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Forecasting banks' stock realized volatilities with mixed-frequency data

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Abstract

This research compares the Mixed Data Sampling (MIDAS) approach, where the regressand is measured on a lower frequency than the regressor, with an AR(1) model where both of the variables are measured at the same frequency. In the first half of the research some of the results from Clements and Galvão [2009] are replicated. In their paper the researchers forecast quarterly output growth using 10 or 5 macroeconomic leading indicators. For the second part the models are used to make 1- and 2-step ahead forecast of the weekly realized volatility of four banks' stocks for two different time periods. Two variants of the Multivariate MIDAS (M-MIDAS) models are considered: with the Almon Lag polynomial or the Step function as the weighting scheme. Furthermore, a calm and a turmoil period for forecasting are considered. For the replicate part I found that the M-MIDAS is more accurate in all cases compared to the AR(1) model except for the replicate part when 5 leading indicators are used. In the second part the M-MIDAS model was more accurate in most of the cases for the calm period, for the turmoil period there was no difference in accuracy compared to the AR(1) model.

1 Introduction

Many time series regressions need data sampled at the same frequency. For example, in macroeconomics the DGP is measured at a quarterly scale and this has led to the fact that many macroeconomic models are now specified on quarterly data.

In this research the focus lies on working with the mixed data sampling (MIDAS) approach as described in Ghysels et al. [2004]. This approach allows you to work with a dependent variable which is measured at a different frequency compared to the independent variable. The regressand however is sampled at the lower frequency.

In the first part of the research I will replicate some of the results from Clements and Galvão [2009] where they used leading indicators to predict output growth at horizons up to 1 year using a MIDAS model and an autoregressive (AR) model. To be clear, I am going to replicate table II from their paper and especially the results in the AR and Multivariate MIDAS (M-MIDAS) columns.

After that I use daily measures of realized volatility for four large banks, namely Deutsche Bank (DEU), JPMorgan Chase & Co (JPM), HSBC Holdings (HSBC) and Mitsubishi UFJ Financial Group (MUFG) to perform 1- and 2-step ahead forecasts of the weekly realized volatility in two different periods. The reason that I chose for these particular stocks was that these four banks are, at this moment, among of the largest banks in the world. Moreover the stocks of these banks are listed on four different financial markets which causes some diversification within this research.

The use of two different periods is particularly interesting since one of the periods seems to be more turmoil than the other, due to the presence of the financial crisis in 2008.

The model I use to make the forecasts in the second part of the paper is the M-MIDAS model using either the Almon Lag or the step weighting function. The results from these models are then compared to the results of the benchmark model: AR(1) by considering the Root Mean Squared Forecast Error (RMSFE), which is defined as follows:

$$RMSFE(\hat{Y}) = \sqrt{\frac{1}{n} \sum_{i=1}^n (\hat{Y}_i - Y_i)^2}$$

where \hat{Y}_i is the i^{th} forecasted value of the variable Y and where Y_i is the actual value of the i^{th} variable.

The research problem of this paper is as follows:

Does using the M-MIDAS approach in forecasting 1- and 2-step ahead realized volatility result in better out-of-sample performance compared to the AR(1) model?

Furthermore, the following sub-questions are defined as:

1. Does using the Almon lag as the weighting scheme for the M-MIDAS lead to lower RMSFE than when using the step function?
2. How do the M-MIDAS models perform when forecasting in the two different periods?

3. How accurate are the h -step ahead forecasts, when forecasting in the different MIDAS methods and in the different periods (with $h = 1, 2$)?

In this research I will refer to the first period as the 'calm period' and the other will be called as the 'turmoil period'. For the 'calm period' the estimation sample will run from January 11, 2002 until September 8, 2006 and for the 'turmoil period' it runs from January 11, 2002 until December 7, 2007.

The two different out-of-sample periods are as follows:

- 'Calm period': September 15, 2006 - August 3, 2007.
- 'Turmoil period': December 15, 2007 - December 12, 2008.

The used periods are the same as the periods used in Alper et al. [2009].

Furthermore, after the RMSFE's are obtained from the forecasts of the weekly realized volatilities of the banks' stocks, I will use the Conditional Predictive Ability (CPA) test to check whether the comparisons with the value of the RMSFE's of the AR(1) model are significantly different from zero. Below I will give a brief explanation of the test, for more details I refer to Giacomini and White [2006]. The test is a complement to the predictive ability testing which is represented by Diebold and Mariano [2012] and West [1996] (DMW), but the test can also be seen as an extension to the DMW test because it applies in all cases in which the DWM applies and in many more besides. Note that the CPA test is applicable to both nested and unnested models.

For this test the null hypothesis is as follows:

$$H_0 : E[L_{t+h}(Y_{t+h}, f_t(\hat{\beta}_{1t})) - L_{t+h}(Y_{t+h}, g_t(\hat{\beta}_{2t})) | \mathcal{G}_t] = 0$$

where $L_{t+h}(\cdot)$ is the loss function and in this research I will use the quadratic loss function. It can be seen that the losses depend on the estimates for $\hat{\beta}_{1t}$ and $\hat{\beta}_{2t}$ and that the expectation is conditional on an information set \mathcal{G} . Regardless of the choice of this information set, when one expresses the null hypothesis in terms of parameters estimates then it allows to capture the impact of estimation uncertainty on relative forecast performance. For this research I chose to use the $\mathcal{G}_t = \mathcal{F}_t$ information set, the so called time- t information set which is appropriate when one wants to produce a forecast for a specific time date h periods in the future. Conditioning on this information set is useful because in case of misspecification of the models one can expect that there is some predictability in future loss differences.

When considering 1-step ahead forecasts, the test statistic is of the form:

$$T_{m,n} = n(n^{-1} \sum_{t=m}^{T-1} F_t \Delta L_{m,t+1})' \hat{\Omega}_n^{-1} (n^{-1} \sum_{t=m}^{T-1} F_t \Delta L_{m,t+1}) = n \bar{Z}'_{m,n} \hat{\Omega}_n^{-1} \bar{Z}_{m,n}$$

where F_t is called the *test function* as in Stinchcombe and White [1998].

$$\bar{Z}_{m,n} \equiv n \sum_{t=m}^{T-1} \bar{Z}_{m,t+1}$$

$$Z_{m,t+1} \equiv F_t \Delta L_{m,t+1}$$

and $\hat{\Omega}_n \equiv n^{-1} \sum_{t=n}^{T-1} Z_{m,t+1} x Z'_{m,t+1}$ is a qxq matrix that consistently estimates the variance of $X_{m,t+1}$.

The null hypothesis of equal conditional predictive ability is rejected when $T_{m,n} > \chi_{q,1-\alpha}^2$, where $\chi_{q,1-\alpha}^2$ is the $(1 - \alpha)$ quantile of a χ_q^2 distribution.

When the forecast horizon $h > 1$ and the information set is the same as above then the test statistic is the same as stated above only the $\tilde{\Omega}_n$ is described as follows:

$$\tilde{\Omega}_n \equiv n^{-1} \sum_{t=m}^{T-h} Z_{m,t+h} Z'_{m,t+h} + n^{-1} \sum_{j=1}^{h-1} w_{n,j} x \sum_{t=m+j}^{T-h} [Z_{m,t+h} Z'_{m,t+h-j} + Z_{m,t+h-j} Z'_{m,t+h}]$$

where $w_{n,j}$ is a weights function such that $w_{n,j} \Rightarrow 1$ as $n \Rightarrow \infty$ for each $j = 1, \dots, h-1$. The null hypothesis is rejected in the same situation as mentioned in the $h = 1$ case.

