Internet Appendix for

"Predictable Financial Crises"

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Contents:

A. Data and Sample Construction

Tables A1, A2, and A3 present the data sources used to construct our panel of debt and price growth. Table A1 presents the equity price indices used to calculate 3-year real equity price growth.[1] The equity data is drawn from four sources: Global Financial Data (GFD), the International Monetary Funds (IMF) International Financial Statistics, Bloomberg and the Jordá, Schularick and Taylor MacroHistory database (JST). Table A2 presents the house price indices used to calculate 3-year real house price growth. The data is drawn from Bank of International Settlements' Property Price Statistics (BIS), the OECD's Household Prices database (OECD), and JST. Finally, Table A3 presents the measures of debt outstanding used to calculate 3-year changes in debt to GDP for the non-financial business and household sector. The data is drawn from the International Monetary Funds' Global Debt Database (IMF), the Bank of International Settlements' Total Credit Statistics (BIS), and JST. Panel A presents an overview of the sources for business debt, while Panel B presents the sources for household debt.

When constructing our panel, we occasionally need to combine data from different sources to create time-series of changes within countries. When doing so, we calculate the changes within each data source to ensure smooth time-series. For example, to create a time-series of 3-year changes in real house prices for Denmark we combine data from the Jordá, Schularick and Taylor Macrohistory Database from 1950 to 1972, with data from the Bank of International Settlements' Property Price Statistics from 1970 to 2018. Thus, in 1972 we calculate the 3-year change in real house prices for Denmark using only the JST data, and in 1973 we calculate the 3-year change in real house prices for Denmark using only the BIS data.

B. The Use of Linear Probability Models

The econometric specifications reported in the text are Linear Probability Models (LPM)—i.e., we run linear regressions where the dependent variable is a binary indicator.

[1] We primarily rely on price indices to calculate equity price growth, but for a small subset of countries we use total return indices instead as no suitable price index was available. See Table A1 for details.

The use of LPMs offers a number of advantages relative to maximum likelihood models for handling binary outcomes such as Logit or Probit. First, the LPM coefficients are automatically interpretable as marginal effects, which show how the conditional probability of a future crisis changes as a function of the covariates. Second, LPMs allow us to include country fixed effects without encountering the incidental parameters problem. And, finally, LPM make it easier to conduct appropriate statistical inference on the marginal effects of interest (without using the delta method) by computing Driscoll-Kraay (1998) standard errors.

The downside of using LPMs is that they can generate predicted probabilities that lie outside the $[0,1]$ interval. If the predicted probabilities fall outside the $[0,1]$ interval for a significant portion of the sample, this can signal model misspecification, leading the LPM-implied marginal effects to diverge significantly from those implied by Logit and Probit models.

Fortunately, it turns out that the use of Linear Probability Models (LPMs) makes almost no difference in our setting: We obtain nearly identical marginal effects using Logit or Probit models.

Let us now explain in greater detail.

Analysis without country fixed effects: If we omit the country fixed-effects, Logit and Probit models deliver the exact same marginal effects as LPMs in our setting.

To see why, note that the covariates in our specifications are a set of binary indicators that define a discrete partition of the sample. As a result, the predicted probabilities from our LPMs are just the empirical historical probabilities in each cell of the partition and, thus, always lie in the [0,1] interval. Our estimated LPM coefficients are differences between these empirical conditional probabilities and, thus, are proper marginal effects.

Going further, since the covariates define a discrete partition of the sample, any maximum likelihood model for handling binary outcome variables—including Logit or Probit—is going to yield the same predicted probabilities as a LPM and hence the same marginal effects.

Formally, our baseline regressions divide country-years into the following 2-by-2 partition:

		Debt growth	
		Low	High
Price growth	Low	$\hat{p}_{L,L} = n_{L,L}/N_{L,L}$	$\hat{p}_{L,H} = n_{L,H}/N_{L,H}$
	High	$\hat{p}_{H,L} = n_{H,L}/N_{H,L}$	$\hat{p}_{H,H} = n_{H,H}/N_{H,H}$

where N is the number of country-years in each cell in our sample, n is the number of country-years in each cell in which a crisis later materializes, and $\hat{p}$ is the in-sample conditional probability of a crisis in that cell. For instance, $\hat{p}_{H,H}$ is the sample probability that a crisis arrives within the next 3 years conditional on starting from inside the *R*-zone.

If we then estimate the following multivariate LPM model:

$$Crisis_{i,t+1 \text{ to } t+3} = \alpha + \beta \cdot High\text{-}Debt\text{-}Growth_{it} + \delta \cdot High\text{-}Price\text{-}Growth_{it} + \gamma \cdot R\text{-}zone_{it} + \varepsilon_{i,t+1 \text{ to } t+3},$$

the coefficient estimates are $\hat{\alpha} = \hat{p}_{L,L}$, $\hat{\beta} = \hat{p}_{L,H} - \hat{p}_{L,L}$, $\hat{\delta} = \hat{p}_{H,L} - \hat{p}_{L,L}$, and $\hat{\gamma} = (\hat{p}_{H,H} - \hat{p}_{L,H}) - (\hat{p}_{H,L} - \hat{p}_{L,L})$. As noted, the estimated coefficients from our LPMs are just differences—or differences-in-differences—between empirical conditional probabilities and, thus, are proper marginal effects.[2] Similarly, if we consider a Logit or Probit model in which

$$\text{Prob}\big(Crisis_{i,t+1\text{ to }t+3}\big) = \alpha + \beta \cdot High\text{-}Debt\text{-}Growth_{it} + \delta \cdot High\text{-}Price\text{-}Growth_{it} + \gamma \cdot R\text{-}zone_{it},$$

this yields the exact same estimated marginal effects—i.e., $\hat{\alpha} = \hat{p}_{L,L}$, $\hat{\beta} = \hat{p}_{L,H} - \hat{p}_{L,L}$, $\hat{\delta} = \hat{p}_{H,L} - \hat{p}_{L,L}$, and $\hat{\gamma} = (\hat{p}_{H,H} - \hat{p}_{L,H}) - (\hat{p}_{H,L} - \hat{p}_{L,L})$.[3]

Adding country fixed effects: Next, we consider what happens once we add country fixed effects. As we emphasize on page 12 of the paper, the inclusion of country fixed effects in our LPMs has almost no impact on the coefficients of interest—i.e., on the LPM-implied marginal effects. Thus, one would expect that, while no longer perfectly identical, LPM, Logit, and Probit would imply nearly identical marginal effects. Indeed, this is what we find.

Formally, once we include country fixed effects, the independent variables no longer define a discrete partition of the sample as they did above. For instance, two observations with high-credit-growth and high-price-growth can have different predicted probabilities if they come from different countries. As the referee notes, this means that the predicted probabilities from our LPM models with country fixed effects can lie outside of [0,1]. However, looking across our specifications, the predicted values from our fixed-effects LPMs lie in the [0,1] interval for between 96% and 100% of the observations, suggesting that any misspecification is very minor. And, naturally, the marginal effects implied by fixed-effect Logits and Probits are extremely close to those from our fixed-effects LPM models.[4]

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[2] Analogously, if we estimate the univariate LPM model

$$Crisis_{i,t+1\text{ to }t+3} = \alpha + \gamma \cdot R\text{-}zone_{it} + \varepsilon_{i,t+1\text{ to }t+3},$$

we obtain $\hat{\gamma} = (\hat{p}_{H,H} - \hat{p}_{Not(H,H)})$ where $\bar{p}_{Not(H,H)} = (n_{L,L} + n_{L,H} + n_{H,L})/(N_{L,L} + N_{L,H} + N_{H,L})$.

[3] Of course, these estimated marginal effects are different from the estimates of the underlying Logit and Probit parameters, which are of less economic interest. Specifically, letting $\Lambda[z] = \exp[z]/(1+\exp[z])$ denote the logistic function, the Logit parameters satisfy:

$$\text{Prob}\big(Crisis_{i,t+1\text{ to }t+3}\big) = \Lambda[a + b \cdot High\text{-}Debt\text{-}Growth_{it} + d \cdot High\text{-}Price\text{-}Growth_{it} + g \cdot R\text{-}zone_{it}].$$

Thus, the discrete marginal effects for the Logit model are given by the following expressions:

$$\hat{\alpha} = \Lambda[\hat{a}] = \hat{p}_{L,L},$$

$$\hat{\beta} = \Lambda\big[\hat{a} + \hat{b}\big] - \Lambda[\hat{a}] = \hat{p}_{L,H} - \hat{p}_{L,L},$$

$$\hat{\delta} = \Lambda\big[\hat{a} + \hat{d}\big] - \Lambda[\hat{a}] = \hat{p}_{H,L} - \hat{p}_{L,L}, \text{ and}$$

$$\hat{\gamma} = (\Lambda\big[\hat{a} + \hat{b} + \hat{d} + \hat{g}\big] - \Lambda\big[\hat{a} + \hat{b}\big]) - (\Lambda\big[\hat{a} + \hat{d}\big] - \Lambda[\hat{a}]) = (\hat{p}_{H,H} - \hat{p}_{L,H}) - (\hat{p}_{H,L} - \hat{p}_{L,L}).$$

Similarly, the underlying Probit parameters satisfy:

$$\text{Prob}\big(Crisis_{i,t+1\text{ to }t+3}\big) = \Phi[a + b \cdot High\text{-}Debt\text{-}Growth_{it} + d \cdot High\text{-}Price\text{-}Growth_{it} + g \cdot R\text{-}zone_{it}],$$

where $\Phi[z]$ is the standard normal CDF. And, the marginal effects take the prior form replacing $\Phi[z]$ with $\Lambda[z]$.

