The role of high frequency data and regime changes in predicting economic activity with financial variables

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Abstract

When assessing the predictive content of financial variables for economic activity, researchers usually aggregated data available at higher frequency before estimating a forecasting model that takes the relation between the financial variable and the dependent variable as linear. This paper proposes a model that relaxes both these assumptions by directly using high frequency data while taking into account regime changes in the slope parameters, called smooth transition mixed data sampling (STMIDAS) regression. The model is applied to the use of financial variables, such as term spreads, short-term interest rates, and stock returns, for out-of-sample forecasting of UK and US output growth in real time. The empirical results suggest that regime changes have a more important role in affecting the measurement of the predictive ability of financial variables for economic activity than the direct use of high frequency data.

Key words: smooth transition, MIDAS, predictive ability, asset prices, economic activity
JEL codes: C22, C53, E44

1 Introduction

Asset prices incorporate expectations of future economic activity because they are set on the basis of expectations about future dividends, interest rates. This forward-looking characteristic suggests that bond and stock returns should be useful predictors of output growth (Harvey, 1988; Stock and Watson, 2003). Empirical evaluations of out-of-sample predictability have found instabilities on the predictive power of asset prices for economic activity (see, Stock and Watson (2003) for a survey). The typical forecasting model of empirical evaluations is an autoregressive distributed lag model employing one measure of asset returns as predictor. The forecasting performance of the model that includes the information of the financial variable is then compared with the forecasting performance of autoregressive models for economic activity. Because measures of economic activity, such as real output and industrial production, are available at quarterly and monthly frequencies, daily financial data are aggregated before the estimation of the forecasting model. The typical forecasting model assumes a linear relation between the financial predictor and the future economic activity; as a consequence, asymmetries in the impact of the predictor on the future of economic activity depending on business cycles phases, monetary policy regimes and market cycles are not taken into account.[1]

This paper improves the forecast model employed to extract the information of financial variables for forecasting economic activity with the inclusion of high frequency data and regime changes. The out-of-sample predictive power of asset returns on future economic activity economic activity is then reassessed using this new forecasting model. The forecasting accuracy of the model with nonlinearities and direct use of high frequency data is compared with the linear specification with aggregated data of previous empirical exercises (Stock and Watson, 2003). This paper also presents strong evidence of instability on the predictive content of financial variables for forecasting US and UK economic activity using real-time data, in agreement with Stock and Watson (2003) and Estrella, Rodrigues and Schich (2003), and Giacomini and Rossi (2006). Of interest is to assess whether the inclusion of regime-switching in the forecasting model is capable of providing more reliable forecasts using financial variables.

The direct inclusion of high frequency data on the forecasting model is obtained by the application of the mixed-data sampling (MIDAS) approach of Ghysels, Santa-Clara and Valkanov (2004). In the context of macroeconomic forecasting, the MIDAS approach has been successfully applied to forecast quarterly macroeconomic series using monthly data (Clements and Galvão, 2008; Clements and Galvao, 2009; Kuzin, Marcellino and Schumacher, 2009). However, Andreou, Ghysels and Kourtellos (2009a) study on the properties of MIDAS regressions suggests that the impact on the slope coefficient from disaggregation should be larger when considering weekly and daily data for forecasting quarterly

[1] Asymmetries were found in the predictive power of the term spread for output growth by Galbraith and Tkacz (2000), Anderson and Vahid (2001) and Galvão (2006).

series.[2]

When using monthly predictors, the MIDAS approach improves forecasts by using current quarter information on the indicators (Clements and Galvão, 2008) and by providing a parsimonious specification when combining a small group of indicators (Clements and Galvao, 2009). In this paper I aim at exploiting improvements in forecast accuracy from disaggregation. The evaluated MIDAS specifications exclude the possibility of forecast accuracy improvements from lag selection and from the use of current quarter information for nowcasting. As a consequence, the objective of this paper differs from Andreou, Ghysels and Kourtellos (2009b) that search for large improvements in forecasting accuracy from the use of high frequency predictors using a large number of candidates. My objective instead is to evaluate the relative role of high frequency data and regime changes on the inference about out-of-sample predictive power of a small group of financial predictors for future economic activity.

In addition to the use of mixed frequency data, the slope of the new forecasting model switches repeatedly over time with a transition function that depends on an observed transition variable. Therefore, I add regimes with smooth transition over time (Teräsvirta, 1998) to the MIDAS regressions (Ghysels et al., 2004). In the context of the empirical application, the assumption of a linear specification may be inadequate and could explain the evidence of instability on the ability of financial variables in predicting economic activity. Indeed if the reported instability is caused by changes in the slope because of monetary policy regimes, business cycle regimes or market trend (bull/bear) regimes, tests for instabilitity in the predictive ability should find no instability when employing smooth transition MIDAS as forecasting model. However, if out-of-sample tests still detect instability even after considering regime-switching, this new evidence suggests that instabilities are more likely caused by structural changes that alter the way expectations about future economic activity affect asset prices than by a functional form mispecification.

The new forecasting model is applied to forecast US and UK output growth when using three types of financial indicators. One of the most popular leading indicators of US growth is the spread between long-term and short-term interest rates (Estrella and Hardouvelis, 1991; Hamilton and Kim, 2002). Stock returns, in contrast, have only marginal content for predicting output growth as concluded by Stock and Watson (2003), although the results of Estrella and Mishkin (1998) suggest some power in predicting recessions at short horizons. Short-term interest rates are not as popular indicators as the spread, but recently, Ang, Piazzesi and Wei (2006) argue that short-rates are a better leading indicator than the spread from 1990 onwards. I evaluate forecasting models with these three types of financial indicators using real-time data on US and UK output growth.

The assessment of the predictive ability of financial variables for economic activity is carried out using the fluctuation test of Giacomini and Rossi (2009) such that instability is taken into account

[2] Ghysels and Wright (2009) apply MIDAS regressions to use the information of daily financial indicators to anticipate forecasters expectations regarding the future of macroeconomic variables.

while testing for equal forecast accuracy. The test of equal forecast accuracy compares the forecast performance of a model with the financial predictor with an autoregressive model. I also apply tests for equal forecast accuracy (Clark and McCracken, 2005a) for different subsamples in the out-of-sample period such that it is possible to identify periods in which financial variables have predictive content for economic activity.

The Smooth Transition MIxed Data Sampling (STMIDAS) regression is described in section 2 in comparison with the previous literature on MIDAS regression and nonlinear models. Section 2 also presents monte carlo evidence on the properties of nonlinear least squares when estimating STMIDAS regressions. Section 3 discusses the design of the empirical exercise to test for out-of-sample predictive ability of a group of financial indicators in forecasting US and UK output growth. Section 3 also presents details of the testing procedures employed and discusses the empirical results. Section 4 presents concluding remarks.

2 Smooth Transition Mixed Data Sampling Regression

2.1 MIDAS Approach

Ghysels et al. (2004) proposed the MIDAS approach, which is aimed at using different sampling frequencies in a regression so that a low frequency variable can be directly regressed on a high frequency variable. In this paper, I apply the MIDAS approach to directly employ financial variables available at high frequencies to forecast quarterly measures of economic activity.

A MIDAS regression that employs x_t for directly forecast y_t at h-steps ahead is:

$$y_{t+h} = \beta_{0,h}^{(m)} + \beta_{1,h}^{(m)} w(L^{1/m}) x_t^{(m)} + \varepsilon_{t+h} \tag{1}$$

where $w(L^{1/m}) = \sum_{j=1}^{K} w(j) L^{j/m}$ is a polynomial in the lag operator $L^{1/m}$ such that $L^{j/m} x_t = x_{t-j/m}$. $\beta_{1,h}^{(m)}$ is the impact of one unit change in $x_t^{(m)}$, which is aggregated using weights $w(j)$, on y_t at h-steps-ahead. The impact is identified if $\sum_{j=1}^{K} w(j) = 1$. For example, when y_t is sampled quarterly and $x_t^{(m)}$ is sampled weekly, but only one quarter of information on $x_t^{(m)}$ is considered, one has the following equation with $K = m = 13$:

$$y_{t+h} = \beta_{0,h}^{(13)} + \beta_{1,h}^{(13)} \left[w(1) x_t^{(13)} + w(2) x_{t-1/13}^{(13)} + \cdots + w(13) x_{t-12/13}^{(13)} \right] + \varepsilon_{t+h}.$$ [3]

A problem with this specification is that the number of parameters in $w(L^{1/m})$ increases with the frequency of the predictor. A solution is the use of a function to approximate the weights. A

[3] Of course, not all quarters have 13 full weeks consequently, $m = 13$ is an approximation. Empirically, the last 13 observations from the date of the end of quarter are employed as information on the current quarter. Similar reasoning applies when setting $m = 65$ for the use of daily data.

weighting function that depends on the vector of parameters $\kappa = (\kappa_1, \kappa_2, ..., \kappa_q)$ is:

$$w(j;\kappa) = \frac{f(j,\kappa)}{\sum_{k=1}^{K} f(j,\kappa)}.$$

Two specifications for $f(j,\kappa)$ are popular in the literature, Ghysels, Santa-Clara and Valkanov (2005), Clements and Galvão (2008), Kuzin et al. (2009), Andreou et al. (2009b) use exponential polynomial functions:

$$f(j,\kappa) = \exp(\kappa_1 j + \kappa_2 j^2 + ... + \kappa_q j^q).$$

And Ghysels, Santa-Clara, Sinko and Valkanov (2007) use a beta function with only two parameters:

$$f(j,\kappa) = \frac{(k)^{\kappa_1 - 1}(1-k)^{\kappa_2 - 1}\Gamma(\kappa_1 + \kappa_2)}{\Gamma(\kappa_1)\Gamma(\kappa_2)}; k = j/(K+1)$$

