

# Online Appendix for ‘Common Correlated Effect Cross-sectional Dependence Corrections for Non-linear Conditional Mean Panel Models’\*

Sinem Hacıoğlu Hoke<sup>†</sup>  
Bank of England and DAFM

George Kapetanios<sup>‡</sup>  
King’s College, London

June 23, 2020

## Online Appendix

This document provides supplementary material for the main manuscript of ‘Common Correlated Effect Cross-sectional Dependence Corrections for Non-linear Conditional Mean Panel Models’. We present an additional Monte Carlo exercise in Appendix [A](#). We provide two additional empirical applications in Appendix [B](#).

---

\*The views expressed here are those of authors and do not necessarily reflect those of Bank of England or the Monetary Policy Committee, the Financial Policy Committee or the Prudential Regulation Committee.

<sup>†</sup>Bank of England, London, E-mail address: [sinem.hacioglu@bankofengland.co.uk](mailto:sinem.hacioglu@bankofengland.co.uk). Data Analytics for Finance and Macro (King’s College, London).

<sup>‡</sup>Corresponding Author: King’s College, London, E-mail address: [george.kapetanios@kcl.ac.uk](mailto:george.kapetanios@kcl.ac.uk).

## A Additional Monte Carlo Analysis

In this section, we present the results of an additional Monte Carlo experiment. Except for the data generating process (DGP), the design of the simulations and the presentation of the results are the same as in Section 4 of the main manuscript.

Let the DGP be ,

$$\begin{aligned}
 y_{it} &= \beta_{i1}x_{it} + \beta_{i2}g(q_{it} : \gamma, c)x_{it} + u_{it} \\
 g_{it} &= 1/(1 + \exp(-\gamma(q_{it} - c))), \\
 x_{it} &= \sum_{m=1}^M \lambda_{1m} f_{m_t} + \varepsilon_{it} \\
 u_{it} &= \sum_{m=1}^M \lambda_{2m} f_{m_t} + v_{it}
 \end{aligned} \tag{A.1}$$

where  $x_{it}$  is the observable regressors on the  $i$ th cross-sectional dimension at time  $t$  for  $i = 1, \dots, N$ ,  $t = 1, \dots, T$ ;  $f_{m_t}$  is the unobserved factors for  $m = 1, \dots, M$  with the total number of factors indicated by  $M$ . The factors, their coefficients and the idiosyncratic components are generated as

$$\begin{aligned}
 f_{m_t} &\sim \text{IIDN}(0, 1) \\
 \lambda_{l_m} &\sim \text{IIDN}(1, 1) \\
 \varepsilon_{it} &\sim \text{IIDN}(0, 1) \\
 v_{it} &\sim \text{IIDN}(0, 1).
 \end{aligned}$$

We address the non-linear term  $x_{it}g(q_{it} : \gamma, c)$  as  $w_{it}$ . The model in Eq. (A.1) is a panel smooth transition model, as in [González et al. \(2017\)](#), with additional cross-sectional dependence through the unobserved factors,  $\mathbf{f}$ .

The rank condition here has a different structure than the simulations in Section 4. The DGP in Eq. (A.1) includes only one explanatory variable. When the number of factors is more than the number of explanatory variables, i.e. in our case when  $M > 1$ , the rank condition is not satisfied. To test how the rank condition affects the performance of the model, we conduct different experiments and take  $M = 1$  where the rank condition is satisfied, and  $M = 2$  and  $M = 3$  where the rank condition is not satisfied.

As in Section 4, we consider two experiments with homogeneous and heterogeneous slope parameters. For all experiments, we have two options for the correction of cross-sectional dependence: correction with  $\bar{y}$ ,  $\bar{x}$ ,  $\bar{w}$  and  $\bar{y}$ ,  $\bar{x}$ , which are cross-sectional averages of respective

variables.

