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# The Impact of Stock Market illiquidity on Real UK GDP Growth

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## Abstract

We empirically test the hypothesis that stock market illiquidity affects real UK GDP growth using data over the period 1989q1-2012q2. We conduct our empirical exercise within a standard linear model as well as a non-linear model, which allows for regime switching behavior in terms of a liquid versus an illiquid regime and over the phases of the business cycle. Our findings strongly support a statistically significant negative impact of stock market illiquidity over and above the usual macroeconomic controls on UK GDP growth; the impact becomes stronger during periods of highly illiquid market conditions and weak economic growth. Our out-of-sample forecasting analysis provides evidence in favor of a regime-switching model of illiquid versus liquid market conditions in predicting UK growth better than any other model; further, this very model is the only one to outperform the GDP growth forecasts published in the Bank of England's *Inflation Report*.

**JEL Codes:** G12, C32, C51, C52

**Keywords:** stock market illiquidity, divisia money, GDP growth, non-linear model.

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## 1. Introduction

The President of the Federal Reserve Bank of Boston Eric Rosengren (2010) pointed out that the seriousness of the recent financial crisis was underestimated by economic forecasters because financial links (such as provision of liquidity) to the real economy were “*only crudely incorporated into most macroeconomic modeling*” (p. 221). Indeed, provision of liquidity has become a central issue in the literature since the recent financial crisis (see Bridges and Thomas, 2012; Angelini et al, 2011; Naes et al, 2011; Acharya et al, 2011; Joyce et al, 2011; Blanchard et al, 2010; Hameed et al, 2010; Brunnermeir and Pedersen, 2009; Borio, 2008; Adrian and Shin, 2008). In response to the crisis, UK (and global) monetary policy followed an unprecedented path of interest rate cuts. UK interest rate cuts came to a halt in March 2009 and since then the Bank of England (BoE) base interest rate stands at a record low of 0.5%. The BoE also decided to support the economy further by boosting liquidity. The above operation, known as Quantitative Easing (QE), consisted of large purchases of mainly longer-term government bonds and related assets. Between March 2009 and July 2012, the Monetary Policy Committee (MPC) authorized a total of £375 bn of QE.

The impact of QE on the economy works via three main channels: the *macro/policy news channel*, the *signaling channel* and the *portfolio rebalancing channel*. The macro/policy news channel relates to BoE’s announcements regarding QE. The signaling channel describes the effects of announcements about the future course of monetary policy; it suggests that through QE, policymakers signal their intention to maintain very low nominal rates for a sustained period, thus reducing long-term interest rates. The portfolio rebalancing channel examines how QE induces portfolio adjustment as central bank bond purchases of government bonds lead to lower gilt yields and so increase demand for substitute assets.

In this paper we argue that one additional channel through which QE may affect economic growth is by improving liquidity conditions in the stock market. There are various reasons why stock market liquidity can be an informative leading indicator for future economic conditions. Firstly, market liquidity can act as a signaling mechanism, revealing the information set of investors. During periods of high uncertainty or negative outlook regarding the future state of the economy, investors move their capital away from

high-risk investments, reducing their exposure or fleeing the stock market altogether, investing in short-term fixed income securities, preferably government debt (flight to quality or flight to safety). If these shifts in investors' portfolio composition are related to fears that stock market liquidity may dry up, then a "*flight to liquidity*" is observed (Longstaff, 2004). These effects become more pronounced during periods of financial distress, where the actions of market participants, and in particular institutional investors, tend to be correlated. Brunnermeier and Pedersen (2009) show that a reinforcing mechanism between market liquidity and funding liquidity (the interaction between securities' market liquidity and financial intermediaries' availability of funds) leads to liquidity spirals and institutional investors (e.g. mutual funds) are forced to shift their liquidity provision towards stocks with low margins. Stock market liquidity can alternatively affect the real economy through an investment channel. In particular, a liquid secondary market can facilitate the financing of long-run projects in the real economy (Levine and Zervos, 1998). It is also well-established that liquidity has a first-order effect on the premium that investors demand to withhold risky assets (see, for example, Amihud, 2002 and Acharya and Pedersen, 2005). As a result, a liquid stock market may lower the cost of capital for firms, and hence boost high return projects that stimulate earnings and productivity growth (Levine, 1991).

In this paper, we empirically test the hypothesis that stock market illiquidity influences real UK GDP growth using data for the period 1989q1-2012q2. In doing so, we pay attention to a particular aspect of stock market illiquidity, namely price-impact, which measures the resilience of stock prices to changes in trading activity (e.g. trading volume and turnover rate). Following Naes et al (2011), we use the illiquidity measure of Amihud (2002), which is defined as the average monthly ratio of daily absolute returns to daily trading volume in monetary terms (RtoV). This measure is appealing because it is easy to compute for long time periods given the wide availability of returns and trading volume data.<sup>1</sup> It is also considered a good proxy for trading costs and the depth of the market without requiring intraday data, as we need for bid-ask spreads to be meaningful

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<sup>1</sup> In addition, it is intuitively attractive because the average daily price response associated with a dollar of trading volume renders it a good proxy for the theoretically founded Kyle's price impact coefficient (Goyenko et al, 2009).

(see Acharya and Pedersen, 2005).<sup>2</sup> Additionally, we use a modified price impact ratio, which is defined as the average monthly ratio of daily absolute stock return to its turnover ratio (hereafter RtoTR), essentially replacing the trading volume of a stock with its turnover ratio in the denominator of Amihud's ratio (see Florackis et al., 2011). In the time series dimension, RtoTR presents an important advantage relative to RtoV. Trading volume in monetary values has an upward time trend in line with the general price level, and hence RtoV inherits a downward trend. To the contrary, there is no inherent time trend in turnover ratio or, as a result, in RtoTR. By focusing on the RtoV and RtoTR measures of illiquidity, we assess their impact on the UK business cycle.

From a methodological perspective, an important aspect of our study is that it allows for an asymmetric impact of liquidity upon economic growth and ultimately links stock market liquidity to monetary policy interventions. As Joyce et al (2011) observe, central banks purchases of assets can improve market functioning when financial markets are dysfunctional or, in other words, when liquidity has dried up.<sup>3</sup> In other words, one might expect injections of liquidity to be more pronounced in periods where liquidity is too low and when the economy is underperforming. This suggests a regime-switching model which assesses the impact of liquidity on economic growth depending on the existence of a liquid/illiquid regime as well as during different phases of the business cycle. To this end, our study deviates from Naes et al (2011), who provide robust evidence of the impact of stock market liquidity on GDP growth in the US and in Norway after controlling for the effects of other financial variables.

Our study also contributes to the academic literature concerned with the impact of alternative financial variables on GDP growth. Existing literature has focused on possible financial variables such as the yield curve (see e.g. Chinn and Kucko, 2010, Estrella, 2005 and Estrella and Hardouvel, 1991), asset prices (see e.g. Zaher, 2007) and stock market uncertainty (Fornari and Mele, 2009) as leading indicators for real economic activity. Stock and Watson (2003) have extensively reviewed the literature on forecasting

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<sup>2</sup> See also Florackis et al (2011) for the advantages of RtoV over traditional proxies of liquidity.

<sup>3</sup> Acknowledging the considerable uncertainty of the impact of QE on the economy, Bank of England Deputy Governor (Monetary Policy) Charlie Bean (2012), points out that "it is possible that the effectiveness of policy depends on the state of the economy". Prominent economic commentators appear mindful of this very issue. For instance, David Smith (Economics Editor of *The Sunday Times*) referred to QE as an emergency tool and noted that its implementation depends on whether one thinks that "this is an emergency or merely a period of soft growth" (Smith, 2011).

macroeconomic variables, namely inflation and real output growth, by using, in addition to monetary aggregates, asset prices. Their work concludes that most assets (short-term interest rates, term spreads and stock returns) do not provide stable and strong predictive power. We build upon this strand of research by proposing stock market illiquidity as an additional determinant of GDP growth.

Using data available to policymakers in real time, we assess the impact of market illiquidity on UK economic growth within a linear model as well as a non-linear model which allows for regime switching behavior in terms of a liquid versus an illiquid regime and over the phases of the business cycle. We identify a statistically significant negative impact of illiquidity over and above the usual macroeconomic controls of economic growth (that is, real money, slope of the term structure and global economic activity). We also provide evidence that divisia money, which has a close relationship to aggregate spending, is a better predictor of UK growth than the routinely used M4 money measure.

We also provide evidence that the impact of both illiquidity and divisia money becomes stronger during periods of illiquid conditions and during periods of (very) weak economic growth. Using a counterfactual experiment, our findings suggest that had liquidity not dried up so dramatically since 2007, the depth in UK recession would have been less severe by some 2.3 percentage points. To this end, our findings offer indirect support to the implementation of QE by the BoE since 2009. Indeed, QE, which boosts liquidity and supports monetary growth, is bound to be more effective in the current context of illiquid conditions and weak economic growth where both liquidity and monetary growth are strong drivers of economic growth. Finally, our out-of-sample forecasting analysis provides evidence in favor of a regime-switching model of illiquid versus liquid conditions in predicting UK growth better than any other linear or non-linear model. Further, using formal statistical tests, this is the only model (from a wide range of models utilized) that provides more accurate UK GDP growth forecasts than those published in the BoE's *Inflation Report*.

