? Journal of Monetary Economics, Elsevier, vol. 55(6), pages 1081-1093, September.
- Mendoza, E. and V. Yue, 2008. A solution to the default risk-business cycle disconnect. International Finance Discussion Papers 924, Board of Governors of the Federal Reserve System (U.S.).
- Milesi-Ferretti, G-M & Razin, A, 1996. Current-Account Sustainability. Princeton Studies in International Economics 81, International Economics Section, Department of Economics Princeton University.
- Moody's Investors Service 2011. Sovereign Default and Recovery Rates, 1983-2010. Moody's May 10.
- Neyman, J. and E. L. Scott. 1948. Consistent estimates based on partially consistent observations. Econometrica, 16:1-32.
- Nickell, S. 1981. Biases in Dynamic Models with Fixed Effects. Econometrica, 49, 1417-1426.
- Political Risk Services. International Country Risk Guide. New York: Political Risk Services, 2007.
- Reinhart, C., K. Rogoff and M. Savastano, 2003. Debt Intolerance. Brooking Papers on Economic Activity.
- Reinhart, C., and K. Rogoff, 2004. Serial Default and the "Paradox" of Rich-to-poor Capital Flows. American Economic Review, Vol.94(2), pp.53-58.
- Reinhart, Carmen M., and Kenneth S. Rogoff . 2009. This Time Is Different: Eight Centuries of Financial Folly. Princeton, NJ: Princeton University Press.
- Reinhart, Carmen M., and Kenneth S. Rogoff . 2010. Growth in a Time of Debt. American Economic Review, 100(2): 57378.
- S. Reinhart, Carmen М., and Kenneth Rogoff 2011. From Finan-. cial Crash to Debt Crisis: Dataset. American Economic Review. http://www.aeaweb.org/articles.php?doi=10.1257/aer.101.5.1676.
- Rodrik, D. and A. Velasco (1999). Short-Term Capital Flows. Working Paper 7634, NBER.
- Suter, Christian. 1992. Debt Cycles in the World-Economy: Foreign Loans, Financial Crises, and Debt Settlements, 18201990. Boulder, CO: Westview Press.

- Tomz, M., and M. Wright, 2007. Do Countries Default in "Bad" Times? Journal of the European Economic Association, Vol.5(2-3), pp.352-360.
- Tomz, Michael. 2007. Reputation and International Cooperation: Sovereign Debt across Three Centuries. Princeton, NJ: Princeton University Press.
- Tomz, M., and M. Wright, 2013. Empirical Research on Sovereign Debt and Default. Annual Review of Economics, Annual Reviews, vol. 5(1), pages 247-272.
- Vella, F., Verbeek, M., 1998. Whose wages do unions raise? A dynamic model of unionism and wage rate determination for young men. Journal of Applied Econometrics.