The results are presented in Tables A1 to A6 for both experiments for  $M = 1$  (1 factor),  $M = 2$  (2 factors) and  $M = 3$  (3 factors) respectively. Under option 1, the bias and RMSE of the pooled and MG estimators of  $\beta_1$  and  $\beta_2$  tend to be large for small samples but drop substantially with increasing  $N$  and  $T$ . The results of the case where  $M = 1$  are presented in Tables A1 and A2. Heterogeneity of the coefficients has a minimal impact on the bias and RMSE of the coefficients. As the number of factors increases, Tables A3 to A6, the increase in the bias is very small but the increase in the RMSE is more substantial. However, as the sample size increases, the RMSE tends to drop considerably. Rank deficiency, when  $M > 1$ , increases both the bias and RMSE of both coefficients for both pooled and MG estimators in both experiments. Additionally, under option 2, results presented on the bottom right of each table, both coefficients are substantially biased with large RMSEs for both pooled and MG estimators.

The bias and RMSE of  $\gamma$  and  $c$  tend to be larger than the bias of the coefficients in general. This is due to the numerical optimization we employ to estimate these non-linear parameters. Heterogeneity of the coefficients improve the bias and RMSE of the parameters especially in the cases of  $M = 1$  and  $M = 2$ . Moreover,  $\gamma$  is substantially biased under option 2. Curiously,  $c$  has smaller bias under option 2.

The Monte Carlo evidence seem to favor the pooled estimator over the MG estimator in terms of leading to smaller bias and RMSE. However there are exceptions. For instance, in Table A1, the MG estimator consistently leads to larger bias and RMSE for both coefficients. The same holds in Table A2 with some exceptions. For  $N = T = 200$  in Table A3, the MG estimator leads to smaller bias and RMSE for  $\beta_1$  however this changes in favor of the pooled estimator for  $\beta_2$  in the same case and for  $N = T = 400$ . Heterogeneity of the coefficients does not seem to have a structured effect on the asymptotic efficiency. In Table A4, the MG estimator leads to smaller bias and RMSE in  $\beta_1$  for  $N = T = 400$  but not for  $\beta_2$ . Rank deficiency has a minimal effect on the bias and RMSE of both coefficients.

The empirical size of both coefficients is oversized in case of homogeneous coefficients when  $M = 1$ , Table A1. As the number of the factors increases, there is considerable gain in the empirical size in all homogeneous cases. In the heterogeneous coefficients case, the empirical size is oversized mainly for small samples. As the sample size increases, the empirical size becomes very close to the nominal size of 5%. Heterogeneity of the coefficients seem to improve the size

in all cases. Moreover, in all cases and even for small samples, the empirical size is very close to the desired level under true transition function parameters.

The power of the tests are reported in the last block of columns in each table. In the case of  $M = 1$ , Tables A1 and A2, both the pooled and MG estimators display the desired power, both for homogeneous and heterogeneous coefficients. As the number of the factors increases, i.e. as the system becomes rank deficient, the power of  $\beta_1$  drops substantially both for the pooled and MG estimators even for large samples. Surprisingly, the power of  $\beta_2$  continues to be quite high for large samples.















## B Additional Empirical Applications

### B.1 The non-linear effect of solvency on wholesale funding costs at UK banks

When banks need to raise large amounts of funding in addition to retail deposits they hold, they turn to wholesale funding markets. In times of stress, banks bid to raise additional funds to finance their activities while uncertainty over bank solvency leads market participants to charge higher interest rates to make these funds available. Historically, there have been cases where banks were shut out from wholesale funding markets due to loss of credibility and concerns over their ability to repay their debt (Shin (2009)).

Understanding how wholesale funding costs work and why they change over time is essential. There has been increasing attention to non-linear estimation techniques to model banks' funding costs (Aymanns et al. (2016)). In simple terms, we expect troubled banks to face higher costs to borrow. This relationship, however, is unlikely to be linear. When a bank draws closer to its default threshold, the cost of funding it faces is expected to increase at an increasing rate (Korsgaard (2017)). Similarly, beyond a certain point, an improvement in the solvency position of a healthy bank has little impact on the interest rate it must face. Therefore we expect to see a (negative) non-linear relationship between the wholesale funding costs of banks and their solvency levels.

