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Accounting for the Business Cycle Reduces the Estimated Losses from Systemic Banking Crises

Rob Luginbuhl
Adam Elbourne

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Abstract

We re-estimate the effects of systemic banking crises in industrialised countries reported by Cerra and Saxena[1] 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.

1 Introduction

Financial crises are typically associated with large falls in output and sluggish growth (Reinhart and Rogoff[2]). In a much cited study, Cerra & Saxena[1], 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.

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[3] 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[3]. 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

[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.

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[3].

Recent research by Candelon et al.[4] has addressed the problem of estimation bias by simultaneously estimating the impact of a number of types of crises. They also extend the original C&S model to include principal components. Their research however suffers from the same drawback as the original C&S article in that they only include a permanent shock in their model.

Our approach has 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 US 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,[2] one of the sub groupings 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.[3] Recent research by Chaudron and de Haan[7] indicates that the systemic banking crisis datings produced by Laeven and Valencia[5] and [6] are more reliable. We have nonetheless opted to use the C&S datings to enable us to compare our results directly with those from the original C&S article.

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 $(i = 1, \dots, N)$ in period t $(t = 1, \dots, T)$ 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 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 $(\xi_1, \dots, \xi_N) \sim N(0, \Sigma_\xi)$ and Σ_ξ is a diagonal covariance matrix with variances $\sigma_{\xi,i}$, $i = 1, \dots, N$ on the main diagonal.

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

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

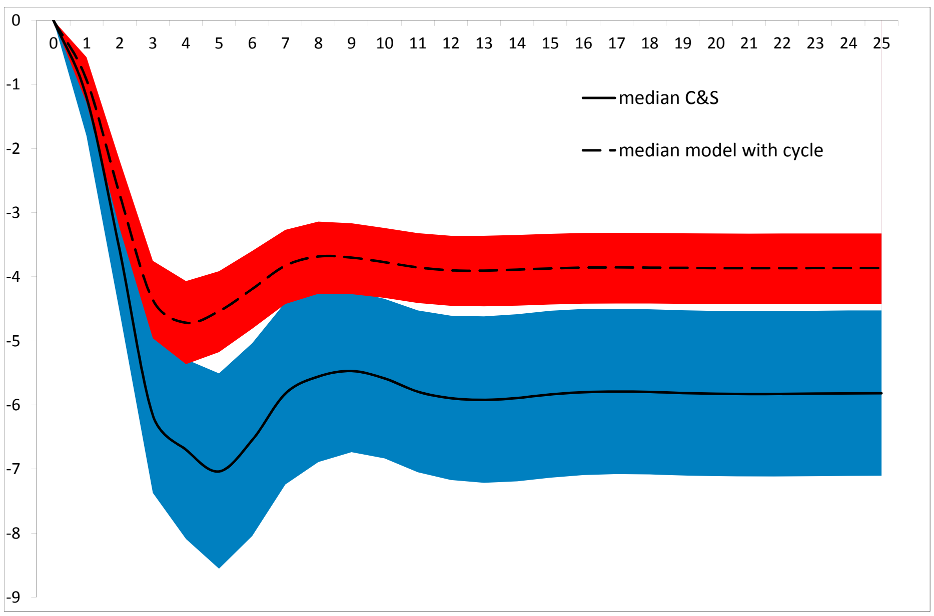
Here $y_{i,t}$ denotes the logarithm of the level of GDP (multiplied by 100) for country i in period t and $\mu_{i,t}$ is the trend in the level of GDP. The estimated average response to a banking crisis is shown in

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

[3] The banking crisis dummies of C&S deviate from the episodes of systemic banking crises reported by Laeven and Valencia[5] and [6]. Specifically, C&S have a financial crisis for France in 1994, not found in Laeven and Valencia[5] and [6]. The appendix explores this matter further. C&S also use a starting date for the Japanese financial crisis of 1991, while in Laeven and Valencia[5] and [6] the first year is dated as 1997.