Appendix A

Table A: Sovereign debt default episodes

COUNTRY		YEARS		EXTERNAI	. DEBT TO (GDP (%)	DEBT SEF	RVICE TO O	GDP (%)	GDP G	ROWT	н (%)
	Start	End	Length	Start	Mean	End	Start	Mean	End	Start	Mean	End
Algeria	1991	1996	6	57.4	61.6	66.6	19.7	14.2	8.5	-0.9	0.9	4.2
Argentina	1982	1993	12	18.8	33.7	19.4	2.8	4.6	1.9	-4.6	1.9	6.3
Argentina	2001	2005	5	30.9	56.5	29.6	2.6	9.6	1.7	-4.4	2.4	9.3
Bolivia	1980	1984	5	48.1	51.9	54.7	6.4	7.2	10.3	-1.3	-1.9	0.0
Bolivia	1986	1997	12	102.8	74.1	52.1	6.1	5.5	4.0	-2.2	3.5	5.1
Brazil	1983	1994	12	29.6	25.4	17.5	3.7	2.9	1.6	-3.4	2.6	5.1
Brazil	2002	2002	1	19.7	19.7	19.7	4.3	4.3	4.3	3.4	3.4	3.4
Chile	1972	1972	1	22.4	22.4	22.4	0.9	0.9	0.9	-0.7	-0.7	-0.7
Chile	1974	1975	2	24.4	38.0	51.6	1.8	4.4	6.9	3.0	-4.3	-11.6
Chile	1983	1990	8	33.4	56.4	33.0	4.3	6.1	5.1	-3.7	5.6	3.7
Costa Rica	1981	1981	1	84.3	84.3	84.3	23.8	23.8	23.8	-2.3	-2.2	-2.3
Costa Rica	1983	1990	8	79.0	62.8	41.3	15.3	9.8	5.9	3.0	4.5	3.9
Côte d'Ivoire	1983	1998	16	70.8	93.3	84.5	13.9	9.5	6.9	-4.1	1.8	4.7
Côte d'Ivoire	2000	2010	11	87.0	64.6	45.4	8.3	5.6	0.0	-3.7	0.7	2.4
Dominican Republic	1982	1994	13	20.9	39.3	24.9	3.5	4.7	3.1	2.0	3.2	2.7
Dominican Republic	2005	2005	1	17.9	17.9	17.9	3.2	3.2	3.2	9.2	9.2	9.2
Ecuador	1982	1995	14	29.5	72.8	59.1	8.4	11.0	6.3	0.0	2.2	2.0
Ecuador	1999	2000	2	79.7	73.9	68.2	10.3	8.5	6.8	-6.1	-1.7	2.6
Ecuador	2008	2008	1	18.5	18.5	18.5	N.A.	N.A.	N.A.	7.2	7.2	7.2
Egypt	1984	1984	1	83.7	83.7	83.7	9.3	9.3	9.3	6.5	6.5	6.5
Ghana	1970	1970	1	22.9	22.9	22.9	N.A.	N.A.	N.A.	6.0	6.0	6.0
Ghana	1974	1974	1	18.1	18.1	18.1	0.7	0.7	0.7	6.7	6.7	6.7
Ghana	1987	1987	1	44.3	44.3	44.3	3.5	3.5	3.5	4.9	4.9	4.9
Guatemala	1986	1986	1	31.9	31.9	31.9	5.5	5.5	5.5	0.1	0.1	0.1
Guatemala	1989	1989	1	24.8	24.8	24.8	3.5	3.5	3.5	4.0	4.0	4.0
Honduras	1981	2010	30	43.9	65.0	18.2	4.2	6.6	0.0	2.5	3.3	2.8
India	1972	1976	5	13.5	12.6	13.2	0.9	0.8	0.8	-0.6	2.9	1.7
Indonesia	1970	1970	1	37.1	37.1	37.1	N.A.	N.A.	N.A.	8.1	8.1	8.1
Indonesia	1998	2000	3	70.8	55.3	42.2	10.3	8.3	5.3	-13.2	-2.4	5.3
Indonesia	2002	2002	1	36.4	36.4	36.4	3.7	3.7	3.7	4.9	4.9	4.9
Kenya	1994	2003	10	77.1	46.2	39.0	10.0	4.9	3.4	2.6	2.5	2.9
Mexico	1982	1990	9	29.7	42.2	28.9	5.7	5.7	3.0	-0.6	1.1	5.0

Source: Author's calculation from data in Reinhart and Rogoff (2011) and World Bank (WDI).

Table A: Sovereign debt default episodes (cont'd)