We apply our technique to this issue by following Dent et al. (2018). Solvency measures, such as leverage ratio, are good measures to explore banks' health and therefore, to identify the stressful periods they go through. Following a similar approach to Dent et al. (2018), we utilize a market-based data approach to proxy for bank solvency. We use market-based capital ratio (MBLR) which is defined as  $\left(\frac{\text{Market Value of Equity}}{\text{Book Value of Assets}}\right)$ , as the solvency measure.

For measuring the wholesale funding costs that banks face, market participants use banks' Credit Default Swap (CDS) premia as a proxy, e.g. Beau et al. (2014). CDS premium the insurance premia that investors are willing to pay to be compensated if the debt issuer, such as the bank that borrows money, defaults. CDS premia tend to go up for all financial institutions during banking or financial crises due to market-wide factors. However, banks' characteristics are important determinants of the incremental increase in their funding costs over the market-wide increase.

We use CDS premia to proxy for banks Euro wholesale cost of funding (Beau et al. (2014)).

The daily five-year senior euro CDS premia data are acquired from Bloomberg. To construct the MBLR series, we obtain the market capitalisation data from Datastream. The book value of assets are taken from banks' published results. The risk free rate is essentially the daily yield on the five year treasury data from Bloomberg. VFTSE index is from Bloomberg.

Our data set is a panel of the four largest banks in the UK: Barclays plc, HSBC Holdings plc, Lloyds Banking Group plc and Royal Bank of Scotland plc. The UK banking sector is highly concentrated, limiting the number of cross sections which motivates the use of higher frequency data, such as market data, to increase the time dimension of the panel. The panel data set is in weekly frequency, aggregated from daily to eliminate outliers and noise, and run from January 2007 to December 2016 with total of 522 observations for each bank.

We see merit in employing such an exercise even though the cross-sectional dimension of the dataset is small because the results provide us with a reasonable interpretation of solvency and whole funding cost interactions. However, before we explain the details of this empirical model, we provide Monte Carlo simulation results for a short experiment designed to show how our method performs under a very small number of cross sections. This is to show that this empirical illustration leads to sensible results although the banking data set we use has data for only four banks. The data generating process and the parameters are the same as in Section 4. The only difference is that we choose  $N = 4$  and  $T = 521$ . We run the simulation for the homogeneous full rank case with 1000 replications. In Table A7, we report the bias and RMSE of  $\beta_1$ ,  $\beta_2$ , and  $\gamma$  and  $c$ , under correction with  $\bar{x}$ ,  $\bar{y}$  and  $\bar{w}$ , correction with only  $\bar{x}$ ,  $\bar{y}$ , and under no correction.

Table A7: Simulation Results of Homogeneous Full Rank Case for  $N = 4$  and  $T = 521$ ,  $\times 100$

		$\beta_1$		$\beta_2$		$\gamma$	$c$
		Pooled	MG	Pooled	MG		
Correction with $\bar{x}$ , $\bar{y}$ and $\bar{w}$	Bias	-0.21	-0.22	0.10	0.01	19.69	0.57
	RMSE	10.53	10.09	12.09	12.44	91.80	33.54
Correction with $\bar{x}$ , $\bar{y}$	Bias	32.45	36.15	-66.33	-73.55	-49.13	0.05
	RMSE	51.61	52.40	101.62	103.23	105.44	170.65
No correction	Bias	19.52	17.03	-0.26	0.77	31.27	-3.85
	RMSE	29.99	29.66	35.94	38.92	103.18	58.62

The table shows that correction with only  $\bar{x}$ ,  $\bar{y}$  and no correction both create larger bias and RMSE for both coefficients than correction with  $\bar{x}$ ,  $\bar{y}$  and  $\bar{w}$ . As mentioned in Section 4 that

correction with only  $\bar{x}$ ,  $\bar{y}$  leads to substantially larger bias and RMSE. We observe that this holds true also when compared to no correction.