The plan of the rest of this paper is as follows. Section 2 describes the datasets that were used for conducting both parts of the research. Section 3 describes the different models that were used when in 3.1, first the models used for the replicate part were discussed, followed in 3.2 by the models used for the estimation and forecasting of the banks' stock. Then in section 4 the results from the out-of-sample forecasting will be discussed, again in the same order as in section 3 and in subsection 4.3 I will describe some remarks and recommendations. After that the conclusion follows in section 5, where the research question and the sub-questions will be answered.

For this research I have used Matlab version R2015a and Eviews 9.

2 Data

For the first part (replicating part) the low frequency data will be the quarterly measured output growth and the higher frequency data, measured on a monthly scale will, consist of the following 10 indicators:

Table 1: Descriptions of the 10 leading indicators

Name	Description
1. Spread	Term spread (10-year Federal Funds)
2. Stock	Stock price index (500 common stocks)
3. Hours	Average weekly hours in manufacturing
4. Claims	New claims for unemployment insurance
5. Building	Building permits
6. Vendor	Vendor performance diffusion index
7. ordersc	Orders - consumer goods and materials
8. ordersn	Orders- non defence capital goods
9. Expect	Consumer confidence index (Michigan)
10. M2	Real money supply M2

The data I collected for the replicate part are from <http://qed.econ.queensu.ca/jae/2009-v24.7/clements-galvao/>, the data archief of the Journal of Applied Econometrics where

the paper was published. The following parts are present in the dataset: quarterly output growth for 1959Q1 until 2004Q4 and the quarterly vintages for this variable since 1965Q4. Furthermore, it contains the final data (monthly and quarterly) of the 10 indicators as mentioned in table 1 for the period of 1959M1 until 2003M12. At last, it also has the real-time monthly vintages and the monthly vintages (the latter used for the end-of-sample vintage data) for the leading indicators hours and building for the period of 1959M1 until 2003M12.

In Clements and Galvão [2009] they used two types of approaches for using past data in the models for the leading indicators to estimate a regression in real time, namely the Real-time vintage data (RTVint) and the End-of-sample vintage (EndVint). For the latter approach, to estimate the forecasting model, one uses at the forecast horizon t the output growth data that is obtained from the current vintage that is measured at time $t+1$. However, this approach can sometimes lead to difficulties because the vintages measured at time $t+1$ will be a mixture of first-released data, data that is revised only for a few times and data that has been revised for some large amount of times. This brings us to the real-time vintage data approach, which only uses first-released data for the estimation of the models as for the forecasting parts. For the part where only five out of ten leading indicators are used in the M-MIDAS model, we only include the five indicators where the data is available in real-time monthly vintages. These indicators are: Spread, Stock, Hours, Building and Expect.

For the second part of the research I collected the closing prices, measured daily and weekly, from Bloomberg for the four banks' stocks as mentioned before. I chose to leave the currency of the stocks as it is and not to convert it to a common currency because I will examine all the stocks apart within the models and only the RMSFE (which are not dependent on currency) are then compared to the other stocks.

It should be mentioned that in this research a week consists of 5 days because the weekends are left away. For both the weekly and the daily measured prices the data runs from December 7, 2001 until December 19, 2008. In the datasets, there were some missing observations due to for example holidays, I chose to fill these gaps with the closing price of the day/week before to make it a complete time series. I think this is an appropriate way because when the markets are closed, the stock prices don't change.

Another feature I found was that in the MUFNG dataset the closing prices of the stock until October 11, 2007 were 1000 times larger than the successive ones. I assumed this was because after October 11, 2007 it has been decided to sell the stock in 1/1000 tranches. For this research I divided all the values before October 11, 2007 by 1000 as to assume that the stock was always sold in tranches. Leaving the dataset as it was leads to a biased time series and could not be an option.

The amount of observations for the weekly measured closing prices is 368, and the daily variant contains 1836 observations.

After the transformations described above, the closing prices are then transformed to returns which are defined as: $r_t = \log(P_t) - \log(P_{t-1})$, where r_t and P_t stands for respectively the return and the closing price at time t . Then I will use the weekly measured returns to calculate realized volatilities (RV) in the following way:

$$RV_t = r_t^2$$

and for the daily measured returns, the returns are defined as: $r_{t-1} = \log(P_{t-1}) - \log(P_{t-1-n/d})$, where n is 1 for the first lag, 2 for the second lag and so on and d stands for trading days. Then the right-hand side (RHS) variables, also RV's are calculated as follows:

$$\begin{aligned} RV_{t-1-1/d} &= r_{t-1}^2 = (\log(P_{t-1}) - \log(P_{t-1-1/d}))^2 \\ RV_{t-1-2/d} &= r_{t-1}^2 = (\log(P_{t-1}) - \log(P_{t-1-2/d}))^2 \\ &\vdots \\ RV_{t-1-15/d} &= r_{t-1}^2 = (\log(P_{t-1}) - \log(P_{t-1-15/d}))^2 \end{aligned}$$

For the 1-step ahead forecast all the variables above are included in the model, for the 2-step ahead forecast the first lag is omitted. In the formula above the $-1/d$ part for example means that you take the 1 day lagged value of the realized volatility and where -1 (week) equals $-5/d$, due to a five-day week.

Then RHS' realized volatilities are basically the squared n^{th} -daily returns, measured from day $t - n$ until t , with $n = 5, \dots, 20$.

3 Methodology

In the following two subsection I will describe the models that I have used in this research.

3.1 Models for replicate part

In the replicate part of the paper I will be using a M-MIDAS model and an AR(1) model as the benchmark to compare the RMSFE of the M-MIDAS model with.

3.1.1 AR(1) model

The AR(1) model is defined as follows:

$$(1 - \beta_1 L)Y_t = \alpha + \epsilon_t$$

where Y_t stands for the quarterly output growth at time t and L is the lag operator such that $LY_t = Y_{t-1}$. Furthermore ϵ_t is *i.i.d* and $E[\epsilon_{t+1}|Y_t] = 0$.

3.1.2 Multiple-MIDAS model

To describe the multivariate MIDAS model, I will first show the general univariate MIDAS model for a single explanatory variable and h -step ahead forecast:

$$Y_t = \beta_0 + \beta_1 B(L^{1/m}; \theta) X_{t-h}^{(m)} + \epsilon_t$$

where Y_t stands for the variable measured at the lower frequency at time t and $X_t^{(m)}$ stands for the higher frequency measured variable at time t . This t stands for the basic time unit and m is the higher sampling frequency. Furthermore, $B(L^{1/m}; \theta) =$

$\sum_{j=1}^K b_i(j; \theta) L^{(j-1)/m}$, and $L^{s/m} X_{t-1}^{(m)} = X_{t-1-s/m}^{(m)}$. For simplicity in the rest of the paper I will refer to $X_t^{(m)}$ using just X_t because the variable at the right-hand side is always the variable measured at the higher frequency.

