The Impact of Subprime Mortgage Crisis on Cross-currency Linkage of LIBOR-OIS Spreads

Philip Inyeob Ji * and Francis In

Department of Accounting and Finance, Monash University, Clayton, VIC 3800, Australia

Abstract

This paper examines the cross-currency linkage of LIBOR-OIS spreads. We consider daily spread data in five major currencies for the period of March 1, 2006 to Nov 11, 2008. The impulse response analysis is conducted in a multivariate setting, adopting the bias-corrected bootstrap as a means of statistical inference. The overall evidence suggests that the crisis has substantially changed the nature of the cross-country interactions in liquidity premium. Global money markets fail to contain the US dollar term funding shocks and the role of Japanese yen in terms of liquidity source appears to be significant. Also the US dollar and yen spreads drive the cross-currency system of liquidity premium, whereas the premium in the euro, pound and Australian dollar funding equilibrate to errors in long-run relation of liquidity premium.

JEL classifications: G15; C32

Key Words: Subprime mortgage crisis, LIBOR-OIS spreads, Vector autoregressive model, Cointegration, Vector error correction

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*Corresponding author.
Tel.: +61-3-9905-2373; Fax: +61-3-9905-5475.
Email address: Philip.ji@buseco.monash.edu.au

1. Introduction

It has been more than a year, at the time of writing this paper, since the US subprime mortgage crisis broke out mid 2007. The impacts of the crisis are still waving across financial markets around the world. Not many are optimistic of what aftermath the crisis will leave. Already housing bubble has burst and international stock market indices have experienced unprecedented declines. Another such phenomenon is the dramatic increase in spread between the LIBOR (London Inter-Bank Offer Rates) and the OIS (Overnight Indexed Swap) over the course of the crisis, which not only monetary authorities but also market participants take a vigilant interest in. This is because the LIBOR-OIS spread is one of the widely accepted key measures of liquidity and counterparty risk[1] along with CDS (credit default swaps) prices, TED (spread between eurodollar rate and T-bill yield), spread between T-bill yield and the OIS. (See, for details, Brunnermeier, 2008; Mizen, 2008; Taylor and Williams, 2008)

Moreover, the LIBOR-OIS spread as measure of liquidity and credit pressures deserves a particular importance in highly securitised modern financial environments.[2] Current

[1] Despite this interpretational consensus on the LIBOR-OIS spread, some argue that the spread better represents liquidity risk rather than credit risk. (See, for example, Michaud and Upper, 2008) Also von Thadden (1999) quotes "the definition of liquidity is elusive" to claim that the distinction between liquidity risk and credit risk is unclear and that, particularly in the case of financial institutions.

[2] For example, issuance of asset-backed securities totaled $652.3 billion in the first half of 2007.

banking practice extensively uses so-called "originate and distribute" model which involves a vast amount of securitisation.[3] The benefits of securitisation are enhancement of liquidity and efficient usage of credit in capital markets, which measures such as LIBOR-OIS spread capture.

However, to our best knowledge, little attention has been paid to the spread in financial economic literature. Some recent attempts to study the spread include McAndrews et al (2008), Taylor and Williams (2008) and In et al (2008). A common theme of these papers is the effectiveness of Term Auction Facility (TAF) on LIBOR-OIS spread. As the LIBOR-OIS spread had been widening rapidly since August 2007, Federal Reserve introduced the TAF to ease liquidity strains and reduce the spreads in December 2007. McAndrews et al (2008) present empirical results to advocate the efficacy of the TAF, whereas Taylor and Williams (2008) use a no-arbitrage model of the term structure and conduct empirical testing to obtain no evidence for the TAF to be effective. In et al (2008) consider whether psychological effect exists on the spread in a time period between bid-submission date and the actual timing of liquidity injection. These authors also extend their interest to volatility transmission using the spread in multivariate

[3] See, Brunnermeier (2008), for an overview of modern banking practice and a summary of the main events of the credit crunch in 2007 and 2008.

Exponential Generalized Autoregressive Conditional Heteroskedasticity (E-GARCH) models.

Since the financial turmoil is not only limited to the US, we pay attention to the cross-currency linkage of LIBOR-OIS spreads in major currencies of the Australian dollar, the British pound, the Euro, the Japanese yen and the US dollar. An earlier work on the cross-country linkage of the spreads has been available. Imakubo et al (2008) notice some co-movements in the spreads for the US dollar, euro and Japanese yen.[4] The authors utilise vector autoregressive (VAR) models to examine interdependence of these spreads. Conventional benefits of the VAR models, variance decompositions, causality tests and impulse responses, are employed to show that the cross-currency transmission mechanism of term funding premia changed and the risk premium associated with term funding became highly correlated across currencies over the commencement of the crisis in August 2007. The authors find that during the crisis the US dollar spread affects the other two currencies in stronger interdependence which was not present before the crisis. Their interpretation is that US dollar funding shocks due to US dollar shortage

[4] This paper conducts decomposition of the spreads into credit risk and liquidity premium to argue that the spread better represents liquidity premium than credit risk based on the reasoning that internationally active banks should pay the same credit premium in all currency markets and the LIBOR panels are similar across currencies. Michaud and Upper (2008) also argue the same for the role of the spread.

were not efficiently absorbed in global money markets and have caused financial institutions to rebalance their position through Foreign Exchange (FX) swaps where the institutions convert their euro and yen borrowing to the US dollar. Also changes, caused by the crisis, in propagation mechanism that is affected by uncertainty for the institutions and central banks' stance on market operations are found to have a much larger impact on liquidity premium for the dollar and euro than yen. According to the authors, this implies relatively little uncertainty of funding in the yen markets compared to the dollar and euro markets, for which Japanese banks' lower exposure to subprime-related products and Japanese central bank's effective liquidity supply action are responsible.

We extend this interest in pre-crisis and crisis dichotomy of cross-currency transmission in money market strains. Our contributions are three folds. First, a larger scope of sample currencies is selected to provide an extensive overview of LIBOR-OIS linkages over global money markets. Second, we conduct improved statistical inference for the impulse response analysis in the VAR analysis. Imakubo et al (2008) rely on conventional VAR methodologies without statistical inferences. Also, as shown in subsequent sections, financial data such as ours are likely to exhibit conditional heteroskedasticity. To remedy this, we resort to confidence intervals based on the bootstrap method (Efron, 1979). Bootstrap inference is useful in small samples, especially when the data is non-normal or heteroskedastic, where conventional asymptotic inference based on a normal approximation may perform poorly. In addition, small sample biases of VAR parameter estimators (see, for example, Pope, 1990) can further undermine the reliability of the asymptotic method. In this paper, we use the bias-corrected bootstrap confidence interval that Kilian (1998a, 1998b) propose.[2] It has been found to exhibit much better small sample properties than conventional confidence intervals, especially for VAR models whose characteristic roots are close or equal to one. It can be made applicable to VAR models with non-normal or heteroskedastic innovations using the wild bootstrap of Mammen (1993). Third, long-run equilibrium relationship is examined in cointegration tests. Since all spreads appear to be I(1) in the crisis period, it is worthwhile to test whether and which spreads are driving the system as common stochastic trends. This leads to a vector error correction model in which short-run equilibrating dynamics can be detected.