It is worth to mention that  $\beta_2$  shows relatively small bias under no correction however the bias is still larger than the correction with  $\bar{x}$ ,  $\bar{y}$  and  $\bar{w}$ . Compared to the bias and RMSE of both coefficients in  $N = 20$ ,  $T = 400$  case of Table 1 of the main manuscript,  $\beta_1$  shows a slightly inferior performance as the number of cross sections is small. On the other hand, an increase in  $T$  seems to favour less bias in  $\beta_2$ . Overall, the simulation results address the importance of correcting cross-sectional dependence and estimating such a model even with a small number of cross sections.

Having shown the simulation results, we specify the main model as follows:

$$\begin{aligned} \Delta y_{it} &= \alpha_i + \beta_1' \Delta x_{it} + \beta_2' \Delta x_{it} g(q_{it}; \gamma, c) + e_{it} \\ g(q_{it}; \gamma, c) &= (1 + \exp(-\gamma(q_{it} - c)))^{-1}, \end{aligned} \tag{B.1}$$

where  $y_{it} = \{\text{CDS premia}_{it}\}$ ,  $x_{it} = \{\text{MBLR}_{it}\}$ . Bank fixed effects are indicated by  $\alpha_i$ . The subscript  $i$  identifies the individuals, in our case UK banks, i.e.  $i = 1, \dots, N$  where  $N = 4$ . The subscript  $t$  identifies time. All the variables are in first differences to ensure stationarity. We take  $q_{it} = \text{MBLR}$  so that the transition of  $\beta_2$  is governed by the level of MBLR. To estimate (B.1), we need to eliminate the fixed effects as outlined in the previous section.

The main feature of this model is the non-linear relationship between  $\Delta\text{CDS}$  premia and  $\Delta\text{MBLR}$ . The change in CDS premia is nonlinear with respect to the level of MBLR. Namely, we assume that wholesale funding costs of UK banks change with respect to the level of their solvency. Therefore, for each solvency level, we expect a different coefficient on  $\Delta\text{MBLR}$ , which is bounded between  $\beta_1$  and  $\beta_1 + \beta_2$ , as a result of a straightforward interpretation of the transition function  $g(q_{it}; \gamma, c)$ .

We estimate two model specifications. Model I only includes MBLR as a dependent variable as defined in (B.1). Model II, presented in B.2, includes the first differences of risk free rate and volatility of FTSE index (VFTSE) to proxy for the macroeconomic environment, i.e.  $\Delta Z_t = \{\Delta\text{Risk Free Rate}_t, \Delta\text{VFTSE}_t\}$ . Similar variables are used in empirical work, [Annaert et al. \(2013\)](#). The model is linear with respect to these exogeneous variables.

$$\Delta y_{it} = \alpha_i + \beta_1' \Delta x_{it} + \beta_2' \Delta x_{it} g(q_{it}; \gamma, c) + \delta_1 \Delta z_{1,t} + \delta_2 \Delta z_{2,t} + e_{it} \tag{B.2}$$

Additionally, we estimate two variants of each model. We estimate Model I and II first by not correcting for cross-sectional dependence. The estimated coefficients are given in the second and

third column of Table A8 for both pooled and MG estimators for Model I, and in the sixth and seventh columns for Model II. The second variant corrects for cross-sectional dependence. The results are presented under the columns of correction for both model specification in Table A8.

