The Losses From Systemic Banking Crises: An Update To Include The Great Recession

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Abstract

Using data for 29 developed countries with a sample period that includes the Great Recession, I estimate the effects of systemic banking crises on the level of output. In models with an explicit role for transitory business cycle shocks proposed in Luginbuhl and Elbourne[1] the estimated permanent drop in the level of output is as low as 4%. This is in dramatic contrast to the estimate of 13% I obtain based on the original model used in the seminal article by Cerra & Sexena[2], which only includes one permanent shock to the level of output. In this research I also generalize the cyclical model in Luginbuhl and Elbourne to include time trends, or alternatively, a random walk specification for the growth rates of output, both as methods to capture the secular declines in the growth rates of developed countries over the past 40 years. In addition I propose imposing rank reduction in the covariance matrices of the model shocks to obtain more parsimonious models. Based on the AIC model selection criteria and model interpretation, I argue for the use of the random walk specification with rank reduction.

1 Introduction

In this article I update the estimated permanent loss in the level of output due to systemic banking crises based on data that includes the systemic banking crises associated with the Great Recession. I employ the same modeling technique used in Luginbuhl and Elbourne[1] where the authors include a cyclical component with a temporary shock to the level of output to model the business cycle. I also extend their work to model the secular decline in the growth rates of developed countries over the last 40 years by either including time trends in the model or by allowing the growth rates to follow random walks. I also explore the additional extension of imposing rank restriction on the covariances of model shocks to obtain a more parsimonious model. This method of imposing rank reduction shares similarities with the literature based on priciple components, as recently proposed in this context of systemic banking crises by Candelon et al.[3]. Both methods imply that there are a small number of components driving the series.

I estimate the permanent decline in output to be as little as 4% for the sample of 29 developed countries, depending on the model version used. The estimates are based on the systemic banking crisis dates from the IMF working papers of Laeven & Valencia [4] and [5].[1] The annual data has a sample period beginning in 1970 and ending in 2014. In general I also find that including time trends in the growth rates to the general decline in growth rates of most of the 29 developed countries in the sample reduces the estimated decline due to systemic banking crises. This is presumably the result of the fact that most systemic banking crises occur later in the sample period when the growth rates are generally lower.

In general, however, time trends involve introducing more parameters to the model and restrict the development of the underlying growth rates. The forecast of the time trend also suffers from the fact that it can quickly become unrealistic by imposing a continuation of the trend. The random walk specification is more parsimonious without restricting the development of the underlying growth rate to always be moving in the same direction. The forecast function of the random walk is, I argue, more realistic than a time trend, as it is simply given by the last estimated growth rate in the sample period. I also find that the AIC model selection criterion supports the random walk specification, and therefore conclude that the random walk specification is the better model. This despite the fact that the alternative of an autoregressive specification for the growth rates generally results in lower likelihood values.

This research corroborates the results reports in Luginbuhl and Elbourne[1] that show a significantly lower estimated decline in output due to systemic banking crises in models that include a cyclical component. Based on the model used in the seminal study by Cerra & Sexena[2], which only includes a permanent shock to the level of output, I obtain an estimated drop in the level of output of 13% for a sample of 29 developed countries. This is more than three times the size of the drop I find for the cyclical model with the smallest estimated decline.

The estimated decline for industrial countries in their sample reported by Cerra & Saxena[2] was 6%. My estimate of a 13% drop using their model on this more up to date data set including the Great Recession is corroborated recently by Candelon et al.[3]. A principle finding of my research here is that this larger estimated drop is significantly reduced by including a cyclical component in the model, which allows for a temporary shock to the level of output.

The remainder of the paper is organized as follows. I present the model used in Cerra & Saxena[2] and the estimated decline in output due to systemic banking crises. I then generalize this model by introducing a time trend to the growth rate and show how this results in a smaller estimated reduction in output due to banking crises. Following this I introduce the cyclical component used in Luginbuhl and Elbourne[1] to the model and show how this further reduces the estimated size of the decline in output. I also discuss a number of possible model variants based on the assumed

[1] Recent research by Chaudron and de Haan[**?**] indicates that the financial crisis datings produced by Laeven and Valencia[4] and [5] are more reliable than those of Reinhart & Rogoff[6] or Caprio et al.[7]

structure of the covariance matrices in the model. This includes the possibility of imposing rank reduction on the covariance matrices to obtain a more parsimonious model. Finally I propose specifying the growth rate of output as a random walk as an alternative to including a the time trend in the growth rate of output in the model. I also discuss the possibility with the random walk specification to specify more parsimonious models by imposing rank reduction on the covariance matrices. As usual I end the article with some concluding remarks.