Main findings of this paper generally support those of Imakubo et al (2008) and are the

[2] The importance of bias-correction in econometric analysis is well documented. See, for example, Andrews and Chen (1994).

following. During the crisis, 1) Japanese yen markets were relatively insulated from the effects of subprime mortgage crisis in better liquidity position. 2) The US dollar money markets failed to contain the US dollar term funding shocks, which led to funding tensions in other currency markets. 3) Liquidity premium in US dollar money markets seems to act as common stochastic trend driving the global system of liquidity premium, whereas yen appeared to be an important liquidity source for financial institutions in meeting liquidity requirements.

This paper is organised as follows. Section 2 describes the data and the methodology. Sections 3 and 4 present the empirical results and conclusions, respectively.

2. Methodology

2.1 VAR Model and Cointegration

We consider the K-dimensional vector autoregressive (VAR) model of the form

$$Y_t = \nu + B_1 Y_{t-1} + \ldots. + B_p Y_{t-p} + u_t, \tag{1}$$

where Y_t is the $K\times1$ vector of variables at time t, ν is the $K\times1$ vector of intercepts, and B_i's are the $K\times K$ matrices of coefficients. Note that u_t is the $K\times1$ vector of innovations with $E(u_t) = 0$ and $E(u_t u_t') = \Sigma_u = PP'$.[5] The above VAR system can be written in the

[5] We assume homoskedastic innovations to begin with, but this assumption may be relaxed later to

vector error correction (VEC) form as

$$\Delta Y_t = \nu + \Gamma_1 \Delta Y_{t-1} + \ldots. + \Gamma_{p-1} \Delta Y_{t-p+1} + \Pi Y_{t-1} + u_t, \quad (2)$$

where $\Pi = B_1 + \ldots + B_p - I_K$ and $\Gamma_i = -(B_{i+1} + \ldots + B_p)$. When Y_t is cointegrated with cointegration rank r, Rank(Π) = $r < K$ and $\Pi = \alpha\beta'$ where α and β are respectively $K \times r$ matrices.

The unknown VAR order p in (1) is determined using the Akaike Information Criterion (AIC). To determine the cointegration rank and estimate the unknown parameters in the VEC model (2), we follow Johansen's (1988) method based on the maximum likelihood principle. The trace and maximal eigenvalue tests of Johansen (1988) are used to determine the cointegration rank. The details of this testing and estimation method are not presented in this paper, because they are well documented elsewhere (see, for example, Lütkepohl, 1991; Chapter 11).

2.2 Impulse Response Analysis

The VAR model given in (1) can be used for the (orthogonalised) impulse response analysis. It is a dynamic multiplier analysis among the variables in the VAR system,

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accommodate heteroskedastic innovations.

measuring how a one-standard deviation shock to a variable is transmitted to others over time (see, for details, Lütkepohl, 1991). It has been applied widely in empirical macroeconomics and international finance (see, for example, Eichenbaum and Evans, 1995). It is also closely related to testing for non-causality, as zero impulse responses between two variables imply no causality (Lütkepohl, 1991; p.45).

The orthogonalised impulse responses are calculated from the coefficients of the MA(∞) representation of the VAR model and the residual covariance matrix. Given n realizations (Y_1, …, Y_n) of (1), the unknown coefficients are estimated using the least-squares (LS) method. The LS estimators for $B = (\nu, B_1, \ldots, B_p)$ and Σ_u are denoted as $\hat{B} = (\hat{\nu}, \hat{B}_1, \ldots, \hat{B}_p)$ and $\hat{\Sigma}_u$, and the associated vector of residuals as $\{\hat{u}_t\}_{t=p+1}^{n}$. The orthogonalised impulse responses are defined as $\Theta_i = \Phi_i P$ where $\Sigma_u = PP'$ and Φ_i's are the coefficients of the MA(∞) representation of (1). A typical element of Θ_i is denoted as $\theta_{kl,i}$, and it is interpreted as the response of the variable k to a one-time impulse in variable l, i periods ago. The plot of $\theta_{kl,i}$ against i is called the impulse response function of the variable k to a one-time impulse in variable l. Using $\hat{B}$ and $\hat{\Sigma}_u$, the estimator for impulse response $\hat{\theta}_{kl,i}$ for $\theta_{kl,i}$, can be calculated.

2.3 Bias-corrected Bootstrap

The bootstrap is a computer-intensive method of approximating the sampling distribution of a statistic. It has been applied widely in econometrics and is often found to provide a superior alternative to the conventional methods in small samples (see, Li and Maddala, 1996; Berkowitz and Kilian, 2000; and MacKinnon, 2002). The conventional bootstrap, however, is applicable to data generated from an identical and independently distributed (i.i.d.) random variable. Similarly, Kilian's (1998a, 1998b) bias-corrected bootstrap is applicable to the VAR model whose innovations follow an i.i.d. distribution. This conventional bootstrap may not work properly when the VAR model shows conditionally heteroskedastic error terms, which is the case for the VAR models fitted in this paper (see Section 3). Recently, a bootstrap procedure called the wild bootstrap (Mammen, 1993) has been developed, which is applicable to a time series with conditional or unconditional heteroskedasticity of unknown form. The theoretical underpinning of the wild bootstrap in the context of univariate AR model can be found in Goncalves and Kilian (2004).

In conducting the impulse response analysis, it is important to test whether impulse response estimates are statistically different from 0. This is closely related to testing for causality among the variables in the VAR system. We employ confidence intervals for the impulse response for this purpose. Note that impulse response estimates are necessarily biased in small samples, due to small sample biases present in the VAR parameter estimators (see Tjostheim and Paulsen, 1983; Nicholls and Pope, 1988; and Pope, 1990). The biases are particularly severe when the VAR model has unit roots or near unit roots; when the VAR dimension K is larger; or when the sample size is smaller. It is highly likely that these biases adversely affect the small sample properties of the confidence intervals.

To obtain confidence intervals with improved small sample properties, Kilian (1998a, 1998b) proposed the use of the bias-corrected bootstrap (or bootstrap-after-bootstrap). It is a bootstrap method of constructing confidence intervals, in which the biases associated with parameter estimators are adjusted in two stages of the bootstrap. Kilian (1998a, 1998b) finds that the bias-corrected bootstrap confidence interval has small sample properties far superior to its conventional alternatives, including those based on the asymptotic method detailed in Lütkepohl (1991).