COUNTRY		YEARS		EXTERNAL DEBT TO GDP (%) DEBT SERVICE TO GDP (%) GDF			GDP G	GDP GROWTH (%)				
	Start	End	Length	Start	Mean	End	Start	Mean	End	Start	Mean	End
Morocco	1983	1983	1	76.1	76.1	76.1	9.4	9.4	9.4	-0.4	-0.4	-0.4
Morocco	1986	1990	5	93.3	93.0	91.6	9.5	8.2	5.8	8.4	4.6	4.0
Nicaragua	1979	2010	32	69.2	212.2	40.5	10.9	18.5	0.0	-26.3	0.9	4.5
Nigeria	1982	1992	11	16.3	80.5	80.9	2.9	11.5	17.4	-0.3	3.1	2.8
Nigeria	2001	2001	1	60.9	60.9	60.9	5.9	5.9	5.9	3.1	3.1	3.1
Nigeria	2004	2005	2	37.0	27.5	18.0	4.0	5.9	7.8	10.7	8.0	5.4
Panama	1983	1996	14	64.0	62.5	55.1	9.8	10.7	8.5	-4.5	2.3	2.8
Paraguay	1986	1992	7	51.5	41.8	21.2	7.5	7.2	9.4	0.0	3.7	3.4
Paraguay	2003	2004	2	39.6	37.3	35.0	4.1	4.5	4.9	3.6	3.8	4.1
Peru	1976	1976	1	23.6	23.6	23.6	2.9	2.9	2.9	2.0	2.0	2.0
Peru	1978	1978	1	44.9	44.9	44.9	6.2	6.2	6.2	0.3	0.2	0.3
Peru	1980	1980	1	30.1	30.1	30.1	7.3	7.3	7.3	3.0	3.0	3.0
Peru	1984	1997	14	46.1	50.2	32.4	8.3	7.8	4.8	5.3	2.7	6.4
Philippines	1981	1992	12	21.0	46.7	48.8	2.4	5.6	7.2	3.4	1.5	0.3
Sri Lanka	1979	1979	1	30.2	30.2	30.2	2.3	2.3	2.3	6.4	6.4	6.4
Sri Lanka	1981	1983	3	34.2	38.1	40.9	2.1	2.8	3.2	5.6	4.9	4.8
Tunisia	1979	1982	4	44.2	42.2	44.7	5.2	6.1	6.7	6.5	4.7	-0.5
Turkey	1978	1979	2	8.2	10.1	11.9	0.6	0.7	0.9	1.6	0.5	-0.6
Turkey	1982	1982	1	24.5	24.5	24.5	3.5	3.5	3.5	3.8	3.8	3.8
Turkey	2001	2001	1	27.4	27.4	27.4	5.9	5.9	5.9	-5.7	-5.7	-5.7
Uruguay	1983	1985	3	49.2	52.8	57.0	6.0	7.7	8.6	-10.1	-3.4	1.2
Uruguay	1987	1987	1	42.4	42.4	42.4	5.5	5.5	5.5	8.1	8.1	8.1
Uruguay	1990	1991	2	32.7	29.3	25.9	7.6	6.7	5.7	0.0	1.8	3.7
Uruguay	2003	2003	1	62.0	62.0	62.0	5.7	5.7	5.7	2.0	2.0	2.0
Venezuela	1983	1988	6	18.9	37.4	43.1	3.5	5.7	5.6	-3.7	2.3	5.9
Venezuela	1990	1990	1	52.1	52.1	52.1	8.9	8.9	8.9	6.7	6.7	6.7
Venezuela	1995	1997	3	38.0	37.0	31.9	5.0	6.4	8.9	4.0	3.3	6.4
Venezuela	2004	2005	2	23.6	22.5	21.3	4.5	3.8	3.0	18.2	14.2	10.2
Zambia	1983	1994	12	75.4	137.1	154.8	6.2	13.4	9.2	-1.8	0.3	-8.6
Zimbabwe	1970	1974	5	12.2	8.6	5.5	0.0	0.5	0.4	22.6	9.7	6.5
Zimbabwe	2000	2009	10	37.5	65.8	64.1	5.7	7.0	0.0	-7.8	-5.8	6.0

Source: Author's calculation from data in Reinhart and Rogoff (2011) and World Bank (WDI).

Appendix B Incidental Parameter Problem and Bias-correction

The incidental parameter bias arises because in the estimation of the parameters of main interest, the specific effects are replaced by estimates. Given that in non-linear panels we can not separate the specific effects, their estimation error will contaminate the main parameter estimates. To see this, let $f_{it}(\theta, \alpha_i) = f(y_{it}|x_{it}; \theta, \alpha_i)$ be the MLE density function of θ_0 where $\theta = (\tau, \beta, \delta)$.