2 The CSM

The CSM is a model of the growth rate of GDP $\beta_{i,t}$ for country i in period t:

$$\beta_{i,t} = \bar{\beta}_i + \sum_{j=1}^{4} \rho_j \beta_{i,t-j} + \sum_{s=0}^{5} \delta_s D_{i,t-s} + \xi_{i,t} \tag{1}$$

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 systemic banking crisis that began in period $t - s$.[2] The disturbance term in the model is $\xi_{i,t}$.

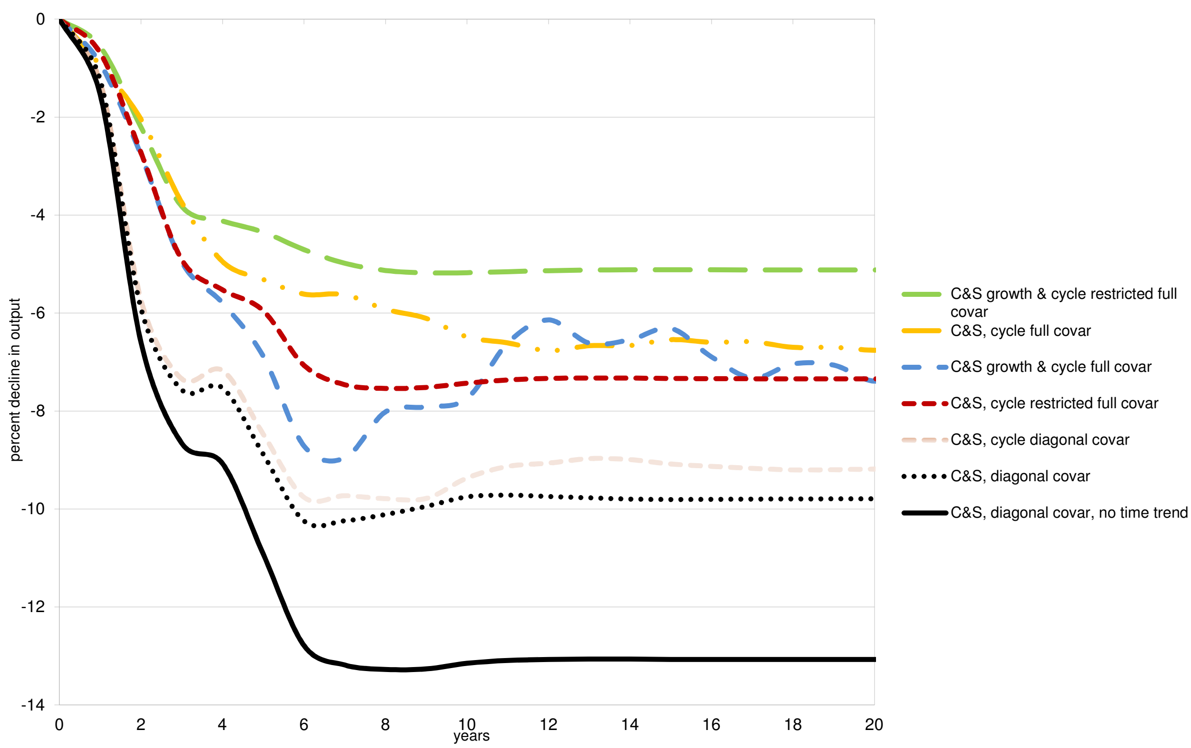
In order to be able to generalize the CSM I first re-write the model in SSF, as follows.

$$\begin{aligned} y_{i,t} &= \mu_{i,t} \\ \mu_{i,t} &= \mu_{i,t-1} + \bar{\beta}_i + \beta_{i,t} \\ \beta_{i,t} &= \sum_{j=1}^{4} \rho_j \beta_{i,t-j} + \sum_{s=0}^{5} \delta_s D_{i,t-s} + \xi_{i,t} \end{aligned} \tag{2}$$

