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Accounting for the business cycle reduces the estimated losses from systemic banking crises

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Abstract We re-estimate the effects of systemic banking crises in industrialised countries reported by Cerra and Saxena (Am Econ Rev 98(1):439–457, 2008) with a model that includes transitory business cycle shocks. We use the correlation between countries' business cycles to identify temporary business cycle shocks, which helps prevent these transitory shocks being incorrectly explained by the crisis dummy. Doing so results in estimated permanent losses from systemic banking crises of 4% rather than the 6% reported in the original article. In contrast, accounting for the business cycle has no effect on the estimated losses from currency and debt crises. These typically occur when the crisis country becomes sufficiently uncorrelated with the country to which it has tied itself, so accounting for the cross-correlation in business cycles does not improve the counterfactual of what would have happened without a crisis.

Keywords Systemic banking crisis · State-space models · Cycle component

1 Introduction

Financial crises are typically associated with large falls in output and sluggish growth (Reinhart and Rogoff 2009). In a much cited study, Cerra and Saxena (2008), hereafter C&S, report that the output losses following a systemic banking crisis are largely permanent. For the industrialised countries, they report that the permanent loss after a typical systemic banking crisis is 6% of GDP.

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However, we argue that the empirical specification used by C&S is too restrictive. In their model, C&S allow for only one type of innovation in GDP growth rate. This innovation permanently alters the level of output. We relax their specification to also allow for innovations which only temporarily effect the level of output by adding a cyclical business cycle component with temporary shocks to the model. Based on our model, the estimated permanent decline in output from a banking crisis falls from C&S's reported 6% to 4%.

This finding corroborates Cai and Den Haan (2009) who argue that models which only allow for a banking crisis with permanent effects will overestimate the average effect of banking crises. Intuitively, this follows from the fact that if you add an $I(1)$ process to an $I(0)$ process, the resulting time series will be $I(1)$—if you only allow one type of shock in the aggregated series, it will have permanent effects since the aggregated series is $I(1)$. We expand on this analysis and argue that if the banking crisis dummies are correlated with a typical temporary business cycle downturn, the temporary cyclical downturn will be captured by the banking crisis dummy. The resulting banking crisis dummy will account for too much of the observed movement in the time series and generate too large permanent effects through the mechanism described by Cai and Den Haan (2009). If we have no ex ante information to distinguish between different types of banking crisis, we can at least make sure that transitory business cycle movements are not being confused with the effects of banking crises.[1]

To identify business cycle movements, we take advantage of the fact that business cycles are correlated across countries, which gives us a benchmark for what would have happened without a banking crisis. In contrast, the empirical specification of C&S assumes that innovations in GDP growth rates are uncorrelated across countries. Relaxing the specification of C&S to allow for business cycle components that are correlated across countries reduces the estimated permanent effects from 6 to 4% even though we still only allow for one type of banking crisis, and hence, our results are still likely to be biased towards larger permanent effects by the mechanism described by Cai and Den Haan (2009).

Recent research by Candelon et al (2016) has addressed the problem of estimation bias by simultaneously estimating the impact of a number of types of crises. They specify their model as an autogregressive panel model of the growth rate of output similar to C&S, but include dummies for five different types of crises. They extend C&S further by also including common factors, which they use to capture the effects of globalisation and contagion, but potentially could also capture the effects of the business cycle. In our model, however, we explicitly model the business cycle with a business cycle component in which the effects on the level of output are temporary. In the model proposed by Candelon et al., the effects of the common factors on the level of output are not constrained to be transitory. As such, their approach will also

[1] We have also attempted to estimate a version of our model which also allows for temporary effects from a banking crisis. However, estimates from this model exhibited strong signs of multicolinearity between the estimated permanent and temporary effects from a banking crisis. We conclude that it is asking too much of the data to try to distinguish between temporary and permanent level effects from a banking crisis.

be subject to the one-type-of-shock critique where the estimated effects are dominated by the permanent component.[2]

Generally, our approach otherwise shares some similarities with the principal components approach in that we are able to impose rank reduction on the covariance matrices for the shocks in our model. This effectively reduces the number of underlying business cycle components influencing industrialised countries to two: one from the USA and one from Japan. The principal components approach also implies a reduced number of underlying shock processes equal to the number of principal components used. Both approaches result in a more parsimonious model. This is important given that our data set includes 18 countries and would therefore otherwise result in very large covariance matrices involving a large number of parameters.