[4] The fixed-effect Logit model takes the form

$$\text{Prob}\big(Crisis_{i,t+1\text{ to }t+3}\big) = \Lambda[a_i + b \cdot High\text{-}Debt\text{-}Growth_{it} + d \cdot High\text{-}Price\text{-}Growth_{it} + g \cdot R\text{-}zone_{it}],$$

where a_i is the fixed effect for country *i*. Due to the inclusion of country fixed effects, the marginal effects vary across countries. Specifically, the marginal effects for country *i* are:

$$\hat{\beta}_i = \Lambda[\hat{a}_i + \hat{b}] - \Lambda[\hat{a}_i],$$

$$\hat{\delta}_i = \Lambda[\hat{a}_i + \hat{d}] - \Lambda[\hat{a}_i], \text{ and}$$

$$\hat{\gamma}_i = (\Lambda[\hat{a}_i + \hat{b} + \hat{d} + \hat{g}] - \Lambda[\hat{a}_i + \hat{b}]) - (\Lambda[\hat{a}_i + \hat{d}] - \Lambda[\hat{a}_i]).$$

We obtain the *average* Logit-implied marginal effects by computing the average of these country-specific marginal effects across all country-years in our sample. (Thus, countries with a longer time-series receive a

Table A4: Estimated Marginal Effects: LPM versus Logit or Probit Models

					Multivariate						Univariate	
					High credit		High price		R-zone		R-zone	
	Model	Fixed effects	Countries	N	β	[t]	δ	[t]	γ	[t]	γ	[t]
Panel A: Business sector												
(1)	LPM	No	42	1,258	13.44	(2.67)***	6.91	(1.11)	19.11	(2.66)***	35.44	(3.46)***
(2)	Logit	No	42	1,258	13.44		6.91		19.11		35.44	
(3)	Probit	No	42	1,258	13.44		6.91		19.11		35.44	
(4)	LPM	Yes	42	1,258	11.47	(2.66)***	7.37	(1.10)	19.39	(2.81)***	33.67	(3.28)***
(5)	LPM&	Yes	29	1,103	12.80	(2.64)***	8.48	(1.04)	19.75	(2.86)***	35.80	(3.45)***
(6)	Logit&	Yes	29	1,103	12.79		8.59		20.09		35.28	
(7)	Probit&	Yes	29	1,103	13.57		8.99		18.97		35.33	
Panel B: Household sector												
(1)	LPM	No	40	1,107	11.70	(2.01)**	-0.47	(0.17)	17.69	(2.45)**	27.78	(3.03)***
(2)	Logit	No	40	1,107	11.70		-0.47		17.69		27.78	
(3)	Probit	No	40	1,107	11.70		-0.47		17.69		27.78	
(4)	LPM	Yes	40	1,107	9.13	(2.27)**	0.00	(0.00)	20.94	(3.18)***	28.60	(3.44)***
(5)	LPM&	Yes	25	991	9.48	(2.22)**	0.16	(0.04)	22.68	(3.22)***	30.85	(3.62)***
(6)	Logit&	Yes	25	991	9.73		0.08		23.19		31.20	
(7)	Probit&	Yes	25	991	8.83		0.13		23.18		30.45	

& These rows drop all countries where there is no variation in the binary outcome—i.e., countries that never experienced a crisis. Fixed-effects MLEs can perfectly predict the outcomes in these countries by setting $\hat{a}_i \rightarrow -\infty$, so these countries play no role in identifying the shared coefficients and marginal effects from fixed-effects MLEs.

Table A4 compares the marginal effects implied by LPM, Logit, and Probit models. We are predicting whether a financial crisis will arrive in the next 3 years and the format follows Table 5. Consider the results for the business sector in Panel A. The first three rows compare LPM, Logit, and Probit marginal effects when we omit the country fixed effects. As noted above, these are identical by necessity. Row (4) show the LPM-implied marginal effects once we include country fixed effects. Comparing the results in row (4) to those in rows (1), we see that the inclusion of country fixed effects has almost no impact on our LPM estimates. In row (5), we estimate an LPM after dropping the 13 countries in our sample that never experience a crisis: these countries will be dropped in fixed-effect Logit and Probit models. This has almost no impact. Finally, row (6) shows that the fixed-effects Logit yields very similar marginal effects as the fixed-effects LPM in row (5). And, row (7) shows that the fixed-effects Probit also generates nearly identical marginal effects as the fixed-effects LPM.

C. Cumulative and Incremental Probabilities of Crisis Onset at Different Horizons

In our setting, one can roughly infer the incremental probability of crisis onset at different horizons by tracking how the cumulative probability of crisis onset grows with the forecast horizon. Specifically, since it is rare to have multiple distinct crises in the same country over a short period of time, for small h we have:

$$\begin{aligned} Crisis_{i,t+1 \text{ to } t+h} &\equiv \max\{Crisis\text{-}Start_{i,t+1}, \ldots, Crisis\text{-}Start_{i,t+h}\} \\ &\approx \textstyle\sum_{k=1}^{h} Crisis\text{-}Start_{i,t+k}. \end{aligned}$$

Equivalently, this means that:

larger weight in this average). We obtain Probit-implied marginal effects in an analogous fashion.

$$Crisis\text{-}Start_{i,t+h} \approx Crisis_{i,t+1\text{ to }t+h} - Crisis_{i,t+1\text{ to }t+h-1}.$$

As a result, one can approximately deduce the coefficients from a regression where $Crisis\text{-}Start_{i,t+h}$ is the dependent variable—which describe the relevant incremental probabilities—by comparing the coefficients from regressions involving $Crisis_{i,t+1\text{ to }t+h}$ and $Crisis_{i,t+1\text{ to }t+h-1}$ across the columns in our existing tables. (These statements are exact using the BVX crisis indicator when $h = 2$, but only approximate when $h = 3$ and 4.)

Table A5 illustrates this point. Consider the results for the business sector in Panel A. Panel A1 reproduces our baseline analysis from Table 4 where the dependent variable is the cumulative crisis indicator, $Crisis_{i,t+1\text{ to }t+h}$. In Panel A2, the dependent variable is $Crisis_{i,t+1\text{ to }t+h} - Crisis_{i,t+1\text{ to }t+h-1}$: this indicator switches on if the *first* subsequent crisis onset occurs in year $t + h$. Thus, the coefficients in Panel A2 are simply differences between those in Panel A, but we now report a t-statistic for this difference. In Panel A3, the dependent variable is $Crisis\text{-}Start_{i,t+h}$: this indicator switches on if *any* crisis begins in year $t + h$ (even if there has already been a prior crisis onset).

Panels A2 and A3 both show that the incremental probability of crisis onset remains elevated for three years following a business R-zone event. This corresponds to the fact that the cumulative probability of crisis arrival in Panel A1 climbs steadily with the forecast horizon until year three.[5] And, as expected, the coefficients in the Panels A2 and A3 are very similar.[6]

As shown in Panel B, a similar pattern holds for the household sector.

D. Using the Bootstrap to Assess the Impact of Small-Sample Statistical Problems

When estimating h-year forecasting regressions for $h > 1$, we use Driscoll-Kraay (1998) standard errors allowing for residual correlation at up to $m = \text{ceiling}(1.5 \times h)$ lags. We compute p-values using the "fixed-b" asymptotic theory of Kiefer and Vogelsang (2005). Fixed-b asymptotics were designed to address the tendency for traditional statistical tests based on heteroskedasticity and autocorrelation consistent (HAC) standard errors to over-reject in finite samples. Intuitively, HAC variance estimators tend be quite noisy in small samples because of the need to non-parametrically estimate a series of higher order autocorrelations. And, the resulting noise in the variance estimator leads t-statistics based on HAC standard errors to have fatter-than-Gaussian tails in small samples. Kiefer and Vogelsang (2005) show that their fixed-b asymptotic theory delivers more conservative p-values and has better small-sample properties than traditional Gaussian asymptotic theory.[7]

[5] For the business R-zone, the marginal probability of onset is highest in the third year following an R-zone event. However, this is not statistically different from the probability of onset in the first or second year after an R-zone event. For the household, R-zone the marginal probability of onset is roughly constant for the first three years for an R-zone event.

[6] If anything, since $Crisis\text{-}Start_{i,t+h} \geq Crisis_{i,t+1\text{ to }t+h} - Crisis_{i,t+1\text{ to }t+h-1}$, the coefficients in Panel C are slightly larger than those in Panel B for $h = 3$ and 4.

[7] In contrast to the traditional asymptotic theory for inference for HAC inference, which is derived under the assumption that $m \to \infty$ and $m/T \to 0$ as $T \to \infty$, Kiefer and Vogelsang (2005) assume that $m = bT$ for some $b \in (0,1]$—i.e., that bandwidth m is a fixed fraction b of the length T of the panel. Let $t_b = (\hat{\theta} - \theta_0)/\sqrt{\hat{V}_b}$denote the t-statistic using the Driscoll-Kraay (1998) variance estimator with bandwidth $m = bT$. Then as $T \to \infty$, Kiefer and Vogelsang (2005) show that $t_b \xrightarrow{d} B(1)/\sqrt{Q(b)}$, where $B(r)$ is a standard Brownian motion, $\tilde{B}(r) = B(r) - rB(1)$, and $Q(b) = (2/b)\int_0^1 \tilde{B}(r)dr - (2/b)\int_0^{1-b} \tilde{B}(r+b)\tilde{B}(r)dr$. Furthermore, they show that $Q(b) \xrightarrow{p} 1$ as $b \to 0$, so that these

Gonglaves and Vogelsang (2008) show that inference using this fixed-*b* approach is asymptotically equivalent to inference using a moving-block bootstrap. However, for smaller samples, Gonglaves and Vogelsang (2008) argue that better approximations can be obtained via a moving-block bootstrap with a suitably chosen block length. Thus, to better assess statistical significance, we use a nonparametric bootstrap to estimate the small-sample distribution of our *t*-statistics.