Here I denote the level of GDP for country i in period t by $y_{i,t}$. The variable $\mu_{i,t}$ is the trend in the level of GDP. I have estimated the CMS based on (2) using the matrix language OX[8] and the Kalman Filter routines in SsfPack[9]. I include 29 developed countries in the sample: The United States, Japan, Korea, Germany, France, The UK, Italy, Canada, Spain, Portugal, Greece, Denmark, The Netherlands, Belgium, Norway, Sweden, Finland, Austria, Australia, Argentina, Brazil, Chile, Turkey, South Africa, Israel, Singapore, Iceland, Ireland and Mexico. As mentioned earlier the dummy variables are based on the systemic banking crisis datings in the IMF working papers of Laeven & Valencia [4] and [5]. The annual data has a sample period running from 1970 until 2014. The resulting IRF for the systemic banking crisis dummy is given by the solid black line in figure 1. The figure shows a permanent loss in output of 13%.

[2] Specification tests indicate that the model should include 5 lags, one more than in the original CSM.

Figure 1: Financial Crisis Impulse Response Function, AR Models



3 CSM with a Time Trend

Most developed countries have experienced a slow decline in their growth rate of output over the past 40 years. Most of the systemic banking crises occur later in the sample period when most growth rates tended to be lower. In a model such as the CSM with fixed long-run growth rates, given by $\bar{\beta}$, the decline in the growth rate will be partially captured by the crisis dummy, thereby inflating the estimated decline.

To avoid this problem, I introduce a time trend to the CSM. This model with a time trend is given by

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

The estimated decline in output is given by the IRF for the crisis dummy shown in figure 1 by the dotted black line. We can see from the figure that including a time trend in the model reduces the estimated loss of a crisis from 13% down to just under 10%.

3.1 The CSM with Cycle

We now also introduce a cyclical component to the model as proposed in Luginbuhl and Elbourne[1]. The orginal specification of the CSM only has one shock to the growth rate of output. This implies that all shocks to output will results in a permanent change to the level of output. Banking crises occur when banks lose sufficient money on their asset holdings that their solvability comes into question. Losses on loans increases 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. This generalization of the CSM with a time trend in (3) to include the cyclical component, $\psi_{i,t}$ is shown below.

$$\begin{aligned} y_{i,t} &= \mu_{i,t} + \psi_{i,t} \\ \mu_{i,t} &= \mu_{i,t-1} + \bar{\beta}_i + b_i\, t + \beta_{i,t} \\ \beta_{i,t} &= \sum_{j=1}^{4} \rho_j \beta_{i,t-j} + \sum_{s=0}^{5} \delta_s D_{i,t-s} + \xi_{i,t} \end{aligned} \tag{4}$$

Here the cyclical component is given by,

$$\begin{pmatrix} \psi_{i,t} \\ \psi^*_{i,t} \end{pmatrix} = \rho \begin{bmatrix} \cos\lambda & \sin\lambda \\ -\sin\lambda & \cos\lambda \end{bmatrix} \begin{pmatrix} \psi_{i,t-1} \\ \psi^*_{i,t-1} \end{pmatrix} + \begin{pmatrix} \zeta_{i,t} \\ \zeta^*_{i,t} \end{pmatrix}, \tag{5}$$

where ρ is an autoregressive dampening coefficient and λ is the angular frequency of the cycle.[3] The vector of shocks ζ_t and ζ_t^* are assumed to be uncorrelated, and have the same covariance matrix:

$$\begin{pmatrix} \zeta_t \\ \zeta_t^* \end{pmatrix} \sim N\left(0, \begin{bmatrix} \Sigma_\zeta & 0 \\ 0 & \Sigma_\zeta \end{bmatrix}\right), \quad (\zeta_{1,t}, \ldots, \zeta_{n,t})' \equiv \zeta_t \tag{6}$$

In the first instance I have opted to estimate this model using the restriction that there is no correlation between the cyclical innovations $\zeta_{i,t}$ and $\zeta_{j,t}$ for $i \neq j$ or between $\zeta_{i,t}^*$ and $\zeta_{j,t}^*$ for $i \neq j$. This assumption implies that the business cycle in each country is independent of the other countries' business cycles. The IRF estimated with this model for the systemic banking crisis dummy is shown in figure 1 by the dashed grey line. The result is a somewhat smaller long run drop in output of roughly 9%.

