Online Appendix

Sovereign Debt Pricing with Shifting Long-run Growth Expectations

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A Descriptive statistics for real-time estimation errors in potential output growth estimates

We report descriptive statistics for the real-time estimation errors in potential output growth rates, $\tilde{\gamma}_t^{i,err}$, in Table A.1. Similar to Paluszynski (2023), we divide the sample into subgroups. As shown, estimation errors for GIIPS countries are larger than the average of non-GIIPS countries, as measured by both the mean, standard deviation and root mean squared error (RMSE). We also observe overestimation in trend growth ($\tilde{\gamma}_t^{i,err} > 0$) prior to and during the recession (2008–2011), and prevalent underestimation ($\tilde{\gamma}_t^{i,err} < 0$) in the post-recession phase (2012–2015).

Similarly, Table A.2 reports the descriptive statistics for components of $\tilde{\gamma}_t^{i,err}$: real-time estimates of potential GDP growth rates $\tilde{\gamma}_t^i$ and the HP-filtered ex post trend growth γ_t^i. Statistics are also divided into sub-samples.

Table A.1: Descriptive stats for $\tilde{\gamma}_t^{i,err}$ data among EU economies

	EEF $\tilde{\gamma}_t^{i,err}$			WEO $\tilde{\gamma}_t^{i,err}$		
	Mean	Std	RMSE	Mean	Std	RMSE
Full sample: 1999-2019						
Greece	0.73	1.48	1.62	0.75	0.94	1.18
Ireland	-0.62	2.73	2.74	-0.77	2.25	2.32
Italy	0.42	0.55	0.68	0.37	0.58	0.68
Spain	0.11	0.86	0.84	0.31	0.72	0.77
Portugal	0.18	0.71	0.71	0.31	0.60	0.66
Non-GIIPS	0.11	0.46	0.49	0.11	0.38	0.40
Pre-recession: 1999-2007						
Greece	0.96	1.54	1.74	-0.34	0.62	0.63
Ireland	2.03	0.90	2.20	1.48	0.94	1.73
Italy	0.69	0.64	0.91	0.72	0.24	0.76
Spain	0.44	1.04	1.07	0.28	0.91	0.90
Portugal	0.64	0.45	0.77	0.75	0.27	0.79
Non-GIIPS	0.13	0.56	0.57	0.17	0.39	0.42
Recession: 2008-2011						
Greece	2.27	1.36	2.56	1.81	0.80	1.92
Ireland	-2.88	1.79	3.27	-2.72	1.26	2.93
Italy	0.61	0.16	0.63	0.14	1.17	1.02
Spain	0.06	0.42	0.37	0.55	0.70	0.82
Portugal	0.08	0.24	0.22	0.43	0.25	0.49
Non-GIIPS	0.20	0.24	0.34	0.03	0.45	0.44
Post-recession: 2012-2015						
Greece	-0.58	0.28	0.63	1.12	0.35	1.16
Ireland	-3.54	0.98	3.64	-2.80	0.92	2.91
Italy	-0.17	0.16	0.22	-0.003	0.19	0.16
Spain	-0.81	0.25	0.84	-0.13	0.52	0.47
Portugal	-0.95	0.38	1.01	-0.69	0.08	0.69
Non-GIIPS	-0.22	0.17	0.33	-0.10	0.24	0.26

Notes: $\tilde{\gamma}_t^{i,err}$ values are expressed in percentage points. Std denotes the standard deviation. In calculating RMSE, the HP-filtered trend growth rate γ_t^i is treated as the benchmark (true value). "Non-GIIPS" refers to the average of statistics across non-GIIPS countries: Austria, Belgium, Germany, Finland, France, and the Netherlands. All real-time trend growth estimates $\tilde{\gamma}_t^i$ are taken from the Spring editions of the EEF and WEO.