The bias-corrected bootstrap of Kilian (1998a, 1998b) involves two stages of bias-correction for VAR parameter estimates. Here we follow Kilian (1998b) in using Pope's (1990; p.253) asymptotic bias formula to obtain bias-corrected parameter estimators. Note that Pope's (1990) formula estimates bias to the order of n^{-1}, and is applicable to the VAR model with martingale difference innovations with a fixed covariance matrix, which includes non-normal or conditionally heteroskedastic errors as special cases.

The bias-corrected confidence interval for $\theta_{kl,i}$ can be obtained as below:

In Stage 1, Pope's (1990) formula is applied to $\hat{B} = (\hat{\nu}, \hat{B}_1, ..., \hat{B}_p)$ to obtain the bias-corrected estimator $\hat{B}^c = (\hat{\nu}^c, B_1^c, ..., B_p^c)$ for B. It is possible that $\hat{B}$ satisfies the condition of stationarity, while $\hat{B}^c$ does not. In this case, Kilian (1998a, 1998b) suggested an adjustment to $\hat{B}^c$ so that it implies stationarity. This adjustment is called the stationarity correction, and its details can be found in Kilian (1998a, 1998b).

In Stage 2, generate a pseudo data set following the recursion

$$Y_t^* = \hat{\nu}^c + \hat{B}_1^c Y_{t-1}^* + ... + B_p^c Y_{t-p}^* + u_t^* \qquad (3)$$

using the first p values of the original data as starting values.[6] When the innovations are

[6] Note that the wild bootstrap described here is referred to as the recursive-design wild bootstrap, which

heteroskedastic, we adopt the wild bootstrap that involves generating $u_t^* = \eta_t \hat{u}_t$, where η_t is any scalar random variable whose mean is zero and variance is one. When the innovations are homoskedastic, u_t^*'s are generated as random resampling of $\hat{u}_t$'s with replacement following Kilian (1998b).

In Stage 3, using $\{Y_t^*\}_{t=1}^n$, the VAR coefficient matrices are re-estimated and denoted as $\hat{B}^* = (\hat{v}^*, \hat{B}_1^*, ..., \hat{B}_p^*)$. Pope's (1990) bias formula is again applied to $\hat{B}^*$ in order to obtain a bias-corrected version $\hat{B}^{*c} = (\hat{v}^{*c}, B_1^{*c}, ..., B_p^{*c})$ of $\hat{B}^*$. The stationarity correction is again applied to $\hat{B}^{*c}$ if necessary.

Repeat Stages 2 and 3 sufficiently many times, say *m*, to generate bootstrap replicates of $\left\{\hat{B}^{*c}(j)\right\}_{j=1}^m$, from which *m* bootstrap replicates $\left\{\hat{\theta}_{kl,i}^*(j)\right\}_{j=1}^m$ of impulse responses are obtained. In this paper, *m* is set to 2000, which is sufficiently large to obtain reliable bootstrap confidence intervals (see Efron and Tibshirani, 1993). The 100(1-2α)%

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is preferred by Gonclaves and Kilian (2004) to the other types of the wild bootstrap on the basis of superior small sample performance. The distinctive feature of the wild bootstrap is that u_t^*'s are generated as a random weighting of $\hat{u}_t$'s, so that $E(u_t^* | \hat{u}_t) = 0$ and $E(u_t^* u_t^{*}{}' | \hat{u}_t) = u_t u_t'$. Throughout the paper, we report the results associated with the case where η_t follows the standard normal distribution, since the results are not sensitive to the other choices.

bias-corrected bootstrap confidence intervals for $\theta_{kl,i}$ can be obtained as the interval $[\hat{\theta}^*_{kl,i}(\alpha),\ \hat{\theta}^*_{kl,i}(1\text{-}\alpha)]$, where $\hat{\theta}^*_{kl,i}(q)$ is the qth percentile from the distribution of m bootstrap replicates $\left\{\hat{\theta}^*_{kl,i}(j)\right\}_{j=1}^{m}$, based on the percentile method of Efron and Tibshirani (1993, p.160).

3. Data and Empirical Findings

3.1 Data Details and Preliminary Analysis

Three month maturity LIBOR-OIS spreads data in daily frequency are collected from Bloomberg for the period of March 1, 2006 to Nov 12, 2008.[7] We use the 9th of August , 2007 as the commencement of the subprime mortgage crisis, which provides an approximately balanced data panel of 364 observations for pre-crisis period and 321 for the crisis period.[8] We consider spreads in the Australian dollar (AUD), British pound (GBP), Euro (EUR), Japanese yen (JPY) and the US dollar (USD). These currencies represent a variety of funding sources from major currencies to less traded ones for international financial institutions.

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[7] Practitioners commonly suggest that three month LIBOR is used as a reference rate more than other maturities. For OIS it has been reported that 50 percent of daily turnover is in maturities out to three month. (See, for example, Reserve Bank of Australia Bulletin, June, 2002)

[8] In et al (2008), MacAndrews (2008), and Taylor and Williams (2008) all use the date as break point when BNP Paribas announced closure of its funds that held US subprime mortgage debts. Data plots in Figure 1 as well shows an abrupt jump on this date.

Visual inspection of the time plots presented in Figure 1 indicates that the spreads show local trends with highly volatile fluctuations in the crisis period.[9] Summary statistics in Table 1 show that means and variances of all the spreads are higher in the crisis period than pre-crisis, suggesting that liquidity premium have increased due to the crisis across money markets. The mean of 0.12 and variance of 0.13 for the yen spread are the largest among the five spreads before the crisis but they are ranked the lowest during the crisis. The low liquidity premium and volatility in yen hints at the conjecture that yen money markets have experienced less liquidity pressure than other currencies. Another notable feature of the data is non-normality and conditional heteroskedasticity that are commonly observed in financial data. As the ARCH LM test statistics in Table 1 indicate, conditional heteroskedasticity are present in most spreads, which motivates the wild bootstrap in bias correction bootstrap procedure.[10]

3.2 Impulse Response Analysis

In conducting the orthogonalized impulse response analysis, the ordering of the variables in the VAR system is important. In this paper, we specify the ordering on the

[9] On this basis, we decide not to include a linear time trend in our testing and estimation below.
[10] The null hypothesis of no conditional heteroskedasticity is not rejected for the yen. Goncalves and Kilian (2004), however, note that the wild bootstrap equally performs for homoskedasticity, since it is a special case of heteroskedasticity.

basis of the Wold-causality (see, Lütkepohl, 1991; p.52). We place the US dollar spread first, followed by the euro, pound, yen and the Australian dollar spreads. In the context of orthogonalized impulse response analysis, this amounts to assuming the instantaneous causality running one way from the US dollar spread to the Australian dollars spread. This is reasonable considering the relative influence of the currencies.[11]

Figure 2 presents impulse response functions and their 95% confidence intervals for the pre-crisis period. There are five panels in Figure 2, each exhibiting dynamic responses of all spreads when a shock is given to a particular spread. Crisis panels are shown in Figure 3. If a confidence interval contains zero, the null hypothesis that the true response is zero cannot be rejected at the specified level of significance.