Ghysels et al. (2007) argue that even with only two parameters, the beta function is flexible enough to accommodate different weighting shapes. For comparison purposes, the exponential function is also employed with only two parameters in the remainder of this paper, that is,

$$f(j,\kappa) = \exp(\kappa_1 j + \kappa_2 j^2).$$

The main advantage of MIDAS regression is to give an opportunity to consider information on x_t that may otherwise be smoothed out after the aggregation process (taking the mean over quarter, for example) to contribute for forecasting y. It also improves efficiency of the estimates in comparison with the use of only equal frequency and may eliminate a bias created by aggregation when the predictor is described by an autoregressive process (Andreou et al., 2009a). Because the aim of this paper is evaluate the effect of disaggregation in forecasting, I assume that $K = m$. The notation can be then simplified by writing the weighted sum of $x_t^{(m)}$, that is, the aggregated high frequency data as

$$x_{t(\kappa,m)}^{(m)} = \sum_{j=1}^{m} w(j,\kappa) L^{j/m} x_t^{(m)}, \tag{2}$$

such that MIDAS regression is simply:

$$y_{t+h} = \beta_{0,h}^{(m)} + \beta_{1,h}^{(m)} x_{t(\kappa,m)}^{(m)} + \varepsilon_{t+h}.$$

The comparison of MIDAS regressions with predictive regressions can be done by noting that the weighting scheme that implies taking the average over the quarter is nested in the MIDAS regression. The imposition of the restrictions that $\kappa = 1$ in the case of beta functions or $\kappa = 0$ in the case of exponential weight functions in the MIDAS regression delivers the following predictive regression when $K = m$:

$$y_{t+h} = \beta_{0,h} + \beta_{1,h} x_t + \varepsilon_{t+h}. \tag{3}$$

This type of regression was employed to measure the ability of the spread to predict output growth (Estrella and Hardouvelis, 1991; Hamilton and Kim, 2002; Ang et al., 2006), of dividend/price ratios for excess returns (see Cochrane (2005), ch. 20 for a survey), and of economic fundamentals for exchange rates (Kilian and Taylor, 2003).

2.2 Smooth Transition MIDAS

Switching regimes are a popular way to model nonlinear dynamics in regressions by using piecewise linear regimes linked by a transition function (Tong, 1990). When the transition between regimes is smooth and depends on the size of an observed transition variable, switching-regime models are called smooth transition regressions (surveyed by Van Dijk, Teräsvirta and Franses (2002)). This type of non-linear approach permits the simple modelling of regime changes in the parameters of MIDAS regressions, as switches between regimes depend on the sign and the size of the weighted high frequency predictor.

The smooth transition MIDAS (STMIDAS) regression is:

$$y_{t+h} = \beta_{0,h}^{(m)} + \beta_{1,h}^{(m)} x_{t(\lambda,m)}^{(m)} \left[1 - G_t(x_{t(\alpha,m)}^{(m)}; \gamma, c)\right] + \beta_{2,h}^{(m)} x_{t(\lambda,m)}^{(m)} \left[G_t(x_{t(\alpha,m)}^{(m)}; \gamma, c)\right] + \varepsilon_{t+h}, \quad (4)$$

where

$$G_t(x_{t(\alpha,m)}^{(m)}; \gamma, c) = \frac{1}{1 + \exp(-(\gamma/\hat{\sigma}_x)(x_{t(\alpha,m)}^{(m)} - c)}.$$

The transition function $G_t(x_{t(\alpha,m)}^{(m)}; \gamma, c)$ is a logistic function that depends on the weighted sum of the explanatory variable in the current quarter. The parameters of the function that weights the transition variable $x_{t(\alpha,m)}^{(m)}$ may differ from the parameters weighting the predictor $x_{t(\lambda,m)}^{(m)}$.

The function $G_t(x_{t(\alpha,m)}^{(m)}; \gamma, c)$ has values between 0 and 1. When the smoothing parameter γ is large, the function is similar to an indicator function that is zero when $x_{t(\alpha,m)}^{(m)} \leq c$ and equal to 1 when $x_{t(\alpha,m)}^{(m)} > c$. Thus, the impact of $x_{t(\lambda,m)}^{(m)}$ in predicting y_{t+h} is $\beta_{1,h}^{(m)}$ when the weighted sum of $x_t^{(m)}$ is small, and $\beta_{2,h}^{(m)}$ when the weighted sum $x_{t(\alpha,m)}^{(m)}$ is large. When γ is small but is not equal to zero, the impact of $x_{t(\lambda,m)}^{(m)}$ in predicting y_{t+h} is a time-variable weighted sum of $\beta_{1,h}^{(m)}$ and $\beta_{2,h}^{(m)}$ depending on the value of $G_t(x_{t(\alpha,m)}^{(m)}; \gamma, c)$.

For checking the restrictions required for identification of all the parameters, note that the STMIDAS regression can be rewritten as:

$$y_{t+h} = \beta_{0,h}^{(m)} + \beta_{1,h}^{(m)} x_{t(\lambda,m)}^{(m)} + (\beta_{2,h}^{(m)} - \beta_{1,h}^{(m)}) x_{t(\lambda,m)}^{(m)} \left[G_t(x_{t(\alpha,m)}^{(m)}; \gamma, c)\right] + \varepsilon_{t+h} \quad (5)$$

The assumption that the weights in $w(j; \lambda)$ sum up to 1 guarantees the identification of the slope parameter $\beta_{1,h}^{(m)}$, as in the case of MIDAS regressions. When applying the same restriction for $w(j; \alpha)$, the identification of γ and c are warranted. Finally, if in addition $\gamma > 0$, $\beta_{2,h}^{(m)}$ is identified. Similar restrictions are imposed to obtain identification of the parameters of the transition function in the flexible smooth transition regression of Medeiros and Veiga (2005). A discussion of the application of nonlinear least squares to estimate STMIDAS regressions is found in Appendix A.

This specification nests other regressions proposed in the literature to model regime switching. When the parameters of the weight functions are such that each lag is equally weighted ($\lambda = \alpha = 1$ for beta functions and $\lambda = \alpha = 0$ for exponential functions), the STMIDAS regression simplifies to a

smooth transition regression with data on the predictor and the dependent variable sampled at the same frequency:

$$y_{t+h} = \beta_{0,h} + \beta_{1,h} x_t \left[1 - G_t(x_t; \gamma, c)\right] + \beta_{2,h} x_t \left[G_t(x_t; \gamma, c)\right] + \varepsilon_{t+h}. \tag{6}$$

An important advantage of the STMIDAS regression is that the delay of the transition variable does not need to be estimated/chosen when the transition variable is the weighted sum of past values. Becker and Osborn (2007) use a specification similar to STMIDAS regressions, but with aggregated regressors ($\lambda = 0$ or $\lambda = 1$ depending on the type of function), to test for nonlinearity.

Another feature of STMIDAS regressions is that they are designed for direct forecasting. Previous applications of non-linear time series models for verifying changes in the dynamic relationship between output growth and the spread (Galbraith and Tkacz, 2000; Anderson and Vahid, 2001; Galvão, 2006) have specified models only for one-step-ahead forecasts. Forecasts for longer horizons were then obtained iteraction with the aid of monte carlo methods to take into account the nonlinearity of the conditional expectation.

Another alternative for modelling switching regimes is to make the regimes dependent on a latent variable that is controlled by a Markov process (Hamilton, 1989). In comparison with this alternative, the STMIDAS has a regime-switching behaviour that depends on the size and sign of an observable variable available at high frequency.

Finally, STMIDAS is able to capture asymmetries in the predictive content of $x_t^{(m)}$ to y_{t+h}. Galbraith and Tkacz (2000) argue that the slope of the yield curve has only predictive content for future output growth when it is small or negative. This kind of asymmetry can be easily captured by a STMIDAS model.

2.2.1 Inclusion of an Autoregressive Term

Specifications (3), (1), (4) and (6) can be extended to allow for autoregressive behaviour. If there is some weak memory in y_t, it is likely that an autoregressive term may improve out-of-sample forecasts as in the case of Ang et al. (2006). The STMIDAS specification with an autoregressive term is:

$$\begin{aligned} y_{t+h} &= \beta_{0,h}^{(m)} + \beta_{1,h}^{(m)} x_{t(\lambda,m)}^{(m)} \left[1 - G_t(x_{t(\alpha,m)}^{(m)}; \gamma, c)\right] + \beta_{2,h}^{(m)} x_{t(\lambda,m)}^{(m)} \left[G_t(x_{t(\alpha,m)}^{(m)}; \gamma, c)\right] \\ &\quad + \rho_h y_t + \varepsilon_{t+h}. \end{aligned} \tag{7}$$

Clements and Galvão (2008) discuss the problem of including autoregressive terms in MIDAS modelling. Because of the polynomial in $L^{1/m}$, the lag structure, with the inclusion of a lag dependent variable, generates a "seasonal" behaviour on the effect of $x_t^{(m)}$ for y_{t+h} with stronger peaks at the end of each quarter. The solution proposed was to use a common factor structure. However, the lag structure of $x_t^{(m)}$ does not go beyond a quarter because $K = m$; as a consequence, one can simply add y_t as an explanatory variable on the left-hand-side of the regressions.