Table A.2: Descriptive stats for $\tilde{\gamma}_t^i$ and γ_t^i data among EU economies

	EEF $\tilde{\gamma}_t^i$		WEO $\tilde{\gamma}_t^i$		HP-filtered γ	
	Mean	Std	Mean	Std	Mean	Std
Full sample: 1999-2019						
Greece	0.88	2.76	0.46	1.97	0.15	2.42
Ireland	4.33	3.45	4.17	3.05	4.94	1.94
Italy	0.70	0.95	0.65	1.07	0.29	0.71
Spain	1.72	1.61	1.93	1.30	1.61	1.29
Portugal	1.01	1.41	1.15	1.23	0.84	0.86
Non-GIIPS	1.64	0.73	1.64	0.70	1.53	0.60
Pre-recession: 1999-2007						
Greece	3.56	0.32	3.42	0.40	2.60	1.38
Ireland	6.92	1.27	6.37	1.58	4.89	1.60
Italy	1.64	0.43	1.68	0.37	0.96	0.55
Spain	3.37	0.35	3.21	0.23	2.93	0.81
Portugal	2.14	0.98	2.25	0.66	1.50	0.80
Non-GIIPS	2.23	0.46	2.28	0.33	2.11	0.41
Recession: 2008-2011						
Greece	0.45	2.14	-0.35	1.30	-1.82	0.80
Ireland	-0.40	1.56	-0.24	1.28	2.48	0.35
Italy	0.25	0.26	-0.22	1.17	-0.36	0.15
Spain	0.73	0.74	1.21	1.04	0.66	0.35
Portugal	0.00	0.39	0.35	0.37	-0.08	0.15
Non-GIIPS	1.34	0.30	1.17	0.50	1.14	0.14
Post-recession: 2012-2015						
Greece	-2.93	0.62	-1.22	0.23	-2.34	0.39
Ireland	1.45	2.07	2.19	1.86	4.99	1.11
Italy	-0.53	0.22	-0.36	0.31	-0.35	0.14
Spain	-0.38	0.39	0.30	0.66	0.44	0.16
Portugal	-0.80	0.62	-0.54	0.33	0.15	0.28
Non-GIIPS	0.81	0.19	0.92	0.25	1.02	0.05

Notes: Data are expressed in percentage points. $\tilde{\gamma}_t^i$ denotes real-time potential output growth rate estimates published by Spring editions of the EEF and WEO, γ_t^i denotes the growth rate for HP-filtered GDP trend growth rate (source: Eurostat). Std denotes the standard deviation. "Non-GIIPS" refers to the average of statistics across non-GIIPS countries: Austria, Belgium, Germany, Finland, France, and the Netherlands.

B Supplementary details for Evidence 1: Systematic errors in real-time potential GDP growth estimates

To supplement the analysis of errors in real-time potential output growth estimates relative to HP-filtered trend growth rates, Table B.1 reports results using three alternative filtering methods commonly used in macroeconomic analysis: the Hamilton filter, the Christiano-Fitzgerald (CF) filter, and the Baxter-King (BK) filter.

For the Hamilton filter, we set a lead length of 2 and a lag length of 1. For both the CF and BK filters, we use a lower cutoff of 2, an upper cutoff of 8, and a lag length of 3, all suitable for annual frequency data. All filtering calculations are implemented using MATLAB's built-in functions in the Econometrics Toolbox.

Table B.1: Estimated autocorrelation coefficients for $\tilde{\gamma}_t^{i,err}$ and correlation coefficients $corr(\gamma_t^i, z_t^i)$, with γ_t^i from alternative filters

	Hamilton filter			CF filer			BK filter		
	$\hat{\rho}(\tilde{\gamma}_t^{i,err})$ EEF	$\hat{\rho}(\tilde{\gamma}_t^{i,err})$ WEO	$corr(\gamma_t^i, z_t^i)$	$\hat{\rho}(\tilde{\gamma}_t^{i,err})$ EEF	$\hat{\rho}(\tilde{\gamma}_t^{i,err})$ WEO	$corr(\gamma_t^i, z_t^i)$	$\hat{\rho}(\tilde{\gamma}_t^{i,err})$ EEF	$\hat{\rho}(\tilde{\gamma}_t^{i,err})$ WEO	$corr(\gamma_t^i, z_t^i)$
Greece	0.32	0.62	0.81***	0.89***	0.77***	0.13	0.91***	0.78**	0.17
Ireland	-0.11	-0.09	0.31	0.82***	0.66***	0.09	0.82***	0.72***	0.14
Italy	0.10	0.13	0.12	0.62**	0.09	-0.07	0.73***	0.07	0.06
Portugal	-0.09	0.00	0.41	0.62**	0.72***	0.11	0.68***	0.77***	0.27
Spain	0.28	0.26	0.46**	0.77***	0.80***	-0.09	0.81***	0.85***	0.02
Austria	0.08	0.07	−0.16	0.58**	0.58**	-0.13	0.75***	0.65***	-0.04
Belgium	-0.27	-0.17	−0.24	0.54**	0.24	-0.10	0.62***	0.30	0.03
Finland	-0.03	-0.04	−0.12	0.65***	0.58**	0.07	0.75***	0.64***	0.15
France	0.10	-0.00	−0.12	0.58***	0.51	-0.11	0.76***	0.62***	-0.00
Germany	-0.09	-0.05	−0.32	0.35	0.33	0.13	0.44**	0.46**	0.03
Netherlands	0.08	0.26	0.16	0.65***	0.60***	0.23	0.69***	0.59***	0.37