Formally, we create a large number of bootstrap samples by resampling observations from our original dataset. We then estimate the unknown finite-sample distribution of $t = (\hat{\theta} - \theta_0)/\sqrt{\hat{V}}$ using the distribution of $t^* = (\hat{\theta}^* - \hat{\theta})/\sqrt{\hat{V}^*}$ across these bootstrap samples, where $\hat{\theta}^*$ and $\hat{V}^*$ are the parameter estimate and its variance estimate in a given bootstrap sample. A major benefit of this bootstrap-*t* procedure (Efron (1982) and Hall (1988)) is that it allows us to assess the impact of a host of small-sample statistical problems in one fell swoop. These problems include (1) any small-sample biases in our coefficient estimates due Stambaugh (1999) bias or the fact that our predictors make use of full-sample quantiles; (2) the fact that sampling variation in the variance estimates leads the distribution of *t*-statistics to have fat tails in small samples; and (3) any correlation between coefficient and variance estimates which can lead *t*-statistics to have non-symmetric distributions in small samples.

For each bootstrap iteration, we construct a pseudo country-year panel dataset using a panel moving-blocks procedure (detailed below) that resamples blocks of temporally contiguous cross-sections from our original panel. For our 3-year crisis forecasting regressions the cross-section at time t is $\mathbf{Z}_t = \{(Crisis_{i,t \text{ to } t+h}, \Delta_3(Debt/GDP)_{it}), \Delta_3 \log(Price_{it})\}_{i \in S_t}$ where S_t is the set of countries in the panel at time *t*. After constructing this pseudo panel, we redefine our $High\text{-}Debt\text{-}Growth_{it}$, $High\text{-}Price\text{-}Growth_{it}$, and $R\text{-}zone_{it}$ indicator variables based on the quantiles in this pseudo panel. We then estimate our forecasting regression and compute Driscoll-Kraay (1998) standard errors using this pseudo panel dataset and save the resulting bootstrapped *t*-statistics: $t^* = (\hat{\theta}^* - \hat{\theta})/\sqrt{\hat{V}^*}$. We compute bootstrap-implied *p*-values by comparing the *t*-statistic we obtain from our actual country-year panel to the resulting distribution of bootstrapped *t*-statistics.

To preserve the cross-sectional and time-series dependence within our country-year panel dataset, we create pseudo panel datasets by adapting the stationary moving blocks bootstrap of Politis and Romano (1994). We adapt the standard procedure slightly to deal with the unbalanced nature of our panel—i.e., the fact that number of observations in each cross-section, N_t, varies over time.

Let $\mathbf{Z}_t$ for $t = 1, \dots, T$ denote the T cross-sections in our original panel. Let $\mathbf{B}_{t,k} = \{\mathbf{Z}_t, \mathbf{Z}_{t+1}, \dots, \mathbf{Z}_{t+k-1}\}$ be the block of *k* consecutive cross-sections starting from time *t*. If $t + i > T$ for some $i \leq k - 1$, we let $\mathbf{Z}_{t+i} = \mathbf{Z}_{mod\{t+i,T\}}$—i.e. we "wrap the data around the circle". Letting $\{L_j\}$ be a sequence of *iid* draws from the geometric distribution with probability q and $\{I_j\}$ be a sequence of *iid* draws from the discrete uniform distribution on $\{1, 2, \dots, T\}$, we create a pseudo panel by resampling blocks of *random* length as $\{\mathbf{B}_{I_1,L_1}, \mathbf{B}_{I_2,L_2}, \dots\}$. This process is stopped once *T* cross-sections have been selected. As discussed in Politis and Roman (1994), this procedure ensures that all cross-sections are equally likely to be resampled. This procedure also ensures that the pseudo panels will be stationary if the original panel is stationary.

We adapt this standard moving-blocks procedure to deal with the unbalance nature of our panel. The expected number of country-years from these pseudo equals the number of country years in our original panel. However, while the time-series length of these panels is fixed at *T*, the number

fixed *b* asymptotics converge to standard asymptotics in the limit where $b \to 0$.

of countries years be distributed in a roughly bell-curved shape about this mean. To ensure that our pseudo panels have a similar number of country years, we only keep those pseudo panels where the number of countries years is within plus or minus one standard deviation (across bootstrap replications) of the mean (across bootstrap replications). Since the width of the cross-sections, N_t, is roughly linear in time *t*, this has an almost negligible impact on the likelihood that a given cross-section ends up in one of our pseudo-panels. However, this means that we throw out both pseudo panels that over-represent the earlier years in our sample when N_t was smaller as well those that over-represent the later years when N_t is larger.

Let $t^* = (\hat{\theta}^* - \hat{\theta})/\sqrt{\hat{V}^*}$ and let $T_{Boot}(\alpha)$ denote the α percentile of this distribution—i.e., $\Pr[t^* \leq T_{Boot}(\alpha)] = \alpha$. Consider an asymmetric 2-tailed confidence interval with coverage probability $1-\alpha$. We have

$$\begin{aligned} 1-\alpha &= \Pr[T_{Boot}(\alpha/2) \leq (\hat{\theta}^* - \hat{\theta})/\sqrt{\hat{V}^*} \leq T_{Boot}(1-\alpha/2)] \\ &\approx \Pr[T_{Boot}(\alpha/2) \leq (\hat{\theta} - \theta_0)/\sqrt{\hat{V}} \leq T_{Boot}(1-\alpha/2)] \\ &= \Pr[\hat{\theta} - \sqrt{\hat{V}} \times T_{Boot}(1-\alpha/2) \leq \theta_0 \leq \hat{\theta} - \sqrt{\hat{V}} \times T_{Boot}(\alpha/2)]. \end{aligned}$$

Thus, the implied bootstrapped *p*-value for a test of the hypothesis that $\theta_0 = 0$ is given by

$$\alpha_{Boot} = \min\{2 \times T_{Boot}^{-1}(\hat{\theta}/\sqrt{\hat{V}}), 2 \times (1 - T_{Boot}^{-1}(\hat{\theta}/\sqrt{\hat{V}}))\}.$$

Since *t*-statistics using consistent and asymptotically normal estimators are "asymptotically pivotal"—they are asymptotically standard normal regardless of the true underlying parameters—using these bootstrapped *p*-values offers asymptotical refinement in finite samples.

These results are presented in Table A6. We use 100,000 replications for each regression and a parameter of q = 1/8, so that the average block length is 8 years. Similar results obtain for other choices of q. While the *p*-values derived from the bootstrap-*t* procedure are larger (i.e., less significant) than those based on asymptotic theory, we find that 3-year forecasting results are significant at the 5% level or better. Thus, *t*-statistics as large as those shown in Table A6 are highly unlikely to obtain by chance, even in finite samples.

We also use this bootstrapping procedure to assess any finite-sample bias of our coefficient estimates, whether due Stambaugh (1999) bias or the fact that our predictors make use of full-sample quantiles. Specifically, we report the standard bootstrap bias estimator $bias(\hat{\theta}) = E_{Boot}[\hat{\theta}^* - \hat{\theta}]$ and the bias-adjusted estimate of θ_0, $\hat{\theta}_{adjust} = \hat{\theta} - bias(\hat{\theta}) = 2\hat{\theta} - E_{Boot}[\hat{\theta}^*]$. As shown in Table A6, our bootstrapping exercise suggests that the magnitude of these estimation biases is negligible.

E. Varying the Cutoffs Used to Define High Debt Growth and High Price Growth

To address concerns about functional-form overfitting, Table A7 asks whether our results are sensitive to the cutoffs we use to construct our indicators for high debt growth and high price growth. Table A7 shows that there is nothing special about the particular cutoffs we use to construct these indicators: we obtain similar results in the full sample, the pre-2000 sample, and the post-2000 sample for a variety of different cutoff values.

For various cutoff pairs (c_D, c_P), we recompute:

$$High\text{-}Debt\text{-}Growth_{it}(c_D) = 1\{\Delta_3(Debt/GDP)_{it} > c_D\}$$

$$High\text{-}Price\text{-}Growth_{it}(c_P) = 1\{\Delta_3\log(Price_{it}) > c_P\}$$

$$R\text{-}zone_{it}(c_D, c_P) = 1\{\Delta_3(Debt/GDP)_{it} > c_D\} \times 1\{\Delta_3 \log(Price_{it}) > c_P\}.$$

Using the resulting indicator variables, we then rerun our baseline forecasting regressions in different samples:

$$Crisis_{i,t+1 \text{ to } t+3} = \alpha_i + \beta \cdot High\text{-}Debt\text{-}Growth_{it}(c_D) + \delta \cdot High\text{-}Price\text{-}Growth_{it}(c_P) + \gamma \cdot R\text{-}zone_{it}(c_D, c_P) + \varepsilon_{i,t+1 \text{ to } t+3}$$

We consider the full sample, the pre-2000 subsample (the last 3-year forecast is in 1996), and the post-2000 subsample (the first forecast is in 1997). For each sample, we report the estimated coefficient $\hat{\gamma}$ on $R\text{-}zone_{it}(c_D,c_P)$ as a function of the cutoffs (c_D,c_P) from a univariate regression and a multivariate regression that controls for $High\text{-}Debt\text{-}Growth_{it}(c_D)$ and $High\text{-}Price\text{-}Growth_{it}(c_P)$. The highlighted cells correspond to our baseline variable definitions. Panel A shows the results for the business sector and Panel B shows those for the household sector.