2.2.2 Example

STMIDAS regressions are able to improve the measurement of the predictive content of high frequency predictors for low frequency dependent variables by the direct use of information on high frequency predictors and by allowing for the predictors' impact on the dependent variable to change over time. Suppose, for example, that one wants to use annual stock returns sampled weekly for forecasting annual output growth one year in advance. The first plot in Figure 1 presents annual returns sampled quarterly, and weekly returns that have been aggregated by using weights estimated with a STMIDAS regression. The figure presents data weighed by two schemes: the first weighting scheme ($xw1$) is estimated while measuring the impact of stock returns on output growth ($x_{t(\hat{\lambda},13)}$), and the second one ($xw2$) while identifying changes on the predictor's impact ($x_{t(\hat{\alpha},13)}$).[4] Figure 1 indicates that the stock data aggregated with MIDAS weights differ from their quarterly counterpart, such that the weighting shifts the series towards values either at the beginning or the end of the quarter. This effect is more dramatic when aggregating with the first weighting scheme ($xw1$).

The second plot in Figure 1 shows how the estimates of stock returns' impact ($\beta_{t,4}$) change over time. The plot shows estimates with the STMIDAS regression and a regression with only quarterly data. When the returns are, say, 20% and -20%, the estimated impacts on next year's output growth, conditional on the output growth mean, are .8 p.p. and -.8 p.p.. However, when using STMIDAS estimates, the estimated impacts for the same values of returns are 1.6 p.p. and .4 p.p.. As a consequence, STMIDAS estimates imply that stock returns have a stronger impact on future output growth when the stock market is booming.

2.3 Monte Carlo Evaluation

My aim in this subsection is to use a Monte Carlo simulation for evaluating the properties of nonlinear least squares (NLS) in the estimation of STMIDAS regressions. I also check for biases when the true data generating process has aggregation weights far from equal weighting and a researcher estimates a model with data aggregated by averaging over the quarter.

The data generating process (DGP) for $x_t^{(m)}$ is similar to the empirical estimates when using the spread between 10-year and 3-month interest rates. The process for $x_t^{(m)}$ is an AR(1) with a large autoregressive coefficient (0.98) and a small drift (0.05). The maximum value of m is set to 65 (daily data), so at least mT observations of $x_t^{(m)}$ are generated, assuming that the disturbances are $N(0,1)$.

The DGP of y_t has switching parameters such that $\beta_{1,1}^{(m)}$ is larger than $\beta_{2,1}^{(m)}$, so $x_t^{(m)}$ has a stronger impact on y_{t+1} in the first regime than in the second regime. The values of the β_s are $\beta_{0,1}^{(m)} = 0.5$ and $\beta_{1,1}^{(m)} = 1.5$. The difference between $\beta_{2,1}^{(m)}$ and $\beta_{1,1}^{(m)}$ is $\delta_1^{(m)} = -0.9$. The y_{t+1} data are generated with the described parameters applied to specification (5) assuming that $\varepsilon_{t+1} \sim N(0, .125)$. This parameterization follows Andreou et al. (2009a) that use slope equal to 1.5 as a high sign/noise case

[4] All estimates of this example were obtained while allowing for an autoregressive term in the regressions.

and equal to .6 as a low sign/noise. In the case of STMIDAS processes, the first regime has a high sign/noise and the second regime has low sign/noise. The threshold c is set to 2.3, which is near the unconditional mean of the $x_t^{(m)}$ process.

The weighting functions are set such that the predictor's weights are inverted U-shape, and the transition variable's weights are decreasing. The specific values of the parameters vary with the type of function (beta and exponential) and m. Figure 2 presents the weighting functions of the data generating process for $m = 13$, 65. Preliminary results show that large biases in the estimates of λ and α do not imply large biases in the estimates of β_0, β_1 and β_2 because the biases in λ and α may not imply significant changes in the shape of the weight function, and in particular in lags that have comparatively higher weights. Therefore, in this Monte Carlo exercise, I evaluate how well the NLS estimator approximates the shape of the true weight function, similar to the analysis of Ghysels and Valkanov (2006). I obtain approximation errors by using the sum of the squared error between the estimated and the true weighting functions, normalized by the squared weights of the true function:

$$\frac{\sum_{j=1}^{m}[w(j,\hat{\lambda}) - w(j,\lambda)]^2}{\sum_{j=1}^{m} w(j,\lambda)^2} + \frac{\sum_{j=1}^{m}[w(j,\hat{\alpha}) - w(j,\alpha)]^2}{\sum_{j=1}^{m} w(j,\alpha)^2} \tag{8}$$

Table 1 presents the biases and approximation errors for $T = 100$, 200 and 500. The biases are computed assuming the right specification (m and weighting function) is known. They are computed for DGPs using both the exponential and the beta functions with the weights described in Figure 2 for $m = 13$ and 65. Table 1 also presents the biases when $m = 1$, that is, when the predictor and the dependent variable are sampled at the same frequency and weighting functions are not estimated. In Andreou et al. (2009a), this is called flat MIDAS.

All biases and the approximation errors decrease with T, but they are reasonable small even when $T = 100$, with exception of the bias in γ. The literature on the estimation of smooth transition models (Teräsvirta, 1998) describes inaccuracies in the estimation of γ when the sample is small. An interesting result presented in Table 1 is that biases in the estimation of the parameters of the transition function for a given T are generally smaller using STMIDAS with $m = 13$, 65 than when using a smooth transition regression ($m = 1$). These results indicate that the direct use of high frequency data improves the estimation of the transition function. STMIDAS models with the beta function deliver smaller biases than with the exponential function for all parameters, especially with $m = 65$, although the slopes' biases are in general small.

The main message of the first panel of Table 1 is that NLS estimator is adequate to estimate STMIDAS regression, but also of interest is the impact of using a model with aggregate data when the true relation between x_t and y_{t+1} uses x_t sampled m times more frequently than y_{t+1}. The data generating process in the second panel of Table 1 assumes that $m = 65$ using the same parameters as the first panel. Then I use a model with $m = 1$ and $m = 13$ to obtain the estimates of the

intercept, slopes and parameters of the transition function. Because the high frequency predictor is described by an AR(1) process with large autoregressive coefficient, the results of Andreou et al. (2009a) suggest that the estimates of the slope are biased when the weighting (aggregating) function is far from equal weighting. The DGP weighting functions in Figure 2 are far from equal weighting.

The biases on the parameters of the transition function in the second panel of Table 2 are generally larger than in the first panel, but biases on the slopes are large only with $m = 1$. When using weekly data instead of daily, the impact on the slopes' estimation is small, but there is some impact on the estimates of the parameters of the transition function especially when using the exponential weighting function. Summarising, if the true relation between x_t and y_{t+1} is described by a STMIDAS regression with a large m, the application of smooth transition regression to aggregated data delivers biased estimates of the parameters. In addition, it is possible to use the beta function to approximate the true STMIDAS relation with a m that is five times smaller than the true one, at least for the data generating processes considered.

3 Out-of-sample forecasting of US and UK output growth using financial predictors

Out-of-sample evaluation allows us to use only the time series of data that were available for the practitioner at each forecast origin. For each forecast origin, forecasts models are estimated for horizons $h = 1, 4$, and forecasts are computed using only data available at that time. This forecasting exercise design differs from Stock and Watson's (2003) pseudo-out-of-sample exercise by making use of quarterly vintages of data available in real-time datasets.[5] Quarterly vintages refer to the time series of data available in the month at middle of the quarter. When using US data, the last value in a given quarterly vintage is the preliminary estimate of the real GDP observed in the previous quarter. The UK real-time data has similar structure such that the last observation in a quarterly vintage is an estimate of the data observed in previous quarter revised just once.

At each forecast origin, the next quarter vintage is employed to estimate the forecasting models and compute forecasts. This implies that if the first forecast origin is 1989:Q3, the time series of data of the 1989:Q4 vintage is used to estimate the forecast models. At each time the forecast origin changes in the out-of-sample period, the vintage of data employed in the estimation also changes. As in the case of pseudo-forecasting exercises, forecast errors are computed using data from the last vintage available as actuals (2009:Q1 vintage). This assumes that we are aiming at forecasting the true data, which is revealed with the revision process.

[5] Real-time data on US real output are from the Philadelphia Fed dataset (http://www.philadelphiafed.org/research-and-data/real-time-center/real-time-data/) and on UK real output are from the Bank of England dataset (http://www.bankofengland.co.uk/statistics/gdpdatabase/). UK real-time data is available in monthly vintages which are converted to quarterly by using the vintage of the middle month in the quarter.

In this forecasting exercise, I consider four specifications that use current quarter information of a financial indicator to predict economic activity. All theses specifications also include an autoregressive term, that is, current quarter information of output growth. Each specification is estimated separately for each forecast horizon, that is, direct forecasts are computed.

The first specification is called R, which adds information on the financial indicator after being aggregated by taking averages over each quarter with weekly data. This forecasting model is equivalent to usual predictive regressions and the flat MIDAS of Andreou et al. (2009a).

The second specification is a MIDAS regression using weekly data on the financial indicator, that is, $m = 13$, and the beta function to compute aggregation weights. The monte carlo results in Table 1 suggest that it may be better to use the beta instead of the exponential function when estimating STMIDAS regressions. Preliminary empirical results (not shown) indicate that the qualitative results do not change when employing either the exponential function or daily data. The results in Table 1 can also be used to justify the use of weekly data since the slope coefficients only suffer a small bias when using weekly data instead of daily even if the true model is generated with daily data.