Notes: "CF filter" refers to the Christiano-Fitzgerald filter. "BK filter" refers to the Baxter-King filter. Data are annual from 1999–2019 for 11 EU countries, consistent with Table 1. $\hat{\rho}(\tilde{\gamma}_t^{i,err})$ denotes the estimated persistence $\hat{\rho}$ in the AR(1) process: $\tilde{\gamma}_t^{i,err} = \rho\tilde{\gamma}_{t-1}^{i,err} + u_t^i$, where $\tilde{\gamma}_t^{i,err} = \tilde{\gamma}_t^i - \gamma_t^i$ is the difference between real-time and filtered trend growth. In the WEO data, $\tilde{\gamma}_t^i$ observations for Greece are missing between 2003 and 2008. *** denotes p-value below 0.01, ** denotes p-value below 0.05.

As shown in Table B.1, the two-sided CF and BK filters yield strong autocorrelation in estimation errors and trend and cycles whose correlations are insignificant. The one-sided Hamilton filter produces insignificant AR(1) persistence coefficients for estimation errors and mostly insignificant correlations between filtered trend and cycle.

We further investigate whether real-time potential output growth estimation errors are systematically related to revisions in output gap estimates, following Coibion and Gorodnichenko (2015) and Adam et al. (2025). Specifically, we estimate:

$$\tilde{\gamma}_{t|t}^{i,err} = \theta_i^r + \xi_t^r + \beta^r \left(\tilde{z}_{t|t}^i - \tilde{z}_{t|t-1}^i\right) + u_t^{i,r}, \tag{B.1}$$

where $\tilde{\gamma}_{t|t}^{i,err}$ is the error in real-time potential output growth estimates. The term $\tilde{z}_{t|t}^i - \tilde{z}_{t|t-1}^i$ captures the revision in the estimated output gap for year t between the spring of year $t+1$ and the spring of year t. θ_i^r and ξ_t^r are country and year fixed effects, and $u_t^{i,r}$ is an idiosyncratic error term.

Note this is a regression at the individual country level. It is a test of rational expectations. A positive (negative) β^r implies an overreaction (underreaction) of trend growth estimates to new information relative to the RE benchmark.[1] Table B.2 presents the regression results. The regression coefficients are generally insignificantly different from zero (with one exception), which does not reject the RE assumption. This is consistent with the assumption of imperfect information RE adopted in the paper.

Table B.2: The relationship between output gap revisions and errors in real-time potential output growth estimates

	EEF			WEO		
	All	GIIPS	Non-GIIPS	All	GIIPS	Non-GIIPS
$\tilde{z}_{t\|t}^i - \tilde{z}_{t\|t-1}^i$	0.244**	0.337	0.084	0.001	0.012	−0.019
	(0.098)	(0.150)	(0.044)	(0.038)	(0.063)	(0.027)
No.Obs	220	100	120	213	93	120
R^2	0.04	0.05	0.02	0.00	0.00	0.00

Notes: Estimation results of regression (B.1). Both variables are expressed in percentage points. The sample covers 1999–2019. Revisions for Greece are unavailable in the WEO for 2003–2010. We confirm that extending the sample to 2022 yields positive and statistically significant coefficients at the 1% level in all specifications. Standard errors (in parentheses) are cluster-robust by country. *** denotes p-value below 0.01, ** denotes p-value below 0.05.

In the main text, Figure 1 illustrates persistent over- and underestimation of potential output growth based on EEF data. As a robustness check, Figure B.1 presents revisions to potential output growth and the output gap using WEO data, defined as the difference

[1] Note that the variable on the left-hand side of this equation is real-time estimates minus realizations.

between the most recent estimates (Q1 2023) and their real-time counterparts. We confirm that excluding non-GIIPS countries yields similar average revision patterns.