Table A8: Estimation results for no correction and correction for specification I and II

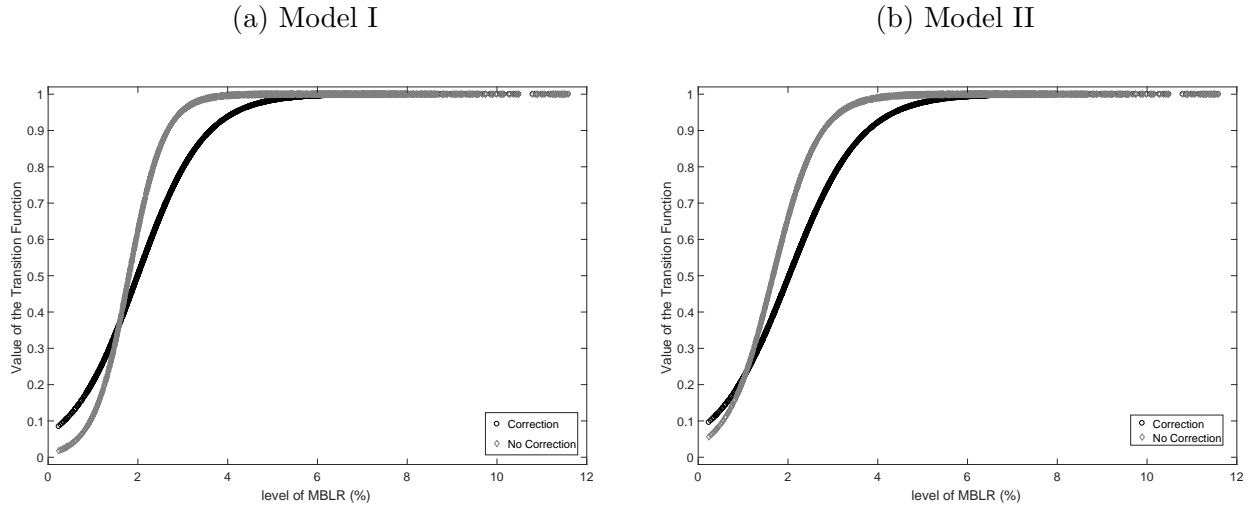
	Model I				Model II			
	No correction		Correction		No correction		Correction	
	Pooled	MG	Pooled	MG	Pooled	MG	Pooled	MG
$\beta_1$	-19.57***	-24.81***	-7.97***	-8.55***	-11.70***	-15.40***	-6.07***	-6.31***
$\beta_2$	12.35	16.14	4.64***	4.26**	11.31	11.22	4.67***	4.16**
$\delta_1$					-40.12***	-39.02***	-29.50***	-28.43***
$\delta_2$					0.64**	0.59**	0.73	0.70

*Notes:* Table shows the linear and the non-linear coefficients for the model presented in B.1. Linear and non-linear coefficients of  $\Delta$ MBLR are  $\beta_1$  and  $\beta_2$ , and coefficients  $\delta_1$  and  $\delta_2$  are for  $\Delta$ Risk Free Rate and  $\Delta$ VTSE respectively. \*, \*\*, \*\*\* denote statistical significance at 10, 5, and 1% respectively.

Three important observations are in order. First, the coefficient of the non-linear term,  $\beta_2$ , is smaller than  $\beta_1$  in magnitude. Therefore, even when  $g(q; \gamma, c) = 1$  for the maximum level of MBLR, the negative relationship of  $\Delta$ MBLR and  $\Delta$ CDS premia is preserved both for no correction and correction of cross-sectional dependence. Second, coefficients  $\beta_1$  and  $\beta_2$  are smaller in magnitude under correction compared to the coefficients of no correction. For instance, for pooled estimators of Model I, the coefficient of MBLR is bounded between  $-19.57$  and  $-7.22$  for no correction, and  $-7.07$  and  $-3.33$  for correction. Therefore, if the first and second points are taken together, the magnitude of the relationship decreases under correction although the direction of the relationship always holds. Moreover, in Model II, the sign and the magnitude of coefficients of the exogenous variables are in line with what structural models for bank default and empirical work on the determinants of CDS premia suggest (Bongaerts et al. (2011), Longstaff and Schwatz (1995), Annaert et al. (2013)). Third, the statistical significance of the coefficients changes once cross-sectional dependence is accounted for. Nonlinearities become significant, i.e.  $\beta_2$  becomes statistically significant, but  $\delta_2$  in Model II loses significance. This highlights the importance of addressing cross-sectional dependence which can otherwise cause incorrect inference or misleading results.