The third specification is called STR, that is, it is a smooth transition regression using aggregated predictor as transition variable. The final specification is a STMIDAS regression (eq. 4) with the same choice of weighting function and predictor's frequency ($m = 13$) as the MIDAS regression. In this empirical exercise, I do not exploit restrictions in the STMIDAS regressions that could reduce the impact of overfitting such as testing whether $\lambda = \alpha$, that is, the predictor and the transition variables have the same weighting function. Preliminary results (not shown) suggest that these restrictions have in general small impact on improving STMIDAS forecasting performance for the majority of cases.

I evaluate the real-time forecasting performance of these four specifications that include financial predictors against an autoregressive model as benchmark. The benchmark model is also estimated for each h using only current quarter aggregated information on output growth as predictor.

The financial predictors are a term spread, a short-rate, and stock prices. The US term spread is measured by the difference between 5-year treasury bond rate and the 3-month bond rate, while the 3-month bond rate is the short-rate. The qualitative results do not change if the long-rate is the 10-year interest rate. Spread with the 10-year interest rate has been considered by Estrella and Hardouvelis (1991), while with the 5-year rate is employed by Ang et al. (2006). UK term spread is measured with a long-term treasury bond rate (Datastream) and the 3-month treasury bond rate. Stock returns have been employed as leading indicators by Zellner, Hong and Min (1991) and Estrella and Mishkin (1998), and they are computed using the annual difference in the price index. For the US, the SP500 is employed, while FTSE100 is employed to measure stock prices for the UK. The US interest rate data are obtained from the FRED database in weekly frequency.[6] The stock prices are obtained daily from Datastream. UK data on financial indicators are obtained

[6] http://research.stlouisfed.org/fred2/.

from Datastream at daily frequency with start date in 1985:Q1 due to availability. Weekly data are obtained using the value of the last day of the week. Note that stock returns are computed as $sr_t^{(13)} = 100(\ln(p_t^{(13)}) - \ln(p_{t-52}^{(13)}))$ with weekly data. Quarterly data are obtained by averaging weekly data of a given quarter.

Following the literature (for example, Estrella and Hardouvelis (1991)), we aim at forecasting $y_{t+h} = (400/h)\,[z_{t+h} - z_t]$, where z_t is the log-level of real GDP.

3.1 The instability of out-of-sample predictive ability

The fluctuation statistic developed by Giacomini and Rossi (2009) tests for equal forecast accuracy even if there is instability in the relative predictive accuracy between two forecasting models. The test is based on a local measure of relative loss function between two forecasting models. In this specific application, if the null hypothesis is rejected, the forecasting model with the predictor is more accurate forecaster than the autoregressive benchmark at least once during the out-of-sample period. An important by-product of the test is the construction of a measure of the local relative forecasting performance that is useful to assess whether the financial variables have predictive power in some specific points in time. Based on the squared loss function, the difference between the benchmark model (AR) and the economic model (EM) loss functions is

$$\Delta L_{h,t} = (y_{t+h} - \hat{y}_{t+h,AR})^2 - (y_{t+h} - \hat{y}_{t+h,EM})^2 \text{ for } t = N+1, ..., P+R$$

where P is the number of observations in the out-of-sample period and N is the number of observations in the in-sample period. When disconsidering the impact of autoregressive terms on sample availability, the total number of observations available is $T = P + N + h$. The relative loss may be computed for subsamples of the out-of-sample period, that is, the local relative loss is:

$$m^{-1} \textstyle\sum_{j=t-m/2}^{t+m/2-1} \Delta L_{h,j} \text{ for } t = N + m/2 + ... + T - m/2 + 1.$$

The fluctuation test statistic standardizes the local relative loss by the variance of the relative loss function computed for the full out-of-sample period, that is,

$$F_{t,h,m} = \hat{\sigma}^{-1} m^{-1/2} \textstyle\sum_{j=t-m/2}^{t+m/2-1} \Delta L_{h,j},$$

where $\hat{\sigma}^2$ is the HAC estimator of σ^2 computed to capture the variance of $\Delta L_{h,t}$ over $t = N + 1, ..., P + N$. Giacomini and Rossi (2009) derived the distribution of this statistic and provide critical values. Their monte carlo exercise on the empirical size and power of the fluctuation test suggests to choose m such that $m/P \approx 0.3$. The one-sided critical value at 5% confidence when $m/P = 0.3$ is 2.77. This means that if $F_{t,h,m}$ cross the critical value during the out-of-sample period, the economic model is more accurate than the autoregressive model at least once. A graphical analysis of the local relative loss can be used to check periods in which the economic model is more accurate. Note that there are no restrictions on the number of times that $F_{t,h,m}$ crosses the critical value: the economic

model may be only more accurate than the autoregressive model in subsamples of the out-of-sample period.

An important assumption to apply this test procedure is that forecasting models are estimated with rolling samples of size N. Previous evaluations of the relative forecasting performance of MIDAS models generally use recursive estimation since efficiency gains from the direct use of disaggregate data may be only available at large samples. In addition, improvements in forecast accuracy from the use of nonlinear models also depend on relatively long time series. In the next part, I also exploit forecasts computed using recursive estimation of the forecasting models, but in order to check instability of predictive performance with the fluctuation test, rolling estimation is employed.

An issue that may affect the properties of fluctuation test is the use of real-time vintages. Clark and McCracken (2009) show that when data revisions reduce measurement errors such that revisions are predictable, the distribution of standard tests of forecasting accuracy is affected. It is less clear if data revisions affect the distribution of tests of forecast accuracy that assume that we are comparing forecasting methods as in the Giacomini and Rossi (2009) approach. Finally, we aim at forecasting final revised data, while the Clark and McCracken (2009) have the actuals extracted also from different vintages of data. Rossi and Sekhposyan (2009) have applied the fluctuation test when using real-time data in the computation of forecasts and final data on the computation of forecasting errors.

Figures 3 and 4 present the local relative squared loss between the four specifications considered in this empirical exercise and the autoregressive model for each one of the predictors when forecasting US and UK output growth at $h = 1$ and $h = 4$. The figures also indicate the one-sided 5% critical value of the fluctuation test that depends on m/P. Figure 3 confirms previous empirical results in the literature: the spread looses predictive power during the 90's (Giacomini and Rossi, 2006), the short-rate has stronger predictive content than the spread up to 1999 (Ang et al., 2006), and stock returns have only predictive content for short horizons (Estrella and Mishkin, 1998). Figure 3 also provides a new empirical result: the spread is back as predictor of US output growth (confirming the enduring predictive power of the spread for recessions argued by Rudebusch and Williams (2009)).

The inference on the predictive power of the spread at one-step-ahead horizon changes with the inclusion of high frequency data and regimes changes (STMIDAS): there is some evidence of predictive ability in the middle of 90's in contrast with models with either aggregated data or constant parameters. The STMIDAS also significantly improves forecasts in comparison with typical forecasting models when using stock returns as predictors in the beginning of 90's. In contrast, there is no evidence that regime changes improve forecasts obtained with the short-rate.

The results for forecasting UK growth (Figure 4) also share the extensive evidence of changes in predictive ability. Figure 4 suggests that the inclusion of high frequency data has almost no effect on the accuracy of forecasts, while regime changes affect negatively the forecast accuracy. An exception is found on the use of the short-rate to forecast next year output growth: models with regime changes

suggest predictive content in the 00's, while models with constant coefficients provide no evidence of predictive content.

3.2 Tests of out-of-sample predictive ability

In addition to the use of fluctuation tests applied to forecasts computed using rolling samples, I also compute forecasts using recursive samples. When using recursive samples to estimate competing nested forecast models, the distribution of tests of equal forecast accuracy are non-standard (Clark and McCraken, 2001) The fluctuation test requires the use of tests of equal forecast accuracy with normal distribution. Therefore, following the approach of Stock and Watson (2008) to identify periods in which the Phillips curve has predictive content for inflation, I divide the out-of-sample period into three sub-samples for US data and two for UK data. Previous section results suggest that financial variables should have predictive power for output growth in at least one of the subperiods for each one of the indicators and horizons, except for stock returns as predictors of US output growth at $h = 4$. Recall that the use of full out-of-sample measures of relative predictive ability is not recommend since structural breaks and instability have a negative impact on the power of the predictive ability test (Clark and McCracken, 2005b).

As discussed previously, an increasing sample size may have a positive impact on the forecast accuracy of more complicated specifications (MIDAS, STMIDAS and STR), but it requires a careful use of tests of equal forecast accuracy since the distribution of standard test statistics is data dependent. We use the MSE-F test statistic of Clark and McCracken (2005a) with bootstrapped critical values to assess the null of no predictive ability of a financial indicator for output growth at a specific forecast horizon for each economic forecasting model. Clark and McCracken (2005a) monte carlo exercise indicates that the MSE-F statistic with bootstrapped critical values delivers a test with good size and power properties when forecasting models are nested.

Clark and McCracken (2009) show the impact of data revisions on the aymptotic distribution of the MSE-F statistic when revisions are predictable and the forecasting aim is output growth after a small number of revisions. Even though the theory developed by Clark and McCracken (2009) suggests a more adequate test procedure when forecasting in real time, the use of MSE-F statistic with bootstrapped p-values performs well in a monte carlo exercise because the size of the revisions has to be really large with respect to variance of the underlying true process in order to real-time data have large effects on the inference of predictive ability. In addition, revisions to output growth are generally hard to predict, and the forecasting aim is final revised data. Summing up, I use MSE-F statistic with bootstrapped p-values, and data from the final vintage to compute bootstrapped p-values. Details of the boostrapped procedure and computation of the statistic are described in the appendix. The split-sample structure is kept when computing the empirical distribution of the test statistics by bootstrap.