The $b_i(j; \theta)$ is the weighting scheme for the variables at the RHS. For this part of the research I will only make use of the Almon Lag model or polynomial distributed lag model (PDL):

$$b_i(j; \theta) = \sum_{j=0}^K \theta_j (i)^j$$

where i stands for the polynomial degree.

Using weighting schemes as the one described above has the benefit that you don't have to estimate many parameters when you consider lags of your RHS variable. This is because the weighting scheme models the lag distribution using a low-order polynomial. When one writes out the MIDAS model (in this case the univariate MIDAS) this can be easily seen from the formula. When filling in the formula of $B(L^{1/m}; \theta)$ into the univariate MIDAS model this gives:

$$Y_t = \beta_0 + \beta_1 \left(\sum_{j=1}^K b(j; \theta) L^{(j-1)/m} \right) X_{t-h} + \epsilon_t$$

this is equal to,

$$Y_t = \beta_0 + \beta_1 \left((b(1; \theta) L^{(0)/m}) + b(2; \theta) L^{1/m} + \dots + b(K; \theta) L^{(K-1)/m} \right) X_{t-h} + \epsilon_t$$

From this it is easy to see that the weighting scheme is used to give a weight to every lag of the variable X .

The Almon Lag model makes the assumption that the lag coefficients follow a polynomial in the lag length, and the K stands for the amounts of lags included. The weights for the Almon lag (that is, θ) are estimated within the model.

In Clements and Galvão [2009] the authors used an Exponential Almon Lag as the weighting scheme, however when conducting this research, Eviews constantly gives the 'overflow' error, when using this Exponential Almon lag.

Except for looking at the predictive power of one variable it is interesting to consider the predictive power of multiple variables as can be done using the M-MIDAS model for an h -step ahead forecast that is used in this research:

$$Y_t = \beta_0 + \sum_{i=1}^{n_l} \beta_{1i} B_i(L^{1/m}; \theta) X_{i,t-h} + \epsilon_t$$

where n_l stands (for this case) for the amount of monthly leading indicators, so in this case it will be equal to 10 or 5. In this model for each leading indicator now only two parameters has to be estimated, the parameter to describe the lag structure (θ_i) and the weight on the impact on the left-hand side (LHS) variable, β_{1i} .

3.2 Models for banks' stocks

For the second part I used the M-MIDAS (sometimes with a modification due to the characteristics of the data) and the AR(1) models for estimation and forecasting, where the AR(1) functions as the benchmark. The AR(1) model will not be described below, since it has already been described in section 3.1.1, only in this case the Y stands for the weekly measured squared returns. The M-MIDAS (differs from the M-MIDAS as described in section 3.1.2) is described below.

3.2.1 M-MIDAS

Compared to the MIDAS models described earlier, this section describes an even more general version of the midas model where lags of the lower frequency variable are included:

$$Y_t = \beta_0 + \sum_{j=1}^p \beta_j L^j Y_t + \sum_{i=1}^{n_l} \beta_{j+1,i} B_i(L^{1/d}; \theta) X_{i,t-h} + \epsilon_t$$

where, in this case, n_l stands for the amount of RHS' realized volatilities and $B(L^{1/m}; \theta) = \sum_{j=1}^K b_i(j; \theta) L^{(j-1)/m}$, where $K = 15$. Furthermore, h depends on the value of i . When $i = 1$ this implies that $X_{1,t-1-1/d}$, or the first lag. In this paper n_l is equal to 15. This inclusion of the lagged lower frequency variable (e.g. Y_{t-1}) is implemented to correct for autocorrelation. When testing for autocorrelation on the estimation models I found that for the calm period all the four stocks has an autocorrelation of lag 1, except for the 2-step ahead version of the M-MIDAS using a step function for the HSBC and MUFG stock where there was no autocorrelation. This means that the M-MIDAS model for the four stocks in the calm period with autocorrelation, the model will all look like:

$$Y_t = \beta_0 + \beta_1 Y_{t-1} + \sum_{i=1}^{n_l} \beta_{2,i} B_i(L^{1/d}; \theta) X_{i,t-h} + \epsilon_t$$

For the tranquil period again autocorrelation seemed to be present, for the 1-step ahead case, for the HSBC and the JPM stock these were again the first lag autocorrelation that were found. For the DEU and the MUFG stock there also seemed to be a second order autocorrelation to be present so the model for the DEU and the MUFG stock are as follows, to account for this kind of autocorrelation:

$$Y_t = \beta_0 + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \sum_{i=1}^{n_l} \beta_{3,i} B_i(L^{1/d}; \theta) X_{i,t-h} + \epsilon_t$$

For the 2-step ahead case in the turmoil period, the M-MIDAS using Almon Lag for the JPM, DEU and HSBC stock has first lag autocorrelation and the MUFG has a second order autocorrelation. In the M-MIDAS model using step function case, only the DEU stock has a first lag autocorrelation. In this second part of the research the M-MIDAS model makes use of two different weighting schemes one at a time. These schemes are the Almon Lag as described earlier (see section 3.1.2) and step function, the latter can be defined as follows:

$$b_i(j; \theta) = \theta_m I[m \leq lag \leq m + 2]$$

where $I(X)$ is an indicator function and equals 1 if X is true, zero otherwise and 'lag' has the value 1 for lag 1, 2 for lag 2 etc. for lag = 0,...,14. Furthermore $m = 0, 4, 7, 10, 13$ and the first value of m (so, value is 0) corresponds to the value for the first step of the step length η . An example $\eta = 3$ then the first three lagged high frequency lags have the same coefficient, say θ_0 (so, here m equals 0). Then the next three lagged high frequency lags uses, say θ_1 and this continuous up to the maximum lag. In this research I chose to use the default step length of 3.

For both the weighting schemes I used 15 lags per variable ($K = 15$) to estimate the parameters for the weights. I chose for this amount of lags because for the $RV_{t-1-1/d}$ variable, this means that 3 weeks of data are used for the estimation and for the other RHS variables it means that more than 3 weeks of data are incorporated in the estimation of the weights. The amount of parameters to be estimated within the weighting schemes were set to three for the Almon Lag, which was the default setting. For the Step function this amount equal five, also a default setting.

4 Results

In this section I will present the results of this research and again I will start with the replicate part.

4.1 Results for replicate part

The results for using the quarterly vintages of data for the output growth, or the lower measured variable in an AR(1) and a M-MIDAS model, and when using all 10 indicators as the leading indicators in the M-MIDAS model can be seen in table 2. The different models and their use of real-time data can be found in the columns and the rows represents the h-step ahead forecast the models have made for $h = 1, 2$ or 4.

In table 2A, the ratios of the RMSFE for the indicated use of real-time data (RTVint or EndVint) to that for when final data are used can be found. Table 2B shows the same ratio but to the use of an AR(1) model with the indicated use of the different real-time data.