The remainder of the paper proceeds as follows. Section 2 outlines our modeling strategy. Section 3 discusses the dataset. Section 4 reports our empirical findings. Finally, Section 5 summarizes our findings, discusses policy implications and offers some suggestions for future research.

## 2. The model

The starting point of our analysis is a linear model of the form

$$y_t = \beta_0 + \beta_{illiq} illiq_{t-l} + \beta_{\mathbf{X}}' \mathbf{X}_{t-l} + v_t, \quad (1)$$

where  $y_t$  is annual GDP growth,  $illiq_{t-l}$  is a measure of illiquidity,  $\mathbf{X}_{t-l}$  is a vector of control variables and  $v_t$  is an error term.<sup>4</sup> A large number of potential candidates exist for the  $\mathbf{X}_{t-l}$  vector of control variables. We proceed by including in the vector  $\mathbf{X}_{t-l}$  the following control variables: lagged GDP growth, the slope of the term structure of interest rates, annual real money growth and a measure of global economic activity. The slope of the term structure is approximated by the spread between the yield on the 10-year government bond and the 3-month T-bill rate. Annual real money growth (nominal money growth less Retail Price Index (RPI) inflation) is approximated by two measures of money: broad money (M4) and divisia money; the latter has been argued to have a closer relationship to expenditure, as it weighs the components of the money supply in proportion to their usefulness in making transactions (see Darrat et al, 2005; Hancock, 2005). Global economic activity is proxied by annual real GDP growth in the US.<sup>5</sup> In preliminary analysis, we also included a measure of oil prices. Oil prices have been shown to affect significantly real economic activity (see e.g. Ravazollo and Rothman, 2012, Hamilton, 2003, Hamilton, 1996 and references therein). We experimented with the annual growth of the real price of oil (annual growth in the price of oil in £ less RPI inflation). This variable entered all our models with a negative sign (higher oil prices depress economic activity) but its statistical effect was extremely weak.<sup>6</sup>

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<sup>4</sup> The  $illiq_t$  and  $\mathbf{X}_t$  regressors do not need to share the same lag length  $l$ . Our empirical models favour a choice of  $l=1$  for both  $illiq_t$  and  $\mathbf{X}_t$  based on the Akaike Information Criterion (AIC).

<sup>5</sup> We proxy global economic activity by US real GDP (US output is ranked 1<sup>st</sup> based on World Bank's database as it accounted in 2011 for approximately 23% of World's GDP). In a VAR model of UK economic growth, Garratt et al (2003) proxy global economic activity by OECD's GDP. In preliminary analysis, we also considered annual real GDP growth for the OECD; this is highly correlated with US growth based on revised data (the correlation coefficient is equal to 0.89). Real-time OECD GDP data are only available for a short time period (from 2002 onwards); for this reason, we make use of the US real-time dataset.

<sup>6</sup> Alquist et al (2011) discuss the issue of using real versus nominal oil prices in predicting real economic activity and Hamilton (1996) considers nonlinear transformations of the oil price. We also considered the nominal growth in oil prices as well as the (real) price of oil relative to its 1-year and 2-year Moving

While considering (in the  $\mathbf{X}_{t-l}$  vector) the commonly used above predictors of economic growth, our study pays particular attention to the role of stock market illiquidity as a leading indicator of the UK business cycle. This modeling choice has been motivated by the channels through which stock market liquidity can affect the real economy, as analyzed above.

To proxy stock market illiquidity ( $illiq_{t-l}$ ), we rely on the illiquidity measures of Amihud (2002) and Florackis et al (2011). These measures are the Return-to-Volume ratio (RtoV; Amihud, 2002) and Return-to-Turnover Ratio (RtoTR; Florackis et al, 2011) calculated for the FTSE100 index. In particular, RtoV is defined as:

$$RtoV_{i,y} = \frac{1}{N_Y} \sum_{d=1}^Y \frac{|R_{i,d}|}{VOL_{i,d}}$$

where  $|R_{i,d}|$  is the absolute return of share  $i$  on day  $d$ ,  $VOL_{i,d}$  is the trading volume (of share  $i$ ) on day  $d$  and  $N_Y$  is equal to the number of days within the chosen trading window  $Y$ , while RtoTR is defined as:

$$RtoTR_{i,y} = \frac{1}{N_Y} \sum_{d=1}^Y \frac{|R_{i,d}|}{TR_{i,d}}$$

where  $|R_{i,d}|$  is the absolute return of share  $i$  on day  $t$ ,  $TR_{i,d}$  is the turnover ratio (of share  $i$ ) on day  $d$  and  $N_Y$  is equal to the number of days within the chosen trading window  $Y$ . An increase in both measures is equivalent to a drop in liquidity; that is our variables are measures of illiquidity.

Assessing the direct impact of stock market illiquidity on economic growth is not that straightforward. This is because stock market illiquidity is highly correlated with changes in monetary policy. For instance, Adrian and Shin (2008), Brunnermeier and Pedersen (2009), Gromb and Vayanos (2010) and Hameed et al (2010), show that the relationship between changes in monetary policy and stock market liquidity appears to be “unevenly” or “asymmetrically” pro-cyclical with monetary policy, that is, expansionary

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Average. All these measures had a very weak statistical effect.



(contractionary) monetary policy leads to smaller (larger) increases in liquidity. We also note that stock market liquidity may be correlated with stock returns and stock volatility; liquidity tends to be lower and volatility tends to be higher during bear markets. Fornari and Mele (2009) pay close attention to the impact of stock market volatility on the US business cycle. They argue in favour of stock market volatility measures derived from absolute returns on the grounds that these measures are more robust to the presence of outliers than volatility measures derived from squared returns. We took notice of this issue in preliminary analysis by allowing stock market volatility to enter as a separate regressor in our empirical models. In particular, following Fornari and Mele (2009) we constructed stock market volatility measures based on the 1-year and 2-year moving average of past annualized absolute FTSE100 returns. Inclusion of these stock market volatility measures did not affect the estimates of our illiquidity measures reported below. We failed to find any statistical evidence in favor of these measures.

To allow for possible asymmetries in the behavior of illiquidity, a non-linear version of (1) is given by

$$y_t = \beta_0 + (\beta_{illiq,1} illiq_{t-1} + \beta_{\mathbf{X},1}' \mathbf{X}_{t-1}) \theta^s_{t-1} + (\beta_{illiq,2} illiq_{t-1} + \beta_{\mathbf{X},2}' \mathbf{X}_{t-1}) (1 - \theta^s_{t-1}) + u_t, \quad (2)$$

where

$$\theta^s_{t-1} = 1 - \frac{1}{1 + e^{-\gamma^s (s_{t-1} - \tau^s) / \sigma(s_{t-1})}} \quad (3)$$

is the logistic transition function discussed in van Dijk et al (2002) and  $s_{t-1}$  is the transition variable. According to (2)-(3), GDP growth  $y_t$  exhibits regime-switching behavior depending on whether  $s_{t-1}$  is below or above an endogenously estimated threshold,  $\tau^s$ , with regime weights  $\theta^s_{t-1}$  and  $(1 - \theta^s_{t-1})$ , respectively. When  $s_{t-1}$  is below the threshold  $\tau^s$ , then  $\theta^s_{t-1} \rightarrow 1$ . In this case, the impact of  $illiq_{t-1}$  and  $\mathbf{X}_{t-1}$  is given by  $\beta_{illiq,1}$  and  $\beta_{\mathbf{X},1}'$ , respectively. When  $s_{t-1}$  is above the threshold  $\tau^s$ , then  $\theta^s_{t-1} \rightarrow 0$ . In this case, the impact of  $illiq_{t-1}$  and  $\mathbf{X}_{t-1}$  is given by  $\beta_{illiq,2}$  and  $\beta_{\mathbf{X},2}'$ , respectively. In (2)-(3), we assume a common intercept  $\beta_0$ ; this is of course testable. The

parameter  $\gamma^s$  ( $\gamma^s > 0$ ) determines the smoothness of the transition between regimes. We make  $\gamma^s$  dimension-free by dividing it by the standard deviation of  $s_{t-l}$  (Granger and Teräsvirta, 1993).

We choose illiquidity ( $illiq_{t-l}$ ) and lagged GDP growth ( $y_{t-l}$ ) as possible alternative transition variable candidates. This allows us to assess the impact of illiquidity during a liquid regime (when  $illiq_{t-l} < \tau^{illiq}$ ) as opposed to an illiquid regime (when  $illiq_{t-l} > \tau^{illiq}$ ) and during periods of low growth (when  $y_{t-l} < \tau^y$ ) as opposed to periods of relatively high growth (when  $y_{t-l} > \tau^y$ ).

### 3. Data description

Both RtoV and RtoTR are calculated for the FTSE100 index and they are expressed in percentage deviations from their 2-year Moving Average (MA) starting from 1989q1.<sup>7</sup> Thomson Reuters Datastream is the source for FTSE 100 daily returns, trading volumes, and market values. Data on M4, money divisia, the slope of the term structure (i.e. the spread between the yield on the 10-year government bond and the 3-month T-bill rate) and real-time vintages of GDP are available from the BoE database. The Retail Price Index (RPI) inflation is available from the Office for National Statistics (ONS) database, whereas real-time vintages of US GDP are available from the website of the Federal Reserve Bank of Philadelphia. GDP and money data are seasonally adjusted.<sup>8</sup>

Figure 1 plots the deviations of RtoTR and RtoV measures from their 2-year MA together with annual GDP growth (based on the last available vintage of data produced by the ONS in 2012q2). From Figure 1, the two measures of illiquidity move close with each other. We note that stock market illiquidity (based on both RtoTR and RtoV) rises up to 20% above its 2-year MA around the 1990-1991 recession. The market turns illiquid

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<sup>7</sup> In preliminary analysis, we also considered the level of illiquidity as well as illiquidity relative to its 1-year Moving Average. Empirical results using these alternative measures were statistically less well-determined compared to the results reported here.