Eyeballing each diagonally located graph through Figures 2 and 3, which shows response of spreads to own shocks, all spreads become quite persistent during the turmoil except for the yen and the Australian dollar. While no notable period-specific in persistence is seen for the Australian dollar, confidence intervals do not contain zero over the full horizon for the yen spread before the crisis but the statistically significant

[11] We have attempted other orderings in the VAR, but the results are found to be qualitatively similar.

life of its response decreases to nine days going into the crisis. On the other hand, the US dollar spread produces larger non-zero response in the crisis period than pre-crisis, which implies that the spread's variance has grown due to the turmoil. Together with summary statistics shown earlier, these multivariate results are consistent with what Imakubo et al (2008) document for the difference in persistence between the dollar and yen spreads.

To explain the smaller volatile liquidity premium in yen funding, the authors point out moderate exposure of Japanese financial institutions to subprime-related products and liquidity supply measures that the Bank of Japan took. Imakubo et al (2008) compare intraday volatility of call rates and federal funds rates to distinguish quite dissimilar liquidity deepness in yen and the US dollar money markets to argue that liquidity gap in yen funding were closed more effectively during the turmoil.

Next question that then arises to consolidate this connection between liquidity and the liquidity premium is what best measures liquidity whose data is widely available for a large set of countries. Adrian and Shin (2008) argue that the growth of collateralized borrowing, repurchase agreements (Repo) growth, appropriately represents the financial market liquidity in modern market-based financial system. These authors also note the empirical inverse relationship between the residuals of the Taylor rule (Taylor, 1993) regression and the Repo trade growth. Their reasoning is that positive residuals (tight monetary policy meaning higher federal funds rate than the Taylor rule implied rate) are associated with decreases in Repo growth and *vice versa*. Since preliminary analysis confirms that this inverse relationship is largely true for countries of our interest at least in recent years up to 2007 (See Figure 4 for the example of Europe) [12], we use aggregate Repo growth as liquidity measure for each currency following Adrian and Shin (2008). Figure 5 reveals that the Japanese yen was better positioned in terms of liquidity than other currencies with Repo growth in 2007 standing the highest at 16 precent. Four-year average growth rate ranks the Japanese Repo market in the first place as well.

This Repo-spread relationship draws attention to the role of Japanese yen in global money markets. Imakubo et al (2008) presents evidence to argue that financial institutions actively used FX swap markets to mitigate the US dollar shortage in their term funding requirements. Facing the excess demand for the dollar, the institutions

[12] Repo growth data and the Taylor Rule residuals for other countries are available upon request.

borrow in euro and yen, and convert their borrowing into the dollar through FX swap transactions. It seems that our impulse response estimates have an unignorable relevance to this argument. Off diagonal graphs in Figures 2 and 3 show response of each spread to shocks to others. The first panels in Figures 2 and 3, for example, show changes in the effects of the US dollar spread on each spread. In the pre-crisis period, the euro, pound, and Australian dollar spreads show small positive but short-lived responses to a shock to the US dollar liquidity premium. The yen spread does not show any statistically significant non-zero responses. During the crisis, however, the US dollar spread positively affects all the other spreads. Crisis term funding premium in the US dollar causes higher premium in other currencies, suggesting the large exposure of internationally operating banks to the subprime products across these currencies. An implication is that the premium is currency-specific and liquidity shocks are mitigated well under normal conditions, but in the crisis-period the liquidity tension in the US dollar funding is not efficiently absorbed. Also the pre-crisis absence and the crisis weak magnitude of the US dollar spread effects on the yen spread support the relatively insulated position of the yen money markets.[13]

[13] For the magnitude of the responses, compare the units of the impulse response on the vertical axis across graphs.

For the euro and pound spreads in the crisis period (Second and third panels in Figure 3) there exists some feedback in liquidity premium, which is not an unexpected outcome, given the regional proximity of the two currencies. Although these two spreads exert temporary influences on the yen and Australian dollar spreads, it may be an indirect impact of the US dollar shocks.[14]

A notable feature for the yen spread presented in the fourth panels in Figures 2 and 3 is the emergence of persistent negative influence of the yen spread on all the other spread in the crisis period.[15] The US dollar and the Australian dollar spreads respond distinctly persistently to the yen over the full horizon of twenty four days. The euro and pound start their responses in about ten days lag but still the magnitudes are permanent and negative. Apparently an increase in liquidity premium in yen term funding leads to release of the liquidity pressure in the other currencies. Recapping on the existing evidence from Imakubo et al (2008) for the linkages between the FW swap markets and money markets, these results for the yen spread certainly look like another sign of the yen money market's contribution to liquidity stability in global markets. Also our results

[14] This indirect channel is noticed in Imakubo et al (2008) based on the evidence from variance decomposition and Granger causality tests.
[15] Our preliminary analysis shows that conventional confidence interval based on asymptotic assumptions fail to detect these prominent results for the yen spread.

indicate that the rebalancing activities via yen may be not only limited to the euro but also apply to pound and the Australian dollar.

In short, the impulse response results suggest that the US liquidity premium shocks spread across money markets in major currency. Also the liquidity position of Japanese yen enabled the yen spread to be relatively robust against the global term funding shocks.

3.3 Cointegration and Error-correction Models

We motivated the wild bootstrapped impulse response because the conventional Wald-type test may show deficient properties due to the strong evidence of non-normal and conditionally heteroskedastic VAR errors from Table 1. However, cointegration test can provide supplementary information on long-run equilibrium relations for the spreads, which we decide to take advantage of. To determine whether the spread series possess unit-roots, we conducted the augmented Dickey-Fuller tests. As reported in Table 2, all spreads appear to be integrated of order 1 for the crisis period at 5% significance level.[16]

[16] A number of papers that model risky debts and credit derivatives including Das and Tufano (1996) and Jarrow, Lando and Turnbull (1997) assume that credit spreads are stationary. Duffee (1999) also argues that individual bond credit spreads follow a stationary process. On the other hand, Pedrosa and Roll(1998) and Bierens, Huang and Kong (2003) find that a vast majority of credit spread indices are non-stationary in their empirical results. Hence, our unit root test results are likely to be period-specific in the sense that

Table 3 reports the Johansen cointegration test results for the crisis period. It is evident that there are three cointegrating vectors during the turmoil. In other words, the number of common trends driving the system is two. One would naturally conjecture that the US dollar spread is likely to be a common trend and that the Australian dollar spread is much less likely to be one. Assuming that the reasoning is true, we tested restrictions on cointegrating vector coefficients in an attempt to identify the other common trend, which amounts to imposing zero restrictions on candidate common trends. All possible pairs of coefficients on the euro, the pound, the yen and the US dollar spreads in cointegrating vector are jointly hypothesized to be zero. The low panel of Table 3 presents the restriction test results. None of the joint hypotheses is rejected but the P-values of 0.18, 0.23 and 0. 27 for EUR-JPY, EUR-USD and JPY-USD pairs are much lower than for the others. This suggests that two of these three spreads may be the two dominant forces. Given that the US dollar and yen spreads show much stronger influences than the other spreads from the impulse response estimates, we argue that the US dollar spreads and the yen spreads drive the system as common trends.

evidence for non-stationarity in the LIBOR-OIS spreads only appear in the crisis period

From the error correction model estimates tabulated in Table 4, we find consistent short run dynamic interactions with cointegration tests among the spreads in the system. Although most of the speed-of-adjustment coefficients are statistically different from zero in each equation, the adjustment coefficients associated with the Australian dollar, the euro and the pound spreads tend to be larger. Also the coefficient for the Australian dollar spread on error correction term (ECM1) is -0.05. For the euro and pound spreads, coefficients on ECM2 and ECM3 respectively are both -0.11. It is apparent from these large negative values that these liquidity premiums in these three spreads equilibrate in response to equilibrium errors in long-run relation for cross-currency liquidity premium.