Transition functions of Models I and II are presented in Figures B.1a and B.1b both for correction and no correction. In Model I, when we do not correct for cross-sectional dependence,

Figure B.1: Transition Functions of Models I and II for the Empirical Application in Section B.1



*Notes:* Transition functions of model presented in B.1 both under no correction (gray diamonds) and correction (black circles). Model I parameters: (i) Correction parameters:  $\gamma = 135$  and  $c = 2\%$ . (ii) No correction parameters:  $\gamma = 255$  and  $c = 1.8\%$ . Model II parameters: (i) Correction parameters:  $\gamma = 125$  and  $c = 2\%$ . (ii) No correction parameters:  $\gamma = 197$  and  $c = 1.7\%$ . We estimate the parameters of the transition function by grid search.

the transition is faster due to the steeper slope, compared to the slope of the transition function under correction. Model II's results are very similar to that of Model I's because the model is linear with respect to the control variables. Inclusion of these variables changes the results slightly; however the qualitative results still hold. In summary, when a bank's MBLR level is above the inflection point,  $c$ , no correction provides an overly optimistic decrease in banks' CDS premia once their solvency levels start improving, i.e. lower CDS premia than it is supposed to be under correction. However, below the inflection point, no correction implies higher CDS premia for a given solvency level.

Our takeaway from this empirical exercise is two-fold. First, the net impact of  $\Delta\text{MBLR}$  on  $\Delta\text{CDS}$  premia is always negative which confirms the findings of Dent et al. (2018). This holds true for all cases regardless of the level of MBLR and hence the value that transition function takes for a given level of MBLR. Second, correcting for cross-sectional dependence leads to smaller coefficients of all variables, except for  $\Delta\text{VFTSE}$ , in absolute terms. This is due to the fact that the cross-sectional averages we add to the system filter out the impact of common factors and decrease the marginal impact that  $\Delta\text{MBLR}$  has on  $\Delta\text{CDS}$  premia.

## B.2 Non-linear Effect of Public Indebtedness on GDP Growth

In this section, we present another empirical application that further illustrates the potential of our proposed methods. The impact of public indebtedness on the economy has increasingly been a focus of empirical studies (Reinhart et al. (2012), Baum et al. (2013)). Although indebtedness promotes economic growth in the short run, it reduces it in the long run. Especially, after the recent financial and sovereign debt crises, the need to investigate potential nonlinearities in the relationship of debt-to-GDP ratio and GDP growth has grown. Recently Chudik et al. (2017) explore the impact of public debt on countries' GDP growth. They investigate a potential debt threshold above which the GDP growth sharply falls due to increasing debt. This debt threshold is important to detect the short run and long run impact of public debt on output growth. However, they are not able to find a common threshold level of debt-to-GDP ratio after correcting cross-sectional dependence. That said, they find statistically significant threshold effects for countries with rising debt levels.

We adopt a simplification of Chudik et al. (2017)'s empirical illustration. We do not aim to replicate their results or claim to find a common threshold. Instead we use their methodology to illustrate the importance of correcting for cross-sectional dependence in non-linear models. We use the same data set Chudik et al. (2017) use with minor modifications to eliminate missing observations. We use the data for 36 countries data over 1971-2010 period which provides us 40 years of annual observations.

The data set and the data explanation are provided by Kamiar Mohaddes in his website, <http://www.econ.cam.ac.uk/people-files/faculty/km418/research.html>. The original data set contains annual data from 1965 to 2010 on the log of CPI, log of GDP, and log of gross government debt/GDP for the following 40 countries: Argentina, Australia, Austria, Belgium, Brazil, Canada, Chile, China, Ecuador, Egypt, Finland, France, Germany, India, Indonesia, Iran, Italy, Japan, Korea, Malaysia, Mexico, Morocco, Netherlands, New Zealand, Nigeria, Norway, Peru, Phillipines, Singapore, South Africa, Spain, Sweden, Switzerland, Syria, Thailand, Tunisia, Turkey, United Kingdom, United States, Venezuela. The construction of data and the underlying sources are described in the Data Appendix of Chudik et al. (2017). To eliminate missing observations, we start the data from 1971 and omit China, Iran, Korea and Nigeria from the sample. For simplicity, we do not distinguish between advanced and developing countries. Moreover, we do not use any lagged regressors in our model.