Table 2: Using quarterly vintages of data only for output growth and using all 10 indicators

[A] benchmark: indicated model with indicated use of final vintage data				
	AR(1)		M-MIDAS	
h-step	RTVint.	EndVint.	RTVint.	EndVint.
h = 1	0.860	0.894	0.694	0.621
h = 2	0.913	0.991	0.762	0.839
h = 4	0.873	0.985	0.918	1.126

[B] benchmark: AR with indicated use of real-time data				
	AR(1)		M-MIDAS	
h-step	RTVint.	EndVint.	RTVint.	EndVint.
h = 1	X	X	1.029	1.024
h = 2	X	X	1.110	1.119
h = 4	X	X	1.617	1.392

The values in both tables are the ratios of the RMSFE of the indicated model to its benchmark. The benchmark in table 2A is the indicated model, but with the use of final data. For table 2B this is the AR(1) when using real-time data. In this table, all 10 indicators are included during estimation and forecasting.

One can see that the ratios from the AR(1) to that of the use of real-time data differs from the ratios in table II of Clements and Galvão [2009]. However, the ratios for the use of the EndVint does seem to be closer to the value in Clements and Galvão [2009] than the use of RTVint.

When looking at the ratios of the RMSFE of the M-MIDAS models to that of the corresponding benchmarks one can again see that the ratios are different from those in the paper I tried to replicate. There is however a simple explanation for this, since in that paper the authors used a different weighting schemes than as I did in this paper (due to the 'overflow'-error as mentioned in section 3.1.2). This makes that the ratios for the M-MIDAS as used in Clements and Galvão [2009] and the ratios obtained from the M-MIDAS used in this paper are not comparable when the goal is just to replicate those values. However I will still analyze the results as stated in this paper and it can be seen that the M-MIDAS model using RTVint or EndVint has a better accuracy than the same model but with the use of final vintage data for almost every case. Only when the model makes a 4-step ahead forecast using EndVint data the model has a lower performance compared to the use of final vintage instead. Looking at the lower part of the table the ratios of the RMSFE indicate that the M-MIDAS model for both uses of real-time data perform (much) worse than the AR(1) model.

As mentioned in section 2 the use of RTVint has the benefit, compared to the use of EndVint, that the data hasn't been revised later on so that the observations has not been some mixture of data. This has led to some better or somewhat equally good accuracy of the M-MIDAS using RTVint compared to the use of EndVint. The only exception is the result for the 4-step ahead forecast.

The next table is the same table as table 2 except that only the leading indicators that are available in real-time monthly vintages are now included as the higher frequency

variables (these include 5 variables instead of 10).

Table 3: Using quarterly vintages of data only for output growth for 5 indicators

[A] benchmark: indicated model with indicated use of final vintage data				
	AR(1)		M-MIDAS	
h-step	RTVint.	EndVint.	RTVint.	EndVint.
h = 1	0.860	0.894	0.748	0.672
h = 2	0.913	0.991	0.733	0.755
h = 4	0.873	0.985	0.881	1.226

[B] benchmark: AR with indicated use of real-time data				
	AR(1)		M-MIDAS	
h-step	RTVint.	EndVint.	RTVint.	EndVint.
h = 1	X	X	0.950	1.088
h = 2	X	X	0.987	1.060
h = 4	X	X	1.695	1.484

The entries in the table are calculated by dividing the RMSFE of the models by the RMSFE of the same models but using final data (in tabel [A]) or the RMSFE of the AR(1) when using real-time data (in tabel [B]). In this table only the 5 leading indicators which are available in real-time monthly vintages are used as the high frequency variables.

Also for these M-MIDAS ratios, as can be found in table 3, the ratios cannot be compared to the ratios of table II in Clements and Galvão [2009], so I will only discuss the ratios of the table above. Again it can be seen that the M-MIDAS model using RTVint or EndVint is more accurate than the same model but using final vintage data, except for the 4-step ahead forecast. When comparing the M-MIDAS with the AR(1) both using one of the two choices for real-time data the M-MIDAS is somewhat equally accurate as the AR(1) except for the 4-step ahead forecast case.

Comparing table 2 and table 3 it seems that for the comparison of the M-MIDAS using rather RTVint or EndVint to the same model but now using final vintage data, the use of only the variables that are available in real-time does not make a difference compared to using all 10 indicators. However when comparing the M-MIDAS using RTVint or EndVint to the AR(1) model using also RTVint or EndVint, the use of the 5 indicators leads to an improvement especially in the 2-step ahead forecast case.

4.2 Results for banks' stock prices

For the results of the second part of this research I will start discussing the results from the first period, the 'Calm period'.

Table 4: RMSFE of M-MIDAS to that of the AR(1) for the Calm Period

h-step	Weighting scheme	JPM	DEU	HSBC	MUFG
1-step	Almon	0.409 (0,001 ⁻)	0.617 (0,153 ⁻)	0.695 (0,097 ⁻)	0.512 (0,000 ⁻)
	Step	0.256 (0,000 ⁻)	0.377 (0,024 ⁻)	0.524 (0,009 ⁻)	0.353 (0,000 ⁻)
2-step	Almon	0.372 (0,000 ⁻)	0.659 (0,022 ⁻)	0.701 (0,218 ⁻)	0.509 (0,000 ⁻)
	Step	0.257 (0,000 ⁻)	0.359 (0,025 ⁻)	0.540 (0,333 ⁺)	0.354 (0,000 ⁻)

This table shows the ratios for the Calm period. These ratios (the entries) are calculated by dividing the RMSFE of the M-MIDAS model, with the use of the corresponding weighting scheme by the RMSFE of the AR(1) model. In the brackets are the p-values calculated using the CPA-test. A + (-) sign indicates that the AR(1) model has a smaller (larger) RMSFE than the M-MIDAS model.

Table 4 shows the ratios of the RMSFE when doing a 1- and 2-step ahead forecast using the M-MIDAS model with either the Almon Lag or the step function as the weighting scheme. The ratios are calculated by dividing the RMSFE of the M-MIDAS by that of the AR(1) benchmark model. In the parentheses, the p-values calculated from the CPA-test are denoted and the + (-) symbol indicates that the AR(1) model has a smaller (larger) RMSFE than the model in the M-MIDAS model. The first thing that can be seen from the table is that in most of the cases the M-MIDAS models perform more accurate compared to the AR(1). For the 1-step ahead forecasts, the large p-value for the model using Almon Lag for the DEU and the HSBC' stock implies that the RMSFE of the stocks are significantly not different from those of the AR(1) model. The same holds for the 2-step ahead forecast of the realized volatility of the HSBC' stock using the Almon Lag or the Step function. For the cases where the RMSFE's of the models are significantly different, all the cases have the '-' sign, which indicates that the M-MIDAS models were more accurate than the AR(1) model. Another interesting fact is that using the Step function as the weighting scheme results in less RMSFE than using the Almon Lag, this holds in all cases as stated in table 4. Furthermore, when comparing the ratios between the 1- and the 2-step ahead forecasts, it can be seen that the ratios are close to each other.

To give the reader a better understanding of how the weighting schemes work (in general case as in this specific case) the plots of the Almon Lag and the Step function can be seen in figure 1 (for the 1-step ahead case). Figure 1 shows the weights for the first three RHS variables of the M-MIDAS model for the HSBC stock in the calm period. It also shows that 15 lags are then given those weights to give the current variable a coefficient for in the M-MIDAS model.

Furthermore, figure 1 shows that the Almon Lag is smooth and the Step function is not. From the figure of the step function one can see that when you divide the lags into groups of three successive lags, each lag in a group have the same weight.

