BANK OF ENGLAND

Staff Working Paper No. 681

Solvency and wholesale funding cost interactions at UK banks

Kieran Dent, Sinem Hacioglu Hoke and Apostolos Panagiotopoulos

October 2017

BANK OF ENGLAND

Staff Working Paper No. 681

Solvency and wholesale funding cost interactions at UK banks

Kieran Dent,[1] Sinem Hacioglu Hoke[2] and Apostolos Panagiotopoulos[3]

Abstract

We study the interaction between solvency and funding costs at UK banks. We use the market-based leverage ratio as a proxy for market participants' perceptions of bank solvency. We investigate the impact that changes in this ratio have on banks' CDS premia, which are a proxy for their marginal cost of wholesale funding. We find that a negative shock to market participants' perception of banks' solvency leads to an increase in banks' marginal cost of wholesale funding. We find evidence that this negative relationship is nonlinear, ie the responsiveness of funding costs to a shock to solvency is greater at lower initial levels of solvency.

Key words: Solvency, funding cost, leverage ratio, CDS premia, panel threshold model, panel smooth transition model.

JEL classification: C33, G21.

(1) Bank of England. Email: kieran.dent@bankofengland.co.uk
(2) Bank of England. Email: sinem.hacioglu@bankofengland.co.uk
(3) Bank of England. Email: apostolos.panagiotopoulos@bankofengland.co.uk

The views expressed are those of the authors and do not necessarily reflect those of the Bank of England or the MPC, FPC or PRC. The authors would like to thank Saleem Bahaj, Rohan Churm, Bonnie Howard, Sujit Kapadia, Amar Radia, Rhiannon Sowerbutts and an anonymous referee for helpful comments and suggestions. All errors remain our own. This paper was finalised in August 2017.

Information on the Bank's working paper series can be found at
www.bankofengland.co.uk/research/Pages/workingpapers/default.aspx

Publications and Design Team, Bank of England, Threadneedle Street, London, EC2R 8AH
Telephone +44 (0)20 7601 4030 email publications@bankofengland.co.uk

ISSN 1749-9135 (on-line)

1 Introduction

This paper empirically investigates the interactions between banks' solvency and wholesale funding costs in the United Kingdom (UK). Our results show that a negative shock to a bank's perceived solvency is associated with an increase in its marginal cost of wholesale funding. The novelty of our approach is to employ non-linear panel models to investigate this relationship, and estimate the thresholds at which the relationship changes endogenously. We find evidence that the relationship between solvency and marginal wholesale funding costs is indeed nonlinear with respect to the level of solvency.

The importance of the interaction between banks' solvency and their cost of funding is well recognised. During the Great Recession, banks suffered significant unexpected losses, which had a direct negative impact on their solvency. Weaker bank solvency increased market uncertainty and led to strains in funding markets, significantly increasing the cost at which banks were able to access funds.

The relationship between solvency and funding costs constitutes one of the more significant channels through which an initial shock to bank capital can be amplified to produce further second-round reductions in bank capital. Through their impact on profitability, marked increases in funding costs have the potential to generate a second round of shocks to bank capital (Gertler, Kiyotaki, and Prestipino (2016)). For these reasons, attempts to better measure and quantify these amplification and feedback mechanisms have become a key focus for policymakers, particularly in the field of stress testing.

This interaction between banks solvency and their cost of funding has been widely studied. Babihuga and Spaltro (2014) find that a one percentage point increase in bank capital reduces funding costs, proxied by CDS premia, in the long run, by approximately 26 basis points. Schmitz, Sigmund, and Valderrama (2016) emphasises the importance of using market-based measures as funding cost proxies to identify potential risks to funding markets. They find a very strong negative relationship between capital ratios and bank funding costs, i.e. a one percentage point increase in the regulatory capital ratio results in a 1.1 percentage point decrease in funding costs.

To date, as in the above-mentioned papers alongside others, empirical analyses have generally tended to assume a linear relationship between solvency and the cost of funding.[1] This is at odds with the theoretical results of more recent studies, which show that at higher levels of solvency, fluctuations in banks capital and leverage ratios appear to have little effect on their

[1] Schmitz, Sigmund, and Valderrama (2016) explore the existence of nonlinearities in such a relationship by adding squared regulatory capital measure into their model specification. They find evidence supporting a non-linear relationship between funding costs and solvency.

cost of funding. Whereas at lower levels of solvency, fluctuations in banks capital and leverage ratios have been associated with much more significant changes in their cost of funding. This suggests that the relationship between banks solvency and their cost of funding is unlikely to be linear. Only recently, have non-linear panel estimation techniques been used to model such relationships, such as Aymanns, Caceres, Daniel, and Schumacher (2016), Korsgaard (2017). Aymanns, Caceres, Daniel, and Schumacher (2016) proxy the wholesale funding costs of banks by a measure of the interbank funding cost. They highlight the importance of accounting for nonlinearities by using a panel threshold approach with a pre-specified threshold on solvency. Their model essentially reduces to a linear panel model given the threshold value of solvency. Using variations of Merton-type models, Korsgaard (2017) points out that the *log* CDS premia has a linear relationship with *log* distance to default. This means that CDS premia increase at an increasing rate as banks get closer to default.

We focus on the UK banks and aim to provide evidence that the relationship between banking solvency and funding cost in the UK is nonlinear. To explore this relationship, we use a panel data set including the largest four UK banks. The number of cross sections is too limited to employ a panel model were we to use balance sheet measures, for instance as in Aymanns, Caceres, Daniel, and Schumacher (2016). Therefore we follow a market-based approach, utilising weekly data to ensure a sufficiently large time series for each bank. We use the market-based leverage ratio (MBLR) as a proxy for UK banks' solvency and credit default swap (CDS) premia as a proxy for their marginal funding costs.

We apply non-linear panel estimation techniques alongside linear panel data models. To find the point at which changes in solvency lead to increasingly higher funding costs, we follow Hansen (1999) and perform a panel threshold estimation. Unlike Aymanns, Caceres, Daniel, and Schumacher (2016), we are interested in estimating the point at which nonlinearities kick in, i.e. estimating the threshold(s). The estimated threshold level can be regarded as the solvency level below which the relationship between solvency and cost of funding is structurally different than for solvency levels above the threshold. Hence, this model provides a way to explore the potentially non-linear relationship between solvency and wholesale funding costs. As well as using a threshold panel model, we also employ a panel smooth transition model proposed by González, Teräsvirta, and van Dijk (2005). This model is a generalisation of the threshold model and allows us to identify how falling solvency increases the sensitivity of marginal funding costs to solvency.

The results of our analysis show that the relationship between solvency and cost of funding is indeed nonlinear. Nonlinearities in this context mean that the impact of MBLR on CDS premia changes with respect to the level of MBLR. For the full sample analysis, the endogenously estimated threshold level of MBLR is around 2.4%. This implies that when MBLR is greater than 2.4%, the response of CDS premia to a shock in MBLR is materially different than when

MBLR is below this threshold. For instance, when the MBLR level is greater than 2.4%, a 100bp decrease in MBLR is associated with around a 6.5 basis point increase in CDS premia. When MBLR is below the threshold, the impact starts to increase in magnitude, adding as much as approximately 30 basis points to a banks' CDS premia. The linear estimation results provide only a 10 basis points increase in CDS premia in response to a 100bp decrease in MBLR. Turning our attention to rolling windows estimation, the threshold level changes over time but generally it is in 0.5% to 3.3% range. We observe that the sensitivity of funding costs to solvency has increased in the aftermath of the Great Recession. The magnitude of the impact of MBLR on CDS premia is substantially larger around the financial crisis compared to normal times.

The paper proceeds as follows. Section 2 explains our methodology and provides the details of the variables we use in our analysis. Section 3 presents the panel data models we employ. We explain the full sample and rolling window results of all the models in Section 4. We present the forecasting performance of our models in Section 5. Section 6 concludes and we provide the descriptive statistics of the series along with their plots in Appendix A.

2 Theoretical Framework and Data

2.1 Theoretical Framework

UK banks use secondary market spreads on existing unsecured bonds to calculate the marginal cost of wholesale funding (Beau, Hill, Hussain, and Nixon (2014)). Using secondary market spreads in econometric analysis, however, presents some challenges. In particular, the volume and characteristics, such as currency and maturity, of bonds in issue can vary significantly over time, making time-series comparisons misleading. We therefore use CDS premia as a proxy for banks marginal cost of funding. A loose no arbitrage relation can be used to argue that, all else equal, the CDS premia should be equal to the credit spread between the yield to maturity on a risky par bond and the risk free rate (Darrell (1999) and Hull and White (2001)). Although the arbitrage is only perfect under restrictive assumptions, CDS premia have nevertheless proved to be a reasonably good proxy for UK banks bond spreads over time (Beau, Hill, Hussain, and Nixon (2014)).