<sup>8</sup> We have access to revised M4 and divisia money data and use these in our estimations. However, we note that revisions of UK monetary aggregates occur mainly as a result of changes to the seasonal adjustment by the ONS (Garratt et al, 2009). The US real-time GDP dataset is available from: <http://www.philadelphiafed.org/research-and-data/real-time-center/real-time-data/data-files/ROUTPUT/>

during the Asian financial crisis and the Russian default in 1997-1998 and following the burst of the dot-com bubble the adverse impact of which reached its height in 2002q3 (e.g. Berger and Bouwman, 2008).<sup>9</sup> During the recent financial crisis, stock market turned very illiquid. Illiquidity rises sharply in 2007 prior to the economic slowdown and reaches its peak in 2008q4. It then eases between 2009 and early 2012 (when £325 bn of Quantitative Easing was implemented). We also note that Figure 1 superimposes a threshold value of -16.141% for the deviation of RtoV from its 2-year MA; we return to this issue below.

Figure 2 plots real money growth (based on the M4 and divisia measures of money), annual GDP growth in the US (based on the last available vintage of data in 2012q2) and the slope of the term structure. We note that the recent US recession has been less deep than in the UK and that the US economy has somewhat recovered since 2010; however, the recovery appears quite fragile with US growth much lower than its pre 2007 era. If money divisia represents money movements in the economy more accurately than M4, one would expect QE injections to show up more in divisia money and less so in M4. We note from Figure 2 that real M4 growth reached its peak in the beginning of 2009 and has been falling rapidly since then. On the other hand, real divisia money increased during the first round of QE in 2009. It then fell between 2010 and mid 2011 and somewhat recovered since then. The slope of the term structure has been decreasing over the 2010-2012 period which suggests that the 2010-2011 recovery has been, at best, anemic. Indeed, the latest release of ONS data (in 2012q2) suggested that the UK economy entered a “double-dip” recession in 2011q4.<sup>10</sup>

## 4. Empirical estimates

### 4.1. In-sample analysis

We begin by estimating, over expanding windows of data, versions of the linear model (1) based on the different measures of money and liquidity. The first data window runs from 1989q2 to 2002q4 and uses the first release of the 2003q1 real-time data

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<sup>9</sup> The stock market collapse of the early 2000s had an adverse impact on capital market conditions. In 2002q3, corporate debt defaults reached record levels: £88 bn of debt rated by Moody’s had defaulted; this figure was markedly higher than the £87 bn of debt defaults for the whole of 2001. Merrill Lynch’s global and sterling spread indices also rose, over the June–October 2002 period, by 50% (Farlow, 2005).

<sup>10</sup> The technical definition of a recession is two successive quarters of negative quarterly growth.

vintage. Each successive data window is extended by one observation; hence, the last data window runs from 1989q2 to 2012q1 and uses the 2012q2 real-time data vintage (this setup delivers 38 expanding windows). We use sequences of expanding windows in which the sample size for estimation is increased by one observation in each successive window, as opposed to sequences of fixed-length rolling windows, simply because the larger (increasing) windows help the estimation procedures for the various models which can be quite computationally intensive; this is arguably more so for the non-linear model (2)-(3).

Table 1 reports estimates of 4 versions of the linear model (1) using the different measures of liquidity and money over the last vintage of data which covers the whole sample period 1989q2-2012q1. In all models, the impact of illiquidity is highly significant; an increase in illiquidity depresses economic growth. The slope of the term structure is also statistically significant. Divisia money is statistically significant too (in column (i) and in column (iii)). On the other hand, the statistical significance of M4 is much weaker; this arguably confirms the superiority of divisia money over M4 in explaining GDP growth.<sup>11</sup> There is some weak evidence that global economic activity (proxied by US GDP growth) affects UK growth only for the model with RtoTR and divisia money. Amongst all estimated models, the model with the RtoV measure of illiquidity (in column iii) delivers the best fit (it has the lowest AIC).<sup>12</sup> It should be mentioned that the disadvantages of RtoV relative to RtoTR, as discussed in Section 1, are not affecting its predictive ability in our analysis. The reason is that we actually use percentage deviations of RtoV relative to its past 2-year moving average, and hence its downward time trend is inherently accounted for.

To get an idea of how the in-sample performance of the estimated linear models evolves over successive real-time vintages, Figure 3 plots their AIC's. From Figure 3, the model with the RtoV measure of illiquidity and the divisia measure of money has the lowest AIC; this is more evident from 2009 onwards. In what follows, we restrict attention to the RtoV measure of illiquidity and the divisia measure of money and proceed by estimating non-linear models using these measures. In addition to the AIC's

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<sup>11</sup> Using a recursive linear VAR, Garratt et al (2009) conclude that money is a weak predictor of real UK growth. Their analysis considers the M0, M3 and M4 measures of money (but not divisia money).

<sup>12</sup> Using recursive estimates, the plots (available on request) of the 1-step residuals +/-2\*standard errors suggest reasonable parameter constancy with the notable exception of most of the 2007-2010 period.

of the linear models, Figure 3 reports the AIC's of an AutoRegressive (AR) process (which we use in the following section for forecasting analysis) and two non-linear versions of (2)-(3) using RtoV and divisia money and allowing for regime switching behavior to depend on RtoV and  $y_{t-1}$ , respectively.<sup>13</sup> These non-linear models deliver lower AIC's compared with the linear models.

Estimates of these non-linear models based on the last available vintage of data are reported in Table 2. Specification (i) uses the RtoV measure of illiquidity as the regime-switching variable, whereas specification (ii) uses  $y_{t-1}$  as the regime-switching variable. Consider first the non-linear model in Table 2(i). The estimate of the smoothness parameter  $\gamma^{illiq}$  suggests a very sharp switch from one regime to the other.<sup>14</sup> During the liquid regime (when illiquidity drops 16% below its 2 year MA; the threshold is statistically significant), real divisia money growth has a significant impact on GDP growth; on the other hand, injections of liquidity do not have any statistical effect. During the illiquid regime, however, both stock liquidity injections and real divisia money growth are strong drivers of GDP growth. Market illiquidity exerts a highly significant effect; at the same time, the impact of real divisia money growth is twice as high as its impact during the liquid regime. Initially, we also allowed for regime-switching effects from the remaining regressors but failed to find convincing evidence; imposing regime-independent effects from lagged growth, the slope of the term structure, global economic activity and the intercept facilitated robust convergence of the non-linear model and improved its statistical fit. Lagged economic growth and the slope of the term structure have a statistically significant impact. Global economic activity exerts a positive but statistically weak effect (with a  $t$ -ratio of 1.60).

Next, we turn our attention to the non-linear model in Table 2(ii). The estimate of the smoothness parameter  $\gamma^y$  suggests a sharp switch from one regime to the other, whereas the estimated (and statistically significant) threshold of 1.22% suggests a regime of weak economic growth (surely significantly below potential GDP growth; the UK

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<sup>13</sup> We also estimated the non-linear model (2)-(3) using RtoTR (with divisia money or M4). These produced an inferior statistical fit to the ones reported in Table 2. In the interest of space, we abstract from reporting these estimates (full details are available upon request).

<sup>14</sup> van Dijk et al (2002) note the difficulty in getting an accurate estimate of  $\gamma$ . The likelihood function is very insensitive to  $\gamma$  and therefore, precise estimation of this parameter is unlikely.

economy has witnessed average growth of 2.27% over our sample period) as opposed to a regime of relatively normal growth or better. Illiquidity effects are insignificant when past (annual) GDP growth exceeds the 1.22% threshold. On the other hand, real divisia money growth exerts a statistically significant impact. During periods of weak economic growth (below 1.22%), stock market illiquidity exerts a strong impact on economic growth; at the same time, the effect of real divisia money growth doubles in magnitude. Our findings offer indirect support to the implementation of QE by the BoE since early 2009; QE, which boosts liquidity and supports monetary growth, is bound to be more effective in the current context of low liquidity conditions and weak economic growth where both liquidity and monetary growth are strong drivers of economic growth.<sup>15</sup> Lagged economic growth and the slope of the term structure have a significant impact which is invariant to the state of the economy, whereas global economic activity has a statistically weak effect (with a *t*-ratio of 1.35). We also note that the non-linear model with RtoV as the transition variable (Table 2(i)) delivers a lower AIC compared to the non-linear model in Table 2(ii) and the linear models in Table 1. Furthermore, both models presented in Table 2 exhibit parameter constancy (i.e. the related test is reported at the bottom of the table).