Table A9: Estimation results for no correction and correction,  $\times 100$ 

	No Correction		Correction	
	Pooled	MG	Pooled	MG
$\beta_1$	-6.99***	-10.24***	-5.93***	-9.09***
$\beta_2$	0.01***	0.03***	0.04***	0.04***
$\delta$	-2.29***	0.20***	-2.64***	-6.51***

*Notes:* Estimation results of the model presented in B.3. Linear and non-linear coefficients of log debt to GDP ratio are  $\beta_1$  and  $\beta_2$  respectively while  $\delta$  is the coefficient of log CPI. \*, \*\*, \*\*\* denote statistical significance at 10, 5, and 1% respectively.

The model is very similar to the model in Section 5 and specified as follows:

$$\begin{aligned} \Delta y_{it} &= \alpha_i + \beta'_1 \Delta x_{it} + \beta'_2 \Delta x_{it} g(q_{it}; \gamma, c) + \delta' \Delta z_{it} + e_{it} \\ g(q_{it}; \gamma, c) &= (1 + \exp(-\gamma (q_{it} - c)))^{-1}, \end{aligned} \quad (\text{B.3})$$

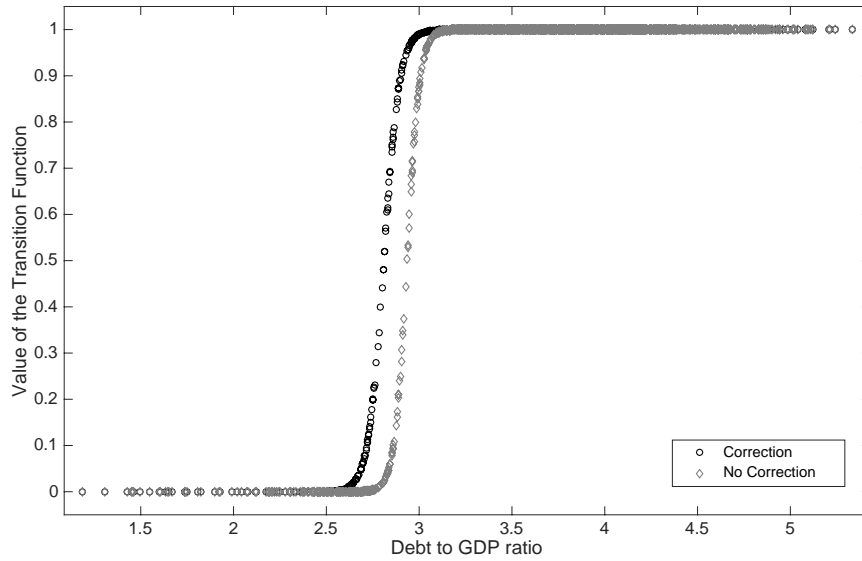
where  $\alpha_i$  is country-specific fixed effects,  $y_{it} = \log(\text{GDP growth}_{it})$ ,  $x_{it} = \log(\text{debt to GDP ratio}_{it})$  and  $z_{it} = \log(\text{CPI}_{it})$ . The subscript  $i$  identifies the countries, i.e.  $i = 1, \dots, N$  where  $N = 36$ . The subscript  $t$  identifies time. All the variables are in first differences. We take  $q_{it} = \text{debt to GDP ratio}$  so that the transition of  $\beta_2$  is governed by the *level* of debt to GDP ratio.