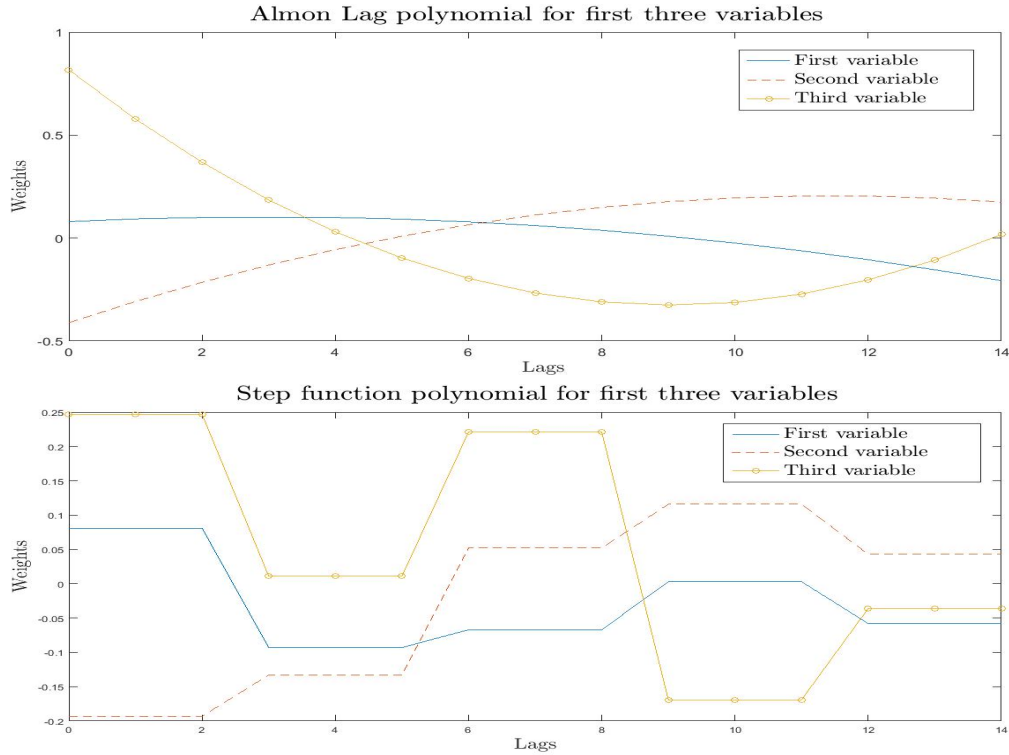


Figure 1: Plots of Almon Lag (upper) and the Step function (lower) for the 1-step ahead forecasting in the calm period. In the figures, the first three lagged high frequency variables are included.

Figure 2 shows the 1-step ahead forecasted realized volatilities of the methods discussed in table 4 to the true values of the RV's for all four stocks (the figures for the 2-step ahead forecasts are not included since these figure look almost the same as the 1-step ahead figures). Note that the AR(1) benchmark model for all four stocks performs poor as the forecasted RV's for this model don't seem to come close to the actual value. Also, in case of a peak the AR(1) gives an indication that a peak is present however this indication comes after the real peak in RV has happend. What also can be seen is that the magnitude of that indication is low compared to the real peak. When looking at the M-MIDAS models it can be seen that in both cases (Almon Lag or Step function as weighting scheme) the models predict the peaks and the valleys more accurate, in sense of time and in sense of value, compared to the AR(1). To illustrate this, take for example the peak in the Deutsche Bank stock' RV that occurred in March, 2007. The M-MIDAS models both forecasted a relatively high value at that time, where the value of the M-MIDAS with Step function was the most close to the actual value. However the AR(1) model predicted a relatively high value for the RV for about a week later.

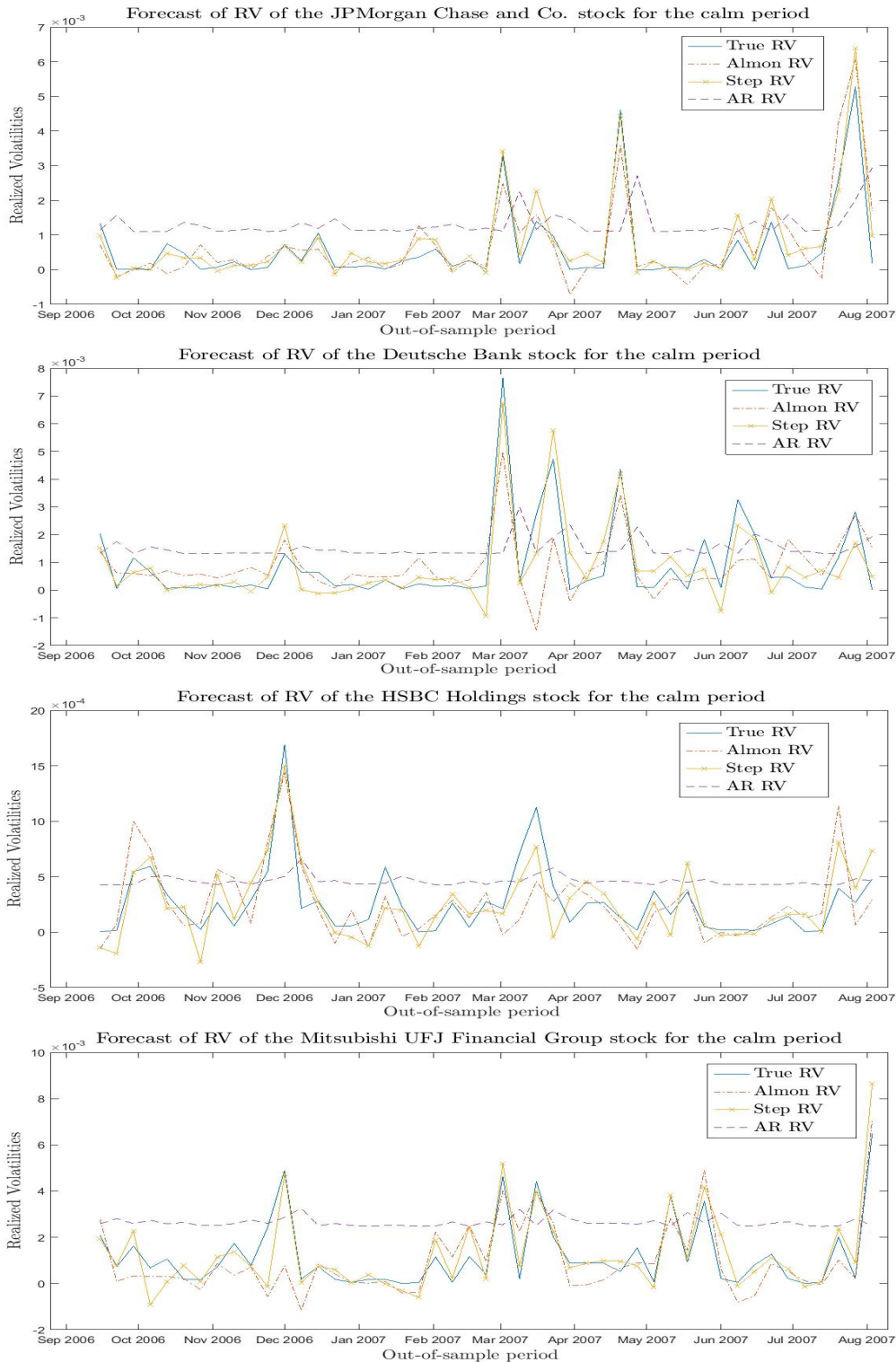


Figure 2: Plots of the actual and the forecasted realized volatilities for the calm period

This figure belongs to the 1-step ahead forecast in the calm period. The first plot belongs to the JPMorgan Chase & Co. stock, the second to the Deutsche Bank stock, the third to HSBC Holdings stock and the last plot belongs to Mitsubishi UFJ Financial Group stock. The solid lines shows the actual realized volatilities, the dash-dot line the forecasted values of realized volatilities forecasted by a M-MIDAS model with Almon lag weighting scheme. The dash-cross line also shows these forecasted value of the M-MIDAS but using a step function as weighting scheme and the dashed line show the forecasted value of realized volatility of the AR(1) benchmark model.