Figure 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.[4] The magnitude of the permanent loss is 6% of GDP. The area around the solid line in blue represents one standard error confidence bands.[5]

Figure 1: Financial Crisis Impulse Response Functions



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

[4]Our estimates are made using the matrix language OX[8] and the Kalman Filter routines in SsfPack[9].

[5]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.

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.[6] The vector of shocks ζ_t and ζ^*_t are assumed to be uncorrelated, and have the same covariance matrix:

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

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 formalize 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.

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.[7] 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 US and Japan.[8]

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.[9] 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 the 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 A.1 in the 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%.

[6]The period of the cycle is given by $2\pi/\lambda$. We estimate the period of the business cycle to be 10.3 years. We obtain an estimated value for the dampening coefficient of $\rho = 0.78$. 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.

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

[8]We have also experimented with a smaller and a larger rank size for Σ_ζ, which does not significantly affect our results, see the appendix for details.

[9]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.

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).[10] In the appendix we discuss the results from a number of model specifications as a check for the robustness of our results.

Table 1: Dummy Coefficients and Model Fit

Model	δ_0	δ_1	δ_2	δ_3	δ_4	log L	AICc
CSM	-1.08^{*}	-1.97^{***}	-1.94^{***}	0.04	-0.55	-1055.6	2209.9
	(0.61)	(0.60)	(0.61)	(0.61)	(0.61)		
CSM	-0.93^{*}	-1.47^{***}	-1.15^{**}	-	-	-968.2	2125.7
with cycle	(0.45)	(0.45)	(0.45)	-	-		

5 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[3]). 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 this is still likely to be an overestimate since our specification only allows for one type of banking crisis.

In future research we would like to update this work using more recent data as well as the systemic banking crisis datings produced by Laeven and Valencia[5] and [6]. We would also like to include currency crisis and sovereign debt crisis dummies in the model. It is also fairly straight forward to also allow for correlation between the growth rates shock ξ_i and allow for rank reduction of this covariance 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 modeled using principal components or a Markov switching process.

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[10] 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 [10] for further discussion.

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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. Table A.1 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 non-zero 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 US. When it is two, it corresponds to the US and Japan, with the US first. The order by a rank of three is US, Japan and Germany, respectively. In other words we assign the weights to the largest industrialised economies. The table shows that we obtain the best fit for a rank of two, but the results for ranks of either three or one also produce similar maximum and final drops.

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 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. Only in the case of the strongly restricted model with $s = 1$ are the estimated permanent declines somewhat smaller. The value of the AICc, however, indicates that this model is not supported by the data.

Table A.1: Model Selection

β	ψ		Parameter Size			Drop		Fit	
$rank\,(\Sigma_\xi)$	$rank\,(\Sigma_\zeta)$	Σ_ζ	AR	Dummies	Total	Max	Final	log L	AICc
1	0	-	4	4	28	-7.3	-5.9	-1116.5	2292.3
						(1.9)	(1.6)		
18	0	-	4	4	45	-7.0	-5.8	-1055.6	2209.9
						(1.5)	(1.3)		
18	18	diag	4	4	65	-5.7	-3.8	-1029.6	2208.1
						(1.3)	(0.9)		
18	3	full	4	4	98	-5.2	-4.3	-952.6	2147.0
						(1.0)	(1.0)		
18	2	full	4	4	82	-4.8	-3.9	-968.0	2131.0
						(0.7)	(0.6)		
18	1	full	4	4	65	-6.1	-5.3	-1000.2	2149.3
						(1.3)	(1.1)		
18	2	full	4	4	83	-4.7	-3.7	-967.3	2132.4
						(0.7)	(0.6)		
18	2	full	3	4	81	-4.6	-4.0	-972.5	2137.1
						(0.7)	(0.7)		
18	2	full	4	3	81	-4.7	-3.9	-968.1	2128.5
						(0.7)	(0.6)		
18	2	full	4	2	80	-4.7	-3.9	-968.2	2125.7
						(0.6)	(0.6)		
18	2	full	4	1	79	-3.5	-2.9	-971.9	2130.4
						(0.6)	(0.5)		

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