In seeking to explore the determinants of movements in UK banks CDS premia, we follow an approach akin to those of Collin-Dufresne, Goldstein, and Martin (2001), Blanco, Brennan, and Marsh (2005) and Longstaff, Mithal, and Neis (2005) among others. These papers utilise insights garnered from structural models of default which generally posit a stochastic firm value process, in which default is triggered when firm value falls below some threshold. Using these insights, they attempt to explain movements in credit spreads and CDS premia with a series of variables that capture both credit risk and liquidity risk. Adopting a similar approach, we consider the factors driving movements CDS premia to be changes in firm leverage, share price volatility, liquidity, and the change in market-wide volatility and the risk free rate.

1. *The risk free rate*: In structural models of default, the risk free rate constitutes the risk neutral drift in the firms valuation process. An increase in the risk free rate therefore increases the risk neutral drift, which in turn reduces the risk-neutral probability of default (Longstaff and Schwatrz (1995)). Moreover, as discussed in Annaert, Ceuster, Roy, and Vespro (2013), the risk free rate can also be used as a proxy to capture the macroeconomic environment. We therefore expect to find a negative relationship between changes in the risk free rate and changes in CDS premia.

2. *Firm leverage*: Leverage enters structural models of default through the default threshold which is triggered when firm value approaches zero. The leverage ratio expresses firm value, or net assets, in relation to its total assets. The lower is the leverage ratio, the closer the firm is to hitting its default threshold. We also provide a simple evidence to this by Figure A.14. As the figure suggests, this relationship is unlikely to be linear, with the dispersion in CDS premia increasing as the leverage ratio falls and an increasing number of observations having a very high CDS premia. We therefore expect to find a negative, non-linear relationship between changes in the market-based leverage ratio and changes in CDS premia. It is highly unlikely to capture such a relationship with linear models.

3. *Share price volatility*: An increase in the volatility of the firm value process increases the probability that the default threshold is hit. We therefore expect to find a positive relationship between changes in banks' share price volatility and changes in CDS premia.

4. *Liquidity*: The market for bank CDS is deep and liquid, more so than that of the secondary market for unsecured bonds. Nevertheless, it has been argued that part of the CDS premia is due to liquidity risk (Bongaerts, De Jong, and Driessen (2011) finds a significant, albeit economically small, impact of liquidity risk on CDS premia). We control for this in our model by including the bid-ask spread of the CDS quotes. We expect to find a positive relationship between changes in the bid-ask spread and CDS premia.

5. *Market-wide volatility*: Previous studies have found that factors describing broader market and macroeconomic conditions play a significant role in driving credit spreads, default probabilities and recovery rates (Fama and French (1989)). We use market-wide volatility to proxy for the broader business climate and overall uncertainty over economic prospects and returns. We expect to find a positive relationship between changes in market-wide volatility and CDS premia.

2.2 Data

We use financial market data to explore the link between bank resilience and their marginal cost of funding. Our choice of a market-based over a balance sheet approach is driven by the highly concentrated nature of the UK banking system, which is dominated by a few large banks. This high level of concentration makes it difficult to collect sufficient observations to implement an approach that utilises balance sheet data and yields robust results, particularly for non-linear estimation. While an oft-cited shortcoming of market data is that it tends only to be available for a subset of large, publicly-listed banks, the absence of medium-sized banks in the UK reduces this problem for our analysis. A second reason for preferring market-based over balance-sheet measures is that it is ultimately the actions of market participants that determine the marginal cost of funding faced by banks. We might reasonably expect, therefore, that market perceptions of solvency will play an important role in determining these marginal funding costs.

The variables we use as proxies for the endogenous and exogenous factors included in our model, and the sources and data used to obtain them are listed below.

1. *CDS premia*: We use the daily five-year senior euro CDS premia obtained from Bloomberg. This is generally the most liquid contract for UK banks, and proxies for the five-year unsecured bond spread, the metric most commonly used by banks to proxy for their marginal cost of wholesale funding (Beau, Hill, Hussain, and Nixon (2014)).

2. *The risk free rate*: Consistent with the maturity of the CDS quotes, we use the daily yield on the five-year gilt obtained from Bloomberg to proxy for the risk free rate.

3. *Firm leverage*: At high frequency, we proxy for firm leverage with the market-based leverage ratio which we calculate as:

$$\frac{\text{Market Value of Equity}}{\text{Book Value of Assets}}$$

   Daily market capitalisation for each of the banks in our sample is obtained from Datastream. Book value of assets is collected from banks' published results, with the series updating on the day the results are announced. For the banks in our sample, book value of assets is reported semi-annually until 2012 and quarterly thereafter. We choose not to interpolate book value of assets to obtain a higher frequency.

4. *Share price volatility*: We use the daily 30-day share price volatility series obtained for each bank from Bloomberg.

5. *Liquidity*: We calculate the bid-ask spread of the CDS quotes as the difference between the daily bid and ask quotes obtained from Bloomberg.

6. *Market-wide volatility*: We use the daily VFTSE Index obtained from Bloomberg to proxy for market-wide volatility, because it is the volatility on UK markets to which UK banks are most exposed.

Our dataset is a panel of the four largest banks in the UK: Barclays plc (henceforth Barclays), HSBC Holdings plc (henceforth HSBC), Lloyds Banking Group plc (henceforth LBG) and Royal Bank of Scotland plc (henceforth RBS). Our sample runs from January 2007 to December 2016. Although our data are constructed daily, we aggregate all the series to weekly frequency. This helps to eliminate noise in the data and hedges against outliers significantly affecting the estimation results. The resulting data set is balanced. In total we have 522 observations for each bank.

3 Panel Models

This section explains the models we estimate. We believe that modelling the relationship between solvency and marginal funding cost should account for possible nonlinearities. In the following subsections, we first introduce the linear model we employ, and then elaborate on the non-linear panel models. In all models, all variables are in first-differences to ensure stationarity. This is supported by the unreported unit root tests. Due to first-differencing, we lose one observation; hence we have 521 observations for each bank.

3.1 Panel linear model

The linear panel data model we propose is given by the following equation,

$$\Delta y_{it} = \alpha_i + \beta' \Delta x_{it} + \delta' \Delta Z_{it} + e_{it}, \;\; i = 1, \ldots, N \text{ and } t = 1, \ldots, T, \tag{1}$$

where α_i is the bank specific effects[2], $y_{it} = \{\text{CDS premia}_{it}\}$, $x_{it} = \{\text{MBLR}_{it}\}$ and $Z_{it} = \{\text{Risk Free Rate}_t, \text{Bid Ask Spread}_{it}, \text{VFTSE}_t, \text{Share Price Volatility}_{it}\}$. The subscript i identifies the individuals, in our case UK banks, i.e. $i = 1, \ldots, N$ where $N = 4$. The subscript t identifies time. We employ fixed effects panel estimation with robust standard errors clustered within cross sections to correct for heteroskedasticity (Wooldridge (2003)).

Results of the linear model, in Section 4, are mainly provided to enable a comparison between the linear and non-linear models. As will be shown, the linear model falls short of capturing the impact of solvency on wholesale funding costs.

[2] We tested fixed effects against random effects in our panel specification. Hausman (1978) test statistic results favored incorporating fixed effects. The random effects model provides very similar estimates.