In the table below, the values of the parameters for the 1-step ahead forecasting case can be seen for the HSBC stock. Table 5 is included to give the reader an impression of the values for the parameters (the values for the 2-step ahead case are included in the appendix (B) since the explanation, and so the impression is the same as for the 1-step ahead case).

Table 5: 1-step ahead forecasting parameter values for the HSBC Holdings stock

Period		β_0	β_1		Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	
[A] Calm period	Almon	0.000	-0.343 (0.056)	PDL_1	0.063	-0.523	1.083	-0.787	-0.212	
				PDL_2	0.020	0.117	-0.281	0.216	0.037	
				PDL_3	-0.003	-0.005	0.014	-0.012	-0.001	
	Step	0.000	$Step_1$	0.081	-0.193	0.247	-0.275	0.166		
			$Step_2$	-0.093	-0.133	0.011	0.216	-0.06		
			$Step_3$	-0.067	0.052	0.221	-0.366	0.060		
			$Step_4$	0.003	0.116	-0.169	-0.057	0.155		
			$Step_5$	-0.058	0.043	-0.036	0.275	-0.061		
	Lag 6	Lag 7	Lag 8	Lag 9	Lag 10	Lag 11	Lag 12	Lag 13	Lag 14	Lag 15
	0.150	0.108	0.125	0.522	-0.684	0.091	0.032	-0.087	0.322	-0.208
-0.011	-0.02	-0.03	-0.101	-0.110	0.003	-0.018	0.043	-0.061	0.030	
-0.00	0.00	0.001	0.005	-0.005	-0.000	0.000	-0.003	0.003	-0.001	
-0.132	-0.036	0.242	-0.063	-0.165	0.027	0.014	0.1231	0.065	-0.116	
0.360	-0.213	0.080	0.227	-0.447	0.082	-0.016	0.1901	-0.072	0.001	
0.132	-0.005	-0.046	0.182	-0.198	-0.016	-0.023	0.071	0.084	-0.073	
0.000	-0.293	0.263	0.028	-0.277	0.197	-0.009	-0.040	0.091	-0.028	
-0.071	0.089	-0.127	0.057	-0.115	0.120	-0.103	0.005	0.072	-0.04	
Period		β_0	β_1		Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	
[B] Turmoil period	Almon	0.000	-0.363 (0.048)	PDL_1	0.338	-0.675	0.979	-0.646	-0.194	
				PDL_2	-0.038	0.135	-0.216	0.146	0.039	
				PDL_3	0.000	-0.005	0.010	-0.007	-0.002	
	Step	0.000	$Step_1$	0.174	-0.232	0.260	-0.291	0.152		
			$Step_2$	-0.048	-0.112	0.048	0.154	-0.015		
			$Step_3$	-0.014	0.016	0.188	-0.300	-0.036		
			$Step_4$	0.027	0.07	-0.122	-0.09	-0.139		
			$Step_5$	-0.058	0.055	-0.045	0.238	-0.050		
	Lag 6	Lag 7	Lag 8	Lag 9	Lag 10	Lag 11	Lag 12	Lag 13	Lag 14	Lag 15
	0.134	0.071	0.052	0.587	-0.637	0.095	-0.067	-0.044	0.373	-0.253
-0.018	-0.001	0.000	-0.114	0.102	-0.032	0.043	0.005	-0.077	0.056	
0.001	0.000	-0.001	0.006	-0.005	0.002	0.003	-0.000	0.004	-0.003	
-0.099	-0.053	0.194	0.007	-0.187	0.016	0.065	0.063	0.075	-0.112	
0.262	-0.213	0.088	0.204	-0.419	0.021	0.113	0.077	-0.043	0.002	
0.197	-0.007	-0.031	0.170	-0.197	-0.054	0.035	0.050	0.069	-0.06	
-0.010	-0.209	0.171	0.110	-0.277	0.097	0.088	-0.078	0.068	-0.01	
-0.051	0.020	-0.041	0.029	-0.095	0.080	-0.026	-0.059	0.067	-0.02	

This table shows the estimated value of the indicated models for the HSBC Holdings stock for the calm and the turmoil period. In the brackets the value's of the standard error is reported. The values are checked for significance, therefore the p-values are not reported in the table.

In table 5 the PDL_i (for $i = 1, 2$ and 3) show the weights given to the corresponding lags. The same holds for the $Step_j$ (for $j = 1, \dots, 5$) values. One should note that for example the weight $Step_1$ for lag 1 given by the step function is the same as the weights in the step polynomial for the first three lags. A comparison between the figure of the first three lags in the Step polynomial (figure 1) and the weights for the first three lags given by the Step function, both in the calm period, one can see this relationship. The relationship between the Almon Lag weights figure and the weights presented in table 5 cannot be seen that easily due to having a more complicate formula in comparison to the Step function.

The parameter values for the AR(1) model can be found in appendix B.

Now that I have discussed the first period, let's see how the models are performing in the second period.

Table 6: RMSFE of M-MIDAS to that of the AR(1) for the turmoil Period

h-step	Weighting scheme	JPM	DEU	HSBC	MUFG
1-step	Almon	0.934 (0,632 ⁻)	1.017 (0,195 ⁻)	0.671 (0,371 ⁻)	1.194 (0,751 ⁺)
	Step	0.547 (0,439 ⁻)	0.510 (0,188 ⁻)	0.541 (0,299 ⁻)	0.650 (0,503 ⁻)
2-step	Almon	0.923 (0,307 ⁻)	0.701 (0,333 ⁻)	0.620 (0,394 ⁻)	1.157 (0,338 ⁺)
	Step	0.591 (0,359 ⁻)	0.517 (0,342 ⁻)	0.525 (0,210 ⁻)	0.641 (0,454 ⁻)

The entries are ratios calculated by dividing the RMSFE of the M-MIDAS model, with the use of the corresponding weighting scheme by the RMSFE of the AR(1) model, all models are used in the turmoil period. In the brackets are the p-values calculated using the CPA-test. A + (-) sign indicates that the AR(1) model has a smaller (larger) RMSFE than the M-MIDAS model.

The ratios of the RMSFE of the M-MIDAS models for the turmoil period can be seen in table 6, where again the AR(1) is the benchmark. The p-values calculated using the CPA-test indicates that none of the RMSFE's of all the different cases are significantly different from those of the AR(1) model. This means that for the turmoil period, the different models do not significantly outperform the benchmark, where in most of the cases for the calm period they did outperform the benchmark. Also, this implies that there is significant difference between the accuracy of the 1- and 2-step ahead forecasts of the models.