2 Data

We focus on the effects of systemic banking crises in 18 industrialised countries,[3] one of the subgroupings of countries reported in C&S. We use the same annual output growth rates from the C&S study covering the period from 1973 until 2001. We also use the same banking crisis dummies used in the C&S study.[4] Recent research by Chaudron and de Haan (2014) indicates that the systemic banking crisis datings produced by Laeven and Valencia (2008) and Laeven and Valencia (2012) are more reliable. We have nonetheless opted to use the C&S datings for our main results to enable us to compare our results directly with those from the original C&S article. In Sect. 6, we present results using the Laeven and Valencia crisis dates as well as the Reinhart and Rogoff dates based on a longer time series of 31 OECD countries.

3 C&S model

The C&S model (CSM) specifies that the logarithm of the growth rate of GDP (multiplied by 100) denoted by $\beta_{i,t}$ for country i $(i = 1, \ldots, N)$ in period t $(t = 1, \ldots, T)$ evolves as

$$\beta_{i,t} = \bar{\beta}_i + \sum_{j=1}^{4} \rho_j \beta_{i,t-j} + \sum_{s=0}^{4} \delta_s D_{i,t-s} + \xi_{i,t}. \tag{1}$$

This is an AR(4) model of the growth rate, which implies an ARIMA(4,1,0) model of the level of GDP. The AR coefficients are the ρ_j. The $D_{i,t-s}$ are dummy variables

[2] The authors argue that the common factors in their approach are primarily aimed at capturing the effects of globalisation, not the business cycle. This is also the case in the follow-up article “Globalization and the new normal” (2018, by B. Candelon, A. Carare, J. B. Hasse and J. Lu) .

[3] These countries are Australia, Canada, Germany, Denmark, Spain, Finland, France, UK, Greece, Israel, Italy, Japan, Norway, New Zealand, Sweden, Turkey, USA and South Africa.

[4] The banking crisis dummies of C&S deviate from the episodes of systemic banking crises reported by Laeven and Valencia (2008) and Laeven and Valencia (2012). Specifically, C&S have a financial crisis for France in 1994, not found in Laeven and Valencia (2008) and Laeven and Valencia (2012). “Appendix” explores this matter further. C&S also use a starting date for the Japanese financial crisis of 1991, while in Laeven and Valencia (2008) and Laeven and Valencia (2012) the first year is dated as 1997.

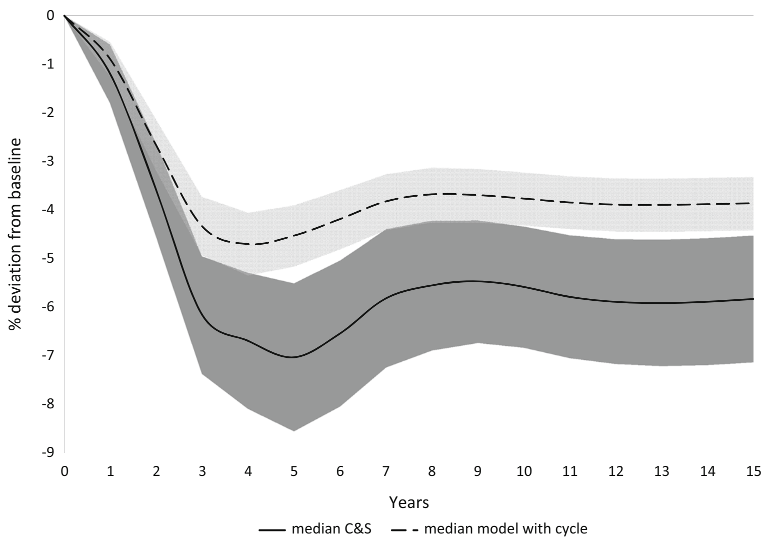

Fig. 1 Banking crisis impulse response functions

where $D_{i,t-s} = 1$ when country i suffers from a banking crisis that began in period $t - s$. The disturbance term in the model is $\xi_{i,t}$, where $(\xi_1, \ldots, \xi_N) \sim N\left(0, \Sigma_\xi\right)$ and Σ_ξ is a diagonal covariance matrix with variances $\sigma_{\xi,i}$, $i = 1, \ldots, N$ on the main diagonal.