If we allow for correlation between the cycles of different countries, then this can help to decompose changes in GDP into temporary ones due to the cycle and permanent ones caused by the systemic banking crisis dummy. In the aftermath of a systemic banking crisis some of the observed fall in output will most likely be temporary and therefore best captured by the cyclical component. A neighboring country that does not suffer a systemic banking crisis may also suffer a downturn, but this cannot be caused by the dummy variable, and will therefore be captured by the cyclical component. The correlation between the cycle of the neighboring country and the country which had a systemic banking crisis will then help to identify the temporary component of the fall in GDP following the crisis.

In figure 1 I show the IRF for the dummy variable estimated from (4) with the unrestricted covariance matrix Σ_ζ. This IRF is given in the figure by the orange dashed line. In this way the model now captures the contemporaneous correlation between the cycles of different countries. The estimated long run drop is now only around 7%.

In a further relaxation of the restrictions imposed by the original CSM, I have also estimated a version of (4) in which the AR(4) disturbance term of the growth rate, $\xi_{i,t}$, is allowed to exhibit contemporaneous correlation with $\xi_{j,t}$ for other countries $i \neq j$. In the original CSM, this is similar to replacing the OLS estimates with GLS ones. If we denote the covariance matrix of the $\xi_{i,t}, \quad i = 1, \ldots, N$ as Σ_ξ, then I now no long restrict this covariance matrix to be diagonal. The resulting IRF for the crisis dummy variable is shown in figure 1 by the dashed blue line. The long run drop in output is now slighter greater than 7%.

[3]The period of the cycle is given by $2\pi/\lambda$. I calibrate the business cycle to be $2\pi/\lambda = 6.95$, or roughly 7 years. I also calibrate the dampening coefficient $\rho = 0.67$. Calibrating these parameters allows for a reduction in the number of parameters estimated, for both parameters it is fairly straight forward to determine plausible values, and their exact values do not substantially effect the results.

4 Rank Reduction

Allowing for correlations between the countries' respective growth and cycle components in the model comes at a cost. The estimation of a component's unrestricted disturbance covariance matrix when the sample consists of 29 countries involves the estimation of no less than 435 parameters. Most likely there is a considerable degree of correlation between the cycles of the developed countries in the sample which results in significant rank reduction in the covariance matrix. This in turn allows the covariance matrix to be specified with few parameters, resulting in a more parsimonious model.

The eigenvalue decomposition of the covariance Σ_ζ of the cycle component disturbance terms shows that nearly 77% of variance can be attributed to the five eigenvectors associated with the five largest eigenvalues. The remaining largest eigenvalue is less than 10% of the sum of the eigenvalues. This implies that there are five underlying cyclical processes which are responsible for nearly all the cyclical movements in the data. I have therefore opted to estimate a version of the model with a cycle covariance matrix Σ_ζ of only rank 5. Using a Cholesky decomposition to parameterize the covariance implies a reduction in the number of parameters required from 435 to 135. The growth disturbance covariance matrix Σ_ξ is assumed to be diagonal in this model. The resulting IRF for the crisis dummy variable is shown in figure fig:csirfs by the red dashed line, which also indicates a long run loss of roughly 7%.

It could be argued that the same rank reduction should be possible for the growth component in the model, only with a considerably greater degree of rank reduction being possible. This is due to the fact that we would expect that growth rates of the developed countries to change fairly slowly and be largely determined by technological progress and for some countries catching up to the technological frontier. In fact the eigenvalue decomposition of the covariance matrix Σ_ξ indicates that only three eigenvectors associated with the three largest eigenvalues are needed to account for more than 60% of the variance, with the next largest eigenvalue accounting for less than 10% of the sum of the eigenvalues. Restricting the rank of the covariance matrix to 3 reduces the number of parameters to 84.