Table A7 shows that our central conclusion—the combination of rapid credit growth and asset price growth is associated with an elevated risk of a financial crisis—holds up in all three samples for a variety of different cutoff pairs (c_D,c_P). As one would expect based on the nonlinear relationship between past debt and asset price growth and the probability of a future crisis that we emphasize throughout, the estimated coefficient $\hat{\gamma}$ on $R\text{-}zone_{it}(c_D,c_P)$ and the associated *t*-statistic are generally increasing in both the cutoff for debt growth (c_D) and the cutoff for asset price growth (c_P). Compared to other cutoff values, our baseline definitions yield neither the strongest nor the weakest results. To be sure, there are specifications where $\hat{\gamma}$ is no longer statistically significant in some subsamples, but our reading of Table A7 is that our key findings are highly robust to the particular choice of cutoffs.

F. Robustness Checks for Table 7

Here we perform several robustness checks on Table 7 in the main text. Specifically, in Table 7, we estimated regressions of the form:

$$Crisis_{i,t+1 \text{ to } t+h} = \alpha_i^{(h)} + \gamma^{Bus(h)} \cdot Local\ R\text{-}zone_{it}^{Bus} + \xi^{Bus(h)} \cdot Global\ R\text{-}zone_{t}^{Bus} + \gamma^{HH(h)} \cdot Local\ R\text{-}zone_{it}^{HH} + \xi^{HH(h)} \cdot Global\ R\text{-}zone_{t}^{HH} + \varepsilon_{i,t+1 \text{ to } t+h}$$

for h = 1, 2, 3, and 4. In the results reported in Table 7, the *Global R-zone* variable is simply the equal-weighted average across all countries in each annual cross-section. However, our results are quite robust to the way that we construct our *Global R-zone* variable. First, as shown in Table A8 below, the results in Table 7 are very similar if the *Global R-zone* variable for each country-year is defined as the equal-weighted fraction of *other* sample countries that are in the *R-zone* in that year—i.e., in a “leave one out” fashion.[8] Second, as shown in Table A9, the results are also qualitatively similar if we compute *Global R-zone* using a GDP-weighted average across countries. While still highly significant, the *t*-statistics on *Global R-zone* are typically somewhat smaller when we use the GDP-weighted version.

[8] As one would expect, relative to the equal-weighted definition of *Global R-zone* shown in Table 7, defining *Global R-zone* in this “leave-one-out” fashion tends to slightly raise the coefficient on *Local R-zone* and slightly reduce the coefficient on *Global R-zone*.

Table A1: Equity Indices

This table presents an overview of the equity indices used in our analysis. The data is retrieved from 4 sources: Global Financial Data (GFD), the International Monetary Funds (IMF) *International Financial Statistics*, Bloomberg and the Jordá, Schularick and Taylor MacroHistory database (JST).

Country	Years	Source	Equity Index
Argentina	1950-2018	GFD	Buenos Aires SE General Index (IVBNG)†
Australia	1950-2018	GFD	Australia ASX All-Ordinaries (w/GFD extension)
Austria	1950-2018	GFD	Austria Wiener Boersekammer Share Index (WBKI)
Belgium	1950-2018	GFD	Brussels All-Share Price Index (w/GFD extension)
Brazil	1950-2018	GFD	GFD Indices Brazil Bolsa de Valores de Sao Paulo (Bovespa) †
Canada	1950-2018	GFD	Canada S&P/TSX 300 Composite (w/GFD extension)
Chile	1975-2001	GFD	Santiago SE Indice de Precios Selectivos Acciones
Chile	1999-2018	IMF	Selective Price Index (IPSA)
Colombia	2001-2018	IMF	Index of prices on the Bogotá Stock Exchange
Czech Republic	1997-2018	IMF	PX-50 index
Denmark	1950-2018	GFD	OMX Copenhagen All-Share Price Index
Finland	1950-2018	GFD	OMX Helsinki All-Share Price Index
France	1950-1989	JST	Stock prices (nominal index)
France	1987-2018	GFD	Paris CAC-40 Index
Germany	1950-1961	JST	Stock prices (nominal index)
Germany	1959-2018	GFD	Germany DAX Price Index
Greece	1952-2018	GFD	Athens SE General Index (w/GFD extension)
Hong Kong	1964-2018	GFD	Hong Kong Hang Seng Composite Index (w/GFD Extension)
Hungary	1994-2018	GFD	Vienna OETEB Hungary Traded Index (Forint)
Iceland	2002-2018	IMF	Index of the 15 largest and most traded Icelandic companies of the OMX
India	1950-2018	GFD	Bombay SE Sensitive Index (w/GFD extension)
Indonesia	1977-2018	GFD	Jakarta SE Composite Index
Ireland	1950-2018	GFD	Ireland ISEQ Overall Price Index (w/GFD extension)
Israel	1991-2019	Bloomberg	TA-125 (last price)
Italy	1950-2018	GFD	Banca Commerciale Italiana Index (w/GFD extension)
Japan	1950-1986	JST	Stock prices (nominal index)
Japan	1984-2017	GFD	Japan Nikkei 500 Index
Korea	1962-2018	GFD	Korea SE Stock Price Index (KOSPI)
Luxembourg	1999-2019	Bloomberg	LUXXX Index (last price)
Malaysia	1973-2018	GFD	Malaysia KLSE Composite
Mexico	1950-2018	GFD	Mexico SE Indice de Precios y Cotizaciones (IPC)
Netherlands	1950-2018	GFD	Netherlands All-Share Price Index (w/GFD extension)
New Zealand	1950-2018	GFD	New Zealand SE All-Share Capital Index
Norway	1950-1971	JST	Stock prices (nominal index)
Norway	1969-2018	GFD	Oslo SE All-Share Index†
Peru	1988-2016	IMF	Share price index of the Lima Stock Exchange (industrials and mining)
Portugal	1950-2018	GFD	Oporto PSI-20 Index
Russia	1993-2018	GFD	Russia Moscow Index (MOEX) Composite
Singapore	1961-2018	GFD	Singapore FTSE Straits-Times Index
South Africa	1960-2018	IMF	All ordinary shares listed on Security Exchange South Africa
Spain	1950-1989	JST	Stock prices (nominal index)
Spain	1987-2018	GFD	Madrid SE IBEX-35
Sweden	1950-2018	GFD	Sweden OMX Affarsvarldens General Index
Switzerland	1950-2018	GFD	Switzerland Price Index (w/GFD extension)
Thailand	1975-2018	GFD	Thailand SET General Index
Turkey	1986-2018	GFD	Istanbul SE IMKB-100 Price Index
United Kingdom	1950-2018	GFD	UK FTSE All-Share Index (w/GFD extension)
United States	1950-2018	GFD	S&P 500/Cowles Composite Price Index (w/GFD extension)

† Return index

Table A2: House Price Indices

This table presents an overview of the house price indices used in our analysis. The data is retrieved from 3 sources: Bank of International Settlements' (BIS) *Property Price Statistics*, the OECD's *Household Prices* database and the Jordá, Schularick and Taylor MacroHistory database (JST).

Country	Years	Source	Variable
Australia	1950-1972	JST	House prices (hpnom) normalized by consumer price index (cpi)
Australia	1970-2018	BIS	Real residential property prices
Austria	2000-2018	BIS	Real residential property prices
Belgium	1950-1972	JST	House prices (hpnom) normalized by consumer price index (cpi)
Belgium	1970-2018	BIS	Real residential property prices
Brazil	2001-2018	BIS	Real residential property prices
Canada	1950-1972	JST	House prices (hpnom) normalized by consumer price index (cpi)
Canada	1970-2018	BIS	Real residential property prices
Chile	2002-2018	BIS	Real residential property prices
Colombia	1988-2018	BIS	Real residential property prices
Czech Republic	2008-2018	BIS	Real residential property prices
Denmark	1950-1972	JST	House prices (hpnom) normalized by consumer price index (cpi)
Denmark	1970-2018	BIS	Real residential property prices
Finland	1950-1972	JST	House prices (hpnom) normalized by consumer price index (cpi)
Finland	1970-2018	BIS	Real residential property prices
France	1950-1972	JST	House prices (hpnom) normalized by consumer price index (cpi)
France	1970-2018	BIS	Real residential property prices
Germany	1950-1972	JST	House prices (hpnom) normalized by consumer price index (cpi)
Germany	1970-2018	BIS	Real residential property prices
Greece	1997-2017	OECD	Real residential property prices
Hong Kong	1979-2018	BIS	Real residential property prices
Hungary	2007-2018	BIS	Real residential property prices
Iceland	2000-2018	BIS	Real residential property prices
India	2009-2018	BIS	Real residential property prices
Indonesia	2002-2018	BIS	Real residential property prices
Ireland	1970-2018	BIS	Real residential property prices
Israel	1994-2018	BIS	Real residential property prices
Italy	1950-2018	BIS	Real residential property prices
Japan	1950-1957	JST	House prices (hpnom) normalized by consumer price index (cpi)
Japan	1955-2018	BIS	Real residential property prices
Korea	1975-2018	BIS	Real residential property prices
Luxembourg	2007-2018	BIS	Real residential property prices
Malaysia	1988-2018	BIS	Real residential property prices
Mexico	2005-2018	BIS	Real residential property prices
Netherlands	1950-1972	JST	House prices (hpnom) normalized by consumer price index (cpi)
Netherlands	1970-2018	BIS	Real residential property prices
New Zealand	1970-2018	BIS	Real residential property prices
Norway	1950-1972	JST	House prices (hpnom) normalized by consumer price index (cpi)
Norway	1970-2018	BIS	Real residential property prices
Peru	1998-2018	BIS	Real residential property prices
Portugal	1988-2017	OECD	Real residential property prices
Russia	2001-2018	BIS	Real residential property prices
Singapore	1998-2018	BIS	Real residential property prices
South Africa	1966-2018	BIS	Real residential property prices
Spain	1971-2018	BIS	Real residential property prices
Sweden	1950-1972	JST	House prices (hpnom) normalized by consumer price index (cpi)
Sweden	1970-2018	BIS	Real residential property prices
Switzerland	1950-1972	JST	House prices (hpnom) normalized by consumer price index (cpi)
Switzerland	1970-2018	BIS	Real residential property prices
Thailand	1991-2018	BIS	Real residential property prices
Turkey	2010-2018	BIS	Real residential property prices
United Kingdom	1950-1970	JST	House prices (hpnom) normalized by consumer price index (cpi)
United Kingdom	1968-2018	BIS	Real residential property prices
United States	1950-1972	JST	House prices (hpnom) normalized by consumer price index (cpi)
United States	1970-2018	BIS	Real residential property prices