In order to be able to generalise this model, we first rewrite the model in the state-space form as

$$
\begin{aligned}
y_{i,t} &= \mu_{i,t} \\
\mu_{i,t} &= \mu_{i,t-1} + \bar{\beta}_i + \beta_{i,t} \\
\beta_{i,t} &= \sum_{j=1}^{4} \rho_j \beta_{i,t-j} + \sum_{s=0}^{4} \delta_s D_{i,t-s} + \xi_{i,t}.
\end{aligned} \tag{2}
$$

Here $y_{i,t}$ denotes the logarithm of the level of GDP (multiplied by 100) for country i in period t and $\mu_{i,t}$ is the trend in the level of GDP. The estimated average response to a banking crisis is shown in Fig. 1 as the solid black line and reproduces the response reported by C&S: a large response in the year following the crisis which is largely permanent.[5] The magnitude of the permanent loss is 6% of GDP. The area around the solid line in blue represents one standard error confidence bands.[6]

[5] Our estimates are made using the matrix language OX (Doornik and Ooms 2007) and the Kalman filter routines in SsfPack (Koopman et al 1999).

[6] Our bands are somewhat tighter than those reported in C&S. Those reported in C&S are based on one thousand Monte Carlo simulations, whereas ours are based on the asymptotic distribution given by the Hessian obtained for the AR parameters and dummy coefficients only. We opted for this method, because other methods would not have been computationally feasible with our alternative model.

4 CSM with cycle

Banking crises occur when banks lose sufficient money on their asset holdings that their solvability comes into question. Losses on loans increase in cyclical downturns. It is, therefore, reasonable to assume that banking crises are more likely to occur simultaneously with economic downturns and that some of the causality behind the large observed GDP contraction runs from cyclical downturn to banking crisis. We capture this by adding a transitory cyclical component for country i in period t, $\psi_{i,t}$, to the model, such that

$$
\begin{aligned}
y_{i,t} &= \mu_{i,t} + \psi_{i,t} \\
\mu_{i,t} &= \mu_{i,t-1} + \bar{\beta}_i + \beta_{i,t} \\
\beta_{i,t} &= \sum_{j=1}^{4} \rho_j \beta_{i,t-j} + \sum_{s=0}^{4} \delta_s D_{i,t-s} + \xi_{i,t}.
\end{aligned} \tag{3}
$$

Here the cyclical component is given by,

$$
\begin{pmatrix} \psi_{i,t} \\ \psi^*_{i,t} \end{pmatrix} = \rho \begin{bmatrix} \cos\lambda & \sin\lambda \\ -\sin\lambda & \cos\lambda \end{bmatrix} \begin{pmatrix} \psi_{i,t-1} \\ \psi^*_{i,t-1} \end{pmatrix} + \begin{pmatrix} \zeta_{i,t} \\ \zeta^*_{i,t} \end{pmatrix}, \tag{4}
$$

where ρ is an autoregressive dampening coefficient and λ is the angular frequency of the cycle.[7] The vector of shocks ζ_t and ζ^*_t are assumed to be uncorrelated and have the same covariance matrix:

$$
\begin{pmatrix} \zeta_t \\ \zeta^*_t \end{pmatrix} \sim N\left(0, \begin{bmatrix} \Sigma_\zeta & 0 \\ 0 & \Sigma_\zeta \end{bmatrix}\right), \quad \left(\zeta_{1,t}, \ldots, \zeta_{n,t}\right)' \equiv \zeta_t \tag{5}
$$

To better identify the transitory business cycle, we allow for cross-country correlation of the cycle. It is also important to realise that the banking crises only affect a few countries at any time in our sample. Furthermore, most of the countries in our sample can be thought of as small open economies so if country A has a banking crisis, the effects of that banking crisis on neighbouring country B will be dominated by the cyclical movements in the rest of the world. Hence, we can use the estimated cycles for the non-crisis countries to identify the cycle in country A that would have occurred without a banking crisis.

Implicitly, this story assumes that countries share a small number of common underlying business cycles. We formalise this notion by reducing the rank of the covariance matrix Σ_ζ when we estimate it. In this manner, we also avoid the pitfalls of over-fitting the data. This would be likely if we were to estimate the unrestricted covariance matrix Σ_ζ with 171 parameters for the 18 countries in our sample.