We also report an alternative measure of revisions, defined as ex post HP-filtered trend growth and cyclical components minus their corresponding real-time estimates of potential output growth and the output gap. We illustrate this alternative measure of estimation errors in Figure B.2 (using real-time estimates from EEF) and Figure B.3 (using real-time estimates from WEO).

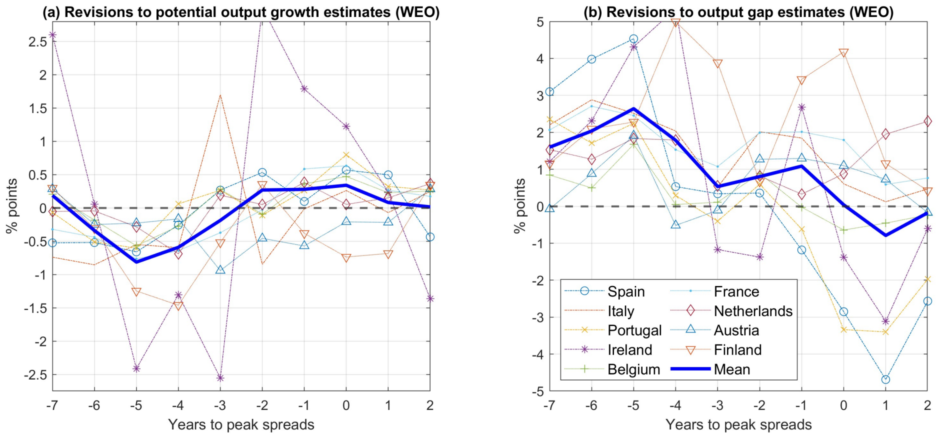

Figure B.1: Revisions of potential growth and output gap estimates (most recent minus real-time) from the WEO. The horizontal axis indicates the number of years after peak spreads. For Ireland and Finland, the peak occurred in 2011; for all other countries, in 2012. The blue solid line shows the average revision across countries. Greece is excluded due to missing pre-crisis data.

Compared with revisions from EEF (Figure 1), revisions from WEO (Figure B.1) and negative estimation errors measured by HP-filtered minus and real-time estimates (Figure B.2 and B.3) exhibit similar and clear patterns, reinforcing Evidence 1(iii): revisions and negative errors in real-time potential output growth estimates indicate optimism before the debt crisis and pessimism during it. Meanwhile, output gaps are systematically underestimated prior to the crisis and overestimated during the crisis.

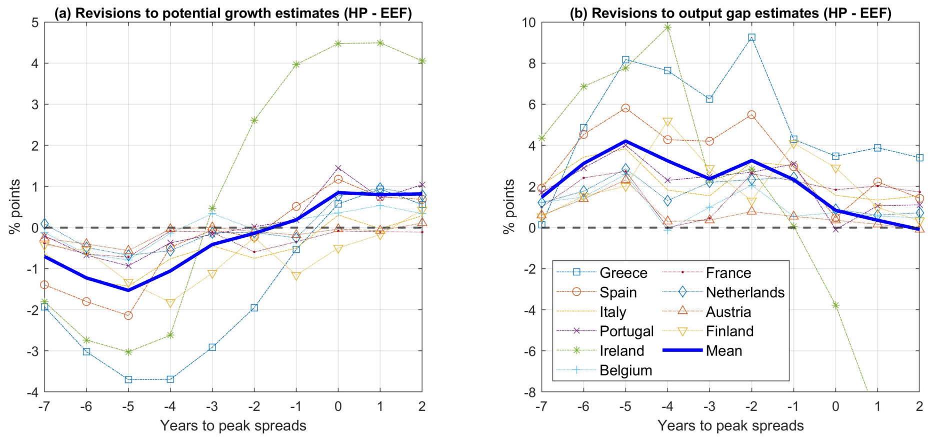

Figure B.2: Negative estimation errors in potential output growth and output gap (HP-filtered minus real-time). Real-time estimates are based on EEF. HP-filtered trend and cycle are computed using Eurostat output data for 1995–2022. The horizontal axis shows the number of years after peak spreads. The blue solid line denotes the average revision across countries.