Our use of expanding windows of data and successive real-time vintages allows us to examine how policy perceptions about the drivers of GDP growth evolve over time. This is because the release of additional data together with data revisions trigger re-estimation of empirical models. We demonstrate this in Figure 4 which gives an idea of how the use of expanding windows of data and successive real-time vintages affect the estimated coefficients (plus/minus 2\*standard errors) of illiquidity, divisia money, global economic activity and for the slope of the term structure from linear model in Table 1 (iii) which has the best in-sample fit amongst all linear models. As the financial crisis kicks in, the impact of real divisia money growth increases. Illiquidity has a statistically significant, and rising impact from 2009 onwards. Quite strikingly, the coefficient on global economic activity is statistically significant until 2011q3. Between 2009 and 2011q3, global economic activity

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<sup>15</sup> On the effectiveness of monetary policy over the business cycle, Weise (1999), amongst others, employs a VAR model to find that money effects on US output growth are stronger when output growth is low. In the context of a Markov-regime switching model, Simpson et al (2001) find that interest rates are ineffective in combating UK recessions.

has a rising impact and then drops in size and significance at the same time when divisia money and illiquidity effects become stronger. Finally, the coefficient on slope of the term structure is fairly stable and always significant. From Figure 4, re-estimation of the empirical model (based on the release of additional data and data revisions) delivers the message that monetary, liquidity and global economic activity developments are all important drivers during the 2008-2009 UK recession and the subsequent (short-lived) recovery, whereas global economic conditions appear to weigh less since the 2011q4 “double-dip”.

To save space, we abstract from providing plots of the parameter estimates of the non-linear models over expanding windows and successive real-time vintages. With the exception of the parameter estimate on the global economic activity (which remains, as in the case of the linear models, statistically significant only until 2011q3), these plots confirm to a large extent the results of Table 2 and are available on request. To assess the regime-switching impact of illiquidity on UK GDP growth, we restrict our attention to the non-linear model in Table 2(i) which delivers the best statistical fit. Using the estimates in Table 2(i), Figure 5 plots together annual UK GDP growth and the regime-switching impact of illiquidity calculated as  $\beta_{illiq,1}\theta^{illiq}_{t-1} + \beta_{illiq,2}(1 - \theta^{illiq}_{t-1})$ . Compared with the estimates of the linear models reported in Table 1, our non-linear model reveals a more subtle response of GDP growth to market illiquidity. The impact switches from zero during liquid conditions (when illiquidity fluctuates below the estimated threshold; see Figure 1) to -0.009 during illiquid conditions. In the latter case, the lack of liquidity takes its toll on the economy as it drags GDP growth down; this is indeed very notable during the 1990-1991, 2008-2009 and 2011q4-2012q1 recessions and to a much lesser extent during the 1997-1998 Asian and Russian crises and following the burst of the dot-com bubble in the early 2000s (see Figure 5).

To further assess the implications of our non-linear model estimates of Table 2(i) since the beginning of the financial crisis in 2007q3, Figure 6 compares actual GDP growth with the counterfactual GDP growth rates implied by the liquid (when  $illiq_{t-1} < \tau^{illiq}$ ) and the illiquid (when  $illiq_{t-1} > \tau^{illiq}$ ) regimes.<sup>16</sup> Returning to Figure 1,

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<sup>16</sup> Counterfactual GDP growth rates are given by  $y_t^{liquid} = \beta_0 + \beta_{illiq,1}illiq_{t-1} + \beta_{X,1}'\mathbf{X}_{t-1}$  for the liquid

we note that, since 2007q3, GDP growth was largely determined by the illiquid regime. In fact, illiquidity conditions became much more severe compared with the pre 1990-1991 recession period or any other period. From Figure 6, it is apparent that the GDP growth rate implied by the illiquid regime is much closer to the actual growth rate than the implied growth rate from the liquid regime in this period. Estimates from the illiquid regime imply a recession depth of 7.3% in 2009q1 closely matching the 6.9% figure based on the actual data. By contrast, estimates of the liquid regime, which suggest a much smoother fall in UK GDP, also predict a less severe recession depth of 4.6% with a delay of one quarter. What is the implication of these estimates? Had liquidity not dried up so sharply from 2007q3 onwards, the UK economy would have witnessed a substantially less severe recession of 2.3 (i.e. 6.9 minus 4.6) percentage points and delayed by one quarter. But as QE is implemented and liquidity conditions improve (from Figure 1 illiquidity eases up between 2009-2012), the GDP growth implied by the illiquid and liquid regimes draw closer to each other. That said, in 2012q1, the GDP growth implied by the illiquid regime was still tracking “better” actual GDP growth which was, nonetheless, flat. This, arguably, provided a valid justification for additional QE which was eventually authorised by the MPC in July 2012.

## 4.2. Forecasting

Our expanding windows setup delivers, in real time, 37 one-step-ahead forecasts for all linear and non-linear models. These are compared with one-step-ahead forecasts derived from an AutoRegressive (AR) process of order one (the order has been chosen by the AIC), the real-time mean projections published in the BoE’s *Inflation Report* (these are based on the assumption that the BoE base interest rate follows market expectations; see Britton et al, 1998), and the median value of all forecasts.<sup>17</sup>

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regime and by  $y_t^{illiquid} = \beta_0 + \beta_{illiq,2} illiq_{t-1} + \beta_{X,2}' \mathbf{X}_{t-1}$  for the illiquid regime.

<sup>17</sup> The BoE forecasts refer to the MPC’s best collective judgement of the outlook for GDP growth and are available from <http://www.bankofengland.co.uk/publications/Pages/inflationreport/irprobab.aspx>. The BoE also reports one-step-ahead predictions that assume constant interest rates over the forecast period. Their correlation with the one-step-ahead GDP growth forecasts based on market interest rate expectations is 0.99.



Table 3 reports the Root Mean Squared Error (RMSE) and the Mean Absolute Error (MAE) criteria of the above forecasts. According to both criteria, the non-linear model with RtoV as the transition variable and divisia money (Model 5 in the Table) is ranked first. The linear version of the above model, that is, linear model with RtoV and divisia money (Model 3), is ranked second. The non-linear model with lagged growth as the transition variable (Model 6) is ranked third and the median of all forecasts (Model 9) is ranked fourth. According to the RMSE (MAE), the BoE forecasts (Model 7) are ranked seventh (eighth) whereas the AR model (Model 8) is ranked last.

Table 4 reports the pair-wise out-of-sample forecast comparison of the models reported in Table 3 using the modified Diebold and Mariano test DM\* (for more details, see Harvey et al, 1997, and Diebold and Mariano, 1995 and Appendix 1). The first entry in cell  $(i,j)$  (for  $i=1,\dots,9$  and  $j=1,\dots,9$ ) contains the  $p$ -values of the DM\* statistic for testing the null hypothesis of equal forecast accuracy of models  $i$  and  $j$  against the one-sided alternative that the RMSE of model  $j$  is lower. The second entry in  $(i,j)$  contains the  $p$ -values of the DM\* statistic for testing the null hypothesis of equal forecast accuracy of models  $i$  and  $j$  against the one-sided alternative that the MAE of model  $j$  is lower.

The non-linear model with RtoV as the transition variable and divisia money (Model 5), which, according to Table 3, is ranked first, delivers a statistically lower MAE relative to all models. It also delivers a statistically lower RMSE relative to all models except the linear model with RtoV and divisia (Model 3), the non-linear model with lagged growth as the transition variable (Model 6), the BoE forecasts (Model 7) and the median of all forecasts (Model 9). The non-linear model with lagged growth as the transition variable (Model 6), which is ranked third, delivers a statistically lower MAE relative to two models only (Model 2 and Model 8). With the exception of the non-linear model with RtoV as the transition variable and money divisia (Model 5), no other model delivers a statistically lower MAE than the BoE forecasts (Model 7). In terms of the RMSE, however, the non-linear model with RtoV as the transition variable fails to outperform the BoE forecasts. All models (with the exception of the BoE forecasts) deliver a statistically lower RMSE relative to the AR model (Model 8); when the MAE criterion is used, Model 2 and the BoE forecasts fail to outperform the AR model. The pooled forecasts (Model 9),

constructed by taking the median value across the point forecasts generated by all models, deliver statistical lower RMSE and MAE relative to Model 1, Model 2 and Model 8.<sup>18</sup>

To get a visual idea of how the models forecast out-of-sample GDP growth, Figure 7 plots GDP real-time growth together with the forecasts. The forecasting performance of the estimated models appears rather similar during liquid conditions and up until 2007. When growth turns negative in 2008q4, a negative outcome is predicted only by the two non-linear models. The non-linear model with lagged growth as the transition variable predicts a deeper recession compared to all remaining models. It also predicts the depth of the recession one quarter earlier than it occurred (in 2009q1 instead of 2009q2), whereas the remaining models forecast the depth of the recession with a delay of one quarter. We also note that the two non-linear models come closer than any other model in predicting the 0.01% real-time (flat) growth in 2012q1.

## 5. Concluding remarks

This paper considers the impact of stock market illiquidity on real UK GDP growth. We focus on two measures of stock market illiquidity (suggested by Florackis et al, 2011 and Amihud, 2002, respectively) and use data available to policymakers in real time to identify a statistically significant impact of illiquidity over and above the usual macroeconomic controls of economic growth (namely real money, slope of the term structure and global economic activity). Furthermore, our findings support the use of divisia money (which has a close relationship to aggregate spending) as a better predictor of UK growth than the routinely used M4 money measure. Therefore, we provide evidence that divisia money is a useful monetary indicator for policymakers to pay attention to.