[7] The period of the cycle is given by $2\pi/\lambda$. We calibrate the period of the business cycle to be 10 years. We estimate the value of the dampening coefficient which consistently is about $\rho = 0.8$. Estimated impulse response functions for a banking crisis we obtain by calibrating these parameters ($2\pi/\lambda = 7$ years and $\rho = 0.7$) do not substantially change our results.

Table 1 Dummy coefficients and model fit

Model	δ_0	δ_1	δ_2	δ_3	δ_4	log L	AICc
CSM	−1.20*	−2.08***	−2.07***	−0.08	−0.68	−1056.8	2206.7
	(0.60)	(0.60)	(0.61)	(0.62)	(0.61)		
CSM	−0.90**	−1.47***	−1.18***	–	–	−967.9	2103.4
with cycle	(0.35)	(0.35)	(0.36)	–	–		

We impose rank reduction on Σ_ζ by specifying only 2 of the 18 possible weights in the diagonal weighting matrix D from the Cholesky decomposition of $\Sigma_\zeta = L\,D\,L'$. Here the matrix L is a diagonal matrix of parameters with ones along the main diagonal.[8] The weights on the main diagonal of D are similar in nature to the eigenvalues of Σ_ζ. From the unrestricted estimation of Σ_ζ, we were able to determine that the two largest eigenvalues represent 55% of the sum of all 18 eigenvalues. This would imply that two business cycles account for more than half of the observed business cycle fluctuations in the data. The two weights in the Cholesky decomposition correspond to the USA and Japan.[9]

Figure 1 shows the estimated average effect of a banking crisis for the CSM in the dashed black line. The permanent loss following a banking crisis is now only 3.9%. The one standard error bands are shown in red. In Table 1, we also compare the banking crisis dummy coefficient estimates for both the CSM and CSM with cycle.[10] As the table shows, our model with a cycle only has three dummies, because this model provided the best compromise between parsimony and fit. We discuss the model fit and robustness of our results in Appendix. We can see from the table that the estimated dummy coefficients for the CSM with cycle in the first three years following a crisis are all smaller than for the CSM. Table 2 in Appendix also shows that the CSM produces an estimated maximum drop of 7% with a final drop of 5.8%, while our CSM with cycle model results in a maximum estimated drop of 4.7%, followed by a partial recovery to a drop of only 3.9%.

Table 1 also provides some insight into the model fit for both models. The CSM with cycle produces a higher likelihood value (which is to be expected for a model with a greater number of parameters), but also scores lower (i.e. better) on the Akaike information criterion corrected for finite sample sizes (AICc).[11] In Appendix, we discuss the results from a number of model specifications as a check for the robustness of our results.

[8] This reduces the number of parameters needed to specify Σ_ζ down to 35.

[9] We have also experimented with a smaller and a larger rank size for Σ_ζ, which does not significantly affect our results; see "Appendix" for details.

[10] We adopt the convention in the table that an estimate is denoted with one asterisk if it is significant at the 5% level, two at the 1% level and three at the 0.1% level.

[11] The AIC favours the CSM with cycle even more strongly than does the AICc, because it penalises larger models less than the AICc does. We prefer the AICc over alternatives such as the Bayesian information criterion or BIC, which a priori tend to over-penalise larger models. See Davis et al (2002) for further discussion.

5 Currency and debt crises

This section extends the model to allow for other types of crisis. We add dummies for currency and debt crises[12] based on the Reinhart and Rogoff datings.[13] This involves replacing the specification for the growth rate in (3) with

$$\beta_{i,t} = \bar{\beta}_i + \sum_{j=1}^{4} \rho_j \beta_{i,t-j} + \sum_{k=1}^{3} \sum_{s_k=0}^{m_k} \delta_{s_k} D_{k,i,t-s} + \xi_{i,t}, \tag{6}$$

where k now indexes the type of crisis.

In contrast to a banking crisis,[14] where the cross-country correlation of business cycles provides useful information about what would have happened without a banking crisis, estimates of the effects of currency and external debt crises do not differ significantly when we model the business cycles. Figure 2 shows impulse response functions for currency and debt crises using crisis dummies from Reinhart and Rogoff in the model with and without the business cycle component. In both cases, accounting for the cross-correlation in business cycles has no effect on the estimated losses. For currency crises, accounting for the business cycle only has a marginal effect: the point estimate of the permanent loss increases from 0.7 to 0.8%. For debt crises, both specifications produce a point estimate of about 5%. For both currency and debt crises, the differences are statistically highly insignificant, since the point estimate for each specification lies within the one standard deviation error bands for the entire impulse response function.