4. Concluding Remarks

As the subprime mortgage crisis has deteriorated tensions in funding markets around the world, LIBOR-OIS spreads as a measures of liquidity and credit risk has lately widened and become exceedingly volatile. This paper examines cross-currency linkages of LIBOR-OIS spreads. We consider daily data for the Australian dollar, euro, pound, yen and the US dollar spreads from March 1, 2006 to November 11, 2008. From the bootstrap bias-corrected impulse response analysis, we find that term funding premium became highly interelated across currencies. This suggests that US dollar term funding shocks were not efficiently absorbed within global money markets. Also better liquidity condition in Japanese yen may have favourably affected liquidity premium in other currencies. The US dollar and yen spreads appear to be the driving forces for the system of cross-currency liquidity premium, while Australian dollar, euro and pound term funding premium equilibrate to errors in long-run liquidity premium relation across currencies.

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Table 1 Summary Statistics of LIBOR-OIS Spreads

	AUD	EUR	GBP	JPY	USD
Panel A. Pre-crisis period					
Mean	0.01	0.05	0.09	0.12	0.08
Median	0.01	0.05	0.09	0.13	0.08
Maximum	0.08	0.12	0.20	0.19	0.18
Minimum	-0.08	0.03	-0.07	0.03	0.01
Std. Dev.	0.02	0.01	0.02	0.03	0.01
Skewness	-1.04	2.17	-1.86	-0.62	1.09
Kurtosis	5.68	14.19	27.69	3.25	9.27
Jarque-Bera	175.486*	2186.88*	9461.87*	24.53*	670.68*
Diagnostic Tests					
Normality	764.64*	6102.15*	22808.83*	180.27*	1543.36*
ARCH	2.25	1.10	0.29	6.74*	5.62*
Auto	1.48	0.93	1.85	1.71	11.94*
Adjusted R^2	0.74	0.34	0.27	0.90	0.47
Panel B. Crisis period					
Mean	0.54	0.73	0.86	0.43	0.91
Median	0.43	0.64	0.76	0.4	0.73
Maximum	2.42	2.05	2.98	0.66	3.64
Minimum	0.09	0.18	0.25	0.19	0.24
Std. Dev.	0.41	0.34	0.46	0.06	0.64
Skewness	2.46	2.04	1.9	1.21	2.6
Kurtosis	8.67	6.84	6.47	5.13	9.14
Jarque-Bera	755.04*	421.63*	356.03*	140.67*	868.99*
Diagnostic Tests					
Normality	206.44*	308.75*	23849.09*	1578.13*	455.17*
ARCH	24.72*	20.17*	52.39*	0.85	7.92*
Auto	4.19*	0.64	5.65*	5.30*	1.17
Adjusted R^2	0.98	0.99	0.97	0.97	0.98

- Source: Authors' calculations, Bloomberg.
- "*" indicates the significance of the coefficients (or rejection of the null hypothesis) at 5% level.
- VAR order 2 for pre-crisis and 6 for crisis are chosen to ensure no serial correlation in residuals.
- Normality is the Jarque-Bera test for the normality of residuals
- ARCH is the Lagrange multiplier test for ARCH(4) model applied to residuals
- Auto is the Ljung-Box test for no serial correlation applied to the residuals with lag 4

Table 2 The Augmented Dickey-Fuller Test

	Period	ADF test statistic Intercept only				ADF test statistic Intercept and trend				AR lag order
		Level		First Difference		Level		First Difference		
AUD	Pre-crisis	-5.00*	(0.00)	-21.69*	(0.00)	-5.55*	(0.00)	-21.66*	(0.00)	1
EUR	Pre-crisis	-6.29*	(0.00)	-14.98*	(0.00)	-6.36*	(0.00)	-15.00*	(0.00)	2
GBP	Pre-crisis	-7.05*	(0.00)	-16.98*	(0.00)	-7.30*	(0.00)	-12.81*	(0.00)	2
JPY	Pre-crisis	-2.64	(0.08)	-26.72*	(0.00)	-3.11	(0.10)	-26.70*	(0.00)	2
USD	Pre-crisis	-1.38	(0.59)	-17.21*	(0.00)	-1.92	(0.63)	-17.23*	(0.00)	5
AUD	Post-crisis	-1.29	(0.63)	-14.60*	(0.00)	-2.08	(0.54)	-14.59*	(0.00)	5
EUR	Post-crisis	-0.29	(0.92)	-9.91*	(0.00)	-1.04	(0.93)	-9.96*	(0.00)	3
GBP	Post-crisis	-1.46	(0.55)	-6.05*	(0.00)	-2.07	(0.55)	-6.04*	(0.00)	4
JPY	Post-crisis	-2.55	(0.10)	-17.04*	(0.00)	-2.6	(0.27)	-17.01*	(0.00)	2
USD	Post-crisis	-1.23	(0.65)	-14.62*	(0.00)	-1.7	(0.74)	-14.60*	(0.00)	6

- Source: Authors' calculations.
- "*" indicates the rejection of the null hypothesis at 5% level.
- The AR lag orders are the orders to ensure no serial correlation in residuals
- P-values are in parenthesis.