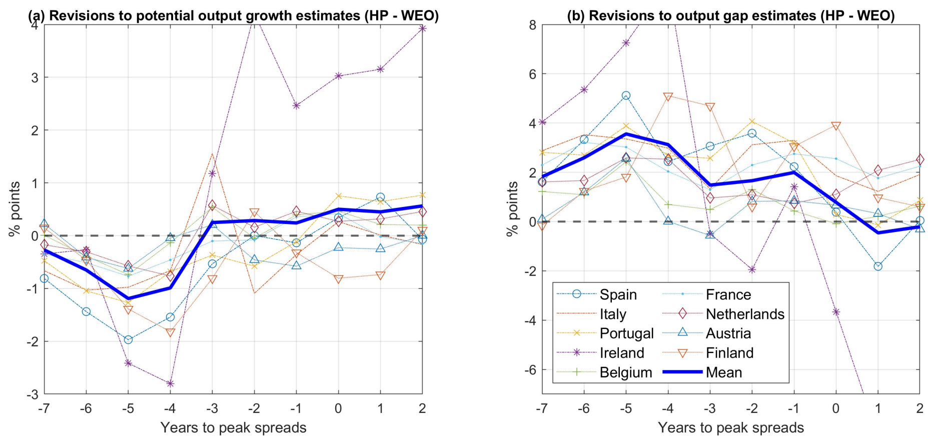

Figure B.3: Negative estimation errors in potential output growth and output gap (HP-filtered minus real-time). Real-time estimates are based on WEO. HP-filtered trend and cycle are computed using Eurostat output data fror 1995-2022. Horizontal axes labels show the number of years after peak spreads. The horizontal axis shows the number of years after peak spreads. The blue solid line denotes the average revision across countries. Greece excluded because 2003-2008 data are missing in WEO.

C Supplementary details for Evidence 2: A negative and nonlinear relationship between real-time potential GDP growth estimates and sovereign debt spreads

In this section, we provide supplementary information for the second strand of empirical evidence discussed in the main text. First, to visualize the extent to which the nonlinearity in the relationship between spreads and real-time potential output growth estimates among GIIPS countries (upper panels of Figure 2) is influenced by outliers, Figure C.1 presents alternative scatter plots excluding outliers. We use the empirical cumulative distribution function to remove the top 4% and bottom 4% observations, in terms of either spreads (panel (a) and (b)) or potential growth estimates (panel (c) and (d)). As shown in Figure C.1, the non-linearity persists among GIIPS countries, with crisis-period observations (in red color) being the primary contributors.

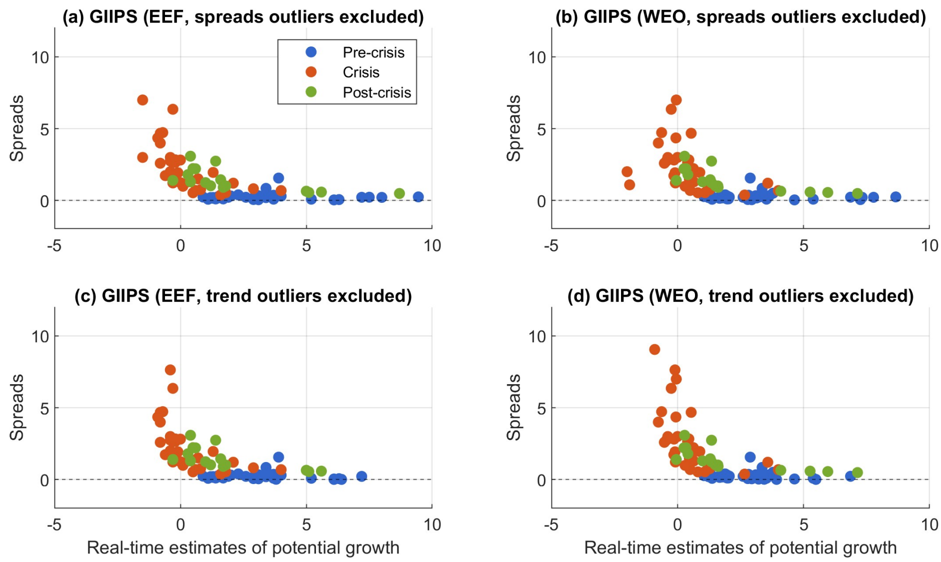

Figure C.1: Non-linear relationships between spreads (in bps) and real-time potential output growth estimates (in percentage points) among GIIPS countries, excluding outliers. Data are annual and in the range of 1999 to 2019. Greek data after its default (from 2013 to 2019) are excluded. Pre-crisis period refers to year 1999-2007, crisis period is between 2008-2015, and post-crisis period is between 2016-2019. Left (Right) panels corresponds to data from the EEF (WEO) database.