A distinction between banking crises and currency and debt crises is intuitively plausible. In a textbook story of a banking crisis, a business cycle slowdown leads to loan defaults, which in a vulnerable banking system leads to a banking crisis. We can extract information about the counterfactual from other countries' business cycles, since these are correlated. The mechanism for currency and external debt crises is different. A textbook currency or external debt crisis occurs when the business cycle of a country deviates significantly from the business cycle of the country to which it is linked, either by a fixed exchange rate or by external debt. In the case of a currency crisis, domestic monetary policy can longer defend the fixed exchange rate or, in the case of an external debt crisis, the holders of externally valued debt can no longer make the required payments to service the debt after the differential performance of their economy has led to an exchange rate depreciation. It is also widely recognised

[12] In our sample of industrialised countries, there are not many external and sovereign debt crises during the sample period, so we have combined these together under the name "debt crises". We achieve this by setting the debt dummy equal to 1 at either the start of an external debt crisis or at the start of the domestic debt crisis.

[13] We have discovered that there are some differences between the banking crisis dummies used by C&S and those published by Reinhart and Rogoff, and have opted here to use the Reinhart and Ruggoff dummies for all three crises. As a result, the esimated effect of a banking crisis is now somewhat lower due to the differences in the banking crisis dummies, although the difference between the model with a correlated business cycle and the model without is robust to this choice.

[14] Our estimates of the effect of incorporating a correlated business cycle on the estimated losses following a banking crisis are unaffected by the addition of the currency and debt crisis dummies.

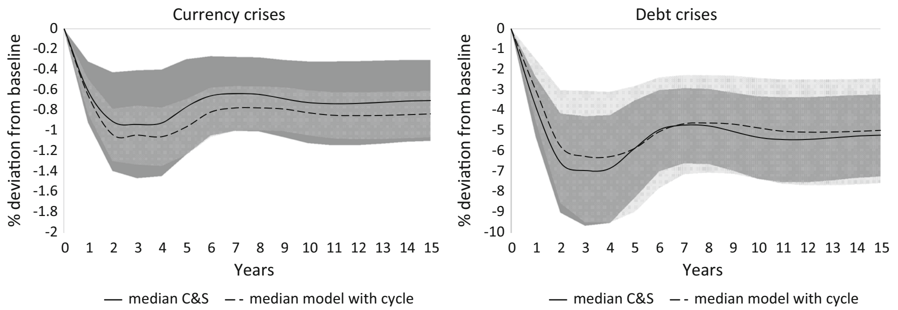

Fig. 2 Impulse response functions for currency and debt crises

that countries cannot experience a sovereign debt crisis if they borrow in their own currency. Therefore, differential economic performance between the crisis country and the country in whose currency it has borrowed is also fundamental to sovereign debt crises. As such, the common component of the business cycle is less informative by construction since currency and debt crises occur when business cycles become uncorrelated.

6 Robustness

In this section, we provide two alternative specifications which illustrate the robustness of our main result. The alternative specifications revolve around the subjective nature of classifying banking crises. The original C&S article provided evidence based on 18 industrialised countries over a sample period of 1973–2001. Many of the banking crises in these countries in this period were not large, which makes classifying these as systemic or not open to interpretation. In this section, we increase the cross section to 31 OECD countries[15] and extend the sample period to cover the Great Financial Crisis of 2008 and 2009, which was clearly the most severe banking crisis in the industrialised countries in recent decades. We also provide estimates where we replace the banking crisis dummies based on Reinhart and Rogoff with dummies based on the alternative banking crisis datings of Laeven and Valencia, which Chaudron and de Haan (2014) argue are more reliable. Figure 3 shows impulse responses for the sample period 1970–2015 with Reinhart and Rogoff dummies and the alternative datings provided by Laeven and Valencia. For the extended sample including the Great Financial Crisis, the estimated average permanent losses from a banking crisis fall from 8 to 4% when we account for business cycle synchronicity. The alternative Laeven and Valencia dummies are a stricter definition of a banking crisis so only the more systemic crises remain in their datings. As a consequence, when we use the Laeven and Valencia

[15] The countries in our sample are Argentina, Austria, Australia, Belgium, Chile, Brazil, Canada, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Israel, Italy, Japan, Korea, the Netherlands, Mexico, New Zealand, Norway, Portugal, Spain, Singapore, South Africa, Sweden, Switzerland, Turkey, UK and USA. Israel is included here but not in the Reinhart and Rogoff dummies; we use the Laeven and Valencia dummy here for Israel.