$$\hat{\theta} \equiv \arg \max_{\theta} \frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} \log f_{it}(\theta, \hat{\alpha}_{i}(\theta))$$
$$\hat{\alpha}_{i}(\theta) \equiv \arg \max_{\alpha} \frac{1}{T} \sum_{t=1}^{T} \log f_{it}(\theta, \alpha_{i})$$

So, $\hat{\theta}$ is inconsistent for θ_0 because it includes the error estimation of the incidental parameters $\alpha_1, ..., \alpha_N$ (Neyman and Scott, 1948). $\hat{\theta}$ converges in probability to θ_T , where

$$\theta_T = \arg \max_{\theta} \frac{1}{T} E_n \left[\sum_{t=1}^T \log f_{it}(\theta, \hat{\alpha}_i(\theta)) \right]$$

Given that the true conditional log-likelihood is $\log f_{it}(\theta_0, \alpha_i)$ the result is that $\theta_T \neq \theta_0$ because $\hat{\alpha}_i(\theta_0) \neq \alpha_i$ when T is finite.

Let μ represents the average marginal effects:⁴³

$$\hat{\mu}(\theta) \equiv \frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} m_{it}(\hat{\theta}, \hat{\alpha}_i(\theta))$$

The average marginal effects also need to be bias-corrected, this estimator has two sources of bias: the estimation errors from $\hat{\alpha}$ and $\hat{\theta}$ respectively.

To tackle the incidental parameter problem, the bias-correction methodology proposed by Hahn and Kuersteiner (2011) is implemented. As a robustness check, two other methodologies were also carried out. The first one, developed by Fernandez-Val (2009), proposes analytical expressions of the bias as does the methodology of Hahn and Kuersteiner (2011). The second one developed by Dhaene and Jochmans (2014), reduces the bias of the profile log-likelihood through a jackknife method. All three methods produce very similar estima-

⁴³The average marginal effect (AME) consists in calculating the marginal effect for each country *i*, with its respective explanatory variables and fixed effect, at every point in time t and then, averaging across time and countries. The AME approach is preferred over computing marginal effects evaluated at the sample mean (MEM), since the former takes into account the observed and unobserved heterogeneity of each country and the correlation of the latter with the explanatory variables. It is especially important to look at AMEs if there is an important degree of heterogeneity across countries and if one is interested in understanding the impact of the country specific effect, α_i , on the probability of default. In MEMs the effect of unobserved heterogeneity is vanished since its computation uses the sample mean of the countries' fixed effects, instead of each country's fixed effects.

tion results for the probability of default equation (see Tables B.1 and B.2). The following subsections explain the three approaches.

Hahn and Kuersteiner (2011) bias correction methodology

The analytical bias correction proposed by Hahn and Kuersteiner (2011) adjusts the estimator using the moment equation. It uses Taylor series expansion of the first-order condition to formulate the expression for the bias. The following notation is used:

$$u_{it}(\theta, \alpha) \equiv \frac{\partial}{\partial \theta} \log f_{it}(y_{it}/\theta, \alpha), \quad v_{it}(\theta, \alpha) \equiv \frac{\partial}{\partial \alpha} \log f_{it}(y_{it}/\theta, \alpha)$$
(1)

$$v_{it}^{\alpha_i} = \frac{\partial}{\partial \alpha} v_{it}(\theta, \alpha), \qquad u_{it}^{\alpha_i} = \frac{\partial}{\partial \alpha} u_{it}(\theta, \alpha)$$
 (2)

$$U_{it}(\theta,\alpha) \equiv u_{it}(\theta,\alpha) - v_{it}(\theta,\alpha) E[v_{it}^{\alpha_i}]^{-1} E[u_{it}^{\alpha_i}]$$
(3)

$$U_{it}^{\alpha_i}(\theta,\alpha) \equiv \frac{\partial U_{it}(\theta,\alpha)}{\partial \alpha_i}, \qquad \qquad U_{it}^{\alpha_i\alpha_i}(\theta,\alpha) \equiv \frac{\partial^2 U_{it}(\theta,\alpha)}{\partial \alpha_i^2} \tag{4}$$

$$I_i \equiv -E[\frac{\partial U_{it}(\theta_0, \alpha_{i0})}{\partial \theta'}] = -E[U_{it}^{\theta}]$$
(5)