3.2 Panel threshold model

Nonlinearities can originate as different regimes of the economy. The response of wholesale funding cost to a particular shock in solvency might differ from one regime to another. To explore nonlinearities induced by different regimes, we first use a panel threshold model proposed by Hansen (1999). The corresponding model is:

$$\Delta y_{it} = \alpha_i + \beta_1' \Delta x_{it} I(q_{it} < r) + \beta_2' \Delta x_{it} I(q_{it} \geq r) + \delta' \Delta Z_{it} + e_{it} \tag{2}$$

Dependent and independent variables are the same as in the linear model. This model is a piecewise linear function with respect to the estimated threshold r which depends on the threshold variable, q_{it}. In our case, the threshold variable is defined as the level of MBLR itself at time t. The threshold value, r, is estimated endogenously. A likelihood ratio (LR) test for detecting the number of the thresholds is adopted by Hansen (1999). The results are provided as bootstrap p-values of the hypothesis test under the null hypothesis of no (additional) thresholds. Fixed effects are treated prior to estimation.[3]

3.3 Panel smooth transition model

We want to explore the possibility that the relationship between MBLR and CDS premia is explained better through a smooth transition function rather than a step function. Thus, we employ a panel smooth transition estimation as in González, Teräsvirta, and van Dijk (2005), which is considered as a generalisation of Hansen (1999) threshold model. The model is specified as follows, in a simpler form, to accommodate two extreme regimes associated with the low and high values of the threshold variable, q_{it},

$$\begin{aligned} \Delta y_{it} &= \alpha_i + \beta_1' \Delta x_{it} + \beta_2' \Delta x_{it} g(q_{it}; \gamma, c) + \delta' \Delta Z_{it} + e_{it} \\ g(q_{it}; \gamma, c) &= \left(1 + \exp\left(-\gamma \left(q_{it} - c\right)\right)\right)^{-1}, \end{aligned} \tag{3}$$

for $i = 1, \ldots, N$ and $t = 1, \ldots, T$ where N and T indicate the cross section and time dimensions, respectively. Dependent and independent variables are the same as in the linear and threshold panel models and the transition variable q_{it} is the level of MBLR, $q_{it} = \text{MBLR}_{it}$.[4]

[3] Hansen (1999)'s methodology for the estimation of threshold panel models is not constructed to accommodate explanatory variables that are common over cross sections. Namely, the risk free rate and VFTSE in our equation are the same for all cross sections in our case, and only change through time. Therefore we need additional analysis to show that the estimation does not cause bias in the estimated coefficients, even in our small N, big T approach. Note that this variable does not enter the distribution of the threshold estimate hence a potential bias in the threshold estimate is not a concern. To explore if there is a bias in the estimated coefficients, we conducted a simple Monte Carlo exercise. The biases in the estimated coefficients are negligible in the Monte Carlo simulations. The estimation results are available upon request. The results indicate that we can use Hansen (1999)'s method in our empirical exercise with common exogenous variables over cross sections.

[4] The issue mentioned in footnote 3 also holds for the panel smooth transition model. The simulation results showing that the common exogenous variable does not cause any biases are available upon request.

We follow González, Teräsvirta, and van Dijk (2005)'s methodology and estimate our model through non-linear least squares. We use a logistic function formulation for the transition function $g(q_{it}; \gamma, c)$, also used by Granger and Teräsvirta (1993), Teräsvirta (1994). The slope parameter γ and the location parameter c are estimated endogenously. Function $g(\cdot)$ is bounded between 0 and 1; hence, the coefficient of x_{it} has the range of β_1 to $\beta_1 + \beta_2$, with respect to the given level of the threshold variable q_{it}. As $\gamma \rightarrow \infty$, $g(\cdot)$ becomes an indicator function so the smooth transition model reduces to a threshold model with two regimes as in Equation 2, i.e. higher slope parameter leads to faster transition. When $\gamma \rightarrow 0$, the model reduces to a linear panel regression with fixed effects. The fixed effects are treated during the non-linear least squares estimation of Equation 3.

4 Results

In this section, we provide the estimation results of all our models, which are discussed in the previous section. We present the full sample results in Section 4.1 and the rolling window estimation results in Section 4.2 for both linear and non-linear models.

4.1 Full sample results

Tables 1 and 2 present the full sample estimation results for linear and non-linear models. We use robust standard errors to compute t-statistics which are given in parenthesis for the corresponding coefficients. The linear model provides evidence that an increase in MBLR is associated with a drop in CDS premia, shown in Table 1. A rise in risk free rate is affiliated with a drop in the CDS premia whereas the relationship between CDS premia and Bid Ask Spread is positive. The relationships between VFTSE, share price volatility, and CDS premia appear to be positive, although share price volatility's coefficient is always insignificant.

Both the threshold and smooth transition models are linear with respect to the exogenous variables, i.e. risk free rate, bid-ask spread, VFTSE and share price volatility. A comparison between Table 1 and 2 reveals that all models provide very similar coefficients for these variables. A 100bp increase in risk free rate is associated with an approximately 30 basis points drop in CDS premia. The magnitude of this drop shows a minimal change within the models. This is consistent with the finding of Collin-Dufresne, Goldstein, and Martin (2001) that aggregate factors appear more important than firm-specific factors in determining credit spread changes. The result is also consistent with the finding of Annaert, Ceuster, Roy, and Vespro (2013), who in their full sample analysis, find that a 100bp increase in the risk free rate is associated with an increase in the CDS premia of 17.65bp. In the crisis period, they find that a 100bp increase in the risk free rate is associated with an increase in the CDS premia of 22bp.

Table 1: Linear Model Estimation Results

	Coefficients
ΔRisk Free Rate	-32.07^{***}
	(-5.51)
ΔBid-Ask Spread	2.94^{***}
	(5.11)
ΔVFTSE	0.57^{***}
	(14.72)
ΔShare Price Volatility	0.062
	(1.66)
β (ΔMBLR)	-9.93^{***}
	(-5.13)
Intercept	-0.24^{***}
	(-3.58)
$SSR/10^5$	2.80
Observations	2084

Notes: t-statistics in parentheses.
*** significant at the confidence level of 0.01,
** significant at the confidence level of 0.05,
* significant at the confidence level of 0.1.

Similarly, a one basis points increase in bid-ask spreads is associated with an approximately 3 basis points increase in CDS premia. A one unit change in VFTSE results in an approximately 0.5 basis points change in CDS premia whereas the impact of share price volatility on the CDS premia appears to be very minimal and also insignificant.

The main difference between the linear and non-linear models is the relationship between MBLR and CDS premia. In the linear model, the parameters of which do not vary with the level of MBLR, a 100bp decrease in MBLR is associated with an approximately 10 basis points increase in CDS premia. In the threshold model (panel (a) in Table 2), the relationship between MBLR and CDS premia varies with the level of MBLR. The threshold value of MBLR is estimated as 2.4%. When a bank's MBLR level is below the estimated threshold of 2.4%, a 100bp point decrease in the MBLR is associated with an approximately 29 basis point increase in CDS premia. When the MBLR is above 2.4%, the impact is only around 6.5 basis points.[5]

[5] In Figure 4, the orange straight line at 7.35 is the 5% critical value for the 'no-rejection region' under the null hypothesis $H_0 : r = r_0$ where r_0 is the true value of the threshold value, r. The test rejects the null hypothesis if the likelihood ratio exceeds the critical value. Below the orange line, the null hypothesis cannot be rejected. See Hansen (1999) for details. Therefore the single threshold level of the MBLR is 2.4%. We tested against a second and a third threshold. The second one was rejected with the p-value of 0.81 and the third one with 0.16.

Table 2: Full Sample Non-linear Estimation Results

(a) Panel Threshold Model

	Coefficients
ΔRisk Free Rate	-30.90^{***}
	(-6.73)
ΔBid-Ask Spread	2.89^{***}
	(5.60)
ΔVFTSE	0.52^{**}
	(1.99)
ΔShare Price Volatility	0.03
	(0.52)
β_1 (ΔMBLR $< r$)	-28.92^{***}
	(-4.75)
β_2 (ΔMBLR $\geq r$)	-6.46^{***}
	(-3.98)
r	0.0245^{***}
p-value for r	0.0000
SSR/10^5	2.39
Observations	2084

Notes: t-statistics in parentheses.
*** significant at the confidence level of 0.01,
** significant at the confidence level of 0.05,
* significant at the confidence level of 0.1.

(b) Panel Smooth Transition Model

	Coefficients
ΔRisk Free Rate	-30.44^{***}
	(-12.64)
ΔBid-Ask Spread	2.89^{***}
	(14.87)
ΔVFTSE	0.50^{*}
	(5.29)
ΔShare Price Volatility	0.026
	(0.86)
β_1 (ΔMBLR)	-31.58^{***}
	(-9.44)
β_2 (ΔMBLR*$g(q;\gamma,c)$)	25.09^{***}
	(7.28)
γ	4.18×10^8
c	0.0242
SSR/10^5	2.38
Observations	2084

Notes: t-statistics in parentheses.
*** significant at the confidence level of 0.01,
** significant at the confidence level of 0.05,
* significant at the confidence level of 0.1.