To impose both a rank reduction of 5 on Σ_ζ as well as a rank reduction on Σ_ξ of 3, an additional disturbance must be added to the model to mop up any left over variation. To achieve this I add a shock $\epsilon_{i,t}$ to the trend component. As a result the model 4 becomes

$$\begin{aligned} y_{i,t} &= \mu_{i,t} + \psi_{i,t} \\ \mu_{i,t} &= \mu_{i,t-1} + \bar{\beta}_i + b_i\, t + \beta_{i,t} + \epsilon_{i,t} \\ \beta_{i,t} &= \sum_{j=1}^{4} \rho_j \beta_{i,t-j} + \sum_{s=0}^{5} \delta_s D_{i,t-s} + \xi_{i,t}. \end{aligned} \tag{7}$$

The $\epsilon_{i,t}$ are assumed to be serially uncorrelated, and uncorrelated across countries. In other words, if the covariance matrix of the $\epsilon_{i,t}, \quad i = 1, \ldots, N$ is Σ_ϵ, then I restrict this covariance to be diagonal.

The estimated IRF for the crisis dummy is shown in figure fig:csirfs by the dashed green line. The estimated permanent decline in output in this case has dropped to just 5%.

Based on the likelihood ratio test I have determined that each model extension is significantly different from any of its restricted counterparts at the 0.1% level. However, I have also calculated values of the AIC model selection criterion for each model variant. These values are shown in table 4. Both the likelihood ratio test as the AIC indicate that the best model with an AR process for the growth rate component is the most fully parameterized one with full covariance matrices for the growth and the cycle components.

Table 1: AIC model selection criterion values

model	parameters	log likelihood	AIC
C&S diagonal no TT	68	-2921.2967	5978.5934
C&S diagonal	97	-2881.6238	5957.2476
C&S cycle diagonal	126	-2841.6875	5935.375
C&S cycle restricted full	232	-2534.0004	5532.0008
C&S cycle full	466	-2283.3541	5498.7082
C&S both full	719	-1904.3077	5246.6154
C&S restricted full	314	-2457.8528	5543.7056
C&S random walk	621	-1987.4075	5216.815
C&S restricted random walk	491	-2233.8919	5449.7838
C&S restricted random walk, both	251	-2512.7586	5527.5172

The table however also shows AIC values for two random walk specifications. The random walk specification for the growth rate can be used instead of the time trend in the growth rate. This results in a model known as the local linear trend model with a cycle. The trend in this model evolves as a random walk plus a time-varying drift or growth rate. The drift is free to evolve up and down over time to capture changes in the underlying growth rate potential in a country's output. I discuss this model specification in the next section.

4.1 Local Linear Trend Model with Cycle: An Alternative to the CSM

The final model I estimate is the same as the model in (4), only I restrict the specification of the drift component, $\beta_{i,t}$ to be a random walk. In other words I impose the following restriction on the AR parameters: $\rho_1 = 1$ and $\rho_2 = \rho_3 = \rho_4 = 0$. In order for the dummy variables to have the same permanent effect on the level of GDP, the dummy variables must be included in the model in the equation for the level, and not the drift. This also implies that the time trend $\bar{\beta}_i + b_i\, t$ drops out of the specification for the trend $\mu_{i,t}$ As a result (4) becomes

$$y_{i,t} \quad = \quad \mu_{i,t} + \psi_{i,t}$$

$$\begin{aligned} \mu_{i,t} &= \mu_{i,t-1} + \beta_{i,t} + \sum_{s=0}^{5} \delta_s D_{i,t-s} \\ \beta_{i,t} &= \beta_{i,t-1} + \xi_{i,t}, \quad (\xi_{1,t}, \ldots, \xi_{N,t})' \equiv \xi_t \sim N\left(0, \Sigma_\xi\right). \end{aligned} \tag{8}$$

Without the cyclical component, this model is commonly referred to as the local linear trend model, see Harvey[10].

A random walk specification for the growth rate has a number of advantages over a time trend. The forecast of a model with a time trend is typically unrealistic in the long run. This contrasts with the forecast for a random walk which is given by a constant value equal to the estimated value in the final period of the sample. This reflects the most current information about the current growth potential, while still remaining neutral about the future movement either up or down in this growth rate. A random walk is also generally less restrictive than a time trend, because in each period a random walk is free to move either up or down. A time trend on the other hand imposes a fixed step movement in the same direction each period. An additional benefit of the random walk specification is that it is more parsimonious than the time trend.

The estimation via maximum likelihood is also much faster for the random walk specification (8) than the AR growth specification used in the CSM. This is because the size of the state needed in the SSF for the CSM is much greater: an AR(4) specification requires 4N elements be included in the state[4], while the random walk only involves N elements.