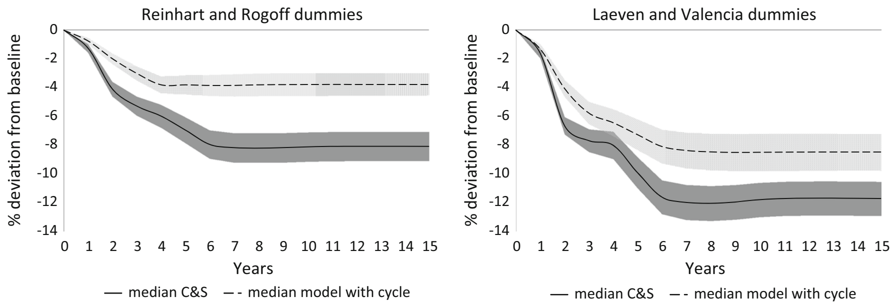

Fig. 3 Impulse response functions for extended sample 1973–2015

dummies, we find larger permanent losses than with the Reinhart and Rogoff dummies. Nonetheless, we still find a 4% difference with the Laeven and Valencia dummies: the estimated permanent losses fall from 12 to 8%.

7 Conclusion

It is well known that models with only one type of shock will display properties dominated by the permanent component (Cai and Den Haan 2009). We re-estimate the effects of banking crises estimated by C&S allowing an explicit role for transitory business cycle shocks. To better identify the transitory business cycle movements that would have happened without a banking crisis, we use the fact that business cycles are correlated across countries. Doing so results in estimated permanent losses from banking crises of 4% instead of the 6% reported in C&S. We note that these estimates remain largely unchanged when we extend our model to account for the effects of currency and debt crises. We also show that accounting for the cross-correlation in business cycles has no effect on the estimated losses from currency and debt crises. This is intuitively plausible because currency and debt crises occur when the crisis country becomes sufficiently uncorrelated with the country to which it has tied itself.

The results we have presented here are also related to the recent "New normal hypothesis" (see Candelon et al 2016 for a more detailed discussion). The new normal hypothesis argues that following a large financial crisis output and employment growth will be low for a sustained period of time, if not permanently low. Qualitatively all of our results mirror those of C&S. For our main specification, growth is lower for 4 years following a banking crisis, followed by a short period of marginally faster growth before leveling out with a permanent loss compared to baseline. Four years is much longer than a typical recession, so our results also support the idea that banking crises are followed by a sustained period of lower growth. Our contribution is to highlight that if you fail to adequately distinguish between permanent and transitory shocks you will be overly pessimistic about how bad the new normal will be.

In future research, we would like to update this work by allowing for correlation between the growth rates shock ξ_i and allowing for rank reduction of this covariance

Table 2 Model selection

β	ψ		Parameter size			Drop		Fit	
rank (Σ_{ξ})	rank (Σ_{ζ})	Σ_{ζ}	AR	Dummies	Total	Max	Final	log L	AICc
1	0	–	4	5	28	7.3 (1.8)	5.9 (1.3)	− 1116.5	2290.2
18	0	–	4	5	45	7.0 (1.5)	5.8 (1.3)	− 1056.8	2206.7
18	18	Diag	4	5	64	8.1 (0.6)	7.3 (1.5)	− 1033.1	2200.4
18	3	Full	4	5	97	4.9 (1.0)	4.0 (1.0)	− 950.8	2110.2
18	2	Full	4	5	81	4.7 (0.7)	3.9 (0.6)	− 967.9	2107.9.0
18	1	Full	4	5	64	6.1 (1.2)	5.3 (1.1)	− 1000.3	2134.8
18	2	Full	5	5	82	4.7 (0.7)	3.7 (0.6)	− 967.3	2109.0
18	2	Full	3	5	80	4.6 (0.7)	4.1 (0.7)	− 972.4	2114.6
18	2	Full	4	4	80	4.7 (0.7)	3.9 (0.6)	− 967.9	2105.6
18	2	Full	4	3	79	4.7 (0.6)	3.9 (0.5)	− 967.9	2103.4
18	2	Full	4	2	78	3.5 (0.6)	2.8 (0.5)	− 971.8	2108.9

matrix as well. Experimenting with Bayesian methods is likely to prove useful in determining the appropriate level of rank reduction for the covariance matrices. Alternatively, the business cycle could be modelled using a Markov switching process.