As Hahn and Kuersteiner (2011) explain, the analytical expression for the bias can be found by "considering an infeasible estimator $\check{\theta}$ based on $\hat{\alpha}_i(\theta_0)$ rather than $\hat{\alpha}_i(\hat{\theta})$, where $\check{\theta}$ solves the first order conditions $0 = \sum_{i=1}^{N} \sum_{t=1}^{T} U_{it}(x_{it}, \check{\theta}, \hat{\alpha}_i(\theta_0))$ ". The authors show that the analytical expression for the bias is:

$$B = \left(\lim_{n \to \infty} \frac{1}{N} \sum_{i=1}^{N} I_i\right)^{-1} \lim_{n \to \infty} \frac{1}{N} \sum_{i=1}^{N} b_i(\theta_0)$$
(6)

where $b_i(\theta_0)$ is the bias of the score function and

$$b_i(\theta_0) = -\left(\frac{f_i^{VU^{\alpha}}}{E[v_{it}^{\alpha_i}]} - \frac{E[U_{it}^{\alpha_i\alpha_i}]f_i^{VV}}{2(E[v_{it}^{\alpha_i}])^2}\right)$$
(7)

where $f_i^{VU^{\alpha}} \equiv \sum_{l=-\infty}^{\infty} cov(v_{it}, U_{it-l}^{\alpha_i})$ and $f_i^{VV} \equiv \sum_{l=-\infty}^{\infty} cov(v_{it}, v_{it-l})$

The intuition is that the estimation noise from estimating alpha distorts the properties of the likelihood estimator. This can be seen in equation (7) where the correlation between the scores of theta and alpha determine the bias. Also see the discussion on page 1160 of Hahn and Kuersteiner (2011), where the authors expand the first order condition for theta in terms of alpha and show that the noise from estimating alpha is correlated with the score of theta.

According to Hahn and Kuersteiner (2011), the bias correction proceeds as follows:

First, compute the fixed effects estimator $\hat{\theta}$ and $\hat{\alpha}_1, ..., \hat{\alpha}_N$.

- **Secondly,** construct the sample analogs of the expressions 1 to 4, i.e. \hat{u}_{it} , \hat{v}_{it} , $\hat{u}_{it}^{\alpha_i}$, \hat{U}_{i
- **Thirdly,** using the sample analogs from step 2 calculate $\hat{I}_i \equiv -\frac{1}{T} \sum_{t=1}^T \hat{U}_{it}^{\theta}$, $\hat{E}[U_{it}^{\alpha_i \alpha_i}] \equiv -\frac{1}{T} \sum_{t=1}^T \hat{U}_{it}^{\alpha_i \alpha_i}$, $\hat{E}[v_{it}^{\alpha_i}] \equiv -\frac{1}{T} \sum_{t=1}^T \hat{v}_{it}^{\alpha_i}$
- **Fourthly,** select a bandwidth m^{44} and compute the estimators of $f_i^{VU^{\alpha}}$ and f_i^{VV} , $\hat{f}_i^{VU^{\alpha}} \equiv \frac{1}{T} \sum_{l=-m}^m \sum_{t=\max(1,l)}^{\min(T,T+l)} (\hat{v}_{it}, \hat{U}_{it-l}^{\alpha_i})$ and $\hat{f}_i^{VV} \equiv \frac{1}{T} \sum_{l=-m}^m \sum_{t=\max(1,l)}^{\min(T,T+l)} (\hat{v}_{it}\hat{v}_{it-l})$
- **Finally,** plug the sample analogs from the previous steps in the estimator of the bias of the score function $\hat{b}_i(\theta)$ and then, together with \hat{I}_i compute the bias of the estimator $\hat{\theta}, \hat{B}$:

$$\hat{B} = \left(\frac{1}{N}\sum_{i=1}^{N} \hat{I}_i\right)^{-1} \frac{1}{N}\sum_{i=1}^{N} \hat{b}_i(\theta)$$

Then, the bias-corrected estimator, $\tilde{\theta}$, is:

$$\tilde{\theta} \equiv \hat{\theta} - \frac{\hat{B}}{T}$$

Fernandez-Val (2009) bias correction methodology

The analytical bias correction proposed by Fernandez-Val (2009) construct an estimate of the bias in the score function using expected quantities instead of the observed ones.