Note that for the full sample analysis, the smooth transition model (panel (b) in Table 2) reduces to a panel threshold model with the location parameter, $c = 2.4\%$, due to very large slope parameter, γ. Therefore, there is no significant difference between the threshold and smooth transition models in terms of the coefficients of the MBLR. Above the threshold value, a 100bp change in MBLR changes CDS premia by 32 basis points. Below the threshold level, this impact is $-6.5(= \beta_1 + \beta_2)$ basis points.[6]

To assess goodness of fit, we calculate the sum of squared residuals (SSR) of all the models. It shows that the non-linear models fit the data better than the linear model. We do not report the R^2 values for the models. There is not a straightforward expression for R^2 for either the

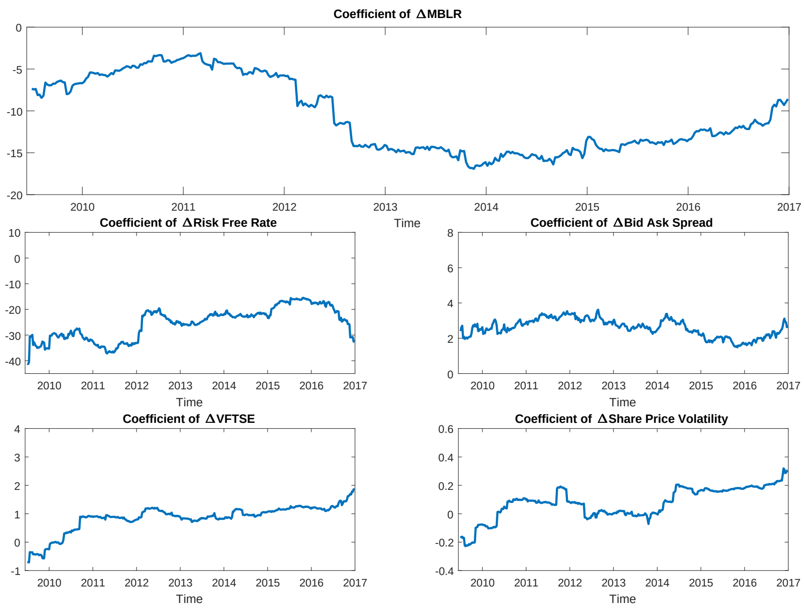
[6] The minor difference between the threshold and smooth transition model results, when the smooth transition model reduces to a threshold model, originate from the non-linear squares estimation of the panel smooth transition model. Estimating the slope (γ) and location (c) parameters requires a grid search to compute starting values for these parameters. Once the function $g(\cdot)$ is evaluated, even if it is a step function, there are minor computational differences to the threshold model.

threshold model or the smooth transition model, which itself reduces to a threshold model in the full sample.

4.2 Rolling Window Estimation Results

We appreciate that the period over which we have estimated our model is one of significant macroeconomic and financial market volatility, and broader regulatory change. Hence, we see merit in running all our models over rolling windows to investigate the impact of this on our estimation results. Moreover, the smooth transition model in the full sample analysis does not fully exploit its potential as it reduces to a threshold model. Clearly, this suggests that an indicator function fits to the full sample better than a smooth transition function, i.e. an abrupt change in regimes is better suited to the nature of the economy in that particular sample. This, however, is likely to differ depending on the sample we utilise. Hence, we run rolling window estimations for all the models also to fully utilise the smooth transition model.

Figure 1: Linear Model Rolling Windows Estimation Results

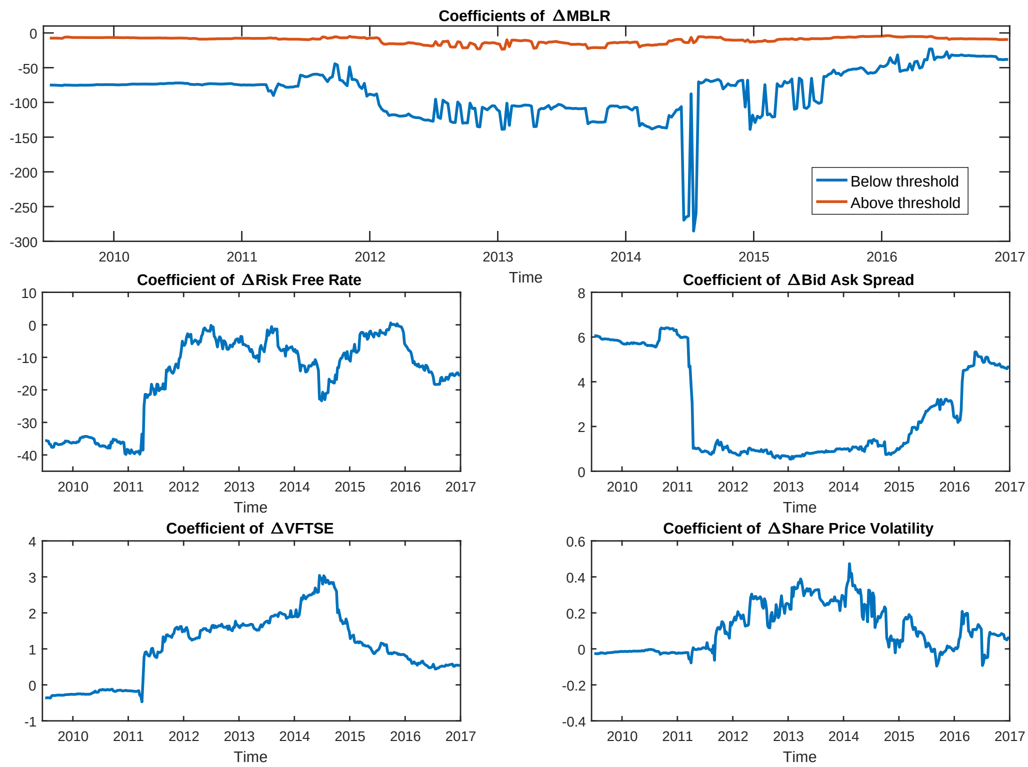


Notes: The estimations are run over 130 week (2.5 year) rolling windows. The size of the rolling windows is chosen by minimizing the 1-step-ahead forecast error. Over the rolling windows, 84% of MBLR's coefficients, 99% of Risk Free Rate's coefficients, 98% of Bid-Ask Spread's coefficients, 85% of VFTSE's coefficients and 42% of share price volatility's coefficients are statistically significant at the confidence level of 0.05.

As widely discussed, mainly in the out-of-sample forecasting literature, rolling window size is chosen arbitrarily (Hashimzade and Thornton (2013)). We choose the window size as 130 weeks, 2.5 years, which minimizes the mean squared forecast error for one step ahead forecasts in each model, á la Inoue, Jin, and Rossi (2017). The evolution in the rolling window estimates of the linear model can be found in Figure 1. It shows how, over time, the magnitude of the coefficient on MBLR initially increased before falling back. This may be consistent with an increase in the sensitivity of CDS premia to MBLR in the aftermath of the crisis, before falling back possibly in response to policy change. The coefficients on the risk free rate and bid-ask spread show moderate volatility over time.

The evolution in the rolling window estimates of the threshold model are given in Figure 2. The coefficient on MBLR takes two values, i.e. different coefficients below and above the estimated threshold values. Estimated threshold values over the rolling windows are shown in Figure 5. The upper panel of Figure 2 shows the difference between the coefficients of MBLR when it is below and above the estimated threshold. For lower levels of MBLR, a change in MBLR has a larger impact on CDS premia in magnitude. When the solvency of a bank recovers and goes above the estimated threshold level, the impact that MBLR has on CDS premia becomes much smaller in magnitude.