Table A3: Debt Sample Overview

This table presents an overview of the sources for business debt (Panel A) and household debt (Panel B) used in our analysis. The data is retrieved from 3 sources: the International Monetary Funds (IMF) *Global Debt Database*, the Jordá, Schularick and Taylor MacroHistory database (JST) and the Bank of International Settlements' (BIS) *Total credit statistics.*

Panel A: *Business Debt Sources*

Country	Years	Source	Variable
Argentina	1994-2017	IMF	Loans and debt securities by non-financial corporations (nfc_ls_data)
Australia	1950-1979	JST	Total loans to business (tbus)
Australia	1977-2017	IMF	Loans and debt securities by non-financial corporations (nfc_ls_data)
Austria	1995-2017	IMF	Loans and debt securities by non-financial corporations (nfc_ls_data)
Belgium	1950-1982	JST	Total loans to business (tbus)
Belgium	1980-2017	IMF	Loans and debt securities by non-financial corporations (nfc_ls_data)
Brazil	1994-2017	IMF	Loans and debt securities by non-financial corporations (nfc_ls_data)
Canada	1961-1971	JST	Total loans to business (tbus)
Canada	1969-2017	IMF	Loans and debt securities by non-financial corporations (nfc_ls_data)
Chile	2002-2017	IMF	Loans and debt securities by non-financial corporations (nfc_ls_data)
Colombia	1996-2017	IMF	Loans and debt securities by non-financial corporations (nfc_ls_data)
Czech Republic	1995-2016	IMF	Loans and debt securities by non-financial corporations (nfc_ls_data)
Denmark	1951-1996	JST	Total loans to business (tbus)
Denmark	1994-2017	IMF	Loans and debt securities by non-financial corporations (nfc_ls_data)
Finland	1950-1972	JST	Total loans to business (tbus)
Finland	1970-2017	IMF	Loans and debt securities by non-financial corporations (nfc_ls_data)
France	1958-1979	JST	Total loans to business (tbus)
France	1977-2017	IMF	Loans and debt securities by non-financial corporations (nfc_ls_data)
Germany	1950-1972	JST	Total loans to business (tbus)
Germany	1970-2017	IMF	Loans and debt securities by non-financial corporations (nfc_ls_data)
Greece	1994-2017	IMF	Loans and debt securities by non-financial corporations (nfc_ls_data)
Hong Kong	1990-2017	IMF	Loans and debt securities by non-financial corporations (nfc_ls_data)
Hungary	1969-2017	IMF	Loans and debt securities by non-financial corporations (nfc_ls_data)
Iceland	1970-2016	IMF	Loans and debt securities by non-financial corporations (nfc_ls_data)
India	1998-2017	IMF	Loans and debt securities by non-financial corporations (nfc_ls_data)
Indonesia	2001-2017	IMF	Loans and debt securities by non-financial corporations (nfc_ls_data)
Ireland	2002-2017	IMF	Loans and debt securities by non-financial corporations (nfc_ls_data)
Israel	1992-2017	IMF	Loans and debt securities by non-financial corporations (nfc_ls_data)
Italy	1950-2017	IMF	Loans and debt securities by non-financial corporations (nfc_ls_data)
Japan	1950-1966	JST	Total loans to business (tbus)
Japan	1964-2017	IMF	Loans and debt securities by non-financial corporations (nfc_ls_data)
Korea	1962-2017	IMF	Loans and debt securities by non-financial corporations (nfc_ls_data)
Luxembourg	2002-2017	IMF	Loans and debt securities by non-financial corporations (nfc_ls_data)
Malaysia	2006-2016	IMF	Loans and debt securities by non-financial corporations (nfc_ls_data)
Mexico	1994-2017	IMF	Loans and debt securities by non-financial corporations (nfc_ls_data)
Netherlands	1990-2017	IMF	Loans and debt securities by non-financial corporations (nfc_ls_data)
New Zealand	1990-2017	IMF	Loans and debt securities by non-financial corporations (nfc_ls_data)
Norway	1975-2017	IMF	Loans and debt securities by non-financial corporations (nfc_ls_data)
Peru	2001-2016	IMF	Loans and debt securities by non-financial corporations (nfc_ls_data)
Portugal	1979-2017	IMF	Loans and debt securities by non-financial corporations (nfc_ls_data)
Russia	1998-2017	IMF	Loans and debt securities by non-financial corporations (nfc_ls_data)
Singapore	1991-2017	IMF	Loans and debt securities by non-financial corporations (nfc_ls_data)
South Africa	2008-2017	IMF	Loans and debt securities by non-financial corporations (nfc_ls_data)
Spain	1950-1982	JST	Total loans to business (tbus)
Spain	1980-2017	IMF	Loans and debt securities by non-financial corporations (nfc_ls_data)
Sweden	1961-2017	IMF	Loans and debt securities by non-financial corporations (nfc_ls_data)
Switzerland	1950-2001	JST	Total loans to business (tbus)
Switzerland	1999-2017	IMF	Loans and debt securities by non-financial corporations (nfc_ls_data)
Thailand	1991-2017	BIS	Credit to Non-financial corporations from all sectors
Turkey	1986-2017	IMF	Loans and debt securities by non-financial corporations (nfc_ls_data)
United Kingdom	1950-1968	JST	Total loans to business (tbus)
United Kingdom	1966-2017	IMF	Loans and debt securities by non-financial corporations (nfc_ls_data)
United States	1950-1952	JST	Total loans to business (tbus)
United States	1950-2017	IMF	Loans and debt securities by non-financial corporations (nfc_ls_data)

Panel B: *Household Debt Sources*

Country	Years	Source	Variable
Argentina	1994-2017	IMF	Loans and debt securities by households (hh_ls_data)
Australia	1950-1979	JST	Total loans to households (thh)
Australia	1977-2017	IMF	Loans and debt securities by households (hh_ls_data)
Austria	1995-2017	IMF	Loans and debt securities by households (hh_ls_data)
Belgium	1950-1982	JST	Total loans to households (thh)
Belgium	1980-2017	IMF	Loans and debt securities by households (hh_ls_data)
Brazil	1994-2017	IMF	Loans and debt securities by households (hh_ls_data)
Canada	1956-1971	JST	Total loans to households (thh)
Canada	1969-2017	IMF	Loans and debt securities by households (hh_ls_data)
Chile	2002-2017	IMF	Loans and debt securities by households (hh_ls_data)
Colombia	1996-2017	IMF	Loans and debt securities by households (hh_ls_data)
Czech Republic	1995-2016	IMF	Loans and debt securities by households (hh_ls_data)
Denmark	1951-1996	JST	Total loans to households (thh)
Denmark	1994-2017	IMF	Loans and debt securities by households (hh_ls_data)
Finland	1950-1972	JST	Total loans to households (thh)
Finland	1970-2017	IMF	Loans and debt securities by households (hh_ls_data)
France	1958-1979	JST	Total loans to households (thh)
France	1977-2017	IMF	Loans and debt securities by households (hh_ls_data)
Germany	1950-1972	JST	Total loans to households (thh)
Germany	1970-2017	IMF	Loans and debt securities by households (hh_ls_data)
Greece	1994-2017	IMF	Loans and debt securities by households (hh_ls_data)
Hong Kong	1990-2017	IMF	Loans and debt securities by households (hh_ls_data)
Hungary	1964-2017	IMF	Loans and debt securities by households (hh_ls_data)
Iceland	1970-2016	IMF	Loans and debt securities by households (hh_ls_data)
India	1998-2017	IMF	Loans and debt securities by households (hh_ls_data)
Indonesia	2001-2017	IMF	Loans and debt securities by households (hh_ls_data)
Ireland	2002-2017	IMF	Loans and debt securities by households (hh_ls_data)
Israel	1992-2017	IMF	Loans and debt securities by households (hh_ls_data)
Italy	1950-2017	IMF	Loans and debt securities by households (hh_ls_data)
Japan	1950-1966	JST	Total loans to households (thh)
Japan	1964-2017	IMF	Loans and debt securities by households (hh_ls_data)
Korea	1962-2017	IMF	Loans and debt securities by households (hh_ls_data)
Luxembourg	2002-2017	IMF	Loans and debt securities by households (hh_ls_data)
Malaysia	2006-2016	IMF	Loans and debt securities by households (hh_ls_data)
Mexico	1994-2017	IMF	Loans and debt securities by households (hh_ls_data)
Netherlands	1990-2017	IMF	Loans and debt securities by households (hh_ls_data)
New Zealand	1990-2017	IMF	Loans and debt securities by households (hh_ls_data)
Norway	1975-2017	IMF	Loans and debt securities by households (hh_ls_data)
Peru	2001-2017	IMF	Loans and debt securities by households (hh_ls_data)
Portugal	1979-2017	IMF	Loans and debt securities by households (hh_ls_data)
Russia	1998-2017	IMF	Loans and debt securities by households (hh_ls_data)
Singapore	1991-2017	IMF	Loans and debt securities by households (hh_ls_data)
South Africa	2008-2017	IMF	Loans and debt securities by households (hh_ls_data)
Spain	1950-1982	JST	Total loans to households (thh)
Spain	1980-2017	IMF	Loans and debt securities by households (hh_ls_data)
Sweden	1950-2017	IMF	Loans and debt securities by households (hh_ls_data)
Switzerland	1950-2001	JST	Total loans to households (thh)
Switzerland	1999-2017	IMF	Loans and debt securities by households (hh_ls_data)
Thailand	1991-2017	BIS	Credit to Households and NPISHs from all sectors
Turkey	1986-2017	IMF	Loans and debt securities by households (hh_ls_data)
United Kingdom	1950-1968	JST	Total loans to households (thh)
United Kingdom	1966-2017	IMF	Loans and debt securities by households (hh_ls_data)
United States	1950-1952	JST	Total loans to households (thh)
United States	1950-2017	IMF	Loans and debt securities by households (hh_ls_data)