The asymptotic expansion of the bias in the parameter of main interest is:

$$\theta_T = \theta_0 + \frac{B}{T} + O(\frac{1}{T})$$

The higher-order expansion of the asymptotic bias of the individual effects estimator, evaluated at its true value, is the following:

$$\hat{\alpha}_i(\theta_0) = \alpha_{i0} + \frac{\psi_i}{(T)^{1/2}} + \frac{\tau_i}{T} + O_p(\frac{1}{T})$$
(8)

Then, the estimator of the bias is:

$$\hat{B}(\theta) = -\hat{J}(\theta)^{-1}\hat{b}(\theta) \tag{9}$$

where $\hat{J}(\theta)$ and $\hat{b}(\theta)$ are the estimators of the Jacobian and the bias of the estimating equation for θ , respectively. The bias of the estimating equation, $b(\theta)$, arises from the bias present in $\hat{\alpha}_i(\theta_0)$. Thus, $b(\theta)$ comprises the correlation between the score function of θ_1^{45} and the first-order term of the asymptotic bias present in $\hat{\alpha}_i(\theta_0)$ (the influence function ψ_i in equation 8); it also contains the higher-order bias (τ_i in equation 8) and the variance of

⁴⁴See Hahn and Kuersteiner (2011) Appendix G for bandwidth selection.

⁴⁵The partial derivative of the score function -that generates the estimating equation for θ_1 - with respect to α_1 .

 $\hat{\alpha}_i(\theta_0)$, both arising from nonlinearities. For a full characterization of the bias components, see Fernandez-Val (2009).

The author also proposed the following bias correction for the average marginal effects:

$$\tilde{\mu} \equiv \hat{\mu}(\tilde{\theta}_1) - \frac{1}{NT} \sum_{i=1}^N \hat{\Delta}_i$$

where $\hat{\mu}(\tilde{\theta}_1)$ are the AMEs evaluated at the bias-corrected estimates $\tilde{\theta}_1$ and $\tilde{\alpha}_{1i}$. For the full characterization of the bias $\hat{\Delta}_i$ see Fernandez-Val (2009) page 76.

Dhaene and Jochmans (2014) bias correction methodology

The Split-panel Jackknife Estimator (SPJE) from Dhaene and Jochmans (2014) consists on splitting the panel into blocks of data, so the bias can be estimated from the sub-panels. They propose a bias-correction methodology for the maximum likelihood estimator (MLE), the profile likelihood and for the average marginal effects. This paper focus on the bias correction of the objective function and estimate the marginal effects with the bias-corrected estimates. The reasons for choosing to bias correct the objective function instead of the MLE are the following. First, the latter is more sensitive than the former to observations that might drop the sub-panels (because they do not present a change in status that allows the parameters to be identified). Secondly, the bias correction of the objective function can be extended to include an unbalanced panel.

The first-order bias-correction of the objective function is as follows. The panel is split into two sub-panels of T/2 time periods keeping all the N cross-sectional units. Let the subpanels be: $S_1 = \{1, ..., T/2\}$ and $S_2 = \{T/2 + 1..., T\}$. Let $\hat{l}(\theta) = \frac{1}{NT} \sum \sum \log f_{it}(\theta, \hat{\alpha}_i(\theta))$, so the half-panel jackknife profile log-likelihood is:

$$\hat{l}_{T/2}(\theta) = 2\hat{l}(\theta) - \bar{l}_{T/2}(\theta)$$

where $\bar{l}_{T/2}(\theta) \equiv \frac{1}{2}(\hat{l}_{S_1}(\theta) + \hat{l}_{S_2}(\theta)).$