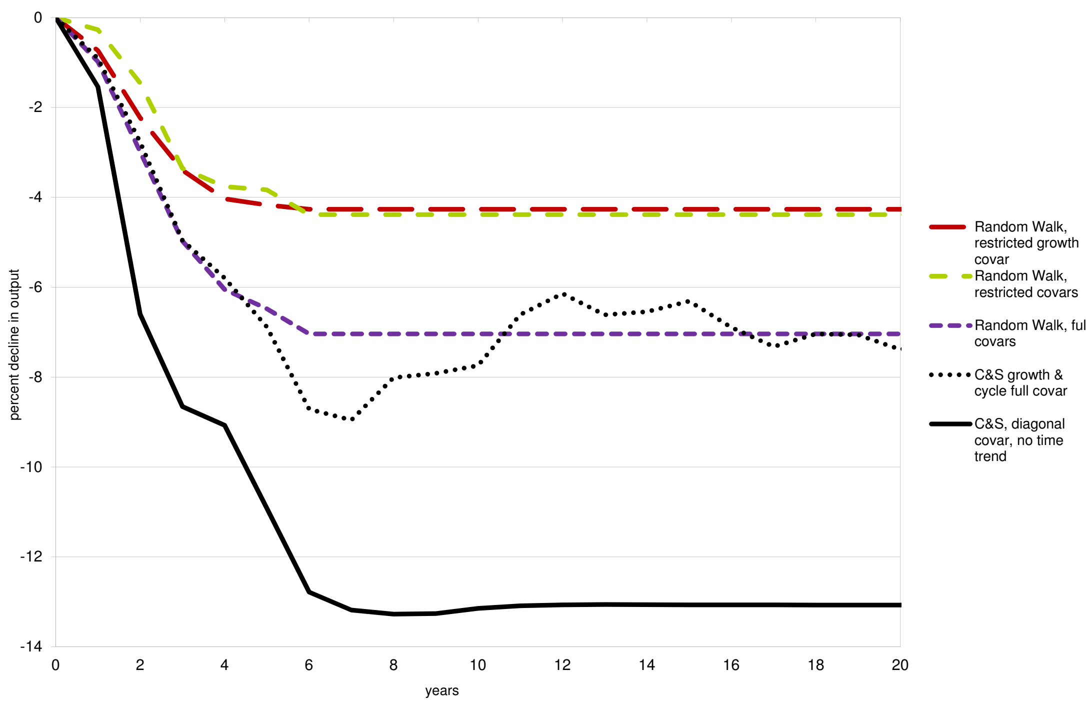
On the other hand, an implication of the random walk specification I propose here is that the long run forecast variance of the growth rate of output goes to infinity. This is admittedly unrealistic. However the constant long run growth rate implied by the AR specification is also unrealistic. The flexible and parsimonious specification of the random walk makes it well suited to capture the developments in the long run growth potential without imposing the direction of the change. I argue that this flexibility and the more realistic forecasting function of the random walk make it an interesting alternative to including a time trend in the CSM.

Figure 2 shows the resulting IRF in the dashed purple line for the model in (8) with a full covariance matrices for the cyclical and random walk growth components. The permanent drop in output is roughly 7%, which is the same decline obtained for the CSM model with cycle and unrestricted covariance matrices shown in the figure as the dotted black line. The solid black line in the figure shows the IRF for the original CSM in (2) without time trend.

The covariance matrices of the components of this model are require 435 parameters for the 29 countries in the sample. For this reason I also estimate two restricted version of this model with reduced rank covariance matrices. In the first case I opted to restrict the rank of the covariance for the disturbance driving the random walk growth rate. I reduced the rank down to just 2. The eigenvalue decomposition indicated that the 2 eigenvectors corresponding to the two largest eigenvectors could account for nearly 55% of the variation. Two underlying processes also matches my expectation that there are two main types of countries in this sample

[4] In addition to any other elements in the state required by the model.

Figure 2: Financial Crisis Impulse Response Function, model (8)



of developed countries: countries at or near the technological frontier experiencing slowing growth rates, and catch up countries experiencing faster growth, at least earlier in the sample period.

Using an unrestricted covariance on the cyclical component together with the restricted covariance on the random walk growth component I obtained the IRF for the crisis dummy variable shown in figure 2 as the red dotted line. For this model the decline in output has been reduce to just over 4%.