We also find that the impact of both stock market illiquidity and divisia money is regime-switching; it becomes stronger during periods of illiquid conditions and during periods of (very) weak economic growth. We provide a counterfactual experiment which suggests that had liquidity not dried up so dramatically since 2007, the depth in UK

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<sup>18</sup> In a forecasting exercise based on final-time data, Kapetanios, Labhard and Price (2008) consider a wide range of linear and non-linear models of UK growth and conclude that although individual models hardly outperform Autoregressive (AR) forecasts, combining forecasts does help forecast performance. Their models do not consider liquidity measures.

recession would have been substantially less severe by some 2.3 percentage points. The above findings offer indirect support to the implementation of QE by the BoE over the last three years. Indeed, QE, which boosts liquidity and supports monetary growth, is bound to be more effective in the current context of illiquid conditions and weak economic growth where both liquidity and monetary growth are strong drivers of economic growth.

An out-of-sample forecasting exercise confirms the superiority of a regime-switching model of illiquid versus liquid conditions in predicting UK growth better than any other model; in fact, this is the only model that outperforms (using formal statistical tests) the forecasts published in the BoE's *Inflation Report*.

To further assess the importance of stock market liquid versus stock market illiquid conditions for the macro-economy, our work can be extended to allow for regime-switching liquidity effects in joint estimates of output growth, inflation and the policy interest rate within a structural Vector Autoregressive framework. We also view the construction of global measures of stock market liquidity by pooling information from e.g. the US, UK and Eurozone stock markets as a very promising avenue for research towards identifying a successful predictor of the world business cycle. We intend to return to these issues in future research.

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## Appendix 1

### Diebold-Mariano (DM) and modified DM test statistic

At forecast horizon  $h$ , this is computed by weighting the forecast loss differentials between two competing models  $i$  and  $j$  equally, where the loss differential for observation  $t$  is given by  $d_t \equiv [g(e_{it|t-h}) - g(e_{jt|t-h})]$ , where  $g(\cdot)$  is a general function of forecast errors (e.g. RMSE or MAE). The null hypothesis of equal accuracy of the forecasts of two competing models, can be expressed in terms of their corresponding loss functions,  $E[g(e_{it|t-h})] = E[g(e_{jt|t-h})]$ , or equivalently, in terms of their loss differential,  $E[d_t] = 0$ .

Let  $\bar{d} = \frac{1}{P} \sum_{t=R+h}^{R+P+h-1} d_t$  denote the sample mean loss differential over  $t$  observations, such that there are  $P$  out-of-sample point forecasts and  $R$  observations have been used for estimation. The Diebold-Mariano test statistic follows asymptotically the standard normal distribution:

$$DM = \frac{\bar{d}}{\sqrt{\frac{2\pi\hat{f}_d(0)}{P}}} \xrightarrow{d} N(0,1), \text{ where } N(\cdot) \text{ is the normal distribution and}$$

$\hat{f}_d(0)$  is a consistent estimate of the spectral density of the loss differential at frequency 0. To counteract the tendency of the  $DM$  test statistic to reject the null too often when it is true in cases where the forecast errors are not bivariate normal, Harvey et al (1997) propose a modified Diebold-Mariano test statistic:

$$DM^* = \left[ \frac{P+1-2h+P^{-1}h(h-1)}{P} \right]^{1/2} DM \xrightarrow{d} t_{(P-1)}, \text{ where } DM \text{ is the original Diebold and}$$

Mariano (1995) test statistic for  $h$ -step-ahead forecasts and  $t_{(P-1)}$  refers to the Student's  $t$  distribution with  $P-1$  degrees of freedom.

## List of Tables

**Table 1**  
**Linear estimates of UK GDP growth, 1989q2-2012q1 (based on the 2012q2 vintage)**

	<u>Dependent Variable</u>			
	(i) Illiquidity measured by RtoTR	(ii) Illiquidity measured by RtoTR	(iii) Illiquidity measured by RtoV	(iv) Illiquidity measured by RtoV
<u>Explanatory Variables</u>				
Intercept	-0.141 (-0.84)	-0.064 (-0.30)	-0.077 (-0.48)	-0.025 (-0.12)
GDP growth <sub>t-1</sub>	0.784 (10.72)	0.882 (12.62)	0.786 (11.22)	0.886 (13.20)
illiquidity <sub>t-1</sub>	-0.006 (-3.06)	-0.007 (-3.42)	-0.006 (-4.22)	-0.007 (-4.43)
real divisia money growth <sub>t-1</sub>	0.104 (3.49)	-	0.106 (3.72)	-
real M4 growth <sub>t-1</sub>	-	0.031 (1.49)	-	0.035 (1.74)
slope <sub>t-1</sub>	0.130 (2.86)	0.134 (2.69)	0.134 (3.10)	0.143 (2.99)
US GDP growth <sub>t-1</sub>	0.084 (1.27)	0.032 (0.52)	0.040 (0.66)	-0.014 (-0.17)
Adjusted R <sup>2</sup>	0.88	0.87	0.89	0.88
Regression standard error	0.77	0.81	0.74	0.78
AIC	2.38	2.49	2.30	2.41

**Notes:** t-ratios are given in parentheses. AIC stands for the Akaike Information Criterion.



**Table 2**  
**Non-linear estimates of UK GDP growth, 1989q2-2012q1**  
**(based on the 2012q2 vintage)**

	Dependent Variable	
	<i>Specification (i)</i>	<i>Specification (ii)</i>
	<i>Illiquidity measured by RtoV</i>	<i>Illiquidity measured by RtoV</i>
Intercept	0.046 (0.28)	0.036 (0.21)
GDP growth <sub>t-1</sub>	0.746 (11.06)	0.760 (12.47)
Slope <sub>t-1</sub>	0.151 (3.63)	0.134 (3.32)
US GDP growth <sub>t-1</sub>	0.090 (1.60)	0.084 (1.35)
	Illiquid regime:	Growth regime of
	$illiq_{t-1} < \tau^{illiq}$	$y_{t-1} < \tau^y$
Illiquidity <sub>t-1</sub>	0.001 (0.01)	-0.010 (-3.83)
Real divisia money growth <sub>t-1</sub>	0.083 (2.15)	0.178 (4.23)
	Illiquid regime:	Growth regime of
	$illiq_{t-1} > \tau^{illiq}$	$y_{t-1} > \tau^y$
Illiquidity <sub>t-1</sub>	-0.009 (-5.48)	-0.001 (-0.80)
Real divisia money growth <sub>t-1</sub>	0.160 (4.62)	0.084 (2.35)
$\tau^{illiq}$	-16.141 (-6.71)	-
$\gamma^{illiq}$	99.29 (0.37)	-
$\tau^y$	-	1.224 (4.66)
$\gamma^y$	-	46.24 (0.18)
Adjusted R <sup>2</sup>	0.90	0.90
Regression standard error	0.70	0.71
AIC	2.21	2.23
Parameter constancy F-test [p-value]	0.67 [0.74]	0.62 [0.78]

**Notes:** t-ratios are given in parentheses. Parameter constancy is an F-test of parameter constancy of the non-linear model which involves testing the statistical significance of the cross-product of all regressors in the non-linear model and time trend (see van Dijk et al, 2002).

**Table 3**  
**Ranking of forecasts by RMSE and MAE criteria**

Model <i>i</i>	RMSE (Ranking in parenthesis)	MAE (Ranking in parenthesis)
<i>i</i> =1 Linear model with RtoTR and Divisia money	0.872 (6)	0.633 (5)
<i>i</i> =2 Linear model with RtoTR and M4	0.924 (8)	0.675 (7)
<i>i</i> =3 Linear model with RtoV and Divisia money	0.805 (2)	0.588 (2)
<i>i</i> =4 Linear model with RtoV and M4	0.859 (5)	0.635 (6)
<i>i</i> =5 Non-linear model with RtoV and Divisia money (RtoV is the transition variable)	0.704 (1)*	0.505 (1)**
<i>i</i> =6 Non-linear model with RtoV and Divisia money (lagged GDP growth is the transition variable)	0.820 (3)	0.592 (3)
<i>i</i> =7 BoE forecasts published in the BoE's <i>Inflation Report</i> .	0.885 (7)	0.689 (8)
<i>i</i> = 8 AR model	1.027 (9)	0.732 (9)
<i>i</i> =9 Median of all forecasts	0.828 (4)	0.604 (4)

**Notes:** This Table reports the Root Mean Squared Error (RMSE) and the Mean Absolute Error (MAE) criteria of the forecasts associated with each model (from *i*=1 to *i*=9). RMSE and MAE criteria are based on the expanding windows one-step-ahead forecasts over the 2003q1-2012q1 period. The ranking of each model, in terms of its forecasting accuracy, is reported in parentheses. \* (\*\*) indicates the models with the highest ranking based on RMSE (MAE).