Figure 2: Threshold Model Rolling Windows Estimation Results

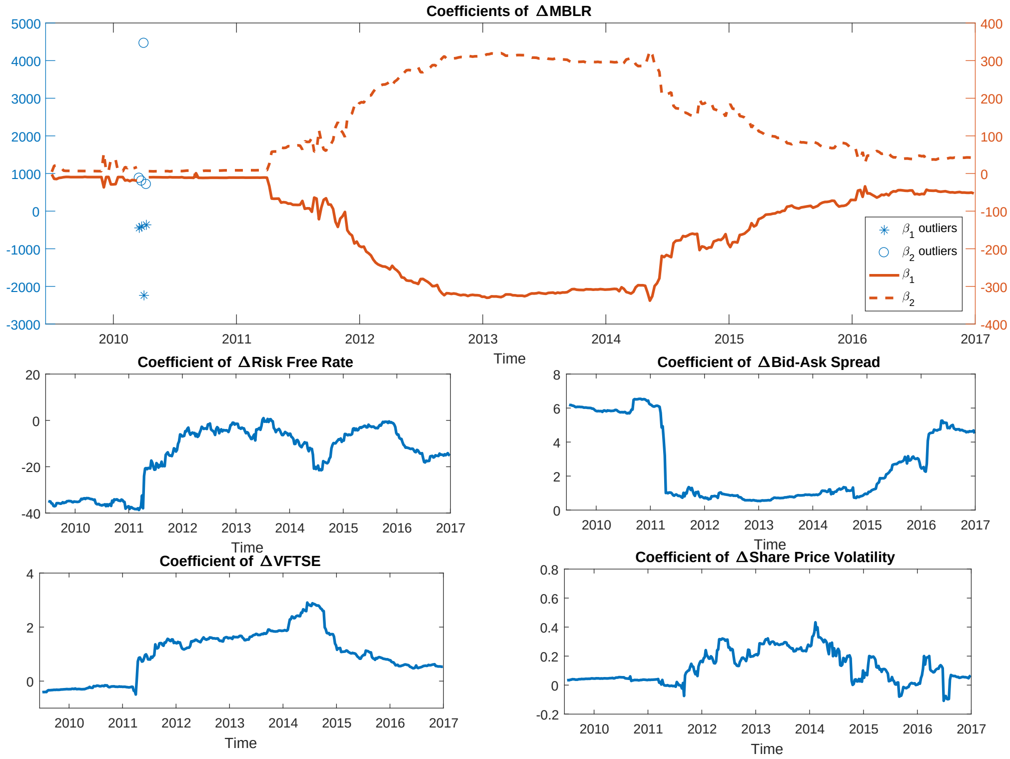


Notes: The estimations are run over 130 week (2.5 year) rolling windows. The size of the rolling windows is chosen by minimizing the 1-step-ahead forecast error. Over the rolling windows, 100% of MBLR's coefficients for below the threshold and 96% of MBLR's coefficients for above the threshold, 59% of Risk Free Rate's coefficients, 92% of Bid-Ask Spread's coefficients, 76% of VFTSE's coefficients and 0.4% of share price volatility's coefficients are statistically significant at the confidence level of 0.05.

Unlike the linear model coefficients, there is a certain pattern to all coefficients in Figure 2. All the variables show considerable changes after the beginning of 2011. Especially after the beginning of 2011, there is a big decline in the magnitude of risk free rate's coefficients. Similarly, around the same time, bid-ask spread's coefficient significantly declines, and the behaviour of VFTSE's and share price volatility's coefficients seem to change after 2011. There is a reasonable explanation for why these coefficients change so abruptly. Until the beginning of 2011, the rolling windows include some non-crisis observations. Beyond early 2011, the windows only include post-crisis observations only. Interestingly, after the peak crisis observations begin to drop out of the window, e.g. 2013 to mid-2015, the coefficients do not go back to their pre-crisis levels in general. The extreme coefficients around mid-2014 are caused by the abrupt change of the estimated threshold value, as shown in Figure 5.

Figure 3 shows the evolution in the rolling window estimates of the smooth transition model. For ease of interpretability, we aggregate the coefficients of MBLR, β_1 and β_2. The slope and location parameters in the rolling windows estimation are given in Figure 6. The most important observation is that the coefficients of MBLR are always negative and generally significantly different from zero. Coefficients of the exogenous variables are very similar to those of threshold model. Following a similar interpretation as in the threshold model estimates, the Great Recession seems to be very influential on the magnitude of the coefficients. Figure 7 shows the transition functions of the full sample and the last rolling windows with respect to the level of MBLR.

Figure 3: Smooth Transition Model Rolling Windows Estimation Results



Notes: The estimations are run over 130 week (2.5 year) rolling windows. The size of the rolling windows is chosen by minimizing the 1-step-ahead forecast error. Coeffients β_1's and β_2's axis given on the *right*. For some levels of γ and c, smooth transition models reduces to a threshold model. These parameters over the rolling windows are given in Figure 6. Over the rolling windows, 51% of the linear coefficients of MBLR and 30% of the non- linear coefficients of MBLR, 73% of Risk Free Rate's coefficients, 93% of Bid-Ask Spread's coefficients, 80% of VFTSE's coefficients and 0.9% of share price volatility's coefficients are statistically significant at the confidence level of 0.05. A couple of rolling sample coefficient estimates tend to behave suboptimal due to the non-responsiveness of CDS premia data to the changes in solvency in the beginning of the sample, roughly until 2008. Therefore rolling windows 38, 39, 40 and 41 have explosive coefficients. We report them separately. Their range is given by the *left* axis. This is just to having the scale of the charts in a sensible range so that the behaviour of the rest of the rolling window coefficients can be observed.

5 Forecast Evaluation

The evolution in the panel rolling window estimates provides insight into the time-varying nature of the model coefficients. We can also use the rolling window estimates to construct 1-step-ahead out-of-sample CDS premia forecasts. This allows us to infer which model is more likely to produce more accurate out-of-sample forecasts.

For each bank, we construct 1-step-ahead out-of-sample forecasts of CDS premia. For the smooth transition model, we evaluate the transition function with the MBLR level in the next period. Naturally, the level of MBLR at $t + 1$ may exceed the maximum level of MBLR used in the estimation of the transition function parameters. If $MBLR_{i,t+1}$ exceeds the maximum value of MBLR observed in the rolling sample, the straightforward strategy is to take the maximum value of the transition function, i.e. $g(\cdot) = 1$. If $MBLR_{i,t+1}$ is smaller than the minimum value of MBLR level, then the transition function takes its minimum value, zero. On checking whether $MBLR_{i,t+1}$ ever exceeds the maximum or minimum value of MBLR over the rolling window samples, it appears that this is never the case.

We compare the rolling window forecasts for each bank with the outturns and calculate the forecast errors associated with each model. We then employ the Diebold-Mariano (DM) test for predictive accuracy (Diebold and Mariano (1995)).[7] The null hypothesis of the DM test is ($H_0 : L(\hat{e}_{\text{linear}}) - L(\hat{e}_{\text{non-linear}}) = 0$) rejected when the expected forecast loss function (L) is *not* equal for both procedures. We pick the loss function as the mean squared forecast error.

We conduct a one-sided DM test to check if the linear model results in larger mean squared forecast errors ($H_1 : L(\hat{e}_{\text{linear}}) > L(\hat{e}_{\text{non-linear}})$). The results are given in the first rows of each bank's subtable in Table 4. At the 5% significance level, we expect the test statistics to be larger than 1.645 when one of the non-linear models is superior than the linear model. The test statistics support our expectations about the superiority of the threshold and smooth transition models against the linear model for all the banks. We also test the smooth transition model against the threshold model for each bank. In all cases, the null hypothesis cannot be rejected, implying that the forecasting performances of these models are not distingushable at 5% significance level.

[7] Although DM test is designed for time-series, there are papers using it for comparing forecast accuracy in panel models, see for instance Kholodilin, Siliverstovs, and Kooths (2007), Madden, Mayer, and Dang (2014), Ince (2014).

Table 4: DM Test Results

	Threshold	Smooth Transition
Barclays		
Linear	4.85	5.47
Threshold		−1.04
HSBC		
Linear	4.26	4.17
Threshold		−1.64
LBG		
Linear	6.08	5.77
Threshold		−1.26
RBS		
Linear	8.60	8.81
Threshold		−0.96

Notes: DM test statistics to compare 1-step-ahead forecast performances of all the models for each bank. First, both the threshold and the smooth transition models are tested against the linear model. The associated null hypothesis is $H_0 : L(\hat{e}_{\text{linear}}) - L(\hat{e}_{\text{non-linear}}) = 0$ with the alternative $H_1 : L(\hat{e}_{\text{linear}}) > L(\hat{e}_{\text{non-linear}})$ where L is the loss function which is taken to be symmetric and quadratic, mean squared sum of forecast errors. The results are given in the first row of the each bank's subtables. Second, the smooth transition model is tested against the threshold model. These results are given in the second row of each bank's subtable. To reject the null hypothesis, the test statistics should be larger than 1.645 at 5% significance level.

6 Concluding Remarks

This paper empirically investigates the relationship between a banks solvency and its marginal wholesale funding cost. We focus on the nonlinearities of the underlying relationship. We employ three panel models, namely a linear, a threshold, and a smooth transition model. We find strong evidence that the relationship is indeed nonlinear and as expected, the linear model falls short of fully capturing this relationship.

Our results suggest that the sensitivity of banks' cost of funding to solvency has increased over time after the Great Recession approximately until 2014. The impact of solvency on funding cost has fallen in magnitude since then but the negative relationship between the MBLR and CDS premia remains significant and elevated relative to pre-crisis levels. Indeed, the relationship between MBLR and CDS premia might never return to its pre-crisis level in light of post-crisis regulatory reforms aimed at addressing too big to fail and removing the implicit funding subsidies enjoyed by systemically important financial institutions (FSB (2017)). We also evaluate the forecasting performances of the different panel data models. According to the DM test results, we conclude that the non-linear models are superior to the linear model. We are not able to find evidence on the superiority of one of the non-linear models over the other.