Tables 2 and 3 also present results of tests of equal predictive ability using rolling estimates of

the forecasting model as in the previous section. The t-statistic for the test is computed separately for each subsample and critical values are taken from the normal distribution (Giacomini and White, 2006).

Table 2 indicates that the forecasting model specification has an impact on the inference on the predictive ability of stock returns and spread at $h = 4$. In contrast with the results in Figure 3, recursive forecasts from STR and STMIDAS models suggest that stock returns have predictive ability for US output growth at least in the 95-01 period. There is evidence that the spread has predictive power for output growth in the 01-07 period when using STR and STMIDAS as forecasting model and rolling estimates. The results of Galvão (2006) pointed for both structural breaks and nonlinearities when using the spread as predictor of output growth. These results confirm previous claim since the use of rolling windows may smooth the effect of breaks on models' coefficients, and STR and STMIDAS forecasts improve with rolling estimation.

Both Tables 2 and 3 suggest that significant improvements in forecasting accuracy are more likely to arise from the inclusion of asymmetric dynamics and nonlinearities than from the use of high frequency data on the predictor. The large effect of regime changes on forecast performance may also significantly worsen forecasts as it is the case when using the spread and stock returns for forecasting UK growth. In general, the disaggregation of the predictors has a small effect on forecasting accuracy, while the inclusion of regime changes may affect our inference on the predictive content of a specific financial indicator.

The common wisdom associates recent downturns (2001, 2008) with stock market crashes. Results in Tables 2 and 3 suggest that stock returns can predict UK and US economic activity during the first boom/crash period (96-02:Q2) but not in the second. However, the evidence of episodic predictive ability may suggest that an extension of the estimation period beyond 2007:Q2 may change these results against the predictive power of stock returns. In the more recent period, the spread is the financial variable in the dataset that has predictive content for next year US growth while the short-rate is the variable for UK growth. In both cases, regime-switching in the forecasting model improves one-year-ahead forecasts.

4 Concluding Remarks

When assessing the predictive content of financial variables for economic activity, researchers normally aggregated data available at higher frequency before estimating a forecasting model that takes the relation between the financial variable and the dependent variable as linear. This paper proposes a forecasting model that relaxes both these assumptions by directly using high frequency data while taking into account regime changes in the slope parameters.

A monte carlo exercise shows that the direct use of high frequency data reduces the small sample bias of parameters of the transition function in comparison with equal frequency models. It also

provides evidence of slope biases in large samples when estimating a model with equal weighting aggregation while the true model has a different aggregation pattern.

The forecasting performance of the new model is compared with traditional distributed lag models, smooth transition regressions, and MIDAS regressions. The empirical results for forecasting US and UK output growth using three popular financial indicators - term spreads, short-rates and stock returns - suggest that regime changes have a more important role in affecting the measurement of the predictive ability of financial variables for economic activity than the direct use of high frequency data.

A Estimation of STMIDAS

Recall the STMIDAS regression can be written as:

$$y_{t+h} = \beta_{0,h}^{(m)} + \beta_{1,h}^{(m)} x_{t(\lambda,m)}^{(m)} + (\beta_{2,h}^{(m)} - \beta_{1,h}^{(m)}) x_{t(\lambda,m)}^{(m)} \left[G_t(x_{t(\alpha,m)}^{(m)}; \gamma, c) \right] + \varepsilon_{t+h}$$

The parameters of the STMIDAS are collected in the vector $\theta_h = \left[\beta_{0,h}^{(m)}, \beta_{1,h}^{(m)}, \beta_{2,h}^{(m)}, \lambda, \alpha, \gamma, c \right]'$. The nonlinear regression is written as:

$$y_{t+h} = m(x_t^{(m)}, \theta_h) + \varepsilon_{t+h}.$$

Assuming that the restrictions required for identification described in section 2.2. are imposed, the parameters of this regression can be consistently estimated by minimizing the sum of squared residuals:

$$Q_T(\theta_h) = T^{-1} \sum_{t=1}^{T} (y_{t+h} - m(x_t^{(m)}, \theta_h))^2,$$

because the function $m(x_t^{(m)}, \theta_h)$ satisfies the identification and regularity conditions described in Hayashi (2000), ch. 7, proposition 7.4. Under additional conditions regarding the differentiability of $m(x_t^{(m)}, \theta_h)$ and the behaviour of the Hessian $h\left(\hat{\theta}\right)$, the NLS estimator $\hat{\theta}_h$ is asymptotically normal, so that $\sqrt{n}(\hat{\theta}_h - \theta_h) \longrightarrow^d N(0, h\left(\theta_h\right)^{-1} \Sigma h\left(\theta_h\right)^{-1})$.

The computation of estimates can be simplified by concentrating the sum of the squared residuals function with respect to λ, α, γ, c, so that the parameters in the vector $\beta_h = \left[\begin{array}{ccc} \beta_{0,h}^{(m)} & \beta_{1,h}^{(m)} & \beta_{2,h}^{(m)} \end{array} \right]'$ can be computed with the least squares formula:

$$\hat{\beta}_h = \left(\sum_{t=1}^{T} x_{t(\hat{\lambda},\hat{\alpha},\hat{\gamma},\hat{c})}^{(m)} x_{t(\hat{\lambda},\hat{\alpha},\hat{\gamma},\hat{c})}^{(m)\prime} \right)^{-1} \sum_{t=1}^{T} x_{t(\hat{\lambda},\hat{\alpha},\hat{\gamma},\hat{c})}^{(m)} y_t.$$

In practice, STMIDAS regressions use the estimates of MIDAS regressions as initial values for λ_1 and λ_2. Initial values for κ in the MIDAS regression (eq. 1) are obtained by a search over a grid of values for κ_1, κ_2 such that they imply different shapes for the weight function $w(j, \kappa)$. The initial values for γ and c in the STMIDAS regressions are also computed in joint grid search for initial values of α_1

and α_2 (parameters of the weighting function of the transition variable). The optimisation procedure (with BFGS) imposes constraints in γ such that it is not too large or negative and in c such that it is not smaller (larger) than the 5% (95%) quantile of the empirical distribution of the weight high frequency predictor $x^{(m)}_{t(\alpha,m)}$.

Nonlinear least squares are also employed to estimate the MIDAS regression (equation 1) and the smooth transition regression (equation 6).

B Out-of-sample Test of Equal Forecasting Accuracy

The following statistic, proposed by Clark and McCracken (2005a), is used for comparing the out-of-sample forecasting accuracy of an economic model nested to an AR(1) benchmark:

$$MSE\text{-}F_h = P\left(\frac{MSE_{h,AR} - MSE_{h,M}}{MSE_{h,M}}\right)$$

where $\text{MSE}_{h,M}$ is the mean squared forecast error of the model M at h-steps ahead, and $MSE_{h,AR}$ is the same measure computed with an autoregressive model.

The p-value of this test statistic is computed by a bootstrap, designed similarly to Clark and McCracken (2005a). In the first step, the estimates of an AR(2) for $(z_t - z_{t-1})$ (where z_t is log-level real GDP from the final vintage) are used for simulating a time series of size T ($T = N+R+h$) of y_{t+h} (where $y_{t+h} = (400/h)\,[z_{t+h} - z_t]$) by bootstrapping the residuals of the AR(2) model. Estimates of an AR(5) computed using high frequency data on x_t are used for simulating a time series of size $T * m$ of $x^{(m)}_t$. In the second step, the sample is divided to mimic the in-sample and out-of-sample sizes employed in the computation of the statistic (N, P_1, P_2, P_3 where $P_i/P = 1/3$). Then, the AR and the economic model (using the specification of the empirical exercise) are estimated recursively using the artificial data generated in the previous step. Simulated data on $x^{(m)}_t$ are aggregated if necessary for the estimation of the forecasting model at each forecast origin in the artificial out-of-sample period and for each forecast horizon. At the end of the second step, the $MSE\text{-}F_h$ statistic is computed with the artificial data generated in step 1. In the third step, empirical distributions of the statistics are used for computing the critical values of the test with the MSE-F_h statistic for each one of the economic models considered.

References

Anderson, H. M. and Vahid, F. (2001). Predicting the probability of a recession with nonlinear autoregressive leading indicator models, *Macroeconomic Dynamics* **5**: 482–505.

Andreou, E., Ghysels, E. and Kourtellos, A. (2009a). Regression models with mixed sampling frequencies, *Journal of Econometrics, forthcoming* .

Andreou, E., Ghysels, E. and Kourtellos, A. (2009b). Should macroeconomic forecasters look at daily financial data?, *University of North Carolina (mimeo)* .

Ang, A., Piazzesi, M. and Wei, M. (2006). What does the yield curve tell us about GDP growth?, *Journal of Econometrics* **131**: 359–403.

Becker, R. and Osborn, D. R. (2007). Weighted smooth transition regressions, *University of Manchester, mimeo* .

Clark, T. E. and McCracken, M. W. (2005a). Evaluating direct multistep forecasts, *Econometric Reviews* **24**: 369–404.

Clark, T. E. and McCracken, M. W. (2005b). The power of tests of predictive ability in the presence of structural breaks, *Journal of Econometrics* **124**: 1–31.

Clark, T. E. and McCracken, M. W. (2009). Tests of equal predictive ability with real-time data, *Journal of Business and Economic Statistics* .

Clark, T. E. and McCraken, M. W. (2001). Tests of equal forecast accuracy and encompassing for nested models, *Journal of Econometrics* **105**: 85–110.