Table 3 The Johansen Cointegration Test and Restriction Test

Null hypothesis	Maximal Eigenvalue	Null hypothesis	Trace
r = 0	43.93*	r = 0	117.77*
r ≤ 1	33.68*	r ≤ 1	73.83*
r ≤ 2	30.01*	r ≤ 2	40.14*
r ≤ 3	6.27	r ≤ 3	10.13
r ≤ 4	3.85	r ≤ 4	3.85

Cointegrating Vector Estimate

(a1, a2, a3, a4, a5) = (1.00, -1.43, 0.40, -1.91, 0.08)

Testing the restriction on the cointegrating vector

Null hypothesis	LR Test Statistic
a2=a3=0	0.00 (0.92)
a2=a4=0	1.76 (0.18)
a2=a5=0	1.41 (0.23)
a3=a4=0	0.46 (0.49)
a3=a5=0	0.42 (0.51)
a4=a5=0	1.17 (0.27)

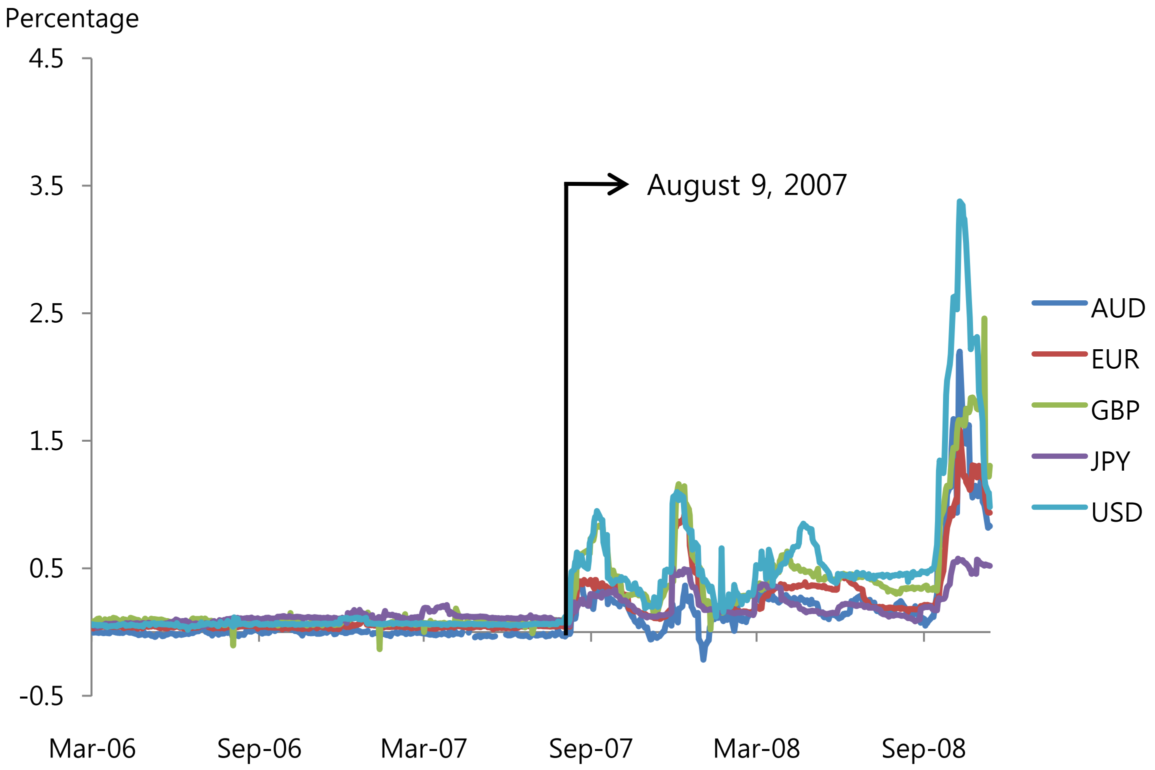
- Source: Authors' calculations.
- "*" denotes rejection of the hypothesis at the 1% level.
- The results are based on VAR(6) model, assuming restricted intercept and no trends in VAR.
- (a1, a2, a3, a4, a5) represent the coefficients of cointegrating vectors associated with AUD, EUR, GBP, JPY, and USD LIBOR-OIS spreads.
- The likelihood ratio test results are given, which asymptotically follows the chi-squared distribution with the degree of freedom one for all cases.
- P-values are in parenthesis.

Table 4 Error Correction Model

	ΔAUD		ΔEUR		ΔGBP		ΔJPY		ΔUSD	
ECM1(-1)	-0.05	*	0.03	*	0.12	*	0.01	*	0.05	*
ECM2(-1)	0.05		-0.11	*	0.04		-0.01	*	-0.07	
ECM3(-1)	0.00		0.05	*	-0.11	*	0.00		0.06	
ΔAUD(-1)	0.07		-0.06		-0.13		0.00		0.15	
ΔAUD(-2)	-0.17	*	-0.20	*	-0.34	*	-0.02	*	-0.27	*
ΔAUD(-3)	-0.13	*	-0.22	*	0.02		-0.01		-0.17	*
ΔAUD(-4)	-0.04		-0.18	*	-0.20	*	-0.02	*	-0.07	
ΔAUD(-5)	0.00		0.09	*	-0.24	*	0.00		0.14	
ΔEUR(-1)	0.12		-0.19	*	0.19		0.01		0.17	
ΔEUR(-2)	0.24	*	0.18	*	-0.04		0.02		0.37	*
ΔEUR(-3)	-0.27	*	0.07		-0.21		0.01		0.26	
ΔEUR(-4)	0.22	*	0.21	*	0.16		0.04		0.57	*
ΔEUR(-5)	-0.10		0.02		-0.08		0.00		0.19	
ΔGBP(-1)	0.05		-0.01		-0.23	*	0.00		-0.11	
ΔGBP(-2)	0.01		-0.07	*	-0.01		0.00		-0.04	
ΔGBP(-3)	0.06		-0.02		-0.03		0.01		0.00	
ΔGBP(-4)	0.01		-0.03		0.26	*	0.02		-0.07	
ΔGBP(-5)	0.12		0.00		0.15		0.00		0.08	
ΔJPY(-1)	-0.65	*	-0.14		-0.02		-0.02		-0.36	
ΔJPY(-2)	-0.05		0.31		0.16		0.09		-0.36	
ΔJPY(-3)	-0.15		0.05		0.04		0.00		0.14	
ΔJPY(-4)	-0.65	*	-0.15		0.12		-0.09		-0.80	*
ΔJPY(-5)	0.10		0.26		0.89	*	0.04		-0.32	
ΔUSD(-1)	0.21	*	0.12	*	0.14	*	0.03	*	0.06	
ΔUSD(-2)	0.10	*	0.05		0.06		0.00		0.06	
ΔUSD(-3)	0.05		0.08	*	0.11		0.02		0.11	
ΔUSD(-4)	0.13	*	0.01		0.00		0.00		0.00	
ΔUSD(-5)	0.18	*	0.04		0.09		-0.01		0.11	