The panel models we employ provide a useful tool for investigating the interaction between solvency and funding costs in regulatory stress tests. Although our models are based on market-based data, they can still be employed subject to appropriate transformation of the balance sheet data typically used in regulatory stress tests. Our models might offer useful insights into how shocks to bank solvency in stress translate into shocks to their marginal wholesale funding costs, potentially altering the rank ordering of funding costs faced by different banks. While the solvency threshold, estimated endogenously in our non-linear models, might serve to inform the calibration of the minimum solvency ratio banks are expected to exceed at the low point of a stress.

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.

Aymanns, C., C. Caceres, C. Daniel, and L. B. Schumacher (2016): "Bank Solvency and Funding Cost," IMF Working Papers 16/64, International Monetary Fund.

Babihuga, R., and M. Spaltro (2014): "Bank Funding Costs for International Banks," IMF Working Papers 14/71, International Monetary Fund.

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.

BIS (2015): "Making supervisory stress tests more macroprudential: Considering liquidity and solvency interactions and systemic risk," BIS Working Paper 29, Bank for International Settlements.

Blanco, R., S. Brennan, and I. W. Marsh (2005): "An Empirical Analysis of the Dynamic Relation between Investment-Grade Bonds and Credit Default Swaps," *The Journal of Finance*, 60(5), 2255–2281.

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.

Breusch, T. S., and A. R. Pagan (1980): "The Lagrange Multiplier Test and its Applications to Model Specification in Econometrics," *The Review of Economic Studies*, 47(1), 239–253.

Collin-Dufresne, P., R. S. Goldstein, and J. S. Martin (2001): "The Determinants of Credit Spread Changes," *The Journal of Finance*, 56(6), 2177–2207.

Darrell, D. (1999): "Credit Swap Valuation," *Financial Analysts Journal*, 55(1), 73–87.

Diebold, F. X., and R. S. Mariano (1995): "Comparing Predictive Accuracy," *Journal of Business & Economic Statistics*, 13(3), 253–263.

Fama, E. F., and K. R. French (1989): "Business conditions and expected returns on stocks and bonds," *Journal of Financial Economics*, 25(1), 23 – 49.

FSB (2017): "Ten years on taking stock of post-crisis resolution reforms," Sixth report on the implementation of resolution reforms, Financial Stability Board.

Gertler, M., N. Kiyotaki, and A. Prestipino (2016): "Chapter 16 - Wholesale Banking and Bank Runs in Macroeconomic Modeling of Financial Crises," vol. 2 of *Handbook of Macroeconomics*, pp. 1345 – 1425. Elsevier.

González, A., T. Teräsvirta, and D. van Dijk (2005): "Panel Smooth Transition Regression Models," SSE/EFI Working Paper Series in Economics and Finance 604, Stockholm School of Economics.

Granger, C., and T. Teräsvirta (1993): *Modelling Non-Linear Economic Relationships.* Oxford University Press.

Hansen, B. E. (1999): "Threshold effects in non-dynamic panels: Estimation, testing, and inference," *Journal of Econometrics*, 93(2), 345–368.

Hasan, I., L. Liu, and G. Zhang (2016): "The Determinants of Global Bank Credit-Default-Swap Spreads," *Journal of Financial Services Research*, 50(3), 275–309.

Hashimzade, N., and M. A. Thornton (2013): *Handbook of Research Methods and Applications in Empirical Macroeconomics*. Edward Elgar Publishing.

Hausman, J. A. (1978): "Specification Tests in Econometrics," *Econometrica*, 46(6), 1251–1271.

Hull, J., and A. White (2001): "Valuing Credit Default Swaps I: No Counterparty Default Risk," *CFA Digest*, 31(2), 91–92.

Ince, O. (2014): "Forecasting exchange rates out-of-sample with panel methods and real-time data," *Journal of International Money and Finance*, 43, 1 – 18.

Inoue, A., L. Jin, and B. Rossi (2017): "Rolling window selection for out-of-sample forecasting with time-varying parameters," *Journal of Econometrics*, 196(1), 55 – 67.

Kholodilin, K. A., B. Siliverstovs, and S. Kooths (2007): "A Dynamic Panel Data Approach to the Forecasting of the GDP of German Lnder," Discussion paper.

Korsgaard, S. (2017): "Incorporating Funding Costs to Top Down Stress Tests," Danmarks NationalBank Working Papers 110, Danmarks NationalBank.

Longstaff, F. A., S. Mithal, and E. Neis (2005): "Corporate Yield Spreads: Default Risk or Liquidity? New Evidence from the Credit Default Swap Market," *The Journal of Finance*, 60(5), 2213–2253.

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.

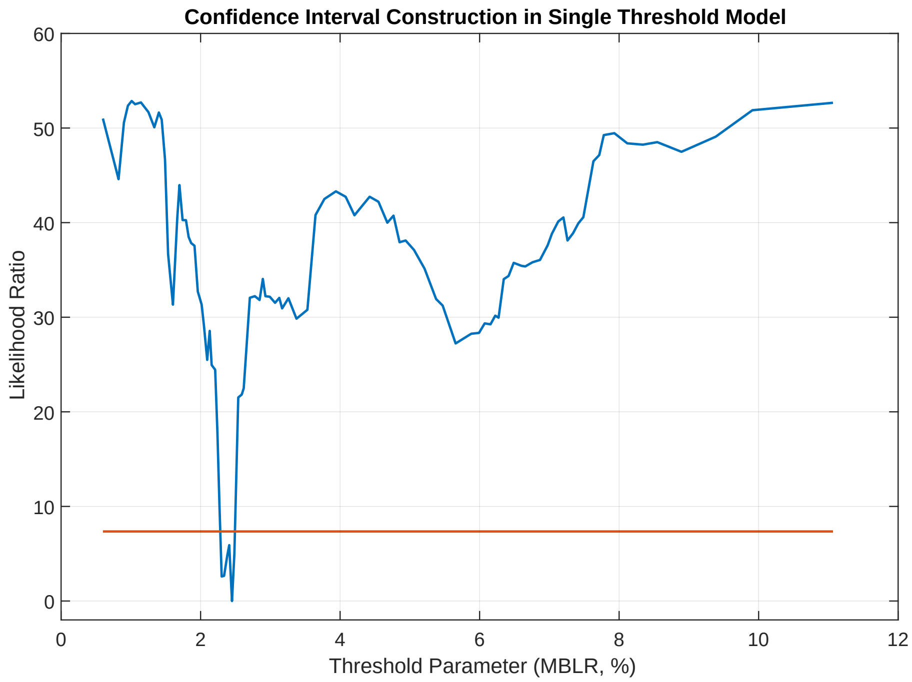
Madden, G., W. J. Mayer, and X. Dang (2014): "More Powerful Tests of Predictive Accuracy with an Application to Predictions of Economic Growth Based on Broadband Infrastructure for OECD Countries," Working Paper 110.

Schmitz, S. W., M. Sigmund, and L. Valderrama (2016): "Bank Solvency and Funding Cost: New Data and New Results," Working paper.

Teräsvirta, T. (1994): "Specification, Estimation, and Evaluation of Smooth Transition Autoregressive Models," *Journal of the American Statistical Association*, 89(425), 208–218.

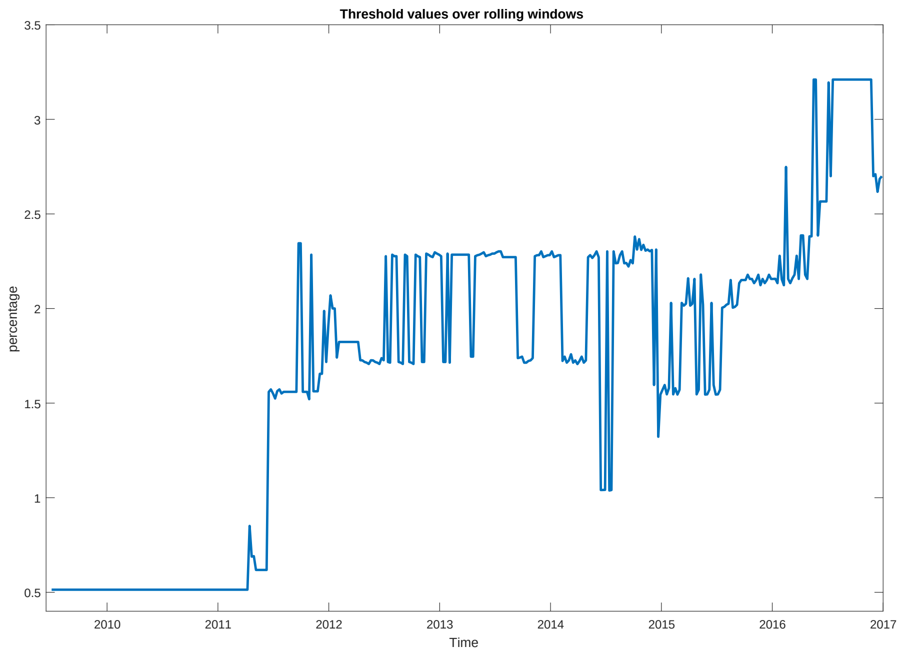
Wooldridge, J. M. (2003): "Cluster-Sample Methods in Applied Econometrics," *The American Economic Review*, 93(2), 133–138.