Clements, M. P. and Galvão, A. B. (2008). Macroeconomic forecasting with mixed frequency data: Forecasting output growth in the United States, *Journal of Business and Economic Statistics* **26**: 546–554.

Clements, M. P. and Galvao, A. B. (2009). Forecasting US output growth using leading indicators: An appraisal using MIDAS models, *Journal of Applied Econometrics* **24**: 1187–1206.

Cochrane, J. H. (2005). *Asset Pricing*, Princeton University Press, Princeton.

Estrella, A. and Hardouvelis, G. A. (1991). The term structure as a predictor of real economic activity, *Journal of Finance* **46**: 555–76.

Estrella, A. and Mishkin, F. S. (1998). Predicting US recessions: Financial variables as leading indicators, *Review of Economics and Statistics* **80**: 45–61.

Estrella, A., Rodrigues, A. P. and Schich, S. (2003). How stable is the predictive power of the yield curve? Evidence from Germany and the United States, *Review of Economics and Statistics* **85**: 629–44.

Galbraith, J. W. and Tkacz, G. (2000). Testing for asymmetry in the link between the yield spread and output in the G-7 countries, *Journal of International Money and Finance* **19**: 657–672.

Galvão, A. B. C. (2006). Structural break threshold VARs for predicting the probability of US recessions using the spread, *Journal of Applied Econometrics* **21**: 463–87.

Ghysels, E., Santa-Clara, P., Sinko, A. and Valkanov, R. (2007). MIDAS regressions: Further results and new directions, *Econometric Reviews* **26**: 53–90.

Ghysels, E., Santa-Clara, P. and Valkanov, R. (2004). The MIDAS touch: Mixed data sampling regressions, *University of North Carolina, mimeo* . (www.unc.edu/ eghysels/).

Ghysels, E., Santa-Clara, P. and Valkanov, R. (2005). There is a risk-return trade-off after all, *Journal of Financial Economics* **76**: 509–48.

Ghysels, E. and Valkanov, R. (2006). Linear time series processes with mixed data sampling and MIDAS regression models, *University of North Carolina, mimeo* .

Ghysels, E. and Wright, J. H. (2009). Forecasting professional forecasters, *Journal of Business and Economic Statistics* **27**: 504–516.

Giacomini, R. and Rossi, B. (2006). How stable is the forecasting performance of the yield curve for output growth?, *Oxford bulletin of economics and statistics* **68**: 783–795.

Giacomini, R. and Rossi, B. (2009). Forecast comparisons in unstable enviroments., *Journal of Applied Econometrics, forthcoming* .

Giacomini, R. and White, H. (2006). Tests of conditional predictive ability, *Econometrica* **74**: 1545–1578.

Hamilton, J. D. (1989). A new approach to the economic analysis of nonstationary time series and the business cycle, *Econometrica* **57**: 357–84.

Hamilton, J. D. and Kim, D. H. (2002). A re-examination of the predictability of economic activity using the yield spread, *Journal of Money, Credit and Banking* **34**: 340–60.

Harvey, C. P. (1988). Forecasts of economic growth from the bond and stock markets, *Financial Analysts Journal* **45**: 38–45.

Hayashi, F. (2000). *Econometrics*, Princeton University Press, Princeton.

Kilian, L. and Taylor, M. P. (2003). Why is so difficult to beat the random walk forecast of exchange rates?, *Journal of International Economics* **60**: 85–107.

Kuzin, V., Marcellino, M. and Schumacher, C. (2009). Pooling versus model selection for nowcasting with many predictors: An application to German GDP, *European University Institute, mimeo* .

Medeiros, M. and Veiga, A. (2005). A flexible coefficient smooth transition time series model, *IEEE Transactions on Neural Networks* **16**: 97–113.

Rossi, B. and Sekhposyan, T. (2009). Has economic models' forecasting performance for US output gorwth and inflation changed over time, and when?, *Duke University (mimeo)* .

Rudebusch, G. and Williams, J. (2009). Forecasting recessions: The puzzle of the enduring power of the yield curve, *Journal of Business and Economic Statistics, forthcoming* .

Stock, J. H. and Watson, M. W. (2003). Forecasting output and inflation: The role of asset prices, *Journal of Economic Literature* **41**: 788–829.

Stock, J. H. and Watson, M. W. (2008). Phillips curve inflation forecasts, *Princeton University (mimeo)* .

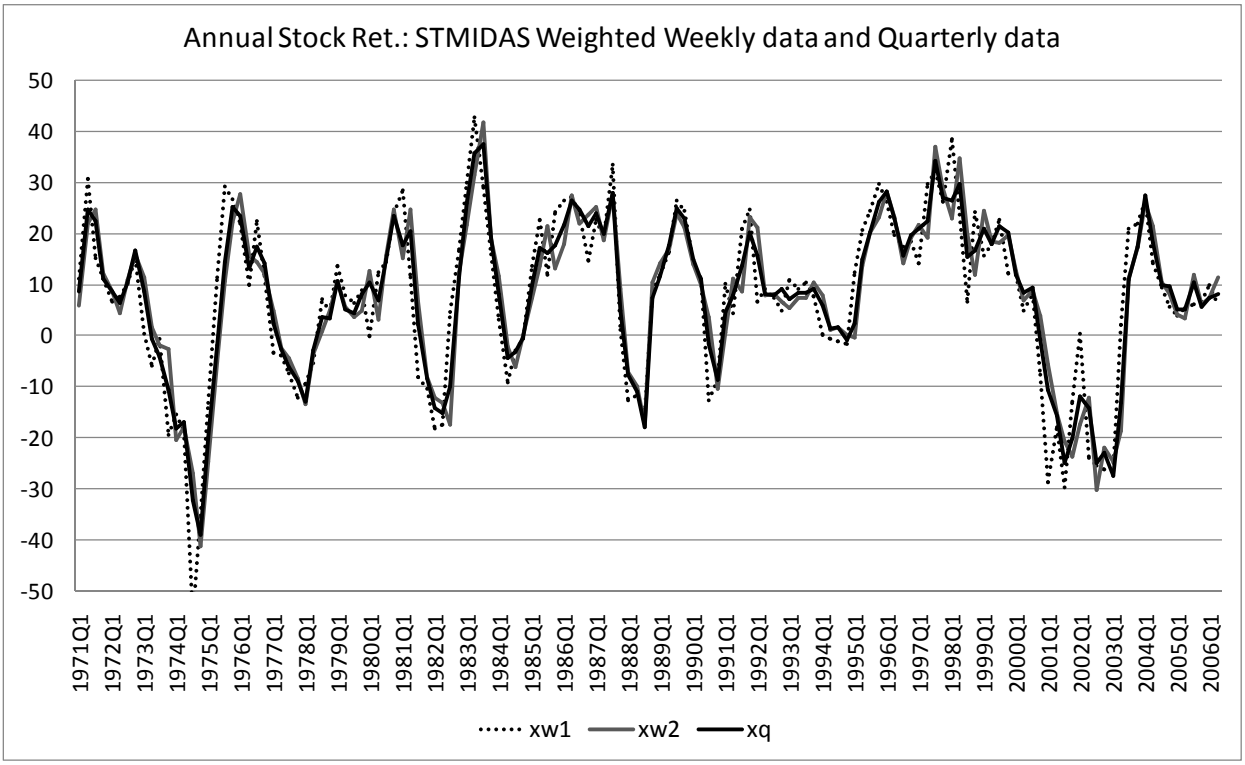
Teräsvirta, T. (1998). Modeling economic relationships with smooth transition regressions, *in* A. Ullah and E. David (eds), *Handbook of Applied Economic Statistics*, Marcel Dekker, New York, pp. 507–52.

Tong, H. (1990). *Non-Linear Time Series: A Dynamical System Approach*, Oxford University Press, Oxford.

Van Dijk, D., Teräsvirta, T. and Franses, P. H. (2002). Smooth transition autoregressive models - A survey of recent developments, *Econometric Reviews* **21**: 1–47.

Zellner, A., Hong, C. and Min, C.-K. (1991). Forecasting turning points in international output growth rates using bayesian exponentially weighted autoregression, time-varying parameter, and pooling techniques, *Journal of Econometrics* **49**: 275–304.

Figure 1: STMIDAS regressions: stock returns as predictor of next year output growth.