Second, to supplement Table 3, we report details for control variables in the nonlinear regression (1) in Table C.1. Estimated coefficients for controls are similar to those in the linear regression (2).

Third, Table C.2 reports the values of real-time potential output growth estimates $\tilde{\gamma}_t^i$ that define the regime thresholds (low, medium, high) in the nonlinear empirical regression (2). These thresholds correspond to the 25th and 75th percentiles in samples (All, GIIPS, Non-GIIPS). Table C.2 also report: (1) the number of observations, (2) the number of distinct countries, and (3) the number of distinct years included, for each regime of real-time potential growth estimates.

Table C.1: Coefficient estimates for control variables in the nonlinear regression (1)

	EEF			WEO		
	All	GIIPS	Non-GIIPS	All	GIIPS	Non-GIIPS
$\tilde{z}_t^i$	-11.2^{**}	-5.60	1.36	-24.3	-38.7^{***}	2.6
	(5.1)	(7.8)	(1.72)	(17.8)	(13.3)	(1.8)
b_t^i/y_t^i	-3.78^{**}	-3.73^{**}	1.7^{**}	-3.6	-4.1	1.4
	(1.48)	(1.88)	(0.71)	(5.9)	(3.4)	(0.71)
No.Obs	183	88	95	177	82	95

Notes: Coefficient estimates for the control variables $\tilde{z}_t^i$ (real-time output gap estimates) and b_t^i/y_t^i (first difference of debt-to-GDP ratios) in the nonlinear regression (1). Same specification and sample as Table 3 in the main text. Standard errors are reported in parentheses. *** denotes p-value below 0.01, ** denotes p-value below 0.05.

Table C.2: Regimes boundaries for $\tilde{\gamma}_t^i$ and the number of observations in each regime for empirical nonlinear regression (1)

		EEF			WEO		
		All	GIIPS	Others	All	GIIPS	Others
$\tilde{\gamma}_t^i$ regimes boundaries	Low to mid	0.8%	-0.05%	1.1%	0.72%	0.25%	1.03%
	Mid to high	2.2%	3.4%	2.1%	2.14%	2.94%	2.06%
No. of Observations	Low regime	48	22	28	44	21	24
	Mid regime	90	44	46	89	41	47
	High regime	45	22	21	44	20	24
No. of Countries	Low regime	9	5	5	9	5	5
	Mid regime	10	5	5	10	5	5
	High regime	9	4	5	9	3	5
No. of Years	Low regime	12	8	9	12	9	8
	Mid regime	19	18	15	19	19	17
	High regime	13	12	8	14	13	8

Notes: This table defines the low (below 25th percentile), medium (25th–75th percentile), and high (above 75th percentile) regimes of real-time potential growth estimates $\tilde{\gamma}_t^i$ used in the empirical nonlinear regression (1). For each dataset (EEF, WEO) and subsample, we report: (i) regime boundary values of $\tilde{\gamma}_t^i$, (ii) the number of observations, (iii) the number of distinct countries, and (iv) the number of distinct years in each regime. The full sample covers 10 EU countries (excluding Germany) over 1999–2019.

C.1 Horse race for the negative relationship between trend growth estimates and spreads

In this section, we conduct a "horse race" to examine the explanatory power of trend growth estimates in predicting sovereign debt spreads. Specifically, we compare the baseline linear model (equation (2) in the main text) to two alternative specifications: The first alternative includes only the control variables $\tilde{z}_t^i$ (real-time estimates of output gaps) and $\Delta(b_t^i/y_t^i)$ (first difference of debt-to-GDP ratio):

$$rs_t^i = \theta_i^1 + \xi_t^1 + \beta_b^1 \Delta(b_t^i/y_t^i) + \beta_{\tilde{z}}^1 \tilde{z}_t^i + u_t^{i,1}, \tag{C.1}$$

and the second alternative has the real-time potential output growth estimate as the only regressor:

$$rs_t^i = \theta_i^2 + \xi_t^2 + \beta_{\tilde{\gamma}}^2 \tilde{\gamma}_t^i + u_t^{i,2}, \tag{C.2}$$

where rs_t^i denotes the sovereign spread, θ_i^1 and ξ_t^1 (θ_i^2 and ξ_t^2) represent country and year fixed effects respectively for the first (second) alternative. Error terms $u_t^{i,1}$ and $u_t^{i,2}$ are assumed to be i.i.d.