The estimator that corrects for the second-order bias requires the panel to be split into two and three sub-panels. The three sub-panel are: $S_1 = \{1, ..., T/3\}, S_2 = \{T/3+1..., 2/3T\}$ and $S_3 = \{2/3T + 1..., T\}$. The second-order bias correction of the objective function is:

$$\hat{l}_{T/\{2,3\}}(\theta) = 3\hat{l}(\theta) - 3\bar{l}_{T/2}(\theta) + \bar{l}_{T/3}(\theta)$$

where $\bar{l}_{T/3}(\theta) \equiv \frac{1}{3}(\hat{l}_{S_1}(\theta) + \hat{l}_{S_2}(\theta) + \hat{l}_{S_3}(\theta))$ and $\bar{l}_{T/2}(\theta)$ as described above. So, the corresponding split the panel jackknife estimators are:

$$\theta_{T/2} \equiv \arg \max l_{T/2}(\theta)$$

 $\dot{\theta}_{T/3} \equiv \arg \max \hat{l}_{T/\{2,3\}}(\theta)$

Then the average marginal effects are computed with the respective bias corrected es-

timates of θ and α_i .⁴⁶

See Tables B.1 and B.2 that report the index coefficients and marginal effects under the three bias-correction methodologies. The first and second columns report the results using Fernandez-Val, 2009 (FV) and Hahn and Kuersteiner, 2011 (HK) bias correction methodologies. The last two columns report the split-panel jackknife estimates (SPJL_1/2 and SPJL_1/{2,3}), which correct the likelihood function for the first and second order bias respectively. The four estimators yield similar results. Only the second order bias correction of the split-panel jackknife estimates (SPJL_1/{2,3}) differs marginally from the other bias-corrected estimates, this can be explained by the fact that splitting the panel in three implies a loss of observations in the sub-panels. This goes in favor of the use of analytical methodologies like FV and HK. However, when looking at the average marginal effects (Table B.2) all the methodologies yield almost same estimates.

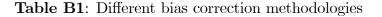


Table B1: Different bias correction methodologies									
Dependent variable: default dummy, 1985-2010									
		INDEX CO	FFICIENTS						
VARIABLE	DIFFERENT BIAS CORRECTION METHODOLOGIES								
	НК	FV	SPJL1/2	SPJL1/{2,3}					
Default lag	1.866***	1.789***	1.936***	2.056***					
	(0.204)	(0.198)	(0.204)	(0.209)					
	[0.350]	[0.292]	[0.329]	[0.401]					
PPG external debt-to-GDP (%)	0.015	0.013	0.017	0.024					
	(0.008)	(0.007)	(0.008)	(0.008)					
	[0.013]	[0.011]	[0.014]	[0.018]					
GDP growth lag (%)	-0.061*	-0.059*	-0.062*	-0.056					
	(0.025)	(0.024)	(0.025)	(0.024)					
	[0.034]	[0.030]	[0.033]	[0.042]					
Political Risk Indicator	-0.075***	-0.065***	-0.077***	-0.087**					
	(0.017) (0.015) (0.017) (0.01								
	[0.028]	[0.022]	[0.026]	[0.040]					
Log GDP per capita	-0.538	-0.413	-0.317	-0.028					
	(0.545)	(0.512)	(0.537)	(0.530)					
	[0.816]	[0.663]	[0.785]	[1.045]					
Observations	650	650	650	650					

Note: Asymptotic standard errors in parenthesis, bootstrap standard errors in brackets (999 replications) Country and year dummies included. Sample size: N=36, T=26. *** p<0.01, ** p<0.05, * p<0.1 (using bootstrap standard errors)

Table B2: Different bias correction methodologies

Dependent variable: default dummy, 1985-2010									
	AVERAGE MARGINAL EFFECTS								
	DIFFERENT BIAS CORRECTION METHODOLOGIES								
VARIABLE	НК	FV	SPJL1/2	SPJL1/{2.3}					
Default lag	0.247***	0.257***	0.252***	0.249***					
	[0.072]	[0.069]	[0.084]	[0.093]					
PPG external debt-to-GDP (%)	0.001	0.001	0.001	0.002					
	[0.001]	[0.001]	[0.001]	[0.002]					
GDP growth lag (%)	-0.005*	-0.005**	-0.005*	-0.005					
	[0.003]	[0.003]	[0.003]	[0.004]					
Political Risk Indicator	-0.006***	-0.006***	-0.006**	-0.007**					
	[0.002]	[0.002]	[0.003]	[0.003]					
Log GDP per capita	-0.042	-0.036	-0.026	-0.002					
	[0.053]	[0.051]	[0.063]	[0.079]					
Observations	650	650	650	650					