Table A5: Cumulative and Incremental Probabilities of Crisis Onset at Different Horizons

The table presents the results of three crisis prediction models:

$$y_{i,t\to t+h} = a_i + \beta \times \text{High Debt Growth}_{it} + \delta \times \text{High Price Growth}_{it} + \gamma \times \text{R-Zone}_{it} + \epsilon_{it}$$

where $y_{i,t\to t+h} \in \{Crisis_{i,t+1 \text{ to } t+h}, Crisis_{t+1 \text{ to } t+h} - Crisis_{t+1 \text{ to } t+h-1}, CrisisStart_{i,t+h}\}\}$. $CrisisStart_{i,t}$ is an indicator variable equal to 1 if a crisis begins in year t in country i. $Crisis_{i,t+1 \text{ to } t+h} = \max\{CrisisStart_{i,t+1}, ..., CrisisStart_{i,t+h}\}$ is an indicator variable, which takes the value of 1 if a crisis has occurred in country i between year $t+1$ and $t+h$. High Debt Growth $\equiv 1\{\Delta_3(Debt/GDP)_{it} > 80^{th}$ percentile$\}$ is an indicator variable which takes the value of 1 if 3-year debt growth is the in the highest quintile, while High Price Growth $\equiv 1\{\Delta_3 \log(Price_{it}) > 66.7^{th}$ percentile$\}$ is an indicator variable which takes the value of 1 if 3-year price growth is in its highest tercile. The R-Zone variable is the intersection of high price growth and high debt growth: R-Zone $\equiv$ High Debt Growth $\times$ High Price Growth. We run the regression on both the *business sector*, using business debt and equity prices to define the indicators (Panel A), and the *household sector*, using household debt and house prices to define the indicators (Panel B). In Panel A1 and B1 t-statistics are based on Driscoll and Kraay (1998) standard errors with lags of 0, 3, 5 and 6 years for prediction horizons 1, 2, 3 and 4 years, respectively. In Panel A2, A3, B2 and B3 t-statistics are based on standard errors clustered by year. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively, using Kiefer and Vogelsang (2005) corrected p-values. Reported coefficients and R^2's are in percent.

Panel A: Business Sector

Panel A1: Predicting $Crisis_{t+1 \text{ to } t+h}$ (Baseline Regression)

	Univariate Regressions									Multivariate Regressions						
Horizon	β	t-statistic	R^2	δ	t-statistic	R^2	γ	t-statistic	R^2	β	t-statistic	δ	t-statistic	γ	t-statistic	R^2
1	6.9	[2.3**]	1.6	0.4	[0.1]	0.0	9.0	[1.1]	1.1	5.3	[2.1**]	-0.4	[−0.2]	5.3	[0.8]	1.9
2	11.6	[3.0***]	2.5	4.8	[0.9]	0.7	17.9	[2.1*]	2.3	9.5	[2.5**]	3.8	[0.8]	7.8	[1.3]	3.6
3	16.8	[3.3***]	3.8	10.5	[1.4]	2.4	33.7	[3.3***]	6.1	11.5	[2.7**]	7.4	[1.1]	19.4	[2.8**]	7.8
4	15.6	[2.7***]	2.8	10.7	[1.5]	2.1	33.0	[3.1**]	4.8	10.3	[2.2*]	7.6	[1.2]	19.4	[2.6**]	6.2

Panel A2: Predicting $Crisis_{t+1 \text{ to } t+h} - Crisis_{t+1 \text{ to } t+h-1}$

	Univariate Regressions									Multivariate Regressions						
Horizon	β	t-statistic	R^2	δ	t-statistic	R^2	γ	t-statistic	R^2	β	t-statistic	δ	t-statistic	γ	t-statistic	R^2
1	6.9	[2.3**]	1.6	0.4	[0.1]	0.0	9.0	[1.1]	1.1	5.3	[2.1**]	-0.4	[−0.2]	5.3	[0.8]	1.9
2	4.7	[2.4**]	0.8	4.4	[1.1]	1.1	8.9	[1.8*]	1.1	4.2	[1.9*]	4.1	[1.2]	2.6	[0.6]	2.0
3	5.2	[2.6***]	1.0	5.7	[1.5]	1.9	15.8	[2.1**]	3.6	2.0	[1.0]	3.6	[1.1]	11.5	[1.8*]	4.2
4	-1.1	[−0.9]	0.1	0.3	[0.2]	0.0	-0.7	[−0.3]	0.0	-1.1	[−0.8]	0.2	[0.2]	0.0	[0.0]	0.1

Panel A3: Predicting $Crisis_{t+h}$

	Univariate Regressions									Multivariate Regressions						
Horizon	β	t-statistic	R^2	δ	t-statistic	R^2	γ	t-statistic	R^2	β	t-statistic	δ	t-statistic	γ	t-statistic	R^2
1	6.9	[2.3**]	1.6	0.4	[0.1]	0.0	9.0	[1.1]	1.1	5.3	[2.1**]	-0.4	[−0.2]	5.3	[0.8]	1.9
2	4.7	[2.4**]	0.8	4.4	[1.1]	1.1	8.9	[1.8*]	1.1	4.2	[1.9*]	4.1	[1.2]	2.6	[0.6]	2.0
3	5.5	[2.8***]	1.1	6.2	[1.6]	2.1	17.1	[2.5**]	4.0	1.9	[1.0]	3.9	[1.2]	12.7	[2.1**]	4.7
4	-0.3	[−0.2]	0.0	1.7	[1.1]	0.2	2.7	[0.9]	0.1	-0.9	[−0.6]	1.2	[0.8]	2.5	[0.8]	0.2

Panel B: Household Sector

Panel B1: Predicting $Crisis_{t+1 \text{ to } t+h}$ (Baseline Regression)

	Univariate Regressions									Multivariate Regressions						
Horizon	β	t-statistic	R^2	δ	t-statistic	R^2	γ	t-statistic	R^2	β	t-statistic	δ	t-statistic	γ	t-statistic	R^2
1	7.3	[2.2**]	1.8	3.6	[1.7*]	0.7	11.2	[2.2**]	2.7	2.4	[1.6]	0.4	[0.3]	8.9	[1.8*]	2.8
2	15.1	[2.8**]	4.1	6.0	[1.4]	1.0	20.5	[2.7**]	4.9	7.3	[2.2**]	0.4	[0.2]	14.1	[2.4**]	5.5
3	20.5	[3.3***]	5.6	8.1	[1.5]	1.4	28.6	[3.4***]	7.0	9.1	[2.3**]	0.0	[0.0]	20.9	[3.2***]	7.6
4	23.7	[3.9***]	6.2	8.5	[1.5]	1.3	29.6	[4.1***]	6.2	14.2	[2.5**]	0.8	[0.2]	17.1	[2.0*]	7.4

Panel B2: Predicting $Crisis_{t+1 \text{ to } t+h} - Crisis_{t+1 \text{ to } t+h-1}$

	Univariate Regressions									Multivariate Regressions						
Horizon	β	t-statistic	R^2	δ	t-statistic	R^2	γ	t-statistic	R^2	β	t-statistic	δ	t-statistic	γ	t-statistic	R^2
1	7.3	[2.2**]	1.8	3.6	[1.7*]	0.7	11.2	[2.2**]	2.7	2.4	[1.6]	0.4	[0.3]	8.9	[1.8*]	2.8
2	7.7	[2.3**]	2.0	2.4	[0.9]	0.3	9.3	[1.8*]	1.9	4.9	[1.7*]	0.0	[0.0]	5.1	[1.1]	2.3
3	5.5	[1.9*]	1.1	2.1	[1.0]	0.2	8.1	[2.3**]	1.5	1.8	[0.7]	-0.4	[−0.2]	6.9	[2.7***]	1.6
4	3.2	[1.1]	0.4	0.4	[0.2]	0.0	1.0	[0.5]	0.0	5.1	[1.1]	0.8	[0.3]	-3.9	[−0.8]	0.6

Panel B3: Predicting $Crisis_{t+h}$

	Univariate Regressions									Multivariate Regressions						
Horizon	β	t-statistic	R^2	δ	t-statistic	R^2	γ	t-statistic	R^2	β	t-statistic	δ	t-statistic	γ	t-statistic	R^2
1	7.3	[2.2**]	1.8	3.6	[1.7*]	0.7	11.2	[2.2**]	2.7	2.4	[1.6]	0.4	[0.3]	8.9	[1.8*]	2.8
2	7.7	[2.3**]	2.0	2.4	[0.9]	0.3	9.3	[1.8*]	1.9	4.9	[1.7*]	0.0	[0.0]	5.1	[1.1]	2.3
3	6.1	[2.1**]	1.3	2.6	[1.2]	0.4	9.7	[2.6***]	2.1	1.5	[0.5]	-0.4	[−0.2]	8.8	[2.7***]	2.1
4	4.9	[1.7*]	0.8	1.6	[0.8]	0.1	4.1	[1.8*]	0.4	5.2	[1.0]	1.0	[0.4]	-1.0	[−0.2]	0.9

Table A6: Bootstrapped P-Values and Bias Estimates

This table presents p-values for coefficient estimates from our main crisis prediction model at the 3-year horizon:

$$Crisis_{i,t+1\ to\ t+3} = a_i + \beta \times \text{High Debt Growth}_{it} + \delta \times \text{High Price Growth}_{it} + \gamma \times \text{R-Zone}_{it} + \epsilon_{it}$$

We show the p-values calculated using standard asymptotics, fixed-b asymptotics as in Kiefer and Vogelsang (2005) and p-values calculated using the block bootstrap procedure described in section D. For the bootstrap we draw 100,000 samples with the block sizes being drawn from a geometric distribution with success probability 0.125. We show the p-values for coefficient estimates obtained from univariate regressions (corresponding to columns (3.1), (3.2) and (3.4) in Table 4), and p-values for coefficient estimates obtained from multiple regressions (corresponding to column (3.3) in Table 4). All t-statistics are calculated using Driscoll and Kraay (1998) standard errors with 5 lags. Panel A and B present the results for the *business sector* and *household sector*, respectively.