Appendix A

In this Appendix, we provide a brief overview of various alternative model specifications we have explored in an attempt to gauge the robustness of our estimates in Sects. 3 and 4 . Table 2 provides an overview. This table indicates that our results are robust to alternative model specifications.

The estimates shown in the first row of the table are for a restricted version of the CSM in which all countries are assumed to have the same value of the variance $\sigma_{\xi} = \sigma_{\xi,i}$, $i =, \ldots, N$. According to the AICc this restricted model does not fit the data as well as the standard CSM listed in the second row, as lower values for AICc indicate a better fit. We note, however, that the estimated maximum and final drop due to a systemic banking crisis are essentially same.

For the remainder of the models listed in the table, the specification of the covariance matrix Σ_{ξ} is the same diagonal specification used in the CSM in the second row. These models all represent variants of the CSM with cycle. The second column in the table indicates the number of nonzero elements in the diagonal matrix D of the Cholesky decomposition of Σ_{ζ}, the covariance matrix of the cycle innovation ζ. This number is also equal to the rank of Σ_{ζ}. When the rank is one, the weight corresponds to the USA. When it is two, it corresponds to the USA and Japan, with the USA first. The order by a rank of three is USA, Japan and Germany, respectively. In other words we assign the weights to the largest industrialised economies. The table shows that we

Table 3 Model selection

ψ rank (Σ_ζ)	Number parameters	Source dummies	Final drop Banking	Currency	Debt	AICc
0	76	L&V	11.7 (2.2)	2.3 (1.0)	6.4 (2.2)	6345.0
3	167	L&V	8.5 (1.3)	3.1 (1.0)	7.4 (2.2)	5958.2
0	76	R&R	8.1 (1.0)	1.8 (0.4)	4.8 (1.5)	6426.5
3	167	R&R	3.8 (0.8)	0.9 (0.6)	6.8 (1.5)	5962.7

obtain the best fit for a rank of two, but the results for ranks of three or more also produce similar maximum and final drops.[16]

We also experiment with various autoregressive (AR) lengths for the growth rate component, $\beta_{i,t}$, and find that an AR(4) model produces the best fit. Similarly by varying the number of lags, s, of the dummy variable, $D_{i,t-s}$, we find that we obtain an optimal fit with $s = 2$. In all cases the maximum and final drops estimated for these models are of a similar magnitude and all permanent drops in the level of output are significant at well under the $p = 0.001$ level.

Based on a similar model selection exercise, we obtain optimal models based on the crisis dummies produced by Laeven and Valencia for the larger panel of 31 countries discussed in Sect. 6. In Table 3, we report only the final model specifications used in the paper to avoid presenting too many models. We obtained models with an optimal fit according to the AICc criterion using a business cycle component with covariance matrix Σ_ζ of rank 3. All the models assume a diagonal covariance matrix Σ_ξ of full rank. The number of lags for the banking crisis dummies is $s = 5$, while for both the currency crisis and debt crisis dummies $s = 1$. In the table, we also include the estimates for the same model specifications using the dummies produced by Reinhart and Rogoff. We denote those models we estimate with the crisis dummies produced by Laeven and Valencia by L&V, and those produced by Reinhart and Rogoff by R&R. Finally, we note that the models we use in Sect. 5 also employ the same specifications shown in Table 3 for the Reinhart and Rogoff dummy variables.

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[16] We have also obtained estimates not listed in the table using a rank of four and higher. We note that the estimates with either no correlation across the business cycle or with a covariance rank of only 1 show a larger decline more in line with the estimates from the CSM. We conclude that these simpler specifications are too restrictive to adequately account for the effects of the business cycle. As Tabel 2 shows, these model specifications are not well supported by the data.

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