Figure 4: Full Sample Estimated Threshold Confidence Interval



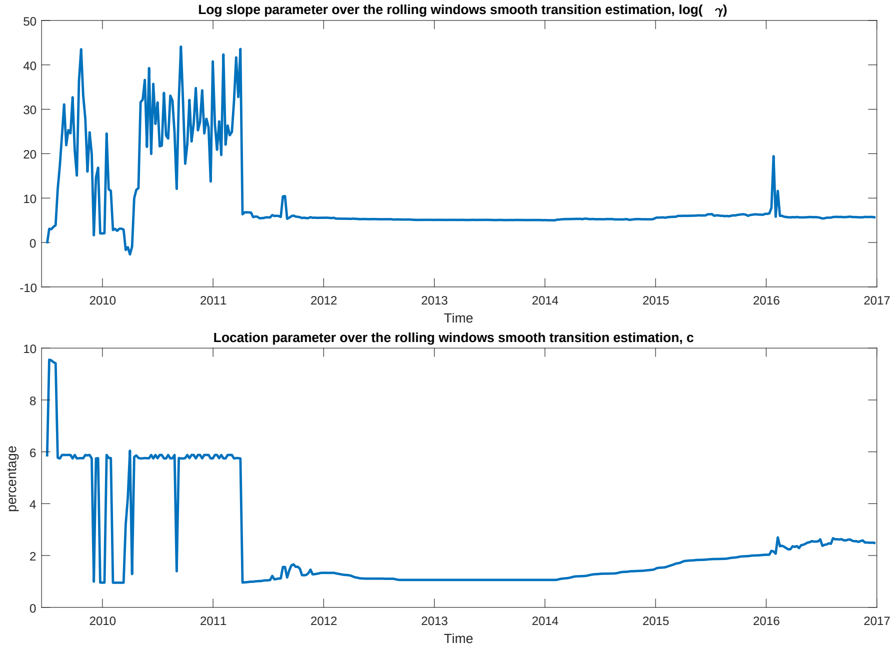
Notes: The confidence interval for the likelihood ratio test for the single endogeous threshold. The orange straight line at 7.35 is the 5% critical value for the 'no-rejection region' under the null hypothesis $H_0 : r = r_0$ where r_0 is the true value of the threshold value, r. The test rejects the null hypothesis if the likelihood ratio exceeds the critical value. Below the orange line, the null hypothesis cannot be rejected. Therefore the single threshold level of the MBLR is 2.4%.

Figure 5: Threshold values in the rolling windows estimation of the threshold model



Notes: The estimations are run over 130 week (2.5 year) rolling windows. The size of the rolling windows is chosen by minimizing the 1-step-ahead forecast error.

Figure 6: Slope and location parameters in the rolling windows estimation of the smooth transition model

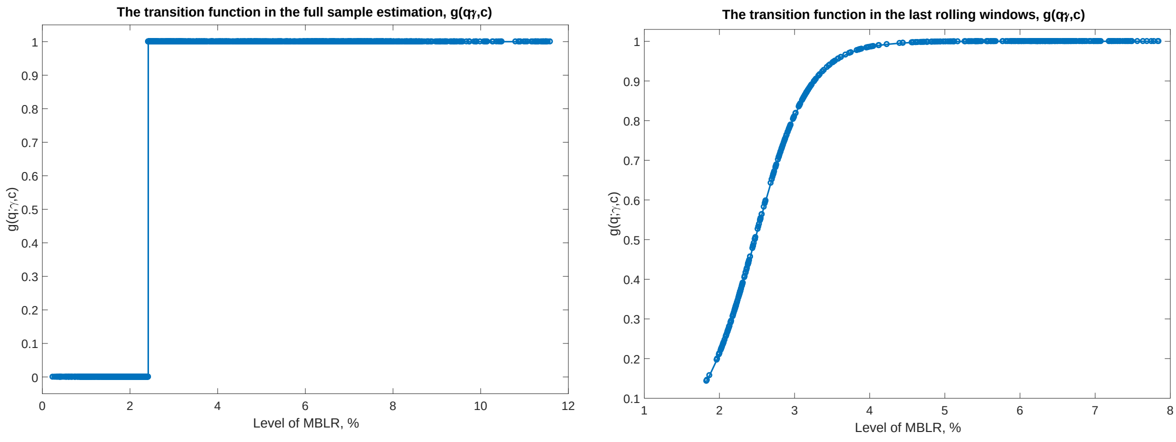


Notes: The estimations are run over 130 week (2.5 year) rolling windows. The size of the rolling windows is chosen by minimizing the 1-step-ahead forecast error. The slope parameter is in the range of $(0.0689, 1.4 \times 10^{19})$. Therefore we report the logged value of the slope parameter. When the slope parameter is large in magnitude, the smooth transition model reduces to a threshold model.

Figure 7: Transition Functions in the Smooth Transition Model

(a) Full Sample Transition Function

(b) Last Rolling Windows Transition Function



Notes: The circles indicate the observations. For the full sample, the smooth transition estimates reduces to a threshold estimation. The estimation results for the full sample are given in panel (b) of Table 2. The last rolling window has the slope parameter $\gamma = 277$ and location parameter $c = 0.0247$.

Appendix

A Data and Descriptive Statistics

We take the data from the sources explained in Section 2. This section provides the descriptive statistics and plots of the series.

Table A.1 presents summary statistics for five-year CDS premia, MBLR, Bid Ask Spread and Risk Free Rate.

Table A.1: Summary statistics

	CDS premia	MBLR	Bid Ask Spread	Risk Free Rate	VFTSE	Share Price Volatility
Mean	113.82	4.24	6.31	2.18	20.36	41.47
Median	99.87	3.38	5.75	1.74	17. 88	31.45
Maximum	387.06	11.6	19.00	5.72	71.71	374.41
Minimum	3.97	0.24	1.62	0.16	10.32	6.53
Std Deviation	70.82	2.58	2.63	1.44	8.62	35.40
Skewness	1.12	0.57	1.03	0.96	2.23	4.08
Kurtosis	4.50	2.34	4.51	2.84	10.15	27.80
Observations	2088	2088	2088	2088	2088	2088

Table A.2: Contemporaneous correlation coefficients of variables

	CDS premia	MBLR	Bid Ask Spread	Risk Free Rate	VFTSE	Share Price Volatility
CDS premia	1					
MBLR	-0.6277	1				
Bid Ask Spread	0.7339	-0.5342	1			
Risk Free Rate	-0.4268	0.3284	-0.3135	1		
VFTSE	0.2535	-0.1909	0.3648	0.2674	1	
Share Price Volatility	0.3813	-0.4412	0.4343	0.0931	0.6976	1

Figures A.8 to A.12 show the series we use in our analysis for each bank. The series plotted are the raw data in weekly frequency, before stationarised by taking the first differences. Figure A.13 depicts the relationship of MBLR and CDS premia.