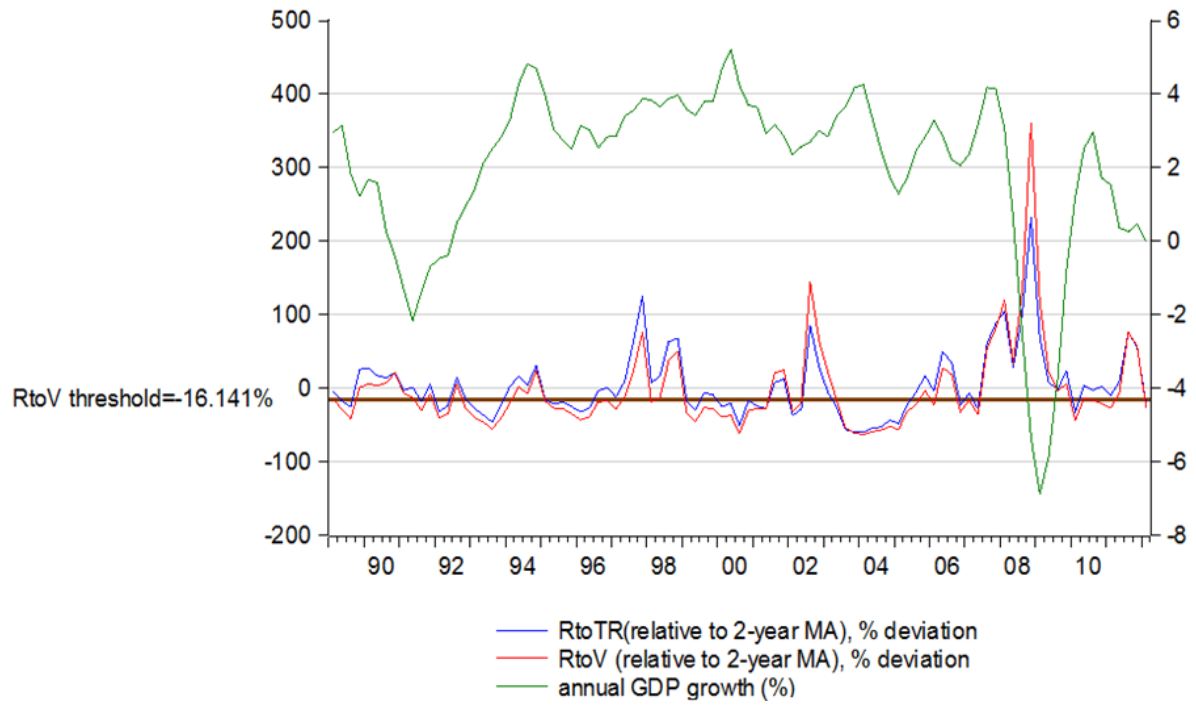
**Table 4**  
**Pair-wise out-of-sample forecast comparison using the modified Diebold-Mariano test (DM\*)**

<i>Model i</i>	<i>Against Model j</i>								
	1	2	3	4	5	6	7	8	9
1	-	0.854 0.866	<b>0.075*</b> <b>0.020*</b>	0.411 0.525	<b>0.095*</b> <b>0.050*</b>	0.210 0.148	0.565 0.746	0.955 0.938	<b>0.074*</b> <b>0.053*</b>
2	0.146 0.134	-	<b>0.041*</b> <b>0.029*</b>	<b>0.061*</b> <b>0.031*</b>	<b>0.063*</b> <b>0.025*</b>	0.139 <b>0.073*</b>	0.353 0.558	0.932 0.855	<b>0.023*</b> <b>0.016*</b>
3	0.925 0.980	0.959 0.971	-	0.876 0.904	0.123 <b>0.089*</b>	0.601 0.551	0.809 0.877	0.977 0.974	0.811 0.817
4	0.589 0.475	0.939 0.969	0.124 <b>0.096*</b>	-	<b>0.078*</b> <b>0.032*</b>	0.331 0.197	0.599 0.724	0.965 0.934	0.216 0.121
5	0.905 0.950	0.937 0.975	0.877 0.911	0.922 0.968	-	0.891 0.918	0.892 0.962	0.966 0.980	0.870 0.920
6	0.790 0.852	0.861 0.927	0.399 0.449	0.669 0.803	0.109 <b>0.082*</b>	-	0.757 0.875	0.935 0.941	0.547 0.618
7	0.435 0.254	0.647 0.442	0.191 0.123	0.401 0.276	0.108 <b>0.038*</b>	0.243 0.125	-	0.834 0.651	0.239 0.147
8	<b>0.045*</b> <b>0.062*</b>	<b>0.068*</b> 0.145	<b>0.023*</b> <b>0.026*</b>	<b>0.035*</b> <b>0.066*</b>	<b>0.034*</b> <b>0.020*</b>	<b>0.065*</b> <b>0.059*</b>	0.166 0.349	-	<b>0.022*</b> <b>0.025*</b>
9	0.926 0.947	0.977 0.984	0.189 0.183	0.784 0.879	0.130 <b>0.080*</b>	0.453 0.382	0.761 0.853	0.978 0.985	-

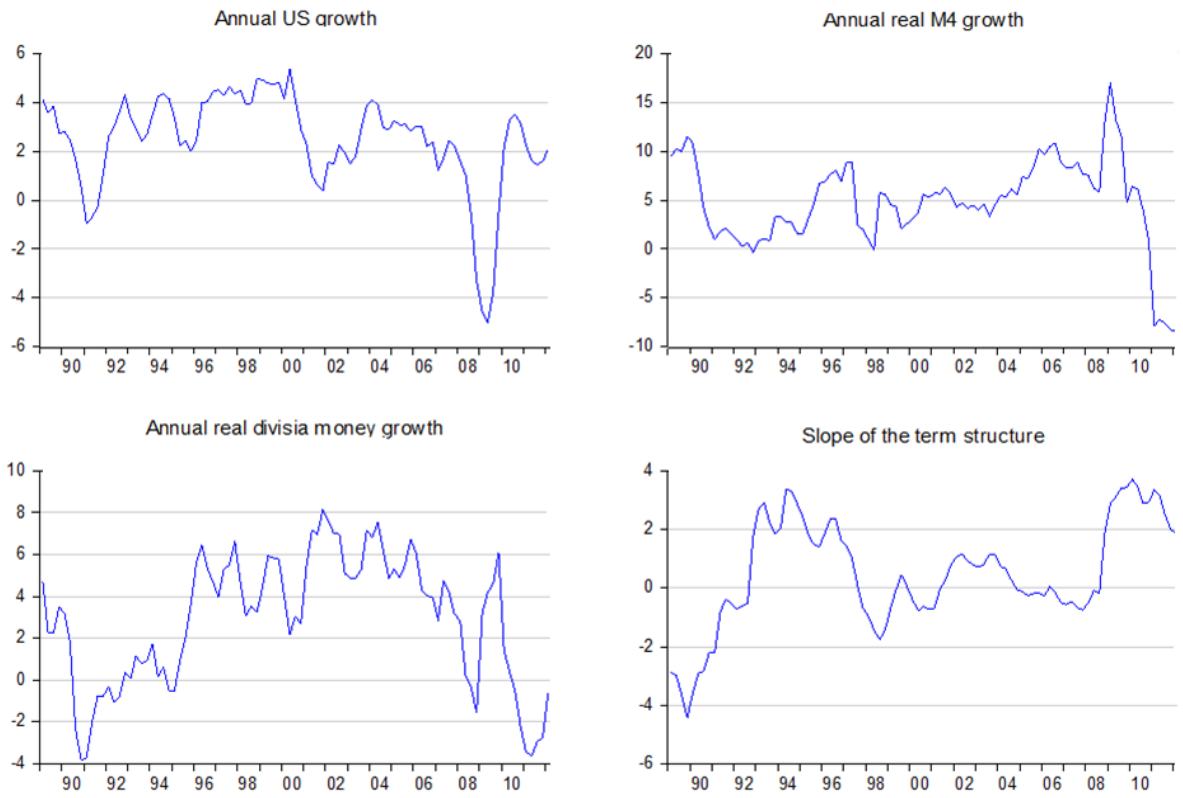
**Notes:** The Table presents pair-wise out-of-sample forecast comparisons for the 9 forecasting models and expanding windows, at the  $h = 1$  forecast horizon using the modified ( $DM^*$ ) Diebold-Mariano test statistic of Harvey et al (1997). The first entry in cell ( $i, j$ ) contains the  $p$ -values of the modified  $DM^*$  statistic of Harvey et al (1997) for testing the null hypothesis of equal forecast accuracy of models  $i$  and  $j$  against the one-sided alternative that the RMSE of model  $j$  is lower. The second entry in ( $i, j$ ) contains the  $p$ -values of the modified  $DM^*$  statistic of Harvey et al (1997) for testing the null hypothesis of equal forecast accuracy of models  $i$  and  $j$  against the one-sided alternative that the MAE of model  $j$  is lower. An asterisk (\*) denotes statistical significance at the 10% level.  $i=1$  refers to the linear model with RtoTR and Divisia money.  $i=2$  refers to the linear model with RtoTR and M4.  $i=3$  refers to the linear model with RtoV and Divisia money.  $i=4$  refers to the linear model with RtoV and M4.  $i=5$  refers to the non-linear model with RtoV and Divisia money (RtoV is the transition variable).  $i=6$  refers to the non-linear model with RtoV and Divisia money (lagged GDP growth is the transition variable).  $i=7$  refers to the BoE forecasts published in the BoE's *Inflation Report*.  $i=8$  refers to the AR model.  $i=9$  refers to the median of all forecasts.