Panel A: Business Sector

	Univariate Regressions			Multivariate Regressions		
	β	δ	γ	β	δ	γ
Coefficient estimate	18.8	9.9	35.4	13.4	6.9	19.1
t-statistic	[3.7]	[1.4]	[3.5]	[2.7]	[1.1]	[2.7]
$P(>\|t\|)$ asymptotic	(0.000)	(0.155)	(0.001)	(0.008)	(0.269)	(0.008)
$P(>\|t\|)$ fixed-b	(0.050)	(0.203)	(0.006)	(0.022)	(0.315)	(0.016)
$P(>\|t\|)$ bootstrap	(0.017)	(0.089)	(0.027)	(0.073)	(0.202)	(0.011)
Bias in Coefficient Estimate	-1.4	-1.0	-3.6	-0.5	-0.3	-2.9
Coefficient Estimate (bias adj.)	20.2	10.9	39.0	13.9	7.2	22.0

Panel B: Household Sector

	Univariate Regressions			Multivariate Regressions		
	β	δ	γ	β	δ	γ
Coefficient estimate	20.7	6.9	27.8	11.7	-0.5	17.7
t-statistic	[3.0]	[1.3]	[3.0]	[2.0]	[-0.2]	[2.4]
$P(>\|t\|)$ asymptotic	(0.003)	(0.182)	(0.002)	(0.044)	(0.864)	(0.015)
$P(>\|t\|)$ fixed-b	(0.005)	(0.183)	(0.004)	(0.047)	(0.999)	(0.007)
$P(>\|t\|)$ bootstrap	(0.011)	(0.114)	(0.030)	(0.047)	(0.880)	(0.036)
Bias in Coefficient Estimate	-0.9	-0.4	-1.5	-0.4	0.1	-1.2
Coefficient Estimate (bias adj.)	21.6	7.4	29.2	12.1	-0.6	18.9

Table A7: Sensitivity of Main Crisis Prediction to Cutoff and Sample Period

The table presents coefficient estimates and t-statistics of our main crisis prediction model:

$$Crisis_{i,t+1 \text{ to } t+3} = a_i + \beta \times \text{High Debt Growth}_{it} + \delta \times \text{High Price Growth}_{it} + \gamma \times \text{R-Zone}_{it} + \epsilon_{it}$$

where $Crisis_{i,t+1 \text{ to } t+h}$ is an indicator variable, which takes the value of 1 if a crisis has occurred in country i within 3 years of time t. $\text{High Debt Growth}_{it} \equiv 1\{\Delta_3(Debt/GDP)_{it} > C_D\}$ is an indicator variable which takes the value of 1 if 3-year debt growth in country i is higher than C_D, while $\text{High Price Growth}_{it} \equiv 1\{\Delta_3 \log(Price_{it}) > C_P\}$ is an indicator variable which takes the value of 1 if 3-year price growth in country i is above C_P. The R-Zone variable is the intersection of high price growth and high debt growth: $\text{R-Zone}_{it} \equiv \text{High Debt Growth}_{it} \times \text{High Price Growth}_{it}$. The indicator variables are defined using a range of cutoffs for debt growth (C_D varies across columns) and price growth (C_P varies across rows), and the model is tested with both a univariate (left) and a multiple regression specification (right). We test the model on both our full sample, a pre-2000 sample where we exclude data after 1999 (last prediction year is 1996), and post-2000 sample where we exclude data prior to 1997 (last prediction year is 2012). We run the regressions on both the *business sector*, using business debt and equity prices to define the indicators (Panel A), and the *household sector*, using household debt and house prices to define the indicators (Panel B). t-statistics are based on Driscoll and Kraay (1998) standard errors with 5 lags. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively, using Kiefer and Vogelsang (2005) corrected p-values.

Panel A: Business Sector

Rows: Price Growth Cutoff (C_P). Columns: **Debt Growth Cutoff (C_D)**

	Univariate Regressions										Multivariate Regressions									
	Coefficient (γ)					t-statistic					Coefficient (γ)					t-statistic				
Full Sample	3	6	9	12	15	3	6	9	12	15	3	6	9	12	15	3	6	9	12	15
9	17.2	17.2	28.3	33.7	42.2	2.6**	2.3**	2.8**	2.6**	3.3***	11.6	7.4	16.4	17.8	28.3	2.1*	1.1	1.8	1.6	2.8**
18	18.1	19.6	31.4	37.6	49.5	2.4**	2.5**	3.2***	3.2***	4.9***	12.2	10.4	19.1	21.7	35.2	2.0*	1.8	2.6**	2.3**	4.6***
27	19.3	21.5	**33.7**	39.6	57.9	2.3**	2.7**	$\mathbf{3.3}^{***}$	3.1***	6.1***	11.5	11.1	**19.4**	21.2	43.5	1.9*	2.1*	$\mathbf{2.8}^{**}$	2.1*	4.9***
36	17.5	21.4	32.1	37.9	53.4	2.0*	2.5**	3.1***	3.1***	5.8***	6.1	9.2	15.9	18.0	36.0	1.0	1.8	2.3**	2.2*	4.5***
45	15.7	20.6	31.3	45.4	58.3	1.8	2.1*	2.7**	3.3***	5.4***	5.8	10.0	16.9	29.6	43.1	0.9	1.5	2.1*	3.0**	4.5***
Pre-2000 Sample	3	6	9	12	15	3	6	9	12	15	3	6	9	12	15	3	6	9	12	15
9	18.8	21.7	38.8	47.3	53.7	2.6**	2.3*	3.1**	2.3**	2.1*	20.4	17.5	32.0	32.4	39.0	2.9**	1.8	2.5**	1.4	1.7
18	17.3	21.0	35.3	44.4	49.4	2.1*	2.1*	2.6**	2.2*	1.9	18.5	17.4	25.9	26.2	32.0	2.1*	1.8	2.0*	1.3	1.5
27	16.0	21.8	**34.0**	41.4	49.4	2.2*	2.3*	$\mathbf{2.8}^{**}$	2.0*	1.9	16.7	19.1	**23.2**	20.8	33.9	2.3*	2.3*	$\mathbf{2.2}^{*}$	1.1	1.6
36	15.8	20.7	34.2	36.2	38.5	1.9*	2.0*	2.6**	1.9	1.5	15.6	15.5	22.5	12.2	15.3	2.0*	1.8	1.9	0.8	0.8
45	13.8	20.5	32.1	43.5	36.7	1.5	1.5	1.9	1.8	1.3	10.8	13.4	17.2	20.8	11.6	1.3	1.2	1.1	1.0	0.5
Post-2000 Sample	3	6	9	12	15	3	6	9	12	15	3	6	9	12	15	3	6	9	12	15
9	11.6	10.1	16.3	19.1	28.8	1.1	1.0	1.3	1.6	2.4	1.6	-0.4	5.8	7.7	19.7	0.2	-0.1	0.8	1.1	2.3
18	14.4	14.6	23.2	26.4	40.3	1.2	1.3	1.7	2.0	4.0**	4.5	5.0	12.6	15.2	30.3	0.5	1.0	1.9	2.3	4.0**
27	17.7	17.8	**27.6**	32.1	56.0	1.4	1.6	**2.0**	2.2	9.8***	5.8	6.1	**14.7**	18.5	44.8	0.6	1.3	**2.2**	2.5*	6.3***
36	13.8	17.6	24.4	31.8	53.5	1.0	1.5	1.7	2.3*	8.4***	-0.7	7.5	12.0	20.1	43.6	-0.1	1.4	1.8	2.7*	5.9***
45	12.1	16.0	24.5	37.3	58.5	0.9	1.2	1.6	2.5	8.7***	3.9	11.0	17.9	31.8	54.1	0.4	1.7	2.1	3.5**	8.8***