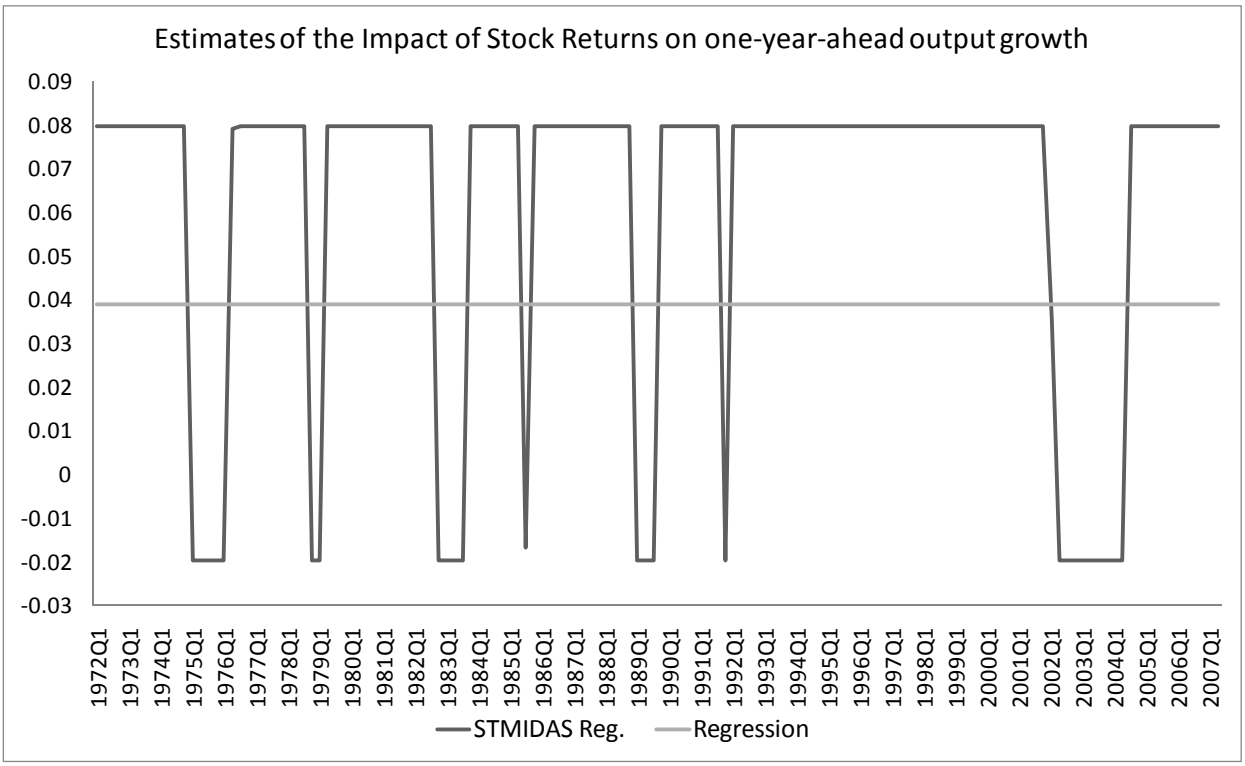


Figure 2: Weighting Functions of the Data Generating Process

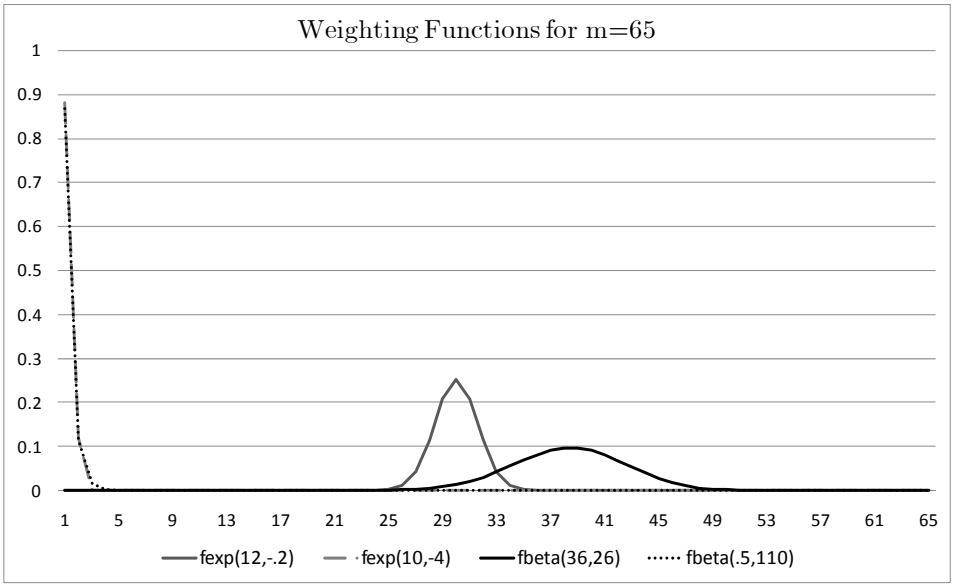


Figure 3: Fluctuation test on the Predictive Ability of Financial Variables for US output growth (forecasting models estimated with rolling windows of 79 observations and test statistic computed with rolling windows of 24 observation; dates are the forecast origin in the middle of 24 obs. window).

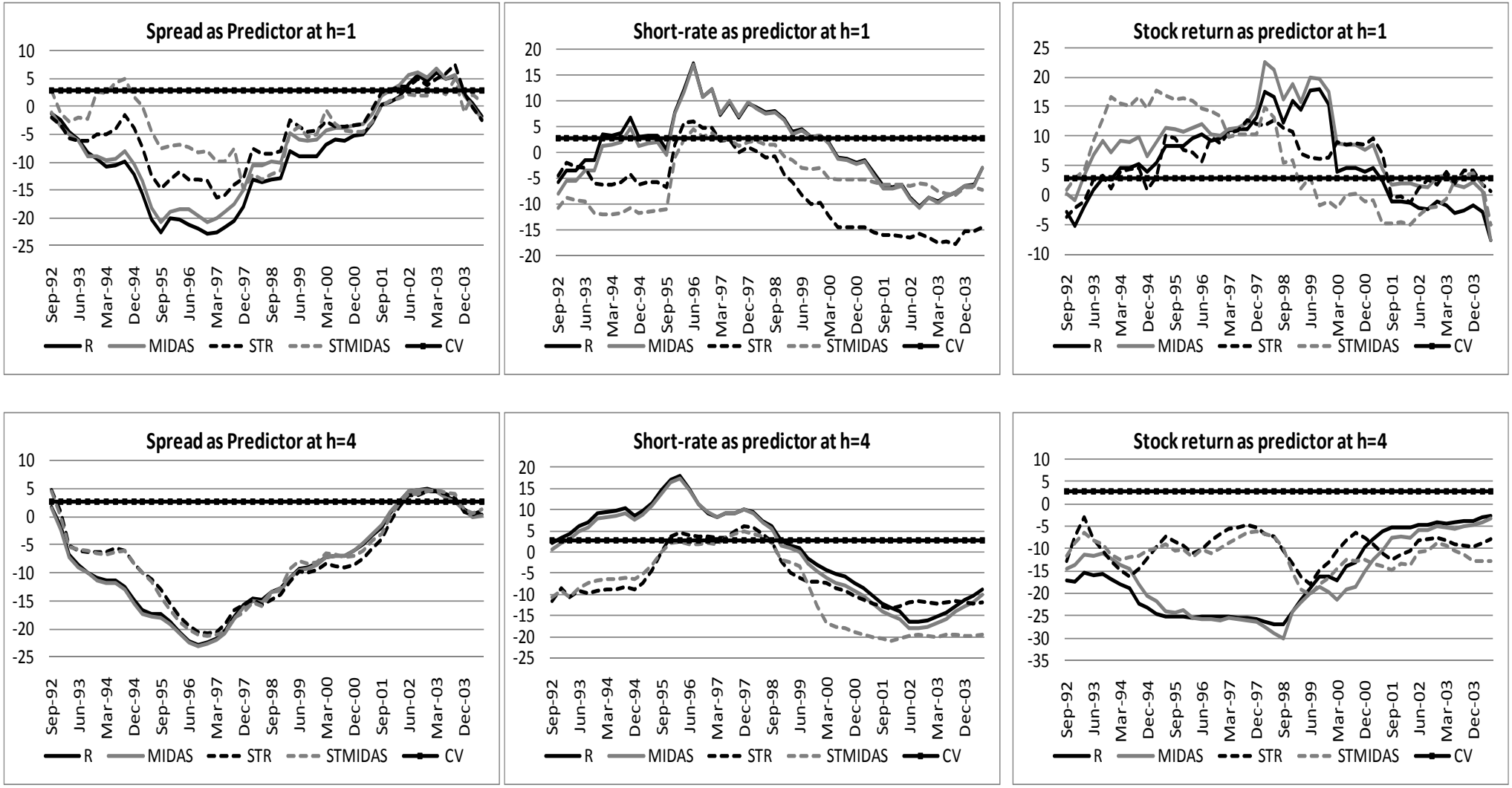


Figure 4: Fluctuation test on the Predictive Ability of Financial Variables for UK output growth (forecasting models estimated with rolling windows of 42 observations and test statistic computed with rolling windows of 24 observation; dates are the forecast origin in the middle of 24 obs. window).