As in the exercises in Section 5 of the main manuscript, we estimate two variants of this model after eliminating the fixed effects. First, we estimate the model first by *not* correcting for cross-sectional dependence. The estimated coefficients are given in the second and third columns of Table A9 both for pooled and MG estimators. As for the second variant, we correct for cross-sectional dependence. The results are presented in the last two columns of Table A9. The transition functions for both variants are given in Figure B.2.

There are some observations that are worth discussing. First, regardless of the value of the transition function, the relationship between debt to GDP ratio and GDP growth is negative. Second, the coefficient of CPI,  $\delta$ , is positive in the MG estimation of no correction case. That is not consistent with the rest of our results. It points out incorrect results under the presence of cross-sectional dependence. Third, the magnitude of  $\beta_1$  and  $\delta$  are quite different between no correction and correction cases. Finally, when not corrected, cross-sectional dependence causes a delay in the transmission of increasing debt to GDP ratio, which can be seen from the shift in the transition function in Figure B.2.

The main conclusion of this exercise is that we need to employ the correction for cross-sectional dependence, as outlined by Chudik et al. (2017). Although direct comparison is not

Figure B.2: Transition Function



*Notes:* Transitions function of the model presented in B.3 both under no correction (gray diamonds) and correction (black circles). Correction:  $\gamma = 24$  and  $c = 2.81$ . No correction:  $\gamma = 30$  and  $c = 2.93$ . These parameters are estimated by grid search as the numerical optimization leads to unstable parameters.

possible, our results are qualitatively in line with their analysis.

## References

- ANNAERT, J., M. D. CEUSTER, P. V. ROY, AND C. VESPRO (2013): “What determines Euro area bank CDS spreads?,” *Journal of International Money and Finance*, 32, 444 – 461.
- AYMANN, C., C. CACERES, C. DANIEL, AND L. B. SCHUMACHER (2016): “Bank Solvency and Funding Cost,” IMF Working Papers 16/64, International Monetary Fund.
- BAUM, A., C. CHECHERITA-WESTPHAL, AND P. ROTHER (2013): “Debt and growth: New evidence for the euro area,” *Journal of International Money and Finance*, 32, 809 – 821.
- BEAU, E., J. HILL, T. HUSSAIN, AND D. NIXON (2014): “Bank funding costs: what are they, what determines them and why do they matter?,” Quarterly Bulletin Q4, Bank of England.
- BONGAERTS, D., F. DE JONG, AND J. DRIESSEN (2011): “Derivative Pricing with Liquidity Risk: Theory and Evidence from the Credit Default Swap Market,” *The Journal of Finance*, 66(1), 203–240.
- CHUDIK, A., K. MOHADDES, M. H. PESARAN, AND M. RAISSI (2017): “Is there a debt-threshold effect on output growth?,” *Review of Economics and Statistics*, 99(1), 135–150.
- DENT, K., S. HACIOĞLU HOKE, AND A. PANAGIOTOPOULOS (2018): “Solvency and wholesale funding cost interactions at UK banks,” *Journal of Financial Stability*, (forthcoming).

- GONZÁLEZ, A., T. TERÄSVIRTA, D. VAN DIJK, AND Y. YANG (2017): “Panel Smooth Transition Regression Models,” SSE/EFI Working Paper Series in Economics and Finance 604, Stockholm School of Economics.
- KORSGAARD, S. (2017): “Incorporating Funding Costs to Top Down Stress Tests,” Danmarks NationalBank Working Papers 110, Danmarks NationalBank.
- LONGSTAFF, F. A., AND E. S. SCHWATRZ (1995): “A Simple Approach to Valuing Risky Fixed and Floating Rate Debt,” *The Journal of Finance*, 50(3), 789–819.
- REINHART, C. M., V. R. REINHART, AND K. S. ROGOFF (2012): “Public Debt Overhangs: Advanced-Economy Episodes since 1800,” *Journal of Economic Perspectives*, 26(3), 69–86.
- SHIN, H. S. (2009): “Reflections on Northern Rock: The Bank Run That Heralded the Global Financial Crisis,” *Journal of Economic Perspectives*, 23(1), 101–19.