Estimation results for these two alternative regressions and the Wald-F test with the baseline regression (2) are reported in Table C.3. The Wald–F test evaluates whether the additional regressors jointly improve the explanatory power of the model relative to the baseline specification. For regression (C.1), higher Wald-F statistics indicate that adding the core explanatory variable $\tilde{\gamma}_t^i$ significantly improves the empirical regression's predictive power. For regression C.2, the higher Wald-F statistics demonstrate that adding control variables $\tilde{z}_t^i$ and $\Delta(b_t^i/y_t^i)$ significantly increases the explanatory power, particularly for GIIPS countries where the default risk is much higher.

Table C.3: Horse race for the empirical linear model (2)

	EEF			WEO		
	All	GIIPS	Non-GIIPS	All	GIIPS	Non-GIIPS
Model (C.1)						
$\tilde{z}_t^i$	-56.4^{***}	-75.5^{***}	-2.6	-47.2^{***}	-70.2^{***}	-1.6
	(6.1)	(9.2)	(1.8)	(7.3)	(12.2)	(2.0)
$\Delta(b_t^i/y_t^i)$	0.33	-1.2	2.5^{***}	3.4	3.2	2.7
	(2.1)	(3.0)	(0.79)	(2.0)	(3.0)	(0.78)
R^2	0.35	0.46	0.11	0.25	0.35	0.16
Wald-F	39.2^{***}	7.7^{***}	7.7^{***}	30.9^{***}	6.0^{***}	11.8^{***}
Model (C.2)						
$\tilde{\gamma}_t^i$	-87.4^{***}	-97.5^{***}	-18.2^{***}	-79.3^{***}	-90.6^{***}	-20.9^{***}
	(7.7)	(11.4)	(3.2)	(9.1)	(14.2)	(3.2)
R^2	0.40	0.44	0.23	0.27	0.35	0.32
Wald-F	13.0^{***}	10.2^{***}	2.2	7.0^{***}	5.8^{***}	2.0
No.Obs	183	88	95	177	82	95

Notes: "Horse race" regressions for the linear model (2). "Wald-F" reports the F-statistic from a Wald test comparing the full (unrestricted) model (2) with each restricted alternatives (C.1) and (C.2). Non-GIIPS refers to Austria, Belgium, Finland, France, and the Netherlands. Standard errors are reported in parentheses. *** denotes p-value below 0.01, ** denotes p-value below 0.05.

D Alternative calibration to Spain

This section presents main quantitative results of an II model calibrated to Spain. The calibration strategy follows the same procedure used for Portugal in the main text. Table D.1 reports the parameters calibrated without solving or simulating the model. The average maturity $1/\lambda$ is based on Spanish data reported by Ayres et al. (2025). Table D.2 shows the simulation-based calibration results. In the FI model, we set $\rho_\gamma = 0.9525$ and $\sigma_\gamma = 0.18\%$ based on the HP-filtered trend growth rate of Spanish log-GDP. The standard deviation of AR(1) innovations in the z_t process is set to $\sigma_z = 3.1\%$ to match the variance of Spanish GDP growth retrieved from Eurostat annual data. Overall, this calibration results in a signal-to-noise ratio of 0.72 and a trend shock share $V = 0.25$, indicating more accurate trend signals and a greater importance of trend shocks compared to the Portuguese calibration.

Table D.1: Parameters independent of simulation, targeting Spain

Description	Parameters	Value	Source
Cyclical growth persistence	ρ_z	0.9	Aguiar and Gopinath (2006)
Trend growth persistence	ρ_γ	0.885	EEF Spanish data
Trend growth SD	σ_γ	0.85%	EEF Spanish data
Average growth rate	$\overline{\gamma}$	1.72%	Spanish data
Noise process persistence	ρ_n	0.9	Uribe and Schmitt-Grohé (2017)
Risk aversion	σ	2	Chatterjee and Eyigungor (2012)
Reentry probability	μ	15.4%	Cruces and Trebesch (2013)
Risk-free rate	r^*	4%	Germany data
Average maturity	$1/\lambda$	6.67	Ayres et al. (2025)

Notes: Table reports calibration that does not require solving and simulating the sovereign default model. The targeted model is in discrete time and annual frequency.