In the case of the eigenvalue decomposition of the cyclical component's covariance matrix for the random walk model, I found that a rank of 6 for the cycle covariance captures roughly 80% of the variance. The eigenvectors corresponding to the smaller eigenvalues each account for less than 5% of the eigenvalue total. I therefore also estimated a restricted model in which both covariance matrices are of reduced rank.

The model I used to impose these rank restrictions is shown below.

$$
\begin{aligned}
y_{i,t} &= \mu_{i,t} + \psi_{i,t} \\
\mu_{i,t} &= \mu_{i,t-1} + \beta_{i,t} + \sum_{s=0}^{5} \delta_s D_{i,t-s} + \epsilon_{i,t} \\
\beta_{i,t} &= \beta_{i,t-1} + \xi_{i,t}, \quad (\xi_{1,t}, \ldots, \xi_{N,t})' \equiv \xi_t \sim N\left(0, \Sigma_{\xi}\right).
\end{aligned} \tag{9}
$$

This model also requires the addition of the shock $\epsilon_{i,t}$ to the trend equation in the same manner as in (7) to mop up any unaccounted for variation in the data not captured by the reduced rank shock processes now driving the cycle and growth rates.

The IRF for this restricted rank variant of the random walk model is shown in figure 2 as the dashed green line. The decline in output for this parsimonious variant of the random walk model has also been reduced to just over 4%. In figures 3 and 4 I show the smoothed estimates of the growth and cyclical components for selected countries to illustrate the results from this restricted model.

If we return to table 4 we can see that the unrestricted random walk variant in (8) is the best model according to the AIC model selection criterion. The restricted random walk specifications may also in some sense be more reliable in that they are more parsimonious and therefore less subject to overfitting. In future research it would be interesting to use Bayesian techniques to impose parsimony using appropriate covariance priors in a similar fashion to those used in Bayesian VAR models.

5 Conclusion

Based on a cross section of 29 developed countries I estimate the level of permanent loss in output due to a systemic banking crisis to be on the order of 4% to 7%. These estimates reflect data covering the period from 1970 until 2014, and therefore also reflect the outcomes from the recent systemic banking crises associated with the Great Recession. My estimates are considerably less than the estimated 13% drop I obtain for the CSM. This corroborates the finding in Luginbuhl and Elbourne[1]

Figure 3: Selected Smoothed Growth Estimates, model (9)