Now I will examine the plots of the forecasted values of the RV by the different models. The graphs can be seen in figure 3 (again, only for the 1-step ahead case since the 2-step ahead graphs looks almost the same as the graphs of the 1-step ahead case).

Also in the turmoil period, the AR(1) model is not accurate in predicting the timing as the magnitude of a peak or a valley. The timing is too late and the magnitude too low. Compared to the M-MIDAS with Almon Lag and the M-MIDAS with Step function these models still looks more accurate than the AR(1) model, however their RMSFE's are not significantly different from those of the AR(1) model. But looking at the period after September 2008, where the crisis somewhat started, the performance of all the models are getting much worse than in the period before.

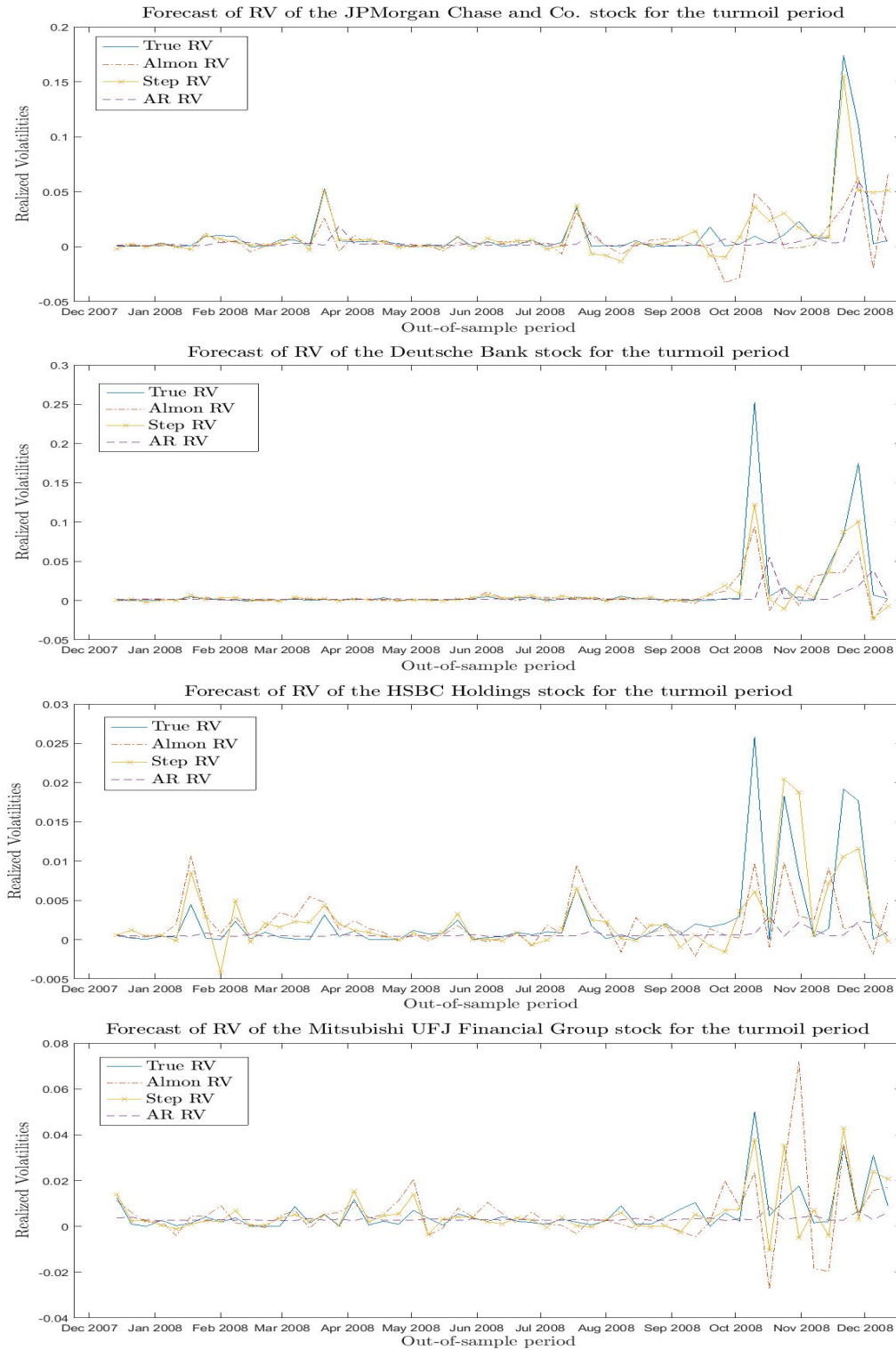


Figure 3: Plots of the actual and the forecasted realized volatilities for the turmoil period

This figure belongs to the 1-step ahead forecast in the turmoil period. The first plot belongs to the JPMorgan Chase & Co. stock, the second to the Deutsche Bank stock, the third to HSBC Holdings stock and the last plot belongs to Mitsubishi UFJ Financial Group stock. The solid lines shows the actual realized volatilities, the dash-dot line the forecasted values of realized volatilities forecasted by a M-MIDAS model with Almon Lag weighting scheme. The dash-cross line also shows these forecasted value of the M-MIDAS but using a step function as weighting scheme and the dashed line show the forecasted value of realized volatility of the AR(1) benchmark model.

4.3 Remarks and Recommendations

In the first part of this paper (replicate part) I considered different kinds of data, namely real-time data (EndVint and RTVint) and final data. Furthermore, I compared the M-MIDAS models with the AR(1) models. For the estimation of the M-MIDAS models I used the Almon Lag and not the Exponential Almon Lag as the authors of Clements and Galvão [2009] had used, due to an error. For further research it would be an idea to compare these models again but using different estimation and forecasting sample (as I did for the banks' stock part) to see how accurate the models then are when using the different kinds of data. Also one could try to use the Exponential Almon Lag when the error is fixed.

For the second part I considered two different weighting schemes for the M-MIDAS model, namely the Almon Lag and the Step function and how they perform when conducting 1- and 2-step ahead forecasts of realized volatility in two different periods. From the comparison of the M-MIDAS models with these weighting schemes to the use of an AR(1) model one saw that the M-MIDAS models were more accurate in most of the cases for the calm period. In particular, the M-MIDAS model with the Step function was the most accurate out of this three models (M-MIDAS using Step function, M-MIDAS using Almon Lag and the AR(1) model). However, in the turmoil period the RMSFE's of the M-MIDAS models were not significantly different from those of the AR(1) model. For further research it would be interesting to also consider other weighting schemes, like the Exponential Almon Lag or the Beta Lag and see how well these weighting schemes for the M-MIDAS are performing.

Furthermore, I used the closing prices of four different banks' stock and derived the realized volatilities which I then used in the different models. A disadvantage for using realized volatilities is that this 'measure' of volatility (which in fact actual volatility is impossible to measure) is not accurate. For further research one could instead of predicting volatilities, for example try to predict the closing values of stock prices using the M-MIDAS model. Another idea is to consider different kinds of stocks' like for example stocks from or indicators from a different sectors and see how accurate the models then are.