Table D.3 compares full-sample and near-crisis statistics. The II model satisfactorily matches data statistics, especially in the near-crises sample. Compared to the FI model, the II model produces higher average spreads and greater spreads volatility, bringing it closer to Spanish data. The correlation between spreads and perceived trend growth rates, i.e., $corr(rs_t, \tilde{\gamma}_t)$, is better replicated by the II model, although the fit is not as strong as in the Portugal calibration. This is largely because the Spanish calibration matches the smaller mean and variance in spreads as observed in data.

In Table D.4, we estimate the non-linear relationship between spreads and perceived

Table D.2: Parameters calibrated to align simulation with data, targeting Spain

Description of parameters	Parameters	Value
Std of AR(1) innovation for z_t	σ_z	3.05%
Std of AR(1) innovation for n_t	σ_n	1.1%
Bargaining power in renegotiation	α	0.67
Subjective discount rate	δ	0.90
Output loss in default	ψ	7.0%
Coupon rate of bond	η	5.0%
Lower bond of price	$\underline{q}$	0.5
Targeted data moments	Data	II Model
Standard deviation of $\Delta\log(Y_t)$	2.44%	2.46%
AR(1) persistence of $\tilde{\gamma}_t$	0.894	0.896
Std of AR(1) innovation for $\tilde{\gamma}_t$	0.67%	0.65%
Correlation between $\tilde{\gamma}_t$ and $\tilde{z}_t$	0.68	0.69
AR(1) persistence of $\tilde{\gamma}_t^{err}$	0.68	0.55
Mean spreads $\mathbb{E}(rs_t)$	1.02%	0.93%
Gov debt-to-GDP $\mathbb{E}(B_t/Y_t)$	70%	71%
Mean haircut $\mathbb{E}(\Phi(\mathbf{s})/b)$	40%	40%

Notes: Statistics are based on annual data from 1999 to 2019 and all simulated periods of good credit records.

Table D.3: Selected statistics around crisis periods vs. full sample, with the II model calibrated to Spain

		II Model		FI Model	
Statistics	Data	Full sample	Near crises	Full sample	Near crises
$\mathbb{E}(rs_t)$	1.02	0.93	1.01	0.39	0.42
$\sigma(rs_t)$	1.12	0.18	0.30	0.05	0.11
$corr(rs_t, \tilde{z}_t)$	-0.68	0.04	-0.27	-0.62	-0.68
$corr(rs_t, \tilde{\gamma}_t)$	-0.85	0.25	-0.13	0.18	-0.06
$corr(\tilde{\gamma}_t, \tilde{z}_t)$	0.68	0.66	0.70	-0.02	-0.02
$corr(rs_t, y_t)$	-0.60	-0.13	-0.46	-0.46	-0.61
$corr(rs_t, c_t)$	-0.50	-0.12	-0.65	-0.24	-0.75

Notes: Data come from Spain, 1999-2019, in annul frequency. "Near crises" refers to subsamples centered around sovereign spread peaks (13 years ahead and 7 years after) where spreads exceed the 97th percentile during non-default periods. Sample only include simulated periods with good credit history.

trend growth using simulated data, parallelizing (29) and (30) in the main text. The II model still exhibits a significant non-linear response, though with smaller magnitudes than in the Portugal calibration. In contrast, the FI model displays a much weaker degree of non-linearity.

Table D.4: Estimation results by growth regime based on II and FI model (calibrated to Spain) simulations

	II Model	FI Model
Linear regression		
$\tilde{\gamma}_t$	-20.2^{***}	-24.5^{***}
	(0.18)	(0.21)
R^2	0.07	0.05
Nonlinear regression		
Low $\tilde{\gamma}_t$	-75.9^{***}	-48.3^{***}
	(0.51)	(0.60)
Medium $\tilde{\gamma}_t$	-29.5^{***}	-40.1^{***}
	(0.23)	(0.37)
High $\tilde{\gamma}_t$	-16.4^{***}	-31.0^{***}
	(0.18)	(0.28)
R^2	0.08	0.05

Notes: The table is similarly organized as Table 8 in the main text, but with II model calibrated to Spanish data. *** denotes p-value below 0.01, ** denotes p-value below 0.05.

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