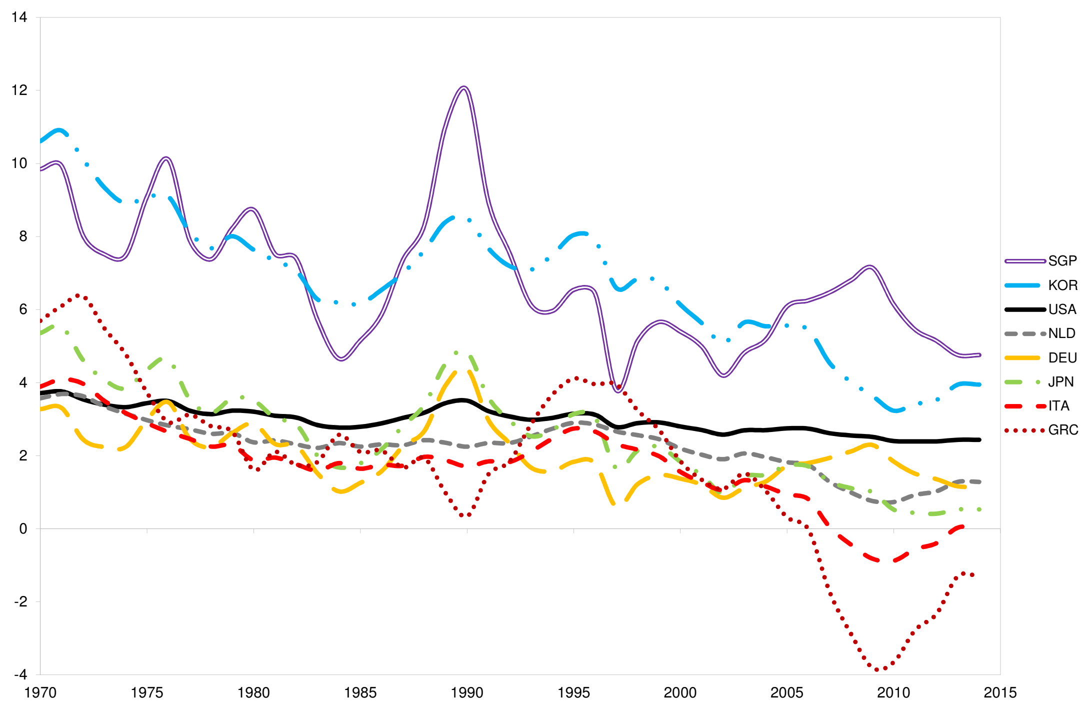
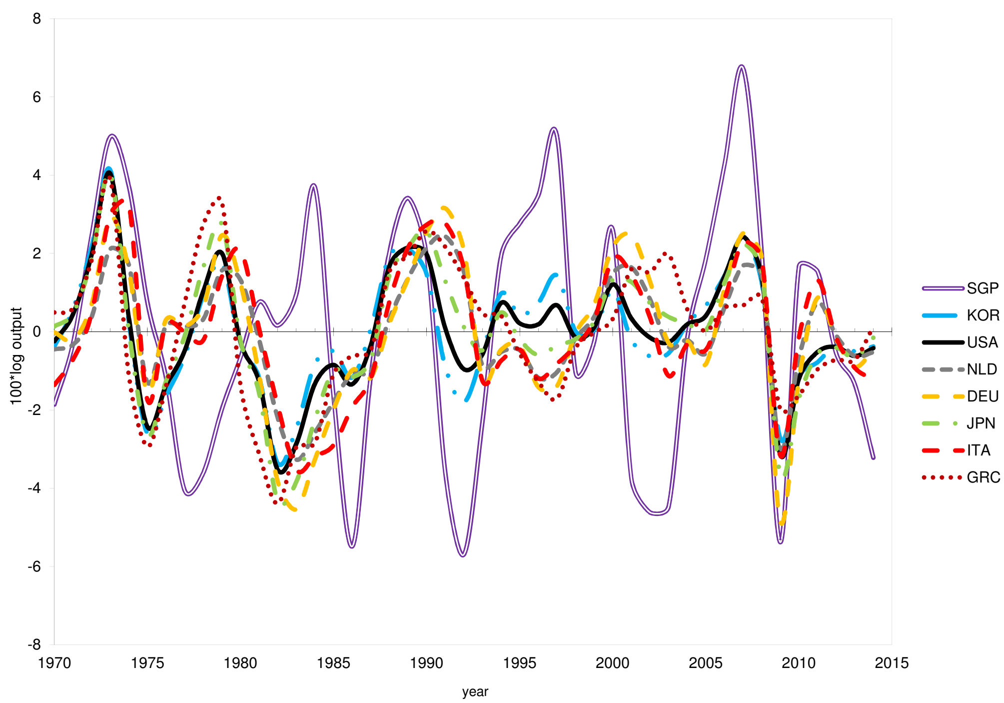


Figure 4: Selected Smoothed Cycle Estimates, model (9)



which indicate that including a cyclical component in the model used in the estimation results in a substantially smaller permanent drop in output following a systemic banking crisis.

The estimates here also demonstrate that extending the CSM to include a time trend in growth to capture the decline in growth rates experienced by most developed countries over the past 40 years reduces the level op the permanent drop estimated for the model. The alternative of using a random walk specification for the growth rate, however, has a number of advantages over the use of the time trend and is supported by the AIC model selection criterion: the random walk model with unrestricted covariance matrices achieves the best score among the models investigated.

I also propose models with restricted ranks of the covariance matrices for the shocks driving the unobserved components in the models. These models are more parsimonious and are therefore presumably less subject to overfitting. These models however do not have the best AIC scores. Bayesian techniques using priors to penalize the over parameterization of the covariance matrices in the models might be useful. This could be achieved in a similar fashion to the approach taken for Bayesian VAR models.

Finally I note that the restricted random walk version of the model I propose here indicates that the current underlying growth rate potential for the US is roughly 2.4%, for Germany 1.2%, The Netherlands 1.3%, Japan 0.5%, Italy 0%, and Greece -1.3%, see figure 3. The smoothed cyclical components indicate that most developed countries are currently still caught in between recession and expansion, see figure 4.

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