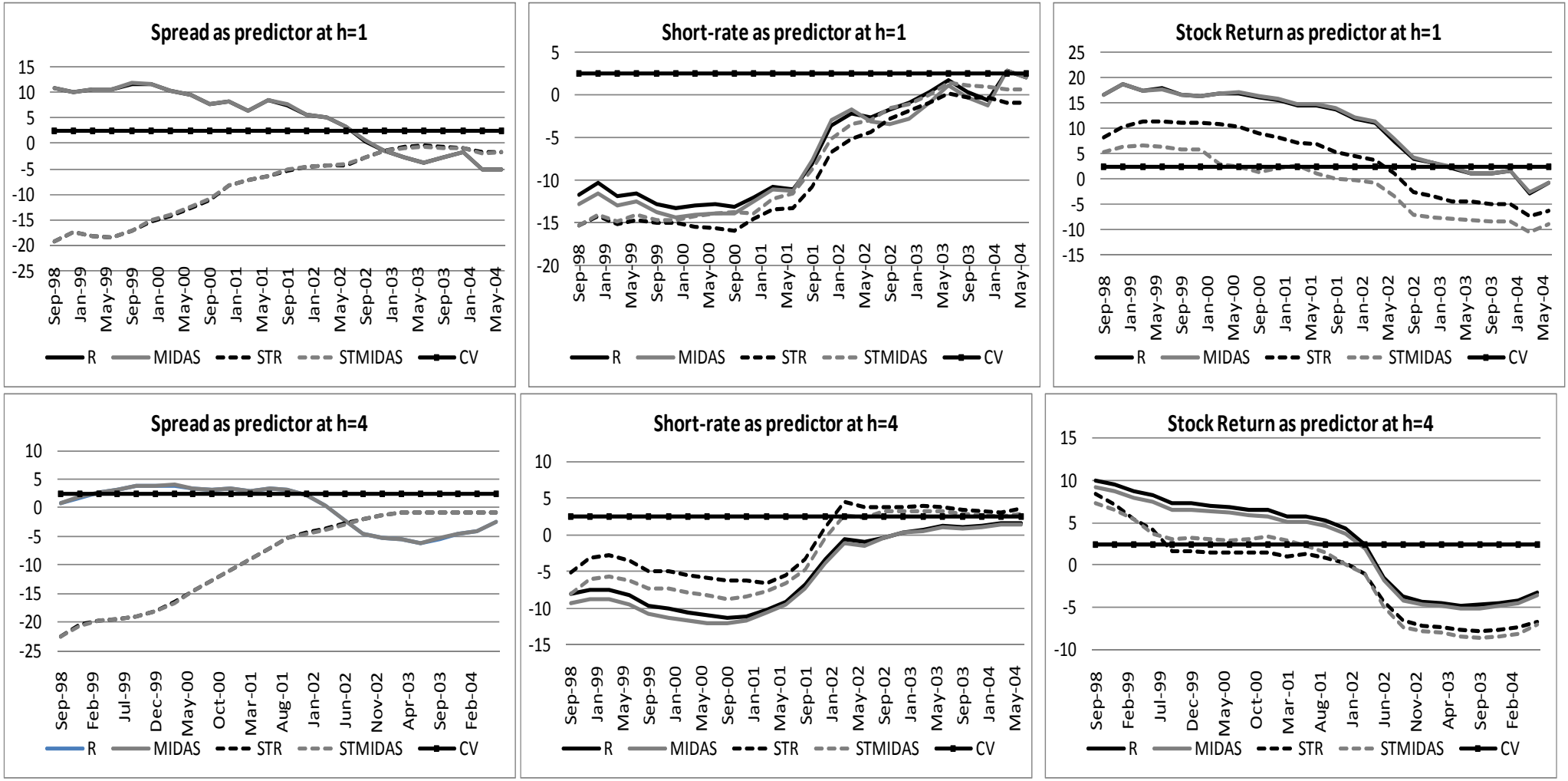


Table 1: Biases in the NLS estimation of STMIDAS regressions

T	weighting function	$\beta_0 = .5$	$\beta_1 = 1.5$	$\beta_1 - \beta_2 = -.9$	$\gamma = 6$	r =2.3	Approx. Error
	m=1						
100		-0.003	0.000	-0.001	-0.962	0.004	
200		-0.002	0.000	0.000	-1.024	0.004	
500		-0.001	0.000	0.001	-1.003	0.007	
	m=13						
100	Exponential	0.001	-0.008	0.007	-0.066	0.005	0.008
	Beta	0.001	0.000	-0.001	-0.066	0.009	0.003
200	Exponential	0.002	-0.005	0.005	-0.102	-0.001	0.005
	Beta	0.000	0.000	-0.001	-0.095	0.005	0.002
500	Exponential	0.000	-0.002	0.002	-0.105	-0.003	0.002
	Beta	0.000	0.000	0.000	-0.127	0.000	0.001
	m=65						
100	Exponential	-0.002	-0.003	0.002	0.060	0.005	0.021
	Beta	-0.001	0.000	0.000	0.067	0.006	0.010
200	Exponential	0.000	-0.001	0.000	-0.146	-0.003	0.015
	Beta	0.000	0.000	0.000	0.007	0.003	0.005
500	Exponential	0.002	0.001	-0.003	-0.196	-0.006	0.006
	Beta	0.000	0.000	0.000	-0.004	0.002	0.003
Data generated with m=65, but STMIDAS estimated with ...							
m=1							
100		-0.115	0.207	-0.139	103.628	0.241	
200		-0.148	0.222	-0.188	33.677	0.135	
500		-0.166	0.203	-0.178	-2.855	0.083	
m=13							
100	Exponential	0.006	0.021	-0.021	0.321	0.109	
	Beta	0.011	0.001	-0.002	0.352	0.081	
200	Exponential	0.003	0.022	-0.022	-0.995	0.122	
	Beta	0.014	0.002	-0.005	-1.009	0.083	
500	Exponential	0.006	0.023	-0.023	-1.217	0.122	
	Beta	0.014	0.003	-0.007	-1.197	0.080	

Note: The approximation error is defined in equation (8) in the text. The weighting functions of the data generating processes are represented in Figure 2. Data generating processes are discussed in detail in section 2.3. Number of replications: 1000.

Table 2: Forecasting US output growth with Financial Variables

Forecasting Origin	1989:Q3 1995:Q2	1995:Q3 2001:Q2	2001:Q3 2007:Q2	1989:Q3 1995:Q2	1995:Q3 2001:Q2	2001:Q3 2007:Q2
Estimation:	Recursive			Rolling		
			h=1			
AR	2.104	2.266	1.815	2.149	2.290	1.857
			with spread			
R	1.066	1.122	1.144	1.007	1.121	1.026
MIDAS	1.057	1.087	1.190	1.003	1.094	1.034
STR	1.076	1.083	1.159	1.013	1.071	1.033
STMIDAS	1.013	1.073	1.185	0.965***	1.101	0.988
			with short-rate			
R	1.082	0.990	1.317	1.046	0.945***	1.028
MIDAS	1.100	1.002	1.373	1.068	0.940***	1.032
STR	1.167	1.003	1.190	1.066	1.011	1.236
STMIDAS	1.249	1.053	1.401	1.236	0.963***	1.207
			with stock return			
R	1.003	0.903***	1.047	1.014	0.928***	1.043
MIDAS	0.979	0.863***	1.107	1.001	0.890***	1.048
STR	1.034	0.896***	0.965*	1.022	0.937***	0.994
STMIDAS	1.024	0.886***	1.222	0.997	0.925	1.025
			h=4			
AR	1.513	1.670	0.984	1.547	1.752	1.018
			with spread			
R	0.978	1.239	1.225	0.915***	1.246	0.979
MIDAS	0.981	1.252	1.246	0.922***	1.253	0.989
STR	0.884*	1.228	1.263	0.851***	1.237	0.923***
STMIDAS	0.874**	1.241	1.247	0.850***	1.242	0.904***
			with short-rate			
R	0.996	0.963	1.647	0.994	0.935***	1.197
MIDAS	1.006	0.966	1.733	1.011	0.932***	1.249
STR	1.492	0.901*	2.037	1.329	0.901***	1.585
STMIDAS	1.419	0.952	2.132	1.390	0.888***	2.141
			with stock return			
R	1.050	1.043	0.999	1.055	1.081	1.022
MIDAS	1.075	1.084	1.032	1.074	1.137	1.037
STR	1.233	0.891**	1.004	1.151	1.083	1.237
STMIDAS	1.206	0.897**	0.954	1.190	1.113	1.471

Entries for the "AR" row are root mean squared forecast errors computed using data from 2009:Q1 vintage as actuals. The entries for R, MIDAS, STR and STMIDAS are ratios to the AR RMSFE. *, **, *** are 1%, 5% and 10% rejection of the null that the model with the predictor is more accurate in forecasting output growth than the autoregressive model. For recursive estimation, we use MSE-F statistic with critical values computed by bootstrap. For rolling estimation, we use the Giacomini and White(2006) t-statistic with critical values from the normal distribution. N=79 (data from 1970). Each subsample of the out-of-sample period has 24 observations.

Table 3: Forecasting UK output growth with Financial Variables

Forecasting Origin	1995:Q3 2001:Q2	2001:Q3 2007:Q2	1995:Q3 2001:Q2	2001:Q3 2007:Q2
Estimation:	Recursive		Rolling	
	h=1			
AR	1.409	1.077	1.530	1.027
	with spread			
R	1.092	1.046	0.852***	1.133
MIDAS	1.091	1.045	0.852***	1.133
STR	1.197	1.394	1.407	1.097
STMIDAS	1.204	1.403	1.411	1.101
	with short-rate			
R	1.014	0.952**	1.075	0.968***
MIDAS	1.024	0.947**	1.086	0.968***
STR	0.974*	0.976*	1.287	1.046
STMIDAS	0.975	1.003	1.300	0.961***
	with stock return			
R	0.787***	0.996	0.725***	1.003
MIDAS	0.785***	1.007	0.716***	0.996
STR	0.871***	1.077	0.751***	1.232
STMIDAS	1.027	0.978	0.838***	1.363
	h=4			
AR	1.054	0.620	1.319	0.587
	with spread			
R	1.609	1.252	0.977	1.229
MIDAS	1.608	1.252	0.976	1.228
STR	2.417	2.569	2.297	1.317
STMIDAS	2.314	2.572	2.288	1.322
	with short-rate			
R	1.093	0.953	1.111	0.873***
MIDAS	1.099	0.932*	1.133	0.877***
STR	1.000	1.127	1.057	0.756***
STMIDAS	0.976	1.166	1.101	0.773***
	with stock return			
R	0.719***	1.308	0.585***	1.280
MIDAS	0.714***	1.311	0.596***	1.324
STR	0.696***	2.082	0.571***	1.804
STMIDAS	0.717***	2.011	0.678***	1.727

See notes of Table 2. N=42 (data from 1985).