## List of Figures

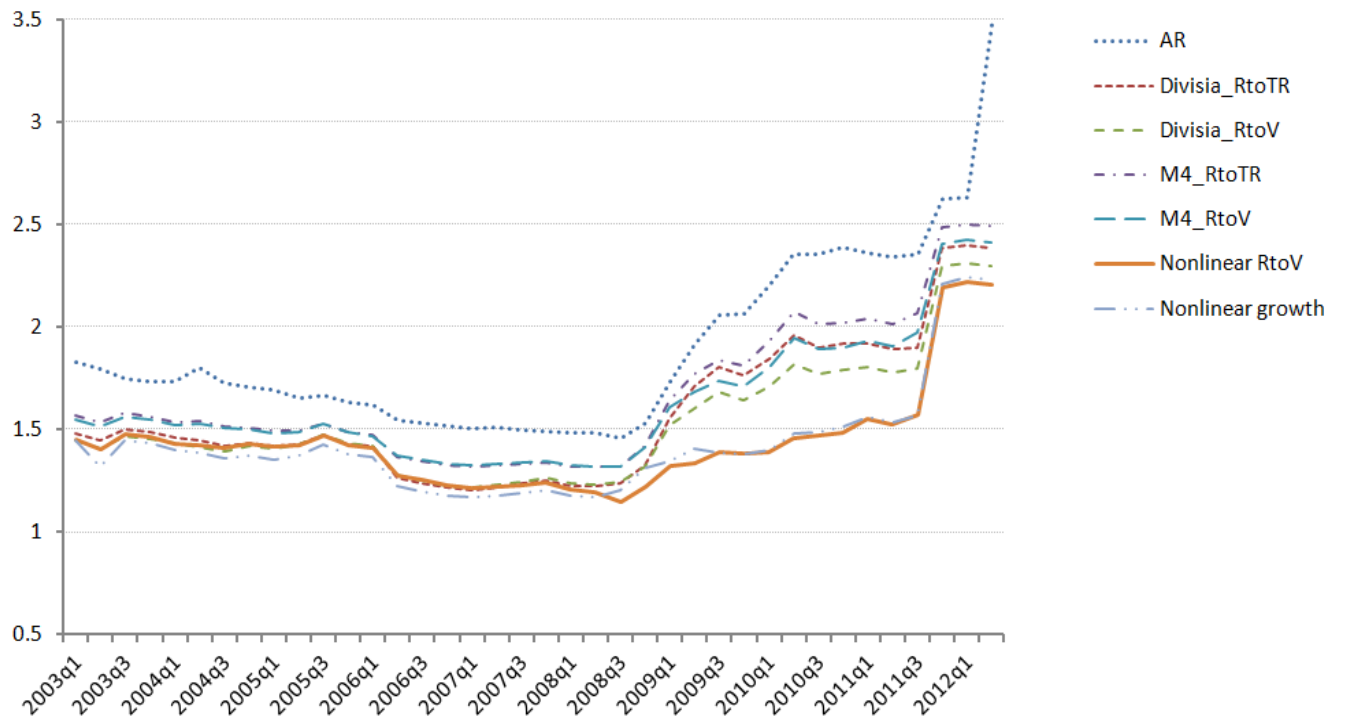
**Figure 1**  
**Illiquidity measures (LHS axis) and UK growth (RHS axis), 1989q2-2012q1**  
**(UK growth is based on the 2012q2 vintage)**



**Figure 2**  
**US GDP growth, real M4 growth, real divisia money growth, slope of the term structure (%)**



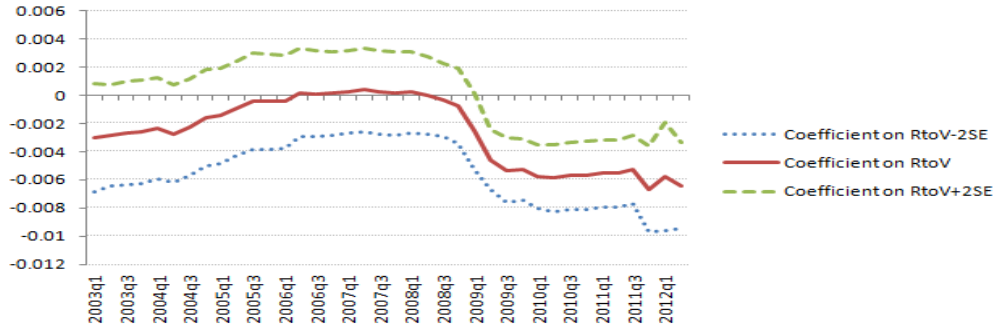
**Figure 3**  
**Akaike Information Criterion (AIC) over successive real-time vintages**



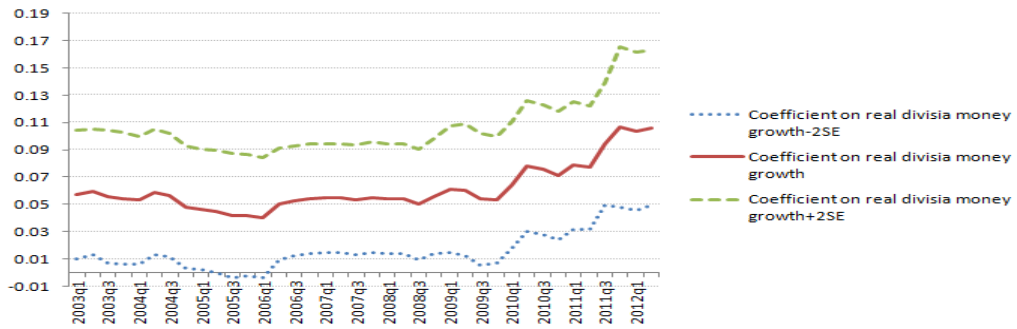
**Note:** AIC over successive real-time vintages for all models defined in Table 1 and in Table 2.