Figure A.8: UK banks' CDS premia

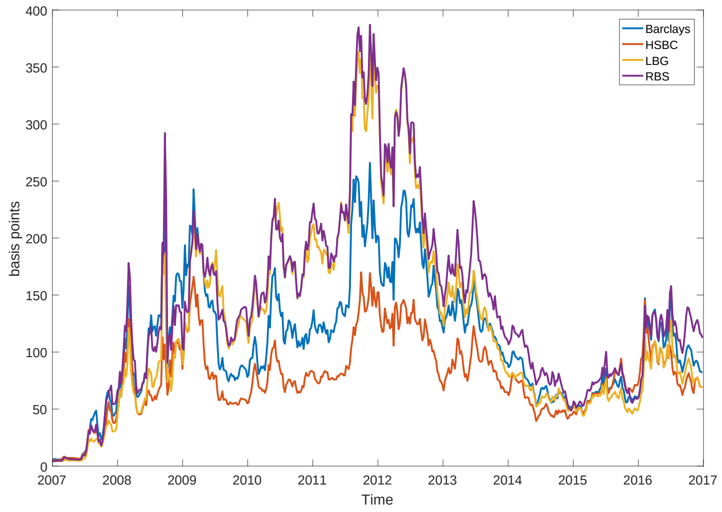


Figure A.9: UK banks' MBLR

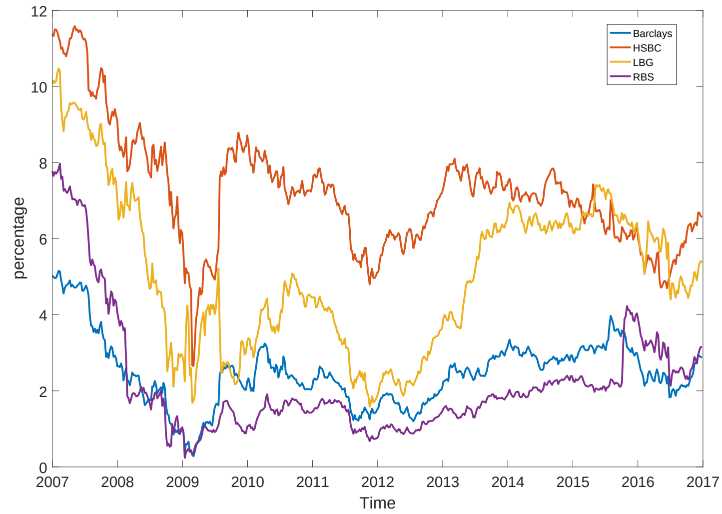


Figure A.10: UK banks' Bid Ask Spreads

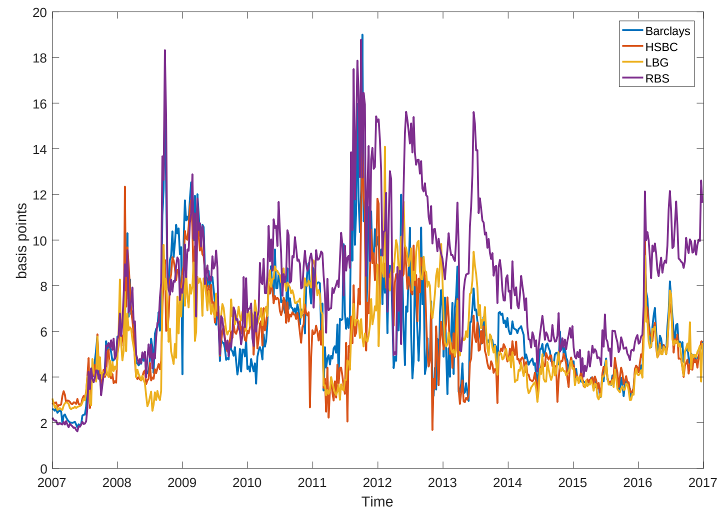


Figure A.11: UK banks' Share Price Volatility

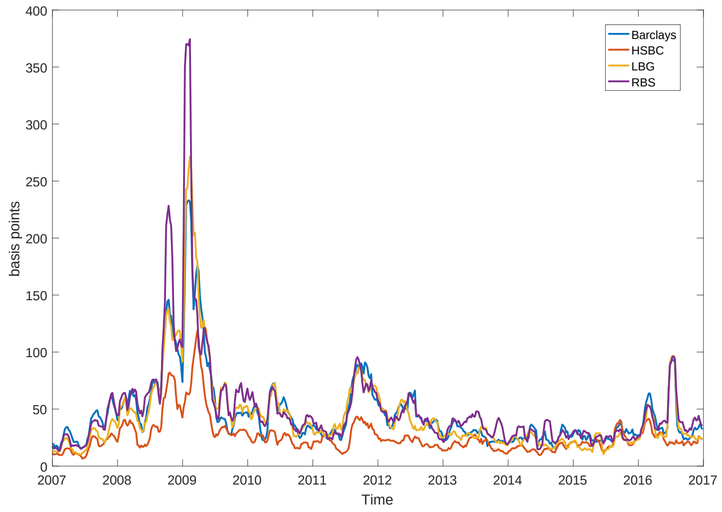


Figure A.12: Risk Free Rate and VFTSE

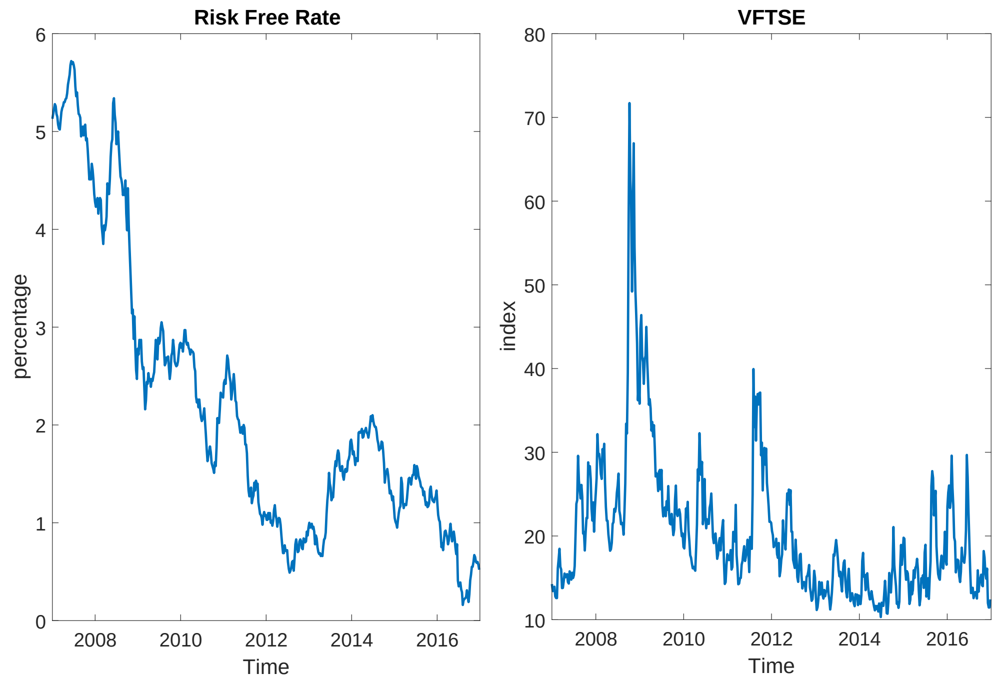


Figure A.13: Scatterplots of MBLR and CDS premia of each bank

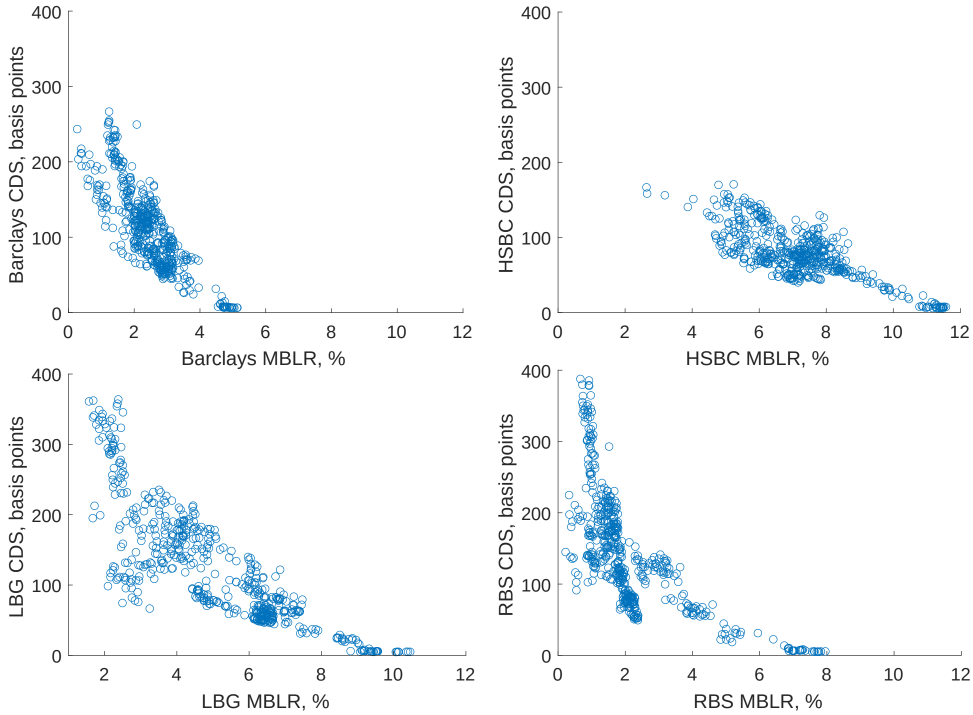


Figure A.14: Combined scatterplot of MBLR and CDS premia of all banks