Panel B: Household Sector

Price Growth Cutoff (C_P)	Univariate Regressions										Multivariate Regressions									
	Coefficient (γ)					t-statistic					Coefficient (γ)					t-statistic				
	Debt Growth Cutoff (C_D)																			
Full Sample	2	5	8	11	14	2	5	8	11	14	2	5	8	11	14	2	5	8	11	14
1	9.7	17.3	20.5	21.4	26.5	1.9*	2.4**	2.9**	3.0**	3.0***	6.2	11.2	7.6	-5.8	-16.8	1.4	1.8	1.0	-0.7	-1.9
7	10.5	18.8	23.0	23.6	29.5	1.8	2.4**	3.0***	3.1***	3.0**	12.0	15.7	15.2	4.0	0.7	2.2*	2.6**	2.6**	0.6	0.1
13	14.3	22.7	**28.6**	28.2	35.3	2.2**	2.8**	**3.4*****	3.6***	3.9***	14.4	18.9	**20.9**	10.8	11.2	2.7**	3.1***	**3.2*****	1.8	1.2
19	16.1	24.8	29.5	29.2	32.0	2.4**	2.9**	3.3***	3.1***	3.7***	16.9	19.2	17.8	8.7	1.0	2.6**	3.1***	2.7**	1.3	0.1
25	18.6	29.4	33.8	32.3	37.5	2.7**	3.6***	3.7***	3.2***	4.2***	21.5	24.2	21.0	10.4	8.9	3.4***	4.2***	2.5**	1.3	1.2
Pre-2000 Sample	2	5	8	11	14	2	5	8	11	14	2	5	8	11	14	2	5	8	11	14
1	6.1	16.0	31.1	38.3	46.8	1.0	1.6	3.2**	3.0**	7.4***	4.9	21.6	35.5	33.5	-1.0	0.7	2.0*	4.0***	3.2***	-0.3
7	6.7	18.2	33.1	42.8	53.9	0.9	1.6	3.3***	3.6***	11.2***	8.3	22.3	33.0	44.5	53.6	1.3	2.1*	3.7***	4.8***	8.3***
13	11.8	27.4	**45.9**	50.1	53.9	1.3	2.3*	**5.6*****	4.4***	11.2***	12.4	30.9	**47.4**	49.4	50.8	1.8	2.7**	**6.6*****	6.1***	6.0***
19	12.4	26.0	43.6	50.5	58.4	1.4	2.1*	4.4***	3.5***	5.1***	14.5	25.5	37.4	40.1	11.4	1.4	2.1*	4.5***	3.1**	0.5
25	14.4	29.7	52.8	58.6	58.4	1.5	2.3*	5.1***	4.5***	5.1***	19.9	29.4	45.0	37.4	12.0	1.8	2.3*	3.5***	2.0*	0.6
Post-2000 Sample	2	5	8	11	14	2	5	8	11	14	2	5	8	11	14	2	5	8	11	14
1	13.9	16.8	14.2	14.7	17.8	2.0	2.2	2.1	2.8*	2.6*	12.7	2.9	-3.9	-13.3	-13.4	2.1	0.5	-0.8	-1.7	-1.1
7	14.7	18.5	17.1	18.0	22.8	2.0	2.3	2.5	3.2**	3.0*	24.8	13.5	8.1	2.2	11.5	2.6*	2.0	1.7	0.3	1.2
13	16.3	19.9	**21.2**	23.2	29.9	2.3	2.6*	**3.0***	4.2**	4.5***	20.2	13.7	**11.5**	9.8	18.1	2.5	2.3	**3.0***	1.7	1.8
19	18.9	22.6	20.9	21.6	25.4	2.6*	2.8*	2.7**	3.2**	4.5***	15.1	11.9	3.0	-1.4	2.6	2.2	2.5*	1.0	-0.3	0.2
25	22.3	27.7	23.6	23.5	29.9	3.4**	4.0**	3.6***	3.5**	5.3***	16.0	16.1	-0.3	-4.8	4.7	3.6**	5.1***	-0.1	-0.6	0.4

Table A8: Crisis Prediction with Global R-Zones (Leave-One-Out)

The table presents the results of the regression model:

$$Crisis_{i,t+1 \text{ to } t+h} = a_i^h + \gamma^{Bus,h} \times \text{Local R-Zone}_{it}^{Bus.} + \xi^{Bus,h} \times \text{Global R-Zone}_{it}^{Bus.} + \gamma^{HH,h} \times \text{Local R-Zone}_{it}^{HH} + \xi^{HH,h} \times \text{Global R-Zone}_{it}^{HH} + \epsilon_{it}^h$$

where Local R-Zone$_{it}^{Bus.}$ is an indicator variable capturing episodes of high business debt growth and equity price growth, while Local R-Zone^{HH} is an indicator variable capturing episodes of high household debt growth and house price growth. Global R-Zone$_{it}^{Bus.}$ measures the fraction of countries excluding country i in the business R-Zone at time t, while Global R-Zone$_{it}^{HH.}$ measures the fraction of countries excluding country i in the household R-Zone at time t. t-statistics are reported in the brackets and based on Driscoll and Kraay (1998) with lags of 0, 3, 5 and 6 years for prediction horizons 1, 2, 3 and 4 years, respectively. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively, using Kiefer and Vogelsang (2005) corrected p-values. Reported coefficients and R^2's are in percent.

	Dependent Variable											
	Crisis within 1 year			Crisis within 2 years			Crisis within 3 years			Crisis within 4 years		
	(1.1)	(1.2)	(1.3)	(2.1)	(2.2)	(2.3)	(3.1)	(3.2)	(3.3)	(4.1)	(4.2)	(4.3)
Local R-Zone$^{Bus.}$ ($\gamma^{Bus,h}$)	4.0		1.7	9.8*		7.0	23.4**		19.5**	23.5**		18.8*
	[1.0]		[0.5]	[1.9]		[1.4]	[2.9]		[2.3]	[2.6]		[2.1]
Global R-Zone$^{Bus.}$ ($\xi^{Bus,h}$)	53.7*		47.1	86.9***		54.0*	110.4***		72.6	101.9***		33.8
	[1.8]		[1.4]	[4.0]		[1.9]	[4.7]		[1.8]	[5.6]		[1.3]
Local R-Zone^{HH} ($\gamma^{HH,h}$)		7.5**	6.6**		12.5***	10.9**		17.7***	14.9**		15.6***	13.9***
		[2.4]	[2.3]		[2.9]	[2.6]		[3.4]	[2.9]		[4.0]	[3.6]
Global R-Zone$^{HH.}$ ($\xi^{HH,h}$)		24.6	5.4		53.4**	29.9*		72.8***	37.7**		92.8***	72.6***
		[1.4]	[0.8]		[2.7]	[1.9]		[4.8]	[2.5]		[7.2]	[5.0]
R^2 *(within)*	6.1	4.8	7.3	9.3	10.3	12.5	14.3	14.4	19.0	10.7	16.1	18.1
Observations	1,258	1,107	1,084	1,258	1,107	1,084	1,258	1,107	1,084	1,258	1,107	1,084

Table A9: Crisis Prediction with Global R-Zones (GDP weighted)

The table presents the results of the regression model:

$$\begin{aligned} Crisis_{i,t+1 \text{ to } t+h} = a_i^h &+ \gamma^{Bus,h} \times \text{Local R-Zone}_{it}^{Bus.} + \xi^{Bus,h} \times \text{GDP Weighted Global R-Zone}_t^{Bus.} \\ &+ \gamma^{HH,h} \times \text{Local R-Zone}_{it}^{HH} + \xi^{HH,h} \times \text{GDP Weighted Global R-Zone}_t^{HH} + \epsilon_{it}^h \end{aligned}$$

where Local R-Zone$_{it}^{Bus.}$ is an indicator variable capturing episodes of high business debt growth and equity price growth, while Local R-Zone^{HH} is an indicator variable capturing episodes of high household debt growth and house price growth. GDP Weighted Global R-Zone$_t^{Bus.}$ measures the fraction of countries in the business R-Zone weighted by their GDP at a given point in time, while GDP Weighted Global R-Zone$_t^{HH.}$ measures the fraction of countries weighted by their GDP in the household R-Zone at a given point in time. t-statistics are reported in the brackets and based on Driscoll and Kraay (1998) with lags of 0, 3, 5 and 6 years for prediction horizons 1, 2, 3 and 4 years, respectively. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively, using Kiefer and Vogelsang (2005) corrected p-values. Reported coefficients and R^2's are in percent.

	Dependent Variable											
	Crisis within 1 year			Crisis within 2 years			Crisis within 3 years			Crisis within 4 years		
	(1.1)	(1.2)	(1.3)	(2.1)	(2.2)	(2.3)	(3.1)	(3.2)	(3.3)	(4.1)	(4.2)	(4.3)
Local R-Zone$^{Bus.}$ ($\gamma^{Bus,h}$)	4.4		2.0	8.4		6.3	22.8**		19.8**	21.4**		18.5**
	[0.8]		[0.4]	[1.4]		[1.1]	[2.6]		[2.3]	[2.3]		[2.1]
Weighted Global R-Zone$^{Bus.}$ ($\xi^{Bus,h}$)	60.2**		62.6*	124.0**		100.6*	142.6***		101.4*	151.8***		91.5**
	[2.0]		[1.9]	[2.7]		[2.0]	[3.7]		[2.1]	[6.2]		[2.9]
Local R-Zone^{HH} ($\gamma^{HH,h}$)		11.2**	9.0***		15.9***	12.0***		20.0***	14.6**		16.4***	11.9***
		[2.5]	[2.6]		[3.4]	[3.0]		[3.7]	[3.0]		[3.7]	[3.2]
Weighted Global R-Zone$^{HH.}$ ($\xi^{HH,h}$)		0.4	-8.6*		22.0	7.6		40.8**	24.9*		62.6***	47.3***
		[0.1]	[-1.9]		[1.2]	[0.6]		[2.3]	[2.0]		[4.1]	[3.8]
R^2 *(within)*	4.2	2.7	5.9	9.4	6.5	11.4	12.9	11.0	17.3	11.3	13.9	18.3
Observations	1,258	1,107	1,084	1,258	1,107	1,084	1,258	1,107	1,084	1,258	1,107	1,084