Another idea for further research is to include some other measure of accuracy (instead of the use of RMSFE) to compare the forecasting power of the different models.

5 Conclusion

This research consists of two part, the goal of the first part (replicate part) was to replicate some of the results in Clements and Galvão [2009]. In that paper the authors forecasted the quarterly output growth using 10 or 5 leading indicators with monthly vintages of macroeconomic variables. The aim of the second part (banks' stock part) was to compare the M-MIDAS models using either the Almon Lag or the Step function as the weighting scheme with the AR(1) model as I measured the accuracy of the model by means of RMSFE. In this part the models conducted a 1- and 2-step ahead forecast of the realized volatilities. In the M-MIDAS model used for this forecasting, the LHS variable was the weekly measured realized volatility and the variables measured on a daily scale can be found on the RHS.

For the replicate part the conclusion was that the M-MIDAS models using the real-time data were more accurate in the forecasting of the quarterly output growth compared to the same model but with the use of final data. This was the case for both the use of the 10 leading indicators and when using only the indicators that were available in real-time monthly vintages. The only exception for this conclusion is the 4-step ahead forecast case where the EndVint version of the M-MIDAS had a poorer performance than the final vintage version. However, it should be mentioned that in this paper the weighting scheme that was used in the M-MIDAS model was the Almon Lag. This is not the same function as the researchers in Clements and Galvão [2009] used, they used the Exponential Almon Lag. I did not use the Exponential Almon Lag because it resulted in an error.

When comparing the M-MIDAS models with the AR(1) with indicated use of real-time data in both the 10 and 5 leading indicator cases and in all the h-step ahead forecast cases (for $h = 1, 2$ or 4) the M-MIDAS model was less or equally accurate as the AR(1) model.

For the second part of the paper I will answer the research problem and the sub-questions. The conclusion of the first sub-question was that the M-MIDAS with step function was more precise in forecasting the RV of the banks' stock compared to the M-MIDAS using the Almon lag for the calm period. For the turmoil period forecasts the models' RMSFE are not significantly different. For the second sub-question I conclude that for the calm period, the M-MIDAS models are more accurate than the AR(1) model in most of the cases, however for the turmoil period all the M-MIDAS' RMSFE were not significantly different from those of the AR(1) indicating equal accuracy. For the third sub-question, the values for the RMSFE of the 1- and 2-step ahead forecast are close to each other. For the calm period, in some cases the 1-step ahead' RMSFE was more accurate than those of the 2-step ahead forecasts. However for some cases the opposite holds. For the turmoil period, the RMSFE's were not significantly different from each other. Now coming back at the main research problem, which was: 'Does using the M-MIDAS approach in forecasting 1- and 2-step ahead realized volatility result in better out-of-sample performance compared to the AR(1) model?'. Using the results and the answers to the sub-questions I conclude that the M-MIDAS approach in forecasting 1- and 2-week ahead weekly realized volatility is more accurate in terms of RMSFE compared to the AR(1) model for the calm period. However, the difference in accuracy for the M-MIDAS and the AR(1) in the turmoil period is not significant.

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A Parameter values M-MIDAS model for HSBC Holdings stock (2-step ahead forecasting)

Table 7: 2-step ahead forecasting

Period		β_0	β_1		Lag 2	Lag 3	Lag 4	Lag 5	
Calm period	Almon	0.000	-0.318 (0.054)	PDL_1	-0.491	1.062	-0.804	-0.178	
				PDL_2	0.130	-0.279	0.220	0.028	
				PDL_3	-0.178	0.028	-0.012	-0.001	
	Step	0.000	$Step_1$	-0.177	0.258	-0.300	0.192		
			$Step_2$	-204	0.063	0.187	-0.042		
				$Step_3$	0.020	0.236	-0.363	0.056	
				$Step_4$	0.116	-0.171	-0.074	0.166	
				$Step_5$	0.030	-0.046	0.288	-0.074	
Lag 6	Lag 7	Lag 8	Lag 9	Lag 10	Lag 11	Lag 12	Lag 13	Lag 14	Lag 15
0.150	0.086	0.144	0.509	-0.675	0.092	0.031	-0.076	0.294	-0.193
-0.006	-0.022	-0.037	-0.094	0.105	0.010	-0.024	0.039	-0.048	0.023
-0.000	0.002	0.001	0.004	-0.005	-0.001	0.001	-0.003	0.003	-0.001
-0.145	-0.041	0.252	-0.071	-0.161	0.024	0.020	0.122	0.061	-0.114
0.352	-0.225	0.082	0.236	-0.455	0.088	-0.019	0.201	-0.091	0.010
0.144	-0.005	-0.056	-0.196	-0.238	0.020	-0.033	0.087	0.068	-0.068
-0.009	-0.264	0.246	0.027	-0.275	0.185	-0.003	-0.032	0.078	-0.023
-0.066	0.084	-0.118	0.051	-0.107	0.106	-0.085	-0.001	0.060	-0.033
Period		β_0	β_1		Lag 2	Lag 3	Lag 4	Lag 5	
Turmoil period	Almon	0.000	-0.333 (0.047)	PDL_1	-0.549	0.967	-0.676	-0.139	
				PDL_2	0.128	-0.215	0.150	0.032	
				PDL_3	-0.006	0.010	-0.007	-0.002	
	Step	0.000	$Step_1$	-0.185	0.268	-0.317	0.191		
			$Step_2$	-0.167	0.089	0.146	-0.011		
				$Step_3$	0.017	0.202	-0.295	-0.044	
				$Step_4$	0.075	-0.120	-0.087	0.246	
				$Step_5$	0.038	-0.039	0.246	-0.065	
Lag 6	Lag 7	Lag 8	Lag 9	Lag 10	Lag 11	Lag 12	Lag 13	Lag 14	Lag 15
0.112	0.057	0.087	0.554	-0.628	0.115	-0.076	-0.034	0.33	-0.22
-0.01	-0.01	-0.002	-0.102	0.094	-0.024	0.035	0.002	-0.060	0.044
0.000	0.001	-0.001	0.005	-0.004	0.001	-0.001	-0.000	0.003	-0.002
-0.121	-0.064	0.224	-0.023	-0.181	0.025	0.060	0.062	0.071	-0.104
0.259	-0.222	0.100	0.206	-0.424	0.028	0.094	0.102	-0.061	0.006
0.192	-0.006	-0.041	0.186	-0.235	-0.008	0.014	0.069	0.061	-0.067
-0.050	-0.178	0.161	0.092	-0.268	0.095	0.090	-0.069	0.054	-0.002
-0.033	0.009	-0.039	0.027	-0.093	0.078	-0.024	-0.052	0.053	-0.017

This table shows the estimated value of the indicated models for the HSBC Holdings stock for the calm and the turmoil period. In the brackets the value's of the standard error is reported. The values that are reported are from the 2-step ahead forecasting case. The values are checked for significance, therefore the p-values are not reported in the table.

B Parameter values of AR(1) model

Table 8: Parameter values of the AR(1) model

Period	α	β_1	p-value
Calm period	0.000 (0.000)	0.137 (0.064)	0.032
Turmoil period	0.000 (0.000)	0.098 (0.057)	0.086

The entries are the values for the parameters for the AR(1) model in the indicated period. In the brackets, the standard error is reported. The p-values are for the corresponding β_1 values.