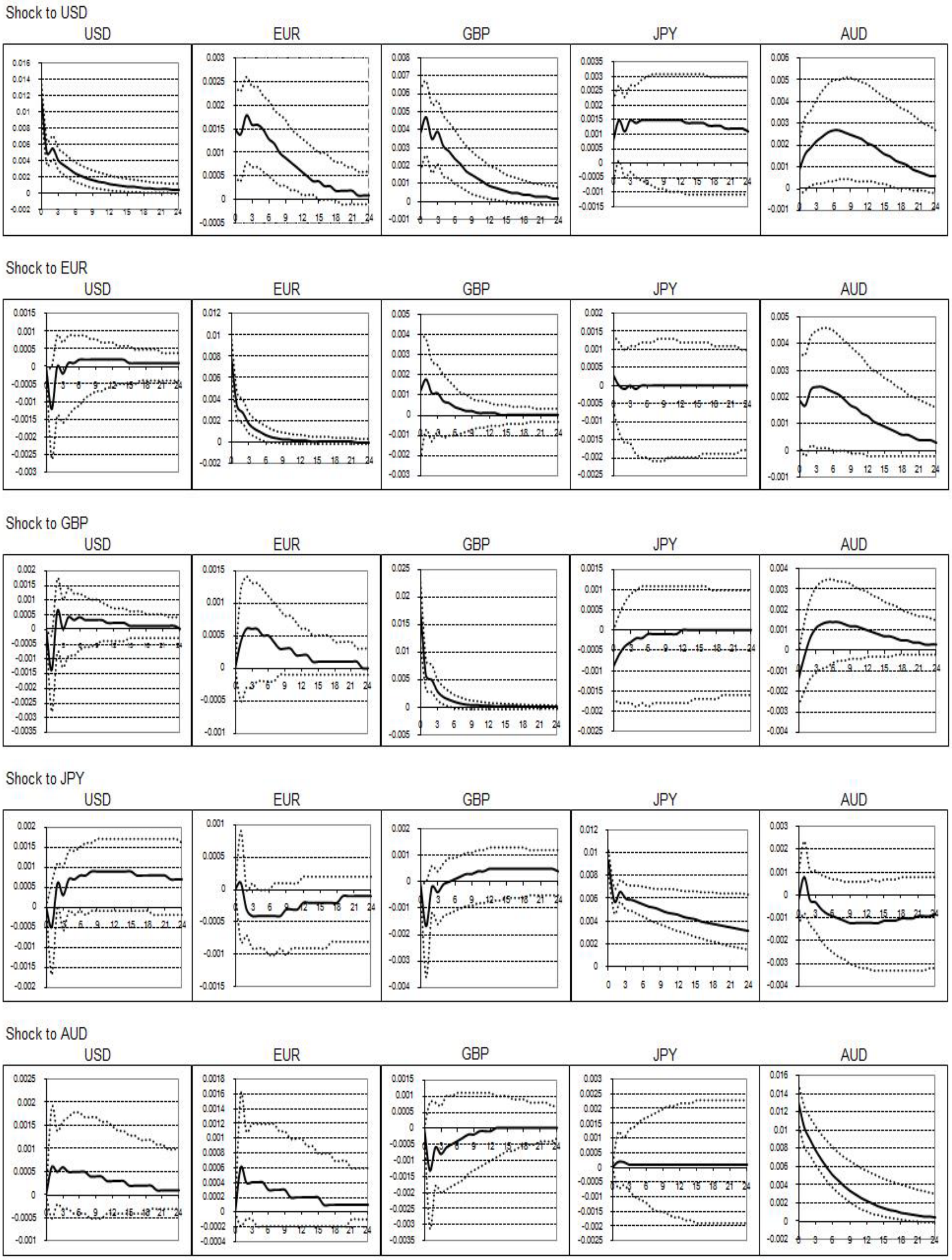
- Source: Authors' calculations.
- "*" indicates the significance of the coefficients at 5% level.
- $\Delta \equiv 1\text{-}B$, where B is the lag operator.
- ECM1 denotes the cointegrating vector of AUD, JPY and USD
- ECM1 denotes the cointegrating vector of EUR, JPY and USD
- ECM1 denotes the cointegrating vector of GBP, JPY and USD

Figure 1 LIBOR-OIS Spreads



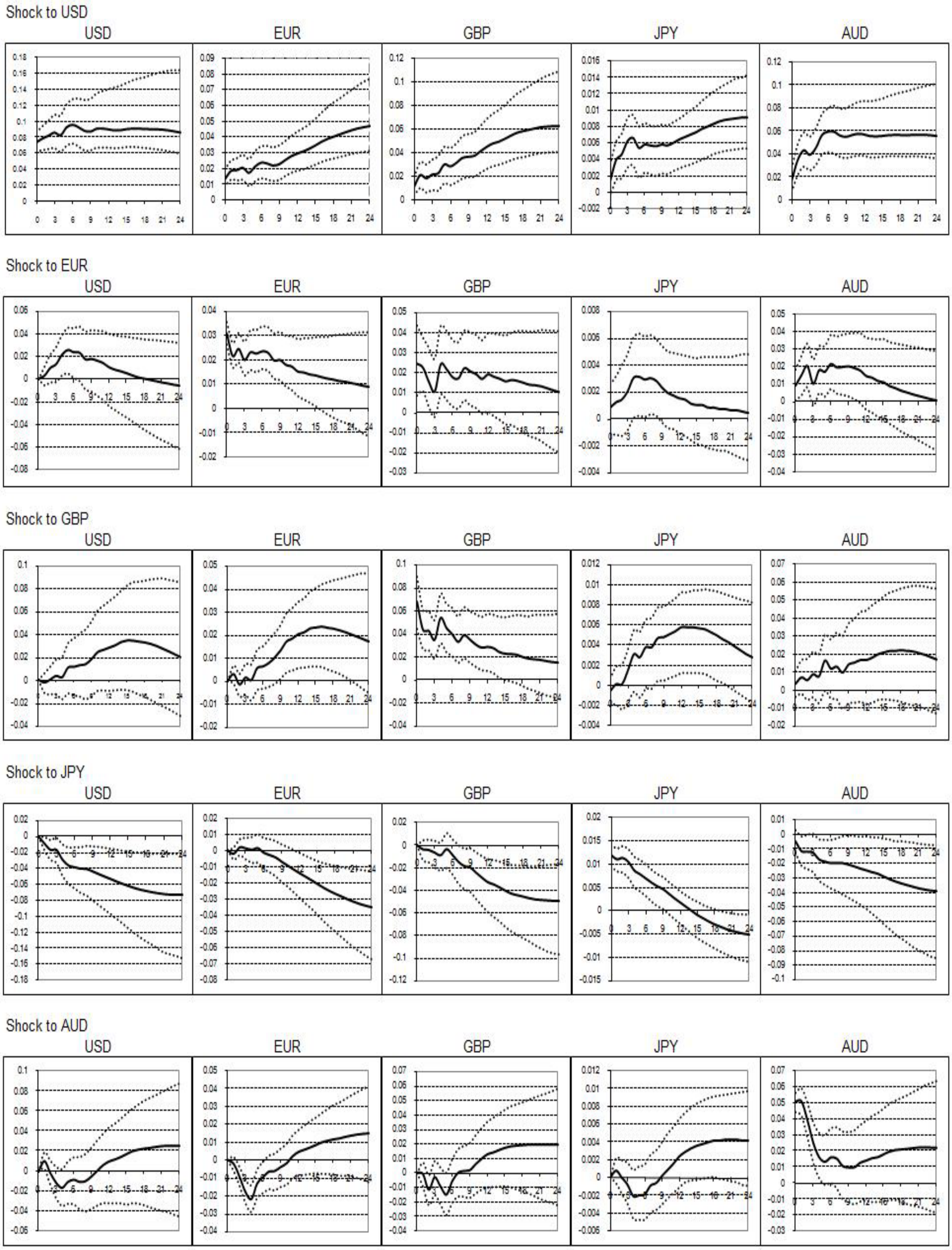
- Source: Authors' calculations, Bloomberg.