**Figure 4**  
**Parameter estimates (plus/minus 2\*standard errors) for:**

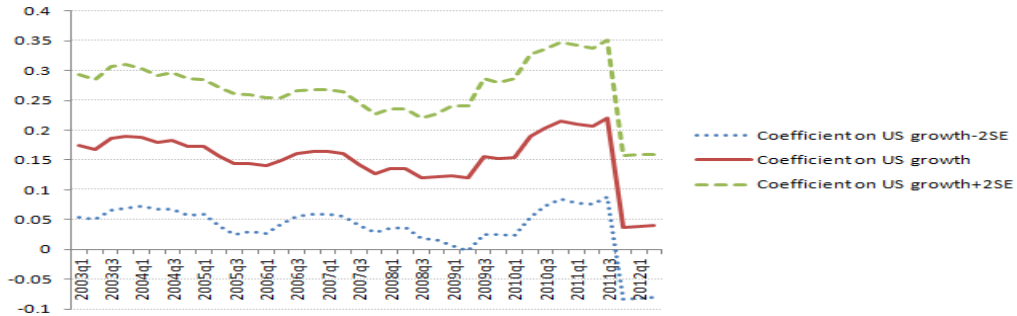
**a. RtoV (stock market illiquidity)**



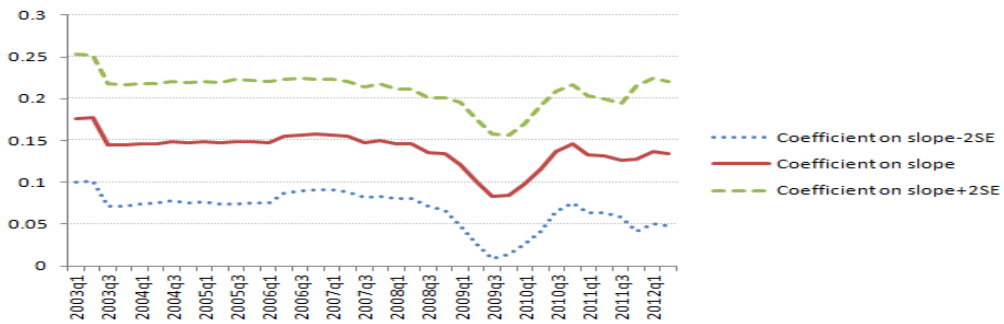
**b. Real divisia money**



**c. Global Economic Activity (US GDP growth)**

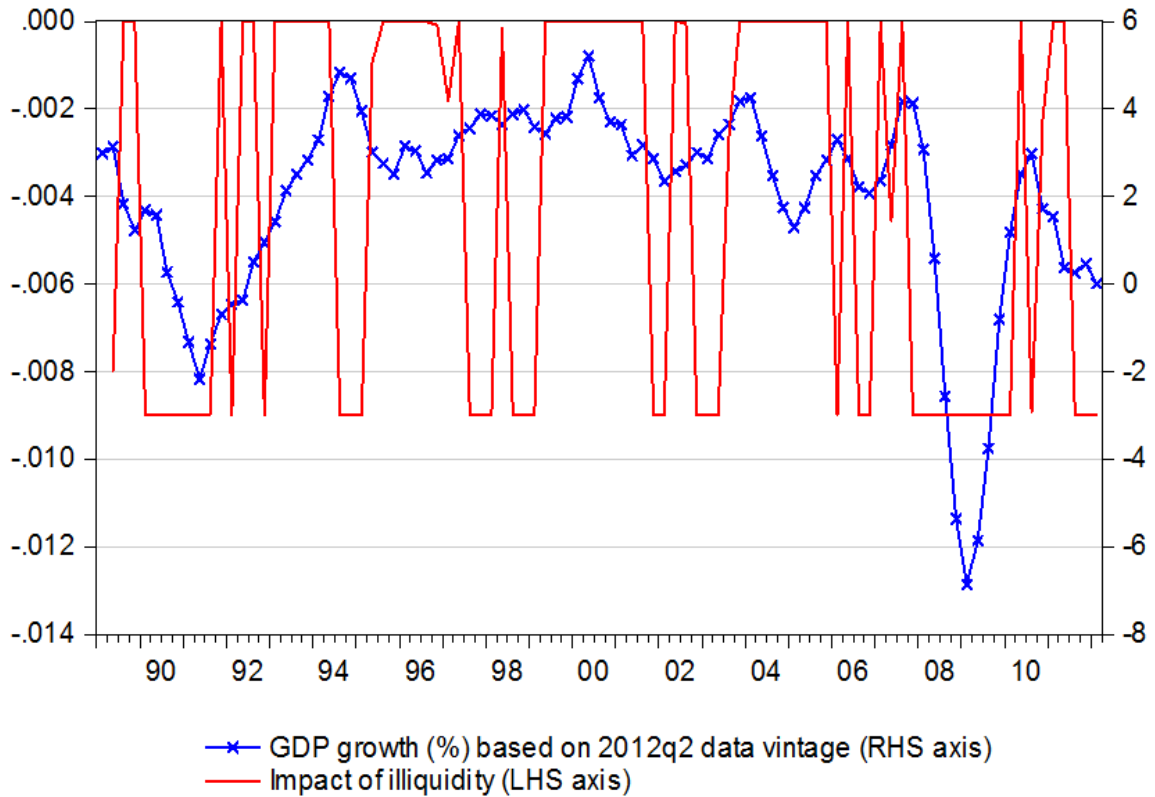


**d. Slope of the Term Structure**



**Note:** Parameter estimates based on linear model with RtoV and divisia money reported in Table 1(iii); expanding windows and successive real-time vintages.

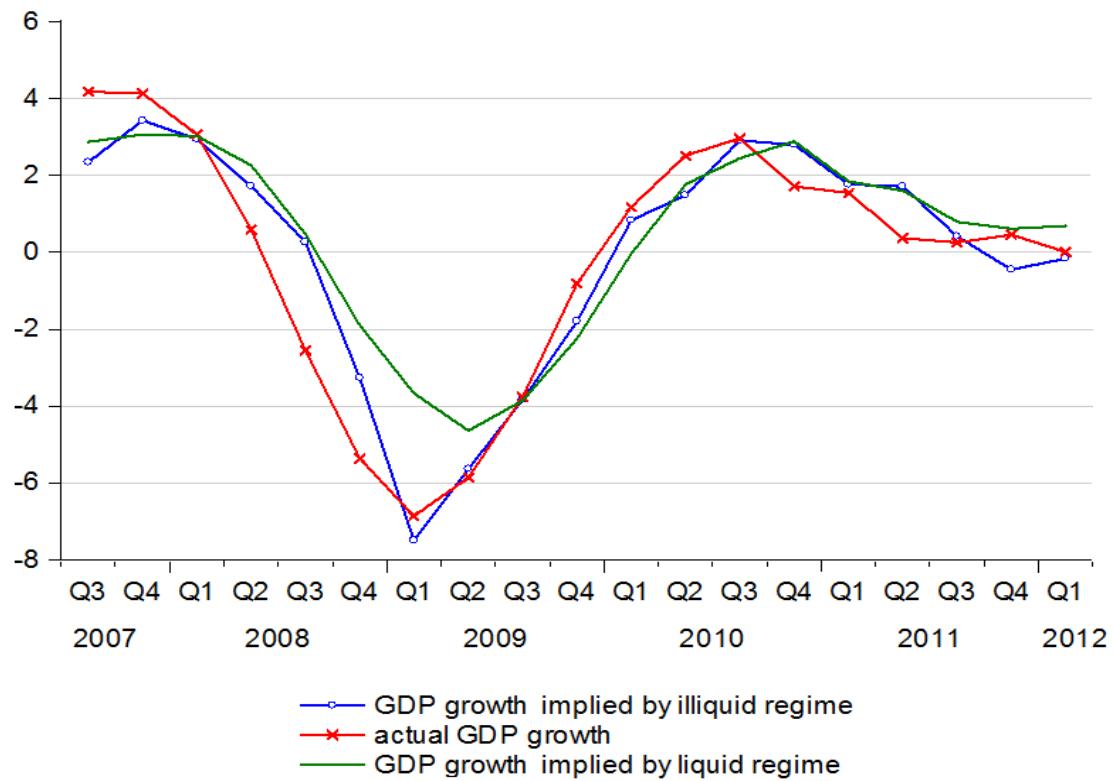
**Figure 5**  
**The regime-switching impact of illiquidity on UK economic growth, 1989q2-2012q1**



**Note:** Impact of illiquidity is calculated as  $\beta_{illiq,1}\theta^{illiq}_{t-1} + \beta_{illiq,2}(1 - \theta^{illiq}_{t-1})$  with  $\beta_{illiq,1}=0$  (imposed),  $\beta_{illiq,2}=-0.009$ ,  $\tau^{illiq}=-16.141\%$ , and  $\gamma^{illiq}=99.29$  based on the estimates reported in Table 2(i) (last vintage of data).

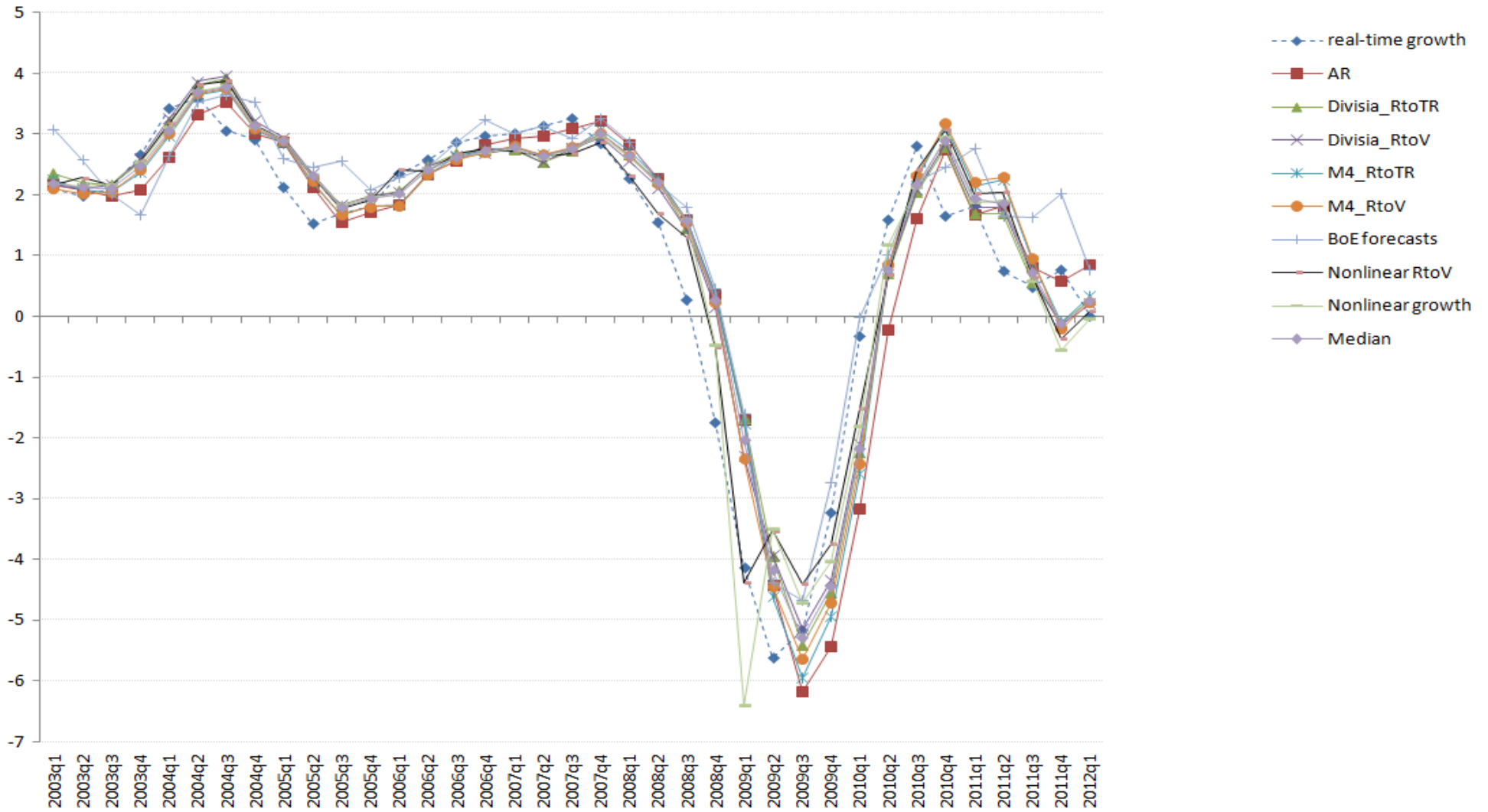


**Figure 6**  
**Actual and implied regime-specific GDP growth rates (%) (from 2007q3 onwards)**



**Note:** Implied growth rates are based on the estimates reported in Table 2(i) (last vintage of data).

Figure 7  
One-step-ahead forecasts



**Note:** Forecasts are based on the models reported in Table 3