Table B2: Different bias correction methodologies Dependent variable: default dummy, 1985-2010

Note: Asymptotic standard errors in parenthesis, bootstrap standard errors in brackets (999 replications). Country and year dummies included. Sample size: N=36, T=26. *** p<0.01, ** p<0.05, * p<0.1 (using bootstrap standard errors)

⁴⁶According to the authors, the bias-corrected estimators have the same variance as the MLE and it is asymptotically unbiased.

Appendix C: Robustness checks

 Table C1: The effect of occurrence dependence

Dependent variable: default dummy, 1985-2010								
	INDEX CO	FFICIENTS	AVERAGE MARGINAL EFFECTS					
VARIABLE	BC MLE	BC MLE	BC MLE	BC MLE				
Default lag	1.789*** (0.198)	1.795*** (0.206)	0.257***	0.258***				
2	[0.292]	[0.317]	[0.069]	[0.070]				
% years in default ²		-0.003 (0.024) [0.035]		-0.0002				
PPG external debt-to-GDP (%)	0.013 (0.007)	0.013 (0.007)	0.001	0.001				
	[0.011]	[0.011]	[0.001]	[0.001]				
GDP growth lag (%)	-0.059* (0.024)	-0.058* (0.024)	-0.005**	-0.005**				
	[0.030]	[0.030]	[0.003]	[0.003]				
Political Risk Indicator	-0.065*** (0.015)	-0.065*** (0.015)	-0.006***	-0.006***				
	[0.022]	[0.022]	[0.002]	[0.002]				
Log GDP per capita	-0.413 (0.512)	-0.416 (0.513)	-0.036	-0.036				
	[0.663]	[0.669]	[0.051]	[0.053]				
Observations	651	651	651	651				

Note1: Asymptotic standard errors in parenthesis, bootstrap standard errors in brackets (999 replications). Country and year dummies included. Sample size: N=36, T=26. *** p<0.01, ** p<0.05, * p<0.1 (using bootstrap standard errors)

Note2: It accounts for the percentage years in default since each country's independence year.

Table C2: Does the type of debt matter?

Dependent variable: default dummy, 1985-2010									
	INI	AVERAGE MARGINAL EFFECTS							
		TYPE OF DEBT		TYPE OF DEBT					
VARIABLE	PPG external debt/GDP (%)	Total debt service/ exports (%)	Present value external debt/GDP (%)	PPG external debt/GDP (%)	Total debt service/ exports (%)	Present value external debt/GDP (%)			
Default lag	1.789*** (0.198)	1.788*** (0.198)	1.778*** (0.198)	0.257***	0.278***	0.277***			
Measure of indebtedness	[0.292] 0.013 (0.007) [0.011]	[0.302] 0.013 (0.010) [0.014]	[0.295] 0.014 (0.008) [0.011]	0.001	0.001	[0.078] 0.001 [0.001]			
GDP growth lag (%)	-0.059* (0.024) [0.030]	-0.051* (0.024) [0.030]	-0.051* (0.024) [0.029]	-0.005*	-0.005*	-0.005*			
Political Risk Indicator	-0.065*** (0.015) [0.022]	-0.058*** (0.015) [0.018]	-0.061*** (0.015) [0.020]	-0.006***	-0.005***	-0.006***			
Log GDP per capita	-0.413 (0.512) [0.663]	-1.090* (0.435) [0.599]	-0.513 (0.531) [0.663]	-0.036	-0.103** [0.047]	-0.049			
Observations	650	650	650	650	650	650			

Note: Asymptotic standard errors in parenthesis, bootstrap standard errors in brackets (999 replications). Country and year dummies included. Sample size: N=36, T=26.

*** p<0.01, ** p<0.05, * p<0.1 (using bootstrap standard errors)