Figure 2 Impulse Response Estimates (Pre-crisis)



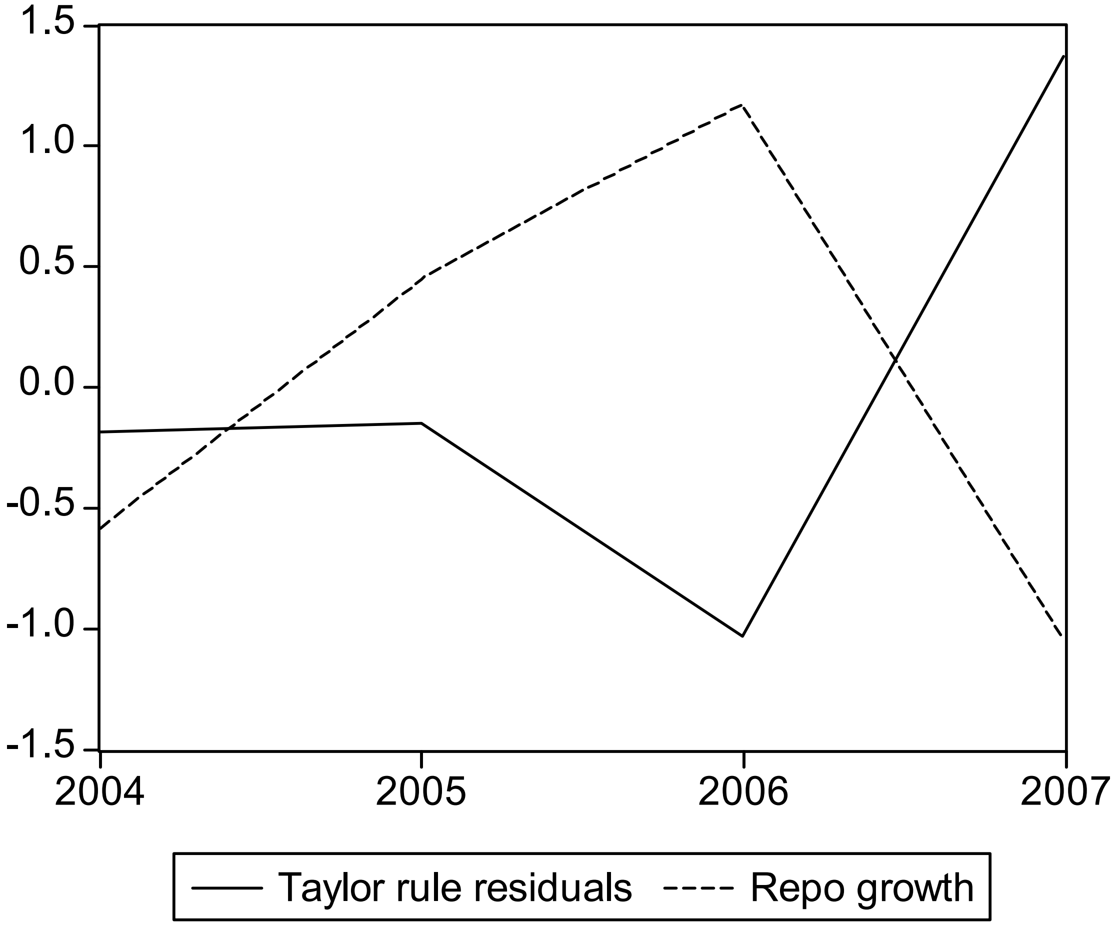
- Each graph plots the responses over period 0 to 24.
- Confidence intervals are calculated using the bias-corrected wild bootstrap

Figure 3 Impulse Response Estimates (Crisis)



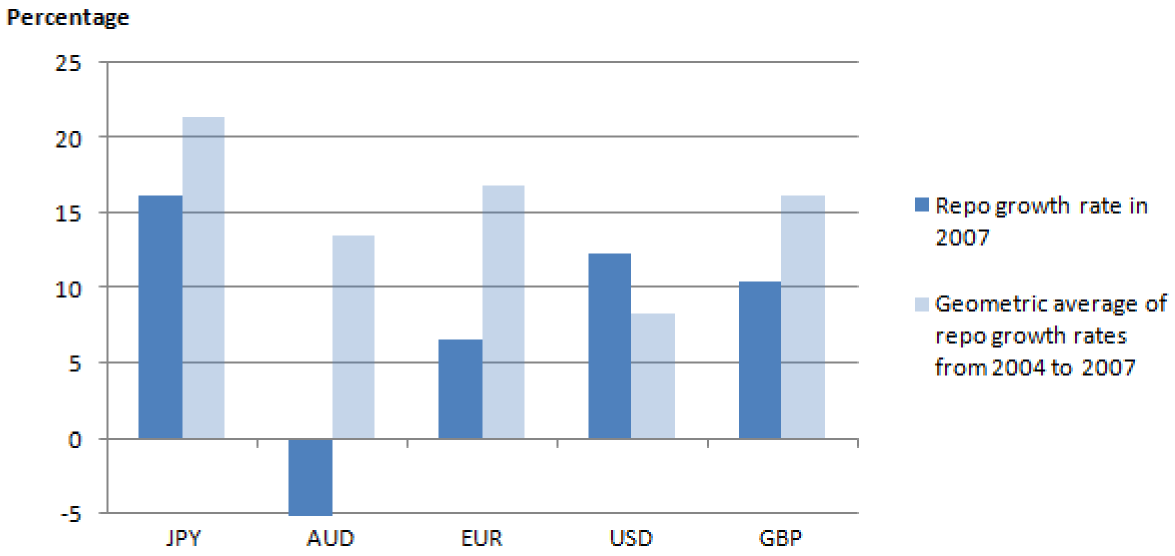
- Each graph plots the responses over period 0 to 24.
- Confidence intervals are calculated using the bias-corrected wild bootstrap

Figure 4 The Taylor Rule Regression Residuals and Repo Growth for Euro Areas



- Source : Authors' calculations, European Central Bank
- Data are normalized for convenience in graphical comparison.

Figure 5 Repo Growth Rate



- Sources: Authors' calculations, Bank of England, Bloomberg, European Central Bank, Federal Reserve Bank of New York, Japan Securities Dealers Association, Organization for Economic Co-operation and Development, Reserve Bank of Australia.